Deep learning for timeseries

```
In [1]: # Download the jena_climate_2009_2016.csv.zip file from AWS S3
         !wget https://s3.amazonaws.com/keras-datasets/jena_climate_2009_2016.csv.zip
         # Unzip the jena_climate_2009_2016.csv.zip file
         !unzip jena_climate_2009_2016.csv.zip
        --2024-04-07 22:30:28-- https://s3.amazonaws.com/keras-datasets/jena_climate_2009
         _2016.csv.zip
        Resolving s3.amazonaws.com (s3.amazonaws.com)... 16.182.37.64, 52.217.87.110, 16.1
        82.70.72, ...
        Connecting to s3.amazonaws.com (s3.amazonaws.com)|16.182.37.64|:443... connected.
        HTTP request sent, awaiting response... 200 OK
        Length: 13565642 (13M) [application/zip]
        Saving to: 'jena_climate_2009_2016.csv.zip'
        2024-04-07 22:30:31 (6.43 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
        Importing the data file
        #Importing csv
In [2]:
         import os
        fname = os.path.join("jena_climate_2009_2016.csv")
In [3]: #Reading Data from file
        with open(fname) as f:
            data = f.read()
In [4]:
        import pandas as pd
         import os
        for dirname, _, filenames in os.walk('/kaggle/'):
             for filename in filenames:
                 print(os.path.join(dirname, filename))
In [5]: # Split the data into lines
        lines = data.split("\n")
        # Get the header row
        header = lines[0].split(",")
        # Remove the header row from the list of lines
        lines = lines[1:]
        # Print the header row
         print(header)
        # Print the number of lines in the data
        print(len(lines))
        ['"Date Time"', '"p (mbar)"', '"T (degC)"', '"Tpot (K)"', '"Tdew (degC)"', '"rh (%)"', '"VPmax (mbar)"', '"VPact (mbar)"', '"VPdef (mbar)"', '"sh (g/kg)"', '"H2OC
        (mmol/mol)"', '"rho (g/m**3)"', '"wv (m/s)"', '"max. wv (m/s)"', '"wd (deg)"']
        420451
```

Parsing the Data

In [6]:

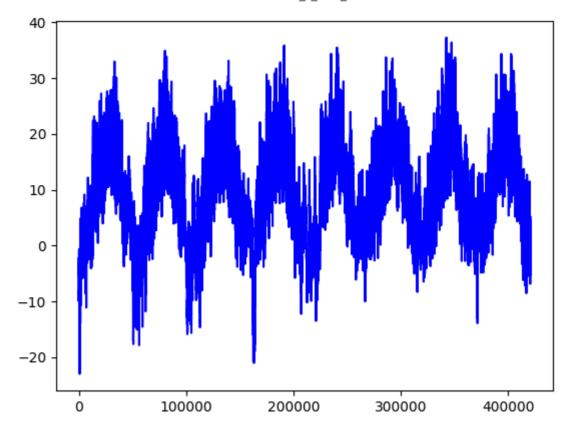
import numpy as np

```
# Create a NumPy array to store the temperature data
         temperature = np.zeros((len(lines),))
         # Create a NumPy array to store the raw data
         raw_data = np.zeros((len(lines), len(header) - 1))
         # Iterate over the lines in the data
         for i, line in enumerate(lines):
             # Split the line into a list of values
             values = [float(x) for x in line.split(",")[1:]]
             # Store the temperature in the temperature array
             temperature[i] = values[1]
             # Store the raw data in the raw_data array
             raw_data[i, :] = values[:]
        temperature[:5]
In [7]:
        array([-8.02, -8.41, -8.51, -8.31, -8.27])
Out[7]:
In [8]:
        view = pd.DataFrame(temperature)
         view.describe()
                          0
Out[8]:
         count 420451.000000
                    9.448567
         mean
                    8.423685
           std
          min
                  -23.010000
          25%
                    3.360000
          50%
                    9.410000
          75%
                   15.470000
                   37.280000
          max
```

Plotting the temparature

```
import matplotlib.pyplot as plt
plt.plot(range(len(temperature)), temperature, color='blue')

Out[9]: [<matplotlib.lines.Line2D at 0x785516972aa0>]
```



Plotting the first 15 days of the temperature timeseries

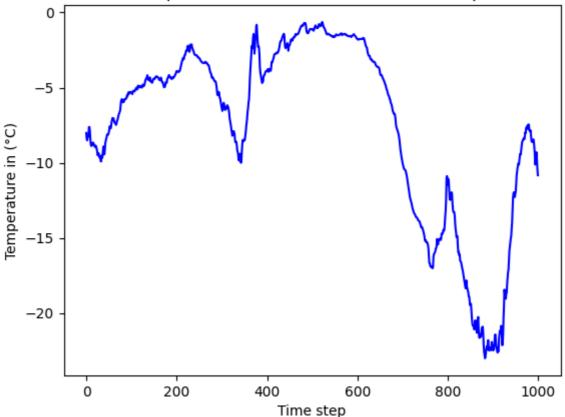
```
In [10]: ## Plot the first 1000 temperature values
    plt.plot(range(1000), temperature[:1000], color='blue')
    # Set the x-axis label
    plt.xlabel("Time step")

# Set the y-axis label
    plt.ylabel("Temperature in (°C)")

# Set the title of the plot
    plt.title("Temperature over the first 1000 time steps")

# Display the plot
    plt.show()
```





Figuring out how many samples each data split will require

```
In [11]: # Split the data into train, validation, and test sets
   num_train_samples = int(0.5 * len(raw_data)) # 50% of the data for training
   num_val_samples = int(0.25 * len(raw_data)) # 25% of the data for validation
   num_test_samples = len(raw_data) - num_train_samples - num_val_samples # The remain
```

Getting the data ready Data normalization

```
In [12]:
         mean = raw_data[:num_train_samples].mean(axis=0)
          raw_data -= mean
          std = raw_data[:num_train_samples].std(axis=0)
          raw_data /= std
          import numpy as np
          from tensorflow import keras
          int_sequence = np.arange(10)
          dummy dataset = keras.utils.timeseries dataset from array(
             data=int_sequence[:-3],
             targets=int_sequence[3:],
              sequence length=3,
             batch_size=2,
         for inputs, targets in dummy_dataset:
              for i in range(inputs.shape[0]):
                  print([int(x) for x in inputs[i]], int(targets[i]))
         [0, 1, 2] 3
         [1, 2, 3] 4
         [2, 3, 4] 5
         [3, 4, 5] 6
         [4, 5, 6] 7
In [13]:
         #Instantiating datasets for training, validation, and testing
          sampling_rate = 6
```

