7BUIS008W Data Mining & Machine Learning Module leader-Panagiotis Chountas Submitted by-Malaya Kumar Mishra Roll No-w1852625

In [ ]:
```
# Prediction of Netflix stock using LSTM model
```

The netflix stock price data was extracted from Yahoo Finance using the yfinance library. To get the to and from date for extracting data we have used datetime library. As the date of the stock starts from 23rd May, 2002, any date prior to it will give us the data from that date only.

In [1]:
```
import pandas as pd
import yfinance as yf
import datetime
from datetime import date, timedelta
today = date.today()

d1 = today.strftime("%Y-%m-%d")
end_date = d1
d2 = date.today() - timedelta(days=10000)
d2 = d2.strftime("%Y-%m-%d")
start_date = d2

data = yf.download('NFLX',
                   start=start_date,
                   end=end_date,
                   progress=False)
data["Date"] = data.index
data = data[["Date", "Open", "High", "Low", "Close", "Adj Close", "Volume"]]
data.reset_index(drop=True, inplace=True)
print(data.tail())
```

```
           Date        Open        High         Low       Close   Adj Close  \
5005 2022-04-08  361.959991  362.500000  354.869995  355.880005  355.880005
5006 2022-04-11  350.000000  354.779999  345.200012  348.000000  348.000000
5007 2022-04-12  355.910004  359.410004  342.250000  344.100006  344.100006
5008 2022-04-13  343.920013  352.000000  341.160004  350.429993  350.429993
5009 2022-04-14  350.950012  352.000000  339.859985  341.130005  341.130005

       Volume
5005  4020500
5006  3777100
5007  3824300
5008  3231000
5009  4338100
```

In [2]:
```
data
```

Out[2]:

	Date	Open	High	Low	Close	Adj Close	Volume
0	2002-05-23	1.156429	1.242857	1.145714	1.196429	1.196429	104790000
1	2002-05-24	1.214286	1.225000	1.197143	1.210000	1.210000	11104800
2	2002-05-28	1.213571	1.232143	1.157143	1.157143	1.157143	6609400
3	2002-05-29	1.164286	1.164286	1.085714	1.103571	1.103571	6757800
4	2002-05-30	1.107857	1.107857	1.071429	1.071429	1.071429	10154200

	Date	Open	High	Low	Close	Adj Close	Volume
...	...	...	...	...	...	...	...
5005	2022-04-08	361.959991	362.500000	354.869995	355.880005	355.880005	4020500
5006	2022-04-11	350.000000	354.779999	345.200012	348.000000	348.000000	3777100
5007	2022-04-12	355.910004	359.410004	342.250000	344.100006	344.100006	3824300
5008	2022-04-13	343.920013	352.000000	341.160004	350.429993	350.429993	3231000
5009	2022-04-14	350.950012	352.000000	339.859985	341.130005	341.130005	4338100

