using-lstm-and-its-implementation

November 11, 2023

Long short term memory (LSTM) is a model that increases the memory of recurrent neural networks. Recurrent neural networks hold short term memory in that they allow earlier determining information to be employed in the current neural networks. For immediate tasks, the earlier data is used. We may not possess a list of all of the earlier information for the neural node. In RNNs, LSTMs are very widely used in Neural networks. Their effectiveness should be implemented to multiple sequence modelling problems in many application domains like video, NLP, geospatial, and time-series. One of the main issues with RNN is the vanishing gradient problem, and it emerges due to the repeated use of the same parameters, in RNN blocks, at each step. We must try to use different parameters to overcome this problem at each time step. We try to find a balance in such a situation. We bring novel parameters at each step while generalizing variable-length sequences and keeping the overall amount of learnable parameters constant. We introduce gated RNN cells like LSTM and GRU. Gated cells hold internal variables, which are Gates. This value of each gate at each time step depends on the information at that time step, including early states. The value of the gate then becomes multiplied by the different variables of interest to influence them. Time-series data is a series of data values gathered over time interims, allowing us to trace differences over time. Time-series data can trace progress over milliseconds, days, and years. Early, our perspective of time-series data meant more static; the everyday highs and lows under temperature, the opening and closing amount of the stock market. Now we will go to the coding part. We will implement LSTM on the stocks dataset.

1 Implementation of LSTM on stocks data

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
```

[2]:
```
google_stock_data = pd.read_csv('GOOG.csv')
google_stock_data.head()
```

[2]:
```
  symbol                       date   close    high       low    open  \
0   GOOG  2016-06-14 00:00:00+00:00  718.27  722.47  713.1200  716.48
1   GOOG  2016-06-15 00:00:00+00:00  718.92  722.98  717.3100  719.00
2   GOOG  2016-06-16 00:00:00+00:00  710.36  716.65  703.2600  714.91
3   GOOG  2016-06-17 00:00:00+00:00  691.72  708.82  688.4515  708.65
4   GOOG  2016-06-20 00:00:00+00:00  693.71  702.48  693.4100  698.77
```

```
   volume  adjClose  adjHigh    adjLow  adjOpen  adjVolume  divCash  \
0  1306065    718.27   722.47  713.1200   716.48    1306065      0.0
1  1214517    718.92   722.98  717.3100   719.00    1214517      0.0
2  1982471    710.36   716.65  703.2600   714.91    1982471      0.0
3  3402357    691.72   708.82  688.4515   708.65    3402357      0.0
4  2082538    693.71   702.48  693.4100   698.77    2082538      0.0

   splitFactor
0          1.0
1          1.0
2          1.0
3          1.0
4          1.0
```

Exploring Dataset:

The dataset contains 14 columns associated with time series like the date and the different variables like close, high, low and volume. We will use opening and closing values for our experimentation of time series with LSTM.

[3]:
```
google_stock_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1258 entries, 0 to 1257
Data columns (total 14 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   symbol       1258 non-null   object
 1   date         1258 non-null   object
 2   close        1258 non-null   float64
 3   high         1258 non-null   float64
 4   low          1258 non-null   float64
 5   open         1258 non-null   float64
 6   volume       1258 non-null   int64
 7   adjClose     1258 non-null   float64
 8   adjHigh      1258 non-null   float64
 9   adjLow       1258 non-null   float64
 10  adjOpen      1258 non-null   float64
 11  adjVolume    1258 non-null   int64
 12  divCash      1258 non-null   float64
 13  splitFactor  1258 non-null   float64
dtypes: float64(10), int64(2), object(2)
memory usage: 137.7+ KB
```

[4]:
```
google_stock_data = google_stock_data[['date','open','close']] # Extracting␣
↪required columns
```

```
google_stock_data['date'] = pd.to_datetime(google_stock_data['date'].
  ↪apply(lambda x: x.split()[0])) # Selecting only date
google_stock_data.set_index('date',drop=True,inplace=True) # Setting date␣
  ↪column as index
google_stock_data.head()
```

[4]:

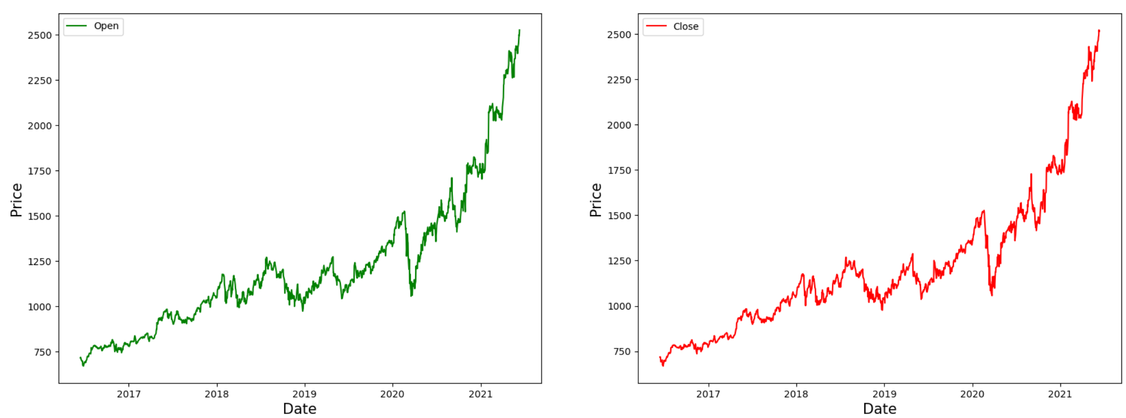
date	open	close
2016-06-14	716.48	718.27
2016-06-15	719.00	718.92
2016-06-16	714.91	710.36
2016-06-17	708.65	691.72
2016-06-20	698.77	693.71

[5]:

```
fg, ax =plt.subplots(1,2,figsize=(20,7))
ax[0].plot(google_stock_data['open'],label='Open',color='green')
ax[0].set_xlabel('Date',size=15)
ax[0].set_ylabel('Price',size=15)
ax[0].legend()

ax[1].plot(google_stock_data['close'],label='Close',color='red')
ax[1].set_xlabel('Date',size=15)
ax[1].set_ylabel('Price',size=15)
ax[1].legend()

fg.show()
```



Data Pre-processing:

We must pre-process this data before applying stock price using LSTM. Transform the values in our data with help of the fit_transform function. Min-max scaler is used for scaling the data so that we can bring all the price values to a common scale. We then use 80 % data for training and the rest 20% for testing and assign them to separate variables.

[6]:
```
from sklearn.preprocessing import MinMaxScaler
MMS = MinMaxScaler()
google_stock_data[google_stock_data.columns] = MMS.
 ↪fit_transform(google_stock_data)
```

[7]:
```
google_stock_data.shape
```

[7]: (1258, 2)

[8]:
```
training_size = round(len(google_stock_data) * 0.80) # Selecting 80 % for␣
 ↪training and 20 % for testing
training_size
```

[8]: 1006

[9]:
```
train_data = google_stock_data[:training_size]
test_data  = google_stock_data[training_size:]

train_data.shape, test_data.shape
```

[9]: ((1006, 2), (252, 2))

[10]:
```
# Function to create sequence of data for training and testing

def create_sequence(dataset):
  sequences = []
  labels = []

  start_idx = 0

  for stop_idx in range(50,len(dataset)): # Selecting 50 rows at a time
    sequences.append(dataset.iloc[start_idx:stop_idx])
    labels.append(dataset.iloc[stop_idx])
    start_idx += 1
  return (np.array(sequences),np.array(labels))
```

[11]:
```
train_seq, train_label = create_sequence(train_data)
test_seq, test_label = create_sequence(test_data)
```

[12]:
```
train_seq.shape, train_label.shape, test_seq.shape, test_label.shape
```

[12]: ((956, 50, 2), (956, 2), (202, 50, 2), (202, 2))

2 Creating LSTM model

[13]:
```
from keras.models import Sequential
from keras.layers import Dense, Dropout, LSTM, Bidirectional
```

[14]:
```
model = Sequential()
model.add(LSTM(units=50, return_sequences=True, input_shape = (train_seq.
 ↪shape[1], train_seq.shape[2])))

model.add(Dropout(0.1))
model.add(LSTM(units=50))

model.add(Dense(2))

model.compile(loss='mean_squared_error', optimizer='adam',␣
 ↪metrics=['mean_absolute_error'])

model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm (LSTM)                 (None, 50, 50)            10600

 dropout (Dropout)           (None, 50, 50)            0

 lstm_1 (LSTM)               (None, 50)                20200

 dense (Dense)               (None, 2)                 102

=================================================================
Total params: 30902 (120.71 KB)
Trainable params: 30902 (120.71 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