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

```
In [14]: train_dataset = keras.utils.timeseries_dataset_from_array(
    raw_data[:-delay], # The input data
    targets=temperature[delay:], # The target data
    sampling_rate=sampling_rate, # The sampling rate
    sequence_length=sequence_length, # The length of the sequences
    shuffle=True, # Whether to shuffle the data
    batch_size=batch_size, # The batch size
    start_index=0, # The start index
    end_index=num_train_samples) # The end index
```

```
In [15]: val_dataset = keras.utils.timeseries_dataset_from_array(
    raw_data[:-delay], # The input data
    targets=temperature[delay:], # The target data
    sampling_rate=sampling_rate, # The sampling rate
    sequence_length=sequence_length, # The length of the sequences
    shuffle=True, # Whether to shuffle the data
    batch_size=batch_size, # The batch size
    start_index=num_train_samples, # The start index
    end_index=num_train_samples + num_val_samples) # The end index
```

```
In [17]: # Iterate over the first sample in the train dataset
for samples, targets in train_dataset:
    # Print the shape of the samples and targets
    print("samples shape:", samples.shape)
    print("targets shape:", targets.shape)

# Break out of the loop after the first iteration
    break
```

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

common-sense, non-machine-learning baseline

```
In [18]: #Computing the common-sense baseline MAE

def evaluate_naive_method(dataset):
    total_abs_err = 0.
    samples_seen = 0
    for samples, targets in dataset:
        preds = samples[:, -1, 1] * std[1] + mean[1]
        total_abs_err += np.sum(np.abs(preds - targets))
        samples_seen += samples.shape[0]
    return total_abs_err / samples_seen
    print(f"Validation MAE: {evaluate_naive_method(val_dataset):.2f}")
    print(f"Test MAE: {evaluate_naive_method(test_dataset):.2f}")
```

```
Validation MAE: 2.44
Test MAE: 2.62

In [19]: from tensorflow import keras
from keras import layers
```

Constructing and assessing a densely linked model

```
In [20]: #Training and evaluating a densely connected model
         from tensorflow import keras
         from tensorflow.keras import layers
         inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
         x = layers.Flatten()(inputs)
         x = layers.Dense(16, activation="relu")(x)
         outputs = layers.Dense(1)(x)
         model = keras.Model(inputs, outputs)
         callbacks = [
              keras.callbacks.ModelCheckpoint("jena_dense.st",
                                              save_best_only=True)
         model.compile(optimizer="rmsprop", loss="mse", metrics=["mae"])
         history = model.fit(train_dataset,
                              epochs=10,
                              validation_data=val_dataset,
                              callbacks=callbacks)
         model = keras.models.load_model("jena_dense.st")
         print(f"Test MAE: {model.evaluate(test_dataset)[1]:.2f}")
```

```
Epoch 1/10
8277 - val_loss: 12.3551 - val_mae: 2.7730
Epoch 2/10
330 - val_loss: 11.0970 - val_mae: 2.6248
Epoch 3/10
274 - val_loss: 11.3616 - val_mae: 2.6611
Epoch 4/10
587 - val_loss: 13.4715 - val_mae: 2.9222
Epoch 5/10
168 - val loss: 10.5612 - val mae: 2.5718
Epoch 6/10
803 - val_loss: 10.9429 - val_mae: 2.6184
Epoch 7/10
513 - val_loss: 11.4363 - val_mae: 2.6894
Epoch 8/10
260 - val_loss: 11.1422 - val_mae: 2.6537
Epoch 9/10
006 - val_loss: 11.2063 - val_mae: 2.6545
Epoch 10/10
811 - val_loss: 11.1233 - val_mae: 2.6475
92
Test MAE: 2.65
```

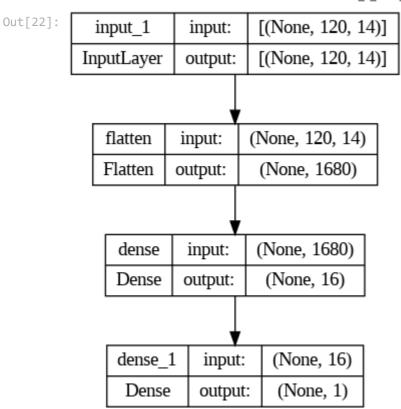
In [21]: model.summary()

Model: "model"

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 120, 14)]	0
flatten (Flatten)	(None, 1680)	0
dense (Dense)	(None, 16)	26896
dense_1 (Dense)	(None, 1)	17
=======================================		========

Total params: 26913 (105.13 KB)
Trainable params: 26913 (105.13 KB)
Non-trainable params: 0 (0.00 Byte)

In [22]: keras.utils.plot_model(model, show_shapes=True)



```
In [23]: import matplotlib.pyplot as plt

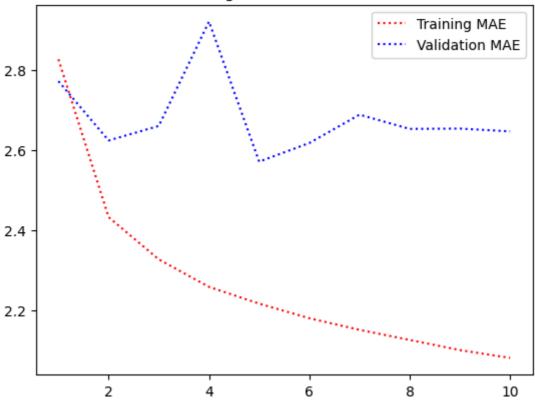
loss = history.history["mae"]
val_loss = history.history["val_mae"]
epochs = range(1, len(loss) + 1)

plt.figure()

# Update the color to red and line style to a dotted line for training MAE
plt.plot(epochs, loss, "r:", label="Training MAE")

# Update the color to blue and line style to a dotted line for validation MAE
plt.plot(epochs, val_loss, "b:", label="Validation MAE")

plt.title("Training and validation MAE")
plt.legend()
plt.show()
```



1D Convolution model with 10 epoch

```
inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
In [24]:
         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.st",
                                              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.st")
         print(f"Test MAE: {model.evaluate(test_dataset)[1]:.2f}")
```

```
Epoch 1/10
819/819 [============ ] - 15s 15ms/step - loss: 21.7765 - mae: 3.
6716 - val_loss: 15.1529 - val_mae: 3.0795
Epoch 2/10
819/819 [============ ] - 12s 14ms/step - loss: 15.7164 - mae: 3.
1405 - val loss: 14.4813 - val mae: 3.0253
819/819 [============= ] - 12s 14ms/step - loss: 14.4108 - mae: 3.
0067 - val_loss: 14.3182 - val_mae: 2.9788
Epoch 4/10
819/819 [============] - 11s 14ms/step - loss: 13.4329 - mae: 2.
9014 - val_loss: 14.8376 - val_mae: 3.0292
Epoch 5/10
819/819 [============ ] - 11s 14ms/step - loss: 12.7203 - mae: 2.
8232 - val loss: 15.4623 - val mae: 3.0842
Epoch 6/10
819/819 [============] - 11s 14ms/step - loss: 12.1124 - mae: 2.
7552 - val_loss: 14.8451 - val_mae: 3.0582
Epoch 7/10
6992 - val_loss: 15.5517 - val_mae: 3.0988
Epoch 8/10
819/819 [==========] - 11s 14ms/step - loss: 11.2676 - mae: 2.
6538 - val_loss: 14.6210 - val_mae: 3.0035
Epoch 9/10
819/819 [============ ] - 11s 14ms/step - loss: 10.9469 - mae: 2.
6150 - val_loss: 17.0661 - val_mae: 3.2570
Epoch 10/10
819/819 [============] - 11s 14ms/step - loss: 10.6152 - mae: 2.
5757 - val_loss: 14.9081 - val_mae: 3.0316
01
Test MAE: 3.17
```