5010 rows × 7 columns

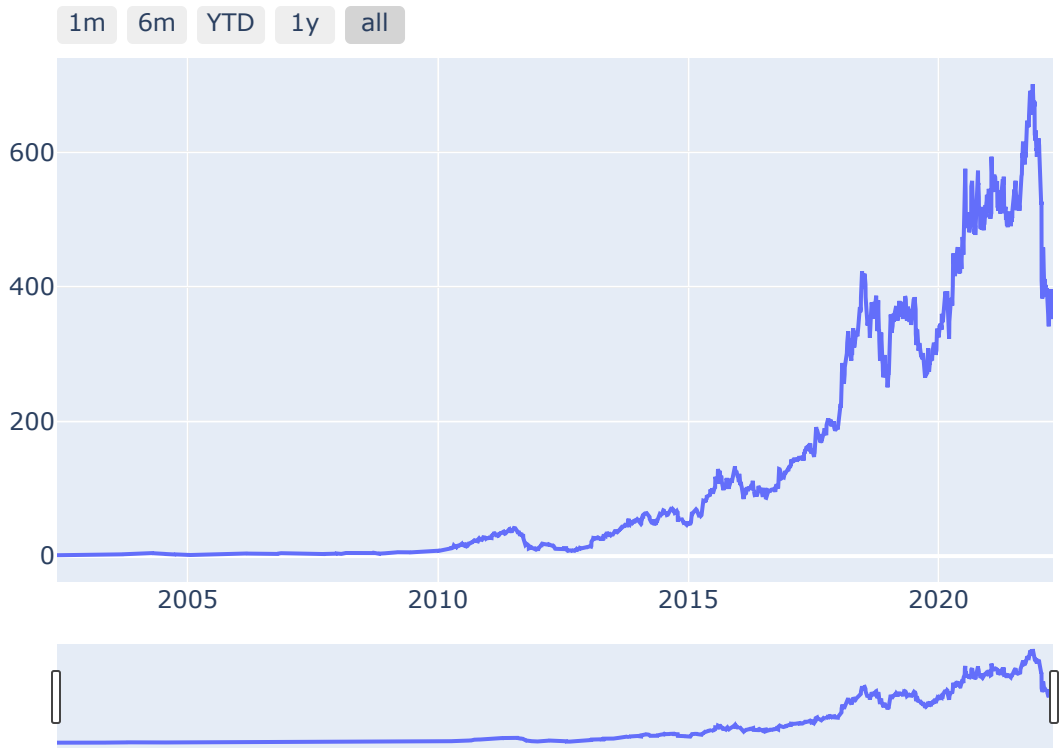
This data shows the OHLC values for netflix stock. These are opening value, closing value, highest value and lowest values for that particular day

From the extracted data we see that we get the data starting from 23rd May, 2002 to present date. Then we visualize the data to see how it changes with time.

In [3]:
```
import plotly.graph_objects as go
figure = go.Figure(data=[go.Candlestick(x=data["Date"],
                                        open=data["Open"],
                                        high=data["High"],
                                        low=data["Low"],
                                        close=data["Close"])])
figure.update_layout(title = "Netflix Stock Price Analysis",
                     xaxis_rangeslider_visible=False)
figure.show()
```

In [4]:

```
import plotly.graph_objects as go
import pandas as pd
fig = go.Figure([go.Scatter(x=data['Date'], y=data['High'])])
fig.update_xaxes(
    rangeslider_visible=True,
    rangeselector=dict(
        buttons=list([
            dict(count=1, label="1m", step="month",
                 stepmode="backward"),
            dict(count=6, label="6m", step="month",
                 stepmode="backward"),
            dict(count=1, label="YTD", step="year",
                 stepmode="todate"),
            dict(count=1, label="1y", step="year",
                 stepmode="backward"),
            dict(step="all")
        ])
    )
)
fig.show()
```



