stock-market-prediction-2

March 31, 2024

[ ]:
```
# This Python 3 environment comes with many helpful analytics libraries␣
 ↪installed
# It is defined by the kaggle/python Docker image: https://github.com/kaggle/
 ↪docker-python
# For example, here's several helpful packages to load

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list␣
 ↪all files under the input directory

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# You can write up to 20GB to the current directory (/kaggle/working/) that␣
 ↪gets preserved as output when you create a version using "Save & Run All"
# You can also write temporary files to /kaggle/temp/, but they won't be saved␣
 ↪outside of the current session
```

[1]:
```
# install some requirement libraries
!pip install torch-summary
!pip install yfinance
```

```
Collecting torch-summary
  Downloading torch_summary-1.4.5-py3-none-any.whl.metadata (18 kB)
Downloading torch_summary-1.4.5-py3-none-any.whl (16 kB)
Installing collected packages: torch-summary
Successfully installed torch-summary-1.4.5
Collecting yfinance
  Downloading yfinance-0.2.37-py2.py3-none-any.whl.metadata (11 kB)
Requirement already satisfied: pandas>=1.3.0 in /opt/conda/lib/python3.10/site-
packages (from yfinance) (2.2.1)
Requirement already satisfied: numpy>=1.16.5 in /opt/conda/lib/python3.10/site-
packages (from yfinance) (1.26.4)
```

```
Requirement already satisfied: requests>=2.31 in /opt/conda/lib/python3.10/site-
packages (from yfinance) (2.31.0)
Collecting multitasking>=0.0.7 (from yfinance)
  Downloading multitasking-0.0.11-py3-none-any.whl.metadata (5.5 kB)
Requirement already satisfied: lxml>=4.9.1 in /opt/conda/lib/python3.10/site-
packages (from yfinance) (5.1.0)
Requirement already satisfied: appdirs>=1.4.4 in /opt/conda/lib/python3.10/site-
packages (from yfinance) (1.4.4)
Requirement already satisfied: pytz>=2022.5 in /opt/conda/lib/python3.10/site-
packages (from yfinance) (2023.3.post1)
Requirement already satisfied: frozendict>=2.3.4 in
/opt/conda/lib/python3.10/site-packages (from yfinance) (2.4.0)
Collecting peewee>=3.16.2 (from yfinance)
  Downloading peewee-3.17.1.tar.gz (3.0 MB)
                           3.0/3.0 MB
26.7 MB/s eta 0:00:0000:0100:01
  Installing build dependencies … done
  Getting requirements to build wheel … done
  Preparing metadata (pyproject.toml) … done
Requirement already satisfied: beautifulsoup4>=4.11.1 in
/opt/conda/lib/python3.10/site-packages (from yfinance) (4.12.2)
Requirement already satisfied: html5lib>=1.1 in /opt/conda/lib/python3.10/site-
packages (from yfinance) (1.1)
Requirement already satisfied: soupsieve>1.2 in /opt/conda/lib/python3.10/site-
packages (from beautifulsoup4>=4.11.1->yfinance) (2.5)
Requirement already satisfied: six>=1.9 in /opt/conda/lib/python3.10/site-
packages (from html5lib>=1.1->yfinance) (1.16.0)
Requirement already satisfied: webencodings in /opt/conda/lib/python3.10/site-
packages (from html5lib>=1.1->yfinance) (0.5.1)
Requirement already satisfied: python-dateutil>=2.8.2 in
/opt/conda/lib/python3.10/site-packages (from pandas>=1.3.0->yfinance)
(2.9.0.post0)
Requirement already satisfied: tzdata>=2022.7 in /opt/conda/lib/python3.10/site-
packages (from pandas>=1.3.0->yfinance) (2023.4)
Requirement already satisfied: charset-normalizer<4,>=2 in
/opt/conda/lib/python3.10/site-packages (from requests>=2.31->yfinance) (3.3.2)
Requirement already satisfied: idna<4,>=2.5 in /opt/conda/lib/python3.10/site-
packages (from requests>=2.31->yfinance) (3.6)
Requirement already satisfied: urllib3<3,>=1.21.1 in
/opt/conda/lib/python3.10/site-packages (from requests>=2.31->yfinance)
(1.26.18)
Requirement already satisfied: certifi>=2017.4.17 in
/opt/conda/lib/python3.10/site-packages (from requests>=2.31->yfinance)
(2024.2.2)
Downloading yfinance-0.2.37-py2.py3-none-any.whl (72 kB)
                          73.0/73.0 kB
3.8 MB/s eta 0:00:00
Downloading multitasking-0.0.11-py3-none-any.whl (8.5 kB)
```

```
Building wheels for collected packages: peewee
  Building wheel for peewee (pyproject.toml) … done
  Created wheel for peewee:
filename=peewee-3.17.1-cp310-cp310-linux_x86_64.whl size=291653
sha256=5752a193600de41f37b854b56fd7d4902aff80d11aba6cd33d8461c584c5a362
  Stored in directory: /root/.cache/pip/wheels/d7/35/5c/1374782be033462df5f40174
d8d879519d64ed8c25a1977554
Successfully built peewee
Installing collected packages: peewee, multitasking, yfinance
Successfully installed multitasking-0.0.11 peewee-3.17.1 yfinance-0.2.37
```