In [25]: model.summary()

Model: "model 1"

Layer (type)	Output Shape	Param #
input_2 (InputLayer)		0
conv1d (Conv1D)	(None, 97, 8)	2696
<pre>max_pooling1d (MaxPooling1 D)</pre>	(None, 48, 8)	0
conv1d_1 (Conv1D)	(None, 37, 8)	776
<pre>max_pooling1d_1 (MaxPoolin g1D)</pre>	(None, 18, 8)	0
conv1d_2 (Conv1D)	(None, 13, 8)	392
<pre>global_average_pooling1d (GlobalAveragePooling1D)</pre>	(None, 8)	0
dense_2 (Dense)	(None, 1)	9

Non-trainable params: 0 (0.00 Byte)

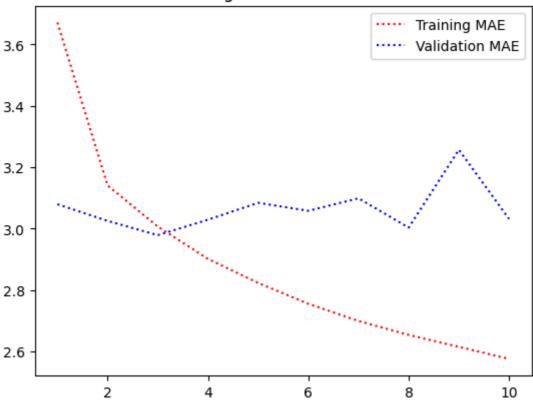
file:///C:/Users/sridh/Downloads/AML_3_Time_series.html

keras.utils.plot_model(model, show_shapes=True) In [26]: Out[26]: input_2 input: [(None, 120, 14)] [(None, 120, 14)] InputLayer output: conv1d (None, 120, 14) input: (None, 97, 8) Conv1D output: max pooling1d (None, 97, 8) input: (None, 48, 8) MaxPooling1D output: conv1d 1 (None, 48, 8) input: Conv1D (None, 37, 8) output: max_pooling1d_1 (None, 37, 8) input: MaxPooling1D output: (None, 18, 8) conv1d 2 (None, 18, 8) input: Conv1D output: (None, 13, 8) global_average_pooling1d input: (None, 13, 8) GlobalAveragePooling1D (None, 8) output: dense_2 (None, 8) input: Dense output: (None, 1) In [27]: import matplotlib.pyplot as plt loss = history.history["mae"] val_loss = history.history["val_mae"] epochs = range(1, len(loss) + 1) plt.figure()

```
# Update the color to red and line style to a dotted line for training MAE
plt.plot(epochs, loss, "r:", label="Training MAE")

# Update the color to blue and line style to a dotted line for validation MAE
plt.plot(epochs, val_loss, "b:", label="Validation MAE")

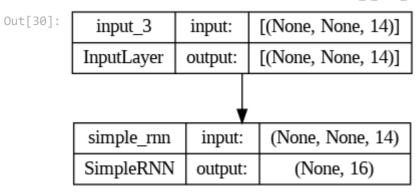
plt.title("Training and validation MAE")
plt.legend()
plt.show()
```



As time goes on, both the training and validation losses decrease, indicating that the model is learning. It is common that the validation loss is marginally greater than the training loss. To ensure that the model is not overfitting the training set, it is crucial to keep an eye on the validation loss. The model may not be properly generalizing to new data, as indicated by the test MAE being considerably higher than the validation MAE. There are several possible reasons for this, including noise in the data or an undertrained model.

A Simple RNN

```
AML 3 Time series
                        validation data=val dataset,
                        callbacks=callbacks)
        model = keras.models.load model("jena SimRNN.st")
        print(f"Test MAE: {model.evaluate(test_dataset)[1]:.2f}")
       Epoch 1/10
       819/819 [============ ] - 47s 56ms/step - loss: 139.1357 - mae:
       9.7067 - val loss: 143.8847 - val mae: 9.8867
       Epoch 2/10
       9.5603 - val_loss: 143.7051 - val_mae: 9.8688
       Epoch 3/10
       819/819 [============= ] - 45s 55ms/step - loss: 136.2942 - mae:
       9.5505 - val_loss: 143.6327 - val_mae: 9.8576
       Epoch 4/10
       819/819 [============ ] - 46s 55ms/step - loss: 136.2349 - mae:
       9.5446 - val_loss: 143.5929 - val_mae: 9.8534
       Epoch 5/10
       819/819 [============] - 46s 56ms/step - loss: 136.1976 - mae:
       9.5403 - val_loss: 143.5897 - val_mae: 9.8548
       819/819 [============= ] - 45s 55ms/step - loss: 136.1642 - mae:
       9.5376 - val_loss: 143.5294 - val_mae: 9.8493
       Epoch 7/10
       819/819 [============ ] - 45s 55ms/step - loss: 136.1381 - mae:
       9.5345 - val_loss: 143.5399 - val_mae: 9.8514
       Epoch 8/10
       819/819 [============ ] - 44s 54ms/step - loss: 136.1289 - mae:
       9.5337 - val_loss: 143.5414 - val_mae: 9.8525
       Epoch 9/10
       819/819 [============= ] - 44s 54ms/step - loss: 136.1107 - mae:
       9.5317 - val_loss: 143.5461 - val_mae: 9.8528
       Epoch 10/10
       819/819 [============ ] - 45s 54ms/step - loss: 136.1015 - mae:
       9.5306 - val loss: 143.5316 - val mae: 9.8517
       405/405 [============ ] - 6s 14ms/step - loss: 151.2813 - mae: 9.
       9175
       Test MAE: 9.92
In [29]: model.summary()
       Model: "model 2"
        Layer (type)
                               Output Shape
                                                     Param #
        ______
                                [(None, None, 14)]
        input 3 (InputLayer)
        simple rnn (SimpleRNN)
                                (None, 16)
                                                     496
       ______
       Total params: 496 (1.94 KB)
       Trainable params: 496 (1.94 KB)
       Non-trainable params: 0 (0.00 Byte)
       keras.utils.plot model(model, show shapes=True)
```



```
In [31]: import matplotlib.pyplot as plt

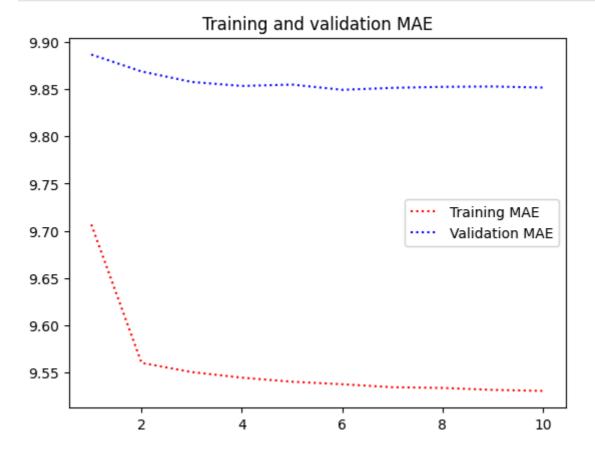
loss = history.history["mae"]
  val_loss = history.history["val_mae"]
  epochs = range(1, len(loss) + 1)

plt.figure()

# Update the color to red and line style to a dotted line for training MAE
  plt.plot(epochs, loss, "r:", label="Training MAE")

# Update the color to blue and line style to a dotted line for validation MAE
  plt.plot(epochs, val_loss, "b:", label="Validation MAE")

plt.title("Training and validation MAE")
  plt.legend()
  plt.show()
```



The solution to the above is to experiment with increasing or decreasing the model complexity. After two epochs, the model has finished learning because the MAE is a constant line and has converged to a specific level of performance. Further training does not result in a meaningful improvement. We can explore other structures, add

more levels, or increase the number of units in the layers that already exist.attempting to stack the RNNs in an attempt to add extra layers to the data collection

Simple RNN - Stacking RNN layers

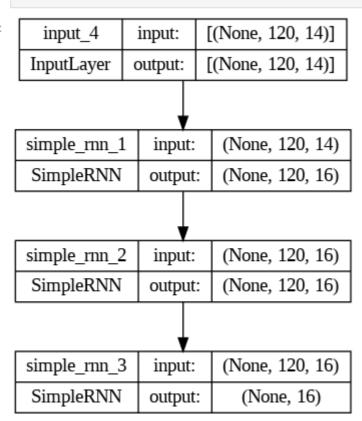
```
In [32]: num_features = 14
        steps = 120
        inputs = keras.Input(shape=(steps, num_features))
        x = layers.SimpleRNN(16, return sequences=True)(inputs)
        x = layers.SimpleRNN(16, return_sequences=True)(x)
        outputs = layers.SimpleRNN(16)(x)
        model = keras.Model(inputs, outputs)
        callbacks = [
            keras.callbacks.ModelCheckpoint("jena_SRNN2.st",
                                        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.st")
        print(f"Test MAE: {model.evaluate(test_dataset)[1]:.2f}")
        Epoch 1/10
        819/819 [============ ] - 188s 227ms/step - loss: 136.9309 - mae:
        9.5741 - val_loss: 143.4676 - val_mae: 9.8414
        Epoch 2/10
        819/819 [============ ] - 187s 228ms/step - loss: 136.0621 - mae:
        9.5274 - val_loss: 143.4446 - val_mae: 9.8393
        Epoch 3/10
        819/819 [============= ] - 184s 225ms/step - loss: 136.0032 - mae:
        9.5181 - val_loss: 143.3821 - val_mae: 9.8310
        Epoch 4/10
        819/819 [============ ] - 184s 225ms/step - loss: 135.9274 - mae:
        9.5083 - val loss: 143.3766 - val mae: 9.8341
        Epoch 5/10
        819/819 [============ ] - 180s 220ms/step - loss: 135.8805 - mae:
        9.5015 - val_loss: 143.3880 - val_mae: 9.8321
        Epoch 6/10
        819/819 [============= ] - 180s 220ms/step - loss: 135.8664 - mae:
        9.4994 - val_loss: 143.3816 - val_mae: 9.8294
        Epoch 7/10
        819/819 [============ ] - 180s 219ms/step - loss: 135.8464 - mae:
        9.4968 - val loss: 143.3848 - val mae: 9.8325
        Epoch 8/10
        819/819 [============ ] - 179s 218ms/step - loss: 135.8250 - mae:
        9.4927 - val_loss: 143.4053 - val_mae: 9.8384
        Epoch 9/10
        819/819 [============ ] - 178s 217ms/step - loss: 135.8163 - mae:
        9.4912 - val_loss: 143.3974 - val_mae: 9.8346
        Epoch 10/10
        819/819 [============ ] - 182s 222ms/step - loss: 135.8105 - mae:
        9.4906 - val loss: 143.3593 - val mae: 9.8296
        9.9015
        Test MAE: 9.90
        model.summary()
In [33]:
```

Model: "model 3"

```
Layer (type)
                             Output Shape
                                                       Param #
                             [(None, 120, 14)]
input_4 (InputLayer)
                            (None, 120, 16)
simple_rnn_1 (SimpleRNN)
                                                       496
simple_rnn_2 (SimpleRNN)
                             (None, 120, 16)
                                                       528
simple_rnn_3 (SimpleRNN)
                             (None, 16)
                                                       528
Total params: 1552 (6.06 KB)
Trainable params: 1552 (6.06 KB)
Non-trainable params: 0 (0.00 Byte)
```

In [34]: keras.utils.plot_model(model, show_shapes=True)

Out[34]:



```
In [35]: import matplotlib.pyplot as plt

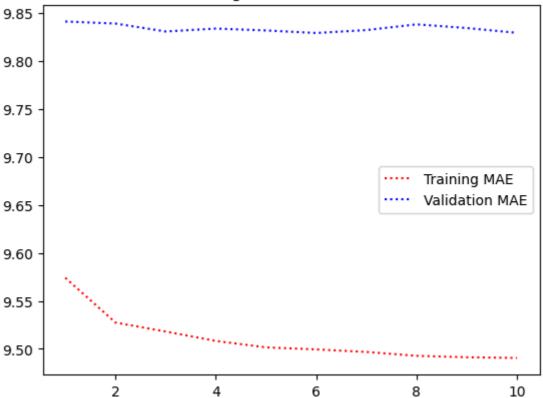
loss = history.history["mae"]
val_loss = history.history["val_mae"]
epochs = range(1, len(loss) + 1)

plt.figure()

# Update the color to red and line style to a dotted line for training MAE
plt.plot(epochs, loss, "r:", label="Training MAE")

# Update the color to blue and line style to a dotted line for validation MAE
plt.plot(epochs, val_loss, "b:", label="Validation MAE")

plt.title("Training and validation MAE")
plt.legend()
plt.show()
```



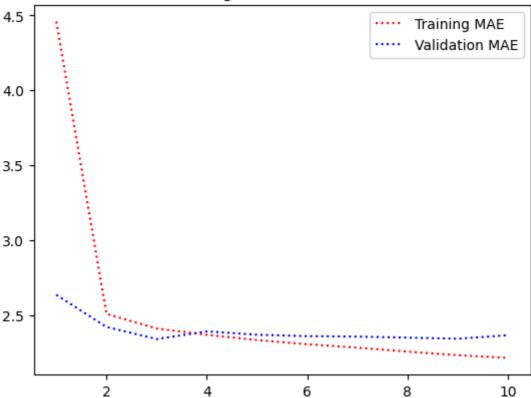
The model's inability to identify the underlying patterns in the data is indicated by the Training and Validation MAE, which seems to be a constant line.

Simple GRU (Gated Recurrent Unit)

```
Epoch 1/10
      819/819 [============ ] - 16s 17ms/step - loss: 37.9946 - mae: 4.
      4591 - val_loss: 12.1957 - val_mae: 2.6376
      Epoch 2/10
      819/819 [============] - 14s 17ms/step - loss: 10.3635 - mae: 2.
      5105 - val loss: 9.9849 - val mae: 2.4236
      Epoch 3/10
      133 - val_loss: 9.1291 - val_mae: 2.3428
      Epoch 4/10
      710 - val_loss: 9.6521 - val_mae: 2.3937
      Epoch 5/10
      360 - val loss: 9.4650 - val mae: 2.3717
      Epoch 6/10
      819/819 [===========] - 12s 14ms/step - loss: 8.6781 - mae: 2.3
      084 - val_loss: 9.3988 - val_mae: 2.3622
      Epoch 7/10
      853 - val_loss: 9.3577 - val_mae: 2.3593
      Epoch 8/10
      592 - val_loss: 9.3445 - val_mae: 2.3525
      Epoch 9/10
      355 - val loss: 9.3027 - val mae: 2.3450
      Epoch 10/10
      172 - val_loss: 9.5235 - val_mae: 2.3687
      80
      Test MAE: 2.49
In [37]: import matplotlib.pyplot as plt
      loss = history.history["mae"]
      val loss = history.history["val mae"]
      epochs = range(1, len(loss) + 1)
      plt.figure()
      # Update the color to red and line style to a dotted line for training MAE
      plt.plot(epochs, loss, "r:", label="Training MAE")
      # Update the color to blue and line style to a dotted line for validation MAE
      plt.plot(epochs, val_loss, "b:", label="Validation MAE")
      plt.title("Training and validation MAE")
      plt.legend()
      plt.show()
```

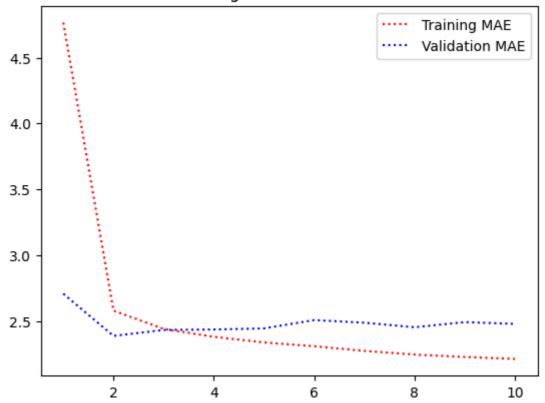
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Training and validation MAE



An abbreviated form of the Long Short-Term Memory (LSTM) network architecture is called LSTM-Simple.

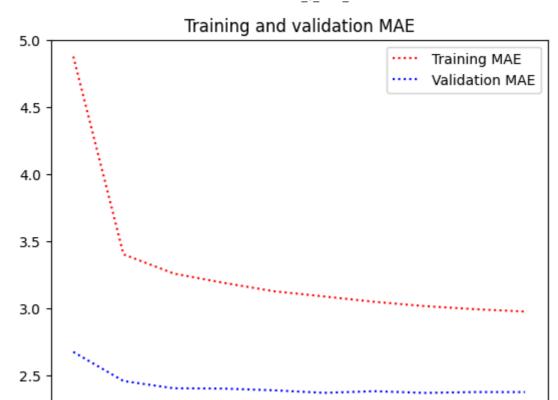
```
Epoch 1/10
     819/819 [============ ] - 17s 18ms/step - loss: 42.4580 - mae: 4.
     7673 - val_loss: 12.7456 - val_mae: 2.7065
     Epoch 2/10
     5781 - val loss: 9.4115 - val mae: 2.3859
     Epoch 3/10
     819/819 [===========] - 12s 15ms/step - loss: 9.7311 - mae: 2.4
     391 - val_loss: 10.0108 - val_mae: 2.4313
     Epoch 4/10
     792 - val_loss: 10.1624 - val_mae: 2.4347
     Epoch 5/10
     363 - val loss: 10.2920 - val mae: 2.4430
     Epoch 6/10
     074 - val_loss: 11.2977 - val_mae: 2.5063
     Epoch 7/10
     720 - val_loss: 10.7163 - val_mae: 2.4862
     Epoch 8/10
     442 - val_loss: 10.1885 - val_mae: 2.4516
     Epoch 9/10
     257 - val_loss: 10.5671 - val_mae: 2.4908
     Epoch 10/10
     112 - val_loss: 10.3527 - val_mae: 2.4772
     41
     Test MAE: 2.57
In [39]: import matplotlib.pyplot as plt
     loss = history.history["mae"]
     val loss = history.history["val mae"]
     epochs = range(1, len(loss) + 1)
     plt.figure()
     # Update the color to red and line style to a dotted line for training MAE
     plt.plot(epochs, loss, "r:", label="Training MAE")
     # Update the color to blue and line style to a dotted line for validation MAE
     plt.plot(epochs, val_loss, "b:", label="Validation MAE")
     plt.title("Training and validation MAE")
     plt.legend()
     plt.show()
```



LSTM - dropout (RNN) regularization that is frequently employed in sequential dataintensive activities like time series analysis and natural language processing. The purpose of LSTM networks is to identify long-term dependencies in data.

```
In [40]:
         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.st",
                                              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.st")
         print(f"Test MAE: {model.evaluate(test_dataset)[1]:.2f}")
         WARNING:tensorflow:Layer lstm_1 will not use cuDNN kernels since it doesn't meet t
         he criteria. It will use a generic GPU kernel as fallback when running on GPU.
```

```
Epoch 1/10
     4.8761 - val_loss: 12.4762 - val_mae: 2.6726
     Epoch 2/10
     3.4003 - val loss: 10.0883 - val mae: 2.4555
     3.2574 - val_loss: 9.4769 - val_mae: 2.4014
     Epoch 4/10
     3.1876 - val_loss: 9.4717 - val_mae: 2.3990
     Epoch 5/10
     3.1250 - val loss: 9.3487 - val mae: 2.3862
     Epoch 6/10
     3.0863 - val_loss: 9.2829 - val_mae: 2.3673
     Epoch 7/10
     3.0463 - val_loss: 9.3961 - val_mae: 2.3797
     Epoch 8/10
     3.0143 - val_loss: 9.2679 - val_mae: 2.3668
     Epoch 9/10
     2.9914 - val loss: 9.3266 - val mae: 2.3732
     Epoch 10/10
     2.9738 - val_loss: 9.3490 - val_mae: 2.3731
     WARNING:tensorflow:Layer lstm_1 will not use cuDNN kernels since it doesn't meet t
     he criteria. It will use a generic GPU kernel as fallback when running on GPU.
     5822
     Test MAE: 2.58
In [41]: import matplotlib.pyplot as plt
     loss = history.history["mae"]
     val loss = history.history["val mae"]
     epochs = range(1, len(loss) + 1)
     plt.figure()
     # Update the color to red and line style to a dotted line for training MAE
     plt.plot(epochs, loss, "r:", label="Training MAE")
     # Update the color to blue and line style to a dotted line for validation MAE
     plt.plot(epochs, val loss, "b:", label="Validation MAE")
     plt.title("Training and validation MAE")
     plt.legend()
     plt.show()
```



