Assignment 3 - RNN - Weather Time Series Forcasting

Name: Dinesh Yechuri

A temperature forecasting sample utilizing data uploaded from AWS and Keras

In [ ]:
```
!pip install tensorflow==2.12
```

```
Requirement already satisfied: tensorflow==2.12 in /usr/local/lib/python3.10/dist-
packages (2.12.0)
Requirement already satisfied: absl-py>=1.0.0 in /usr/local/lib/python3.10/dist-pa
ckages (from tensorflow==2.12) (1.4.0)
Requirement already satisfied: astunparse>=1.6.0 in /usr/local/lib/python3.10/dist
-packages (from tensorflow==2.12) (1.6.3)
Requirement already satisfied: flatbuffers>=2.0 in /usr/local/lib/python3.10/dist-
packages (from tensorflow==2.12) (24.3.25)
Requirement already satisfied: gast<=0.4.0,>=0.2.1 in /usr/local/lib/python3.10/di
st-packages (from tensorflow==2.12) (0.4.0)
Requirement already satisfied: google-pasta>=0.1.1 in /usr/local/lib/python3.10/di
st-packages (from tensorflow==2.12) (0.2.0)
Requirement already satisfied: grpcio<2.0,>=1.24.3 in /usr/local/lib/python3.10/di
st-packages (from tensorflow==2.12) (1.62.1)
Requirement already satisfied: h5py>=2.9.0 in /usr/local/lib/python3.10/dist-packa
ges (from tensorflow==2.12) (3.9.0)
Requirement already satisfied: jax>=0.3.15 in /usr/local/lib/python3.10/dist-packa
ges (from tensorflow==2.12) (0.3.25)
Requirement already satisfied: keras<2.13,>=2.12.0 in /usr/local/lib/python3.10/di
st-packages (from tensorflow==2.12) (2.12.0)
Requirement already satisfied: libclang>=13.0.0 in /usr/local/lib/python3.10/dist-
packages (from tensorflow==2.12) (18.1.1)
Requirement already satisfied: numpy<1.24,>=1.22 in /usr/local/lib/python3.10/dist
-packages (from tensorflow==2.12) (1.23.5)
Requirement already satisfied: opt-einsum>=2.3.2 in /usr/local/lib/python3.10/dist
-packages (from tensorflow==2.12) (3.3.0)
Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-package
s (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 ten
sorflow==2.12) (3.20.3)
Requirement already satisfied: setuptools in /usr/local/lib/python3.10/dist-packag
es (from tensorflow==2.12) (67.7.2)
Requirement already satisfied: six>=1.12.0 in /usr/local/lib/python3.10/dist-packa
ges (from tensorflow==2.12) (1.16.0)
Requirement already satisfied: tensorboard<2.13,>=2.12 in /usr/local/lib/python3.1
0/dist-packages (from tensorflow==2.12) (2.12.0)
Requirement already satisfied: tensorflow-estimator<2.13,>=2.12.0 in /usr/local/li
b/python3.10/dist-packages (from tensorflow==2.12) (2.12.0)
Requirement already satisfied: termcolor>=1.1.0 in /usr/local/lib/python3.10/dist-
packages (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/di
st-packages (from tensorflow==2.12) (1.14.1)
Requirement already satisfied: tensorflow-io-gcs-filesystem>=0.23.1 in /usr/local/
lib/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/dis
t-packages (from astunparse>=1.6.0->tensorflow==2.12) (0.43.0)
Requirement already satisfied: scipy>=1.5 in /usr/local/lib/python3.10/dist-packag
es (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/
dist-packages (from tensorboard<2.13,>=2.12->tensorflow==2.12) (2.27.0)
Requirement already satisfied: google-auth-oauthlib<0.5,>=0.4.1 in /usr/local/lib/
python3.10/dist-packages (from tensorboard<2.13,>=2.12->tensorflow==2.12) (0.4.6)
Requirement already satisfied: markdown>=2.6.8 in /usr/local/lib/python3.10/dist-p
ackages (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/di
st-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/loca
l/lib/python3.10/dist-packages (from tensorboard<2.13,>=2.12->tensorflow==2.12)
(0.7.2)
Requirement already satisfied: tensorboard-plugin-wit>=1.6.0 in /usr/local/lib/pyt
hon3.10/dist-packages (from tensorboard<2.13,>=2.12->tensorflow==2.12) (1.8.1)
```

```
Requirement already satisfied: werkzeug>=1.0.1 in /usr/local/lib/python3.10/dist-p
ackages (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/python3.1
0/dist-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/
dist-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-pac
kages (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<0.5,>=0.4.1->tensorboard<2.13,>=2.12->
tensorflow==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-pack
ages (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/dis
t-packages (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/dis
t-packages (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
-packages (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/d
ist-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-p
ackages (from requests-oauthlib>=0.7.0->google-auth-oauthlib<0.5,>=0.4.1->tensorbo
ard<2.13,>=2.12->tensorflow==2.12) (3.2.2)
```

In [ ]:

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

```
--2024-04-04 20:36:56--  https://s3.amazonaws.com/keras-datasets/jena_climate_2009
_2016.csv.zip
Resolving s3.amazonaws.com (s3.amazonaws.com)... 54.231.169.160, 52.216.57.200, 5
2.217.228.176, ...
Connecting to s3.amazonaws.com (s3.amazonaws.com)|54.231.169.160|:443... connecte
d.
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  43.8MB/s    in 0.3s

2024-04-04 20:36:56 (43.8 MB/s) - ‘jena_climate_2009_2016.csv.zip’ saved [1356564
2/13565642]

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

Examining Jena weather dataset data: 420451 rows and 15 features

In [ ]:

```
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
(mmol/mol)"', '"rho (g/m**3)"', '"wv (m/s)"', '"max. wv (m/s)"', '"wd (deg)"']
420451
Number of variables: 15
Number of rows: 420451
```

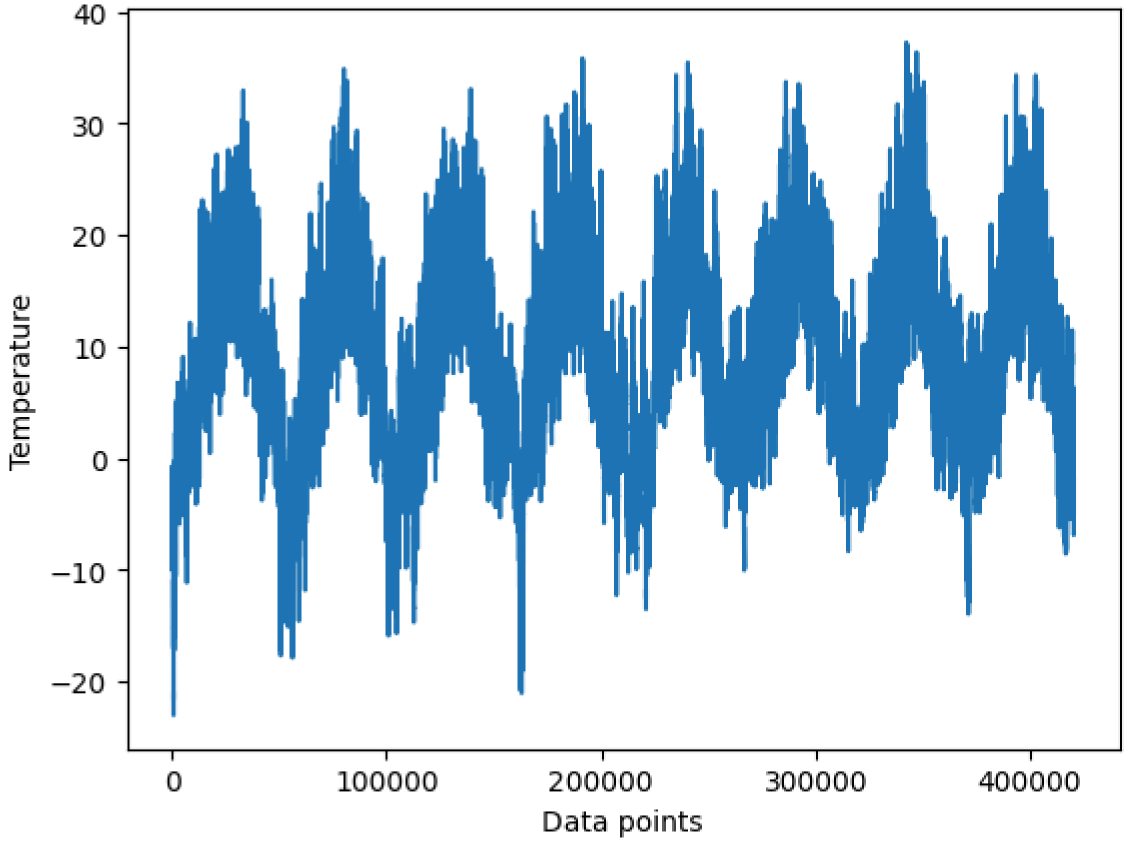
Parsing the data: saving particular values in the raw_data and temperature arrays for additional processing or analysis after turning the comma-separated values into floating-point numbers.

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

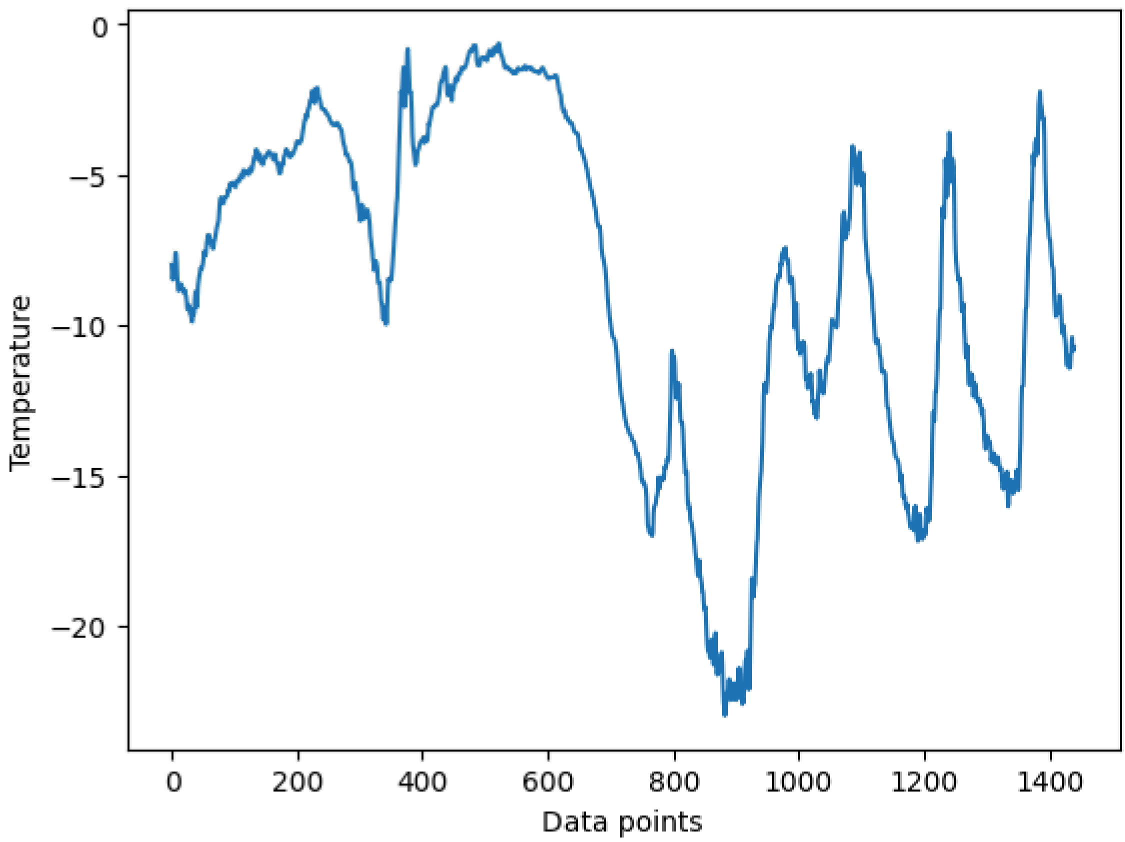
Out[ ]:
```
Text(0, 0.5, 'Temperature')
```



Charting the first ten days of the temperature time series: Since there are 144 data points in a day, there will be 1440 data points in ten days

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

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



Calculating how many samples each data split will require: 50% for train and 25% for validation

In [ ]:
```
numb_train_samples = int(0.5 * len(raw_data))
numb_val_samples = int(0.25 * len(raw_data))
numb_test_samples = len(raw_data) - numb_train_samples - numb_val_samples
print("numb_train_samples:", numb_train_samples)
print("numb_val_samples:", numb_val_samples)
print("numb_test_samples:", numb_test_samples)
```

```
numb_train_samples: 210225
numb_val_samples: 105112
numb_test_samples: 105114
```

Preparing the data

Normalizing the data: Vectorization is not required because the data is already in a numerical format. Nonetheless, it is advised to normalize all variables because the data scales vary amongst them, with temperature ranging from -20 to +30 and pressure measured in millibars.

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

In [ ]:
```
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—this is necessary due to the large degree of redundancy in the dataset's samples. Thus, explicitly allocating memory for every sample would be inefficient. Rather, the samples will be produced dynamically.

In [ ]:
```
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=numb_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=numb_train_samples,
    end_index=numb_train_samples + numb_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=numb_train_samples + numb_val_samples)
```

Inspecting the output of one of our datasets

In [ ]:
```
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 sensible baseline MAE: The "evaluate_naive_method" defined function offers a starting point for assessing the effectiveness of a straightforward forecasting technique that uses the final value in the input sequence to anticipate the value that will come after it.

In [ ]:
```
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 sensible baseline method would be to forecast that the temperature in the next 24 hours will be the same as it is now. The validation MAE (Mean Absolute Error) using the basic baseline is 2.44 degrees Celsius, while the test MAE is 2.62 degrees Celsius.

Put another way, an average divergence of roughly 2.5 degrees would arise from presuming that the future temperature stays constant with the current temperature.

A basic machine-learning model - Dense Layer

Training and evaluating a densely connected model

In [ ]:
```
from tensorflow import keras
from tensorflow.keras import layers

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

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

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

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

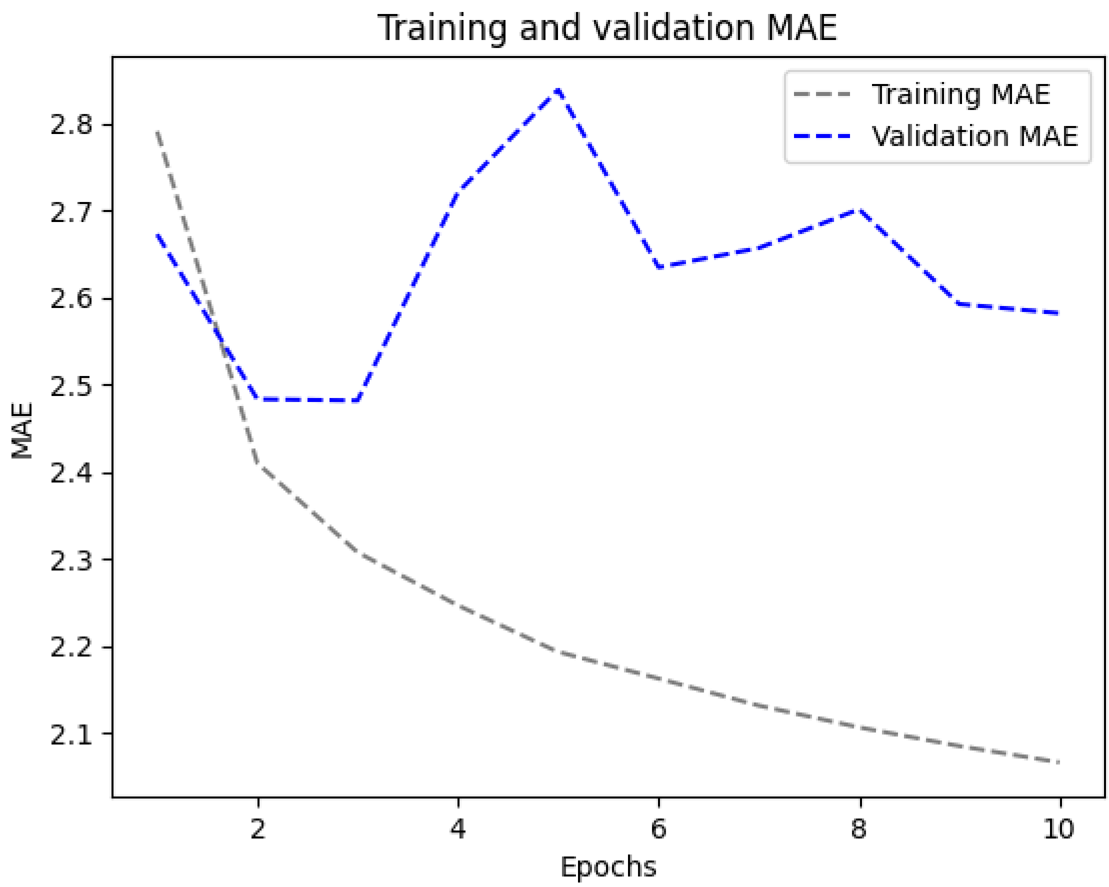
```
Epoch 1/10
819/819 [==============================] - 9s 10ms/step - loss: 13.0130 - mae: 2.7
909 - val_loss: 11.2674 - val_mae: 2.6725
Epoch 2/10
819/819 [==============================] - 8s 10ms/step - loss: 9.3507 - mae: 2.40
99 - val_loss: 9.8002 - val_mae: 2.4829
Epoch 3/10
819/819 [==============================] - 8s 10ms/step - loss: 8.5585 - mae: 2.30
74 - val_loss: 9.8417 - val_mae: 2.4814
Epoch 4/10
819/819 [==============================] - 8s 10ms/step - loss: 8.1064 - mae: 2.24
63 - val_loss: 11.6001 - val_mae: 2.7206
Epoch 5/10
819/819 [==============================] - 8s 10ms/step - loss: 7.7181 - mae: 2.19
27 - val_loss: 12.8736 - val_mae: 2.8388
Epoch 6/10
819/819 [==============================] - 8s 10ms/step - loss: 7.4947 - mae: 2.16
21 - val_loss: 10.9776 - val_mae: 2.6346
Epoch 7/10
819/819 [==============================] - 8s 10ms/step - loss: 7.2731 - mae: 2.13
10 - val_loss: 11.1115 - val_mae: 2.6569
Epoch 8/10
819/819 [==============================] - 8s 10ms/step - loss: 7.1061 - mae: 2.10
60 - val_loss: 11.6140 - val_mae: 2.7014
Epoch 9/10
819/819 [==============================] - 8s 10ms/step - loss: 6.9552 - mae: 2.08
45 - val_loss: 10.6103 - val_mae: 2.5923
Epoch 10/10
819/819 [==============================] - 8s 10ms/step - loss: 6.8311 - mae: 2.06
57 - val_loss: 10.5131 - val_mae: 2.5818
```

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

```
405/405 [==============================] - 3s 7ms/step - loss: 10.9328 - mae: 2.59
78
Test MAE: 2.60
```

Plotting results

In [ ]:
```
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()
```



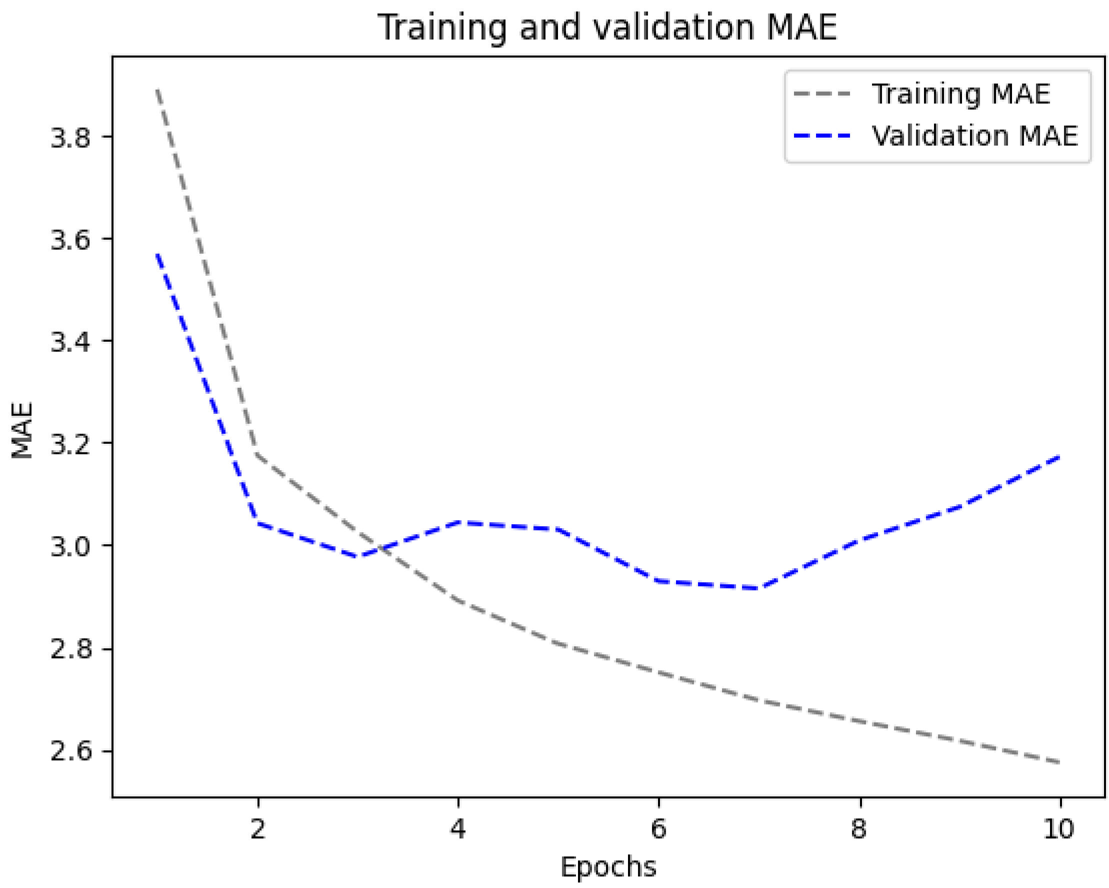
Let's try a 1D convolutional model

In [ ]:
```
inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
din = layers.Conv1D(8, 24, activation="relu")(inputs)
din = layers.MaxPooling1D(2)(din)
din = layers.Conv1D(8, 12, activation="relu")(din)
din = layers.MaxPooling1D(2)(din)
din = layers.Conv1D(8, 6, activation="relu")(din)
din = layers.GlobalAveragePooling1D()(din)
outputs = layers.Dense(1)(din)
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 [==============================] - 13s 15ms/step - loss: 25.5974 - mae: 3.
8903 - val_loss: 20.1408 - val_mae: 3.5686
Epoch 2/10
819/819 [==============================] - 13s 15ms/step - loss: 15.9920 - mae: 3.
1758 - val_loss: 15.1018 - val_mae: 3.0433
Epoch 3/10
819/819 [==============================] - 12s 15ms/step - loss: 14.5163 - mae: 3.
0261 - val_loss: 14.4453 - val_mae: 2.9773
Epoch 4/10
819/819 [==============================] - 13s 15ms/step - loss: 13.3368 - mae: 2.
8922 - val_loss: 15.0482 - val_mae: 3.0447
Epoch 5/10
819/819 [==============================] - 13s 15ms/step - loss: 12.6094 - mae: 2.
8076 - val_loss: 14.7939 - val_mae: 3.0307
Epoch 6/10
819/819 [==============================] - 13s 15ms/step - loss: 12.1340 - mae: 2.
7515 - val_loss: 13.8923 - val_mae: 2.9298
Epoch 7/10
819/819 [==============================] - 12s 15ms/step - loss: 11.6652 - mae: 2.
6970 - val_loss: 13.8451 - val_mae: 2.9156
Epoch 8/10
819/819 [==============================] - 12s 15ms/step - loss: 11.3178 - mae: 2.
6562 - val_loss: 14.6211 - val_mae: 3.0095
Epoch 9/10
819/819 [==============================] - 12s 15ms/step - loss: 10.9996 - mae: 2.
6180 - val_loss: 15.2663 - val_mae: 3.0748
Epoch 10/10
819/819 [==============================] - 12s 15ms/step - loss: 10.6693 - mae: 2.
5758 - val_loss: 16.1614 - val_mae: 3.1731
405/405 [==============================] - 3s 7ms/step - loss: 14.9596 - mae: 3.07
83
Test MAE: 3.08
```

In [ ]:
```
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()
```



It seems that the convolutional data performed poor compared to common sense or dense model. This could be because

- The assumption of translation invariance does not hold well for weather data.

- The order of the data is crucial. Recent past data is significantly more informative for predicting the temperature of the following day compared to data from several days ago. Unfortunately, a 1D convolutional neural network is unable to effectively capture this critical temporal order.

A Simple RNN

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

In [ ]:
```
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 [==============================] - 20s 23ms/step - loss: 138.3046 - mae: 9.6743 - val_loss: 143.9214 - val_mae: 9.8916
Epoch 2/10
819/819 [==============================] - 18s 22ms/step - loss: 136.3698 - mae: 9.5587 - val_loss: 143.6935 - val_mae: 9.8654
Epoch 3/10
819/819 [==============================] - 18s 22ms/step - loss: 136.2469 - mae: 9.5472 - val_loss: 143.6237 - val_mae: 9.8591
Epoch 4/10
819/819 [==============================] - 18s 22ms/step - loss: 136.1637 - mae: 9.5377 - val_loss: 143.5792 - val_mae: 9.8551
Epoch 5/10
819/819 [==============================] - 18s 22ms/step - loss: 136.1308 - mae: 9.5349 - val_loss: 143.5490 - val_mae: 9.8524
Epoch 6/10
819/819 [==============================] - 18s 22ms/step - loss: 136.1190 - mae: 9.5334 - val_loss: 143.5268 - val_mae: 9.8495
Epoch 7/10
819/819 [==============================] - 18s 22ms/step - loss: 136.1046 - mae: 9.5323 - val_loss: 143.5061 - val_mae: 9.8469
Epoch 8/10
819/819 [==============================] - 19s 23ms/step - loss: 136.0873 - mae: 9.5297 - val_loss: 143.5231 - val_mae: 9.8514
Epoch 9/10
819/819 [==============================] - 18s 22ms/step - loss: 136.0713 - mae: 9.5275 - val_loss: 143.5241 - val_mae: 9.8501
Epoch 10/10
819/819 [==============================] - 18s 22ms/step - loss: 136.0613 - mae: 9.5260 - val_loss: 143.5258 - val_mae: 9.8519
405/405 [==============================] - 4s 9ms/step - loss: 151.2778 - mae: 9.9185
Test MAE: 9.92
```

2.Simple RNN - Stacking RNN layers

In [ ]:

```
num_features = 14
steps = 120
inputs = keras.Input(shape=(steps, num_features))
din = layers.SimpleRNN(16, return_sequences=True)(inputs)
din = layers.SimpleRNN(16, return_sequences=True)(din)
outputs = layers.SimpleRNN(16)(din)
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 [==============================] - 57s 66ms/step - loss: 136.7982 - mae:
9.5638 - val_loss: 143.4283 - val_mae: 9.8362
Epoch 2/10
819/819 [==============================] - 54s 66ms/step - loss: 135.9517 - mae:
9.5123 - val_loss: 143.4560 - val_mae: 9.8412
Epoch 3/10
819/819 [==============================] - 54s 66ms/step - loss: 135.9070 - mae:
9.5065 - val_loss: 143.4506 - val_mae: 9.8409
Epoch 4/10
819/819 [==============================] - 54s 66ms/step - loss: 135.8757 - mae:
9.5022 - val_loss: 143.4268 - val_mae: 9.8362
Epoch 5/10
819/819 [==============================] - 54s 65ms/step - loss: 135.8804 - mae:
9.5024 - val_loss: 143.3875 - val_mae: 9.8305
Epoch 6/10
819/819 [==============================] - 53s 65ms/step - loss: 135.8593 - mae:
9.4998 - val_loss: 143.3862 - val_mae: 9.8320
Epoch 7/10
819/819 [==============================] - 54s 65ms/step - loss: 135.8318 - mae:
9.4954 - val_loss: 143.4472 - val_mae: 9.8407
Epoch 8/10
819/819 [==============================] - 53s 65ms/step - loss: 135.8126 - mae:
9.4929 - val_loss: 143.4207 - val_mae: 9.8389
Epoch 9/10
819/819 [==============================] - 54s 65ms/step - loss: 135.8018 - mae:
9.4909 - val_loss: 143.4448 - val_mae: 9.8417
Epoch 10/10
819/819 [==============================] - 54s 66ms/step - loss: 135.7999 - mae:
9.4905 - val_loss: 143.4463 - val_mae: 9.8397
405/405 [==============================] - 9s 20ms/step - loss: 151.0784 - mae: 9.
8988
Test MAE: 9.90
```

A Simple GRU (Gated Recurrent Unit)

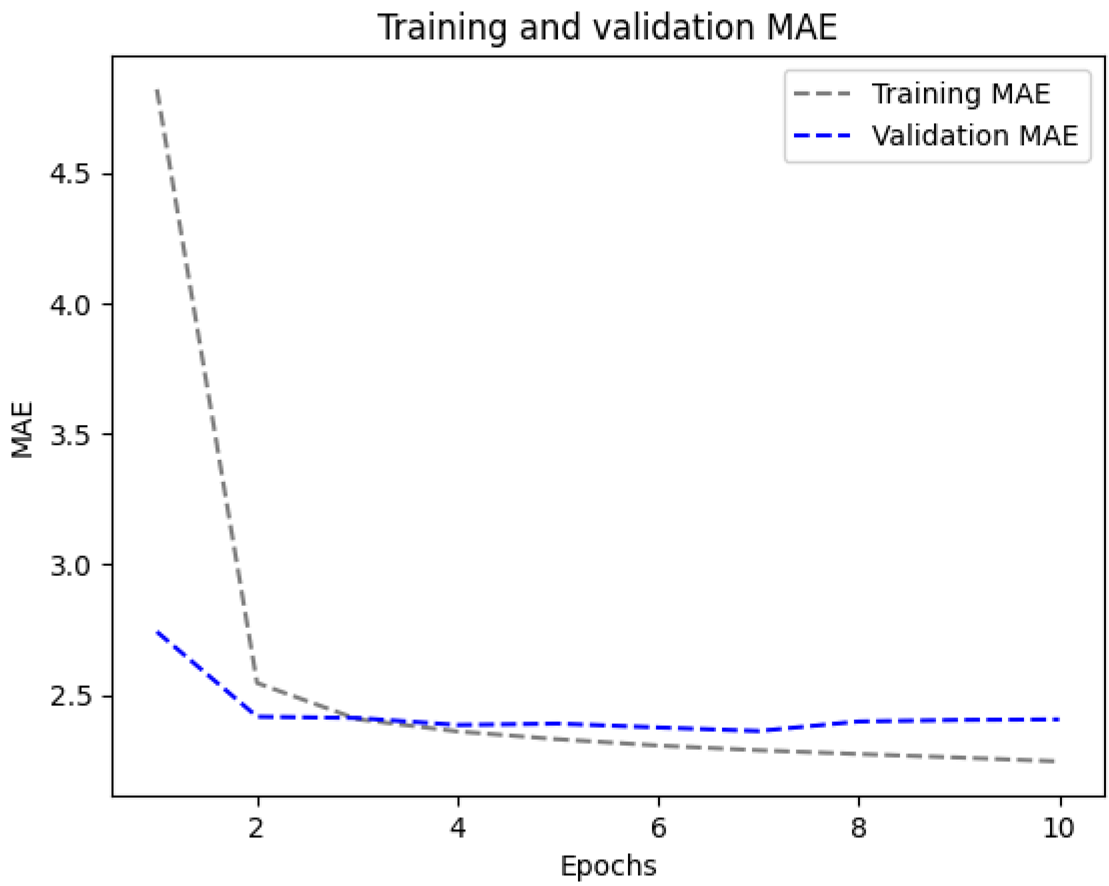
In [ ]:

```
inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
din = layers.GRU(16)(inputs)
outputs = layers.Dense(1)(din)
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)

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

```
Epoch 1/10
819/819 [==============================] - 48s 56ms/step - loss: 44.1053 - mae: 4.
8189 - val_loss: 13.4835 - val_mae: 2.7427
Epoch 2/10
819/819 [==============================] - 44s 53ms/step - loss: 10.6885 - mae: 2.
5463 - val_loss: 9.9603 - val_mae: 2.4172
Epoch 3/10
819/819 [==============================] - 43s 53ms/step - loss: 9.4667 - mae: 2.4
076 - val_loss: 9.9906 - val_mae: 2.4123
Epoch 4/10
819/819 [==============================] - 43s 53ms/step - loss: 9.1369 - mae: 2.3
607 - val_loss: 9.6113 - val_mae: 2.3855
Epoch 5/10
819/819 [==============================] - 43s 53ms/step - loss: 8.9224 - mae: 2.3
308 - val_loss: 9.7930 - val_mae: 2.3907
Epoch 6/10
819/819 [==============================] - 43s 53ms/step - loss: 8.7435 - mae: 2.3
066 - val_loss: 9.6395 - val_mae: 2.3760
Epoch 7/10
819/819 [==============================] - 44s 53ms/step - loss: 8.6059 - mae: 2.2
886 - val_loss: 9.4426 - val_mae: 2.3623
Epoch 8/10
819/819 [==============================] - 43s 52ms/step - loss: 8.4923 - mae: 2.2
742 - val_loss: 9.8011 - val_mae: 2.3989
Epoch 9/10
819/819 [==============================] - 43s 53ms/step - loss: 8.3855 - mae: 2.2
607 - val_loss: 9.7947 - val_mae: 2.4047
Epoch 10/10
819/819 [==============================] - 43s 52ms/step - loss: 8.2733 - mae: 2.2
459 - val_loss: 9.9162 - val_mae: 2.4069
405/405 [==============================] - 8s 18ms/step - loss: 9.7194 - mae: 2.46
55
Test MAE: 2.47
```

In [ ]:

```
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()
```



LSTM(Long Short-Term Memory)

1.LSTM-Simple

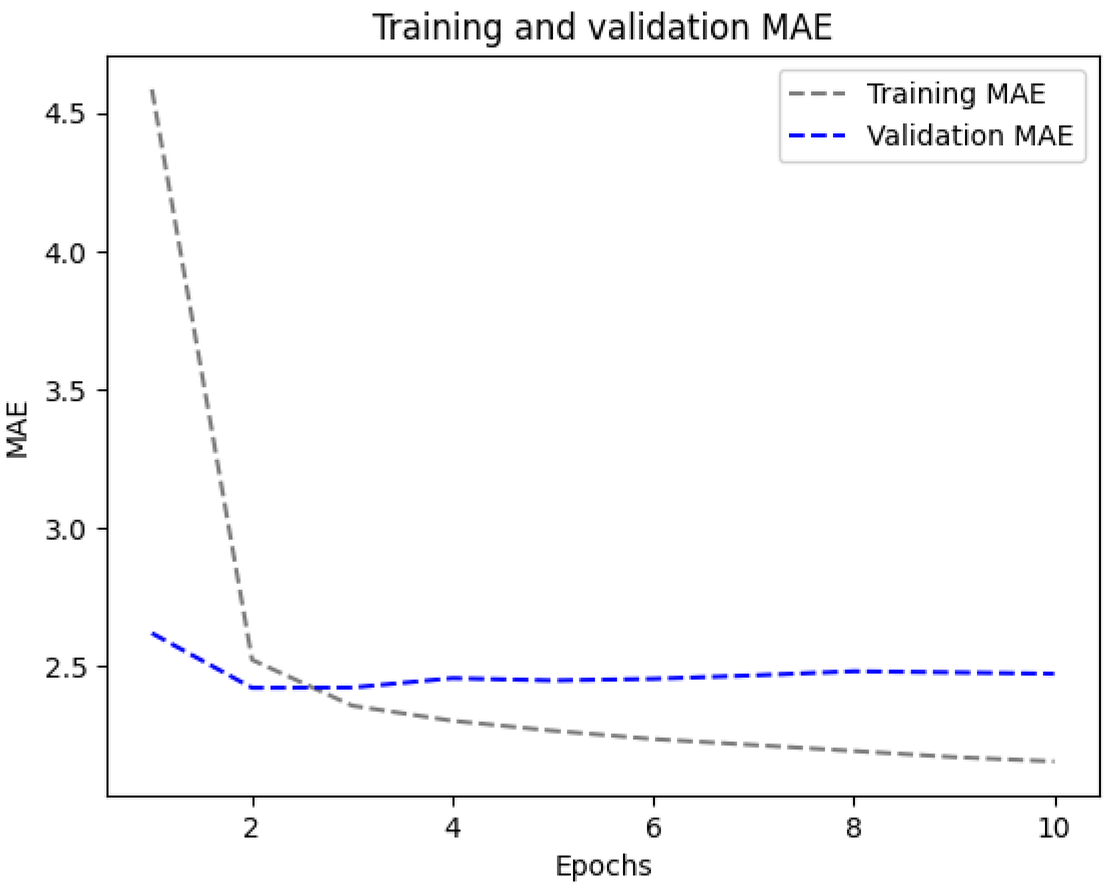
In [ ]:

```
inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
din = layers.LSTM(16)(inputs)
outputs = layers.Dense(1)(din)
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 [==============================] - 48s 56ms/step - loss: 40.0320 - mae: 4.
5834 - val_loss: 13.8590 - val_mae: 2.7392
Epoch 2/10
819/819 [==============================] - 46s 56ms/step - loss: 10.9528 - mae: 2.
5761 - val_loss: 9.7142 - val_mae: 2.4303
Epoch 3/10
819/819 [==============================] - 46s 56ms/step - loss: 10.0329 - mae: 2.
4717 - val_loss: 9.5010 - val_mae: 2.3994
Epoch 4/10
819/819 [==============================] - 46s 56ms/step - loss: 9.6456 - mae: 2.4
185 - val_loss: 9.6409 - val_mae: 2.4260
Epoch 5/10
819/819 [==============================] - 46s 56ms/step - loss: 9.3000 - mae: 2.3
764 - val_loss: 9.4904 - val_mae: 2.4046
Epoch 6/10
819/819 [==============================] - 45s 55ms/step - loss: 9.0161 - mae: 2.3
378 - val_loss: 9.4514 - val_mae: 2.3941
Epoch 7/10
819/819 [==============================] - 46s 56ms/step - loss: 8.7738 - mae: 2.3
055 - val_loss: 9.5102 - val_mae: 2.3987
Epoch 8/10
819/819 [==============================] - 46s 56ms/step - loss: 8.5954 - mae: 2.2
812 - val_loss: 9.4679 - val_mae: 2.3867
Epoch 9/10
819/819 [==============================] - 46s 56ms/step - loss: 8.4547 - mae: 2.2
632 - val_loss: 9.5409 - val_mae: 2.4028
Epoch 10/10
819/819 [==============================] - 46s 56ms/step - loss: 8.3226 - mae: 2.2
466 - val_loss: 9.4517 - val_mae: 2.3873
405/405 [==============================] - 9s 21ms/step - loss: 10.6933 - mae: 2.5
753
Test MAE: 2.58
```