[6]:
```python
# import requirement libraries and tools
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import torch
import torch.optim as optim
import yfinance as yf
import torch.nn as nn
import torch.functional as F
import plotly.graph_objects as go

from tqdm.notebook import tqdm
from torchsummary import summary
from sklearn.preprocessing import MinMaxScaler
from torch.utils.data import TensorDataset, DataLoader
```

[7]:
```python
# create a ticker object for Google (GOOGL)
ticker = yf.Ticker("GOOG")

# Define the start and end dates
start_date = "2016-06-14"

# Get historical data for the specified date range
df = ticker.history(start=start_date, end=None)
df.head()
```

[7]:

Date	Open	High	Low	Close	Volume	Dividends	Stock Splits
2016-06-14 00:00:00-04:00	35.824001	36.123501	35.655998	35.913502			
2016-06-15 00:00:00-04:00	35.950001	36.148998	35.865501	35.945999			
2016-06-16 00:00:00-04:00	35.745499	35.832500	35.162998	35.518002			
2016-06-17 00:00:00-04:00	35.432499	35.441002	34.422600	34.585999			
2016-06-20 00:00:00-04:00	34.938499	35.124001	34.670502	34.685501			

```
2016-06-14 00:00:00-04:00  26122000        0.0           0.0
2016-06-15 00:00:00-04:00  24290000        0.0           0.0
2016-06-16 00:00:00-04:00  39650000        0.0           0.0
2016-06-17 00:00:00-04:00  68048000        0.0           0.0
2016-06-20 00:00:00-04:00  41650000        0.0           0.0
```

[ ]:
```python
# Create a trace for the candlestick chart
candlestick_trace = go.Candlestick(
    x=df.index,
    open=df['Open'],
    high=df['High'],
    low=df['Low'],
    close=df['Close'],
    name='Candlestick'
)

# Create the layout
layout = go.Layout(
    title='GOOG Candlestick Chart',
    xaxis=dict(title='Date'),
    yaxis=dict(title='Price', rangemode='normal')
)

# Create the figure and add the candlestick trace and layout
fig = go.Figure(data=[candlestick_trace], layout=layout)

# Update the layout of the figure
fig.update_layout(xaxis_rangeslider_visible=False)

# Show the figure
fig.show()
```

[9]:
```python
# Move column 'Close' to the first position
col_close = df.pop('Close')
df.insert(0, 'Close', col_close)
df.head()
```

[9]:
```
                                Close       Open       High        Low  \
Date
2016-06-14 00:00:00-04:00  35.913502  35.824001  36.123501  35.655998
2016-06-15 00:00:00-04:00  35.945999  35.950001  36.148998  35.865501
2016-06-16 00:00:00-04:00  35.518002  35.745499  35.832500  35.162998
2016-06-17 00:00:00-04:00  34.585999  35.432499  35.441002  34.422600
2016-06-20 00:00:00-04:00  34.685501  34.938499  35.124001  34.670502

                             Volume  Dividends  Stock Splits
Date
```

```
2016-06-14 00:00:00-04:00  26122000        0.0           0.0
2016-06-15 00:00:00-04:00  24290000        0.0           0.0
2016-06-16 00:00:00-04:00  39650000        0.0           0.0
2016-06-17 00:00:00-04:00  68048000        0.0           0.0
2016-06-20 00:00:00-04:00  41650000        0.0           0.0
```

[10]:
```
df.tail()
```

[10]:
```
                                 Close        Open        High         Low  \
Date
2024-03-22 00:00:00-04:00  151.770004  150.240005  152.559998  150.089996
2024-03-25 00:00:00-04:00  151.149994  150.949997  151.455994  148.800003
2024-03-26 00:00:00-04:00  151.699997  151.240005  153.199997  151.029999
2024-03-27 00:00:00-04:00  151.940002  152.145004  152.690002  150.130005
2024-03-28 00:00:00-04:00  152.259995  152.000000  152.669998  151.330002

                             Volume  Dividends  Stock Splits
Date
2024-03-22 00:00:00-04:00  19226300        0.0           0.0
2024-03-25 00:00:00-04:00  15114700        0.0           0.0
2024-03-26 00:00:00-04:00  19312700        0.0           0.0
2024-03-27 00:00:00-04:00  16622000        0.0           0.0
2024-03-28 00:00:00-04:00  21105600        0.0           0.0
```

[11]:
```
df.shape
```

[11]:
```
(1961, 7)
```

[12]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 1961 entries, 2016-06-14 00:00:00-04:00 to 2024-03-28
00:00:00-04:00
Data columns (total 7 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   Close         1961 non-null   float64
 1   Open          1961 non-null   float64
 2   High          1961 non-null   float64
 3   Low           1961 non-null   float64
 4   Volume        1961 non-null   int64
 5   Dividends     1961 non-null   float64
 6   Stock Splits  1961 non-null   float64
dtypes: float64(6), int64(1)
memory usage: 122.6 KB
```

[13]:
```
df.describe().T
```

[13]:
```
                count          mean           std           min           25%  \
Close          1961.0  8.355114e+01  3.571367e+01  3.341300e+01  5.370800e+01
Open           1961.0  8.348958e+01  3.570089e+01  3.355000e+01  5.369950e+01
High           1961.0  8.439996e+01  3.611610e+01  3.361500e+01  5.419875e+01
Low            1961.0  8.266228e+01  3.531863e+01  3.316420e+01  5.307600e+01
Volume         1961.0  2.989036e+07  1.323155e+07  6.936000e+06  2.144000e+07
Dividends      1961.0  0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00
Stock Splits   1961.0  1.019888e-02  4.516388e-01  0.000000e+00  0.000000e+00