Using numerous LSTM layers placed on top of one another in a neural network is known as a stacked LSTM arrangement. With the ability to capture various levels of abstraction in the input data, each LSTM layer enhances the modeling capabilities of sequential information.

6

8

4

8 UNITS

2

```
In [42]:
         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_stacked1.st",
                                              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.st")
         print(f"Test MAE: {model.evaluate(test_dataset)[1]:.2f}")
```

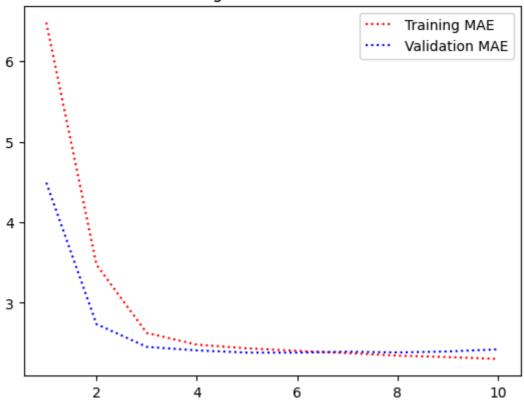
10

Epoch 1/10

```
4814 - val_loss: 36.6526 - val_mae: 4.4927
      Epoch 2/10
      819/819 [============= ] - 19s 24ms/step - loss: 22.0938 - mae: 3.
      4740 - val loss: 13.2498 - val mae: 2.7364
      Epoch 3/10
      819/819 [============] - 20s 25ms/step - loss: 11.5408 - mae: 2.
      6272 - val_loss: 10.0911 - val_mae: 2.4532
      Epoch 4/10
      819/819 [============= ] - 19s 23ms/step - loss: 10.1388 - mae: 2.
      4810 - val_loss: 9.6101 - val_mae: 2.4096
      Epoch 5/10
      355 - val loss: 9.3762 - val mae: 2.3821
      Epoch 6/10
      035 - val_loss: 9.4453 - val_mae: 2.3812
      Epoch 7/10
      761 - val_loss: 9.5335 - val_mae: 2.3936
      Epoch 8/10
      444 - val_loss: 9.5297 - val_mae: 2.3841
      Epoch 9/10
      266 - val loss: 9.5346 - val mae: 2.3958
      Epoch 10/10
      037 - val_loss: 9.8103 - val_mae: 2.4227
      56
      Test MAE: 2.54
In [43]: import matplotlib.pyplot as plt
      loss = history.history["mae"]
      val loss = history.history["val mae"]
      epochs = range(1, len(loss) + 1)
      plt.figure()
      # Update the color to red and line style to a dotted line for training MAE
      plt.plot(epochs, loss, "r:", label="Training MAE")
      # Update the color to blue and line style to a dotted line for validation MAE
      plt.plot(epochs, val_loss, "b:", label="Validation MAE")
      plt.title("Training and validation MAE")
      plt.legend()
      plt.show()
```

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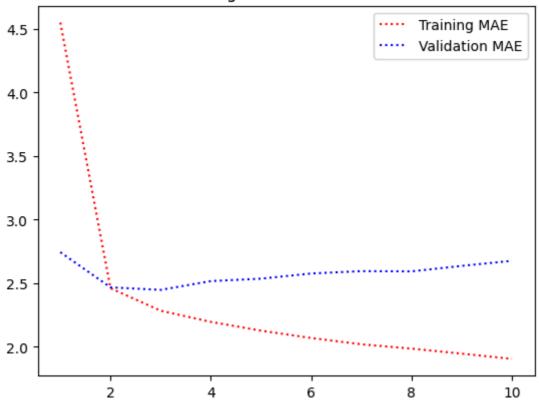
Training and validation MAE



16 UNITS

```
In [44]:
         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_stacked2.st",
                                              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.st")
         print(f"Test MAE: {model.evaluate(test_dataset)[1]:.2f}")
```

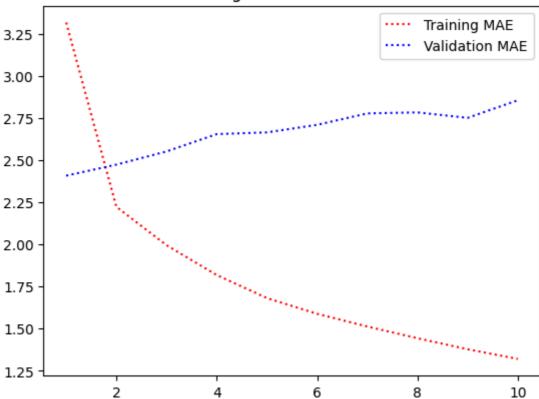
```
Epoch 1/10
     5511 - val_loss: 12.9220 - val_mae: 2.7445
     Epoch 2/10
     819/819 [============= ] - 20s 25ms/step - loss: 10.0461 - mae: 2.
     4608 - val loss: 10.1463 - val mae: 2.4678
     819/819 [===========] - 19s 23ms/step - loss: 8.6005 - mae: 2.2
     838 - val_loss: 9.9778 - val_mae: 2.4478
     Epoch 4/10
     961 - val_loss: 10.4293 - val_mae: 2.5170
     Epoch 5/10
     269 - val loss: 10.5627 - val mae: 2.5360
     Epoch 6/10
     692 - val_loss: 10.8618 - val_mae: 2.5767
     Epoch 7/10
     196 - val_loss: 11.0478 - val_mae: 2.5953
     Epoch 8/10
     857 - val_loss: 10.9654 - val_mae: 2.5935
     Epoch 9/10
     462 - val_loss: 11.3620 - val_mae: 2.6366
     Epoch 10/10
     048 - val_loss: 11.6901 - val_mae: 2.6765
     554
     Test MAE: 2.66
In [45]: import matplotlib.pyplot as plt
     loss = history.history["mae"]
     val loss = history.history["val mae"]
     epochs = range(1, len(loss) + 1)
     plt.figure()
     # Update the color to red and line style to a dotted line for training MAE
     plt.plot(epochs, loss, "r:", label="Training MAE")
     # Update the color to blue and line style to a dotted line for validation MAE
     plt.plot(epochs, val_loss, "b:", label="Validation MAE")
     plt.title("Training and validation MAE")
     plt.legend()
     plt.show()
```



