Assignment 3 - RNN - Time-Series Data

Group - 10

A Temperature-forecasting example- Data Upload from Amazon Web Services (AWS) /keras

In [1]:

```
!pip install tensorflow==2.12
```

```
Collecting tensorflow==2.12
  Downloading tensorflow-2.12.0-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_6
4.whl (585.9 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 585.9/585.9 MB 1.1 MB/s eta 0:00:00
Requirement already satisfied: absl-py>=1.0.0 in /usr/local/lib/python3.10/dist-packa
ges (from tensorflow==2.12) (1.4.0)
Requirement already satisfied: astunparse>=1.6.0 in /usr/local/lib/python3.10/dist-pa
ckages (from tensorflow==2.12) (1.6.3)
Requirement already satisfied: flatbuffers>=2.0 in /usr/local/lib/python3.10/dist-pac
kages (from tensorflow==2.12) (24.3.25)
Collecting gast<=0.4.0,>=0.2.1 (from tensorflow==2.12)
  Downloading gast-0.4.0-py3-none-any.whl (9.8 kB)
Requirement already satisfied: google-pasta>=0.1.1 in /usr/local/lib/python3.10/dist-
packages (from tensorflow==2.12) (0.2.0)
Requirement already satisfied: grpcio<2.0,>=1.24.3 in /usr/local/lib/python3.10/dist-
packages (from tensorflow==2.12) (1.62.1)
Requirement already satisfied: h5py>=2.9.0 in /usr/local/lib/python3.10/dist-packages
(from tensorflow==2.12) (3.9.0)
Requirement already satisfied: jax>=0.3.15 in /usr/local/lib/python3.10/dist-packages
(from tensorflow==2.12) (0.4.23)
Collecting keras<2.13,>=2.12.0 (from tensorflow==2.12)
  Downloading keras-2.12.0-py2.py3-none-any.whl (1.7 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 1.7/1.7 MB 1.8 MB/s eta 0:00:00
Requirement already satisfied: libclang>=13.0.0 in /usr/local/lib/python3.10/dist-pac
kages (from tensorflow==2.12) (18.1.1)
Collecting numpy<1.24,>=1.22 (from tensorflow==2.12)
  Downloading numpy-1.23.5-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_64.whl
(17.1 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 17.1/17.1 MB 1.4 MB/s eta 0:00:00
Requirement already satisfied: opt-einsum>=2.3.2 in /usr/local/lib/python3.10/dist-pa
ckages (from tensorflow==2.12) (3.3.0)
Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-packages
(from tensorflow==2.12) (24.0)
Requirement already satisfied: protobuf!=4.21.0,!=4.21.1,!=4.21.2,!=4.21.3,!=4.21.4,!
=4.21.5,<5.0.0dev,>=3.20.3 in /usr/local/lib/python3.10/dist-packages (from tensorflo
w==2.12) (3.20.3)
Requirement already satisfied: setuptools in /usr/local/lib/python3.10/dist-packages
(from tensorflow==2.12) (67.7.2)
Requirement already satisfied: six>=1.12.0 in /usr/local/lib/python3.10/dist-packages
(from tensorflow==2.12) (1.16.0)
Collecting tensorboard<2.13,>=2.12 (from tensorflow==2.12)
  Downloading tensorboard-2.12.3-py3-none-any.whl (5.6 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 5.6/5.6 MB 1.3 MB/s eta 0:00:00
Collecting tensorflow-estimator<2.13,>=2.12.0 (from tensorflow==2.12)
  Downloading tensorflow_estimator-2.12.0-py2.py3-none-any.whl (440 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 440.7/440.7 kB 1.1 MB/s eta 0:00:00
Requirement already satisfied: termcolor>=1.1.0 in /usr/local/lib/python3.10/dist-pac
kages (from tensorflow==2.12) (2.4.0)
Requirement already satisfied: typing-extensions>=3.6.6 in /usr/local/lib/python3.10/
dist-packages (from tensorflow==2.12) (4.10.0)
Requirement already satisfied: wrapt<1.15,>=1.11.0 in /usr/local/lib/python3.10/dist-
packages (from tensorflow==2.12) (1.14.1)
Requirement already satisfied: tensorflow-io-gcs-filesystem>=0.23.1 in /usr/local/li
b/python3.10/dist-packages (from tensorflow==2.12) (0.36.0)
Requirement already satisfied: wheel<1.0,>=0.23.0 in /usr/local/lib/python3.10/dist-p
ackages (from astunparse>=1.6.0->tensorflow==2.12) (0.43.0)
Requirement already satisfied: ml-dtypes>=0.2.0 in /usr/local/lib/python3.10/dist-pac
kages (from jax>=0.3.15->tensorflow==2.12) (0.2.0)
Requirement already satisfied: scipy>=1.9 in /usr/local/lib/python3.10/dist-packages
(from jax>=0.3.15->tensorflow==2.12) (1.11.4)
```

```
Requirement already satisfied: google-auth<3,>=1.6.3 in /usr/local/lib/python3.10/dis
t-packages (from tensorboard<2.13,>=2.12->tensorflow==2.12) (2.27.0)
Collecting google-auth-oauthlib<1.1,>=0.5 (from tensorboard<2.13,>=2.12->tensorflow==
2.12)
  Downloading google_auth_oauthlib-1.0.0-py2.py3-none-any.whl (18 kB)
Requirement already satisfied: markdown>=2.6.8 in /usr/local/lib/python3.10/dist-pack
ages (from tensorboard<2.13,>=2.12->tensorflow==2.12) (3.6)
Requirement already satisfied: requests<3,>=2.21.0 in /usr/local/lib/python3.10/dist-
packages (from tensorboard<2.13,>=2.12->tensorflow==2.12) (2.31.0)
Requirement already satisfied: tensorboard-data-server<0.8.0,>=0.7.0 in /usr/local/li
b/python3.10/dist-packages (from tensorboard<2.13,>=2.12->tensorflow==2.12) (0.7.2)
Requirement already satisfied: werkzeug>=1.0.1 in /usr/local/lib/python3.10/dist-pack
ages (from tensorboard<2.13,>=2.12->tensorflow==2.12) (3.0.2)
Requirement already satisfied: cachetools<6.0,>=2.0.0 in /usr/local/lib/python3.10/di
st-packages (from google-auth<3,>=1.6.3->tensorboard<2.13,>=2.12->tensorflow==2.12)
(5.3.3)
Requirement already satisfied: pyasn1-modules>=0.2.1 in /usr/local/lib/python3.10/dis
t-packages (from google-auth<3,>=1.6.3->tensorboard<2.13,>=2.12->tensorflow==2.12)
(0.4.0)
Requirement already satisfied: rsa<5,>=3.1.4 in /usr/local/lib/python3.10/dist-packag
es (from google-auth<3,>=1.6.3->tensorboard<2.13,>=2.12->tensorflow==2.12) (4.9)
Requirement already satisfied: requests-oauthlib>=0.7.0 in /usr/local/lib/python3.10/
dist-packages (from google-auth-oauthlib<1.1,>=0.5->tensorboard<2.13,>=2.12->tensorfl
ow==2.12) (1.3.1)
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.10/
dist-packages (from requests<3,>=2.21.0->tensorboard<2.13,>=2.12->tensorflow==2.12)
(3.3.2)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-package
s (from requests<3,>=2.21.0->tensorboard<2.13,>=2.12->tensorflow==2.12) (3.6)
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.10/dist-p
ackages (from requests<3,>=2.21.0->tensorboard<2.13,>=2.12->tensorflow==2.12) (2.0.7)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10/dist-p
ackages (from requests<3,>=2.21.0->tensorboard<2.13,>=2.12->tensorflow==2.12) (2024.
2.2)
Requirement already satisfied: MarkupSafe>=2.1.1 in /usr/local/lib/python3.10/dist-pa
ckages (from werkzeug>=1.0.1->tensorboard<2.13,>=2.12->tensorflow==2.12) (2.1.5)
Requirement already satisfied: pyasn1<0.7.0,>=0.4.6 in /usr/local/lib/python3.10/dist
-packages (from pyasn1-modules>=0.2.1->google-auth<3,>=1.6.3->tensorboard<2.13,>=2.12
->tensorflow==2.12) (0.6.0)
Requirement already satisfied: oauthlib>=3.0.0 in /usr/local/lib/python3.10/dist-pack
ages (from requests-oauthlib>=0.7.0->google-auth-oauthlib<1.1,>=0.5->tensorboard<2.1
3,>=2.12->tensorflow==2.12) (3.2.2)
Installing collected packages: tensorflow-estimator, numpy, keras, gast, google-auth-
oauthlib, tensorboard, tensorflow
  Attempting uninstall: tensorflow-estimator
    Found existing installation: tensorflow-estimator 2.15.0
    Uninstalling tensorflow-estimator-2.15.0:
      Successfully uninstalled tensorflow-estimator-2.15.0
  Attempting uninstall: numpy
    Found existing installation: numpy 1.25.2
    Uninstalling numpy-1.25.2:
      Successfully uninstalled numpy-1.25.2
  Attempting uninstall: keras
    Found existing installation: keras 2.15.0
    Uninstalling keras-2.15.0:
      Successfully uninstalled keras-2.15.0
  Attempting uninstall: gast
    Found existing installation: gast 0.5.4
    Uninstalling gast-0.5.4:
      Successfully uninstalled gast-0.5.4
```

```
  Attempting uninstall: google-auth-oauthlib
    Found existing installation: google-auth-oauthlib 1.2.0
    Uninstalling google-auth-oauthlib-1.2.0:
      Successfully uninstalled google-auth-oauthlib-1.2.0
  Attempting uninstall: tensorboard
    Found existing installation: tensorboard 2.15.2
    Uninstalling tensorboard-2.15.2:
      Successfully uninstalled tensorboard-2.15.2
  Attempting uninstall: tensorflow
    Found existing installation: tensorflow 2.15.0
    Uninstalling tensorflow-2.15.0:
      Successfully uninstalled tensorflow-2.15.0
ERROR: pip's dependency resolver does not currently take into account all the package
s that are installed. This behaviour is the source of the following dependency confli
cts.
chex 0.1.86 requires numpy>=1.24.1, but you have numpy 1.23.5 which is incompatible.
pandas-stubs 2.0.3.230814 requires numpy>=1.25.0; python_version >= "3.9", but you ha
ve numpy 1.23.5 which is incompatible.
tf-keras 2.15.1 requires tensorflow<2.16,>=2.15, but you have tensorflow 2.12.0 which
is incompatible.
Successfully installed gast-0.4.0 google-auth-oauthlib-1.0.0 keras-2.12.0 numpy-1.23.
5 tensorboard-2.12.3 tensorflow-2.12.0 tensorflow-estimator-2.12.0
```

In [3]:

```
!wget https://s3.amazonaws.com/keras-datasets/jena_climate_2009_2016.csv.zip
!unzip jena_climate_2009_2016.csv.zip
```

```
--2024-04-08 16:02:19--  https://s3.amazonaws.com/keras-datasets/jena_climate_2009_20
16.csv.zip
Resolving s3.amazonaws.com (s3.amazonaws.com)... 52.216.58.208, 52.217.64.126, 54.23
1.129.152, ...
Connecting to s3.amazonaws.com (s3.amazonaws.com)|52.216.58.208|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 13565642 (13M) [application/zip]
Saving to: 'jena_climate_2009_2016.csv.zip'

jena_climate_2009_2 100%[===================>]  12.94M  39.1MB/s    in 0.3s

2024-04-08 16:02:20 (39.1 MB/s) - 'jena_climate_2009_2016.csv.zip' saved [13565642/13
565642]

Archive:  jena_climate_2009_2016.csv.zip
  inflating: jena_climate_2009_2016.csv
  inflating: __MACOSX/._jena_climate_2009_2016.csv
```

Inspecting the data of the Jena weather dataset - 420451 rows and 15 Features

In [4]:

```
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))

num_variables = len(header)
```

```
print("Number of variables:", num_variables)
num_rows = len(lines)
print("Number of rows:", num_rows)
```

```
['"Date Time"', '"p (mbar)"', '"T (degC)"', '"Tpot (K)"', '"Tdew (degC)"', '"rh
(%)"', '"VPmax (mbar)"', '"VPact (mbar)"', '"VPdef (mbar)"', '"sh (g/kg)"', '"H2OC (m
mol/mol)"', '"rho (g/m**3)"', '"wv (m/s)"', '"max. wv (m/s)"', '"wd (deg)"']
420451
Number of variables: 15
Number of rows: 420451
```

After Inspecting the data, specific values are stored in the temperature and raw_data arrays for later processing or analysis. The comma-separated values are transformed to floating point numbers.