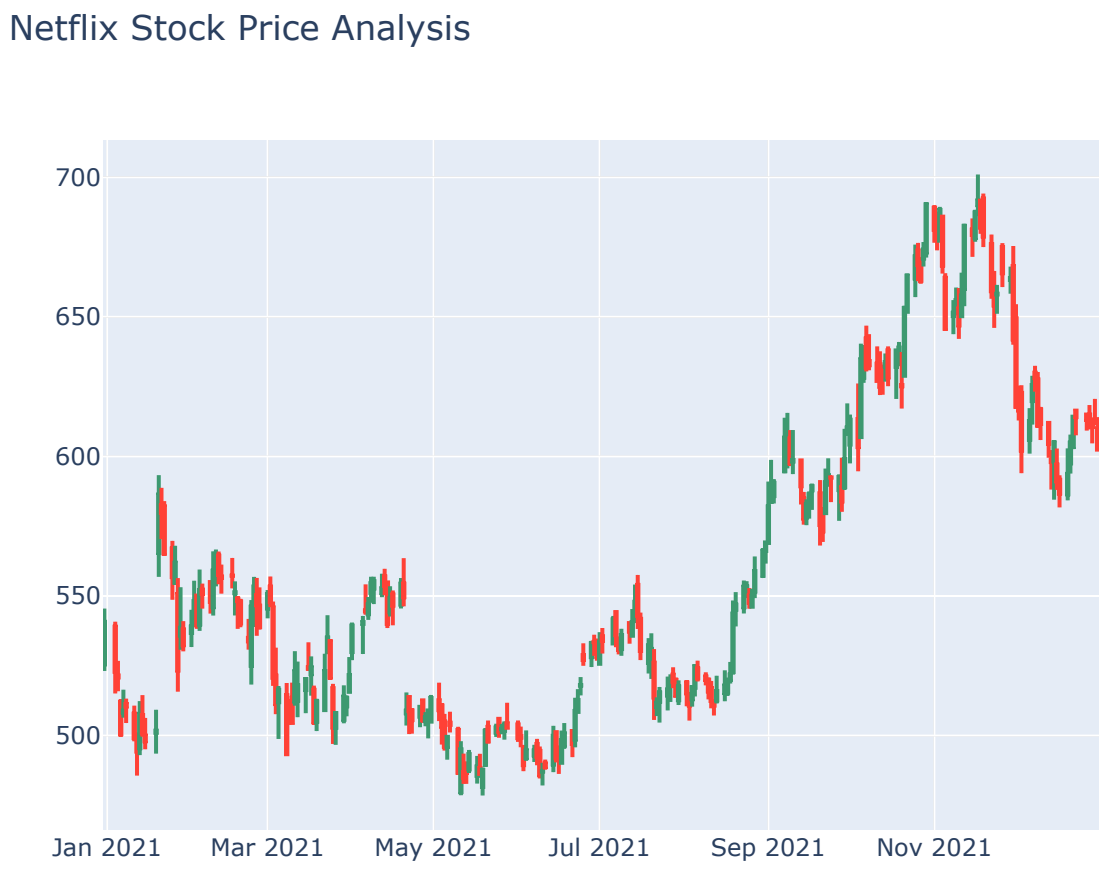
This is a Interactive graph where we can set the bars and look at the data of that period.

Next we visualize the data for previous year(2021)

In [5]:

```
start_date = '2021-01-01'
end_date = '2022-01-01'
m_2021 = yf.download('NFLX',
```

```
                       start=start_date,
                       end=end_date,
                       progress=False)
m_2021["Date"] = m_2021.index
m_2021= m_2021[["Date", "Open", "High", "Low", "Close", "Adj Close", "Volume"]]
m_2021.reset_index(drop=True, inplace=True)
import plotly.graph_objects as go
figure = go.Figure(data=[go.Candlestick(x=m_2021["Date"],
                                        open=m_2021["Open"],
                                        high=m_2021["High"],
                                        low=m_2021["Low"],
                                        close=m_2021["Close"])])
figure.update_layout(title = "Netflix Stock Price Analysis",
                     xaxis_rangeslider_visible=False)
figure.show()
```



Fromt the above graph we can infer that the stock price saw a bit of dip around June 2021, but again the stock price increased at around November 2021 we can see it having peak value.

In [6]:

```
correlation = data.corr()
print(correlation["Close"].sort_values(ascending=False))
```

```
Close        1.000000
Adj Close    1.000000
High         0.999865
Low          0.999859
Open         0.999701
Volume      -0.264646
Name: Close, dtype: float64
```

Model Building

Next we split the data into train and test datasets

In [7]:
```
x = data[["Open", "High", "Low", "Volume"]]
y = data["Close"]
x = x.to_numpy()
y = y.to_numpy()
y = y.reshape(-1, 1)

from sklearn.model_selection import train_test_split
xtrain, xtest, ytrain, ytest = train_test_split(x, y,
                                                test_size=0.2,
                                                random_state=42)
```