[15]:
```
model.fit(train_seq, train_label, epochs=80,validation_data=(test_seq,␣
 ↪test_label), verbose=1)
```

```
Epoch 1/80
30/30 [==============================] - 6s 63ms/step - loss: 0.0088 -
mean_absolute_error: 0.0652 - val_loss: 0.0145 - val_mean_absolute_error: 0.0933
Epoch 2/80
30/30 [==============================] - 1s 33ms/step - loss: 7.2913e-04 -
mean_absolute_error: 0.0205 - val_loss: 0.0024 - val_mean_absolute_error: 0.0387
Epoch 3/80
```

```
30/30 [==============================] - 1s 31ms/step - loss: 5.1146e-04 -
mean_absolute_error: 0.0162 - val_loss: 0.0023 - val_mean_absolute_error: 0.0375
Epoch 4/80
30/30 [==============================] - 1s 32ms/step - loss: 4.8178e-04 -
mean_absolute_error: 0.0158 - val_loss: 0.0029 - val_mean_absolute_error: 0.0428
Epoch 5/80
30/30 [==============================] - 1s 32ms/step - loss: 4.6625e-04 -
mean_absolute_error: 0.0157 - val_loss: 0.0022 - val_mean_absolute_error: 0.0365
Epoch 6/80
30/30 [==============================] - 1s 32ms/step - loss: 4.3704e-04 -
mean_absolute_error: 0.0150 - val_loss: 0.0024 - val_mean_absolute_error: 0.0382
Epoch 7/80
30/30 [==============================] - 1s 30ms/step - loss: 4.3390e-04 -
mean_absolute_error: 0.0148 - val_loss: 0.0028 - val_mean_absolute_error: 0.0419
Epoch 8/80
30/30 [==============================] - 1s 31ms/step - loss: 4.0519e-04 -
mean_absolute_error: 0.0147 - val_loss: 0.0057 - val_mean_absolute_error: 0.0650
Epoch 9/80
30/30 [==============================] - 1s 29ms/step - loss: 4.0324e-04 -
mean_absolute_error: 0.0145 - val_loss: 0.0043 - val_mean_absolute_error: 0.0544
Epoch 10/80
30/30 [==============================] - 1s 31ms/step - loss: 4.4105e-04 -
mean_absolute_error: 0.0153 - val_loss: 0.0028 - val_mean_absolute_error: 0.0417
Epoch 11/80
30/30 [==============================] - 1s 29ms/step - loss: 3.4949e-04 -
mean_absolute_error: 0.0135 - val_loss: 0.0050 - val_mean_absolute_error: 0.0589
Epoch 12/80
30/30 [==============================] - 1s 30ms/step - loss: 3.6129e-04 -
mean_absolute_error: 0.0141 - val_loss: 0.0047 - val_mean_absolute_error: 0.0569
Epoch 13/80
30/30 [==============================] - 1s 29ms/step - loss: 3.4442e-04 -
mean_absolute_error: 0.0136 - val_loss: 0.0048 - val_mean_absolute_error: 0.0569
Epoch 14/80
30/30 [==============================] - 1s 29ms/step - loss: 3.4389e-04 -
mean_absolute_error: 0.0135 - val_loss: 0.0040 - val_mean_absolute_error: 0.0506
Epoch 15/80
30/30 [==============================] - 1s 30ms/step - loss: 3.6732e-04 -
mean_absolute_error: 0.0138 - val_loss: 0.0047 - val_mean_absolute_error: 0.0555
Epoch 16/80
30/30 [==============================] - 1s 30ms/step - loss: 3.1169e-04 -
mean_absolute_error: 0.0130 - val_loss: 0.0044 - val_mean_absolute_error: 0.0524
Epoch 17/80
30/30 [==============================] - 1s 32ms/step - loss: 3.0864e-04 -
mean_absolute_error: 0.0128 - val_loss: 0.0048 - val_mean_absolute_error: 0.0547
Epoch 18/80
30/30 [==============================] - 1s 30ms/step - loss: 3.2108e-04 -
mean_absolute_error: 0.0134 - val_loss: 0.0038 - val_mean_absolute_error: 0.0477
Epoch 19/80
```

```
30/30 [==============================] - 1s 30ms/step - loss: 2.8301e-04 -
mean_absolute_error: 0.0124 - val_loss: 0.0095 - val_mean_absolute_error: 0.0834
Epoch 20/80
30/30 [==============================] - 1s 31ms/step - loss: 2.9921e-04 -
mean_absolute_error: 0.0128 - val_loss: 0.0044 - val_mean_absolute_error: 0.0512
Epoch 21/80
30/30 [==============================] - 1s 30ms/step - loss: 2.6198e-04 -
mean_absolute_error: 0.0120 - val_loss: 0.0045 - val_mean_absolute_error: 0.0522
Epoch 22/80
30/30 [==============================] - 1s 32ms/step - loss: 2.8211e-04 -
mean_absolute_error: 0.0124 - val_loss: 0.0052 - val_mean_absolute_error: 0.0572
Epoch 23/80
30/30 [==============================] - 1s 30ms/step - loss: 2.7692e-04 -
mean_absolute_error: 0.0123 - val_loss: 0.0068 - val_mean_absolute_error: 0.0680
Epoch 24/80
30/30 [==============================] - 1s 30ms/step - loss: 2.8355e-04 -
mean_absolute_error: 0.0124 - val_loss: 0.0086 - val_mean_absolute_error: 0.0771
Epoch 25/80
30/30 [==============================] - 1s 29ms/step - loss: 2.8175e-04 -
mean_absolute_error: 0.0123 - val_loss: 0.0078 - val_mean_absolute_error: 0.0737
Epoch 26/80
30/30 [==============================] - 1s 32ms/step - loss: 2.5858e-04 -
mean_absolute_error: 0.0117 - val_loss: 0.0058 - val_mean_absolute_error: 0.0620
Epoch 27/80
30/30 [==============================] - 1s 30ms/step - loss: 2.5424e-04 -
