Forecasting and Analysis on FAANG Stocks

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Goal of this Notebook

The goal of this notebook is to derive insights and conclusions regarding the price of FAANG stocks. To do this, we look at two different models for forecasting closing prices of stocks. The two models we picked were LSTM and Prophet. We also take a look at the trend of FAANG closing stock prices, historical price to earnings ratios, and attempt to find historical correlations between the highest and lowest percent earning days for each FAANG company.

Data Collection

Here, we are loading S&P500 data into a pandas data frame as well as loading all the data for the FAANG companies into a separate data frame.

Script for collecting up to date data

from datetime import datetime from concurrent import futures

import pandas as pd from pandas import DataFrame import pandas_datareader.data as web

def download_stock(stock): """ try to query the iex for a stock, if failed note with print """ try: print(stock) stock_df = web.DataReader(stock,'yahoo', start_time, now_time) print(stock_df) stock_df['Name'] = stock output_name = stock + '_data.csv' stock_df.to_csv(output_name) print("sucess\n\n\n") except: bad_names.append(stock) print('bad: %s' % (stock))

if **name** == '**main**':

```
""" set the download window """
now_time = datetime.now()
start_time = datetime(1900,1,1)

""" list of s_and_p companies """
s_and_p = ['MMM','ABT','ABBV','ACN','ATVI','AYI','ADBE','AMD','AAP','AES','AET',
    'AMG','AFL','A','APD','AKAM','ALK','ALB','ARE','ALXN','ALGN','ALLE',
    'AGN','ADS','LNT','ALL','GOOGL','GOOG','MO','AMZN','AEE','AAL','AEP',
    'AXP','AIG','AMT','AWK','AMP','ABC','AME','AMGN','APH','APC','ADI','ANDV',
    'ANSS','ANTM','AON','AOS','APA','AIV','AAPL','AMAT','APTV','ADM','ARNC',
    'AJG','AIZ','T','ADSK','ADP','AZO','AVB','AVY','BHGE','BLL','BAC','BK',
    'BAX','BBT','BDX','BRK.B','BBY','BIIB','BLK','HRB','BA','BWA','BXP','BSX',
    'BHF','BMY','AVGO','BF.B','CHRW','CA','COG','CDNS','CPB','COF','CAH','CBOE',
    'KMX','CCL','CAT','CBG','CBS','CELG','CNC','CNP','CTL','CERN','CF','SCHW',
    'CHTR','CHK','CVX','CMG','CB','CHD','CI','XEC','CINF','CTAS','CSCO','C','CFG',
    'CTXS','CLX','CME','CMS','KO','CTSH','CL','CMCSA','CMA','CAG','CXO','COP',
    'ED','STZ','COO','GLW','COST','COTY','CCI','CSRA','CSX','CMI','CVS','DHI',
    'DHR','DRI','DVA','DE','DAL','XRAY','DVN','DLR','DFS','DISCA','DISCK','DISH',
    'DG','DLTR','D','DOV','DWDP','DPS','DTE','DRE','DUK','DXC','ETFC','EMN','ETN',
    'EBAY','ECL','EIX','EW','EA','EMR','ETR','EVHC','EOG','EQT','EFX','EQIX','EQR',
    'ESS','EL','ES','RE','EXC','EXPE','EXPD','ESRX','EXR','XOM','FFIV','FB','FAST',
    'FRT','FDX','FIS','FITB','FE','FISV','FLIR','FLS','FLR','FMC','FL','F','FTV',
    'FBHS','BEN','FCX','GPS','GRMN','IT','GD','GE','GGP','GIS','GM','GPC','GILD',
    'GPN','GS','GT','GWW','HAL','HBI','HOG','HRS','HIG','HAS','HCA','HCP','HP','HSIC',
    'HSY','HES','HPE','HLT','HOLX','HD','HON','HRL','HST','HPQ','HUM','HBAN','HII',
    'IDXX','INFO','ITW','ILMN','IR','INTC','ICE','IBM','INCY','IP','IPG','IFF','INTU',
    'ISRG','IVZ','IQV','IRM','JEC','JBHT','SJM','JNJ','JCI','JPM','JNPR','KSU','K','KEY',
    'KMB','KIM','KMI','KLAC','KSS','KHC','KR','LB','LLL','LH','LRCX','LEG','LEN','LUK',
    'LLY','LNC','LKQ','LMT','L','LOW','LYB','MTB','MAC','M','MRO','MPC','MAR','MMC','MLM',
    'MAS','MA','MAT','MKC','MCD','MCK','MDT','MRK','MET','MTD','MGM','KORS','MCHP','MU',
```

```
        'MSFT','MAA','MHK','TAP','MDLZ','MON','MNST','MCO','MS','MOS','MSI','MYL','NDAQ',
        'NOV','NAVI','NTAP','NFLX','NWL','NFX','NEM','NWSA','NWS','NEE','NLSN','NKE','NI',
        'NBL','JWN','NSC','NTRS','NOC','NCLH','NRG','NUE','NVDA','ORLY','OXY','OMC','OKE',
        'ORCL','PCAR','PKG','PH','PDCO','PAYX','PYPL','PNR','PBCT','PEP','PKI','PRGO','PFE',
        'PCG','PM','PSX','PNW','PXD','PNC','RL','PPG','PPL','PX','PCLN','PFG','PG','PGR',
        'PLD','PRU','PEG','PSA','PHM','PVH','QRVO','PWR','QCOM','DGX','RRC','RJF','RTN','O',
        'RHT','REG','REGN','RF','RSG','RMD','RHI','ROK','COL','ROP','ROST','RCL','CRM','SBAC',
        'SCG','SLB','SNI','STX','SEE','SRE','SHW','SIG','SPG','SWKS','SLG','SNA','SO','LUV',
        'SPGI','SWK','SBUX','STT','SRCL','SYK','STI','SYMC','SYF','SNPS','SYY','TROW','TPR',
        'TGT','TEL','FTI','TXN','TXT','TMO','TIF','TWX','TJX','TMK','TSS','TSCO','TDG','TRV',
        'TRIP','FOXA','FOX','TSN','UDR','ULTA','USB','UAA','UA','UNP','UAL','UNH','UPS','URI',
        'UTX','UHS','UNM','VFC','VLO','VAR','VTR','VRSN','VRSK','VZ','VRTX','VIAB','V','VNO',
        'VMC','WMT','WBA','DIS','WM','WAT','WEC','WFC','HCN','WDC','WU','WRK','WY','WHR','WMB',
        'WLTW','WYN','WYNN','XEL','XRX','XLNX','XL','XYL','YUM','ZBH','ZION','ZTS']

    bad_names =[] #to keep track of failed queries

    """here we use the concurrent.futures module's ThreadPoolExecutor
        to speed up the downloads buy doing them in parallel
        as opposed to sequentially """

    #set the maximum thread number
    max_workers = 50

    workers = min(max_workers, len(s_and_p)) #in case a smaller number of stocks than threads w
    as passed in
    with futures.ThreadPoolExecutor(workers) as executor:
        res = executor.map(download_stock, s_and_p)


    """ Save failed queries to a text file to retry """
    if len(bad_names) > 0:
        with open('failed_queries.txt','w') as outfile:
            for name in bad_names:
                outfile.write(name+'\n')

    #timing:
    finish_time = datetime.now()
    duration = finish_time - now_time
    minutes, seconds = divmod(duration.seconds, 60)
    print('getSandP_threaded.py')
    print(f'The threaded script took {minutes} minutes and {seconds} seconds to run.')
    #The threaded script took 0 minutes and 31 seconds to run.
```

In [41]:

```
import glob
import os
import pandas as pd

all_stock_df_list = []
for filename in glob.glob(os.getcwd() +"/../../data/raw/"+"*.csv"):
    x = pd.read_csv(filename, low_memory=False)
    all_stock_df_list.append(x)

df = pd.concat(all_stock_df_list)
df.reset_index(inplace=True, drop=True)
df
```

Out[41]:

	Date	High	Low	Open	Close	Volume	Adj Close	Name
0	1977-01-03	25.801493	25.527010	25.527010	25.581905	169800.0	5.956707	XRX
1	1977-01-04	25.691700	25.197628	25.581905	25.252525	143200.0	5.880013	XRX

	Date	High	Low	Open	Close	Volume	Adj Close	Name
2	1977-01-05	25.63[illegible]	24.923145	25.252525	25.087835	191000.0	5.841664	XRX
3	1977-01-06	25.362318	24.868248	25.087835	25.032938	168700.0	5.828885	XRX
4	1977-01-07	25.142731	24.483971	25.032938	24.923145	143200.0	5.803314	XRX
...	...	...	...	...	...	...	...	...
3741010	2020-11-04	7.870000	7.630000	7.860000	7.640000	67326800.0	7.640000	F
3741011	2020-11-05	7.990000	7.710000	7.760000	7.990000	61442600.0	7.990000	F
3741012	2020-11-06	8.020000	7.750000	8.010000	7.790000	50912100.0	7.790000	F
3741013	2020-11-09	8.380000	8.080000	8.110000	8.200000	110511300.0	8.200000	F
3741014	2020-11-10	8.590000	8.180000	8.230000	8.380000	87182400.0	8.380000	F

3741015 rows × 8 columns

In [42]:

```
fang = pd.concat([pd.read_csv(f) for f in glob.glob(os.getcwd()+ '/../../data/raw/fang/'+'*.csv')],
ignore_index = True)
fang.to_csv(os.getcwd()+"/../../data/processed/fang.csv",index=False)
fang
```

Out[42]:

	Date	High	Low	Open	Close	Volume	Adj Close	Name
0	2002-05-23	1.242857	1.145714	1.156429	1.196429	104790000.0	1.196429	NFLX
1	2002-05-24	1.225000	1.197143	1.214286	1.210000	11104800.0	1.210000	NFLX
2	2002-05-28	1.232143	1.157143	1.213571	1.157143	6609400.0	1.157143	NFLX
3	2002-05-29	1.164286	1.085714	1.164286	1.103571	6757800.0	1.103571	NFLX
4	2002-05-30	1.107857	1.071429	1.107857	1.071429	10154200.0	1.071429	NFLX
...	...	...	...	...	...	...	...	...
26845	2020-11-04	3244.850098	3139.729980	3159.989990	3241.159912	6839000.0	3241.159912	AMZN
26846	2020-11-05	3366.800049	3288.879883	3319.969971	3322.000000	5789300.0	3322.000000	AMZN
26847	2020-11-06	3322.000000	3232.000000	3304.639893	3311.370117	4647300.0	3311.370117	AMZN
26848	2020-11-09	3289.000000	3112.110107	3231.030029	3143.739990	7190400.0	3143.739990	AMZN
26849	2020-11-10	3114.000000	3019.479980	3095.020020	3035.020020	6563300.0	3035.020020	AMZN

26850 rows × 8 columns

Stock prediction using LSTM

In this notebook, we have attempted to use LSTM to predict the closing price of FANG stocks. First, we need to include some modules that will be used for the plotting and ML models.

In [43]:

```
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns
sns.set_style('darkgrid')
plt.style.use("seaborn-pastel")
%matplotlib inline

from pandas_datareader.data import DataReader
from datetime import datetime
```

For this example, we will use Apple, Google, Microsoft, Amazon, Facebook, and Netflix. We can use DataReader to get live data from Yahoo on these stocks.

In [44]:

```python
companies = ['AAPL', 'GOOG', 'MSFT', 'AMZN', 'FB', 'NFLX']
end = datetime.now()
start = datetime(end.year - 1, end.month, end.day)

for ticker in companies:
    globals()[ticker] = DataReader(ticker, 'yahoo', start, end)
```

We can start by doing analysis on one of the stocks, Amazon. Lets get the stock prices for the past 8 years.

In [45]:

```python
df = DataReader('AMZN', data_source='yahoo', start='2012-01-01', end=datetime.now())
df
```

Out[45]:

	High	Low	Open	Close	Volume	Adj Close
Date						
2012-01-03	179.479996	175.550003	175.889999	179.029999	5110800	179.029999
2012-01-04	180.500000	176.070007	179.210007	177.509995	4205200	177.509995
2012-01-05	178.250000	174.050003	175.940002	177.610001	3809100	177.610001
2012-01-06	184.649994	177.500000	178.070007	182.610001	7008400	182.610001
2012-01-09	184.369995	177.000000	182.759995	178.559998	5056900	178.559998
...	...	...	...	...	...	...
2020-11-09	3289.000000	3112.110107	3231.030029	3143.739990	7190400	3143.739990
2020-11-10	3114.000000	3019.479980	3095.020020	3035.020020	6591000	3035.020020
2020-11-11	3139.149902	3050.000000	3061.780029	3137.389893	4366900	3137.389893
2020-11-12	3175.879883	3086.050049	3159.949951	3110.280029	4362000	3110.280029
2020-11-13	3141.719971	3085.389893	3122.000000	3128.810059	3756200	3128.810059

2233 rows × 6 columns

We have information on the high, low, open, close, and volume for each day in the past year. If we look at the plot of the close price (which is what we'll use for analysis), you can see the fluctiation in price.

In [46]:

```python
plt.figure(figsize=(16,8))
plt.title('Close Price History')
plt.plot(df['Close'])
plt.xlabel('Date', fontsize=18)
plt.ylabel('Close Price USD ($)', fontsize=18)
plt.show()
```

for our dataset, we will just be working with the Close prices. For this example, we can use 60% of the data for training, and 40% for testing.

In [47]:

```
data = df.filter(['Close'])
dataset = data.values
training_data_len = int(np.ceil( len(dataset) * .6 ))

training_data_len
```

Out[47]:

```
1340
```

We need to scale the data so that it is easier to work with in the model.

In [48]:

```
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler(feature_range=(0,1))
scaled_data = scaler.fit_transform(dataset)
scaled_data
```

Out[48]:

```
array([[9.23852679e-04],
       [4.70866468e-04],
       [5.00669928e-04],
       ...,
       [8.82563637e-01],
       [8.74484453e-01],
       [8.80006706e-01]])
```

Next, let's grab some training data for the model.

In [49]:

```
train_data = scaled_data[0:int(training_data_len), :]
x_train = []
y_train = []

for i in range(60, len(train_data)):
    x_train.append(train_data[i-60:i, 0])
    y_train.append(train_data[i, 0])

x_train, y_train = np.array(x_train), np.array(y_train)

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

Keras makes it easy to implement LSTM.

In [50]:

```
from keras.models import Sequential
from keras.layers import Dense, LSTM

model = Sequential()
```

```
model = Sequential()
model.add(LSTM(50, return_sequences=True, input_shape= (x_train.shape[1], 1)))
model.add(LSTM(50, return_sequences= False))
model.add(Dense(25))
model.add(Dense(1))

model.compile(optimizer='adam', loss='mean_squared_error')

model.fit(x_train, y_train, batch_size=1, epochs=1)
```

```
1280/1280 [==============================] - 31s 25ms/step - loss: 1.1807e-
04
```

Out[50]:

```
<tensorflow.python.keras.callbacks.History at 0x7fc7f6f01370>
```

Finally, we can test the model on the 40% left of the data, and calculate the RMSE.

In [51]:

```
test_data = scaled_data[training_data_len - 60: , :]
x_test = []
y_test = dataset[training_data_len:, :]
for i in range(60, len(test_data)):
    x_test.append(test_data[i-60:i, 0])

x_test = np.array(x_test)

x_test = np.reshape(x_test, (x_test.shape[0], x_test.shape[1], 1 ))

predictions = model.predict(x_test)
predictions = scaler.inverse_transform(predictions)

rmse = np.sqrt(np.mean(((predictions - y_test) ** 2)))
rmse
```

Out[51]:

129.66046791795617

As you can see, our model did pretty well. On average, it predicted a bit low on the closing prices.

In [52]:

```
train = data[:training_data_len]
valid = data[training_data_len:]
valid['Predictions'] = predictions
plt.figure(figsize=(16,8))
plt.title('Model')
plt.xlabel('Date', fontsize=18)
plt.ylabel('Close Price USD ($)', fontsize=18)
plt.plot(train['Close'])
plt.plot(valid[['Close', 'Predictions']])
plt.legend(['Train', 'Val', 'Predictions'], loc='upper left')
plt.show()
```

```
<ipython-input-52-de17834f6994>:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  valid['Predictions'] = predictions
```

In [53]:

```
valid
```

Out[53]:

	Close	Predictions
Date		
2017-05-02	946.940002	971.667847
2017-05-03	941.030029	978.138855
2017-05-04	937.530029	983.829590
2017-05-05	934.150024	988.260498
2017-05-08	949.039978	991.286804
...	...	...

Date	Close	Predictions
2020-11-09	3143.739990	3301.803225
2020-11-10	3035.020020	3308.619629
2020-11-11	3137.389893	3298.815918
2020-11-12	3110.280029	3291.394775
2020-11-13	3128.810059	3282.494873

893 rows × 2 columns

Now let's use the method we just developed again, but on the remaining tickers.

In [54]:

```
for i, company in enumerate(companies, 1):
    df = DataReader(company, data_source='yahoo', start='2012-01-01', end=datetime.now())
    data = df.filter(['Close'])
    dataset = data.values
    training_data_len = int(np.ceil( len(dataset) * .6 ))

    scaler = MinMaxScaler(feature_range=(0,1))
    scaled_data = scaler.fit_transform(dataset)


    train_data = scaled_data[0:int(training_data_len), :]
    x_train = []
    y_train = []

    for i in range(60, len(train_data)):
        x_train.append(train_data[i-60:i, 0])
        y_train.append(train_data[i, 0])

    x_train, y_train = np.array(x_train), np.array(y_train)

    x_train = np.reshape(x_train, (x_train.shape[0], x_train.shape[1], 1))
    model = Sequential()
    model.add(LSTM(50, return_sequences=True, input_shape= (x_train.shape[1], 1)))
    model.add(LSTM(50, return_sequences= False))
    model.add(Dense(25))
    model.add(Dense(1))

    model.compile(optimizer='adam', loss='mean_squared_error')

    model.fit(x_train, y_train, batch_size=1, epochs=1)
    test_data = scaled_data[training_data_len - 60: , :]
    x_test = []
    y_test = dataset[training_data_len:, :]
    for i in range(60, len(test_data)):
        x_test.append(test_data[i-60:i, 0])

    x_test = np.array(x_test)

    x_test = np.reshape(x_test, (x_test.shape[0], x_test.shape[1], 1 ))

    predictions = model.predict(x_test)
    predictions = scaler.inverse_transform(predictions)

    rmse = np.sqrt(np.mean(((predictions - y_test) ** 2)))
    train = data[:training_data_len]
    valid = data[training_data_len:]
    valid['Predictions'] = predictions
    plt.figure(figsize=(16,8))
    plt.title(company)
    plt.xlabel('Date', fontsize=18)
    plt.ylabel('Close Price USD ($)', fontsize=18)
    plt.plot(train['Close'])
    plt.plot(valid[['Close', 'Predictions']])
    plt.legend(['Train', 'Val', 'Predictions'], loc='upper left')
    plt.show()
```

```
1280/1280 [==============================] - 33s 26ms/step - loss: 1.4517e-
04
```

```
  valid['Predictions'] = predictions
<ipython-input-54-6a61bcf0e01e>:47: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  valid['Predictions'] = predictions
<ipython-input-54-6a61bcf0e01e>:47: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  valid['Predictions'] = predictions
<ipython-input-54-6a61bcf0e01e>:47: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  valid['Predictions'] = predictions
```

MSFT


Train
Val
Predictions
Close Price USD ($)
Date

AMZN


Train
Val
Predictions
Close Price USD ($)
Date

FB


Train
Val
Predictions
Close Price USD ($)
Date

Forecasting using Prophet

In [55]:

```
import os
import pandas as pd
import numpy as np

# models
from fbprophet import Prophet

# plots
import matplotlib.pyplot as plt
import seaborn as sns

color = sns.color_palette()
sns.set_style('darkgrid')

import warnings
warnings.filterwarnings('ignore')
```

```
Importing plotly failed. Interactive plots will not work.
```

In [56]:

```
df_faang = pd.read_csv(os.getcwd() +"/../../data/processed/fang.csv", low_memory=False)
df_faang.head()
```

Out[56]:

	Date	High	Low	Open	Close	Volume	Adj Close	Name
0	2002-05-23	1.242857	1.145714	1.156429	1.196429	104790000.0	1.196429	NFLX
1	2002-05-24	1.225000	1.197143	1.214286	1.210000	11104800.0	1.210000	NFLX
2	2002-05-28	1.232143	1.157143	1.213571	1.157143	6609400.0	1.157143	NFLX
3	2002-05-29	1.164286	1.085714	1.164286	1.103571	6757800.0	1.103571	NFLX
4	2002-05-30	1.107857	1.071429	1.107857	1.071429	10154200.0	1.071429	NFLX

In [57]:

```
df_faang.isnull().sum()
```

Out[57]:

```
Date         0
High         0
Low          0
Open         0
Close        0
Volume       0
Adj Close    0
Name         0
dtype: int64
```

There is no empty data. No rows needs to be dropped

In [58]:

```
df_faang.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 26850 entries, 0 to 26849
Data columns (total 8 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   Date       26850 non-null  object 
 1   High       26850 non-null  float64
 2   Low        26850 non-null  float64
 3   Open       26850 non-null  float64
 4   Close      26850 non-null  float64
 5   Volume     26850 non-null  float64
 6   Adj Close  26850 non-null  float64
 7   Name       26850 non-null  object 
dtypes: float64(6), object(2)
memory usage: 1.6+ MB
```

We need to make change the Date column to Date type and make it to be the index

Data Cleaning

In [59]:

```
df_faang["Date"] = pd.to_datetime(df_faang["Date"])
df_faang = df_faang.set_index("Date")
df_faang.head()
```

Out[59]:

	High	Low	Open	Close	Volume	Adj Close	Name
Date							
2002-05-23	1.242857	1.145714	1.156429	1.196429	104790000.0	1.196429	NFLX
2002-05-24	1.225000	1.197143	1.214286	1.210000	11104800.0	1.210000	NFLX
2002-05-28	1.232143	1.157143	1.213571	1.157143	6609400.0	1.157143	NFLX
2002-05-29	1.164286	1.085714	1.164286	1.103571	6757800.0	1.103571	NFLX
2002-05-30	1.107857	1.071429	1.107857	1.071429	10154200.0	1.071429	NFLX

Seperate the FAANG dataframe

In [60]:

```
df_facebook = df_faang.loc[df_faang['Name'] == 'FB']
df_apple = df_faang.loc[df_faang['Name'] == 'AAPL']
df_amazon = df_faang.loc[df_faang['Name'] == 'AMZN']
df_netflix = df_faang.loc[df_faang['Name'] == 'NFLX']
df_google = df_faang.loc[df_faang['Name'] == 'GOOGL']
```

```
df_google = df_faang.loc[df_faang['Name'] == 'GOOGL']

list_faang_df = [
    (df_facebook, 'FB'),
    (df_apple, 'AAPL'),
    (df_amazon, 'AMZN'),
    (df_netflix, 'NFLX'),
    (df_google, 'GOOGL')]
```

In [61]:

```
df_google.head()
```

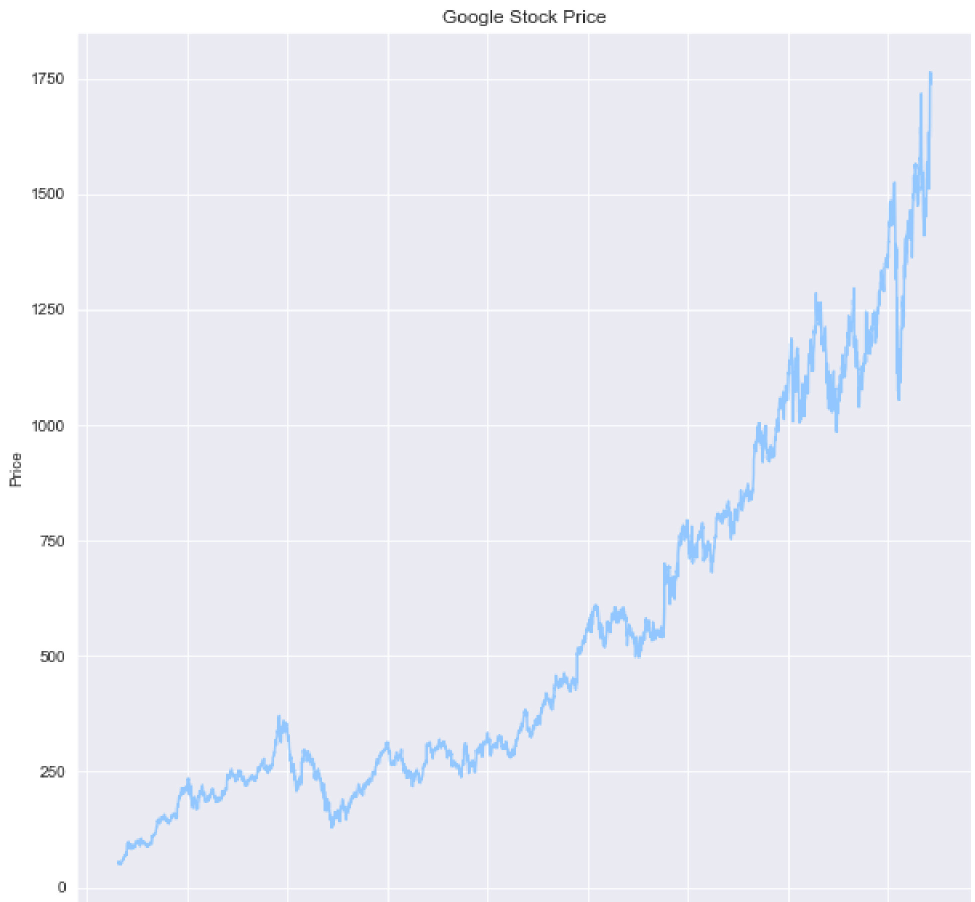
Out[61]:

	High	Low	Open	Close	Volume	Adj Close	Name
Date							
2004-08-19	52.082081	48.028027	50.050049	50.220219	44659000.0	50.220219	GOOGL
2004-08-20	54.594593	50.300301	50.555557	54.209209	22834300.0	54.209209	GOOGL
2004-08-23	56.796795	54.579578	55.430431	54.754753	18256100.0	54.754753	GOOGL
2004-08-24	55.855854	51.836838	55.675674	52.487488	15247300.0	52.487488	GOOGL
2004-08-25	54.054054	51.991993	52.532532	53.053055	9188600.0	53.053055	GOOGL

Understand more about the data with visualisation

In [62]:

```
plt.figure(figsize=(10,10))
plt.plot(df_google['Close'])
plt.xlabel("Date")
plt.ylabel("Price")
plt.title("Google Stock Price")
plt.show()
```



Let's explore further

Moving average

- Moving average is an indicator that smooth the volatility of daily price changes.
- We will be using simple moving average which is the arithmetic mean over a specfic time period

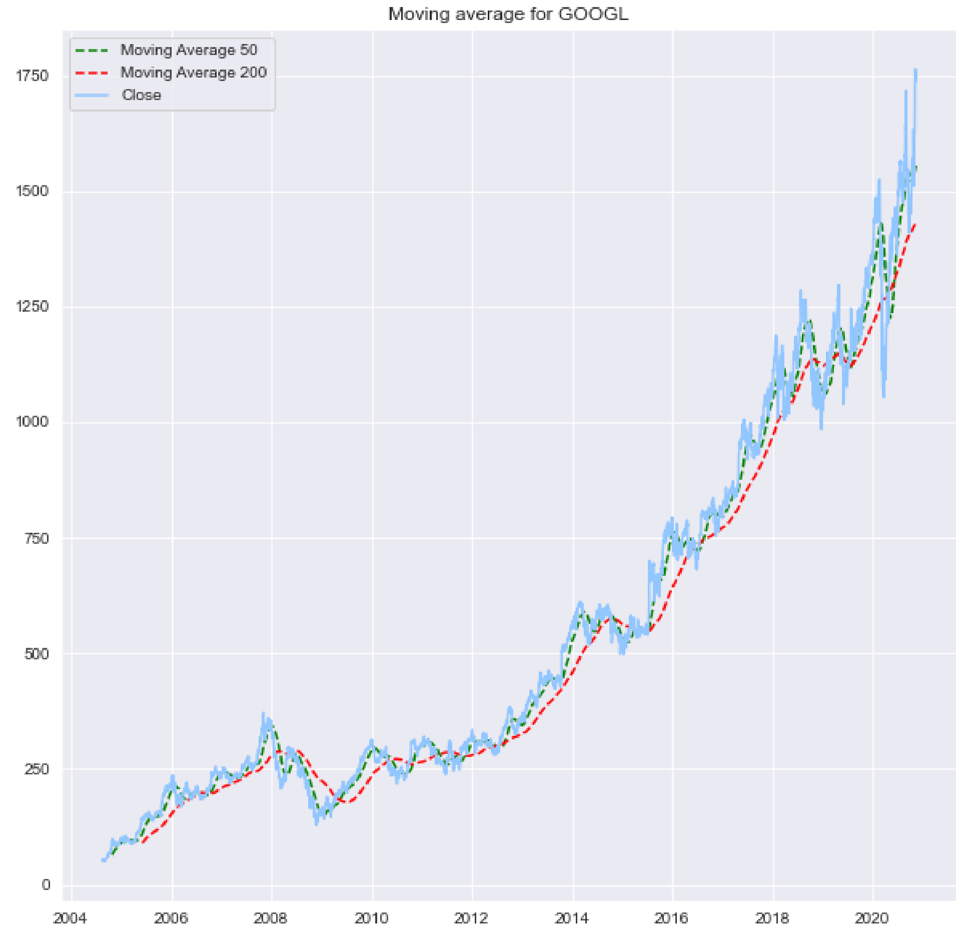
We will use 50 days and 200 days moving average.

In [63]:

```
df_google["MA50"] = df_google['Close'].rolling(window=50).mean()
df_google["MA200"] = df_google['Close'].rolling(window=200).mean()
df_google['ewma'] = df_google['Close'].ewm(halflife=0.5, min_periods=20).mean()
```

In [64]:

```
plt.figure(figsize=(10,10))
plt.plot(df_google['MA50'], 'g--', label="Moving Average 50")
plt.plot(df_google['MA200'], 'r--', label="Moving Average 200")
plt.plot(df_google['Close'], label="Close")
plt.title("Moving average for GOOGL")
plt.legend()
plt.show()
```

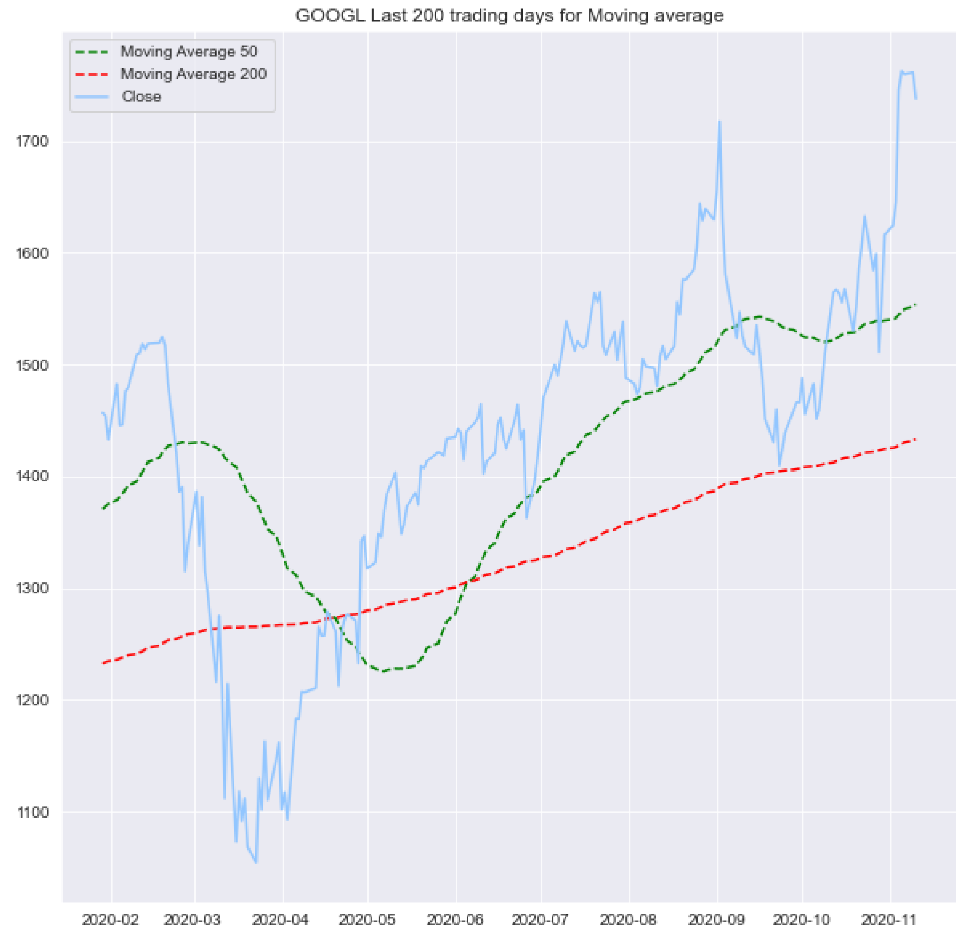


Let's take the last 200 trading days for Moving Average

In [65]:

```
plt.figure(figsize=(10,10))
plt.plot(df_google['MA50'].iloc[-200:], 'g--', label="Moving Average 50")
plt.plot(df_google['MA200'].iloc[-200:], 'r--', label="Moving Average 200")
plt.plot(df_google['Close'].iloc[-200:], label="Close")
```

```
plt.title("GOOGL Last 200 trading days for Moving average")
plt.legend()
plt.show()
```



Moving Average 50 days intersect with Moving Average 200 days. If the MA50 cross above MA200, it is an indication to buy. Otherwise, sell

Our data visualisation with moving average indicate that we should buy

Explore further with Bollinger Bands

1. Middle Band= 20-day simple moving average (SMA)
2. Upper Band= 20-day SMA+(20-day standard deviation of price x 2)
3. Lower Band= 20-day SMA–(20-day standard deviation of price x 2)

Bollinger Bands illustrate the relative strength or momentum of a stock

In [66]:

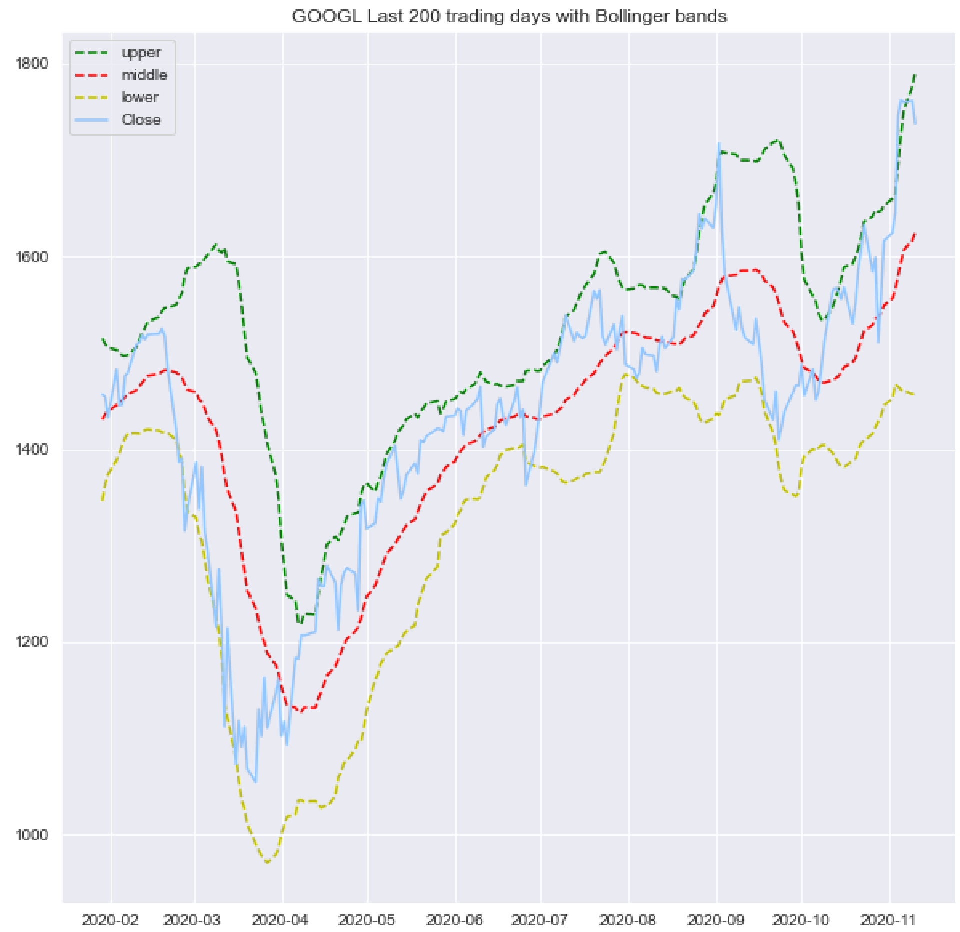
```
df_google['middle_band'] = df_google['Close'].rolling(window=20).mean()
df_google['upper_band'] = df_google['Close'].rolling(window=20).mean() +
df_google['Close'].rolling(window=20).std()*2
df_google['lower_band'] = df_google['Close'].rolling(window=20).mean() -
df_google['Close'].rolling(window=20).std()*2
```

Let's take the last 200 trading days for Bollinger Bands

In [67]:

```
plt.figure(figsize=(10,10))
plt.plot(df_google['upper_band'].iloc[-200:], 'g--', label="upper")
plt.plot(df_google['middle_band'].iloc[-200:], 'r--', label="middle")
plt.plot(df_google['lower_band'].iloc[-200:], 'y--', label="lower")
plt.plot(df_google['Close'].iloc[-200:], label="Close")
plt.title("GOOGL Last 200 trading days with Bollinger bands")
```

```
plt.title('GOOGL Last 200 trading days with Bollinger bands')
plt.legend()
plt.show()
```



From bollinger bands, the trend of GOOGLE stock seems to be increasing

---

Use Prophet Model

Will GOOGLE stock increase in the future just like what we found out from the data visualization?

In [68]:

```
df_prophet = df_google.copy()
df_prophet.reset_index(drop=False, inplace=True)
df_prophet = df_prophet[["Date","Close"]]
df_prophet.head()
```

Out[68]:

	Date	Close
0	2004-08-19	50.220219
1	2004-08-20	54.209209
2	2004-08-23	54.754753
3	2004-08-24	52.487488
4	2004-08-25	53.053055

According to Prophet documentation , we have to only have two column with ds and y columns

In [69]:

```
df_prophet.rename(columns={
    "Date": "ds",
    "Close": "y"
}, inplace=True)
df_prophet.head()
```

Out[69]:

	ds	y
0	2004-08-19	50.220219
1	2004-08-20	54.209209
2	2004-08-23	54.754753
3	2004-08-24	52.487488
4	2004-08-25	53.053055

In [70]:

```
df_prophet.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4087 entries, 0 to 4086
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   ds      4087 non-null   datetime64[ns]
 1   y       4087 non-null   float64
dtypes: datetime64[ns](1), float64(1)
memory usage: 64.0 KB
```

Reduce the GOOGLE stock rows to start from 2017-01-01 to the current date

In [71]:

```
df_prophet = df_prophet.loc[df_prophet["ds"].dt.year >= 2017]
df_prophet.reset_index(drop=True, inplace=True)
df_prophet
```

Out[71]:

	ds	y
0	2017-01-03	808.010010
1	2017-01-04	807.770020
2	2017-01-05	813.020020
3	2017-01-06	825.210022
4	2017-01-09	827.179993
...	...	...
967	2020-11-04	1745.849976
968	2020-11-05	1762.500000
969	2020-11-06	1759.729980
970	2020-11-09	1761.420044
971	2020-11-10	1737.719971

972 rows × 2 columns

In [72]:

```
model_prophet = Prophet(daily_seasonality=True)
```

```
model_prophet.fit(df_prophet)
```

Out[72]:

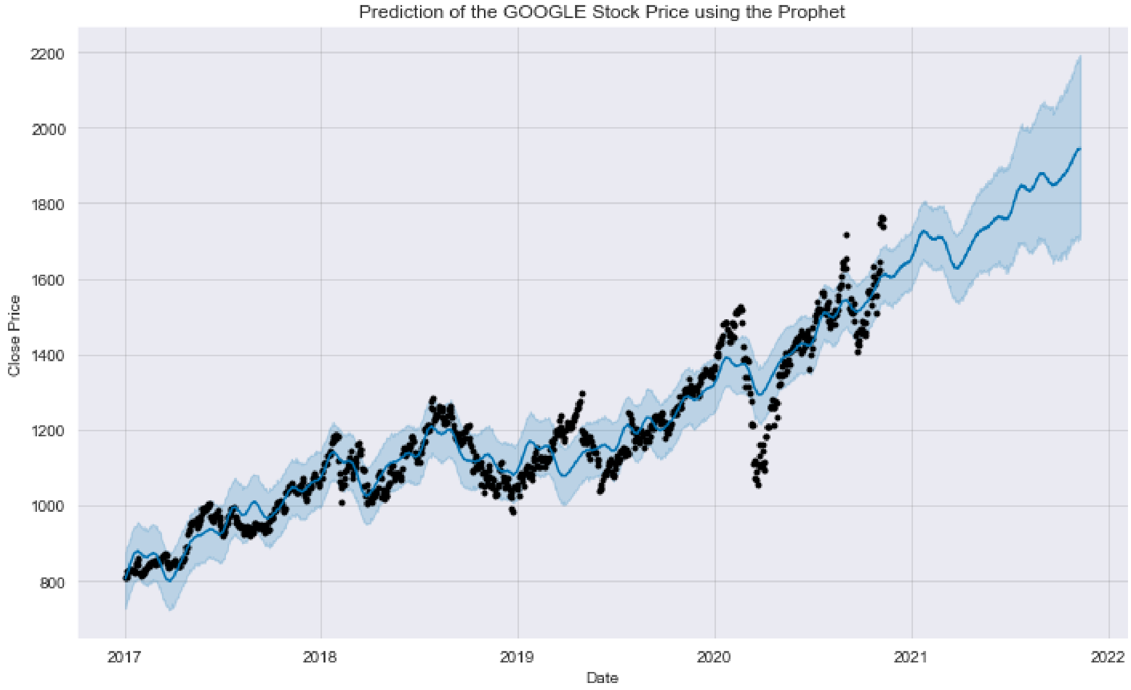
<fbprophet.forecaster.Prophet at 0x7fc820771400>

In [73]:

```
future = model_prophet.make_future_dataframe(periods=365)
prediction = model_prophet.predict(future)
```

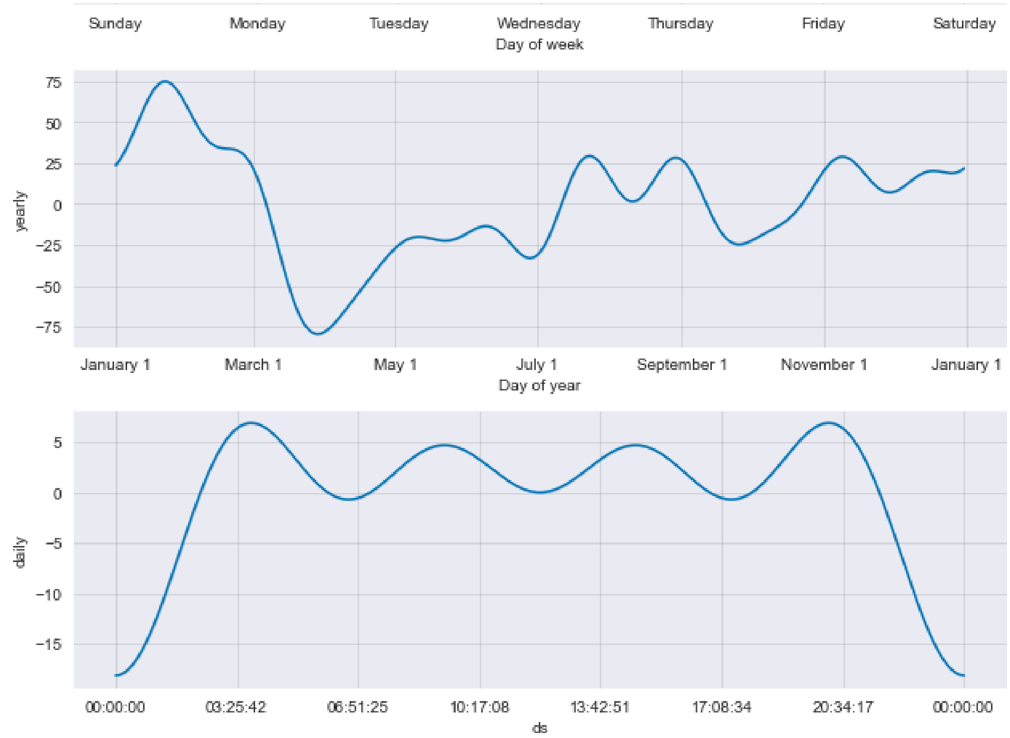
In [74]:

```
model_prophet.plot(prediction)
plt.title("Prediction of the GOOGLE Stock Price using the Prophet")
plt.xlabel("Date")
plt.ylabel("Close Price")
plt.show()
```



In [75]:

```
model_prophet.plot_components(prediction)
plt.show()
```



Based on the estimated trends

- GOOGLE stock price is maximum mostly on Thursday
- Seasonality information indicates it is best to sell in january and buy in April

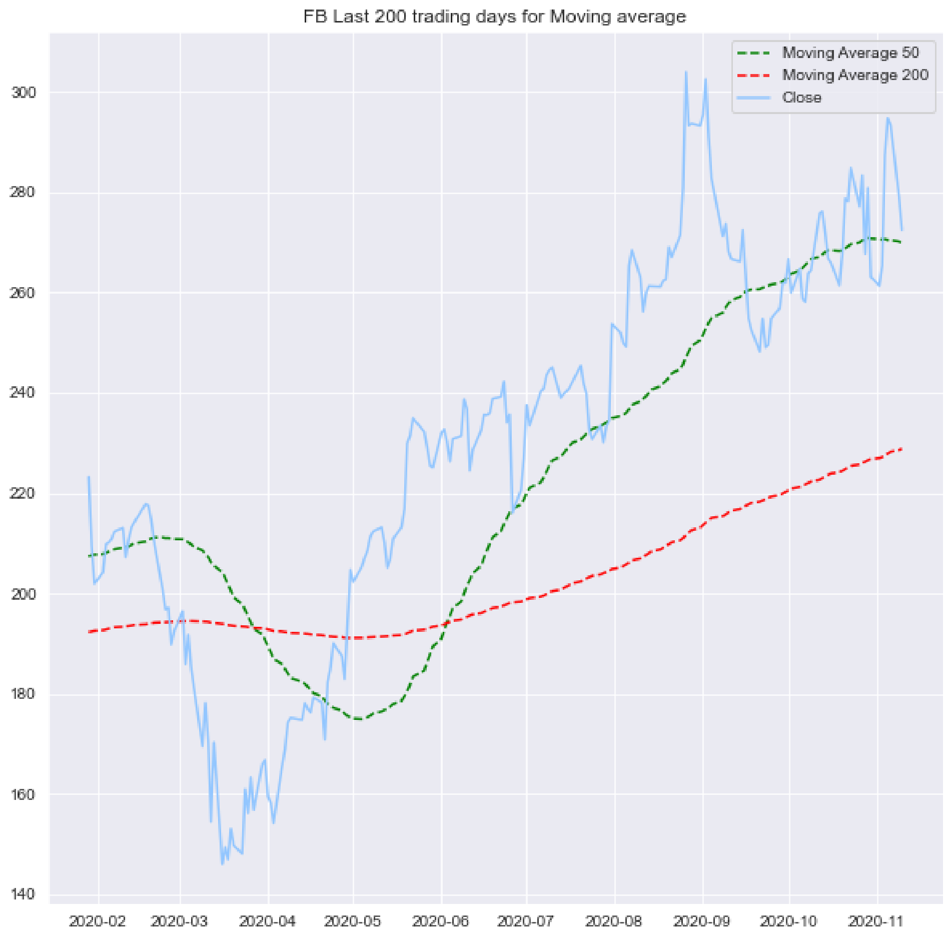
Prophet predicts that GOOGLE stock price will increase in the upcoming year which matches up with our prediction from data visualisation

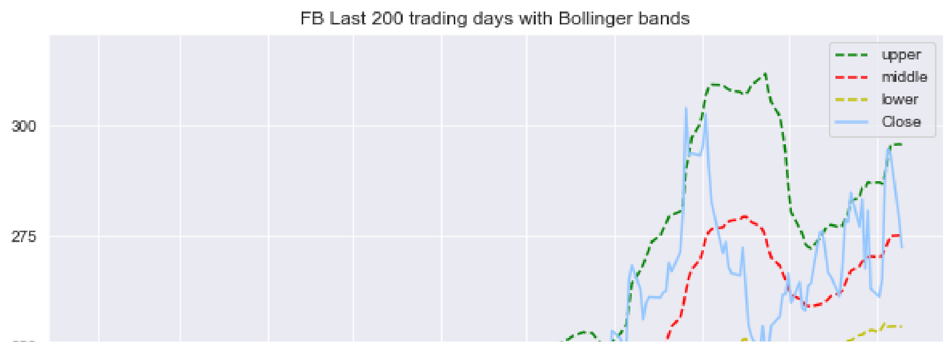
Let's do the prediction for the rest of the tickers

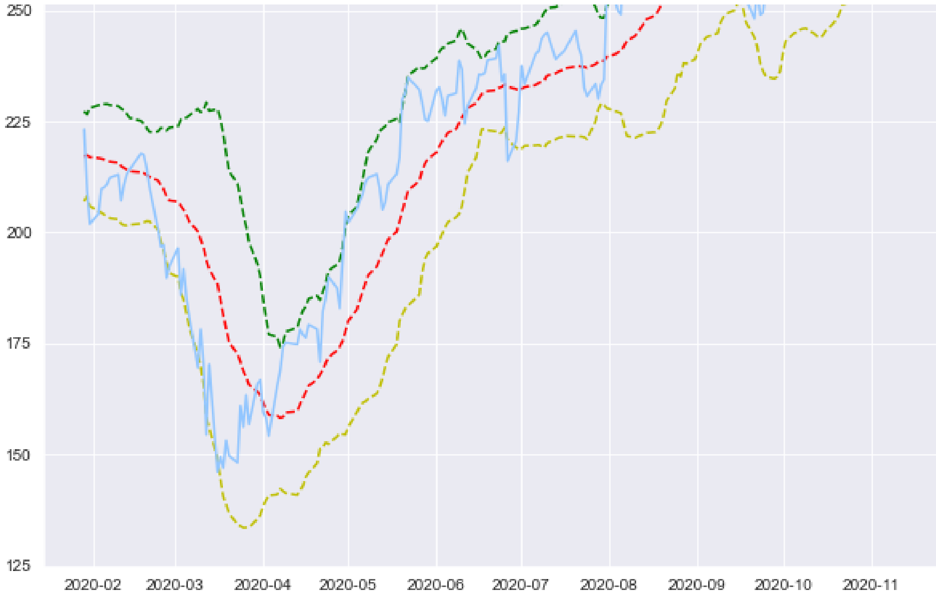
In [76]:

```
for df, ticker_name in list_faang_df[:-1]:

    df["MA50"] = df['Close'].rolling(window=50).mean()
    df["MA200"] = df['Close'].rolling(window=200).mean()
    df['ewma'] = df['Close'].ewm(halflife=0.5, min_periods=20).mean()

    plt.figure(figsize=(10,10))
    plt.plot(df['MA50'].iloc[-200:], 'g--', label="Moving Average 50")
    plt.plot(df['MA200'].iloc[-200:], 'r--', label="Moving Average 200")
    plt.plot(df['Close'].iloc[-200:], label="Close")
    plt.title(f"{ticker_name} Last 200 trading days for Moving average")

    plt.legend()
    plt.show()

    df['middle_band'] = df['Close'].rolling(window=20).mean()
    df['upper_band'] = df['Close'].rolling(window=20).mean() + df['Close'].rolling(window=20).std()
*2
    df['lower_band'] = df['Close'].rolling(window=20).mean() - df['Close'].rolling(window=20).std()
*2

    plt.figure(figsize=(10,10))
    plt.plot(df['upper_band'].iloc[-200:], 'g--', label="upper")
    plt.plot(df['middle_band'].iloc[-200:], 'r--', label="middle")
    plt.plot(df['lower_band'].iloc[-200:], 'y--', label="lower")
    plt.plot(df['Close'].iloc[-200:], label="Close")
    plt.title(f"{ticker_name} Last 200 trading days with Bollinger bands")

    plt.legend()
    plt.show()

    df_prophet = df.copy()
    df_prophet.reset_index(drop=False, inplace=True)
    df_prophet = df_prophet[["Date","Close"]]
```

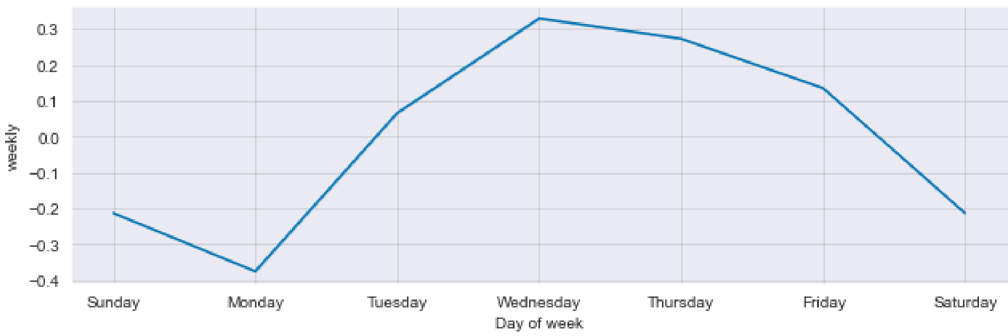
```
df_prophet.head()


df_prophet.rename(columns={
    "Date": "ds",
    "Close": "y"
}, inplace=True)


df_prophet = df_prophet.loc[df_prophet["ds"].dt.year >= 2017]
df_prophet.reset_index(drop=True, inplace=True)

model_prophet = Prophet(daily_seasonality=True)
model_prophet.fit(df_prophet)

future = model_prophet.make_future_dataframe(periods=365)
prediction = model_prophet.predict(future)

model_prophet.plot(prediction)
plt.title(f"Prediction of the {ticker_name} Stock Price using the Prophet")
plt.xlabel("Date")
plt.ylabel("Close Price")
plt.show()

model_prophet.plot_components(prediction)
plt.show()

print("=" *90)
```

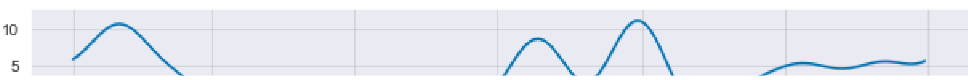


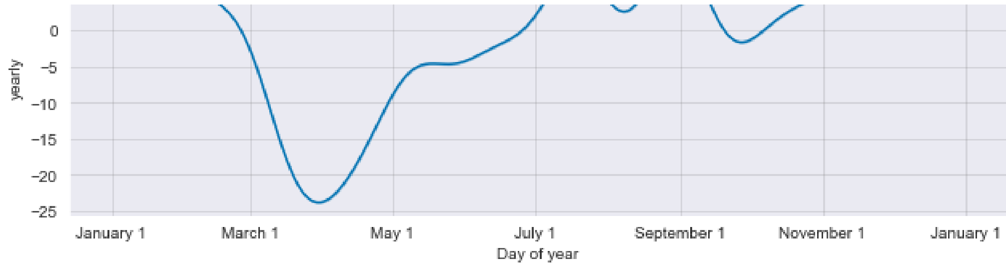


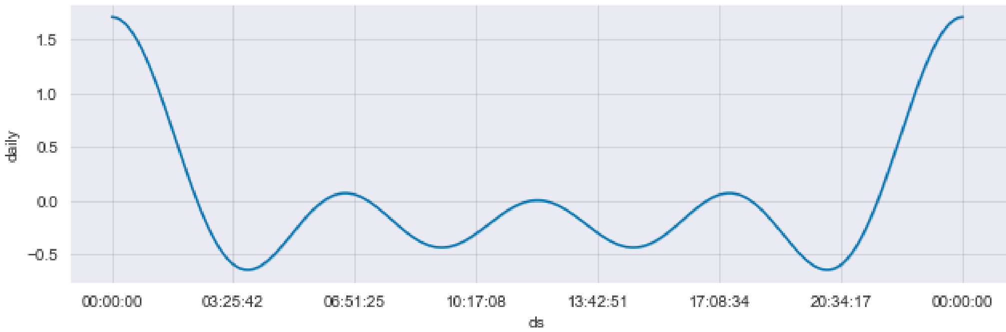


Prediction of the FB Stock Price using the Prophet

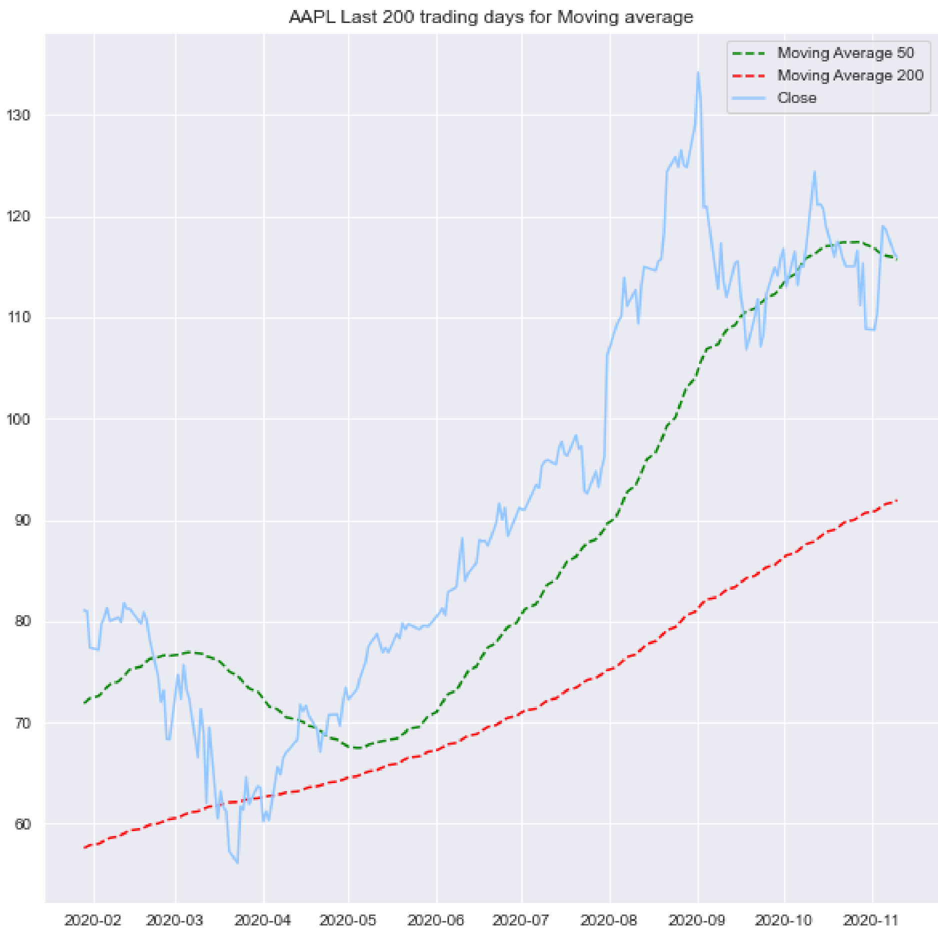


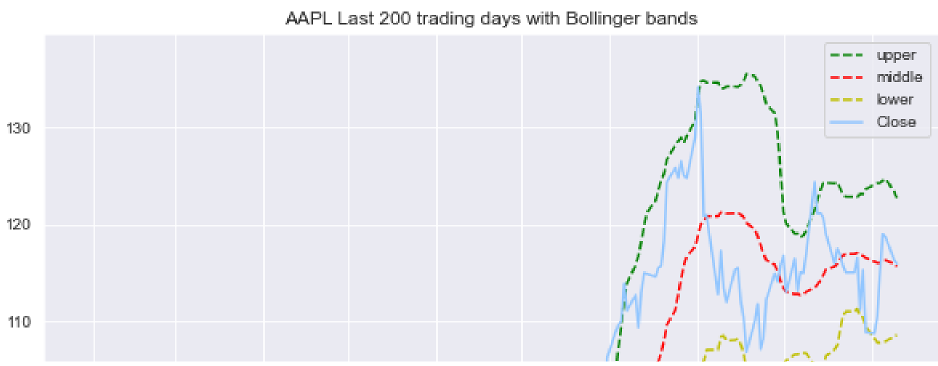


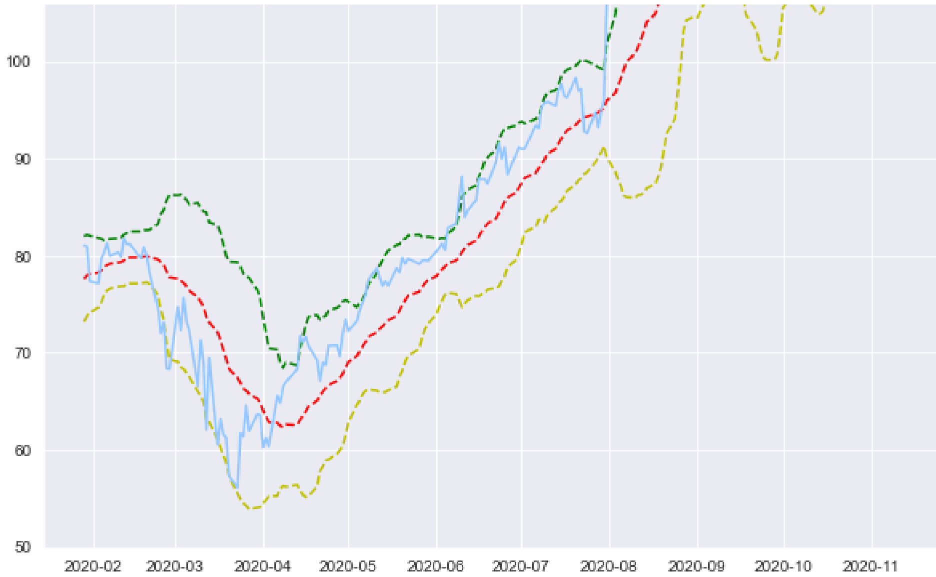

yearly
0
−5
−10
−15
−20
−25
January 1
March 1
May 1
July 1
September 1
November 1
January 1
Day of year


daily
1.5
1.0
0.5
0.0
−0.5
00:00:00
03:25:42
06:51:25
10:17:08
13:42:51
17:08:34
20:34:17
00:00:00
ds

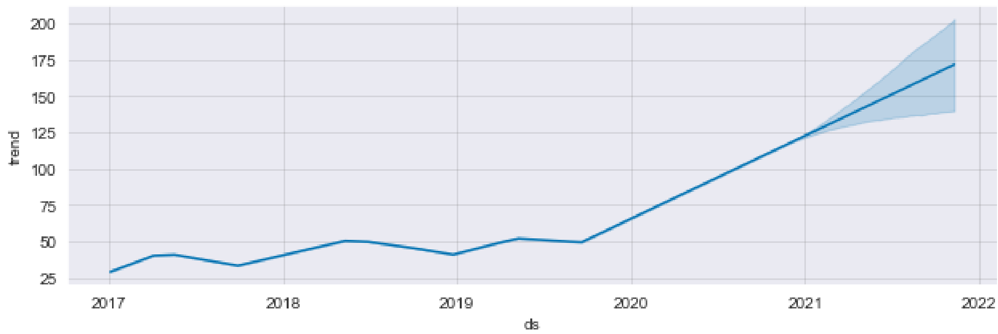
```
================================================================================================
================================================================================================
================================================================================================
================================================================================================
```

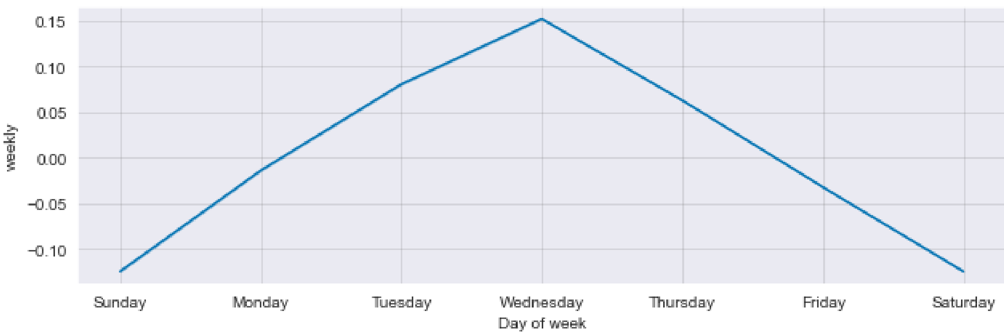

AAPL Last 200 trading days for Moving average
Moving Average 50
Moving Average 200
Close
130
120
110
100
90
80
70
60
2020-02
2020-03
2020-04
2020-05
2020-06
2020-07
2020-08
2020-09
2020-10
2020-11

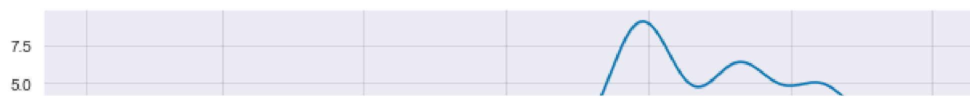

AAPL Last 200 trading days with Bollinger bands
upper
middle
lower
Close
130
120
110

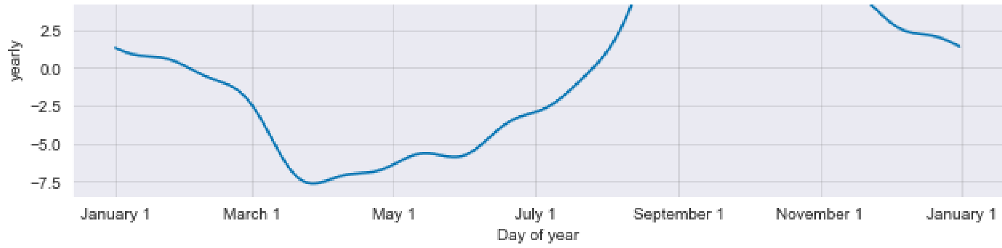


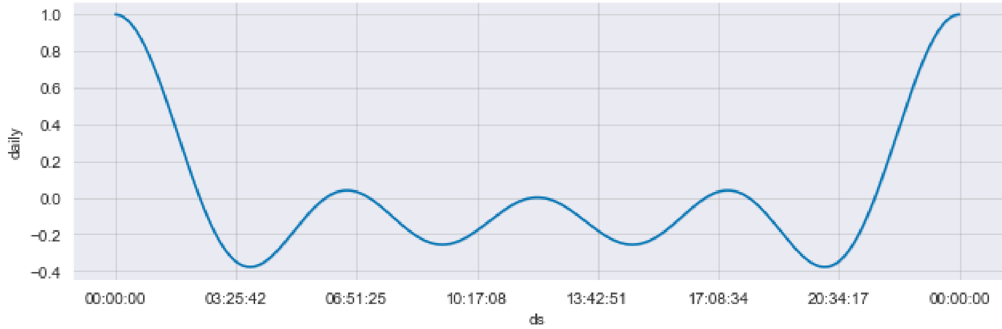
Prediction of the AAPL Stock Price using the Prophet



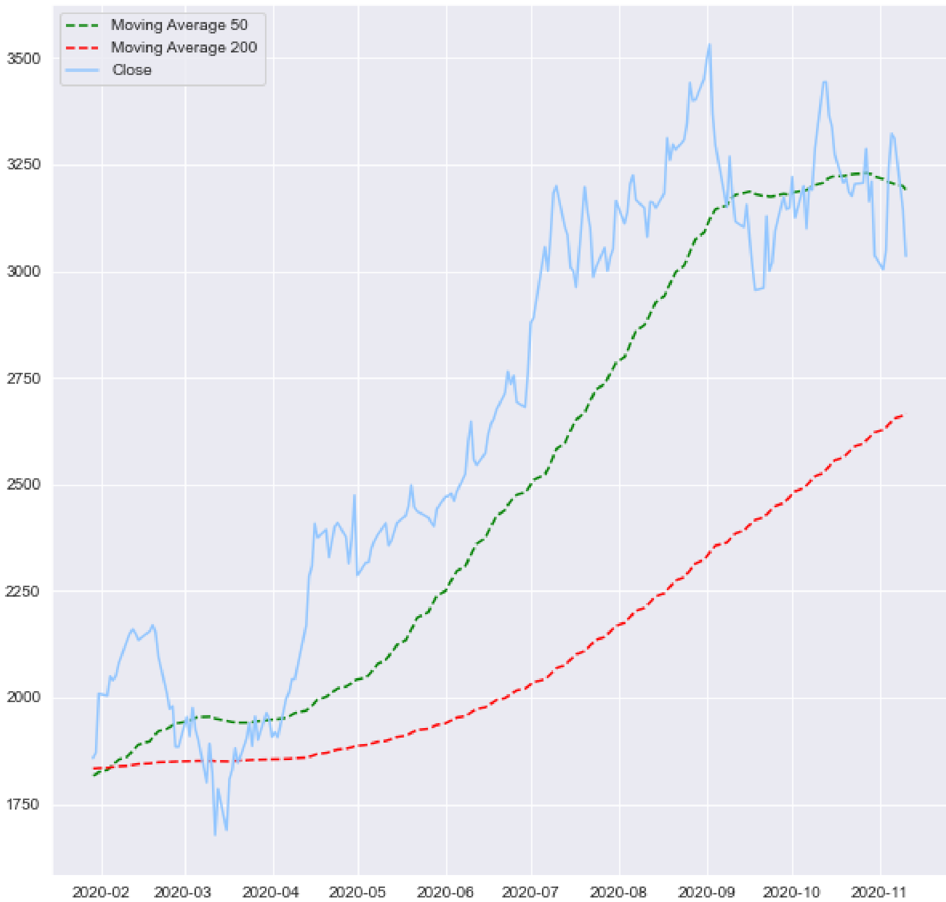




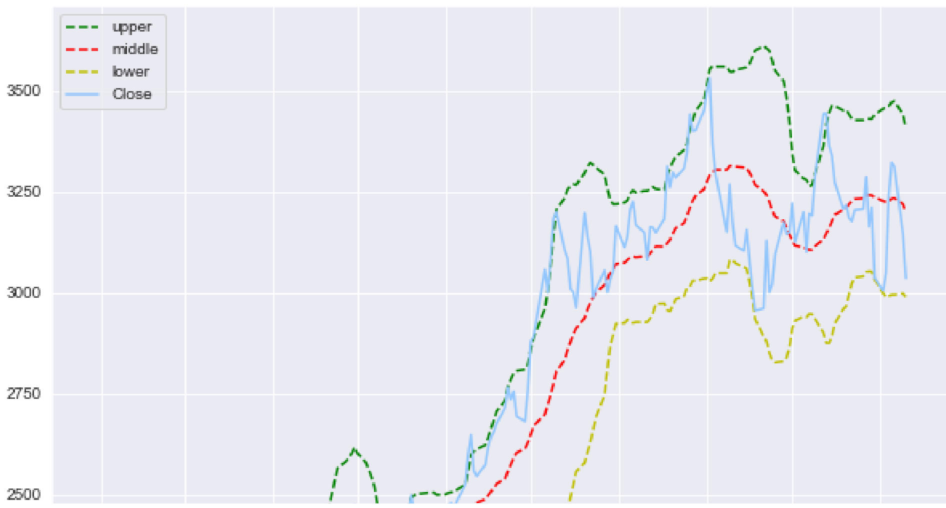


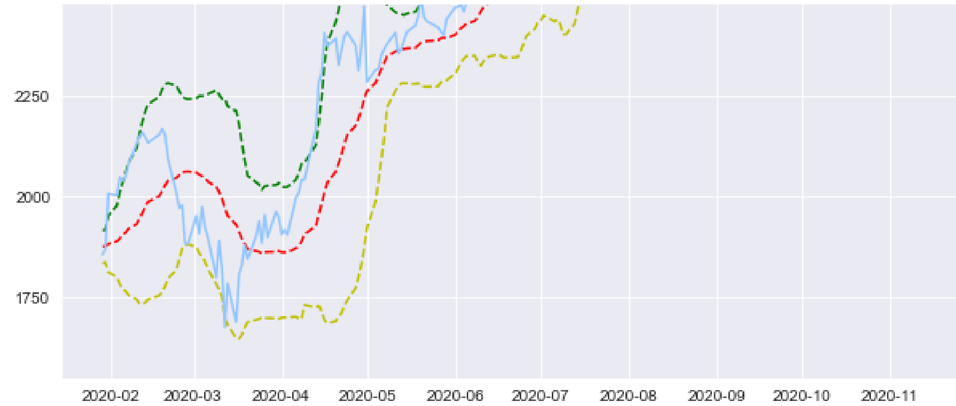


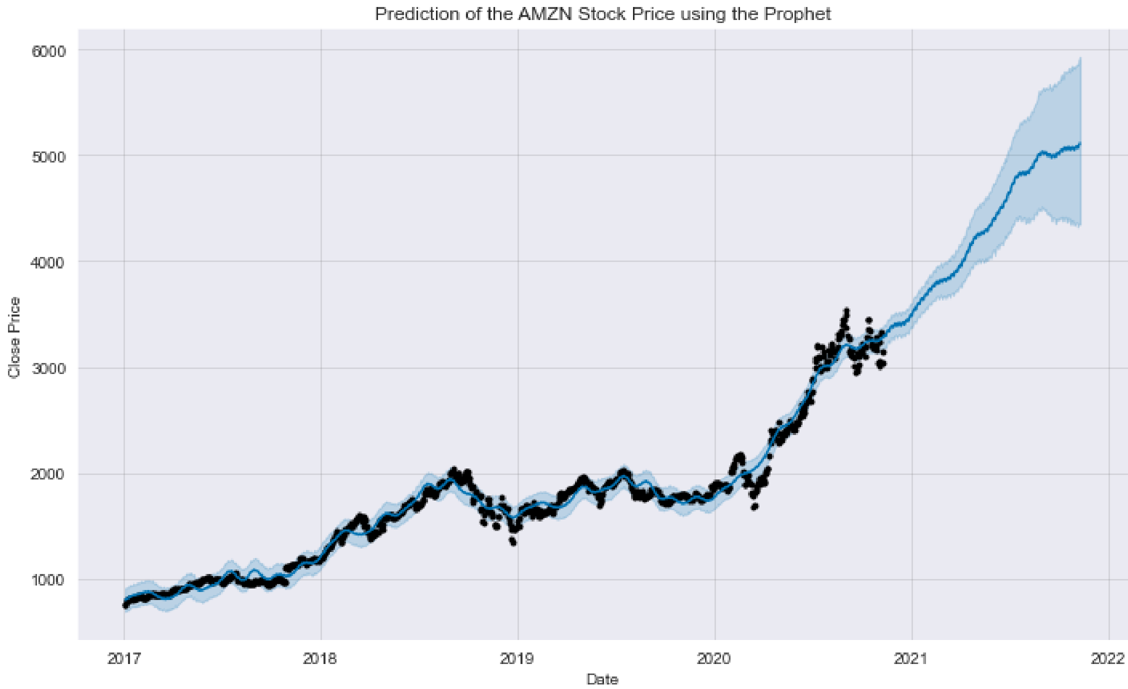
AMZN Last 200 trading days for Moving average

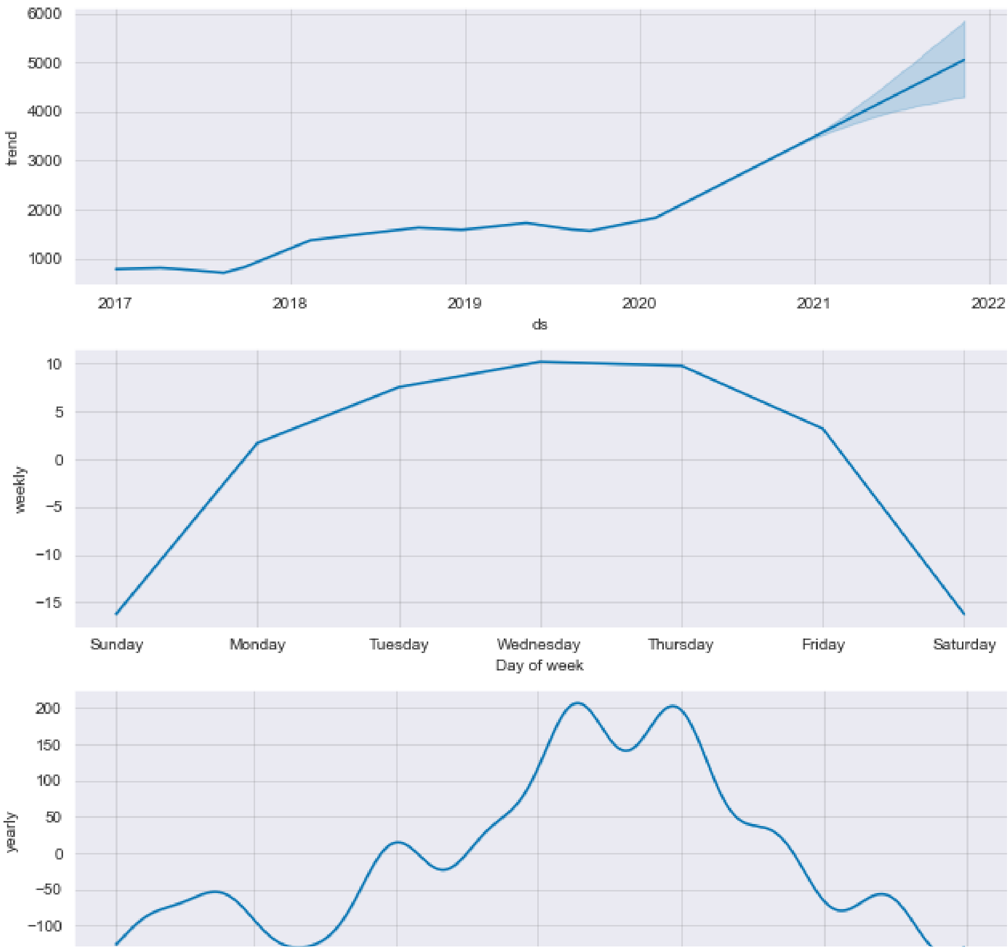


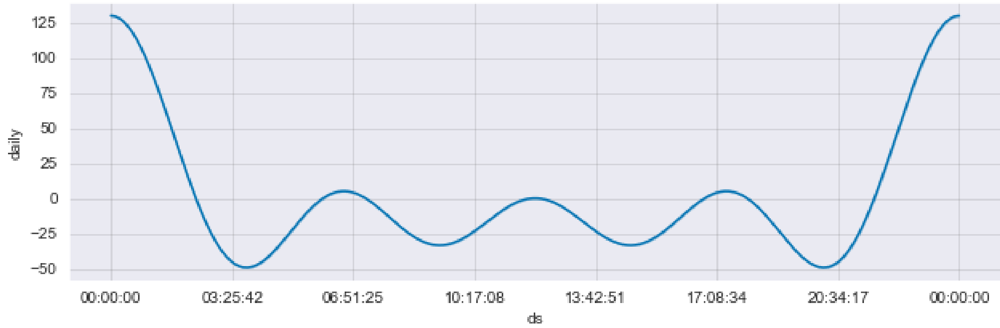
AMZN Last 200 trading days with Bollinger bands



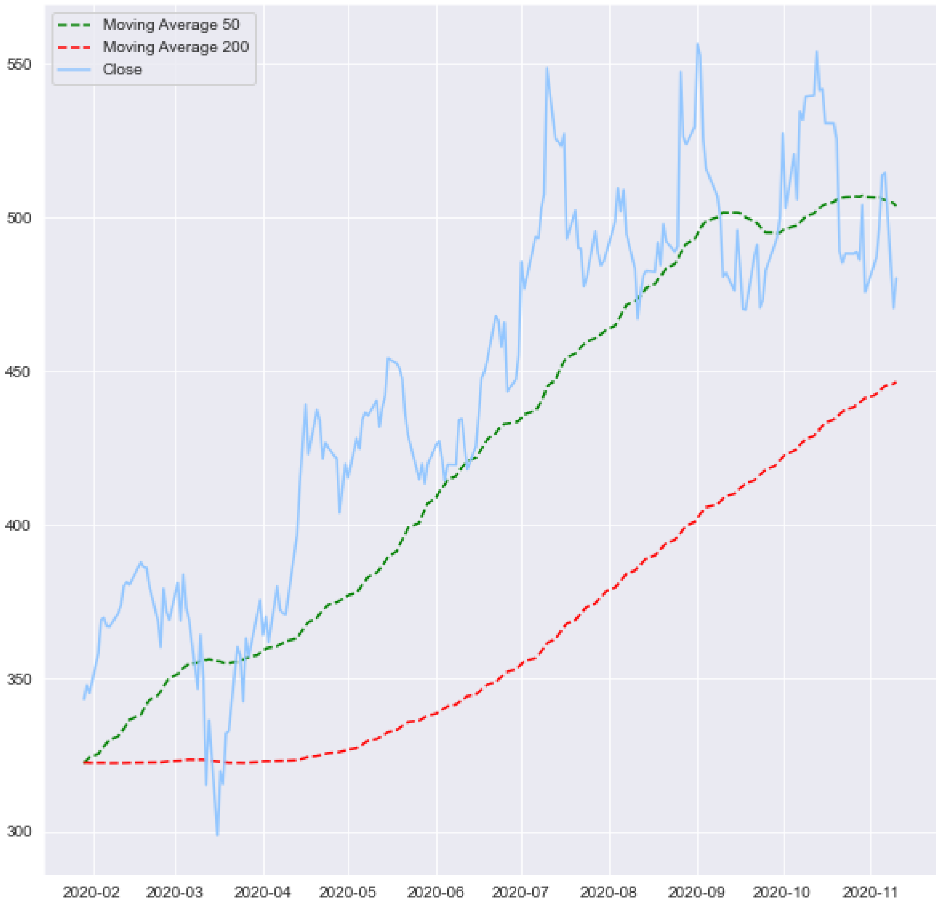

2250
2000
1750
2020-02
2020-03
2020-04
2020-05
2020-06
2020-07
2020-08
2020-09
2020-10
2020-11


Prediction of the AMZN Stock Price using the Prophet
Close Price
6000
5000
4000
3000
2000
1000
2017
2018
2019
2020
2021
2022
Date

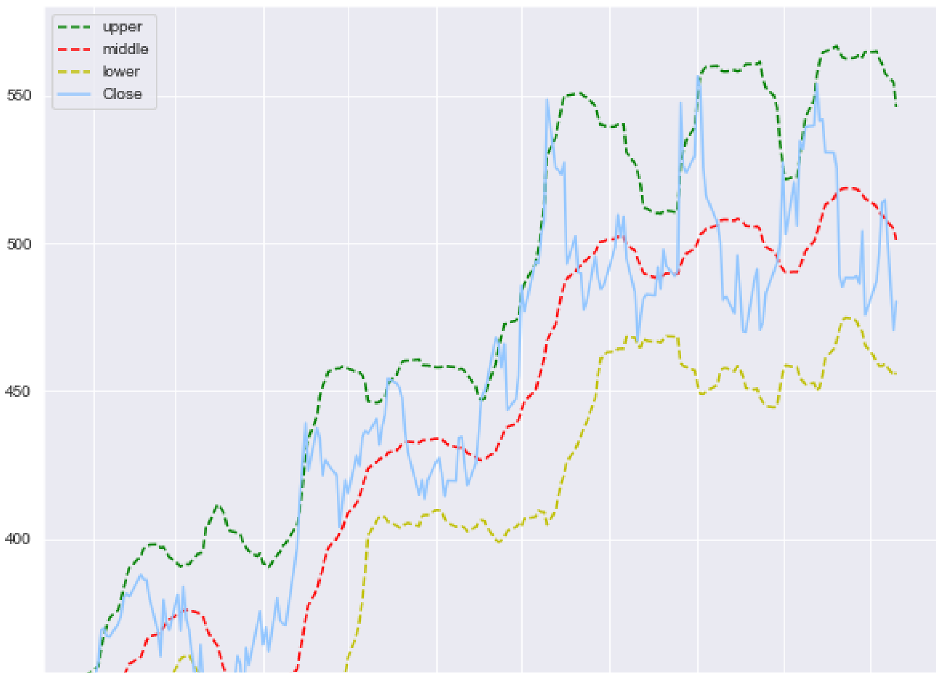

trend
6000
5000
4000
3000
2000
1000
2017
2018
2019
2020
2021
2022
ds
weekly
10
5
0
−5
−10
−15
Sunday
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Day of week
yearly
200
150
100
50
0
−50
−100

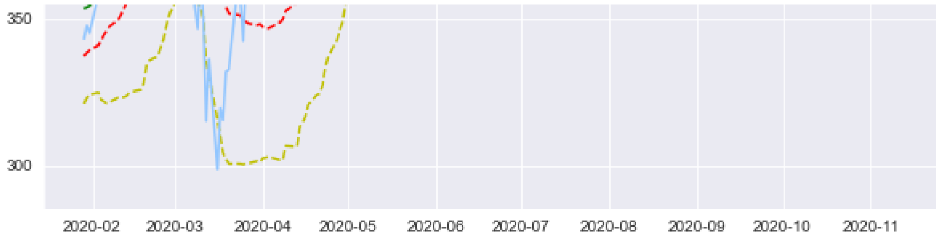


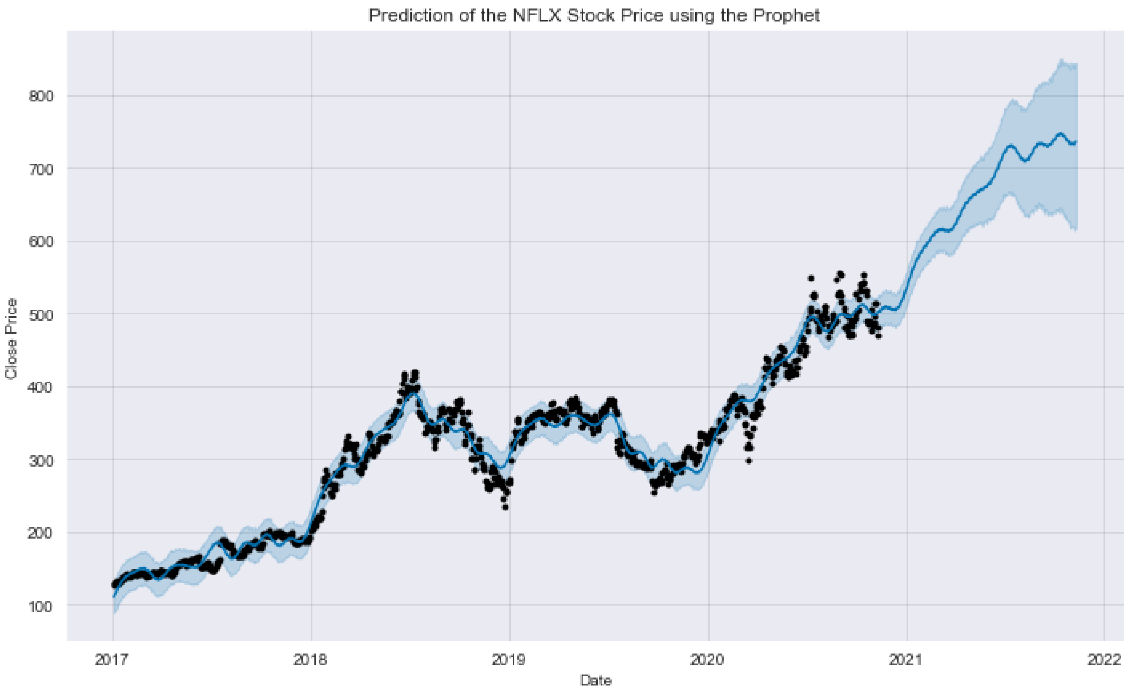
NFLX Last 200 trading days for Moving average



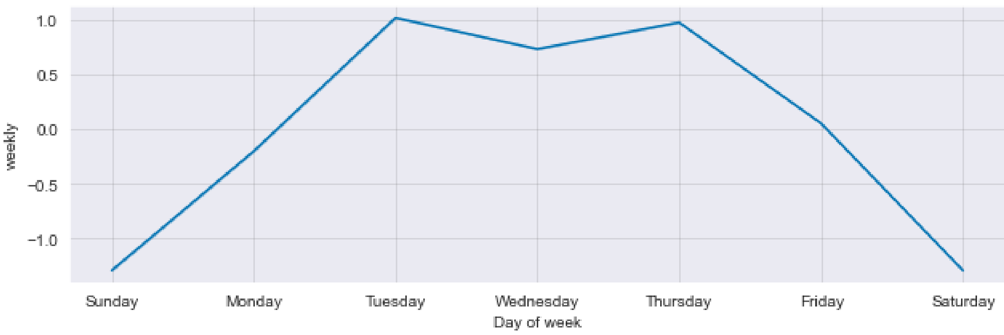
NFLX Last 200 trading days with Bollinger bands

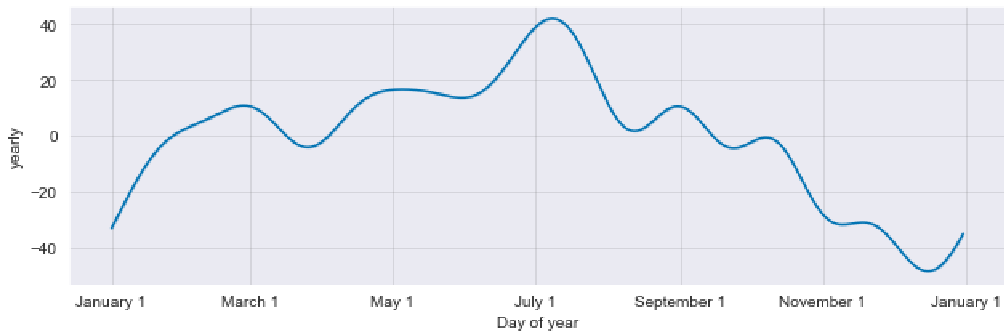


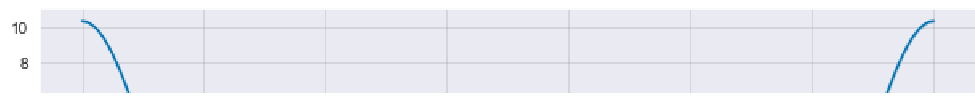

350
300
2020-02
2020-03
2020-04
2020-05
2020-06
2020-07
2020-08
2020-09
2020-10
2020-11

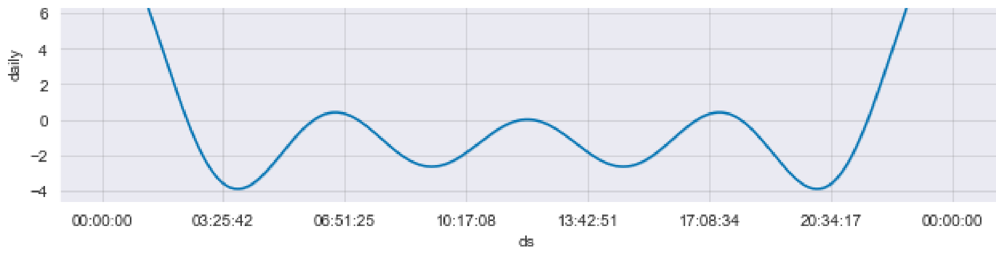

Prediction of the NFLX Stock Price using the Prophet
Close Price
800
700
600
500
400
300
200
100
2017
2018
2019
2020
2021
2022
Date


trend
800
600
400
200
2017
2018
2019
2020
2021
2022
ds


weekly
1.0
0.5
0.0
−0.5
−1.0
Sunday
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Day of week


yearly
40
20
0
−20
−40
January 1
March 1
May 1
July 1
September 1
November 1
January 1
Day of year


10
8



Summary

Based on the estimated trends

- Stock price maximum mostly on:
  - Wednesday for Facebook, Amazon, Apple, Google
  - Thursday for Netflix
- Seasonality information:
  - Buy in April for Facebook, Apple, Amazon, Google
  - Buy in December for Netflix
  - Sell in January for Facebook, Google
  - Sell in September for Apple, Amazon
  - Sell in July for Netflix
- All FAANG stock price will increase in upcoming future

Further Analysis

Is there any additional information that we can obtain from this data set?

Q1. Whether the Stock Market Is in An Uptrend

Stocks go up because investors are optimistic about the future. This is shown on a stock chart in a number of ways. The most important and easiest way is to look for whether the bottoms on the stock chart are rising and if the market is in a general uptrend (moving from the lower left to the lower right). That means that the buyers are in control of the market, making the stock more likely to go higher than lower.

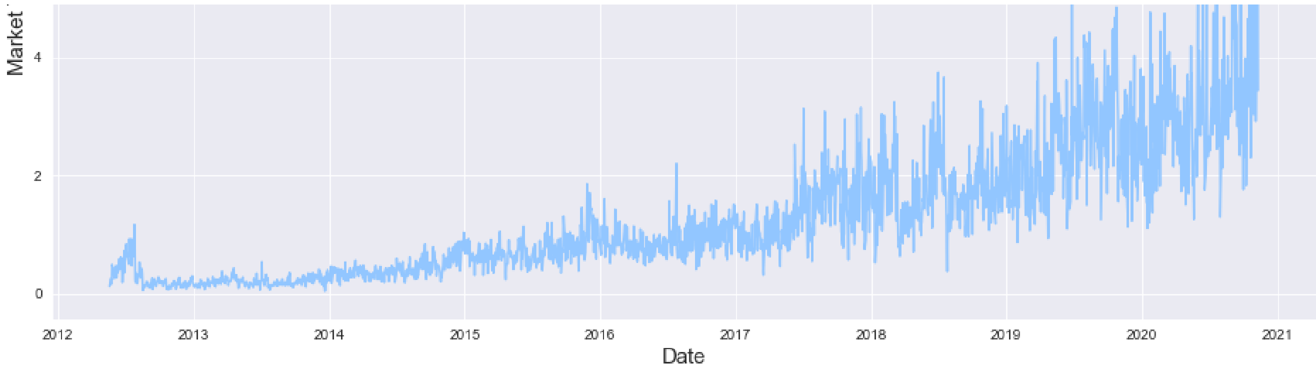
Facebook

In [80]:

```
df_facebook_uptrend = ((df_facebook["High"] - df_facebook["Low"]) / df_facebook["Volume"]) * 100
df_apple_uptrend = ((df_apple["High"] - df_apple["Low"]) / df_apple["Volume"]) * 100
df_amazon_uptrend = ((df_amazon["High"] - df_amazon["Low"]) / df_amazon["Volume"]) * 100
df_netflix_uptrend = ((df_netflix["High"] - df_netflix["Low"]) / df_netflix["Volume"]) * 100
df_google_uptrend = ((df_google["High"] - df_google["Low"]) / df_google["Volume"]) * 100
```

In [81]:

```
plt.figure(figsize=(16,8))
plt.title("The Stock Market Trend of Facebook")
plt.xlabel("Date", fontsize=15)
plt.ylabel("Market Trend", fontsize=15)
plt.plot(df_facebook_uptrend)
plt.show()
```

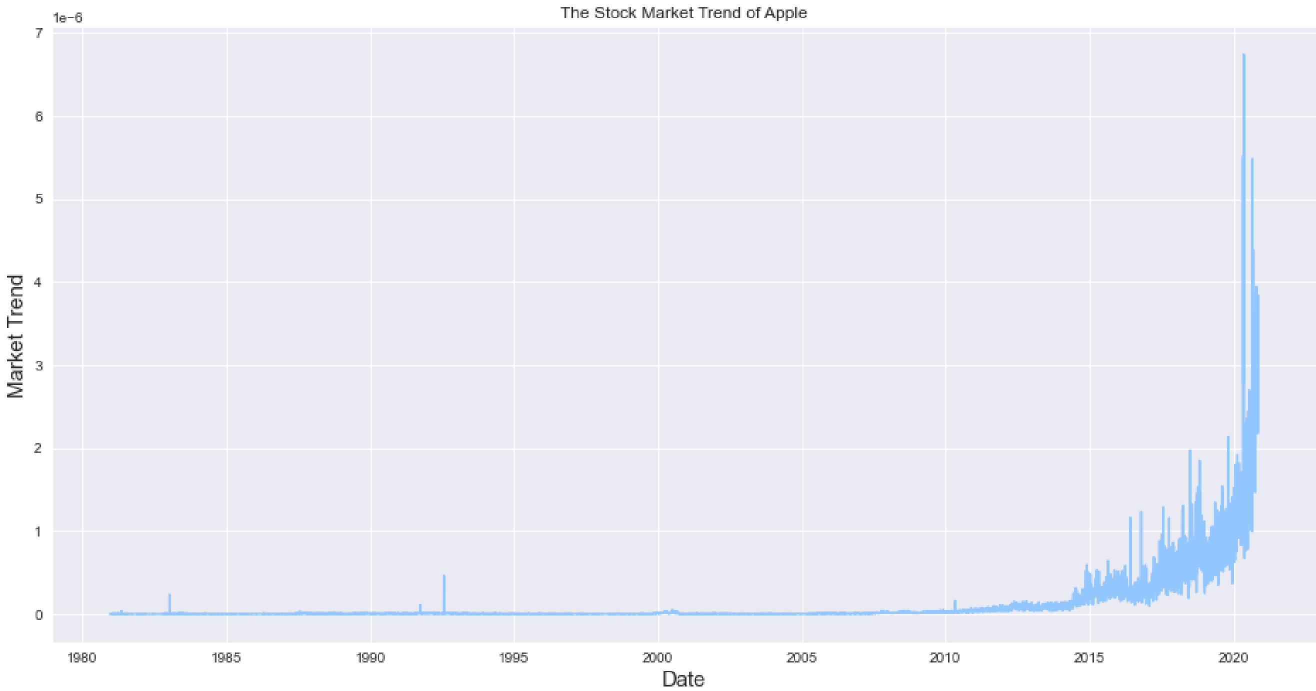


Facebook's stock market is in an uptrend. As the graph shown above, it is rising and the market is generally in an up trend.

Apple

In [82]:

```
plt.figure(figsize=(16,8))
plt.title("The Stock Market Trend of Apple")
plt.xlabel("Date", fontsize=15)
plt.ylabel("Market Trend", fontsize=15)
plt.plot(df_apple_uptrend)
plt.show()
```

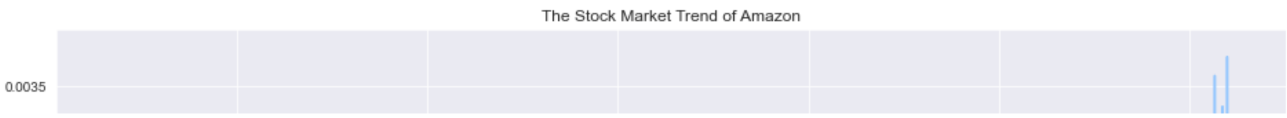


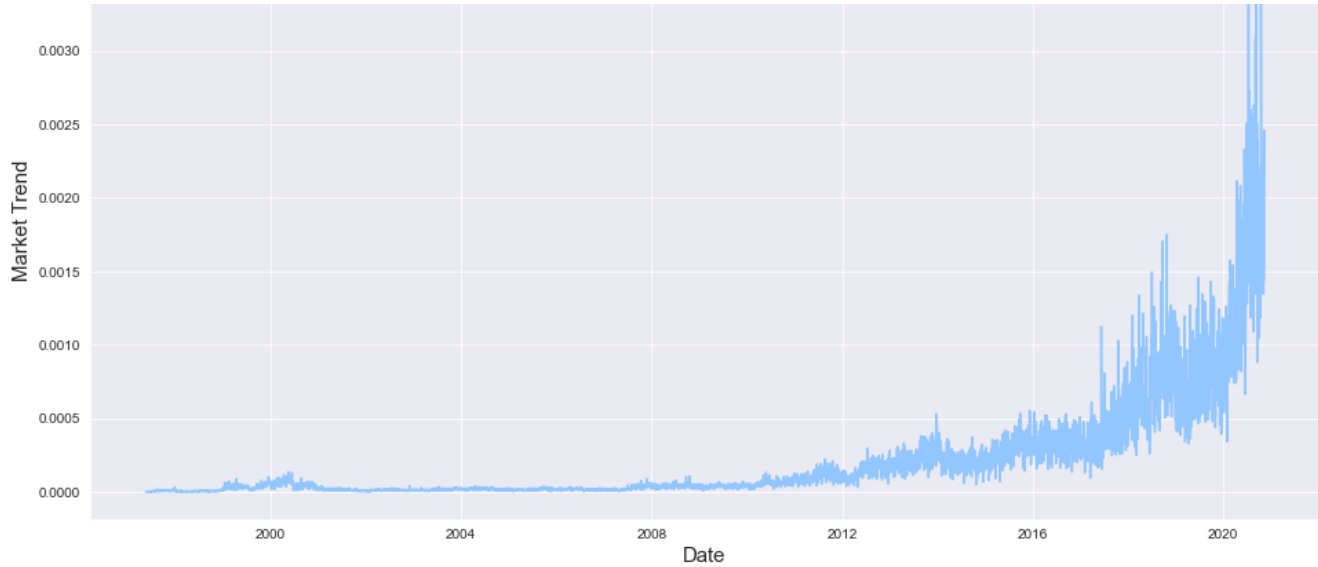
Apple's stock market is in an extreme uptrend. As the graph shown above, it does not rise until 2010. It rises significantly after 2015.

Amazon

In [83]:

```
plt.figure(figsize=(16,8))
plt.title("The Stock Market Trend of Amazon")
plt.xlabel("Date", fontsize=15)
plt.ylabel("Market Trend", fontsize=15)
plt.plot(df_amazon_uptrend)
plt.show()
```



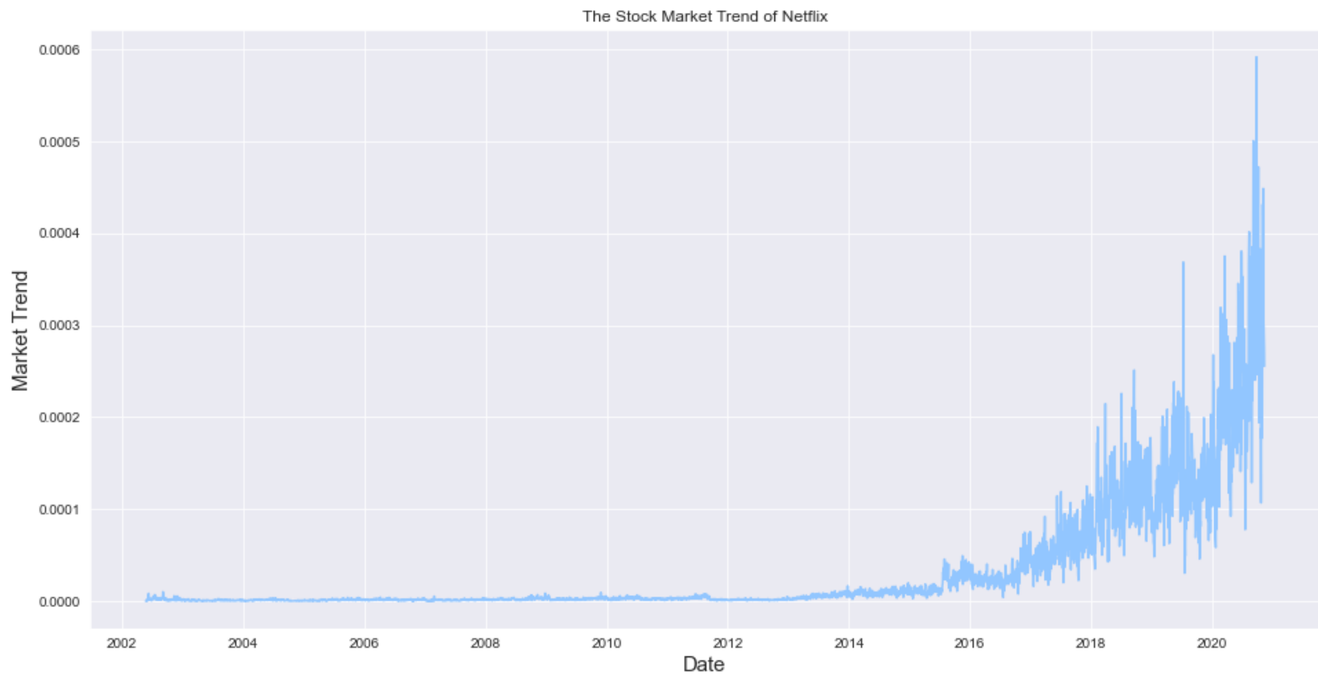


Amazon's stock market is also in an extreme uptrend. As the graph shown above, it does not rise until 2008. It rises significantly after 2016.

Netflix

In [84]:

```
plt.figure(figsize=(16,8))
plt.title("The Stock Market Trend of Netflix")
plt.xlabel("Date", fontsize=15)
plt.ylabel("Market Trend", fontsize=15)
plt.plot(df_netflix_uptrend)
plt.show()
```



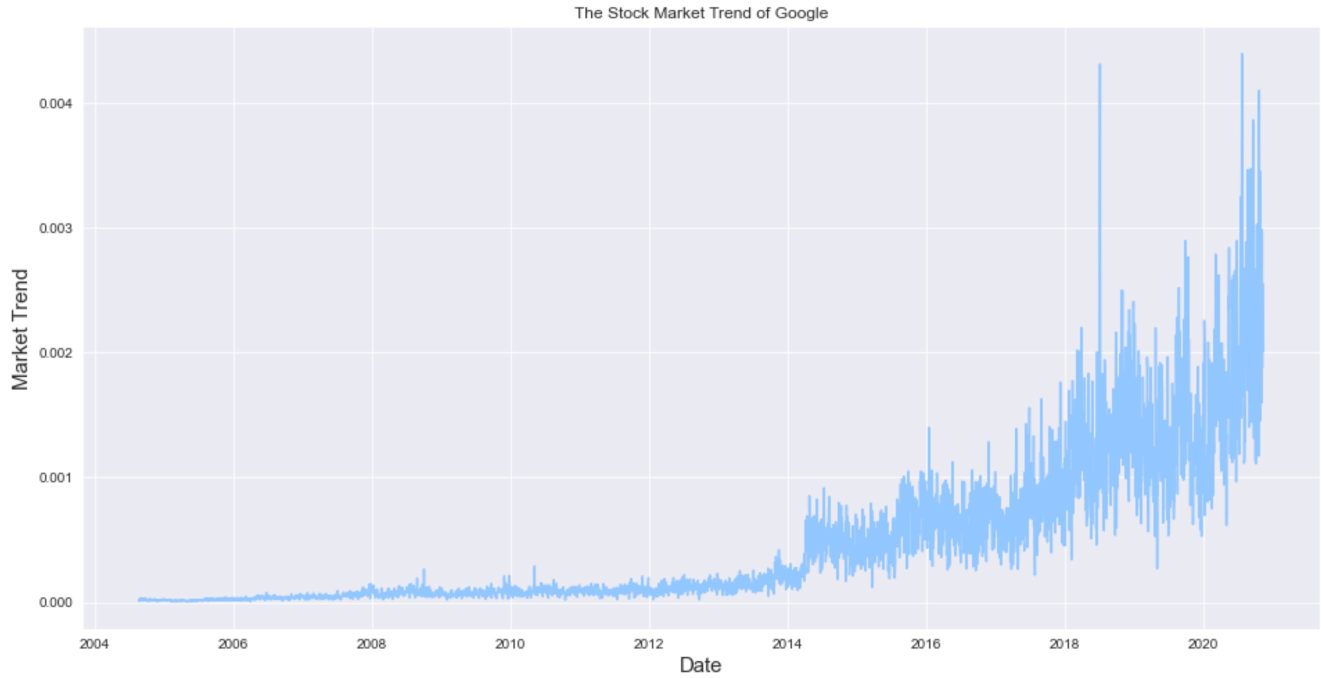
Netfix's stock market is also in an extreme uptrend. As the graph shown above, it does not rise until 2014. It rises significantly after 2016.

Google

In [85]:

```
plt.figure(figsize=(16,8))
plt.title("The Stock Market Trend of Google")
plt.xlabel("Date", fontsize=15)
```

```
plt.ylabel("Market Trend", fontsize=15)
plt.plot(df_google_uptrend)
plt.show()
```



Google's stock market is in an uptrend. As the graph shown above, it rises stably and the market is generally in an up trend.

In Conclusion

FAANG companies all perform pretty well in recent five years. All of their stock prices are in an uptrend obviously.

Q2. Is a Stock Worth Buying?

There are many ways to evaluate if a stock is worth buying. Historical Price is one of them. If the invester wants to invest a stock for the long term, he/ she needs to do more than look at a single company earnings report or current price performance. Looking at the historical price of last ten years or five years will give him/her a sense of whether a company can withstand tough stretches. However, the historical price are not a guarantee of future performance, but can at minimum be illustrative.

To calculate the historical price of a stock, it requires the PE. ratio from the company so I would use simplified method to replace that complicated formula.

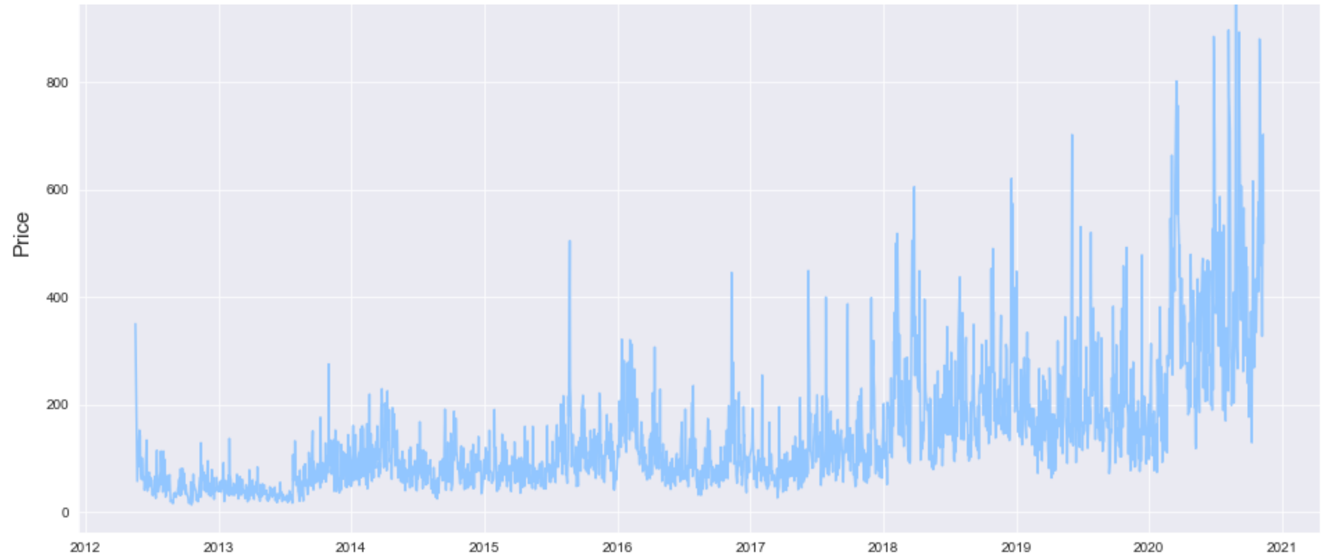
Facebook

In [86]:

```
df_facebook_price = ((df_facebook["High"] - df_facebook["Low"]) / 2) * 100
df_apple_price = ((df_apple["High"] - df_apple["Low"]) / 2) * 100
df_amazon_price = ((df_amazon["High"] - df_amazon["Low"]) / 2) * 100
df_netflix_price = ((df_netflix["High"] - df_netflix["Low"]) / 2) * 100
df_google_price = ((df_google["High"] - df_google["Low"]) / 2) * 100
```

In [87]:

```
plt.figure(figsize=(16,8))
plt.title("Historical Stock Price of Facebook")
plt.ylabel("Price", fontsize=15)
plt.plot(df_facebook_price)
plt.show()
```

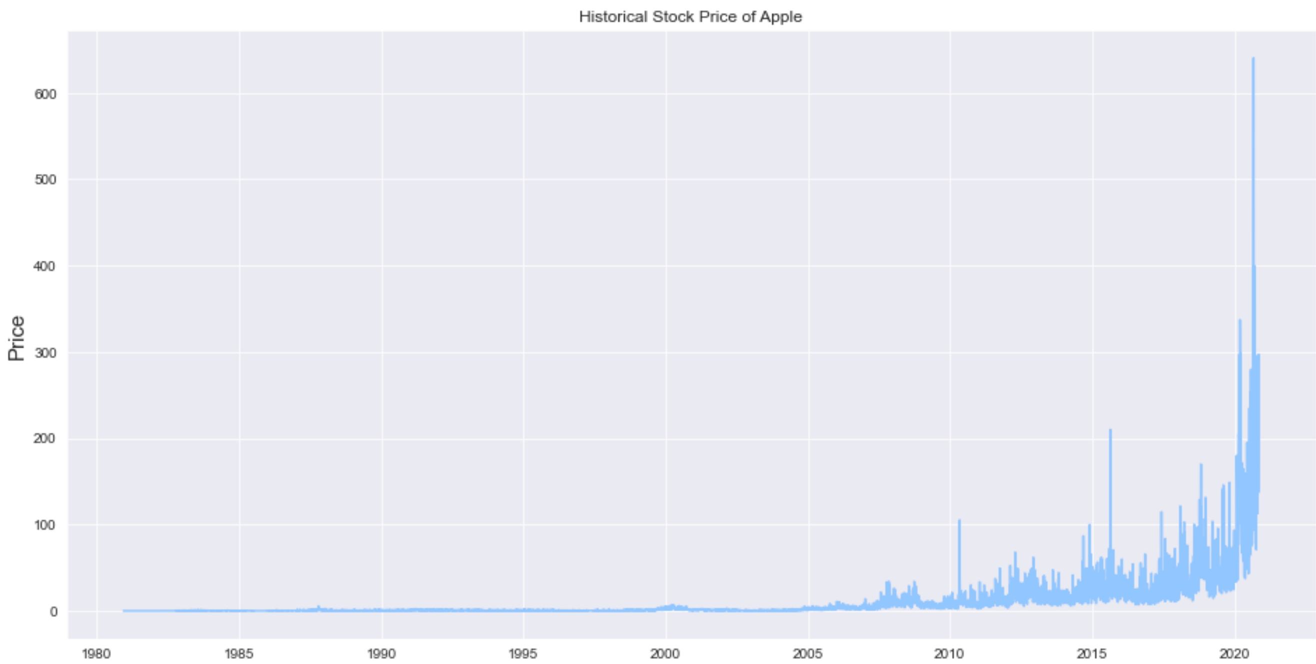


From the long run, the historical price of Facebook's stock increases even though there are some ups and downs

Apple

In [88]:

```
plt.figure(figsize=(16,8))
plt.title("Historical Stock Price of Apple")
plt.ylabel("Price", fontsize=15)
plt.plot(df_apple_price)
plt.show()
```

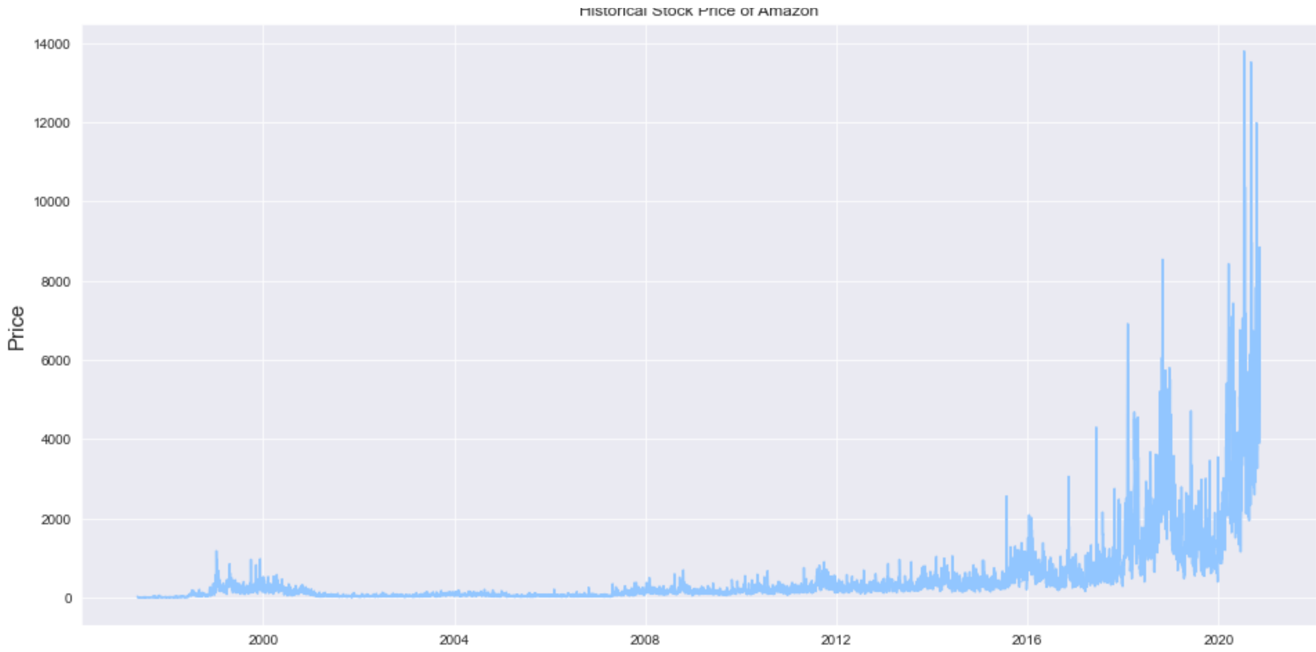


After 2005, the historical price of Apple's stock increases significantly.

Amazon

In [89]:

```
plt.figure(figsize=(16,8))
plt.title("Historical Stock Price of Amazon")
plt.ylabel("Price", fontsize=15)
plt.plot(df_amazon_price)
plt.show()
```

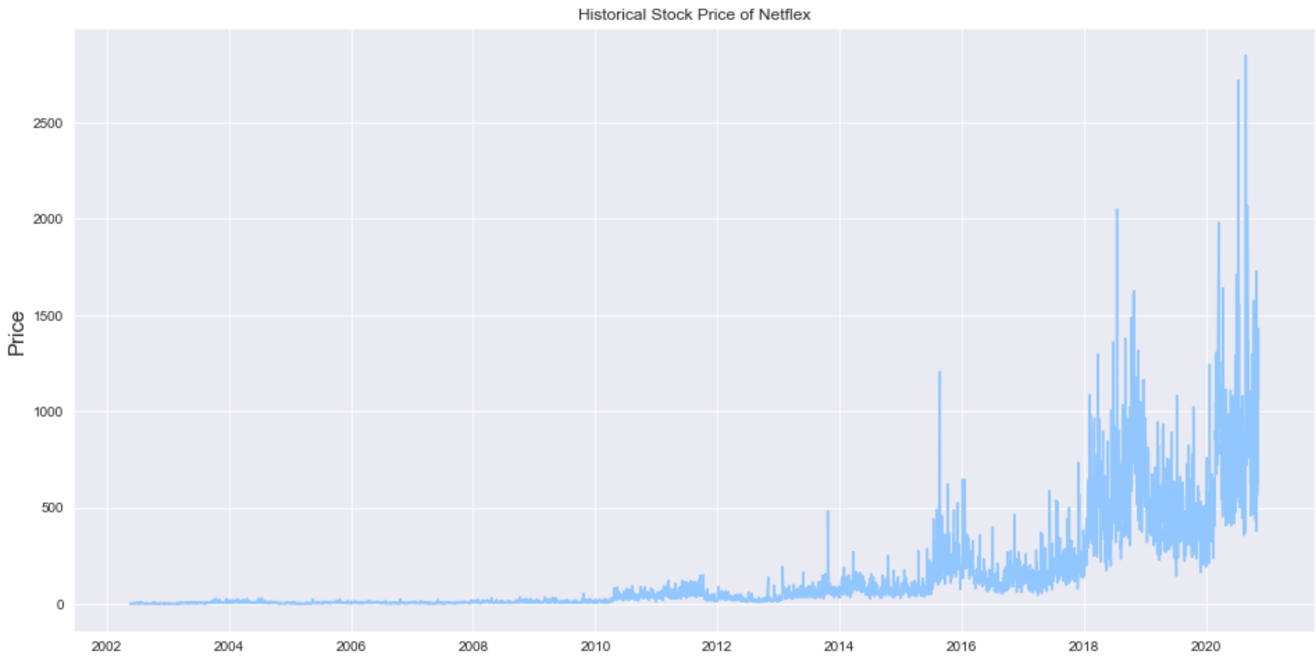


From the long run, the historical price of Amazon's stock increases especially in the 2020.

Netflix

In [90]:

```
plt.figure(figsize=(16,8))
plt.title("Historical Stock Price of Netflex")
plt.ylabel("Price", fontsize=15)
plt.plot(df_netflix_price)
plt.show()
```



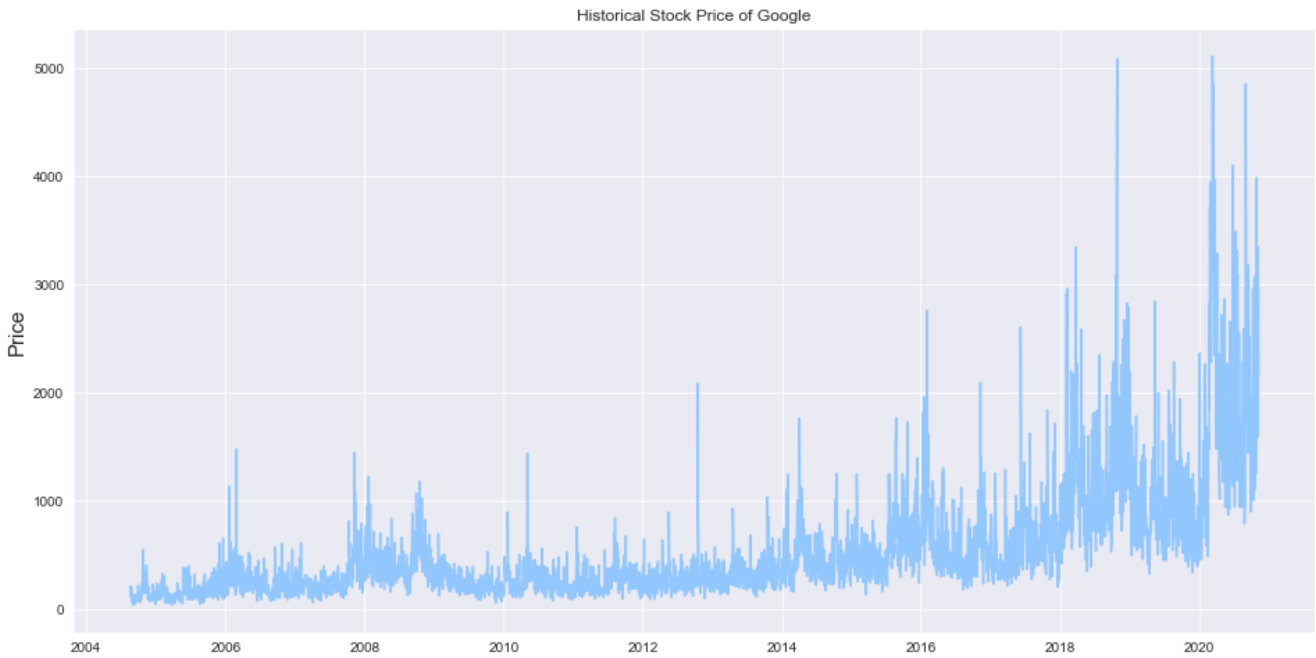
From the long run, the historical price of Netflix's stock increases. Especially after 2016, it increases significantly.

Google

In [91]:

```
plt.figure(figsize=(16,8))
plt.title("Historical Stock Price of Google")
plt.ylabel("Price", fontsize=15)
plt.plot(df_google_price)
```

```
plt.show()
```



In the long run, the historical price of Google's stock increases even though there are some ups and downs.

Q3. Which date provided the highest percentage return / loss for each company?

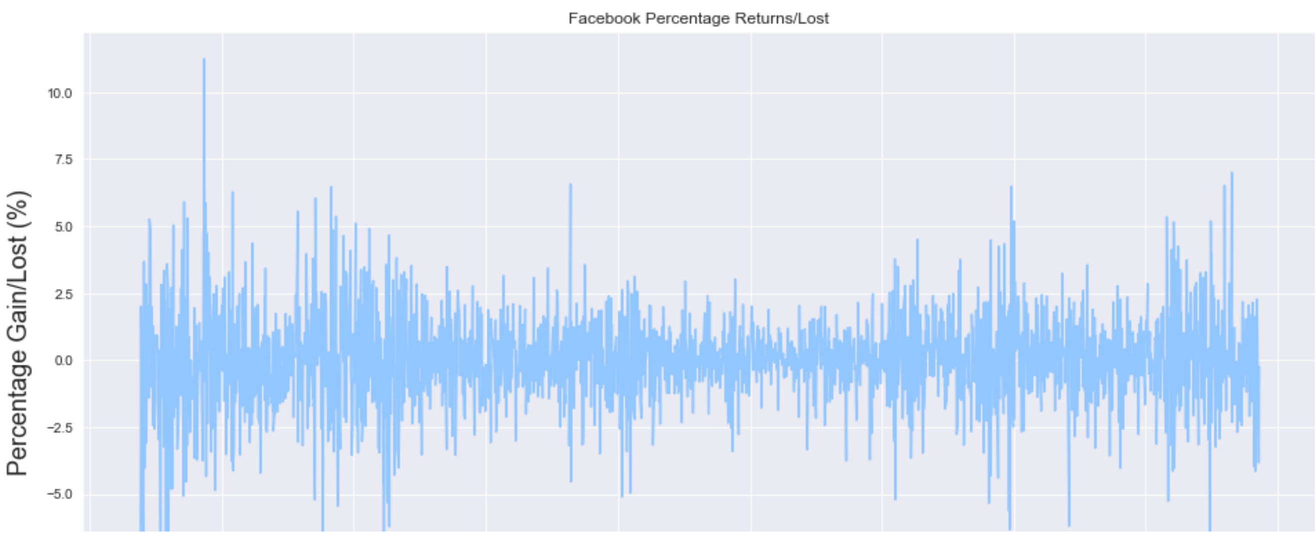
In [95]:

```
df_facebook_returns = ((df_facebook['Close'] - df_facebook['Open']) / df_facebook['Open']) * 100
df_apple_returns = ((df_apple['Close'] - df_apple['Open']) / df_apple['Open']) * 100
df_amazon_returns = ((df_amazon['Close'] - df_amazon['Open']) / df_amazon['Open']) * 100
df_netflix_returns = ((df_netflix['Close'] - df_netflix['Open']) / df_netflix['Open']) * 100
df_google_returns = ((df_google['Close'] - df_google['Open']) / df_google['Open']) * 100
```

Facebook

In [96]:

```
plt.figure(figsize=(16,8))
plt.title('Facebook Percentage Returns/Lost')
plt.xlabel('Date', fontsize=18)
plt.ylabel('Percentage Gain/Lost (%)', fontsize=18)
plt.plot(df_facebook_returns)
plt.show()
```



In [97]:

```
print(df_facebook_returns[df_facebook_returns == df_facebook_returns.min()])
print(df_facebook_returns[df_facebook_returns == df_facebook_returns.max()])
```

```
Date
2012-05-18   -9.084423
dtype: float64
Date
2012-11-14    11.243782
dtype: float64
```

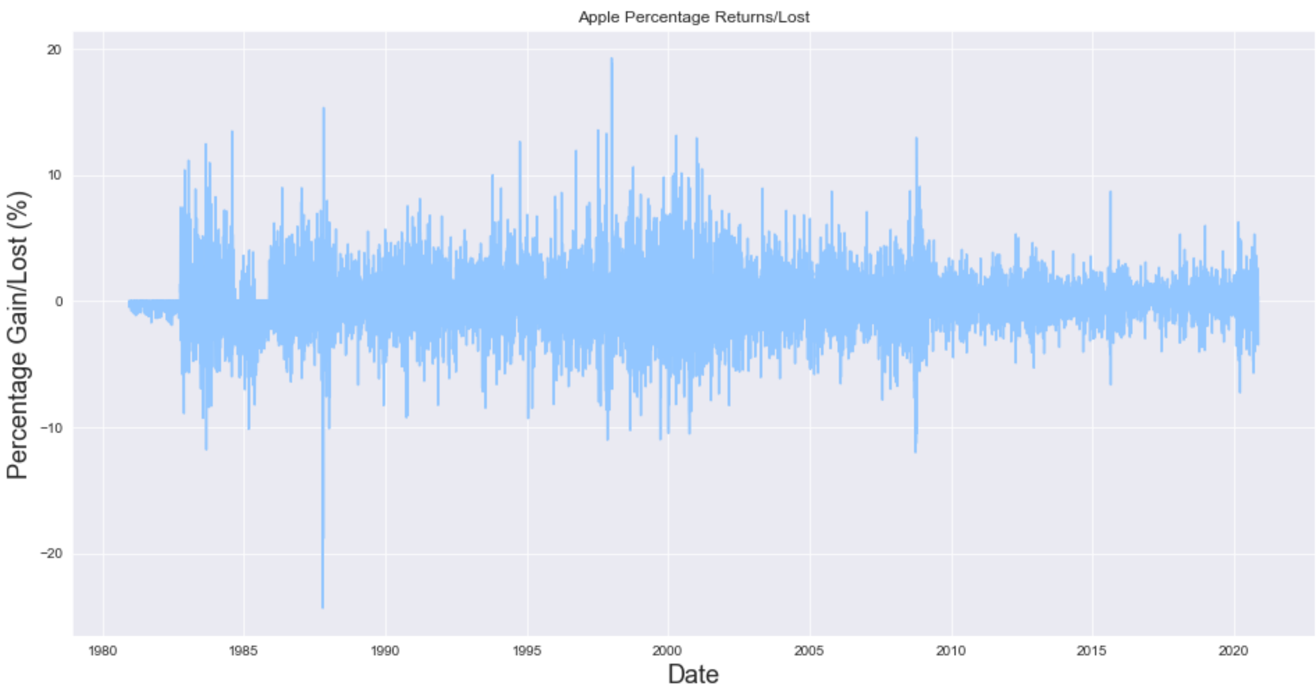
On 18 May 2012, Facebook had its highest percentage decrease. They decreased in value by 9.084423%.

On 14 November 2012, Facebook had its highest percentage increase. They increased in value by 11.243782%.

Apple

In [98]:

```
plt.figure(figsize=(16,8))
plt.title('Apple Percentage Returns/Lost')
plt.xlabel('Date', fontsize=18)
plt.ylabel('Percentage Gain/Lost (%)', fontsize=18)
plt.plot(df_apple_returns)
plt.show()
```



In [99]:

```
print(df_apple_returns[df_apple_returns == df_apple_returns.min()])
print(df_apple_returns[df_apple_returns == df_apple_returns.max()])
```

```
Date
1987-10-19   -24.352329
dtype: float64
Date
1998-01-02    19.266055
dtype: float64
```

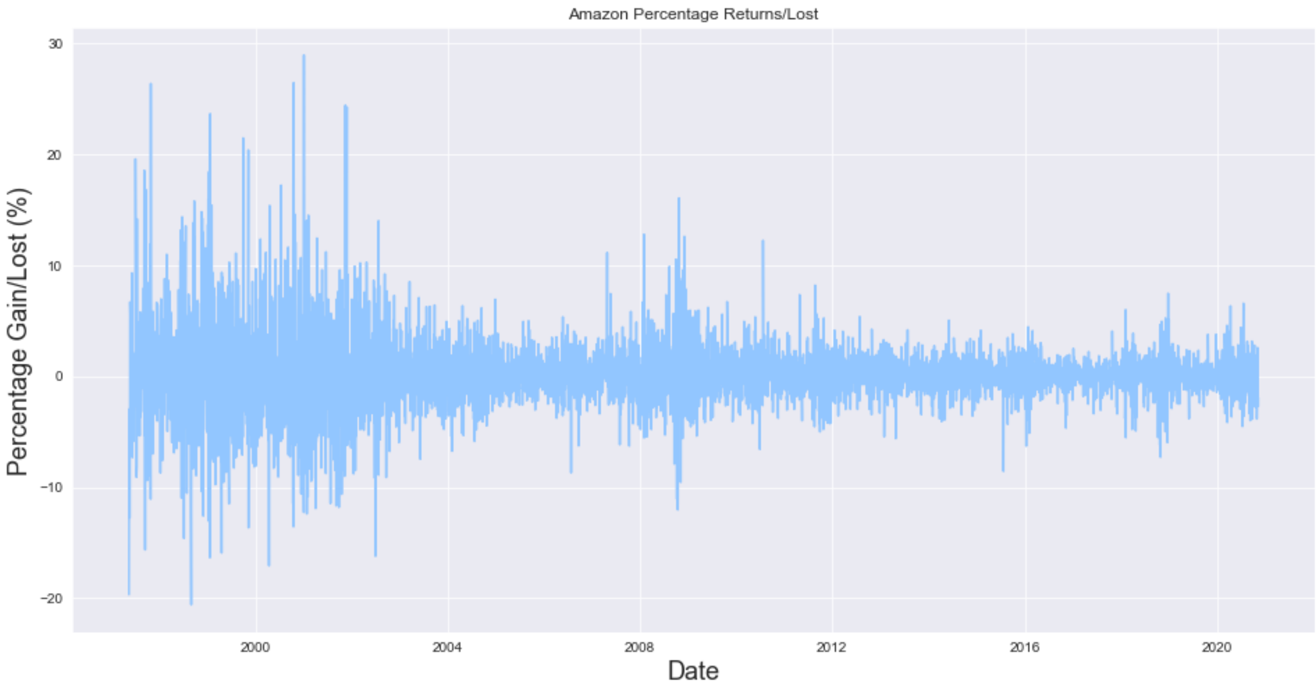
On 19 October 1987, Apple had its highest percentage decrease. They decreased in value by 24.352329%.

On 02 January 1998, Apple had its highest percentage increase. They increased in value by 19.266055%.

Amazon

In [100]:

```
plt.figure(figsize=(16,8))
plt.title('Amazon Percentage Returns/Lost')
plt.xlabel('Date', fontsize=18)
plt.ylabel('Percentage Gain/Lost (%)', fontsize=18)
plt.plot(df_amazon_returns)
plt.show()
```



In [101]:

```
print(df_amazon_returns[df_amazon_returns == df_amazon_returns.min()])
print(df_amazon_returns[df_amazon_returns == df_amazon_returns.max()])
```

```
Date
1998-08-31   -20.569056
dtype: float64
Date
2001-01-03    28.899083
dtype: float64
```

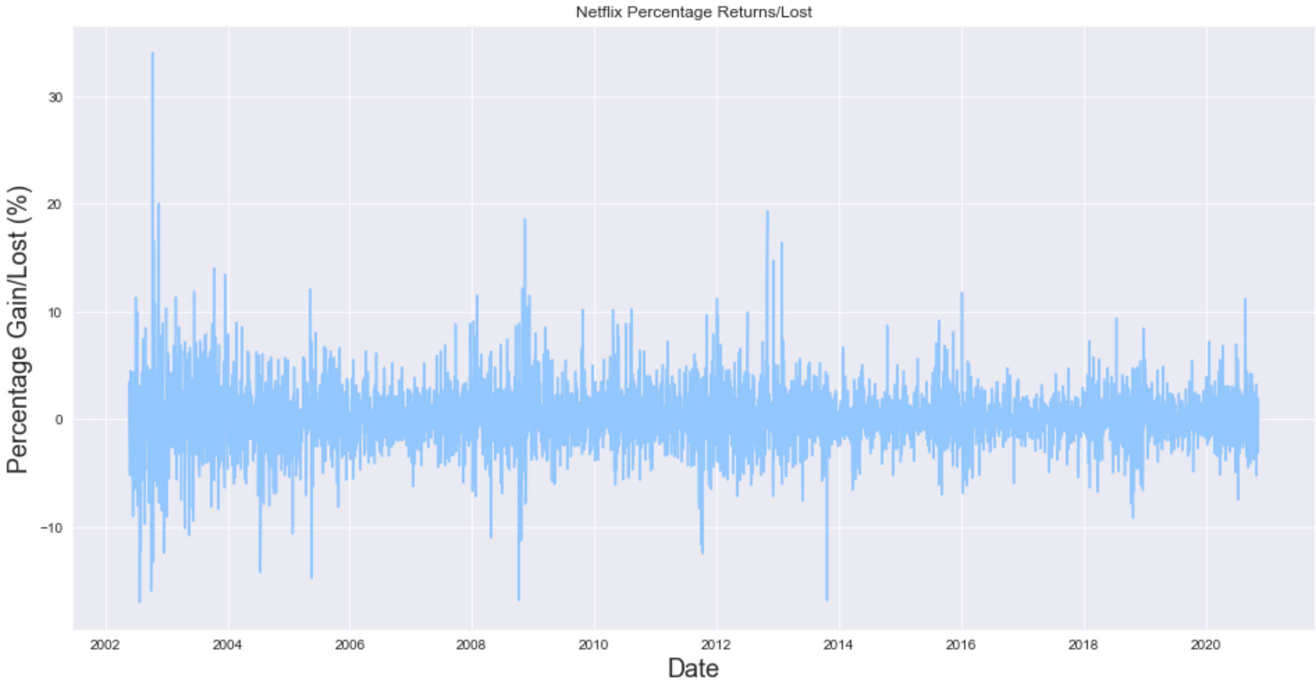
On 31 August 1998, Amazon had its highest percentage decrease. They decreased in value by 20.569056%.

On 03 January 2001, Amazon had its highest percentage increase. They increased in value by 28.899083%.

Netflix

In [102]:

```
plt.figure(figsize=(16,8))
plt.title('Netflix Percentage Returns/Lost')
plt.xlabel('Date', fontsize=18)
plt.ylabel('Percentage Gain/Lost (%)', fontsize=18)
plt.plot(df_netflix_returns)
plt.show()
```



In [103]:

```
print(df_netflix_returns[df_netflix_returns == df_netflix_returns.min()])
print(df_netflix_returns[df_netflix_returns == df_netflix_returns.max()])
```

```
Date
2002-07-26   -17.006801
dtype: float64
Date
2002-10-10    34.02647
dtype: float64
```

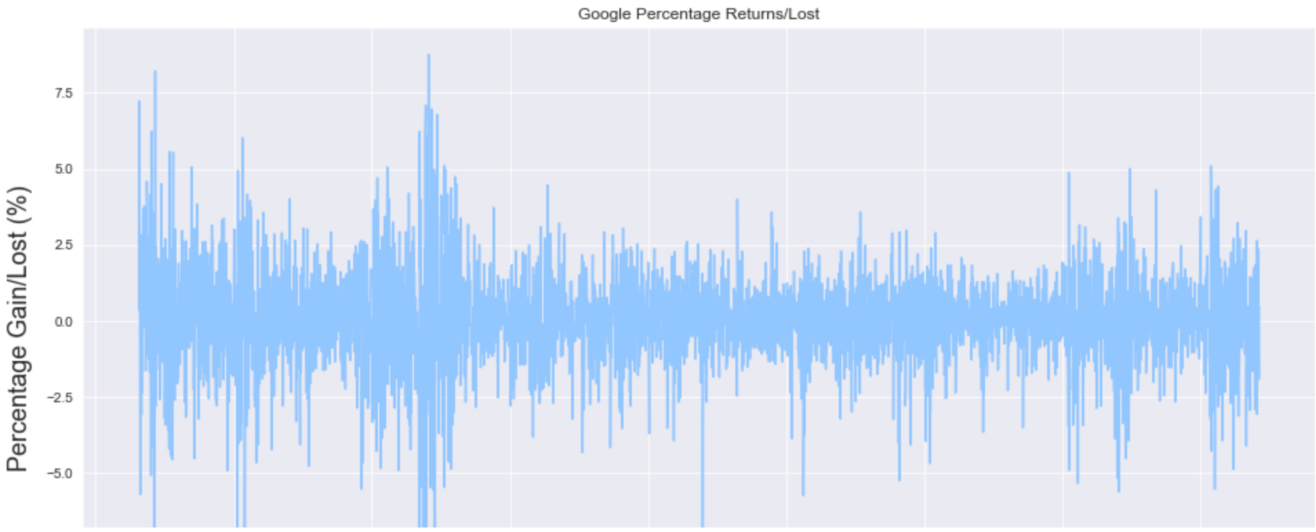
On 26 July 2002, Netlix had its highest percentage decrease. They decreased in value by 17.006801%.

On 10 October 2002, Netflix had its highest percentage increase. They increased in value by 34.02647%.

Google

In [104]:

```
plt.figure(figsize=(16,8))
plt.title('Google Percentage Returns/Lost')
plt.xlabel('Date', fontsize=18)
plt.ylabel('Percentage Gain/Lost (%)', fontsize=18)
plt.plot(df_google_returns)
plt.show()
```



In [105]:

```
print(df_google_returns[df_google_returns == df_google_returns.min()])
print(df_google_returns[df_google_returns == df_google_returns.max()])
```

```
Date
2008-09-29   -9.179758
dtype: float64
Date
2008-10-28    8.759763
dtype: float64
```

On 29 September 2008, Google had its highest percentage decrease. They decreased in value by 9.179758%.

On 28 October 2008, Google had its highest percentage increase. They increased in value by 8.759763%.

Q4. Are there any significance to these dates?

Facebook

18 May 2012, decreased in value by ~9%

18 May 2012 was Facebook's IPO, the day it made its debut to the stock market. It smashed the record for highest trading volume at that time with 570 million shares being traded. Facebook set its final IPO price at \$38. The first trade came in at \$42. However, it quickly took a reverse dropping down to \$38.23 by the end of the day leading to a final decrease by 9%.

(Source: https://money.cnn.com/2012/05/18/technology/facebook-ipo-trading/index.htm)

14 November 2012, Increased in value by ~11%

I was not able to find any significant event on 14 November 2012 relating to Facebook. They however did release their 3rd Quarter 2012 results on October 2012 with some great numbers which may have led to the increased in value.

Data Reported:

```
* Monthly active users (MAUs) were 1.01 billion as of September 30, 2012, an increase of
26% year-over-year
* Daily active users (DAUs) were 584 million on average for September 2012, an increase of
28% year-over-year
* Mobile MAUs were 604 million as of September 30, 2012, an increase of 61% year-over-year
```

(Source: https://investor.fb.com/investor-news/press-release-details/2012/Facebook-Reports-Third-Quarter-2012-Results/default.aspx)

Apple

19 October 1987, decreased in value by ~24%

Black Monday! On 19 October 1987 (also known as the Black Monday) the Dow Jones Industrial Average fell by 508 points (a 22% decrease). According to Investopedia, Economists have attributed the crash to a combination of geopolitical events and the advent of computerized program trading that accelerated the selloff.

(Source: https://www.investopedia.com/terms/b/blackmonday.asp)

02 January 1998, Increased in value by ~19%

There was not any significant event on 2 January 1998 relating to Apple. However on 10 Novemeber 1997, Apple Computer introduces the Power Macintosh G3 computer, released the PowberBook G3, and Steven Jobs announces further changes to Apple's corporate strategy. Apple would now sell computers direct, both over the web and the phone, as Power Computing had done so well in the past. This may have attributed to the increase in Apple's value.

(Source: https://igotoffer.com/apple/history-apple-1997-1998)

Amazon

31 August 1998, decreased in value by ~21%

I was not able to find any significant event on 31 August 1998 relating to Amazon.

03 January 2001, Increased in value by ~29%

There was not any significant event on 03 Januart 2001 but it is important to note that around the year 2000, the dot-com bubble burst destroyed many e-companies in the process, but Amazon survived and moved forward beyond the tech crash to become a huge player in online sales.

(Source: https://www.investopedia.com/terms/d/dotcom-bubble.asp)

Netflix

26 July 2002, decreased in value by ~17%

I was not able to find any significant event on 26 July 2002 relating to Netflix.

10 October 2002, Increased in value by ~34%

I was not able to find any significant event on 10 October 2002 relating to Netflix.

These dates are however really close to Netflix's IPO date which is on 23 May 2002 which may (or may not) play a part on its volatility.

Google

29 September 2008, decreased in value by ~9%

On this day, the stock market crashed yet again with the Dow Jones Industrial Average losing nearly 778 points,after the House rejected the government's /$700 billion bank bailout plan.

(Source: https://money.cnn.com/2008/09/29/markets/markets_newyork/)

28 October 2008, Increased in value by ~9/%

On this day, the Dow Jones industrial average added 889 points after having risen as much as 906 points earlier in the session. It was the Dow's second-biggest one-day point gain ever then, following a 936-point rally two weeks ago. The advance of 10.9/% was the sixth-biggest ever then.

(Source: https://money.cnn.com/2008/10/28/markets/markets_newyork/)

Conclusions

We trained an LSTM and a Prophet model on a dataframe containing FAANG companies using closing prices as the feature we sought to predict. For the LSTM model, we used a mean squared error loss function an were able to obtain reasonable results for all 5 FAANG companies. The LSTM models for each company did a good job of predicting the macro trends related to closing prices. For the prophet model, we were able to do some data visualization beforehand using moving averages and bollinger bands. These two visualizations suggested an upward trend in the stock closing prices. The prophet model itself predicts that all five FAANG stocks will increase in price over the course of the next year. This suggests that all five FAANG companies will be a good investment. By further evaluating the data from the FAANG companies, we were able to see that all five companies have an upward trend. We also looked at the trend of the historical price to earnings ratio and found that all five companies had an upward trend. Lastly, we looked at the days on which each of the FAANG companies had their highest percentage gains and losses and tried to correlate these to real world events.