32 UNITS

```
In [46]:
         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_stacked3.st",
                                              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.st")
         print(f"Test MAE: {model.evaluate(test_dataset)[1]:.2f}")
```

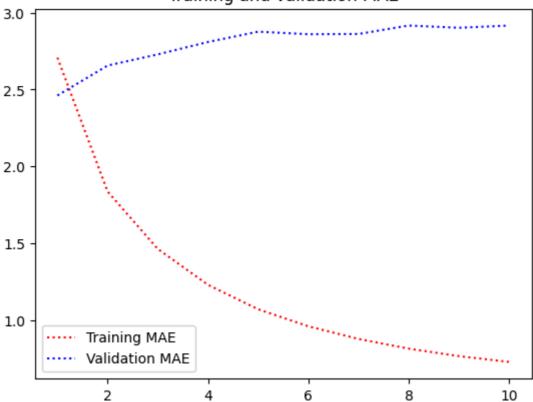
```
Epoch 1/10
     3170 - val_loss: 9.5987 - val_mae: 2.4080
     Epoch 2/10
     231 - val loss: 10.0138 - val mae: 2.4737
     819/819 [===========] - 14s 18ms/step - loss: 6.5997 - mae: 1.9
     952 - val_loss: 10.6741 - val_mae: 2.5519
     Epoch 4/10
     182 - val_loss: 11.5233 - val_mae: 2.6547
     Epoch 5/10
     816 - val loss: 11.6769 - val mae: 2.6649
     Epoch 6/10
     883 - val_loss: 12.1840 - val_mae: 2.7098
     Epoch 7/10
     128 - val_loss: 12.6120 - val_mae: 2.7776
     Epoch 8/10
     433 - val_loss: 12.8054 - val_mae: 2.7836
     Epoch 9/10
     779 - val_loss: 12.6290 - val_mae: 2.7513
     Epoch 10/10
     206 - val_loss: 13.3755 - val_mae: 2.8557
     74
     Test MAE: 2.59
In [47]: import matplotlib.pyplot as plt
     loss = history.history["mae"]
     val_loss = history.history["val_mae"]
     epochs = range(1, len(loss) + 1)
     plt.figure()
     # Update the color to red and line style to a dotted line for training MAE
     plt.plot(epochs, loss, "r:", label="Training MAE")
     # Update the color to blue and line style to a dotted line for validation MAE
     plt.plot(epochs, val_loss, "b:", label="Validation MAE")
     plt.title("Training and validation MAE")
     plt.legend()
     plt.show()
```



```
In [48]:
         inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
         x = layers.LSTM(64, return_sequences=True)(inputs)
         x = layers.LSTM(64)(x)
         outputs = layers.Dense(1)(x)
         model = keras.Model(inputs, outputs)
         callbacks = [
             keras.callbacks.ModelCheckpoint("jena_LSTM_stacked4.st",
                                              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 stacked4.st")
         print(f"Test MAE: {model.evaluate(test_dataset)[1]:.2f}")
```

```
Epoch 1/10
     7081 - val_loss: 10.0222 - val_mae: 2.4617
     Epoch 2/10
     364 - val loss: 11.5892 - val mae: 2.6566
     630 - val_loss: 12.1547 - val_mae: 2.7290
     Epoch 4/10
     298 - val_loss: 12.9282 - val_mae: 2.8097
     Epoch 5/10
     707 - val loss: 13.4367 - val mae: 2.8769
     Epoch 6/10
     599 - val_loss: 13.4157 - val_mae: 2.8603
     Epoch 7/10
     776 - val_loss: 13.2941 - val_mae: 2.8618
     Epoch 8/10
     145 - val_loss: 13.7425 - val_mae: 2.9168
     Epoch 9/10
     659 - val_loss: 13.5821 - val_mae: 2.9022
     Epoch 10/10
     283 - val_loss: 13.7624 - val_mae: 2.9166
     81
     Test MAE: 2.66
In [49]: import matplotlib.pyplot as plt
     loss = history.history["mae"]
     val loss = history.history["val mae"]
     epochs = range(1, len(loss) + 1)
     plt.figure()
     # Update the color to red and line style to a dotted line for training MAE
     plt.plot(epochs, loss, "r:", label="Training MAE")
     # Update the color to blue and line style to a dotted line for validation MAE
     plt.plot(epochs, val_loss, "b:", label="Validation MAE")
     plt.title("Training and validation MAE")
     plt.legend()
     plt.show()
```





64 UNITS

```
inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
In [50]:
         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.st",
                                              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.st")
         print(f"Test MAE: {model.evaluate(test_dataset)[1]:.2f}")
```

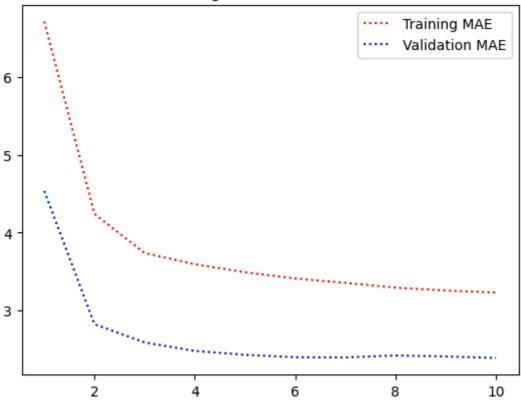
WARNING:tensorflow:Layer lstm_10 will not use cuDNN kernels since it doesn't meet the criteria. It will use a generic GPU kernel as fallback when running on GPU. WARNING:tensorflow:Layer lstm_11 will not use cuDNN kernels since it doesn't meet the criteria. It will use a generic GPU kernel as fallback when running on GPU.

Epoch 1/10

```
6.7153 - val_loss: 37.0579 - val_mae: 4.5377
     Epoch 2/10
     4.2431 - val loss: 14.3928 - val mae: 2.8240
     Epoch 3/10
     3.7393 - val_loss: 11.4730 - val_mae: 2.5901
     Epoch 4/10
     3.5958 - val_loss: 10.4573 - val_mae: 2.4805
     Epoch 5/10
     3.4919 - val loss: 9.9832 - val mae: 2.4313
     Epoch 6/10
     3.4115 - val_loss: 9.6812 - val_mae: 2.3999
     Epoch 7/10
     3.3561 - val_loss: 9.6462 - val_mae: 2.3966
     Epoch 8/10
     3.2944 - val_loss: 9.8613 - val_mae: 2.4231
     Epoch 9/10
     3.2571 - val loss: 9.7556 - val mae: 2.4095
     Epoch 10/10
     3.2307 - val_loss: 9.5700 - val_mae: 2.3912
     WARNING:tensorflow:Layer lstm_10 will not use cuDNN kernels since it doesn't meet
     the criteria. It will use a generic GPU kernel as fallback when running on GPU.
     WARNING:tensorflow:Layer lstm_11 will not use cuDNN kernels since it doesn't meet
     the criteria. It will use a generic GPU kernel as fallback when running on GPU.
     5809
     Test MAE: 2.58
In [51]: import matplotlib.pyplot as plt
     loss = history.history["mae"]
     val loss = history.history["val mae"]
     epochs = range(1, len(loss) + 1)
     plt.figure()
     # Update the color to red and line style to a dotted line for training MAE
      plt.plot(epochs, loss, "r:", label="Training MAE")
     # Update the color to blue and line style to a dotted line for validation MAE
      plt.plot(epochs, val_loss, "b:", label="Validation MAE")
      plt.title("Training and validation MAE")
     plt.legend()
     plt.show()
```