In [5]:

```
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[:]
```

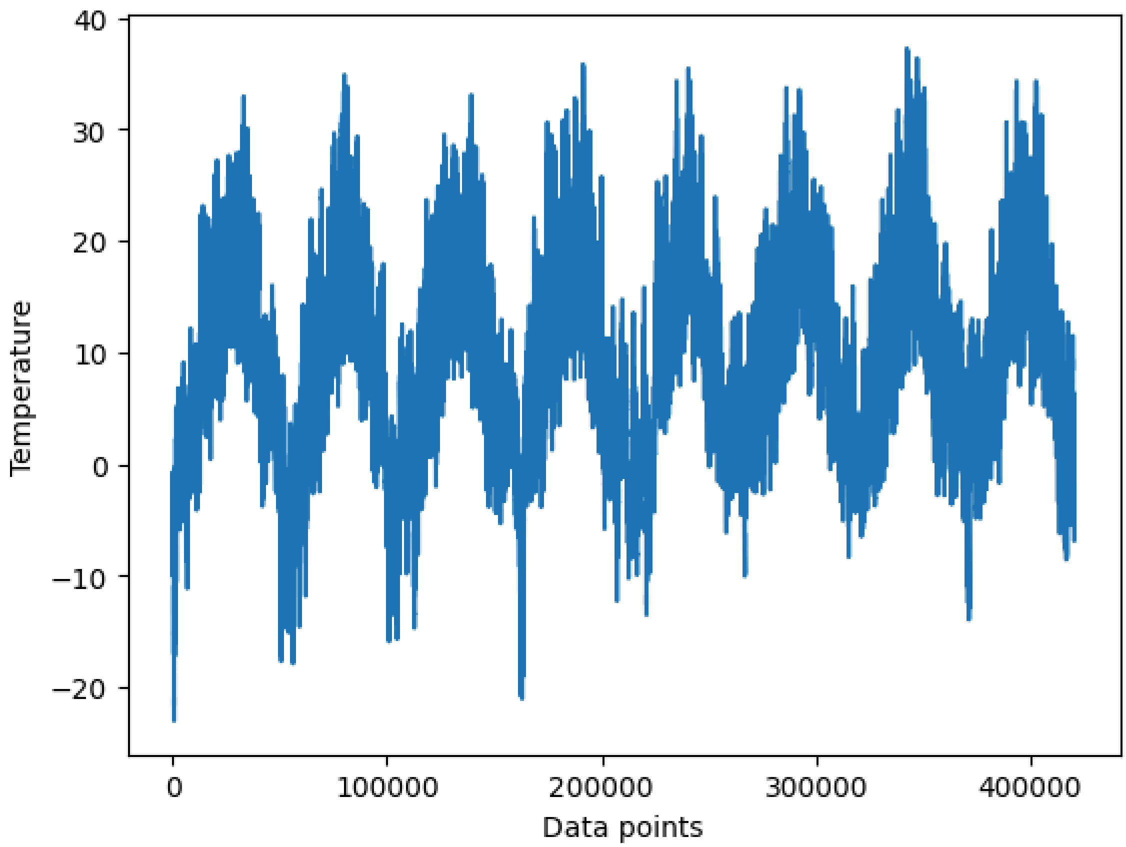
Plotting the graphical representation for temperature timeseries

In [6]:

```
from matplotlib import pyplot as plt
plt.plot(range(len(temperature)), temperature)
plt.xlabel('Data points')
plt.ylabel('Temperature')
```

Out[6]:

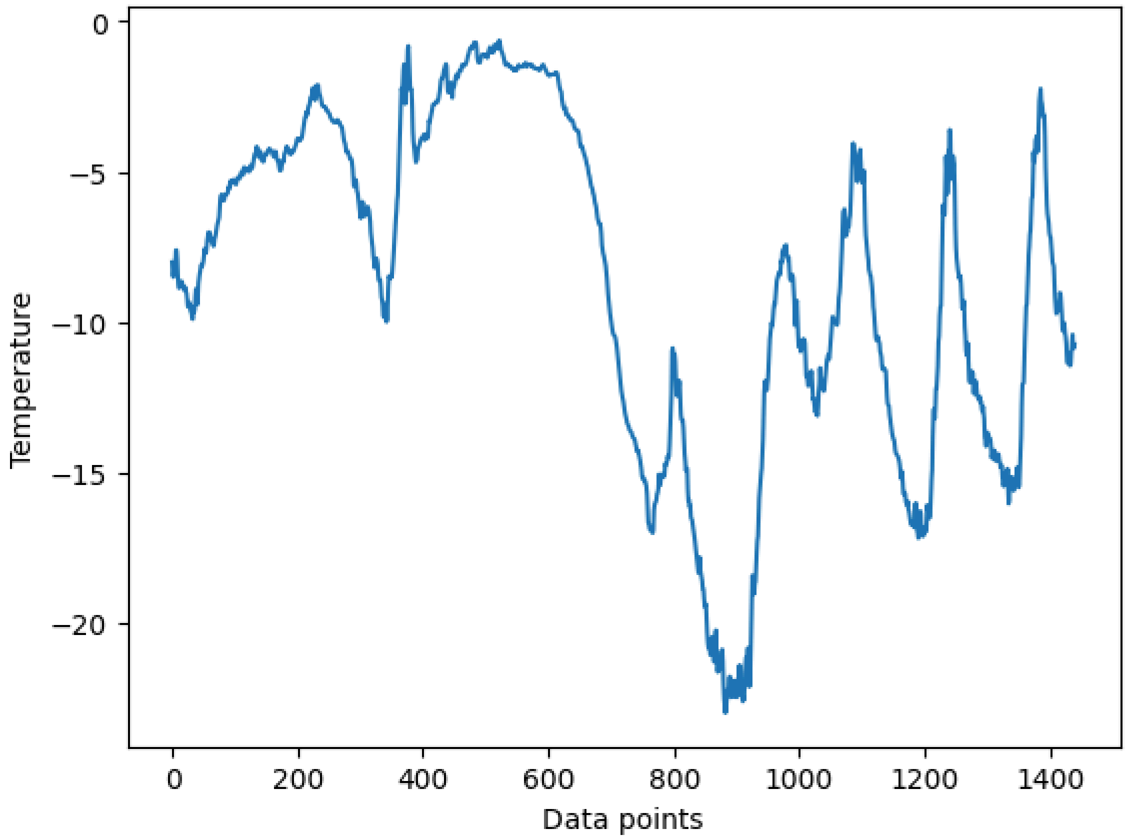
```
Text(0, 0.5, 'Temperature')
```



Plotting the temperature time series for the first ten days: With 144 data points collected in a single day, 10 days will yield 1440 data points.

In [7]:
```
plt.plot(range(1440), temperature[:1440])
plt.xlabel('Data points')
plt.ylabel('Temperature')
```

Out[7]:
```
Text(0, 0.5, 'Temperature')
```



Calculating the number of samples we'll use for each data split 50% designated for training and 25% for validation

In [8]:
```
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: Vectorization is not required because the data is already numerically represented. Nonetheless, it is recommended to normalize all variables because the data scales differ, with temperature ranging from -20 to +30 and pressure measured in millibars..

In [9]:
```
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 [10]:
```
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
```

Generating training, validation, and testing datasets

In [11]:
```
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 this datasets

In [12]:
```
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

Calculating the common sense baseline. MAE: The "evaluate_naive_method" function provides a starting point for evaluating the effectiveness of a basic forecasting strategy that uses the final value in the input sequence to estimate the next value.

In [13]:
```
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
```

The common-sense baseline strategy is to forecast that the temperature in 24 hours will be the same as the current temperature. Using this simple baseline, the validation MAE (Mean Absolute Error) is 2.44 degrees Celsius, while the test MAE is 2.62 degrees Celsius. In other words, assuming that the future temperature remains constant, the average variance would be about two and a half degrees.

A basic machine-learning model - Dense Layer

Training and evaluating a densely connected model

In [14]:
```
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)
```

In [15]:
```
callbacks = [
    keras.callbacks.ModelCheckpoint("jena_dense.keras",
                                    save_best_only=True)]
```

In [16]:
```
model.compile(optimizer="rmsprop", loss="mse", metrics=["mae"])
```

In [17]:
```
history = model.fit(train_dataset, epochs=10,
                    validation_data = val_dataset, callbacks=callbacks)
```

```
Epoch 1/10
819/819 [==============================] - 67s 80ms/step - loss: 12.3279 - mae: 2.724
7 - val_loss: 10.3413 - val_mae: 2.5408
Epoch 2/10
819/819 [==============================] - 52s 63ms/step - loss: 9.0656 - mae: 2.3671
- val_loss: 14.3823 - val_mae: 3.0342
Epoch 3/10
819/819 [==============================] - 56s 68ms/step - loss: 8.3426 - mae: 2.2693
- val_loss: 11.2642 - val_mae: 2.6588
Epoch 4/10
819/819 [==============================] - 53s 64ms/step - loss: 7.8461 - mae: 2.1987
- val_loss: 10.4404 - val_mae: 2.5628
Epoch 5/10
819/819 [==============================] - 52s 64ms/step - loss: 7.5175 - mae: 2.1534
- val_loss: 11.3686 - val_mae: 2.6657
Epoch 6/10
819/819 [==============================] - 57s 70ms/step - loss: 7.2895 - mae: 2.1209
- val_loss: 11.1448 - val_mae: 2.6385
Epoch 7/10
819/819 [==============================] - 54s 65ms/step - loss: 7.0935 - mae: 2.0908
- val_loss: 11.1316 - val_mae: 2.6320
Epoch 8/10
819/819 [==============================] - 58s 70ms/step - loss: 6.9321 - mae: 2.0686
- val_loss: 12.0052 - val_mae: 2.7384
Epoch 9/10
819/819 [==============================] - 55s 66ms/step - loss: 6.7602 - mae: 2.0443
- val_loss: 12.2237 - val_mae: 2.7694
Epoch 10/10
819/819 [==============================] - 52s 63ms/step - loss: 6.6537 - mae: 2.0283
- val_loss: 11.7147 - val_mae: 2.7088
```