mean_absolute_error: 0.0117 - val_loss: 0.0029 - val_mean_absolute_error: 0.0400
Epoch 28/80
30/30 [==============================] - 1s 31ms/step - loss: 2.7501e-04 -
mean_absolute_error: 0.0125 - val_loss: 0.0028 - val_mean_absolute_error: 0.0396
Epoch 29/80
30/30 [==============================] - 1s 30ms/step - loss: 2.4497e-04 -
mean_absolute_error: 0.0114 - val_loss: 0.0062 - val_mean_absolute_error: 0.0649
Epoch 30/80
30/30 [==============================] - 1s 29ms/step - loss: 2.4993e-04 -
mean_absolute_error: 0.0116 - val_loss: 0.0042 - val_mean_absolute_error: 0.0521
Epoch 31/80
30/30 [==============================] - 1s 30ms/step - loss: 2.3241e-04 -
mean_absolute_error: 0.0111 - val_loss: 0.0045 - val_mean_absolute_error: 0.0517
Epoch 32/80
30/30 [==============================] - 1s 31ms/step - loss: 2.6097e-04 -
mean_absolute_error: 0.0118 - val_loss: 0.0059 - val_mean_absolute_error: 0.0600
Epoch 33/80
30/30 [==============================] - 1s 31ms/step - loss: 2.2041e-04 -
mean_absolute_error: 0.0109 - val_loss: 0.0062 - val_mean_absolute_error: 0.0632
Epoch 34/80
30/30 [==============================] - 1s 32ms/step - loss: 2.3018e-04 -
mean_absolute_error: 0.0110 - val_loss: 0.0057 - val_mean_absolute_error: 0.0605
Epoch 35/80
```

```
30/30 [==============================] - 1s 31ms/step - loss: 2.2792e-04 -
mean_absolute_error: 0.0110 - val_loss: 0.0032 - val_mean_absolute_error: 0.0431
Epoch 36/80
30/30 [==============================] - 1s 32ms/step - loss: 2.4600e-04 -
mean_absolute_error: 0.0115 - val_loss: 0.0040 - val_mean_absolute_error: 0.0499
Epoch 37/80
30/30 [==============================] - 1s 31ms/step - loss: 2.2928e-04 -
mean_absolute_error: 0.0110 - val_loss: 0.0050 - val_mean_absolute_error: 0.0573
Epoch 38/80
30/30 [==============================] - 1s 30ms/step - loss: 2.0007e-04 -
mean_absolute_error: 0.0104 - val_loss: 0.0033 - val_mean_absolute_error: 0.0445
Epoch 39/80
30/30 [==============================] - 1s 29ms/step - loss: 2.1046e-04 -
mean_absolute_error: 0.0105 - val_loss: 0.0016 - val_mean_absolute_error: 0.0304
Epoch 40/80
30/30 [==============================] - 1s 31ms/step - loss: 2.1608e-04 -
mean_absolute_error: 0.0107 - val_loss: 0.0035 - val_mean_absolute_error: 0.0466
Epoch 41/80
30/30 [==============================] - 1s 30ms/step - loss: 2.0160e-04 -
mean_absolute_error: 0.0103 - val_loss: 0.0029 - val_mean_absolute_error: 0.0419
Epoch 42/80
30/30 [==============================] - 1s 30ms/step - loss: 2.0080e-04 -
mean_absolute_error: 0.0105 - val_loss: 0.0045 - val_mean_absolute_error: 0.0538
Epoch 43/80
30/30 [==============================] - 1s 31ms/step - loss: 1.8531e-04 -
mean_absolute_error: 0.0099 - val_loss: 0.0024 - val_mean_absolute_error: 0.0378
Epoch 44/80
30/30 [==============================] - 1s 30ms/step - loss: 1.9542e-04 -
mean_absolute_error: 0.0102 - val_loss: 0.0021 - val_mean_absolute_error: 0.0348
Epoch 45/80
30/30 [==============================] - 1s 30ms/step - loss: 1.9134e-04 -
mean_absolute_error: 0.0101 - val_loss: 0.0041 - val_mean_absolute_error: 0.0528
Epoch 46/80
30/30 [==============================] - 1s 31ms/step - loss: 1.9724e-04 -
mean_absolute_error: 0.0101 - val_loss: 0.0024 - val_mean_absolute_error: 0.0374
Epoch 47/80
30/30 [==============================] - 1s 30ms/step - loss: 2.0571e-04 -
mean_absolute_error: 0.0104 - val_loss: 0.0049 - val_mean_absolute_error: 0.0590
Epoch 48/80
30/30 [==============================] - 1s 31ms/step - loss: 1.9851e-04 -
mean_absolute_error: 0.0103 - val_loss: 0.0039 - val_mean_absolute_error: 0.0504
Epoch 49/80
30/30 [==============================] - 1s 32ms/step - loss: 1.7613e-04 -
mean_absolute_error: 0.0097 - val_loss: 0.0015 - val_mean_absolute_error: 0.0291
Epoch 50/80
30/30 [==============================] - 1s 32ms/step - loss: 2.0499e-04 -
mean_absolute_error: 0.0106 - val_loss: 0.0017 - val_mean_absolute_error: 0.0312
Epoch 51/80
```

```
30/30 [==============================] - 1s 29ms/step - loss: 1.9552e-04 -
mean_absolute_error: 0.0101 - val_loss: 0.0043 - val_mean_absolute_error: 0.0532
Epoch 52/80
30/30 [==============================] - 1s 29ms/step - loss: 1.7371e-04 -
mean_absolute_error: 0.0095 - val_loss: 0.0023 - val_mean_absolute_error: 0.0372
Epoch 53/80
30/30 [==============================] - 1s 33ms/step - loss: 1.7557e-04 -
mean_absolute_error: 0.0097 - val_loss: 0.0034 - val_mean_absolute_error: 0.0473
Epoch 54/80
30/30 [==============================] - 1s 37ms/step - loss: 1.7126e-04 -