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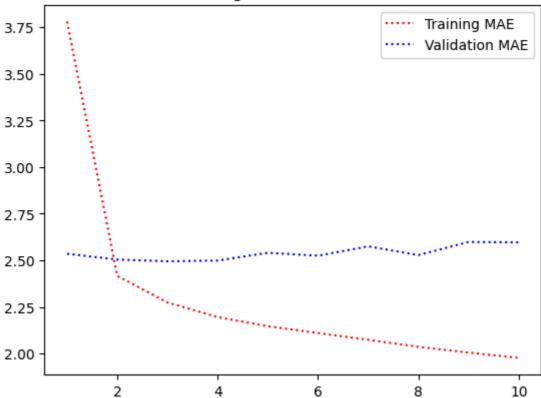
Training and validation MAE



LSTM - dropout-regularized, stacked model

```
In [52]:
         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.st",
                                              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.st")
         print(f"Test MAE: {model.evaluate(test_dataset)[1]:.2f}")
```

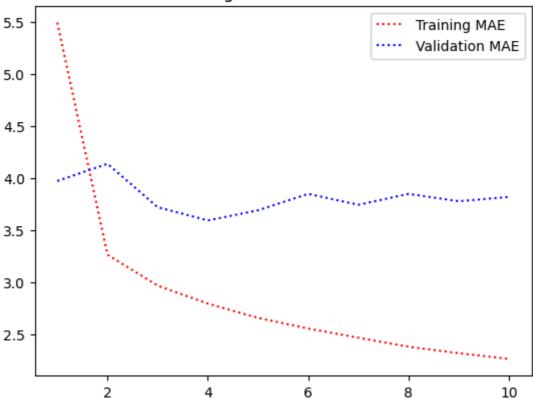
```
Epoch 1/10
     7810 - val_loss: 10.7398 - val_mae: 2.5353
     Epoch 2/10
     162 - val loss: 10.4937 - val mae: 2.5041
     743 - val_loss: 10.3009 - val_mae: 2.4950
     Epoch 4/10
     953 - val_loss: 10.4739 - val_mae: 2.4986
     Epoch 5/10
     465 - val loss: 10.8696 - val mae: 2.5405
     Epoch 6/10
     099 - val_loss: 10.7107 - val_mae: 2.5248
     Epoch 7/10
     738 - val_loss: 11.1661 - val_mae: 2.5750
     Epoch 8/10
     360 - val_loss: 10.8024 - val_mae: 2.5282
     Epoch 9/10
     054 - val loss: 11.4922 - val mae: 2.5985
     Epoch 10/10
     766 - val_loss: 11.3771 - val_mae: 2.5963
     43
     Test MAE: 2.54
In [53]: import matplotlib.pyplot as plt
     loss = history.history["mae"]
     val loss = history.history["val mae"]
     epochs = range(1, len(loss) + 1)
     plt.figure()
     # Update the color to red and line style to a dotted line for training MAE
     plt.plot(epochs, loss, "r:", label="Training MAE")
     # Update the color to blue and line style to a dotted line for validation MAE
     plt.plot(epochs, val_loss, "b:", label="Validation MAE")
     plt.title("Training and validation MAE")
     plt.legend()
     plt.show()
```



Bi Directional LSTM

```
In [54]:
         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.st", save_best_only=True)
          ]
         history = model.fit(train_dataset, epochs=10, validation_data=val_dataset, callback
         model = keras.models.load_model("jena_Conv_LSTM.st")
         print(f"Test MAE: {model.evaluate(test_dataset)[1]:.2f}")
```

```
Epoch 1/10
       819/819 [============ ] - 17s 18ms/step - loss: 53.9860 - mae: 5.
       4955 - val_loss: 26.9692 - val_mae: 3.9739
       Epoch 2/10
       819/819 [============ ] - 12s 14ms/step - loss: 18.0204 - mae: 3.
       2664 - val_loss: 28.0418 - val_mae: 4.1391
       819/819 [============] - 14s 17ms/step - loss: 14.7304 - mae: 2.
       9691 - val_loss: 22.8467 - val_mae: 3.7222
       Epoch 4/10
       819/819 [============] - 14s 17ms/step - loss: 13.1107 - mae: 2.
       7968 - val_loss: 21.0134 - val_mae: 3.5956
       Epoch 5/10
       819/819 [============ ] - 12s 14ms/step - loss: 11.9008 - mae: 2.
       6598 - val loss: 21.6781 - val mae: 3.6927
       Epoch 6/10
       819/819 [============ ] - 12s 14ms/step - loss: 11.0358 - mae: 2.
       5573 - val_loss: 24.4002 - val_mae: 3.8503
       Epoch 7/10
       4694 - val_loss: 21.8322 - val_mae: 3.7457
       Epoch 8/10
       826 - val_loss: 23.0966 - val_mae: 3.8502
       Epoch 9/10
       206 - val_loss: 23.2724 - val_mae: 3.7798
       Epoch 10/10
       658 - val_loss: 23.4737 - val_mae: 3.8206
       41
       Test MAE: 3.77
In [55]: import matplotlib.pyplot as plt
       loss = history.history["mae"]
       val loss = history.history["val mae"]
       epochs = range(1, len(loss) + 1)
       plt.figure()
       # Update the color to red and line style to a dotted line for training MAE
       plt.plot(epochs, loss, "r:", label="Training MAE")
       # Update the color to blue and line style to a dotted line for validation MAE
       plt.plot(epochs, val_loss, "b:", label="Validation MAE")
       plt.title("Training and validation MAE")
       plt.legend()
       plt.show()
```



1D Convnets and LSTM togther

```
In [56]: import matplotlib.pyplot as plt
import numpy as np

Models = ("1","2","3","4","5","6","7","8","9","10","11","12","13","14","15")
Mae = (2.62,2.59,3.04,9.91,9.48,2.51,2.56,2.51,2.57,2.62,2.80,2.76,2.54,2.56,3.90)

# MAE Evaluation
plt.figure(figsize=(10, 6))
plt.scatter(Models, Mae, color="blue")
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()
```

MAE Evaluation

