Netflix Stock Price Forecasting Model

Summary

The dataset for this project originates from kaggle and contains Netflix daily stock prices between 2002 and 2021.

In this project, we will employ Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) to predict stock market indices. We are interested in forecasting the 'Close' series.

Load and Exploratore the Data

In [1]:

```
import sys
import numpy as np
import matplotlib.pyplot as plt
import warnings
warnings.simplefilter(action='ignore')
import pandas as pd
from datetime import datetime
import tensorflow as tf
import keras
from keras.models import Sequential
from keras.layers import Dense, SimpleRNN, LSTM, Activation, Dropout
import math
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error
```

In [2]:

```
data = pd.read_csv('./netflix.csv',sep=",")
data.head()
```

Out[2]:

	Date	High	Low	Open	Close	Volume	Adj Close
0	2002-05-23	1.242857	1.145714	1.156429	1.196429	104790000.0	1.196429

	Date	High	Low	Open	Close	Volume	Adj Close
1	2002-05-24	1.225000	1.197143	1.214286	1.210000	11104800.0	1.210000
2	2002-05-28	1.232143	1.157143	1.213571	1.157143	6609400.0	1.157143
3	2002-05-29	1.164286	1.085714	1.164286	1.103571	6757800.0	1.103571
4	2002-05-30	1.107857	1.071429	1.107857	1.071429	10154200.0	1.071429

In [3]:

```
data['Close'].isnull().sum()
```

Out[3]:

0

In [4]:

```
data = data[['Date', 'Close']]
data.sample(5)
```

Out[4]:

	Date	Close
2710	2013-02-28	26.868570
3536	2016-06-09	97.089996
1581	2008-09-03	4.415714
1341	2007-09-20	2.782857
4383	2019-10-21	278.049988

Feature Transformation

- Replace comma in **Close** column and convert values into float64
- Transform **Date** column into a datetime object

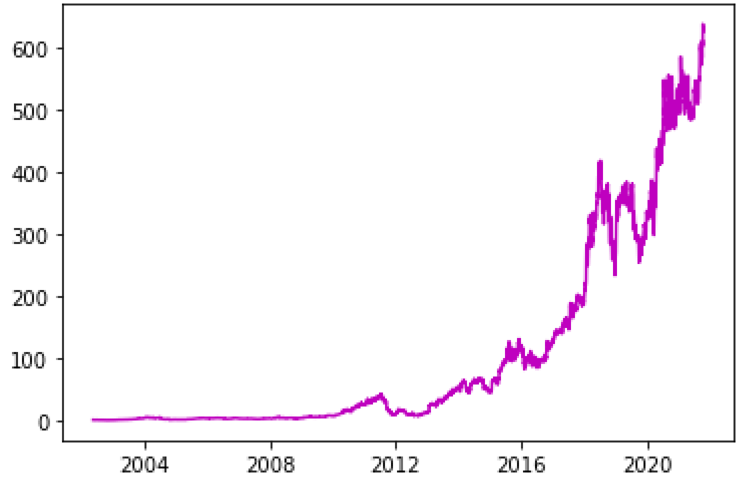
In [5]:

```
def make_date(row):
  return datetime(year = int(row.split('-')[0]),
          month = int(row.split('-')[1]),
          day = int(row.split('-')[2]))
```

```
data['Date'] = data['Date'].apply(make_date)
data.set_index(data.Date,inplace=True)
data.drop(columns=['Date'], inplace=True)

plt.plot(data, 'm')
```

Out[5]:

```
[<matplotlib.lines.Line2D at 0x2201ae954f0>]
```



Split the Data and Apply Feature Scaling

- Split the data into train and test data sets using **timestep = 50 days**
- use **MinMaxScaler** to scale the data

In [6]:

```
timesteps = 50
```

In [7]:

```
train = data[:len(data)-timesteps]['Close'].values
test = data[len(train):]['Close'].values
train=train.reshape(train.shape[0],1)
test=test.reshape(test.shape[0],1)
```

In [8]:

```
sc = MinMaxScaler(feature_range= (0,1))
train = sc.fit_transform(train)
```

In [9]:

```
train_X = []
train_y = []

for i in range(timesteps, train.shape[0]):
    train_X.append(train[i-timesteps:i,0])
    train_y.append(train[i,0])

train_X = np.array(train_X)
train_X = train_X.reshape(train_X.shape[0], train_X.shape[1], 1)
train_y = np.array(train_y)
```

In [10]:

```
print('Training input shape: {}'.format(train_X.shape))
print('Training output shape: {}'.format(train_y.shape))
```

```
Training input shape: (4781, 50, 1)
Training output shape: (4781,)
```

In [11]:

```
inputs = data[len(data) - len(test) - timesteps:]
inputs = sc.transform(inputs)

test_X = []

for i in range(timesteps, 100):
    test_X.append(inputs[i-timesteps:i,0])

test_X = np.array(test_X)
test_X = test_X.reshape(test_X.shape[0], test_X.shape[1], 1)
```

In [12]:

```
test_X.shape
```

Out[12]:

```
(50, 50, 1)
```

Train models

- Simple **RNN** layers each with 50 hidden units and tanh activation function per cell
- **LSTM** with 70 hidden units per cell
- Define the loss function and optimizer strategy
- Fit the model with 100 epochs
- Predict and plot the results

RNN

In [13]:

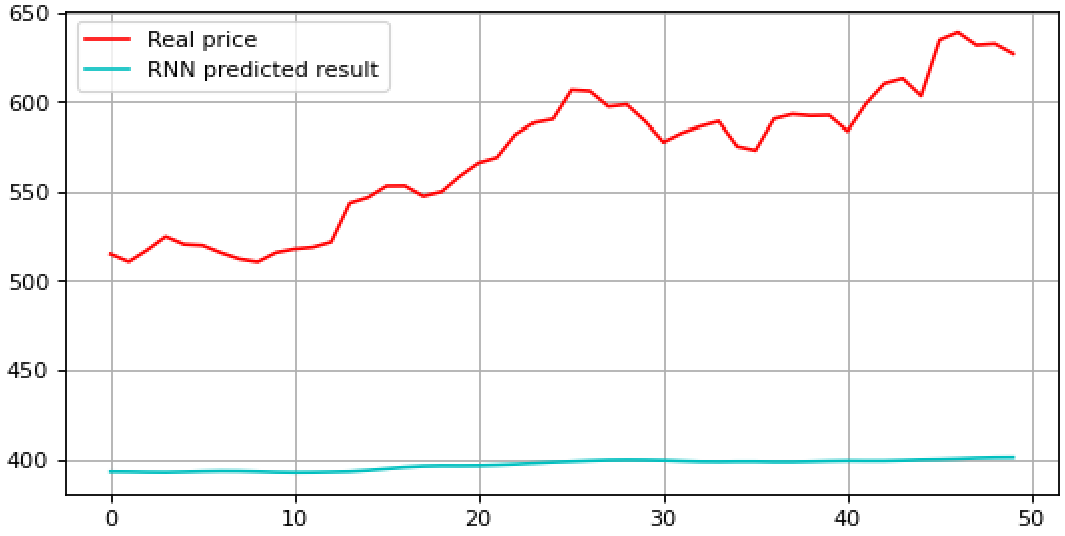
```
model_RNN = Sequential()

model_RNN.add(SimpleRNN(50, activation='tanh',
            input_shape=(train_X.shape[1],1), return_sequences = True))
model_RNN.add(Dropout(0.2))
model_RNN.add(SimpleRNN(50, activation='tanh', return_sequences = True,))
model_RNN.add(Dropout(0.2))
model_RNN.add(SimpleRNN(50, activation='tanh', return_sequences = True,))
model_RNN.add(Dropout(0.2))
model_RNN.add(SimpleRNN(50, activation='tanh'))
# output layer to make final predictions
model_RNN.add(Dense(1))

model_RNN.compile(loss='mean_squared_error', optimizer='adam')
model_RNN.fit(train_X, train_y, epochs=100, batch_size=32, verbose=0)
```

Out[13]:

```
<keras.callbacks.History at 0x2201cbf0fa0>
```

In [14]:

```
predicted_RNN = model_RNN.predict(test_X)
predicted_RNN = sc.inverse_transform(predicted_RNN)

plt.figure(figsize=(8,4), dpi=80, facecolor='w', edgecolor='k')
plt.plot(test,color="red",label="Real price")
plt.plot(predicted_RNN,color="c",label="RNN predicted result")
plt.legend()
plt.grid(True)
plt.show()
```



LSTM

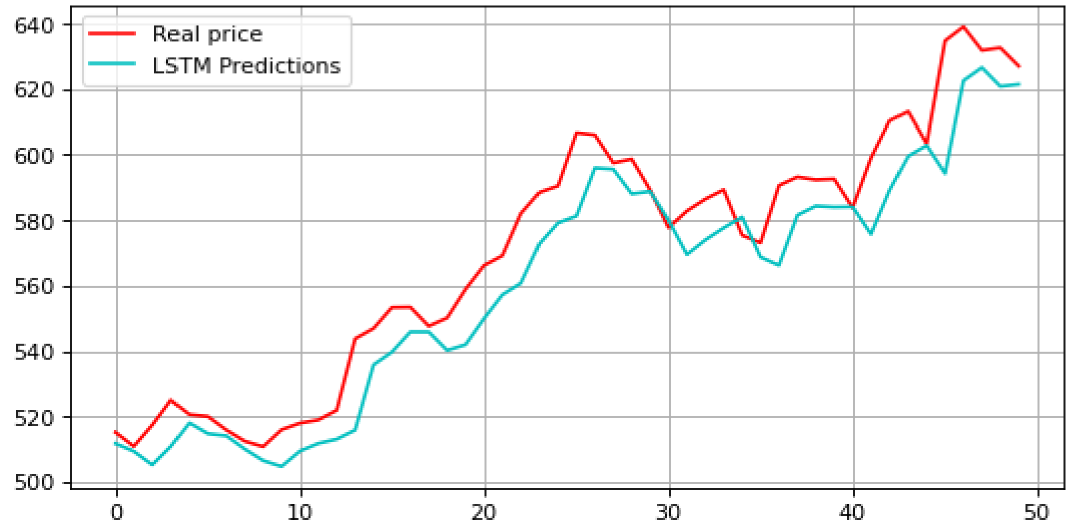
In [15]:

```
model_LSTM = Sequential()
model_LSTM.add(LSTM(70, input_shape=(train_X.shape[1],1)))
model_LSTM.add(Dense(1))

model_LSTM.compile(loss='mean_squared_error', optimizer='adam')
model_LSTM.fit(train_X, train_y, epochs=100, batch_size=32, verbose=0)
```

Out[15]: <keras.callbacks.History at 0x22022678b80>

In [16]:

```
predicted_LSTM = model_LSTM.predict(test_X)
predicted_LSTM = sc.inverse_transform(predicted_LSTM)

plt.figure(figsize=(8,4), dpi=80, facecolor='w', edgecolor='k')
plt.plot(test,color="red",label="Real price")
plt.plot(predicted_LSTM,color="c",label="LSTM Predictions")
plt.legend()
plt.grid(True)
plt.show()
```



In [17]:

```
# RNN structure
model_RNN.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)            Output Shape          Param #
=================================================================
 simple_rnn (SimpleRNN)     (None, 50, 50)         2600

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

 simple_rnn_1 (SimpleRNN)    (None, 50, 50)         5050

 dropout_1 (Dropout)        (None, 50, 50)         0

 simple_rnn_2 (SimpleRNN)    (None, 50, 50)         5050

 dropout_2 (Dropout)        (None, 50, 50)         0

 simple_rnn_3 (SimpleRNN)    (None, 50)            5050

 dense (Dense)            (None, 1)             51

=================================================================
Total params: 17,801
```

```
Trainable params: 17,801
Non-trainable params: 0
_________________________________________________________________
```

In [18]:

```
# LSTM structure
model_LSTM.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm (LSTM)                 (None, 70)                20160

 dense_1 (Dense)             (None, 1)                 71

=================================================================
Total params: 20,231
Trainable params: 20,231
Non-trainable params: 0
_________________________________________________________________
```

Results

If we compare the model summary for **Simple RNN** with the model summary for **LSTM**, we can see that there are more trainable parameters for the **LSTM**, which explains why it took a longer time to train this model.

Overall the plots show that our **LSTM** model with a less complex structure still performed better than our Simple RNN. The latter one predict very weak.

Next Steps

To improve the quality of forecasts over many time steps, we'd need to use more data and more sophisticated LSTM model structures. We could try training with more data or increasing cell_units and running more training epochs.