In [18]:

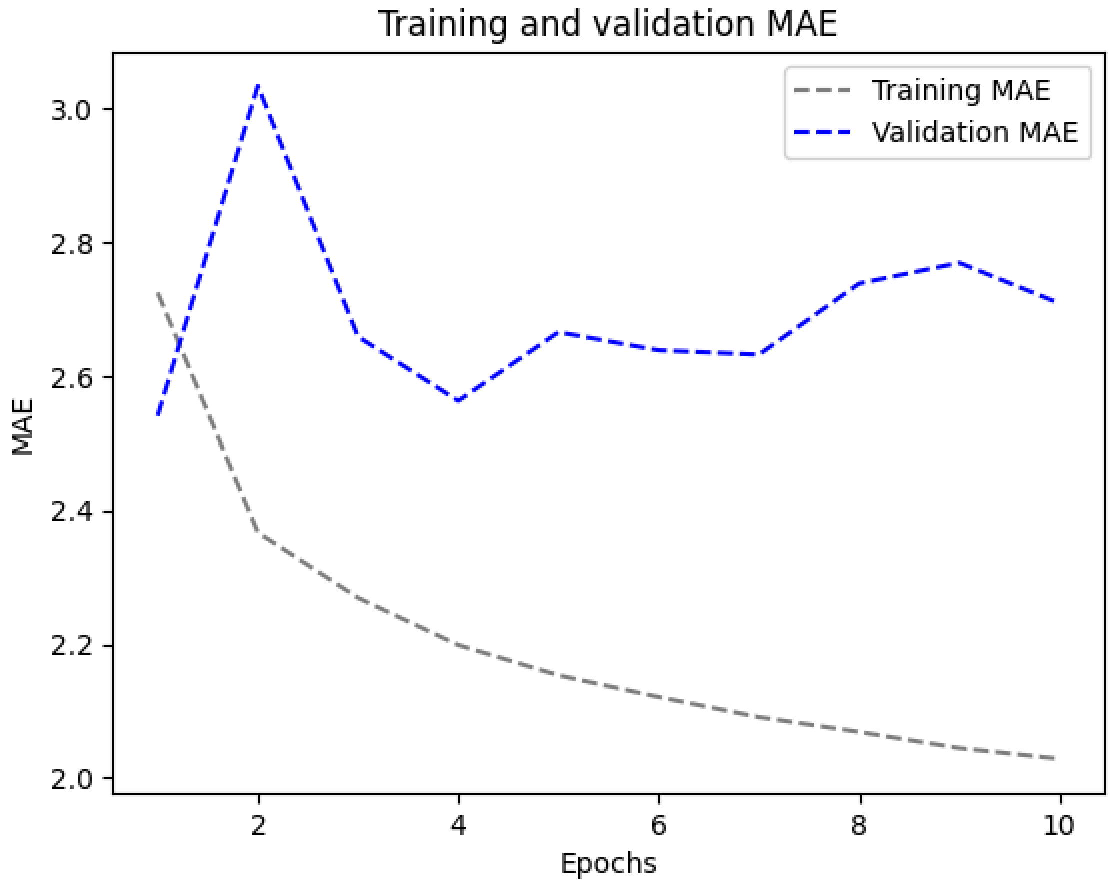
```
model = keras.models.load_model("jena_dense.keras")
print(f"Test MAE: {model.evaluate(test_dataset)[1]:.2f}")
```

```
405/405 [==============================] - 17s 41ms/step - loss: 11.4494 - mae: 2.652
4
Test MAE: 2.65
```

Plotting the results

In [19]:

```
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, color="grey", linestyle="dashed", label="Training MAE")
plt.plot(epochs,  val_loss, color="blue",linestyle="dashed", label="Validation MAE")
plt.title("Training and validation MAE")
plt.xlabel("Epochs")
plt.ylabel("MAE")
plt.legend()
plt.show()
```



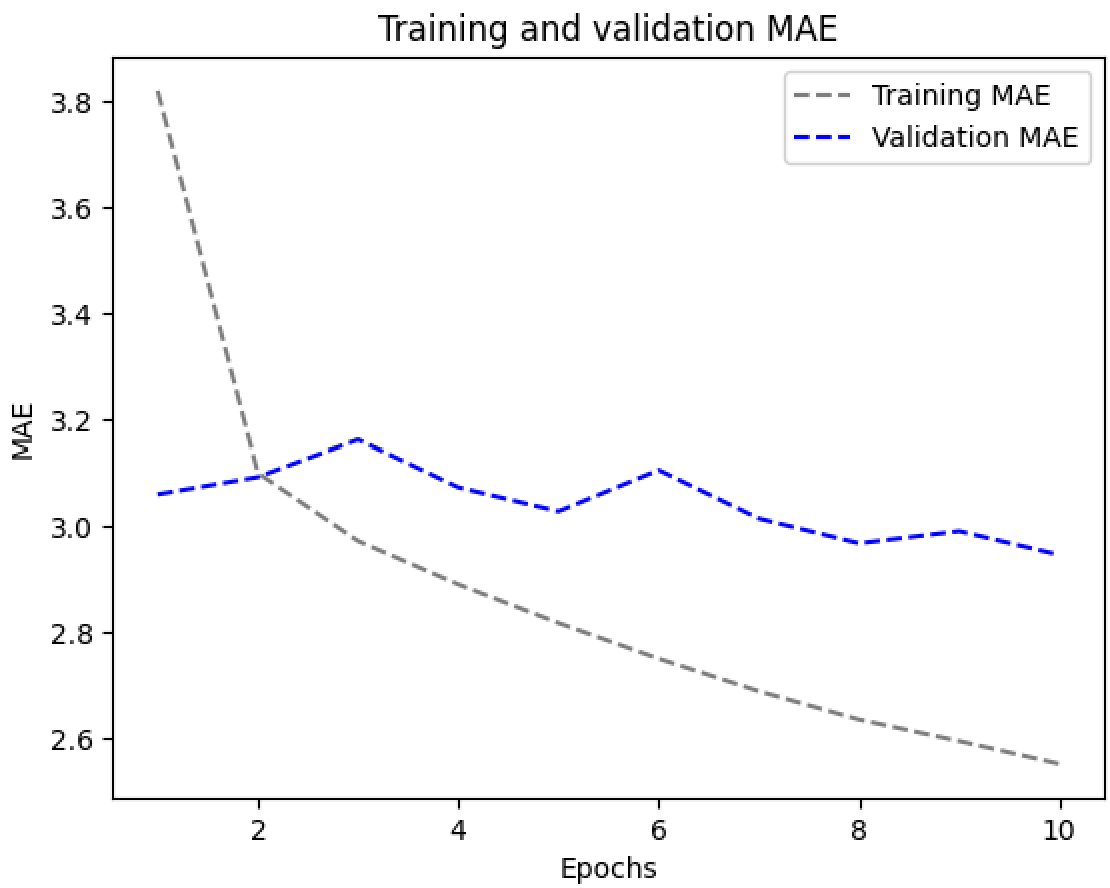
we'll attempt a 1D convolutional model first.

In [20]:
```
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 [==============================] - 88s 105ms/step - loss: 24.8768 - mae: 3.82
09 - val_loss: 15.0230 - val_mae: 3.0605
Epoch 2/10
819/819 [==============================] - 87s 105ms/step - loss: 15.2857 - mae: 3.10
07 - val_loss: 15.4247 - val_mae: 3.0929
Epoch 3/10
819/819 [==============================] - 88s 107ms/step - loss: 14.0077 - mae: 2.97
25 - val_loss: 15.8064 - val_mae: 3.1631
Epoch 4/10
819/819 [==============================] - 86s 105ms/step - loss: 13.2453 - mae: 2.89
06 - val_loss: 15.1340 - val_mae: 3.0736
Epoch 5/10
819/819 [==============================] - 89s 108ms/step - loss: 12.6018 - mae: 2.81
77 - val_loss: 14.6505 - val_mae: 3.0284
Epoch 6/10
819/819 [==============================] - 84s 103ms/step - loss: 12.0375 - mae: 2.75
03 - val_loss: 15.3763 - val_mae: 3.1062
Epoch 7/10
819/819 [==============================] - 87s 106ms/step - loss: 11.5648 - mae: 2.68
89 - val_loss: 14.4824 - val_mae: 3.0149
Epoch 8/10
819/819 [==============================] - 121s 148ms/step - loss: 11.1299 - mae: 2.6
353 - val_loss: 14.0632 - val_mae: 2.9682
Epoch 9/10
819/819 [==============================] - 87s 106ms/step - loss: 10.8000 - mae: 2.59
46 - val_loss: 14.2462 - val_mae: 2.9911
Epoch 10/10
819/819 [==============================] - 85s 103ms/step - loss: 10.4648 - mae: 2.55
17 - val_loss: 13.8290 - val_mae: 2.9462
405/405 [==============================] - 20s 49ms/step - loss: 15.5916 - mae: 3.136
1
Test MAE: 3.14
```

In [21]:

```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, color="grey", linestyle="dashed", label="Training MAE")
plt.plot(epochs,  val_loss, color="blue",linestyle="dashed", label="Validation MAE")
plt.title("Training and validation MAE")
plt.xlabel("Epochs")
plt.ylabel("MAE")
plt.legend()
plt.show()
```



Convolutional data appear to perform worse than dense models or common sense. It might be due to -Weather data does not conform to the assumption of translation invariance. The order in which the data is presented is important. When it comes to estimating the temperature for the following day, recent past data is substantially more informative than data obtained several days ago. Unfortunately, a one-dimensional convolutional neural network cannot capture this critical order of time well..