mean_absolute_error: 0.0095 - val_loss: 0.0011 - val_mean_absolute_error: 0.0259
Epoch 55/80
30/30 [==============================] - 1s 31ms/step - loss: 1.6322e-04 -
mean_absolute_error: 0.0093 - val_loss: 0.0024 - val_mean_absolute_error: 0.0391
Epoch 56/80
30/30 [==============================] - 1s 30ms/step - loss: 1.8788e-04 -
mean_absolute_error: 0.0100 - val_loss: 0.0052 - val_mean_absolute_error: 0.0625
Epoch 57/80
30/30 [==============================] - 1s 31ms/step - loss: 2.0444e-04 -
mean_absolute_error: 0.0104 - val_loss: 0.0019 - val_mean_absolute_error: 0.0347
Epoch 58/80
30/30 [==============================] - 1s 30ms/step - loss: 1.8744e-04 -
mean_absolute_error: 0.0099 - val_loss: 0.0014 - val_mean_absolute_error: 0.0291
Epoch 59/80
30/30 [==============================] - 1s 31ms/step - loss: 1.6599e-04 -
mean_absolute_error: 0.0092 - val_loss: 0.0013 - val_mean_absolute_error: 0.0275
Epoch 60/80
30/30 [==============================] - 1s 30ms/step - loss: 1.6868e-04 -
mean_absolute_error: 0.0094 - val_loss: 0.0016 - val_mean_absolute_error: 0.0310
Epoch 61/80
30/30 [==============================] - 1s 30ms/step - loss: 1.6165e-04 -
mean_absolute_error: 0.0092 - val_loss: 0.0023 - val_mean_absolute_error: 0.0391
Epoch 62/80
30/30 [==============================] - 1s 30ms/step - loss: 1.6290e-04 -
mean_absolute_error: 0.0092 - val_loss: 0.0026 - val_mean_absolute_error: 0.0414
Epoch 63/80
30/30 [==============================] - 1s 30ms/step - loss: 1.4983e-04 -
mean_absolute_error: 0.0088 - val_loss: 0.0024 - val_mean_absolute_error: 0.0407
Epoch 64/80
30/30 [==============================] - 1s 30ms/step - loss: 1.7084e-04 -
mean_absolute_error: 0.0097 - val_loss: 0.0024 - val_mean_absolute_error: 0.0409
Epoch 65/80
30/30 [==============================] - 1s 32ms/step - loss: 1.4696e-04 -
mean_absolute_error: 0.0087 - val_loss: 0.0022 - val_mean_absolute_error: 0.0385
Epoch 66/80
30/30 [==============================] - 1s 32ms/step - loss: 1.4869e-04 -
mean_absolute_error: 0.0088 - val_loss: 0.0037 - val_mean_absolute_error: 0.0522
Epoch 67/80
```

```
30/30 [==============================] - 1s 32ms/step - loss: 1.6588e-04 -
mean_absolute_error: 0.0095 - val_loss: 8.4202e-04 - val_mean_absolute_error:
0.0223
Epoch 68/80
30/30 [==============================] - 1s 35ms/step - loss: 1.4617e-04 -
mean_absolute_error: 0.0087 - val_loss: 0.0018 - val_mean_absolute_error: 0.0339
Epoch 69/80
30/30 [==============================] - 1s 32ms/step - loss: 1.4893e-04 -
mean_absolute_error: 0.0088 - val_loss: 7.3356e-04 - val_mean_absolute_error:
0.0207
Epoch 70/80
30/30 [==============================] - 1s 37ms/step - loss: 1.5442e-04 -
mean_absolute_error: 0.0089 - val_loss: 0.0013 - val_mean_absolute_error: 0.0292
Epoch 71/80
30/30 [==============================] - 1s 42ms/step - loss: 1.5671e-04 -
mean_absolute_error: 0.0092 - val_loss: 0.0014 - val_mean_absolute_error: 0.0291
Epoch 72/80
30/30 [==============================] - 1s 43ms/step - loss: 1.4339e-04 -
mean_absolute_error: 0.0086 - val_loss: 0.0018 - val_mean_absolute_error: 0.0342
Epoch 73/80
30/30 [==============================] - 1s 41ms/step - loss: 1.6757e-04 -
mean_absolute_error: 0.0093 - val_loss: 0.0028 - val_mean_absolute_error: 0.0458
Epoch 74/80
30/30 [==============================] - 1s 42ms/step - loss: 1.3679e-04 -
mean_absolute_error: 0.0083 - val_loss: 0.0011 - val_mean_absolute_error: 0.0256
Epoch 75/80
30/30 [==============================] - 1s 40ms/step - loss: 1.4399e-04 -
mean_absolute_error: 0.0086 - val_loss: 0.0025 - val_mean_absolute_error: 0.0422
Epoch 76/80
30/30 [==============================] - 1s 39ms/step - loss: 1.6204e-04 -
mean_absolute_error: 0.0091 - val_loss: 0.0012 - val_mean_absolute_error: 0.0273
Epoch 77/80
30/30 [==============================] - 1s 40ms/step - loss: 1.4643e-04 -
mean_absolute_error: 0.0088 - val_loss: 0.0011 - val_mean_absolute_error: 0.0256
Epoch 78/80
30/30 [==============================] - 1s 37ms/step - loss: 1.3635e-04 -
mean_absolute_error: 0.0084 - val_loss: 0.0025 - val_mean_absolute_error: 0.0424
Epoch 79/80
30/30 [==============================] - 1s 44ms/step - loss: 1.4359e-04 -
mean_absolute_error: 0.0085 - val_loss: 0.0013 - val_mean_absolute_error: 0.0281
Epoch 80/80
30/30 [==============================] - 1s 41ms/step - loss: 1.3196e-04 -
mean_absolute_error: 0.0083 - val_loss: 0.0028 - val_mean_absolute_error: 0.0446
```

```
[15]: <keras.src.callbacks.History at 0x21e38890850>
```