After this we build the LSTM model to train our data

In [9]:
```
from keras.models import Sequential
from keras.layers import Dense, LSTM
model = Sequential()
model.add(LSTM(128, return_sequences=True, input_shape= (xtrain.shape[1], 1)))
model.add(LSTM(64, return_sequences=False))
model.add(Dense(25))
model.add(Dense(1))
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm (LSTM)                 (None, 4, 128)            66560

 lstm_1 (LSTM)               (None, 64)                49408

 dense (Dense)               (None, 25)                1625

 dense_1 (Dense)             (None, 1)                 26

=================================================================
Total params: 117,619
Trainable params: 117,619
Non-trainable params: 0
_________________________________________________________________
```

In [10]:
```
model.compile(optimizer='adam', loss='mean_squared_error')
model.fit(xtrain, ytrain, batch_size=1, epochs=30)
```

```
Epoch 1/30
4008/4008 [==============================] - 13s 3ms/step - loss: 4116.3062
Epoch 2/30
4008/4008 [==============================] - 10s 2ms/step - loss: 429.7950
Epoch 3/30
4008/4008 [==============================] - 10s 3ms/step - loss: 387.1235
Epoch 4/30
4008/4008 [==============================] - 11s 3ms/step - loss: 341.4461: 0s
Epoch 5/30
4008/4008 [==============================] - 11s 3ms/step - loss: 359.9967
Epoch 6/30
4008/4008 [==============================] - 11s 3ms/step - loss: 352.7533
Epoch 7/30
4008/4008 [==============================] - 11s 3ms/step - loss: 391.9175
Epoch 8/30
```

```
4008/4008 [==============================] - 12s 3ms/step - loss: 403.8867
Epoch 9/30
4008/4008 [==============================] - 12s 3ms/step - loss: 322.7834
Epoch 10/30
4008/4008 [==============================] - 12s 3ms/step - loss: 408.9200
Epoch 11/30
4008/4008 [==============================] - 12s 3ms/step - loss: 232.0684
Epoch 12/30
4008/4008 [==============================] - 12s 3ms/step - loss: 253.1465
Epoch 13/30
4008/4008 [==============================] - 12s 3ms/step - loss: 263.1810
Epoch 14/30
4008/4008 [==============================] - 12s 3ms/step - loss: 256.8597
Epoch 15/30
4008/4008 [==============================] - 13s 3ms/step - loss: 250.2785
Epoch 16/30
4008/4008 [==============================] - 12s 3ms/step - loss: 621.0872
Epoch 17/30
4008/4008 [==============================] - 12s 3ms/step - loss: 321.6961
Epoch 18/30
4008/4008 [==============================] - 12s 3ms/step - loss: 334.7940
Epoch 19/30
4008/4008 [==============================] - 12s 3ms/step - loss: 266.2260
Epoch 20/30
4008/4008 [==============================] - 12s 3ms/step - loss: 253.8124
Epoch 21/30
4008/4008 [==============================] - 12s 3ms/step - loss: 212.2696
Epoch 22/30
4008/4008 [==============================] - 12s 3ms/step - loss: 272.5884
Epoch 23/30
4008/4008 [==============================] - 13s 3ms/step - loss: 231.7941
Epoch 24/30
4008/4008 [==============================] - 13s 3ms/step - loss: 201.4638
Epoch 25/30
4008/4008 [==============================] - 13s 3ms/step - loss: 304.5264
Epoch 26/30
4008/4008 [==============================] - 12s 3ms/step - loss: 237.8254
Epoch 27/30
4008/4008 [==============================] - 12s 3ms/step - loss: 188.6718
Epoch 28/30
4008/4008 [==============================] - 13s 3ms/step - loss: 203.7470
Epoch 29/30
4008/4008 [==============================] - 12s 3ms/step - loss: 167.6825
Epoch 30/30
4008/4008 [==============================] - 12s 3ms/step - loss: 214.9789
```

Out[10]:
```
<keras.callbacks.History at 0x26c53338e50>
```

After the model is trained, we predict ove the test data using this model.