A Simple RNN

1.An RNN layer that can process sequences of any length

In [22]:

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

model = keras.Model(inputs, outputs)

callbacks = [
    keras.callbacks.ModelCheckpoint("jena_SimRNN.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_SimRNN.keras")
print(f"Test MAE: {model.evaluate(test_dataset)[1]:.2f}")
```

```
Epoch 1/10
819/819 [==============================] - 74s 89ms/step - loss: 139.1008 - mae: 9.71
18 - val_loss: 144.0390 - val_mae: 9.9021
Epoch 2/10
819/819 [==============================] - 74s 90ms/step - loss: 136.5197 - mae: 9.57
46 - val_loss: 143.8109 - val_mae: 9.8785
Epoch 3/10
819/819 [==============================] - 88s 107ms/step - loss: 136.2962 - mae: 9.5
541 - val_loss: 143.7273 - val_mae: 9.8734
Epoch 4/10
819/819 [==============================] - 74s 90ms/step - loss: 136.2446 - mae: 9.54
77 - val_loss: 143.6372 - val_mae: 9.8614
Epoch 5/10
819/819 [==============================] - 75s 92ms/step - loss: 136.1528 - mae: 9.53
75 - val_loss: 143.5836 - val_mae: 9.8540
Epoch 6/10
819/819 [==============================] - 74s 89ms/step - loss: 136.1266 - mae: 9.53
45 - val_loss: 143.5898 - val_mae: 9.8559
Epoch 7/10
819/819 [==============================] - 73s 89ms/step - loss: 136.1154 - mae: 9.53
39 - val_loss: 143.5630 - val_mae: 9.8524
Epoch 8/10
819/819 [==============================] - 78s 95ms/step - loss: 136.0999 - mae: 9.53
16 - val_loss: 143.5681 - val_mae: 9.8546
Epoch 9/10
819/819 [==============================] - 76s 93ms/step - loss: 136.1029 - mae: 9.53
26 - val_loss: 143.5909 - val_mae: 9.8579
Epoch 10/10
819/819 [==============================] - 74s 90ms/step - loss: 136.1089 - mae: 9.53
35 - val_loss: 143.5680 - val_mae: 9.8549
405/405 [==============================] - 20s 46ms/step - loss: 151.3239 - mae: 9.92
39
Test MAE: 9.92
```

2.Simple RNN - Stacking RNN layers

- Stacked SimpleRNN layers with increasing units (14, 14) process sequential data.
- RMSprop optimizer is used with Mean Squared Error (MSE) loss and Mean Absolute Error (MAE) metric.

In [23]:

```
num_features = 14
steps = 120
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)
model = keras.Model(inputs, outputs)

callbacks = [
    keras.callbacks.ModelCheckpoint("jena_SRNN2.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_SRNN2.keras")
print(f"Test MAE: {model.evaluate(test_dataset)[1]:.2f}")
```

```
Epoch 1/10
819/819 [==============================] - 160s 188ms/step - loss: 136.7434 - mae: 9.
5610 - val_loss: 143.3921 - val_mae: 9.8306
Epoch 2/10
819/819 [==============================] - 129s 158ms/step - loss: 135.9407 - mae: 9.
5099 - val_loss: 143.5119 - val_mae: 9.8467
Epoch 3/10
819/819 [==============================] - 132s 160ms/step - loss: 135.8973 - mae: 9.
5041 - val_loss: 143.4196 - val_mae: 9.8378
Epoch 4/10
819/819 [==============================] - 145s 177ms/step - loss: 135.8585 - mae: 9.
4986 - val_loss: 143.4881 - val_mae: 9.8492
Epoch 5/10
819/819 [==============================] - 128s 156ms/step - loss: 135.8365 - mae: 9.
4948 - val_loss: 143.4210 - val_mae: 9.8387
Epoch 6/10
819/819 [==============================] - 146s 179ms/step - loss: 135.8218 - mae: 9.
4930 - val_loss: 143.5286 - val_mae: 9.8542
Epoch 7/10
819/819 [==============================] - 146s 178ms/step - loss: 135.8066 - mae: 9.
4904 - val_loss: 143.4942 - val_mae: 9.8516
Epoch 8/10
819/819 [==============================] - 151s 184ms/step - loss: 135.7936 - mae: 9.
4886 - val_loss: 143.4223 - val_mae: 9.8419
Epoch 9/10
819/819 [==============================] - 146s 178ms/step - loss: 135.7872 - mae: 9.
4880 - val_loss: 143.4623 - val_mae: 9.8451
Epoch 10/10
819/819 [==============================] - 145s 177ms/step - loss: 135.7735 - mae: 9.
4856 - val_loss: 143.4931 - val_mae: 9.8522
405/405 [==============================] - 28s 67ms/step - loss: 151.1129 - mae: 9.89
99
Test MAE: 9.90
```

A simpleRNN with two layer has a MAE of 9.90

A Simple GRU (Gated Recurrent Unit)

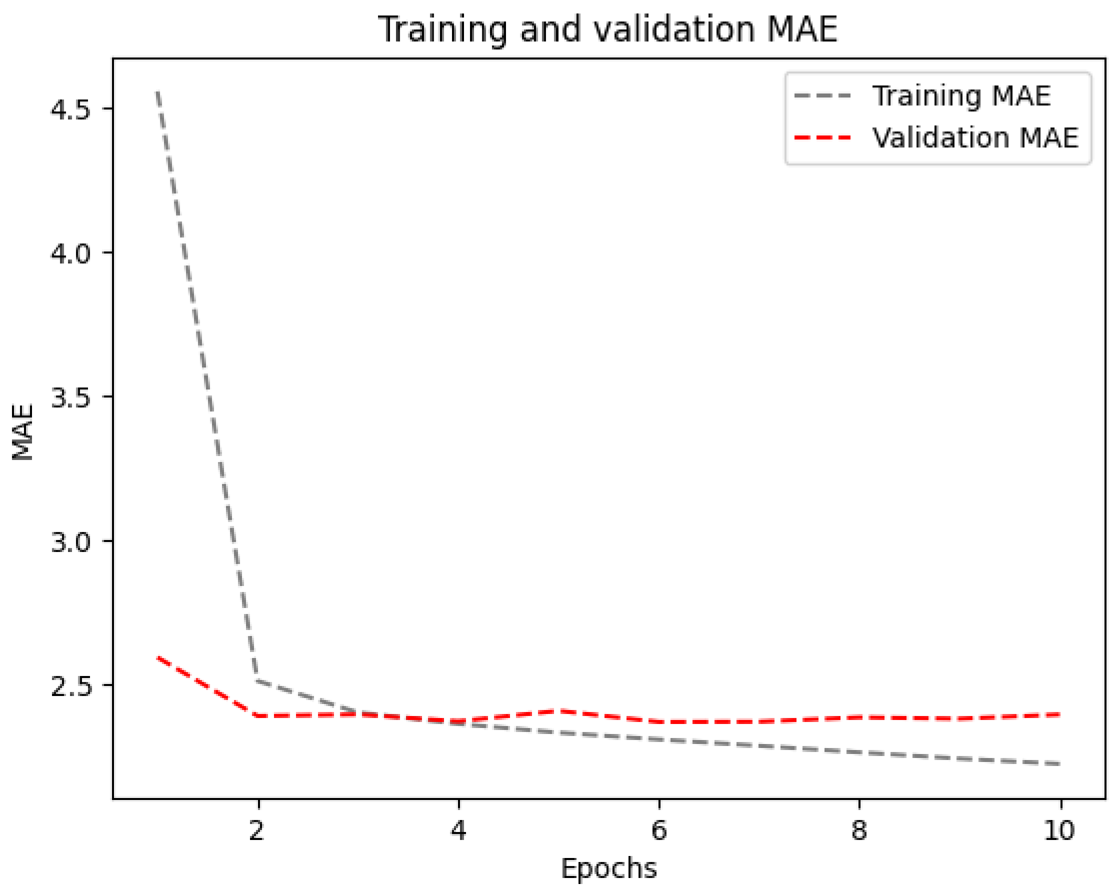
In [24]:
```
inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
x = layers.GRU(16)(inputs)
outputs = layers.Dense(1)(x)
model = keras.Model(inputs, outputs)

callbacks = [
    keras.callbacks.ModelCheckpoint("jena_gru.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)
```

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

```
Epoch 1/10
819/819 [==============================] - 134s 159ms/step - loss: 39.5470 - mae: 4.5
565 - val_loss: 11.9130 - val_mae: 2.5958
Epoch 2/10
819/819 [==============================] - 129s 158ms/step - loss: 10.4367 - mae: 2.5
141 - val_loss: 9.6117 - val_mae: 2.3926
Epoch 3/10
819/819 [==============================] - 128s 156ms/step - loss: 9.4793 - mae: 2.40
48 - val_loss: 9.7162 - val_mae: 2.3981
Epoch 4/10
819/819 [==============================] - 109s 133ms/step - loss: 9.1924 - mae: 2.36
54 - val_loss: 9.5391 - val_mae: 2.3742
Epoch 5/10
819/819 [==============================] - 108s 131ms/step - loss: 8.9557 - mae: 2.33
48 - val_loss: 10.0200 - val_mae: 2.4104
Epoch 6/10
819/819 [==============================] - 125s 153ms/step - loss: 8.7575 - mae: 2.31
11 - val_loss: 9.6091 - val_mae: 2.3719
Epoch 7/10
819/819 [==============================] - 128s 156ms/step - loss: 8.5762 - mae: 2.28
92 - val_loss: 9.5284 - val_mae: 2.3727
Epoch 8/10
819/819 [==============================] - 126s 154ms/step - loss: 8.4031 - mae: 2.26
65 - val_loss: 9.6873 - val_mae: 2.3878
Epoch 9/10
819/819 [==============================] - 107s 131ms/step - loss: 8.2374 - mae: 2.24
48 - val_loss: 9.6477 - val_mae: 2.3830
Epoch 10/10
819/819 [==============================] - 108s 131ms/step - loss: 8.0962 - mae: 2.22
65 - val_loss: 9.8564 - val_mae: 2.3976
405/405 [==============================] - 25s 59ms/step - loss: 9.6709 - mae: 2.4555
Test MAE: 2.46
```

In [25]:

```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, color="grey", linestyle="dashed", label="Training MAE")
plt.plot(epochs,  val_loss, color="red",linestyle="dashed", label="Validation MAE")
plt.title("Training and validation MAE")
plt.xlabel("Epochs")
plt.ylabel("MAE")
plt.legend()
plt.show()
```



LSTM(Long Short-Term Memory)

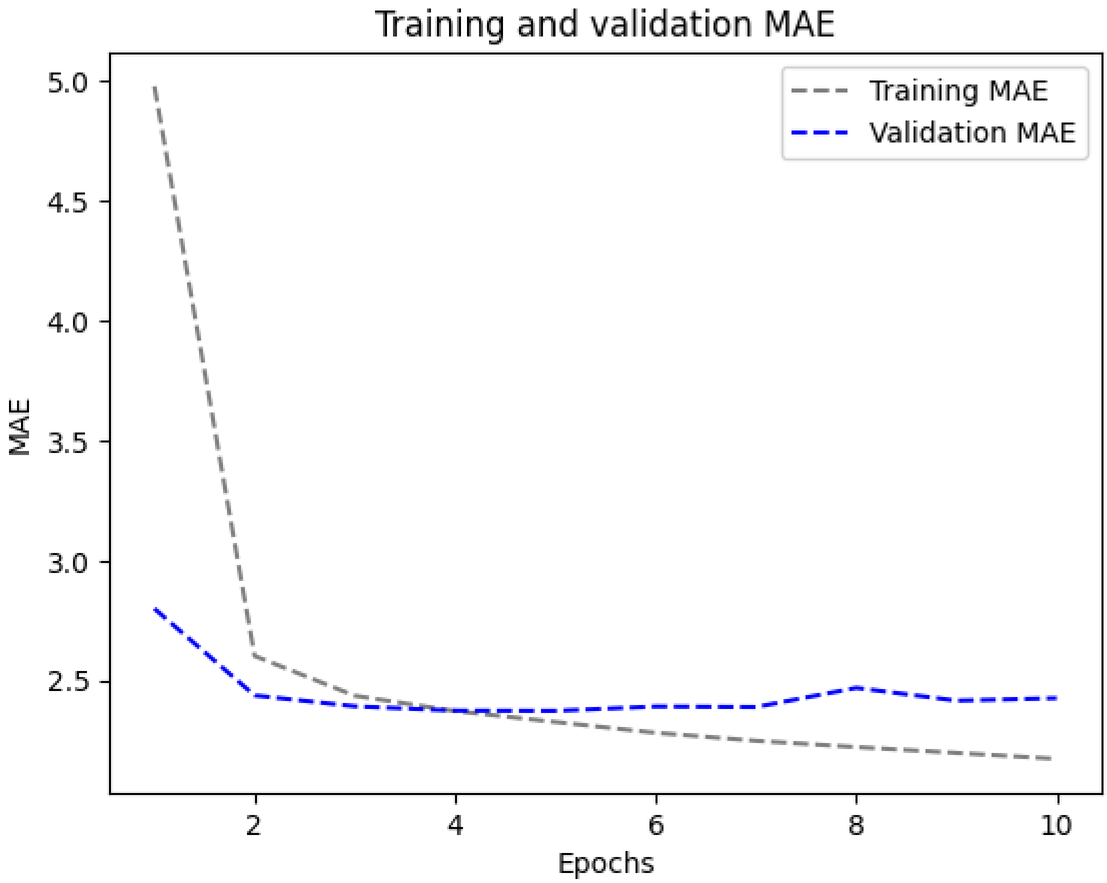
1.LSTM-Simple

In [26]:
```
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 [==============================] - 109s 130ms/step - loss: 46.1355 - mae: 4.9
759 - val_loss: 13.5917 - val_mae: 2.7997
Epoch 2/10
819/819 [==============================] - 128s 156ms/step - loss: 11.3182 - mae: 2.6
025 - val_loss: 9.7433 - val_mae: 2.4377
Epoch 3/10
819/819 [==============================] - 128s 155ms/step - loss: 9.8083 - mae: 2.43
64 - val_loss: 9.4774 - val_mae: 2.3924
Epoch 4/10
819/819 [==============================] - 108s 132ms/step - loss: 9.2604 - mae: 2.37
27 - val_loss: 9.4112 - val_mae: 2.3742
Epoch 5/10
819/819 [==============================] - 126s 153ms/step - loss: 8.8723 - mae: 2.32
68 - val_loss: 9.4437 - val_mae: 2.3734
Epoch 6/10
819/819 [==============================] - 111s 135ms/step - loss: 8.5322 - mae: 2.28
17 - val_loss: 9.5459 - val_mae: 2.3916
Epoch 7/10
819/819 [==============================] - 110s 134ms/step - loss: 8.2569 - mae: 2.24
85 - val_loss: 9.5145 - val_mae: 2.3893
Epoch 8/10
819/819 [==============================] - 108s 132ms/step - loss: 8.0641 - mae: 2.22
23 - val_loss: 10.3989 - val_mae: 2.4692
Epoch 9/10
819/819 [==============================] - 108s 131ms/step - loss: 7.8950 - mae: 2.19
80 - val_loss: 9.8007 - val_mae: 2.4160
Epoch 10/10
819/819 [==============================] - 127s 155ms/step - loss: 7.7070 - mae: 2.17
32 - val_loss: 9.9201 - val_mae: 2.4264
405/405 [==============================] - 27s 63ms/step - loss: 10.7166 - mae: 2.575
7
Test MAE: 2.58
```

In [27]:

```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, color="grey", linestyle="dashed", label="Training MAE")
plt.plot(epochs,  val_loss, color="blue",linestyle="dashed", label="Validation MAE")
plt.title("Training and validation MAE")
plt.xlabel("Epochs")
plt.ylabel("MAE")
plt.legend()
plt.show()
```



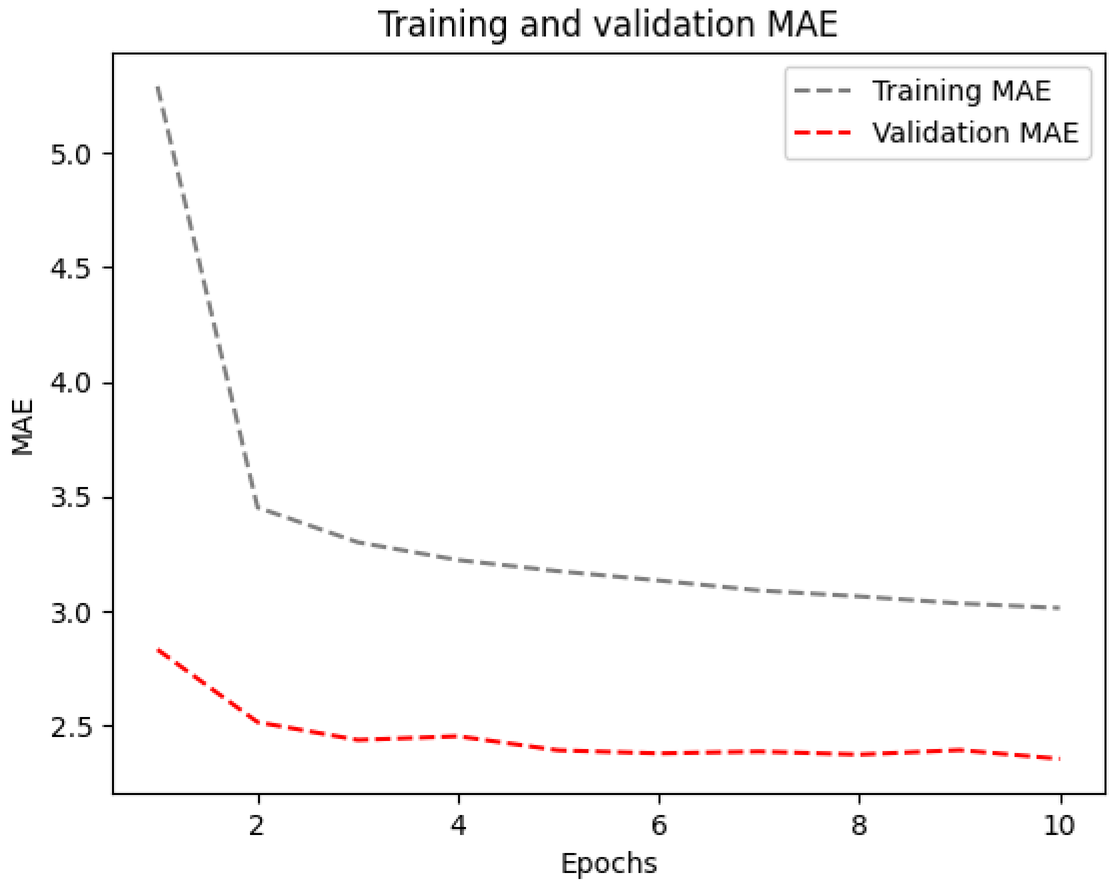
2.LSTM - dropout Regularization

In [28]:
```
inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
x = layers.LSTM(16, recurrent_dropout=0.25)(inputs)
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 [==============================] - 193s 232ms/step - loss: 50.5023 - mae: 5.2
921 - val_loss: 14.0696 - val_mae: 2.8309
Epoch 2/10
819/819 [==============================] - 170s 207ms/step - loss: 20.1604 - mae: 3.4
522 - val_loss: 10.7233 - val_mae: 2.5130
Epoch 3/10
819/819 [==============================] - 172s 210ms/step - loss: 18.3574 - mae: 3.2
998 - val_loss: 9.7014 - val_mae: 2.4351
Epoch 4/10
819/819 [==============================] - 187s 228ms/step - loss: 17.4780 - mae: 3.2
222 - val_loss: 9.8337 - val_mae: 2.4514
Epoch 5/10
819/819 [==============================] - 187s 228ms/step - loss: 16.9700 - mae: 3.1
734 - val_loss: 9.3409 - val_mae: 2.3899
Epoch 6/10
819/819 [==============================] - 188s 230ms/step - loss: 16.4872 - mae: 3.1
325 - val_loss: 9.2639 - val_mae: 2.3763
Epoch 7/10
819/819 [==============================] - 188s 229ms/step - loss: 16.0194 - mae: 3.0
891 - val_loss: 9.3448 - val_mae: 2.3846
Epoch 8/10
819/819 [==============================] - 170s 208ms/step - loss: 15.7572 - mae: 3.0
630 - val_loss: 9.2567 - val_mae: 2.3713
Epoch 9/10
819/819 [==============================] - 185s 225ms/step - loss: 15.4563 - mae: 3.0
326 - val_loss: 9.4359 - val_mae: 2.3909
Epoch 10/10
819/819 [==============================] - 189s 230ms/step - loss: 15.2445 - mae: 3.0
123 - val_loss: 9.1445 - val_mae: 2.3525
405/405 [==============================] - 28s 68ms/step - loss: 10.4929 - mae: 2.555
1
Test MAE: 2.56
```

In [29]:

```
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, color="grey", linestyle="dashed", label="Training MAE")
plt.plot(epochs,  val_loss, color="red",linestyle="dashed", label="Validation MAE")
plt.title("Training and validation MAE")
plt.xlabel("Epochs")
plt.ylabel("MAE")
plt.legend()
plt.show()
```



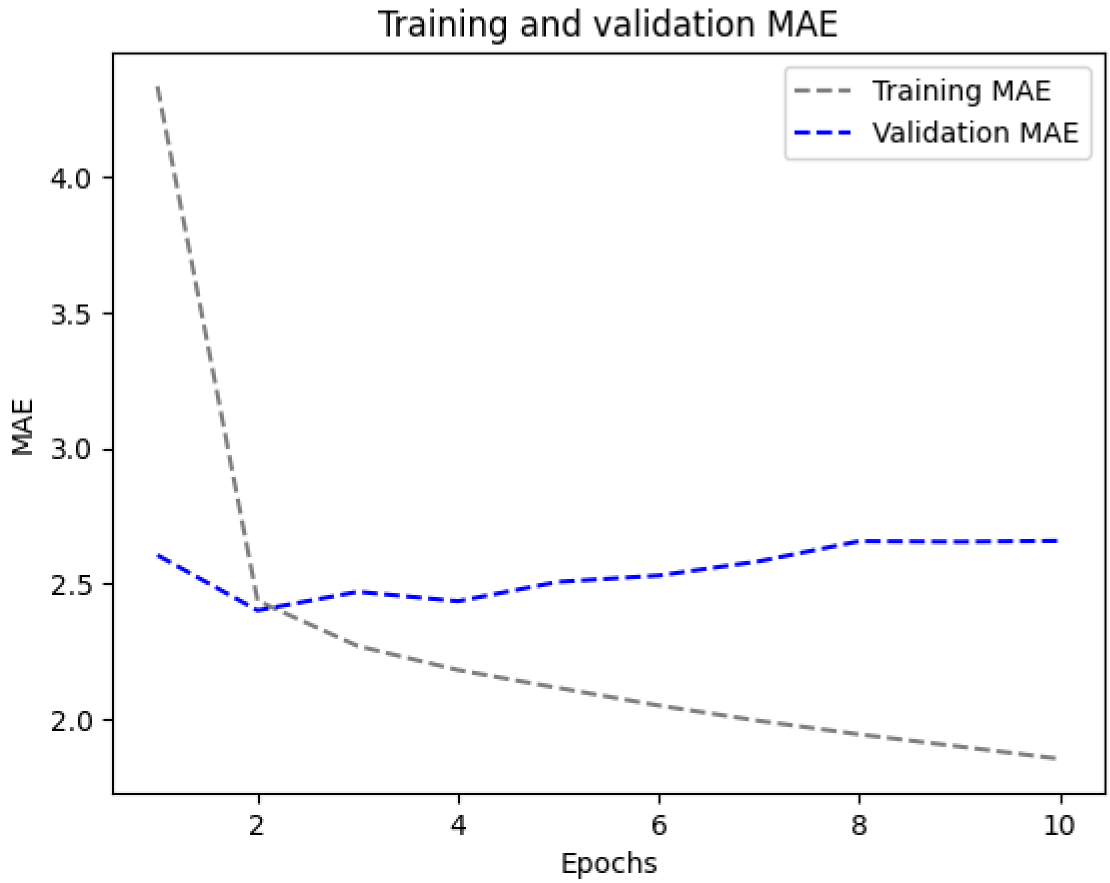
3.LSTM - Stacked setup with 16 units

In [30]:
```
inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
x = layers.LSTM(16, return_sequences=True)(inputs)
x = layers.LSTM(16)(x)
outputs = layers.Dense(1)(x)
model = keras.Model(inputs, outputs)

callbacks = [
    keras.callbacks.ModelCheckpoint("jena_LSTM_stacked1.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_stacked1.keras")
print(f"Test MAE: {model.evaluate(test_dataset)[1]:.2f}")
```