[16]:
```
test_predicted = model.predict(test_seq)
test_predicted[:5]
```

```
7/7 [==============================] - 1s 10ms/step
```

[16]:
```
array([[0.47457188, 0.47725692],
       [0.4813011 , 0.4838558 ],
       [0.48540217, 0.48791692],
       [0.4994955 , 0.5021111 ],
       [0.51155525, 0.5139972 ]], dtype=float32)
```

[17]:
```
test_inverse_predicted = MMS.inverse_transform(test_predicted) # Inversing␣
↪scaling on predicted data
test_inverse_predicted[:5]
```

[17]:
```
array([[1550.8184, 1552.7793],
       [1563.2937, 1565.0093],
       [1570.8969, 1572.5359],
       [1597.0247, 1598.8425],
       [1619.3826, 1620.8716]], dtype=float32)
```

[18]:
```
# Merging actual and predicted data for better visualization

gs_slic_data = pd.concat([google_stock_data.iloc[-202:].copy(),pd.
↪DataFrame(test_inverse_predicted,columns=['open_predicted','close_predicted'],index=google_
↪iloc[-202:].index)], axis=1)
```

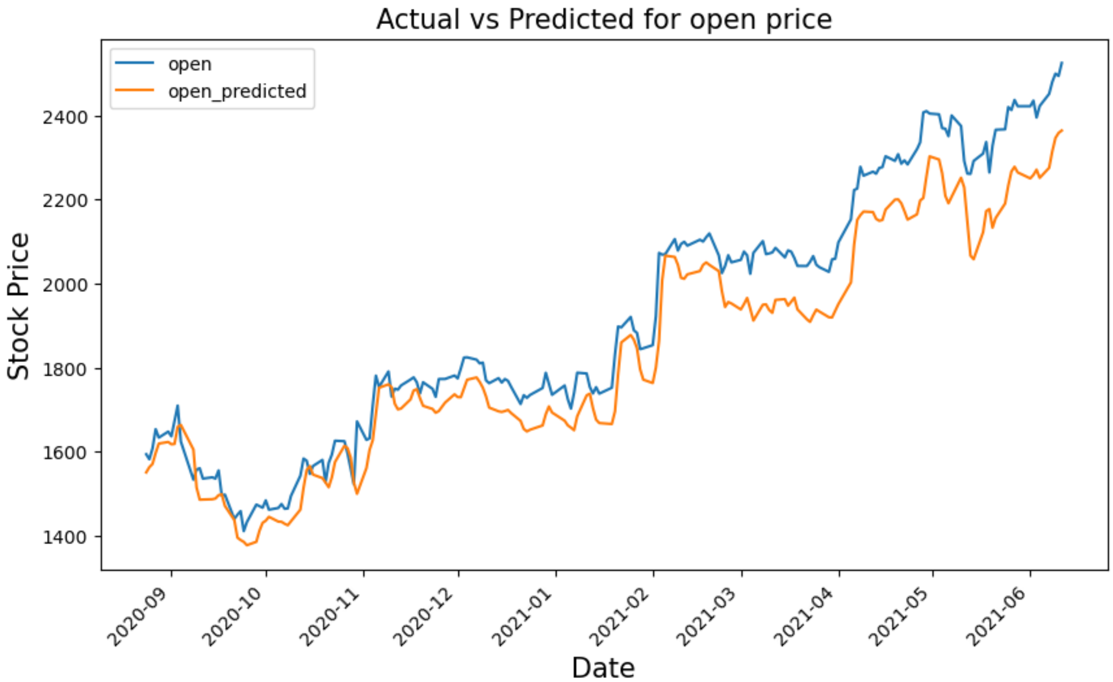
[19]:
```
gs_slic_data[['open','close']] = MMS.
↪inverse_transform(gs_slic_data[['open','close']]) # Inverse scaling
```

[20]:
```
gs_slic_data.head()
```

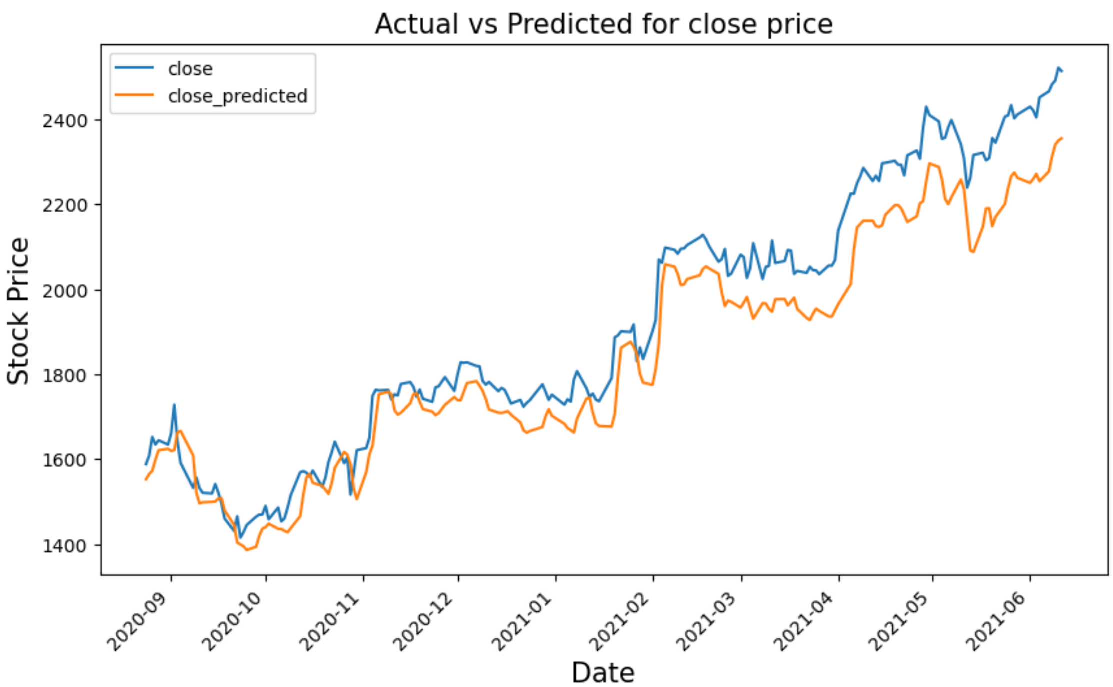
[20]:

date	open	close	open_predicted	close_predicted
2020-08-24	1593.98	1588.20	1550.818359	1552.779297
2020-08-25	1582.07	1608.22	1563.293701	1565.009277
2020-08-26	1608.00	1652.38	1570.896851	1572.535889
2020-08-27	1653.68	1634.33	1597.024658	1598.842529
2020-08-28	1633.49	1644.41	1619.382568	1620.871582

[21]:
```
gs_slic_data[['open','open_predicted']].plot(figsize=(10,6))
plt.xticks(rotation=45)
plt.xlabel('Date',size=15)
plt.ylabel('Stock Price',size=15)
plt.title('Actual vs Predicted for open price',size=15)
plt.show()
```



[22]:
```
gs_slic_data[['close','close_predicted']].plot(figsize=(10,6))
plt.xticks(rotation=45)
plt.xlabel('Date',size=15)
plt.ylabel('Stock Price',size=15)
plt.title('Actual vs Predicted for close price',size=15)
plt.show()
```



3 Predicting upcoming 10 days

[23]:
```
# Creating a dataframe and adding 10 days to existing index

gs_slic_data = gs_slic_data.append(pd.DataFrame(columns=gs_slic_data.
 ↪columns,index=pd.date_range(start=gs_slic_data.index[-1], periods=11,␣
 ↪freq='D', closed='right')))
```

[24]:
```
gs_slic_data['2021-06-09        ':'2021-06-16']
```

[24]:

	open	close	open_predicted	close_predicted
2021-06-09	2499.50	2491.40	2346.403564	2340.447021
2021-06-10	2494.01	2521.60	2358.413330	2350.212402
2021-06-11	2524.92	2513.93	2364.191895	2355.278809
2021-06-12	NaN	NaN	NaN	NaN
2021-06-13	NaN	NaN	NaN	NaN
2021-06-14	NaN	NaN	NaN	NaN
2021-06-15	NaN	NaN	NaN	NaN
2021-06-16	NaN	NaN	NaN	NaN

[25]:
```
upcoming_prediction = pd.DataFrame(columns=['open','close'],index=gs_slic_data.
 ↪index)
upcoming_prediction.index=pd.to_datetime(upcoming_prediction.index)
```

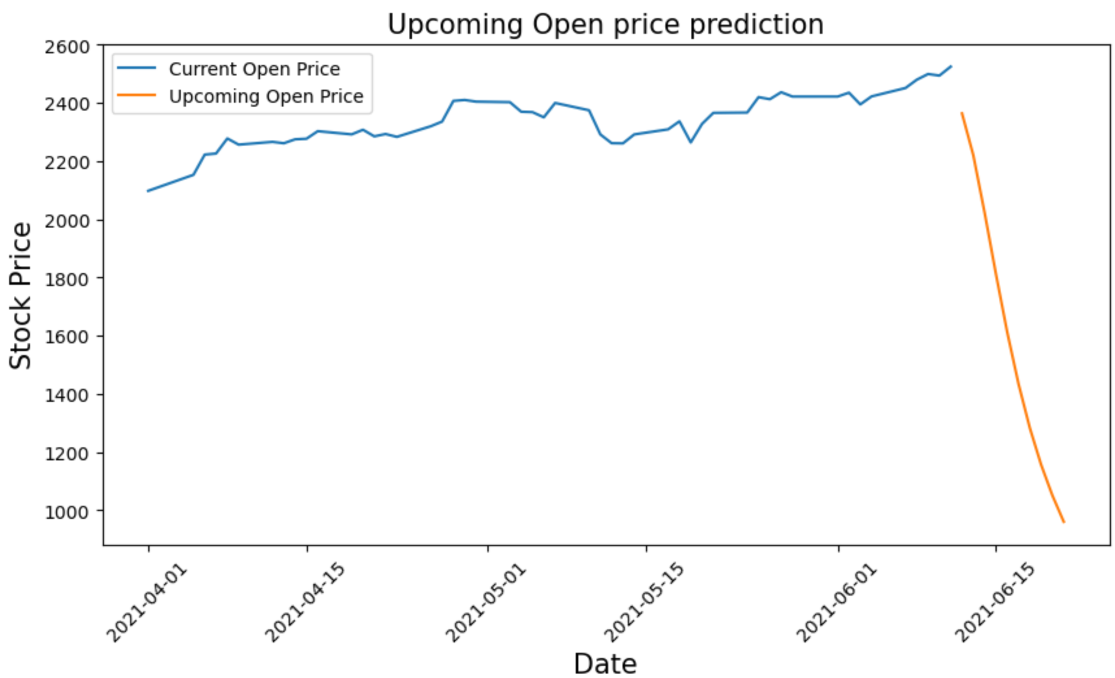
[26]:
```
curr_seq = test_seq[-1:]

for i in range(-10,0):
  up_pred = model.predict(curr_seq)
  upcoming_prediction.iloc[i] = up_pred
  curr_seq = np.append(curr_seq[0][1:],up_pred,axis=0)
  curr_seq = curr_seq.reshape(test_seq[-1:].shape)
```

```
1/1 [==============================] - 0s 29ms/step
1/1 [==============================] - 0s 24ms/step
1/1 [==============================] - 0s 24ms/step
1/1 [==============================] - 0s 26ms/step
1/1 [==============================] - 0s 26ms/step
1/1 [==============================] - 0s 26ms/step
1/1 [==============================] - 0s 31ms/step
1/1 [==============================] - 0s 39ms/step
1/1 [==============================] - 0s 29ms/step
1/1 [==============================] - 0s 27ms/step
```