                    50%           75%           max
Close      7.158600e+01  1.169000e+02  1.548400e+02
Open       7.152750e+01  1.164900e+02  1.540100e+02
High       7.209000e+01  1.182250e+02  1.552000e+02
Low        7.066750e+01  1.151825e+02  1.529200e+02
Volume     2.647240e+07  3.391000e+07  1.241400e+08
Dividends  0.000000e+00  0.000000e+00  0.000000e+00
Stock Splits  0.000000e+00  0.000000e+00  2.000000e+01
```

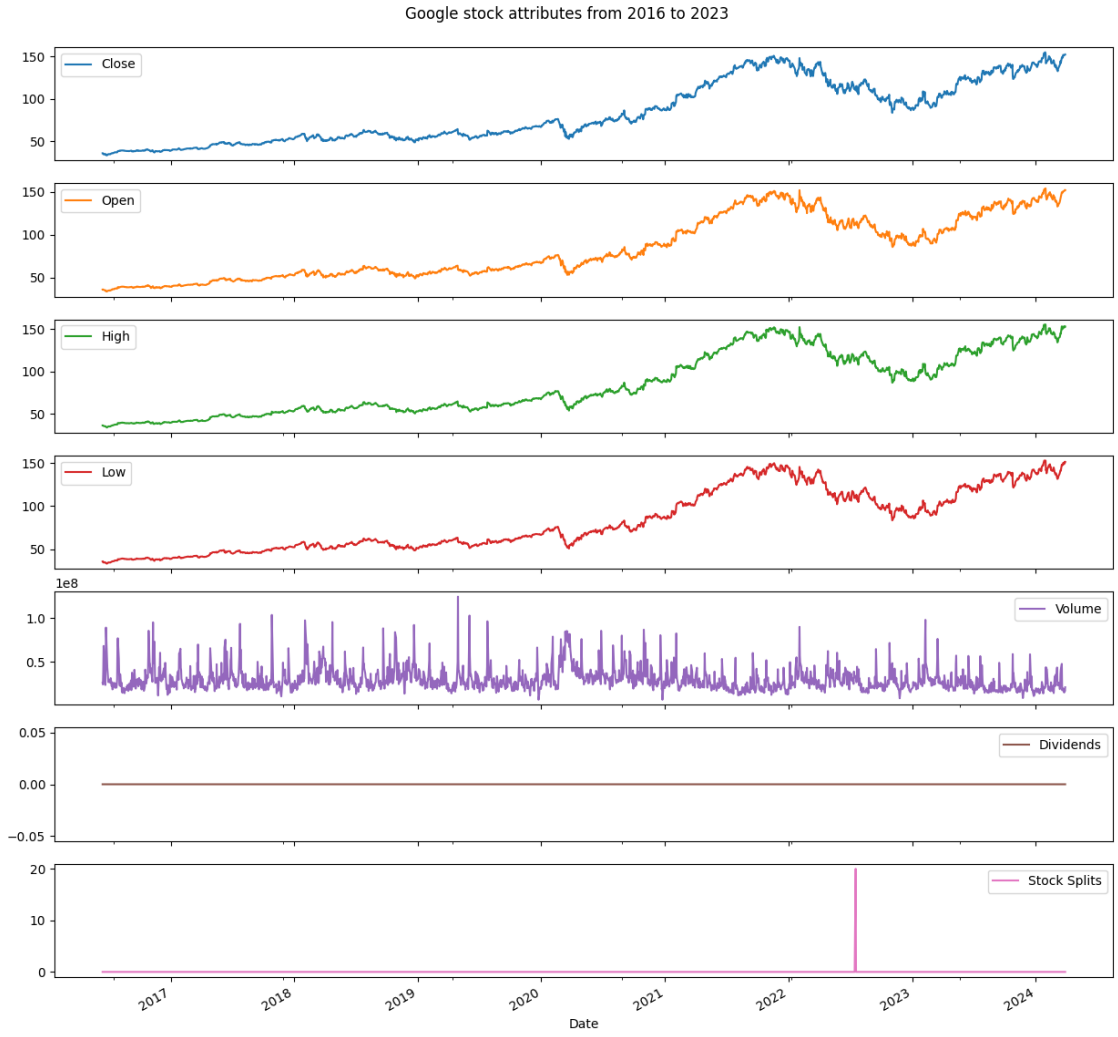
[14]:
```
df.isna().sum().to_frame(name='num_of_NaN')
```

[14]:
```
              num_of_NaN
Close                  0
Open                   0
High                   0
Low                    0
Volume                 0
Dividends              0
Stock Splits           0
```

[15]:
```
df.duplicated().sum()
```

[15]:
```
0
```

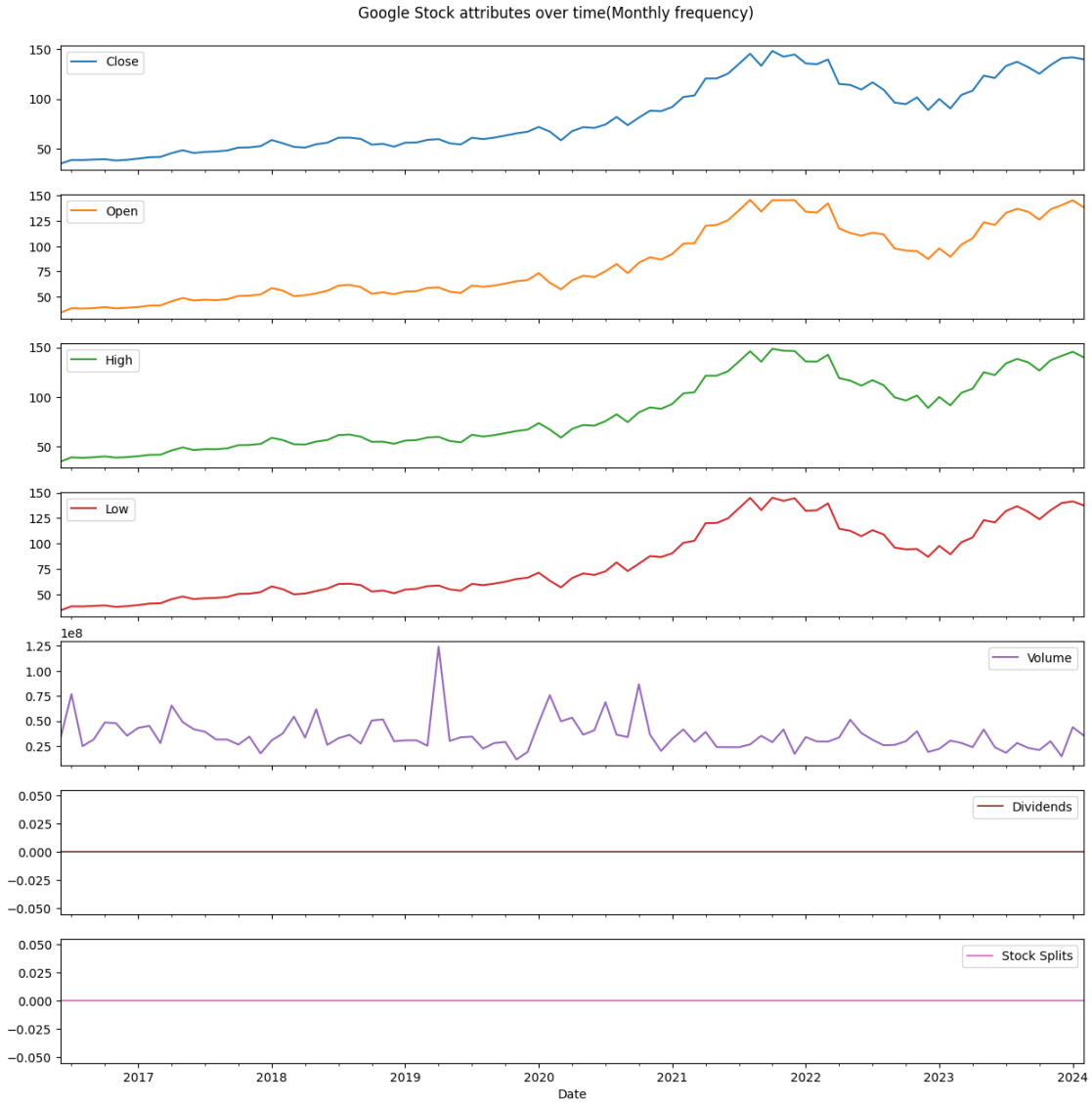
[17]:
```
df.plot(subplots=True, figsize=(15, 15))
plt.suptitle('Google stock attributes from 2016 to 2023', y=0.91)
plt.show()
```



[18]:
```
df.asfreq('M', method='ffill').plot(subplots=True, figsize=(15,15), style='-')
plt.suptitle('Google Stock attributes over time(Monthly frequency)', y=0.91)
plt.show()
```

```
/tmp/ipykernel_33/1413366536.py:1: FutureWarning:

'M' is deprecated and will be removed in a future version, please use 'ME'
instead.
```



[19]:
```
df[['Close']]
```

[19]:

Date	Close
2016-06-14 00:00:00-04:00	35.913502
2016-06-15 00:00:00-04:00	35.945999
2016-06-16 00:00:00-04:00	35.518002
2016-06-17 00:00:00-04:00	34.585999
2016-06-20 00:00:00-04:00	34.685501
…	…
2024-03-22 00:00:00-04:00	151.770004
2024-03-25 00:00:00-04:00	151.149994

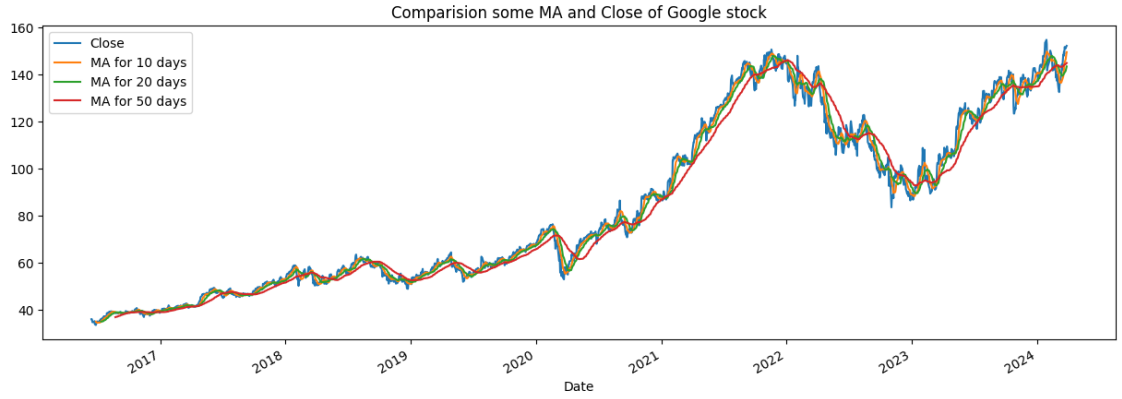
```
2024-03-26 00:00:00-04:00  151.699997
2024-03-27 00:00:00-04:00  151.940002
2024-03-28 00:00:00-04:00  152.259995

[1961 rows x 1 columns]
```

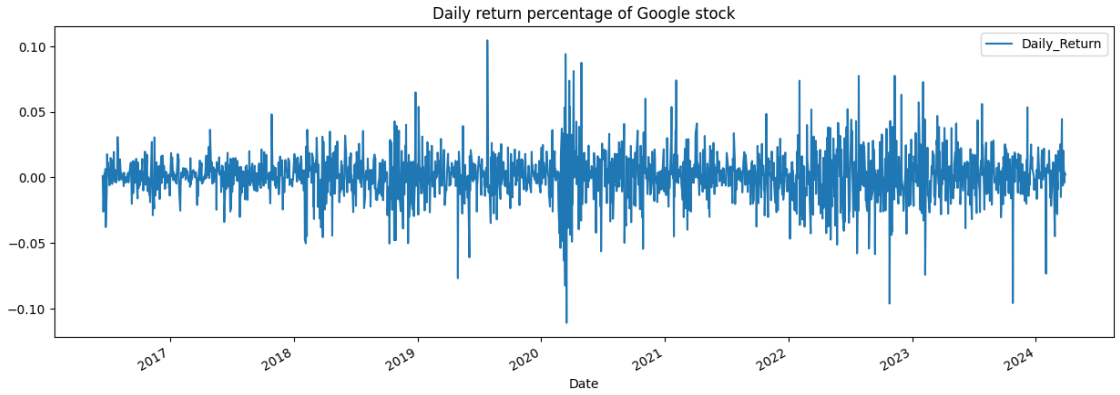
[20]:
```
# computing moving average(ma)
ma_day = [10, 20, 50]

for ma in ma_day:
    col_name = f'MA for {ma} days'
    df[col_name] = df['Close'].rolling(ma).mean()

df[['Close', 'MA for 10 days', 'MA for 20 days', 'MA for 50 days']].
 ↪plot(figsize=(15,5))
plt.title('Comparision some MA and Close of Google stock')
plt.show()
```



[21]:
```
# use pct_change to find the percent change for each day
df['Daily_Return'] = df['Close'].pct_change()
# plot the daily return percentage
df.Daily_Return.plot(legend=True, figsize=(15,5))
plt.title('Daily return percentage of Google stock')
plt.show()
```



[22]:
```
# normalize data
df2 = df.copy(deep=True)
scaler = MinMaxScaler(feature_range=(0,15)).fit(df2.Low.values.reshape(-1,1))
df2['Open'] = scaler.transform(df2.Open.values.reshape(-1,1))
df2['High'] = scaler.transform(df2.High.values.reshape(-1,1))
df2['Low'] = scaler.transform(df2.Low.values.reshape(-1,1))
df2['Close'] = scaler.transform(df2.Close.values.reshape(-1,1))
data = df2[['Open','High','Low', 'Close']].values
data.shape
```

[22]:
```
(1961, 4)
```

[23]:
```
data
```

[23]:
```
array([[ 0.33315316,  0.37066694,  0.31210995,  0.34436352],
       [ 0.3489352 ,  0.37386062,  0.33835125,  0.34843398],
       [ 0.32332031,  0.33421772,  0.25035928,  0.29482519],
       …,
       [14.78957269, 15.03507122, 14.76326832, 14.84718887],
       [14.90292822, 14.97119191, 14.65053968, 14.87725074],
       [14.88476573, 14.96868628, 14.80084517, 14.91733131]])
```

[25]:
```
seq_len=11
sequences=[]
for index in range(len(data) - seq_len + 1):
    sequences.append(data[index: index + seq_len])
sequences= np.array(sequences)
```

[27]:
```
valid_set_size_percentage = 10
test_set_size_percentage = 10

valid_set_size = int(np.round(valid_set_size_percentage/100*sequences.shape[0]))
test_set_size  = int(np.round(test_set_size_percentage/100*sequences.shape[0]))
```