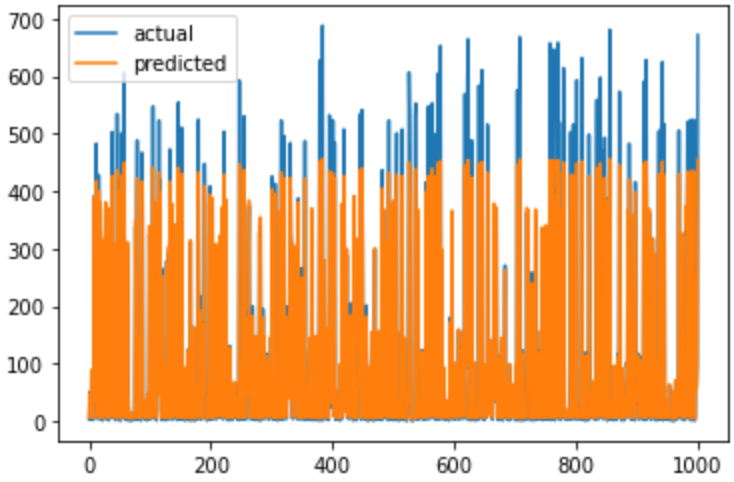
In [12]:
```
model.predict(xtest)
```

Out[12]:
```
array([[  6.4364467],
       [ 47.877735 ],
       [  7.8040657],
       ...,
       [ 56.34328  ],
       [ 98.19425  ],
       [454.99448  ]], dtype=float32)
```

We then visualize this data along with the actual data.

In [44]:
```
import matplotlib.pyplot as plt
plt.plot(ytest,label = 'actual')
plt.plot(model.predict(xtest), label ='predicted')
```

```
plt.legend()
plt.show()
```

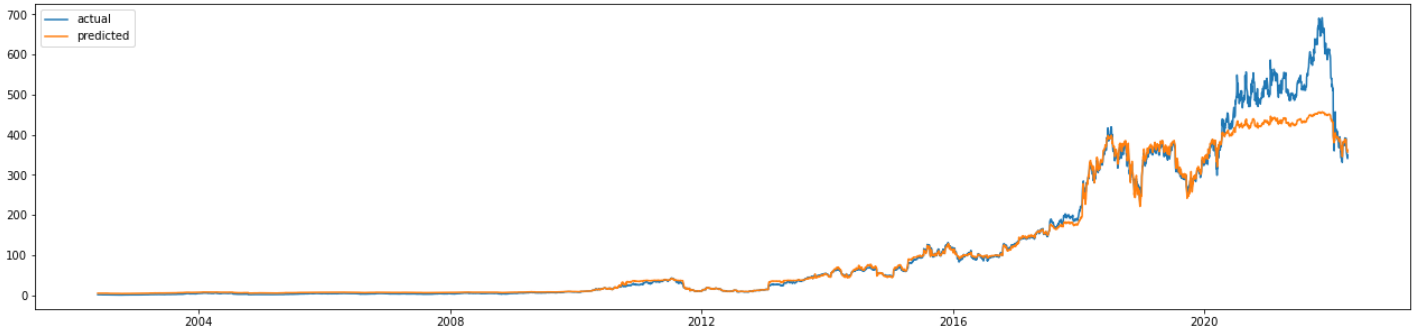


From this we see that it is able to predict somewhat correctly over the test data.

Now checking the prediction over the whole data, we get:

In [37]:
```
df = pd.DataFrame(index = data.Date)
df['Actual'] = y
df['Predicted']=model.predict(x)
```

In [38]:
```
import matplotlib.pyplot as plt
plt.figure(figsize=(22, 5))
plt.plot(df['Actual'],label = 'actual')
plt.plot(df['Predicted'], label ='predicted')
plt.legend()
plt.show()
```



From this we can see that our model is able to capture the pattern. Now predicting for a totally new data.

In [11]:
```
import numpy as np
#features = [Open, High, Low, Adj Close, Volume]
features = np.array([[401.970001, 427.700012, 398.200012, 20047500]])
model.predict(features)
```

Out[11]:
```
array([[397.35785]], dtype=float32)
```