In [ ]:

```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()
```



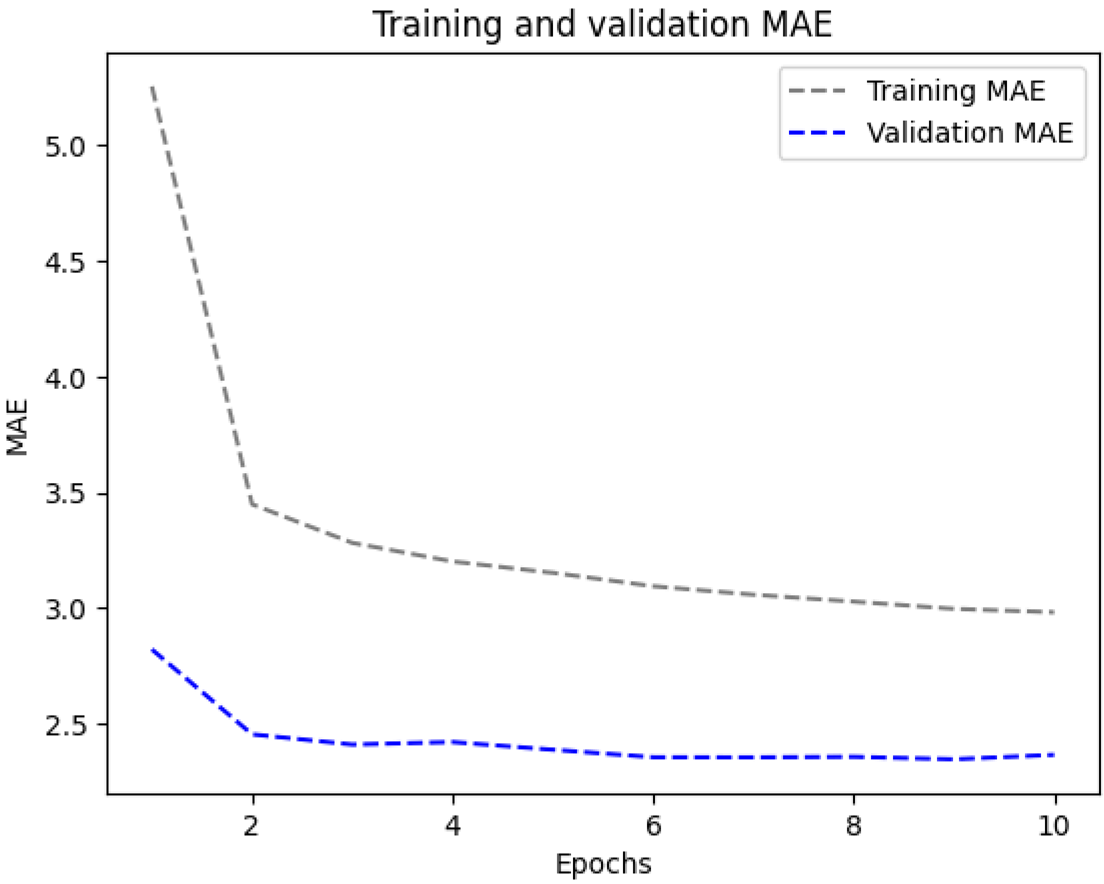
2.LSTM - dropout Regularization

In [ ]:
```
inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
din = layers.LSTM(16, recurrent_dropout=0.25)(inputs)
din = layers.Dropout(0.5)(din)
outputs = layers.Dense(1)(din)
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 [==============================] - 65s 76ms/step - loss: 47.4186 - mae: 5.
1232 - val_loss: 13.2283 - val_mae: 2.7576
Epoch 2/10
819/819 [==============================] - 63s 76ms/step - loss: 19.7332 - mae: 3.
4178 - val_loss: 9.8220 - val_mae: 2.4405
Epoch 3/10
819/819 [==============================] - 63s 77ms/step - loss: 18.0418 - mae: 3.
2699 - val_loss: 9.7304 - val_mae: 2.4416
Epoch 4/10
819/819 [==============================] - 62s 75ms/step - loss: 17.2264 - mae: 3.
1941 - val_loss: 9.4306 - val_mae: 2.4014
Epoch 5/10
819/819 [==============================] - 62s 75ms/step - loss: 16.6897 - mae: 3.
1441 - val_loss: 9.5189 - val_mae: 2.4109
Epoch 6/10
819/819 [==============================] - 62s 75ms/step - loss: 16.2472 - mae: 3.
1060 - val_loss: 9.5465 - val_mae: 2.4269
Epoch 7/10
819/819 [==============================] - 62s 76ms/step - loss: 15.8702 - mae: 3.
0727 - val_loss: 9.1964 - val_mae: 2.3674
Epoch 8/10
819/819 [==============================] - 62s 75ms/step - loss: 15.4684 - mae: 3.
0387 - val_loss: 9.5811 - val_mae: 2.4305
Epoch 9/10
819/819 [==============================] - 61s 75ms/step - loss: 15.2744 - mae: 3.
0190 - val_loss: 9.6137 - val_mae: 2.4236
Epoch 10/10
819/819 [==============================] - 61s 75ms/step - loss: 14.9665 - mae: 2.
9906 - val_loss: 9.3698 - val_mae: 2.3891
405/405 [==============================] - 7s 17ms/step - loss: 10.5592 - mae: 2.5
495
Test MAE: 2.55
```

In [ ]:

```
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()
```



3.LSTM - Stacked setup with 16 units

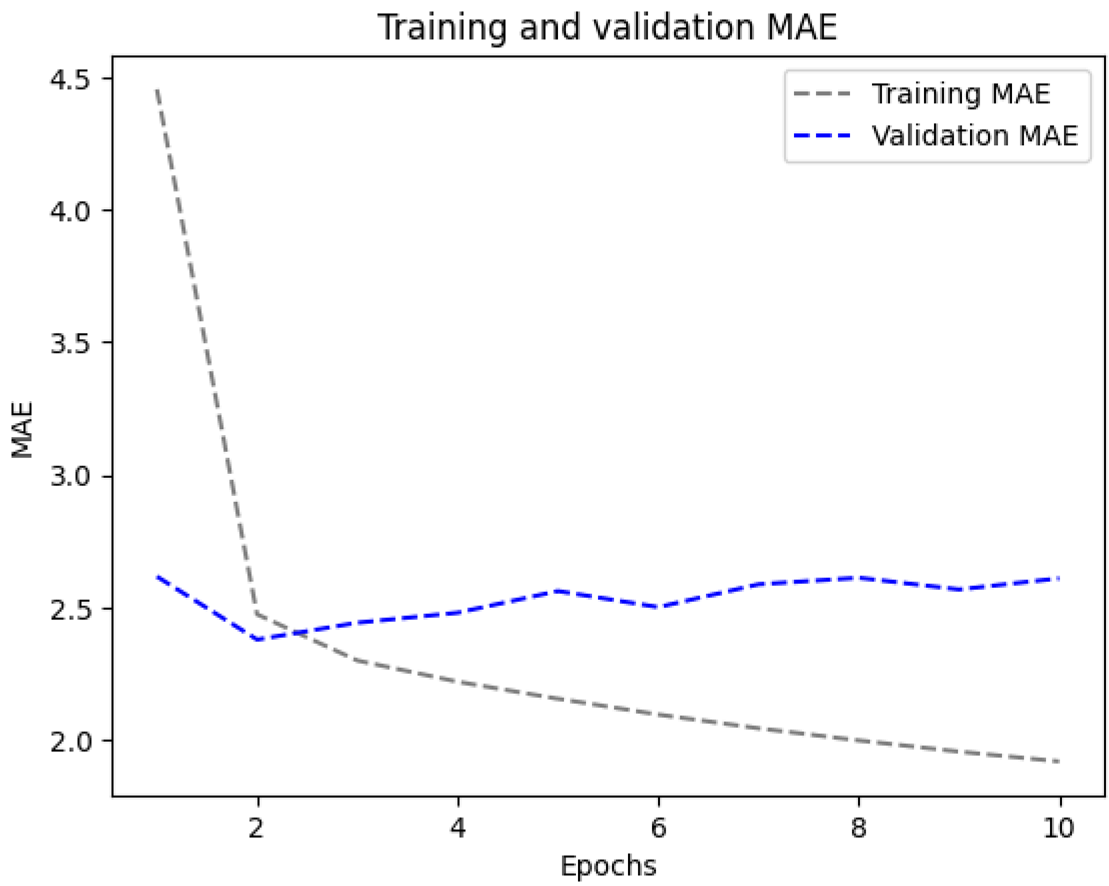
In [ ]:

```
inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
din = layers.LSTM(16, return_sequences=True)(inputs)
din = layers.LSTM(16)(din)
outputs = layers.Dense(1)(din)
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 [==============================] - 94s 110ms/step - loss: 37.8716 - mae: 
4.4548 - val_loss: 12.0147 - val_mae: 2.6167
Epoch 2/10
819/819 [==============================] - 91s 111ms/step - loss: 10.1397 - mae: 
2.4739 - val_loss: 9.2846 - val_mae: 2.3785
Epoch 3/10
819/819 [==============================] - 90s 110ms/step - loss: 8.7363 - mae: 2.
2995 - val_loss: 9.7300 - val_mae: 2.4422
Epoch 4/10
819/819 [==============================] - 90s 110ms/step - loss: 8.1416 - mae: 2.
2195 - val_loss: 9.9249 - val_mae: 2.4799
Epoch 5/10
819/819 [==============================] - 89s 109ms/step - loss: 7.6655 - mae: 2.
1551 - val_loss: 10.5729 - val_mae: 2.5616
Epoch 6/10
819/819 [==============================] - 89s 109ms/step - loss: 7.2693 - mae: 2.
0953 - val_loss: 10.1224 - val_mae: 2.5010
Epoch 7/10
819/819 [==============================] - 89s 108ms/step - loss: 6.9253 - mae: 2.
0434 - val_loss: 10.9319 - val_mae: 2.5873
Epoch 8/10
819/819 [==============================] - 89s 109ms/step - loss: 6.6353 - mae: 1.
9977 - val_loss: 10.9980 - val_mae: 2.6120
Epoch 9/10
819/819 [==============================] - 89s 109ms/step - loss: 6.3805 - mae: 1.
9554 - val_loss: 10.7294 - val_mae: 2.5678
Epoch 10/10
819/819 [==============================] - 90s 109ms/step - loss: 6.1683 - mae: 1.
9184 - val_loss: 11.1039 - val_mae: 2.6099
405/405 [==============================] - 17s 39ms/step - loss: 11.1191 - mae: 2.
6190
Test MAE: 2.62
```

In [ ]:

```
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

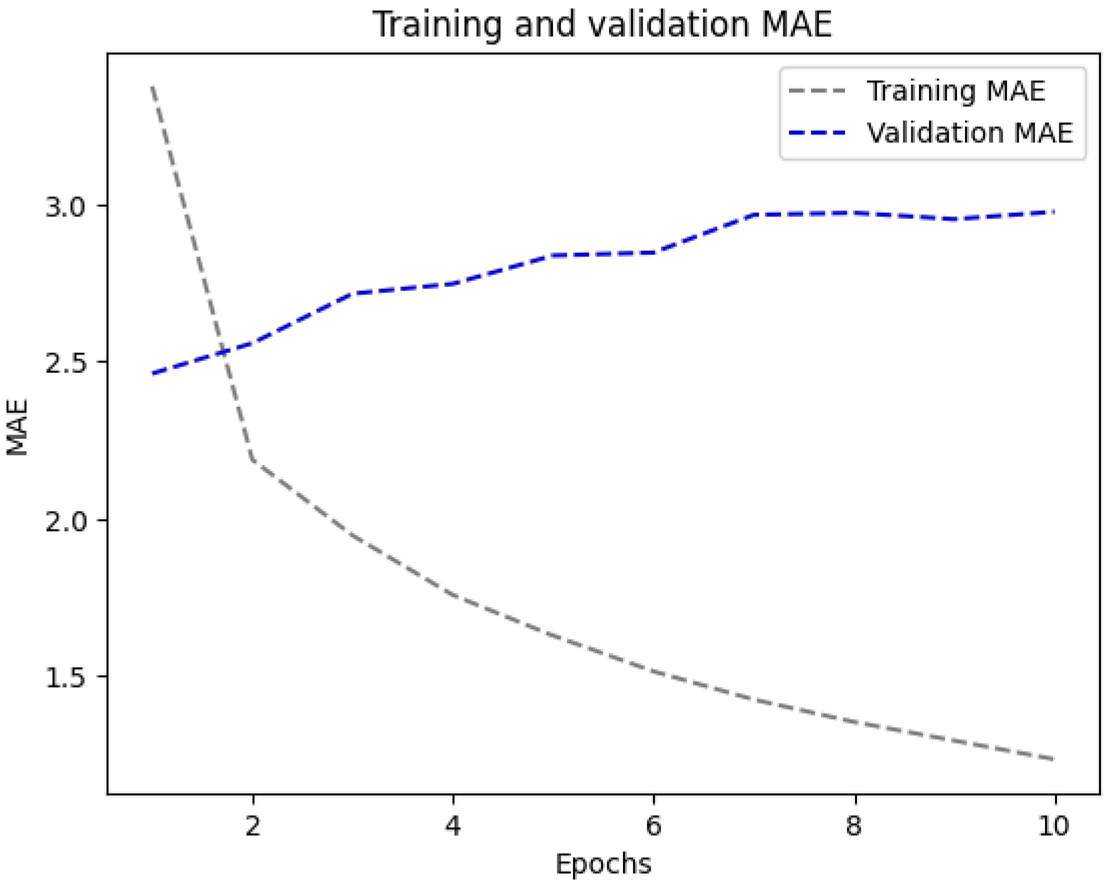
In [ ]:

```
inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
din = layers.LSTM(32, return_sequences=True)(inputs)
din = layers.LSTM(32)(din)
outputs = layers.Dense(1)(din)
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 [==============================] - 137s 164ms/step - loss: 22.5627 - mae:
3.3756 - val_loss: 9.8192 - val_mae: 2.4615
Epoch 2/10
819/819 [==============================] - 132s 161ms/step - loss: 7.8676 - mae:
2.1891 - val_loss: 10.4989 - val_mae: 2.5583
Epoch 3/10
819/819 [==============================] - 131s 160ms/step - loss: 6.2477 - mae:
1.9480 - val_loss: 11.7871 - val_mae: 2.7159
Epoch 4/10
819/819 [==============================] - 132s 161ms/step - loss: 5.1364 - mae:
1.7586 - val_loss: 12.3099 - val_mae: 2.7471
Epoch 5/10
819/819 [==============================] - 132s 161ms/step - loss: 4.4274 - mae:
1.6289 - val_loss: 13.1282 - val_mae: 2.8374
Epoch 6/10
819/819 [==============================] - 133s 162ms/step - loss: 3.8546 - mae:
1.5150 - val_loss: 13.0977 - val_mae: 2.8468
Epoch 7/10
819/819 [==============================] - 133s 162ms/step - loss: 3.4404 - mae:
1.4254 - val_loss: 14.3524 - val_mae: 2.9668
Epoch 8/10
819/819 [==============================] - 133s 162ms/step - loss: 3.1199 - mae:
1.3542 - val_loss: 14.5331 - val_mae: 2.9732
Epoch 9/10
819/819 [==============================] - 133s 162ms/step - loss: 2.8653 - mae:
1.2948 - val_loss: 14.2969 - val_mae: 2.9530
Epoch 10/10
819/819 [==============================] - 133s 162ms/step - loss: 2.6131 - mae:
1.2354 - val_loss: 14.5909 - val_mae: 2.9767
405/405 [==============================] - 25s 61ms/step - loss: 11.5758 - mae: 2.
6647
Test MAE: 2.66
```

In [ ]:

```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()
```



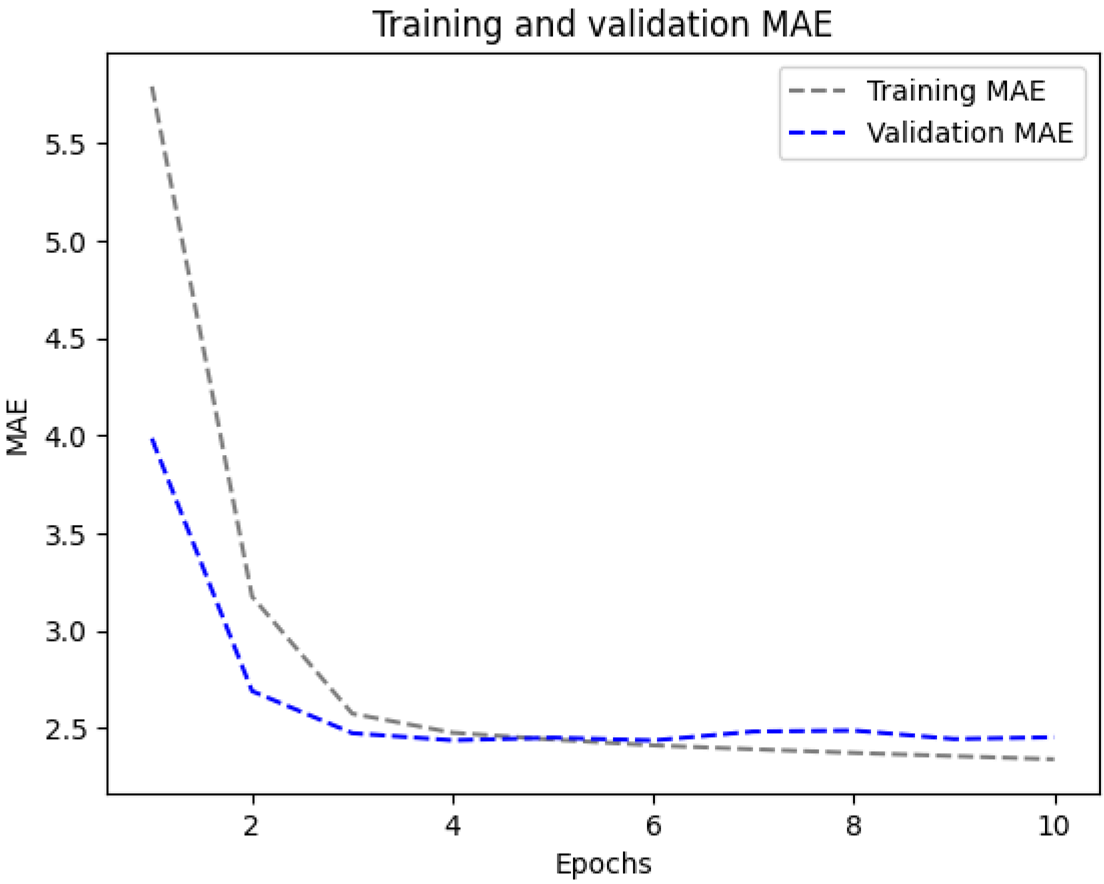
5.LSTM - Stacked setup with 8 units

In [ ]:
```
inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
din = layers.LSTM(8, return_sequences=True)(inputs)
din = layers.LSTM(8)(din)
outputs = layers.Dense(1)(din)
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 [==============================] - 76s 89ms/step - loss: 58.8321 - mae: 5.
7915 - val_loss: 28.8597 - val_mae: 3.9852
Epoch 2/10
819/819 [==============================] - 72s 87ms/step - loss: 18.0468 - mae: 3.
1759 - val_loss: 12.5840 - val_mae: 2.6907
Epoch 3/10
819/819 [==============================] - 73s 89ms/step - loss: 10.9192 - mae: 2.
5750 - val_loss: 10.2721 - val_mae: 2.4747
Epoch 4/10
819/819 [==============================] - 73s 89ms/step - loss: 10.0382 - mae: 2.
4774 - val_loss: 9.9316 - val_mae: 2.4384
Epoch 5/10
819/819 [==============================] - 72s 88ms/step - loss: 9.7695 - mae: 2.4
420 - val_loss: 10.1523 - val_mae: 2.4516
Epoch 6/10
819/819 [==============================] - 72s 88ms/step - loss: 9.5514 - mae: 2.4
124 - val_loss: 10.0573 - val_mae: 2.4375
Epoch 7/10
819/819 [==============================] - 74s 90ms/step - loss: 9.3915 - mae: 2.3
923 - val_loss: 10.3515 - val_mae: 2.4833
Epoch 8/10
819/819 [==============================] - 73s 89ms/step - loss: 9.2611 - mae: 2.3
738 - val_loss: 10.4344 - val_mae: 2.4885
Epoch 9/10
819/819 [==============================] - 74s 91ms/step - loss: 9.1398 - mae: 2.3
572 - val_loss: 9.9636 - val_mae: 2.4449
Epoch 10/10
819/819 [==============================] - 73s 89ms/step - loss: 9.0023 - mae: 2.3
409 - val_loss: 9.9616 - val_mae: 2.4540
405/405 [==============================] - 13s 30ms/step - loss: 11.0765 - mae: 2.
6026
Test MAE: 2.60
```

In [ ]:

```
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()
```



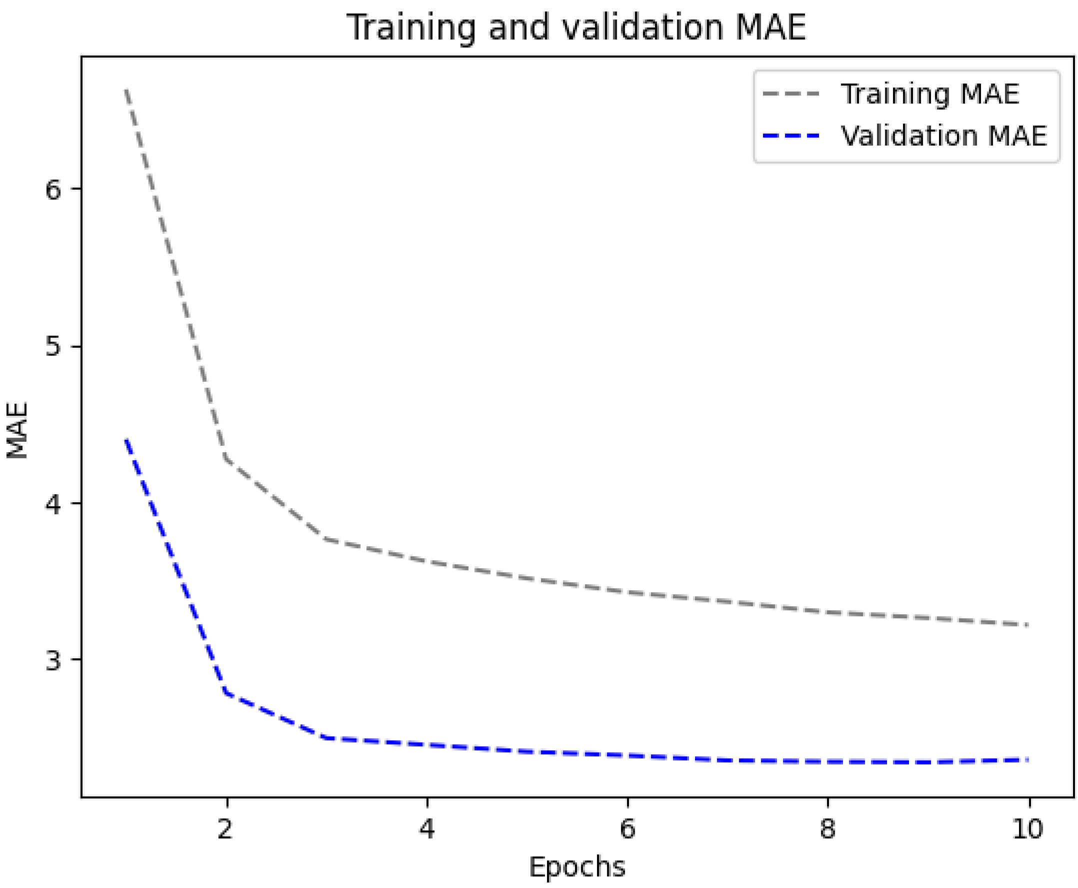
6.LSTM - dropout-regularized, stacked model

In [ ]:
```
inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
din = layers.LSTM(8, recurrent_dropout=0.5, return_sequences=True)(inputs)
din = layers.LSTM(8, recurrent_dropout=0.5)(din)
din = layers.Dropout(0.5)(din)
outputs = layers.Dense(1)(din)
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 [==============================] - 111s 130ms/step - loss: 74.3889 - mae:
6.6296 - val_loss: 34.6505 - val_mae: 4.3987
Epoch 2/10
819/819 [==============================] - 106s 129ms/step - loss: 32.3607 - mae:
4.2755 - val_loss: 13.8734 - val_mae: 2.7839
Epoch 3/10
819/819 [==============================] - 106s 129ms/step - loss: 24.6439 - mae:
3.7648 - val_loss: 10.7099 - val_mae: 2.4971
Epoch 4/10
819/819 [==============================] - 105s 129ms/step - loss: 22.7470 - mae:
3.6237 - val_loss: 10.1412 - val_mae: 2.4543
Epoch 5/10
819/819 [==============================] - 105s 128ms/step - loss: 21.3876 - mae:
3.5157 - val_loss: 9.7281 - val_mae: 2.4106
Epoch 6/10
819/819 [==============================] - 105s 128ms/step - loss: 20.2466 - mae:
3.4268 - val_loss: 9.5135 - val_mae: 2.3863
Epoch 7/10
819/819 [==============================] - 105s 128ms/step - loss: 19.4589 - mae:
3.3669 - val_loss: 9.2690 - val_mae: 2.3548
Epoch 8/10
819/819 [==============================] - ETA: 0s - loss: 18.6451 - mae: 3.2990Ep
och 9/10
819/819 [==============================] - 105s 129ms/step - loss: 18.2652 - mae:
3.2631 - val_loss: 9.0922 - val_mae: 2.3430
Epoch 10/10
819/819 [==============================] - 105s 128ms/step - loss: 17.7624 - mae:
3.2181 - val_loss: 9.1763 - val_mae: 2.3595
405/405 [==============================] - 11s 25ms/step - loss: 10.6426 - mae: 2.
5446
Test MAE: 2.54
```

In [ ]:

```
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()
```



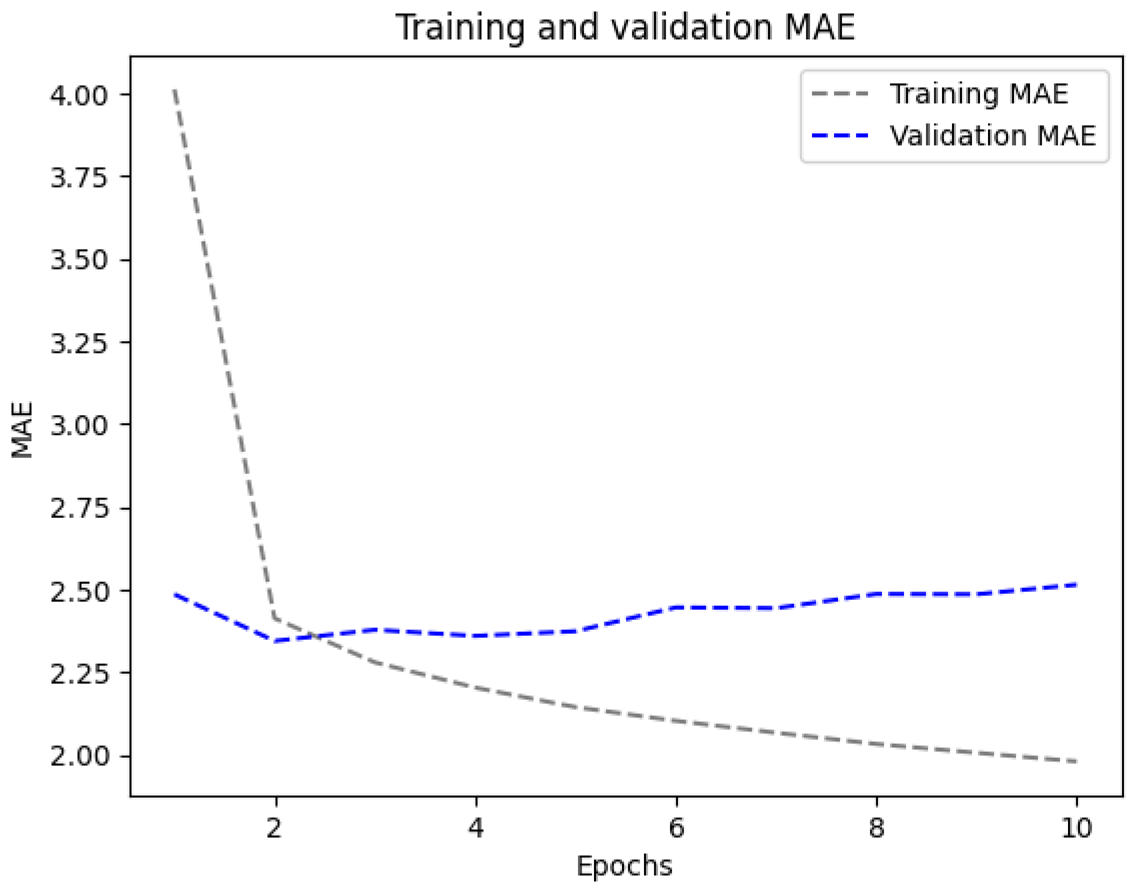
Bidirectional LSTM

In [ ]:
```
inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
din = layers.Bidirectional(layers.LSTM(16))(inputs)
outputs = layers.Dense(1)(din)
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 [==============================] - 51s 58ms/step - loss: 25.9273 - mae: 3.
6567 - val_loss: 10.4757 - val_mae: 2.5175
Epoch 2/10
819/819 [==============================] - 48s 59ms/step - loss: 9.4196 - mae: 2.3
907 - val_loss: 9.4030 - val_mae: 2.3917
Epoch 3/10
819/819 [==============================] - 49s 59ms/step - loss: 8.5676 - mae: 2.2
747 - val_loss: 9.4404 - val_mae: 2.3839
Epoch 4/10
819/819 [==============================] - 49s 60ms/step - loss: 8.0018 - mae: 2.1
993 - val_loss: 9.8783 - val_mae: 2.4401
Epoch 5/10
819/819 [==============================] - 48s 59ms/step - loss: 7.6206 - mae: 2.1
480 - val_loss: 10.4116 - val_mae: 2.5068
Epoch 6/10
819/819 [==============================] - 48s 59ms/step - loss: 7.3127 - mae: 2.1
039 - val_loss: 10.5412 - val_mae: 2.5185
Epoch 7/10
819/819 [==============================] - 48s 59ms/step - loss: 7.1021 - mae: 2.0
737 - val_loss: 10.3589 - val_mae: 2.5068
Epoch 8/10
819/819 [==============================] - 48s 59ms/step - loss: 6.8759 - mae: 2.0
394 - val_loss: 10.1624 - val_mae: 2.4890
Epoch 9/10
819/819 [==============================] - 49s 59ms/step - loss: 6.6680 - mae: 2.0
103 - val_loss: 10.5668 - val_mae: 2.5264
Epoch 10/10
819/819 [==============================] - 48s 59ms/step - loss: 6.5117 - mae: 1.9
841 - val_loss: 10.3266 - val_mae: 2.5042
405/405 [==============================] - 10s 22ms/step - loss: 10.3835 - mae: 2.
5218
Test MAE: 2.52
```

In [ ]:

```
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

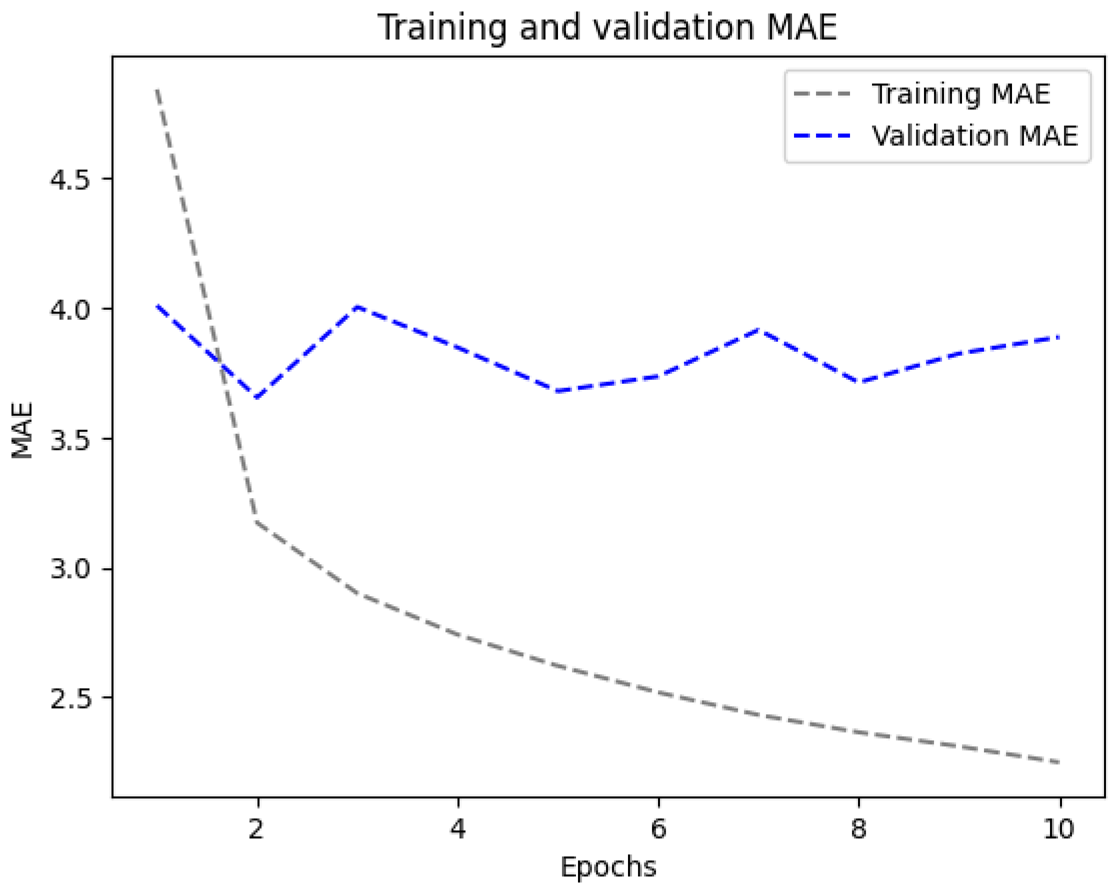
In [ ]:

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

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

```
Epoch 1/10
819/819 [==============================] - 16s 17ms/step - loss: 42.2077 - mae: 4.
8441 - val_loss: 25.6140 - val_mae: 4.0093
Epoch 2/10
819/819 [==============================] - 13s 16ms/step - loss: 16.8472 - mae: 3.
1724 - val_loss: 21.3697 - val_mae: 3.6543
Epoch 3/10
819/819 [==============================] - 13s 16ms/step - loss: 14.0129 - mae: 2.
9000 - val_loss: 24.9389 - val_mae: 4.0038
Epoch 4/10
819/819 [==============================] - 13s 16ms/step - loss: 12.5293 - mae: 2.
7403 - val_loss: 23.2003 - val_mae: 3.8476
Epoch 5/10
819/819 [==============================] - 14s 16ms/step - loss: 11.4930 - mae: 2.
6194 - val_loss: 21.2519 - val_mae: 3.6790
Epoch 6/10
819/819 [==============================] - 13s 16ms/step - loss: 10.6627 - mae: 2.
5168 - val_loss: 22.1726 - val_mae: 3.7358
Epoch 7/10
819/819 [==============================] - 13s 16ms/step - loss: 9.9693 - mae: 2.4
299 - val_loss: 23.6268 - val_mae: 3.9153
Epoch 8/10
819/819 [==============================] - 13s 16ms/step - loss: 9.4603 - mae: 2.3
629 - val_loss: 21.6039 - val_mae: 3.7123
Epoch 9/10
819/819 [==============================] - 13s 16ms/step - loss: 9.0710 - mae: 2.3
086 - val_loss: 22.5814 - val_mae: 3.8237
Epoch 10/10
819/819 [==============================] - 13s 16ms/step - loss: 8.6034 - mae: 2.2
471 - val_loss: 23.4010 - val_mae: 3.8878
405/405 [==============================] - 3s 7ms/step - loss: 22.2735 - mae: 3.76
15
Test MAE: 3.76
```

In [ ]:

```
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 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

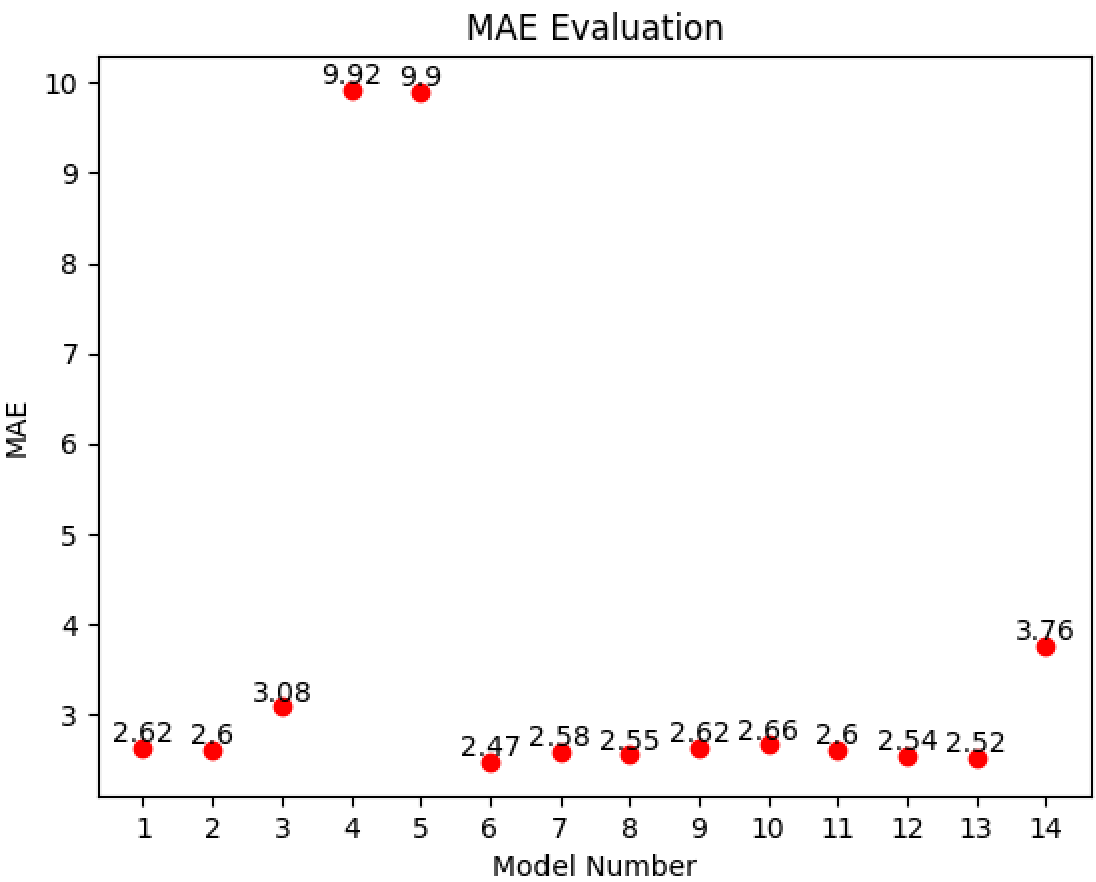
Model 12: LSTM - dropout-regularized, stacked

Model 13: Bidirectional LSTM

Model 14: 1D Convnets and LSTM togther

In [ ]:

```
Models = ("1","2","3","4","5","6","7","8","9","10","11","12","13","14")
Mae = (2.62,2.60,3.08,9.92,9.90,2.47,2.58,2.55,2.62,2.66,2.60,2.54,2.52,3.76)

# 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()

# Creating a table
fig, ax = plt.subplots(figsize=(8, 4))
ax.axis('tight')
ax.axis('off')
table_data = list(zip(Models, Mae))
table = ax.table(cellText=table_data, colLabels=['Model Number', 'MAE'], cellLoc =

# Adding style to the table
table.auto_set_font_size(False)
table.set_fontsize(10)
table.scale(1.2, 1.2)

plt.show()
```



Model Number	MAE
1	2.62
2	2.6
3	3.08
4	9.92
5	9.9
6	2.47
7	2.58
8	2.55
9	2.62
10	2.66
11	2.6
12	2.54
13	2.52
14	3.76