```
train_set_size = sequences.shape[0] - (valid_set_size + test_set_size)

x_train = sequences[:train_set_size,:-1,:]
y_train = sequences[:train_set_size,-1,:]

x_valid = sequences[train_set_size:train_set_size+valid_set_size,:-1,:]
y_valid = sequences[train_set_size:train_set_size+valid_set_size,-1,:]

x_test = sequences[train_set_size+valid_set_size:,:-1,:]
y_test = sequences[train_set_size+valid_set_size:,-1,:]
```

[29]:
```
x_train = torch.tensor(x_train).float()
y_train = torch.tensor(y_train).float()

x_valid = torch.tensor(x_valid).float()
y_valid = torch.tensor(y_valid).float()

train_dataset = TensorDataset(x_train,y_train)
train_dataloader = DataLoader(train_dataset, batch_size=32, shuffle=False)

valid_dataset = TensorDataset(x_valid,y_valid)
valid_dataloader = DataLoader(valid_dataset, batch_size=32, shuffle=False)
```

```
/tmp/ipykernel_33/372158831.py:1: UserWarning:

To copy construct from a tensor, it is recommended to use
sourceTensor.clone().detach() or
sourceTensor.clone().detach().requires_grad_(True), rather than
torch.tensor(sourceTensor).

/tmp/ipykernel_33/372158831.py:2: UserWarning:

To copy construct from a tensor, it is recommended to use
sourceTensor.clone().detach() or
sourceTensor.clone().detach().requires_grad_(True), rather than
torch.tensor(sourceTensor).

/tmp/ipykernel_33/372158831.py:4: UserWarning:

To copy construct from a tensor, it is recommended to use
sourceTensor.clone().detach() or
sourceTensor.clone().detach().requires_grad_(True), rather than
torch.tensor(sourceTensor).

/tmp/ipykernel_33/372158831.py:5: UserWarning:

To copy construct from a tensor, it is recommended to use
```

```
sourceTensor.clone().detach() or
sourceTensor.clone().detach().requires_grad_(True), rather than
torch.tensor(sourceTensor).
```

[31]:
```python
from torch import nn
class NeuralNetwork(nn.Module):
    def __init__(self, num_feature):
        super(NeuralNetwork, self).__init__()
        self.lstm  = nn.LSTM(num_feature,64,batch_first=True)
        self.fc    = nn.Linear(64,num_feature)

    def forward(self, x):
        output, (hidden, cell) = self.lstm(x)
        x = self.fc(hidden)
        return x

model = NeuralNetwork(4)

#push to cuda if available
# device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
# model = model.to(device)
```

[32]:
```python
# print summary of model like summary in tensorflow
summary(model, (4, ))
```

```
==========================================================================
==========
Layer (type:depth-idx)                   Output Shape              Param #
==========================================================================
==========
 LSTM: 1-1                               [-1, 64]                  17,920
 Linear: 1-2                             [-1, 4]                   260
==========================================================================
==========
Total params: 18,180
Trainable params: 18,180
Non-trainable params: 0
Total mult-adds (M): 0.02
==========================================================================
==========
Input size (MB): 0.00
Forward/backward pass size (MB): 0.00
Params size (MB): 0.07
Estimated Total Size (MB): 0.07
==========================================================================
==========
```

[32]:
```
==========================================================================
==========
Layer (type:depth-idx)                   Output Shape              Param #
==========================================================================
==========
 LSTM: 1-1                               [-1, 64]                  17,920
 Linear: 1-2                             [-1, 4]                   260
==========================================================================
==========
Total params: 18,180
Trainable params: 18,180
Non-trainable params: 0
Total mult-adds (M): 0.02
==========================================================================
==========
Input size (MB): 0.00
Forward/backward pass size (MB): 0.00
Params size (MB): 0.07
Estimated Total Size (MB): 0.07
==========================================================================
==========
```

[33]:
```
optimizer = optim.Adam(model.parameters())
mse = nn.MSELoss()
```

[34]:
```
def train(dataloader):
    epoch_loss = 0
    model.train()

    for batch in dataloader:
        optimizer.zero_grad()
        x,y= batch
        pred = model(x)
        loss = mse(pred[0],y)
        loss.backward()
        optimizer.step()
        epoch_loss += loss.item()

    return epoch_loss
```

[36]:
```
def evaluate(dataloader):
    epoch_loss = 0
    model.eval()

    with torch.no_grad():
      for batch in dataloader:
          x,y= batch
```

```
            pred = model(x)
            loss = mse(pred[0],y)
            epoch_loss += loss.item()

    return epoch_loss / len(dataloader)
```

[37]:
```
n_epochs = 50
best_valid_loss = float('inf')

for epoch in range(1, n_epochs + 1):

    train_loss = train(train_dataloader)
    valid_loss = evaluate(valid_dataloader)

    #save the best model
    if valid_loss < best_valid_loss:
        best_valid_loss = valid_loss
        torch.save(model, 'saved_weights.pt')

    # print("Epoch ",epoch+1)
    print(f'\tTrain Loss: {train_loss:.5f} | ' + f'\tVal Loss: {valid_loss:.
↪5f}\n')
```

```
        Train Loss: 965.87060 |         Val Loss: 21.09042

        Train Loss: 839.94175 |         Val Loss: 15.57377

        Train Loss: 488.85676 |         Val Loss: 8.15244

        Train Loss: 321.36456 |         Val Loss: 4.46519

        Train Loss: 200.62544 |         Val Loss: 2.41491

        Train Loss: 130.10850 |         Val Loss: 1.22402

        Train Loss: 89.80438 |  Val Loss: 0.83145

        Train Loss: 64.02528 |  Val Loss: 2.21819

        Train Loss: 47.03885 |  Val Loss: 0.32643

        Train Loss: 37.01210 |  Val Loss: 2.10371

        Train Loss: 56.31582 |  Val Loss: 1.38739

        Train Loss: 42.56531 |  Val Loss: 0.27179
```

```
Train Loss: 35.88709 |  Val Loss: 0.72127

Train Loss: 45.59458 |  Val Loss: 5.29794

Train Loss: 28.38720 |  Val Loss: 0.19872

Train Loss: 53.31867 |  Val Loss: 4.85432

Train Loss: 24.83506 |  Val Loss: 0.33058

Train Loss: 26.39431 |  Val Loss: 0.52581

Train Loss: 28.46118 |  Val Loss: 0.41046

Train Loss: 48.89136 |  Val Loss: 0.27015

Train Loss: 35.98215 |  Val Loss: 0.21380

Train Loss: 13.86930 |  Val Loss: 1.88766

Train Loss: 15.84384 |  Val Loss: 0.57139

Train Loss: 8.90979 |   Val Loss: 0.70980

Train Loss: 8.75816 |   Val Loss: 0.21821

Train Loss: 9.88525 |   Val Loss: 0.32739

Train Loss: 6.73946 |   Val Loss: 0.13731

Train Loss: 5.33245 |   Val Loss: 0.24005

Train Loss: 6.85111 |   Val Loss: 0.18491

Train Loss: 4.63636 |   Val Loss: 0.16805

Train Loss: 4.88544 |   Val Loss: 0.15530

Train Loss: 4.28791 |   Val Loss: 0.29115

Train Loss: 5.58441 |   Val Loss: 0.14856

Train Loss: 3.73215 |   Val Loss: 0.34698

Train Loss: 7.80472 |   Val Loss: 0.30550

Train Loss: 4.09834 |   Val Loss: 0.52923
```

```
Train Loss: 7.61176 |   Val Loss: 0.26254

Train Loss: 3.08120 |   Val Loss: 0.13724

Train Loss: 6.89102 |   Val Loss: 0.40663

Train Loss: 2.98029 |   Val Loss: 0.24778

Train Loss: 8.65062 |   Val Loss: 0.72928

Train Loss: 2.58147 |   Val Loss: 0.11037

Train Loss: 3.42727 |   Val Loss: 0.16694

Train Loss: 2.41050 |   Val Loss: 0.14386

Train Loss: 4.39781 |   Val Loss: 0.32249

Train Loss: 3.36964 |   Val Loss: 0.30997

Train Loss: 4.93713 |   Val Loss: 0.40303

Train Loss: 3.76821 |   Val Loss: 0.32877

Train Loss: 3.98606 |   Val Loss: 0.31160

Train Loss: 3.62645 |   Val Loss: 0.31848
```

[38]:
```
model=torch.load('saved_weights.pt')
```

[39]:
```
x_test= torch.tensor(x_test).float()

with torch.no_grad():
  y_test_pred = model(x_test)

y_test_pred = y_test_pred.numpy()[0]
```

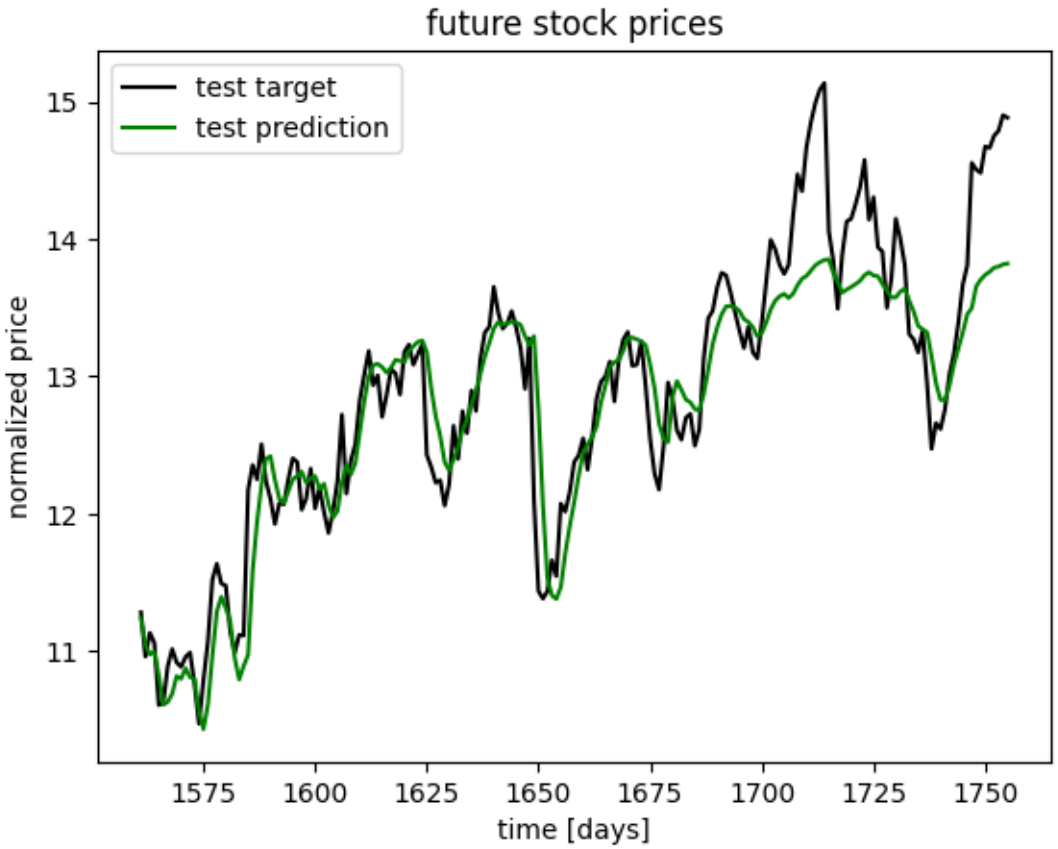
[40]:
```
idx=0
plt.plot(np.arange(y_train.shape[0], y_train.shape[0]+y_test.shape[0]),
         y_test[:,idx], color='black', label='test target')

plt.plot(np.arange(y_train.shape[0], y_train.shape[0]+y_test_pred.shape[0]),
         y_test_pred[:,idx], color='green', label='test prediction')

plt.title('future stock prices')
plt.xlabel('time [days]')
```

```
plt.ylabel('normalized price')
plt.legend(loc='best')
```

[40]: <matplotlib.legend.Legend at 0x786fad76f550>



[41]:
```
index_values = df[len(df) - len(y_test):].index
col_values = ['Open', 'Low', 'High', 'Close']
df_results = pd.DataFrame(data=y_test_pred, index=index_values,␣
 ↪columns=col_values)
```

[42]:
```
# Create a trace for the candlestick chart
candlestick_trace = go.Candlestick(
    x=df_results.index,
    open=df_results['Open'],
    high=df_results['High'],
    low=df_results['Low'],
    close=df_results['Close'],
    name='Candlestick'
)
```

```
# Create the layout
layout = go.Layout(
    title='GOOG Candlestick Chart',
    xaxis=dict(title='Date'),
    yaxis=dict(title='Price', rangemode='normal')
)

# Create the figure and add the candlestick trace and layout
fig = go.Figure(data=[candlestick_trace], layout=layout)

# Update the layout of the figure
fig.update_layout(xaxis_rangeslider_visible=False)

# Show the figure
fig.show()
```

[46]:
```
# Get the last sequence of historical data as features for predicting the next␣
 ↪10 days
last_sequence = sequences[-1:, 1:, :]
last_sequence = torch.from_numpy(last_sequence).float()

# Generate predictions for the next 10 days
PRED_DAYS = 10
with torch.no_grad():
    for i in range(PRED_DAYS):
        pred_i = model(last_sequence)
        last_sequence = torch.cat((last_sequence, pred_i), dim=1)
        last_sequence = last_sequence[:, 1:, :]


pred_days = last_sequence.reshape(PRED_DAYS, 4).numpy()

# inverse transform the predicted values
pred_days = scaler.inverse_transform(pred_days)

df_pred = pd.DataFrame(
    data=pred_days,
    columns=['Open', 'High', 'Low', 'Close']
)

df_pred
```

[46]:

	Open	High	Low	Close
0	143.569107	145.122482	141.634415	142.922333
1	142.824249	144.400345	141.068771	142.295258
2	142.237350	143.775940	140.553696	141.774414
3	141.753799	143.270096	140.114334	141.327118

```
4  141.359467  142.864395  139.748138  140.953171
5  141.040665  142.539642  139.448257  140.646591
6  140.784561  142.280121  139.205536  140.398422
7  140.582138  142.075378  139.013077  140.201736
8  140.425766  141.917297  138.864532  140.050003
9  140.306793  141.796616  138.751709  139.934784
```