```
Epoch 1/10
819/819 [==============================] - 190s 227ms/step - loss: 35.6446 - mae: 4.3
344 - val_loss: 11.7511 - val_mae: 2.6050
Epoch 2/10
819/819 [==============================] - 185s 226ms/step - loss: 9.8278 - mae: 2.43
63 - val_loss: 9.5037 - val_mae: 2.4009
Epoch 3/10
819/819 [==============================] - 186s 227ms/step - loss: 8.4503 - mae: 2.26
91 - val_loss: 10.0366 - val_mae: 2.4695
Epoch 4/10
819/819 [==============================] - 187s 228ms/step - loss: 7.8028 - mae: 2.18
06 - val_loss: 9.7446 - val_mae: 2.4347
Epoch 5/10
819/819 [==============================] - 177s 216ms/step - loss: 7.3276 - mae: 2.11
43 - val_loss: 10.3941 - val_mae: 2.5063
Epoch 6/10
819/819 [==============================] - 177s 216ms/step - loss: 6.8883 - mae: 2.04
93 - val_loss: 10.6075 - val_mae: 2.5297
Epoch 7/10
819/819 [==============================] - 187s 227ms/step - loss: 6.5168 - mae: 1.99
30 - val_loss: 10.9730 - val_mae: 2.5822
Epoch 8/10
819/819 [==============================] - 189s 230ms/step - loss: 6.1904 - mae: 1.94
29 - val_loss: 11.6485 - val_mae: 2.6565
Epoch 9/10
819/819 [==============================] - 188s 229ms/step - loss: 5.8774 - mae: 1.89
80 - val_loss: 11.4418 - val_mae: 2.6544
Epoch 10/10
819/819 [==============================] - 185s 225ms/step - loss: 5.6076 - mae: 1.85
26 - val_loss: 11.5115 - val_mae: 2.6577
405/405 [==============================] - 37s 87ms/step - loss: 11.1342 - mae: 2.603
8
Test MAE: 2.60
```

In [32]:

```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, color="grey", linestyle="dashed", label="Training MAE")
plt.plot(epochs,  val_loss, color="blue",linestyle="dashed", label="Validation MAE")
plt.title("Training and validation MAE")
plt.xlabel("Epochs")
plt.ylabel("MAE")
plt.legend()
plt.show()
```



4.LSTM - Stacked setup with 32 units

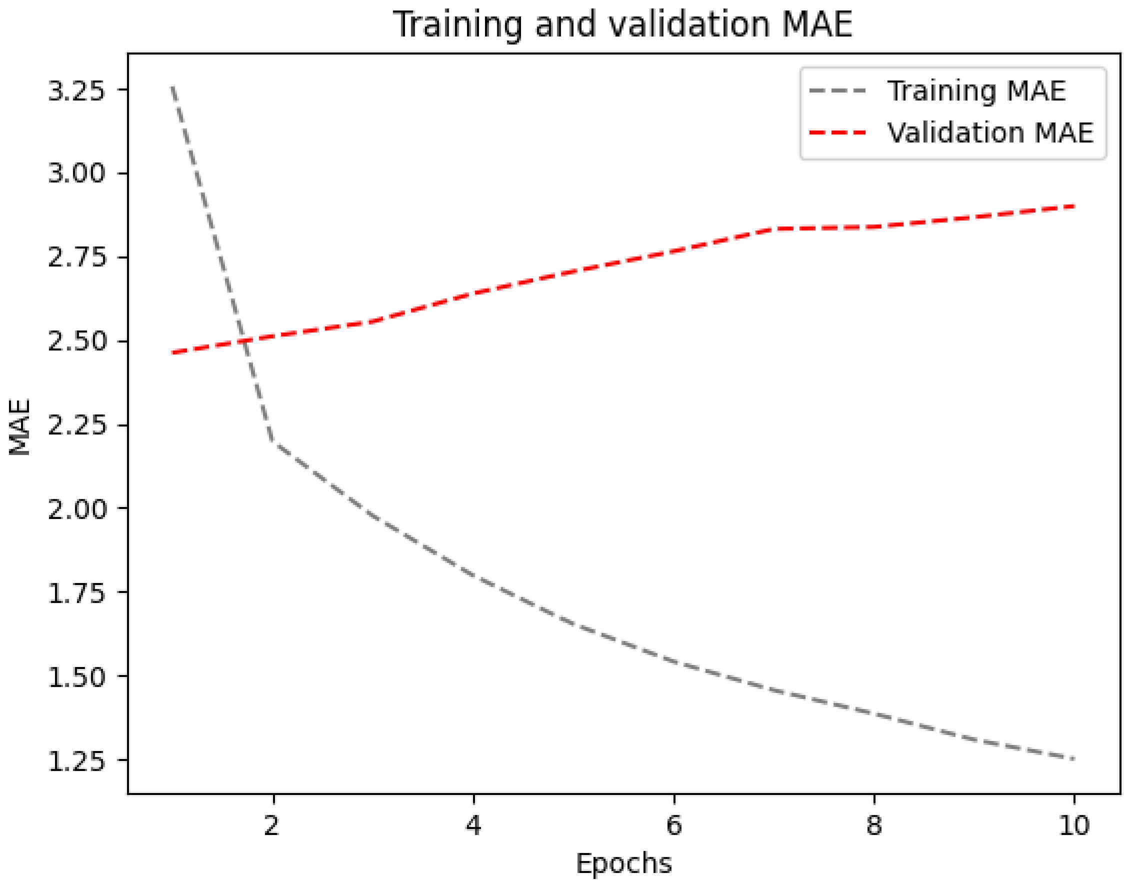
In [33]:

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

callbacks = [
    keras.callbacks.ModelCheckpoint("jena_LSTM_stacked2.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_stacked2.keras")
print(f"Test MAE: {model.evaluate(test_dataset)[1]:.2f}")
```

```
Epoch 1/10
819/819 [==============================] - 289s 337ms/step - loss: 20.5646 - mae: 3.2
552 - val_loss: 10.1024 - val_mae: 2.4611
Epoch 2/10
819/819 [==============================] - 296s 361ms/step - loss: 8.0181 - mae: 2.19
88 - val_loss: 10.5568 - val_mae: 2.5104
Epoch 3/10
819/819 [==============================] - 296s 360ms/step - loss: 6.5299 - mae: 1.97
72 - val_loss: 10.9067 - val_mae: 2.5539
Epoch 4/10
819/819 [==============================] - 296s 361ms/step - loss: 5.4317 - mae: 1.79
95 - val_loss: 11.4266 - val_mae: 2.6375
Epoch 5/10
819/819 [==============================] - 304s 371ms/step - loss: 4.6422 - mae: 1.65
41 - val_loss: 11.9881 - val_mae: 2.7035
Epoch 6/10
819/819 [==============================] - 300s 366ms/step - loss: 4.0481 - mae: 1.54
23 - val_loss: 12.5151 - val_mae: 2.7635
Epoch 7/10
819/819 [==============================] - 272s 332ms/step - loss: 3.6181 - mae: 1.45
70 - val_loss: 13.0589 - val_mae: 2.8302
Epoch 8/10
819/819 [==============================] - 309s 377ms/step - loss: 3.2852 - mae: 1.38
71 - val_loss: 13.1569 - val_mae: 2.8362
Epoch 9/10
819/819 [==============================] - 302s 368ms/step - loss: 2.9314 - mae: 1.30
93 - val_loss: 13.3815 - val_mae: 2.8653
Epoch 10/10
819/819 [==============================] - 301s 367ms/step - loss: 2.6881 - mae: 1.25
23 - val_loss: 13.8184 - val_mae: 2.8984
405/405 [==============================] - 55s 131ms/step - loss: 11.6077 - mae: 2.67
81
Test MAE: 2.68
```

In [34]:

```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, color="grey", linestyle="dashed", label="Training MAE")
plt.plot(epochs,  val_loss, color="red",linestyle="dashed", label="Validation MAE")
plt.title("Training and validation MAE")
plt.xlabel("Epochs")
plt.ylabel("MAE")
plt.legend()
plt.show()
```



5.LSTM - Stacked setup with 8 units

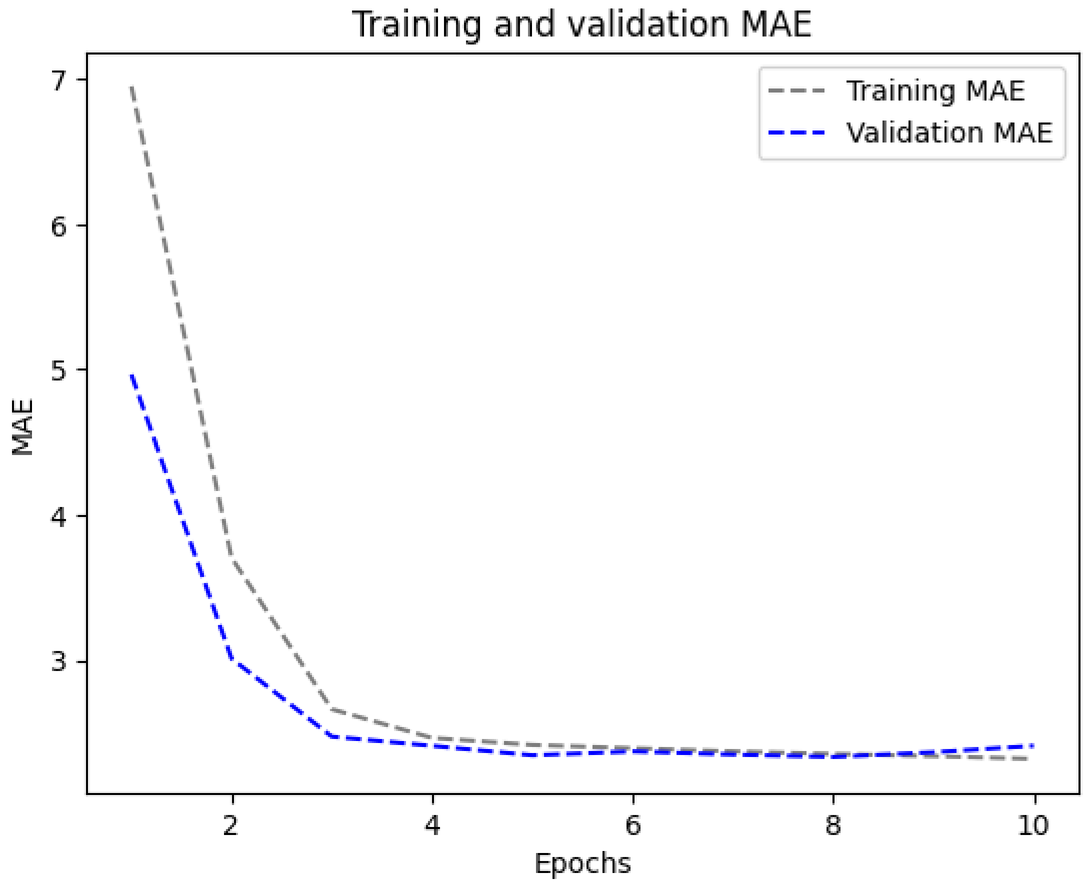
In [35]:

```
inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
x = layers.LSTM(8, return_sequences=True)(inputs)
x = layers.LSTM(8)(x)
outputs = layers.Dense(1)(x)
model = keras.Model(inputs, outputs)

callbacks = [
    keras.callbacks.ModelCheckpoint("jena_LSTM_stacked3.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_stacked3.keras")
print(f"Test MAE: {model.evaluate(test_dataset)[1]:.2f}")
```

```
Epoch 1/10
819/819 [==============================] - 168s 199ms/step - loss: 80.4919 - mae: 6.9
490 - val_loss: 43.6278 - val_mae: 4.9642
Epoch 2/10
819/819 [==============================] - 170s 208ms/step - loss: 25.4033 - mae: 3.7
053 - val_loss: 16.4469 - val_mae: 3.0123
Epoch 3/10
819/819 [==============================] - 159s 194ms/step - loss: 12.0038 - mae: 2.6
634 - val_loss: 10.1599 - val_mae: 2.4749
Epoch 4/10
819/819 [==============================] - 159s 194ms/step - loss: 10.0785 - mae: 2.4
659 - val_loss: 9.6579 - val_mae: 2.4113
Epoch 5/10
819/819 [==============================] - 160s 195ms/step - loss: 9.7105 - mae: 2.41
75 - val_loss: 9.0640 - val_mae: 2.3464
Epoch 6/10
819/819 [==============================] - 160s 195ms/step - loss: 9.5156 - mae: 2.39
47 - val_loss: 9.3260 - val_mae: 2.3728
Epoch 7/10
819/819 [==============================] - 169s 205ms/step - loss: 9.3437 - mae: 2.37
32 - val_loss: 9.1714 - val_mae: 2.3514
Epoch 8/10
819/819 [==============================] - 172s 210ms/step - loss: 9.2049 - mae: 2.35
54 - val_loss: 9.1480 - val_mae: 2.3349
Epoch 9/10
819/819 [==============================] - 176s 214ms/step - loss: 9.0904 - mae: 2.34
02 - val_loss: 9.3738 - val_mae: 2.3671
Epoch 10/10
819/819 [==============================] - 172s 210ms/step - loss: 8.9550 - mae: 2.32
14 - val_loss: 9.7517 - val_mae: 2.4115
405/405 [==============================] - 34s 78ms/step - loss: 10.7810 - mae: 2.563
0
Test MAE: 2.56
```

In [36]:

```
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, color="grey", linestyle="dashed", label="Training MAE")
plt.plot(epochs,  val_loss, color="blue",linestyle="dashed", label="Validation MAE")
plt.title("Training and validation MAE")
plt.xlabel("Epochs")
plt.ylabel("MAE")
plt.legend()
plt.show()
```



6.LSTM - dropout-regularized, stacked model

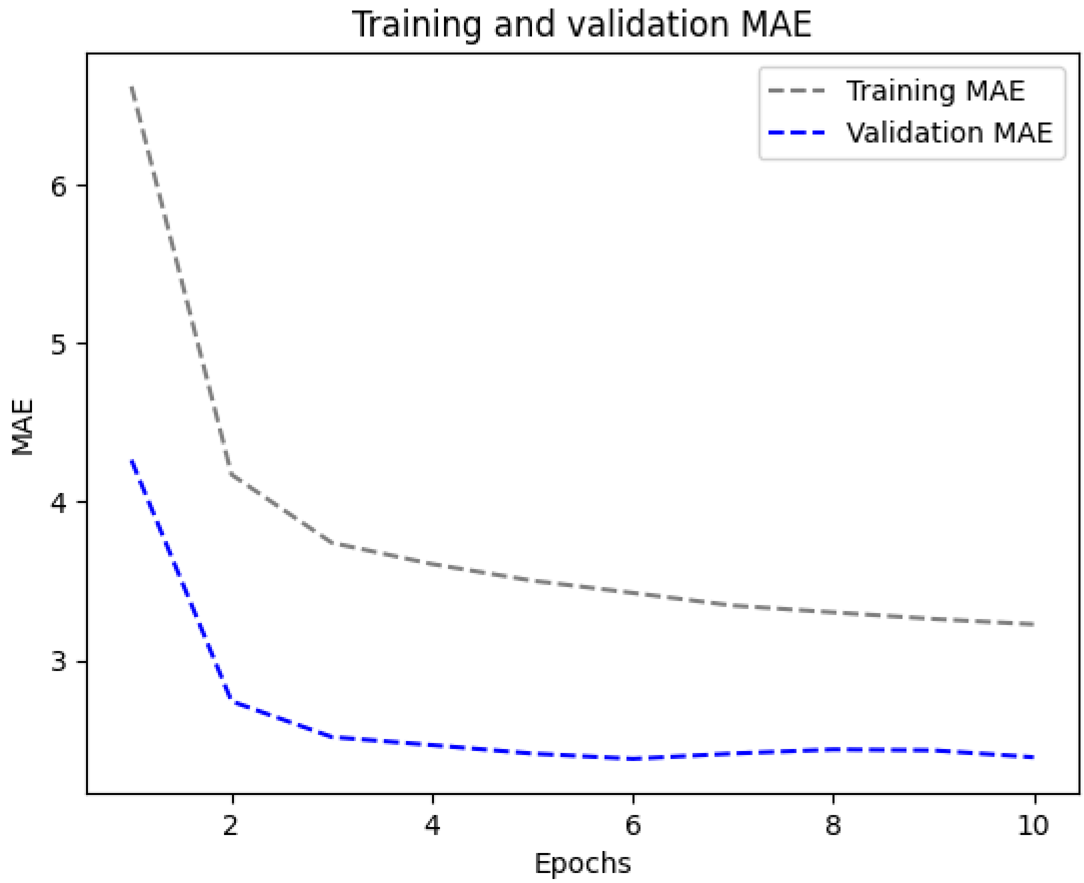
In [37]:

```
inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
x = layers.LSTM(8, recurrent_dropout=0.5, return_sequences=True)(inputs)
x = layers.LSTM(8, 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_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_stacked_LSTM_dropout.keras")
print(f"Test MAE: {model.evaluate(test_dataset)[1]:.2f}")
```

```
Epoch 1/10
819/819 [==============================] - 289s 343ms/step - loss: 74.5529 - mae: 6.6
228 - val_loss: 33.1815 - val_mae: 4.2641
Epoch 2/10
819/819 [==============================] - 283s 345ms/step - loss: 31.0850 - mae: 4.1
720 - val_loss: 13.4745 - val_mae: 2.7395
Epoch 3/10
819/819 [==============================] - 282s 343ms/step - loss: 24.4275 - mae: 3.7
416 - val_loss: 10.7940 - val_mae: 2.5139
Epoch 4/10
819/819 [==============================] - 280s 342ms/step - loss: 22.5763 - mae: 3.6
069 - val_loss: 10.1827 - val_mae: 2.4628
Epoch 5/10
819/819 [==============================] - 286s 349ms/step - loss: 21.2370 - mae: 3.5
019 - val_loss: 9.7306 - val_mae: 2.4093
Epoch 6/10
819/819 [==============================] - 271s 331ms/step - loss: 20.2210 - mae: 3.4
244 - val_loss: 9.4109 - val_mae: 2.3758
Epoch 7/10
819/819 [==============================] - 265s 323ms/step - loss: 19.3058 - mae: 3.3
445 - val_loss: 9.7461 - val_mae: 2.4095
Epoch 8/10
819/819 [==============================] - 276s 337ms/step - loss: 18.7672 - mae: 3.3
015 - val_loss: 9.7408 - val_mae: 2.4350
Epoch 9/10
819/819 [==============================] - 280s 341ms/step - loss: 18.2185 - mae: 3.2
600 - val_loss: 9.7916 - val_mae: 2.4295
Epoch 10/10
819/819 [==============================] - 266s 325ms/step - loss: 17.7810 - mae: 3.2
262 - val_loss: 9.4357 - val_mae: 2.3859
405/405 [==============================] - 36s 86ms/step - loss: 10.9644 - mae: 2.556
0
Test MAE: 2.56
```

In [38]:

```
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, color="grey", linestyle="dashed", label="Training MAE")
plt.plot(epochs,  val_loss, color="blue",linestyle="dashed", label="Validation MAE")
plt.title("Training and validation MAE")
plt.xlabel("Epochs")
plt.ylabel("MAE")
plt.legend()
plt.show()
```



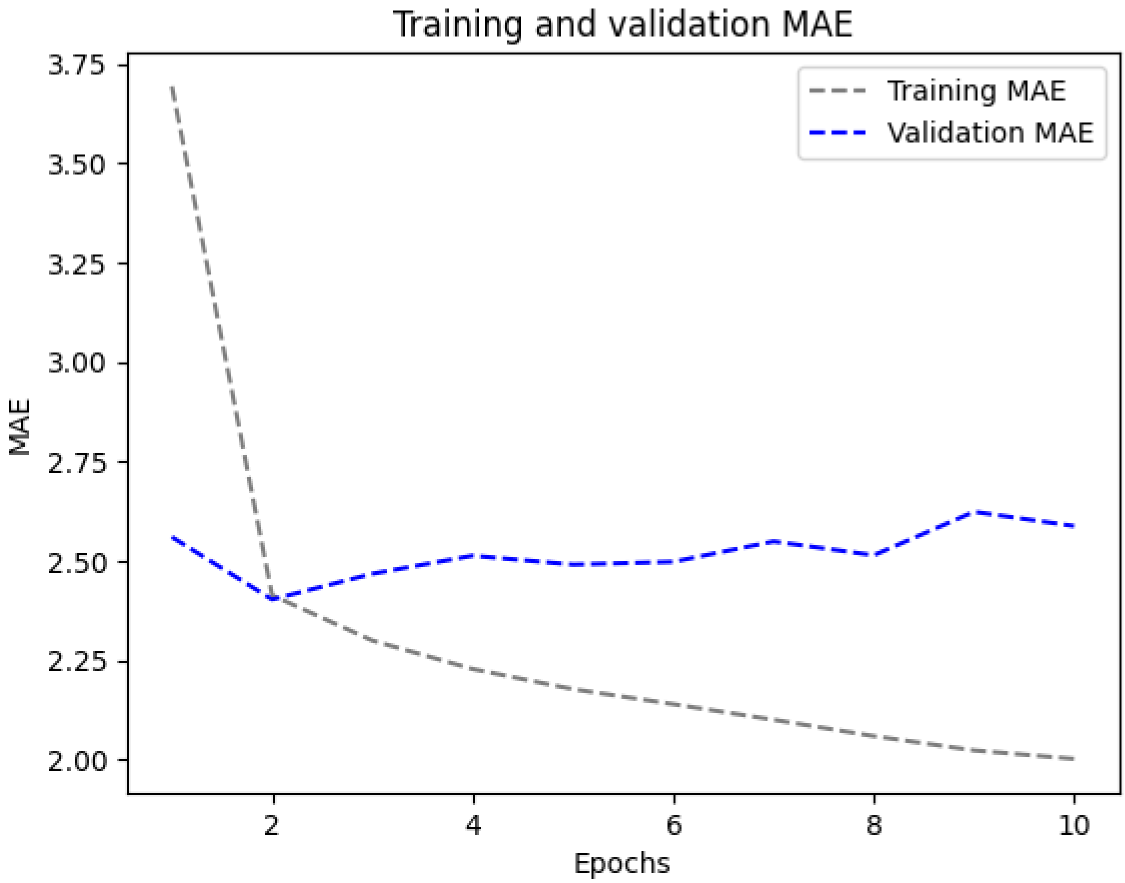
Bidirectional LSTM

In [39]:
```
inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
x = layers.Bidirectional(layers.LSTM(16))(inputs)
outputs = layers.Dense(1)(x)
model = keras.Model(inputs, outputs)

callbacks = [
    keras.callbacks.ModelCheckpoint("jena_bidirec_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_bidirec_LSTM.keras")
print(f"Test MAE: {model.evaluate(test_dataset)[1]:.2f}")
```

```
Epoch 1/10
819/819 [==============================] - 176s 209ms/step - loss: 26.1409 - mae: 3.6
934 - val_loss: 10.7851 - val_mae: 2.5606
Epoch 2/10
819/819 [==============================] - 169s 206ms/step - loss: 9.6015 - mae: 2.41
40 - val_loss: 9.7461 - val_mae: 2.4034
Epoch 3/10
819/819 [==============================] - 168s 205ms/step - loss: 8.7093 - mae: 2.30
01 - val_loss: 10.3606 - val_mae: 2.4680
Epoch 4/10
819/819 [==============================] - 160s 195ms/step - loss: 8.1702 - mae: 2.22
84 - val_loss: 10.7940 - val_mae: 2.5135
Epoch 5/10
819/819 [==============================] - 171s 209ms/step - loss: 7.7944 - mae: 2.17
76 - val_loss: 10.5363 - val_mae: 2.4913
Epoch 6/10
819/819 [==============================] - 171s 209ms/step - loss: 7.5104 - mae: 2.13
98 - val_loss: 10.4645 - val_mae: 2.4982
Epoch 7/10
819/819 [==============================] - 171s 208ms/step - loss: 7.2343 - mae: 2.10
06 - val_loss: 10.9244 - val_mae: 2.5495
Epoch 8/10
819/819 [==============================] - 171s 209ms/step - loss: 6.9309 - mae: 2.05
95 - val_loss: 10.4967 - val_mae: 2.5147
Epoch 9/10
819/819 [==============================] - 173s 211ms/step - loss: 6.6842 - mae: 2.02
36 - val_loss: 11.6070 - val_mae: 2.6240
Epoch 10/10
819/819 [==============================] - 161s 196ms/step - loss: 6.5729 - mae: 2.00
23 - val_loss: 11.1192 - val_mae: 2.5882
405/405 [==============================] - 37s 86ms/step - loss: 11.0267 - mae: 2.622
3
Test MAE: 2.62
```

In [40]:

```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, color="grey", linestyle="dashed", label="Training MAE")
plt.plot(epochs,  val_loss, color="blue",linestyle="dashed", label="Validation MAE")
plt.title("Training and validation MAE")
plt.xlabel("Epochs")
plt.ylabel("MAE")
plt.legend()
plt.show()
```



1D Convnets and LSTM togther

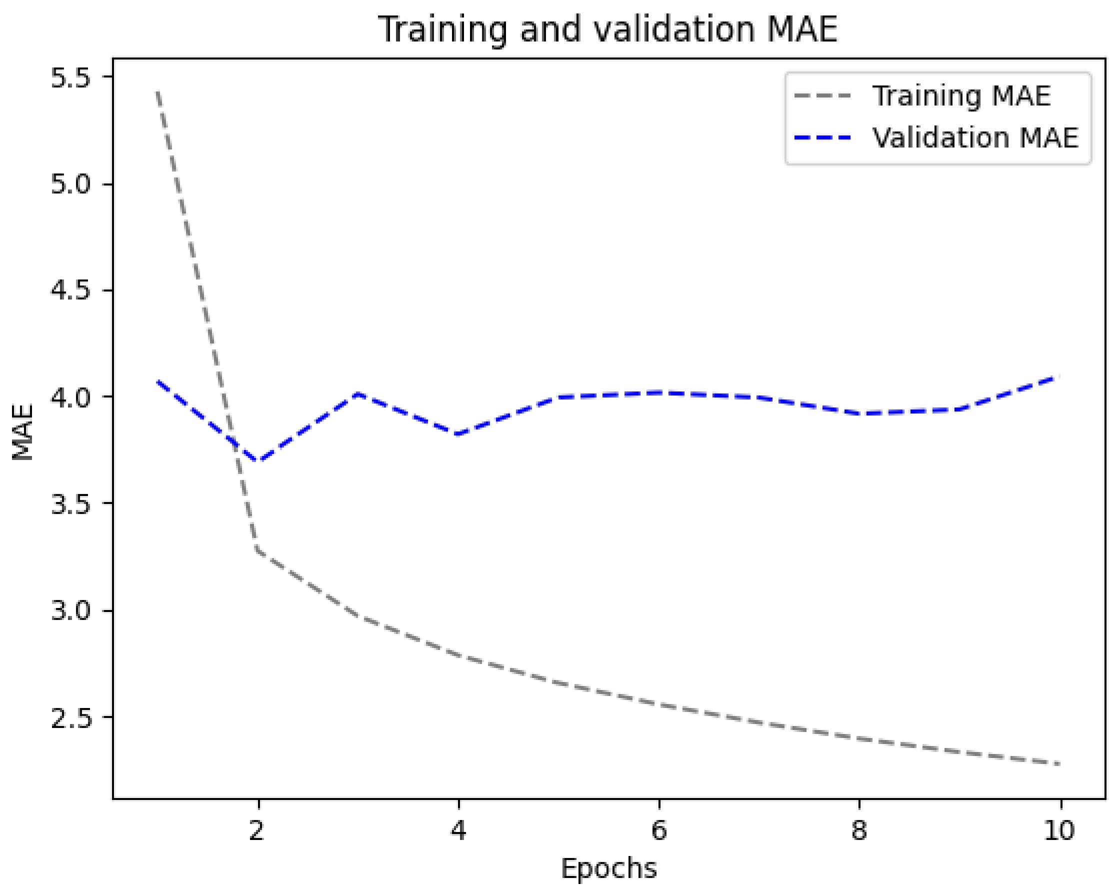
In [41]:

```
inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
x = layers.Conv1D(64, 3, activation='relu')(inputs)
x = layers.MaxPooling1D(3)(x)
x = layers.Conv1D(128, 3, activation='relu')(x)
x = layers.GlobalMaxPooling1D()(x)
x = layers.Reshape((-1, 128))(x)  # Reshape the data to be 3D
x = layers.LSTM(16)(x)
outputs = layers.Dense(1)(x)
model = keras.Model(inputs, outputs)

model.compile(optimizer="rmsprop", loss="mse", metrics=["mae"])

callbacks = [
    keras.callbacks.ModelCheckpoint("jena_Conv_LSTM.keras", save_best_only=True)
]

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

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

```
Epoch 1/10
819/819 [==============================] - 127s 152ms/step - loss: 52.5660 - mae: 5.4
281 - val_loss: 27.7129 - val_mae: 4.0673
Epoch 2/10
819/819 [==============================] - 139s 170ms/step - loss: 17.9697 - mae: 3.2
734 - val_loss: 22.2684 - val_mae: 3.6903
Epoch 3/10
819/819 [==============================] - 138s 168ms/step - loss: 14.6088 - mae: 2.9
679 - val_loss: 26.3144 - val_mae: 4.0073
Epoch 4/10
819/819 [==============================] - 122s 149ms/step - loss: 12.8884 - mae: 2.7
835 - val_loss: 23.1844 - val_mae: 3.8187
Epoch 5/10
819/819 [==============================] - 140s 171ms/step - loss: 11.7555 - mae: 2.6
530 - val_loss: 25.6090 - val_mae: 3.9913
Epoch 6/10
819/819 [==============================] - 122s 149ms/step - loss: 10.9404 - mae: 2.5
524 - val_loss: 24.9357 - val_mae: 4.0139
Epoch 7/10
819/819 [==============================] - 140s 170ms/step - loss: 10.2731 - mae: 2.4
672 - val_loss: 24.8969 - val_mae: 3.9906
Epoch 8/10
819/819 [==============================] - 143s 174ms/step - loss: 9.6992 - mae: 2.39
21 - val_loss: 23.8682 - val_mae: 3.9147
Epoch 9/10
819/819 [==============================] - 123s 150ms/step - loss: 9.2288 - mae: 2.32
89 - val_loss: 24.2859 - val_mae: 3.9350
Epoch 10/10
819/819 [==============================] - 139s 169ms/step - loss: 8.8048 - mae: 2.27
35 - val_loss: 25.7734 - val_mae: 4.0904
405/405 [==============================] - 27s 63ms/step - loss: 24.4174 - mae: 3.892
0
Test MAE: 3.89
```

In [42]:

```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, color="grey", linestyle="dashed", label="Training MAE")
plt.plot(epochs,  val_loss, color="blue",linestyle="dashed", label="Validation MAE")
plt.title("Training and validation MAE")
plt.xlabel("Epochs")
plt.ylabel("MAE")
plt.legend()
plt.show()
```



Built 14 models: Following are the details;

Model 1: common-sense, non-machine-learning baseline

Model 2: A basic machine-learning model

Model 3: 1D convolutional model

Model 4: Simple RNN layer that can process sequences of any length

Model 5: Simple RNN - Stacking RNN layers

Model 6: A Simple GRU (Gated Recurrent Unit)

Model 7: LSTM-Simple

Model 8: LSTM - dropout Regularization

Model 9: Stacked setup with 16 units

Model 10: Stacked setup with 32 units

Model 11: Stacked setup with 8 units

Model 12: LSTM - dropout-regularized, stacked

Model 13: Bidirectional LSTM

Model 14: 1D Convnets and LSTM togther

In [43]:
```
Models = ("1","2","3","4","5","6","7","8","9","10","11","12","13","14")
Mae = (2.62,2.63,3.04,9.92,9.91,2.47,2.57,2.53,2.60,2.63,2.55,2.51,2.54,3.81)

# MAE Evaluation
plt.scatter(Models, Mae, color="red")
plt.title("MAE Evaluation")
plt.xlabel("Model Number")
plt.ylabel("MAE")

for (xi, yi) in zip(Models,Mae):
    plt.text(xi, yi, yi, va='bottom', ha='center')

plt.show()
```