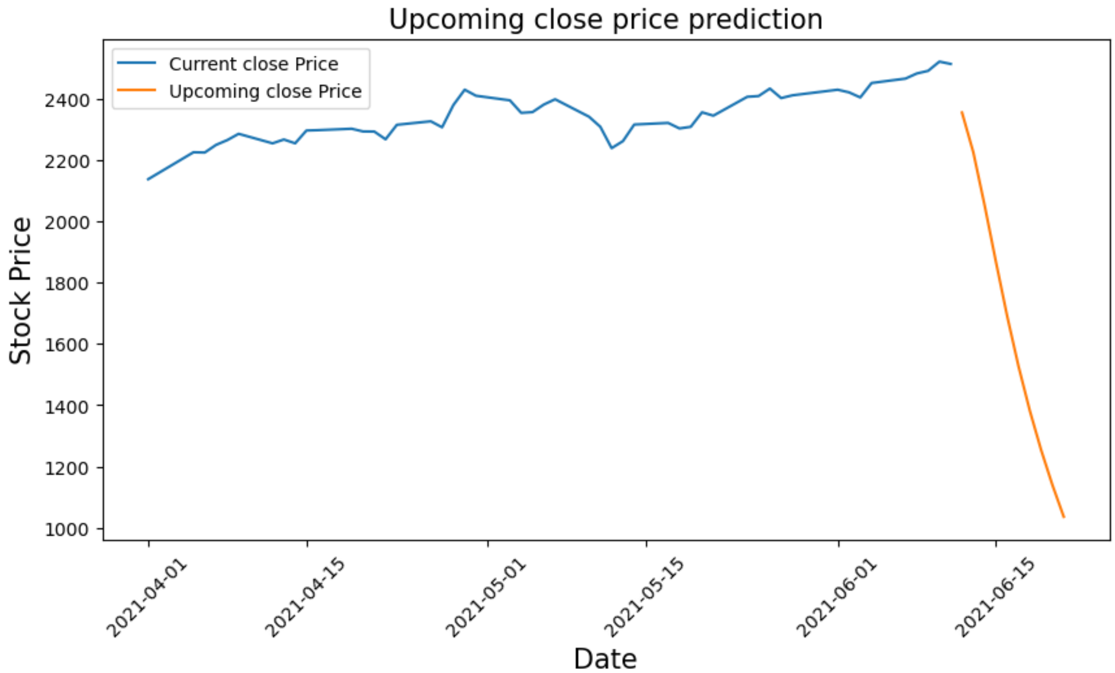
[27]:
```
upcoming_prediction[['open','close']] = MMS.
 ↪inverse_transform(upcoming_prediction[['open','close']])
```

[28]:
```
fg,ax=plt.subplots(figsize=(10,5))
ax.plot(gs_slic_data.loc['2021-04-01':,'open'],label='Current Open Price')
ax.plot(upcoming_prediction.loc['2021-04-01':,'open'],label='Upcoming Open␣
 ↪Price')
plt.setp(ax.xaxis.get_majorticklabels(), rotation=45)
ax.set_xlabel('Date',size=15)
ax.set_ylabel('Stock Price',size=15)
ax.set_title('Upcoming Open price prediction',size=15)
ax.legend()
fg.show()
```



[29]:

```
fg,ax=plt.subplots(figsize=(10,5))
ax.plot(gs_slic_data.loc['2021-04-01':,'close'],label='Current close Price')
ax.plot(upcoming_prediction.loc['2021-04-01':,'close'],label='Upcoming close␣
↪Price')
plt.setp(ax.xaxis.get_majorticklabels(), rotation=45)
ax.set_xlabel('Date',size=15)
ax.set_ylabel('Stock Price',size=15)
ax.set_title('Upcoming close price prediction',size=15)
ax.legend()
fg.show()
```


Upcoming close price prediction
Current close Price
Upcoming close Price
Stock Price
2400
2200
2000
1800
1600
1400
1200
1000
2021-04-01
2021-04-15
2021-05-01
2021-05-15
2021-06-01
2021-06-15
Date

[ ]: