Capstone 2: Stock Market Predictions

This capstone will complete all of the steps of the Data Science Method.

1) Problem identification
2) Data wrangling
3) Exploratory data analysis
4) Pre-processing and training data
5) Modelling
6) Documentation

1) Problem identification

I will be using the Kaggle dataset "S&P 500 stock data". The dataset is at https://www.kaggle.com/datasets/camnugent/sandp500 and it covers 5 years of stocks including the date, open value, high value for that day, low value for that day, close value, volume, and stock name. You will see in the notebook but there are hundreds of stocks, and I will be cutting it to the first five stocks for proof of concept for the modeling process.

I will develop an accurate stock price prediction system in Python to predict the stock performance over a specific period. After doing feature engineering on the dataset, I can use ARMA, ARIMA and LSTM and see how those models do.

Problem statement formation
● Context: The stock market is extremely lucrative. Millions of people trade on it every day, and predicting movement has the potential for lots of profit and gain. It is volatile and hard to predict however, and it is a large industry of analysts on Wall Street to make good decisions for asset managers, banks, and other traders. Can time series analysis also be of use to predict future stock prices? Stock price might not be 100% dependent on past performance, of course, but we can make a model that is helpful.
● Criteria for success: This will be successful if it has more predictive power than a random walk and/or random noise.
● Scope of solution space: the solution space is stock trading advice on certain stocks, and will only depend on what we can infer from the time series prediction model, rather than other factors like what’s going on with those companies and the market
● Constraints: we only have stock price information for a handful of stocks and for a certain period of time so we obviously can’t predict outside of that
● Stakeholders: analysts, amateur traders,
● Data sources: kaggle dataset above, can reference https://rpubs.com/kapage/523169 https://www.projectpro.io/article/stock-price-prediction-using-machine-learning-project/571
Stock Price as a Time Series Data
Treating stock data as time-series, one can use past stock prices (and other parameters) to predict the stock prices for the next day or week. Machine learning models such as

Recurrent Neural Networks (RNNs) or LSTMs are popular models applied to predicting time series data such as weather forecasting, election results, house prices, and, of course, stock prices. The idea is to weigh out the importance of recent and older data and determine which parameters affect the “current” or “next” day prices the most. The machine learning model assigns weights to each market feature and determines how much history the model should look at to predict future stock prices.
LSTM is a Recurrent Neural Network that works on data sequences, learning to retain only relevant information from a time window.

2) Data wrangling

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

sns.set_style('whitegrid')
plt.style.use("fivethirtyeight")
%matplotlib inline
```

In [2]:
```
df=pd.read_csv("all_stocks_5yr.csv")
df.head()
```

Out[2]:

	date	open	high	low	close	volume	Name
0	2013-02-08	15.07	15.12	14.63	14.75	8407500	AAL
1	2013-02-11	14.89	15.01	14.26	14.46	8882000	AAL
2	2013-02-12	14.45	14.51	14.10	14.27	8126000	AAL
3	2013-02-13	14.30	14.94	14.25	14.66	10259500	AAL
4	2013-02-14	14.94	14.96	13.16	13.99	31879900	AAL

In [3]:
```
earliest_date = df['date'].min()
latest_date = df['date'].max()

print("Earliest date: ", earliest_date)
print("Latest date: ", latest_date)
```

```
Earliest date:  2013-02-08
Latest date:  2018-02-07
```

Later on when I am breaking the data into training and test data, I will use the earliest ~80% of data as training.

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 619040 entries, 0 to 619039
Data columns (total 7 columns):
 #   Column  Non-Null Count   Dtype  
---  ------  --------------   -----  
 0   date    619040 non-null  object 
 1   open    619029 non-null  float64
 2   high    619032 non-null  float64
 3   low     619032 non-null  float64
 4   close   619040 non-null  float64
 5   volume  619040 non-null  int64  
 6   Name    619040 non-null  object 
dtypes: float64(4), int64(1), object(2)
memory usage: 33.1+ MB
```

In [5]:
```
df.columns = df.columns.str.strip()
df.columns = df.columns.str.lower()
df.columns
```

Out[5]:
```
Index(['date', 'open', 'high', 'low', 'close', 'volume', 'name'], dtype='objec
t')
```

In [6]:
```
# checking for missing values
print(df.isnull().sum())
```

```
date       0
open      11
high       8
low        8
close      0
volume     0
name       0
dtype: int64
```

Compared to the number of observations, 619,040, there are very few rows with missing values, at most 27 if the missing values are from all different rows. This is relatively negligible so I will drop these rows.

In [7]:
```
df.dropna(inplace=True)
```

In [8]:
```
print(df['name'].unique())
```

```
['AAL' 'AAPL' 'AAP' 'ABBV' 'ABC' 'ABT' 'ACN' 'ADBE' 'ADI' 'ADM' 'ADP'
 'ADSK' 'ADS' 'AEE' 'AEP' 'AES' 'AET' 'AFL' 'AGN' 'AIG' 'AIV' 'AIZ' 'AJG'
 'AKAM' 'ALB' 'ALGN' 'ALK' 'ALLE' 'ALL' 'ALXN' 'AMAT' 'AMD' 'AME' 'AMGN'
 'AMG' 'AMP' 'AMT' 'AMZN' 'ANDV' 'ANSS' 'ANTM' 'AON' 'AOS' 'APA' 'APC'
 'APD' 'APH' 'APTV' 'ARE' 'ARNC' 'ATVI' 'AVB' 'AVGO' 'AVY' 'AWK' 'AXP'
 'AYI' 'AZO' 'A' 'BAC' 'BAX' 'BA' 'BBT' 'BBY' 'BDX' 'BEN' 'BF.B' 'BHF'
 'BHGE' 'BIIB' 'BK' 'BLK' 'BLL' 'BMY' 'BRK.B' 'BSX' 'BWA' 'BXP' 'CAG'
 'CAH' 'CAT' 'CA' 'CBG' 'CBOE' 'CBS' 'CB' 'CCI' 'CCL' 'CDNS' 'CELG' 'CERN'
 'CFG' 'CF' 'CHD' 'CHK' 'CHRW' 'CHTR' 'CINF' 'CI' 'CLX' 'CL' 'CMA' 'CMCSA'
 'CME' 'CMG' 'CMI' 'CMS' 'CNC' 'CNP' 'COF' 'COG' 'COL' 'COO' 'COP' 'COST'
 'COTY' 'CPB' 'CRM' 'CSCO' 'CSRA' 'CSX' 'CTAS' 'CTL' 'CTSH' 'CTXS' 'CVS'
 'CVX' 'CXO' 'C' 'DAL' 'DE' 'DFS' 'DGX' 'DG' 'DHI' 'DHR' 'DISCA' 'DISCK'
 'DISH' 'DIS' 'DLR' 'DLTR' 'DOV' 'DPS' 'DRE' 'DRI' 'DTE' 'DUK' 'DVA' 'DVN'
 'DWDP' 'DXC' 'D' 'EA' 'EBAY' 'ECL' 'ED' 'EFX' 'EIX' 'EL' 'EMN' 'EMR'
 'EOG' 'EQIX' 'EQR' 'EQT' 'ESRX' 'ESS' 'ES' 'ETFC' 'ETN' 'ETR' 'EVHC' 'EW'
 'EXC' 'EXPD' 'EXPE' 'EXR' 'FAST' 'FBHS' 'FB' 'FCX' 'FDX' 'FE' 'FFIV'
 'FISV' 'FIS' 'FITB' 'FLIR' 'FLR' 'FLS' 'FL' 'FMC' 'FOXA' 'FOX' 'FRT'
 'FTI' 'FTV' 'F' 'GD' 'GE' 'GGP' 'GILD' 'GIS' 'GLW' 'GM' 'GOOGL' 'GOOG'
 'GPC' 'GPN' 'GPS' 'GRMN' 'GS' 'GT' 'GWW' 'HAL' 'HAS' 'HBAN' 'HBI' 'HCA'
 'HCN' 'HCP' 'HD' 'HES' 'HIG' 'HII' 'HLT' 'HOG' 'HOLX' 'HON' 'HPE' 'HPQ'
 'HP' 'HRB' 'HRL' 'HRS' 'HSIC' 'HST' 'HSY' 'HUM' 'IBM' 'ICE' 'IDXX' 'IFF'
 'ILMN' 'INCY' 'INFO' 'INTC' 'INTU' 'IPG' 'IP' 'IQV' 'IRM' 'IR' 'ISRG'
 'ITW' 'IT' 'IVZ' 'JBHT' 'JCI' 'JEC' 'JNJ' 'JNPR' 'JPM' 'JWN' 'KEY' 'KHC'
 'KIM' 'KLAC' 'KMB' 'KMI' 'KMX' 'KORS' 'KO' 'KR' 'KSS' 'KSU' 'K' 'LB'
 'LEG' 'LEN' 'LH' 'LKQ' 'LLL' 'LLY' 'LMT' 'LNC' 'LNT' 'LOW' 'LRCX' 'LUK'
 'LUV' 'LYB' 'L' 'MAA' 'MAC' 'MAR' 'MAS' 'MAT' 'MA' 'MCD' 'MCHP' 'MCK'
 'MCO' 'MDLZ' 'MDT' 'MET' 'MGM' 'MHK' 'MKC' 'MLM' 'MMC' 'MMM' 'MNST' 'MON'
 'MOS' 'MO' 'MPC' 'MRK' 'MRO' 'MSFT' 'MSI' 'MS' 'MTB' 'MTD' 'MU' 'MYL' 'M'
 'NAVI' 'NBL' 'NCLH' 'NDAQ' 'NEE' 'NEM' 'NFLX' 'NFX' 'NI' 'NKE' 'NLSN'
 'NOC' 'NOV' 'NRG' 'NSC' 'NTAP' 'NTRS' 'NUE' 'NVDA' 'NWL' 'NWSA' 'NWS'
 'OKE' 'OMC' 'ORCL' 'ORLY' 'OXY' 'O' 'PAYX' 'PBCT' 'PCAR' 'PCG' 'PCLN'
 'PDCO' 'PEG' 'PEP' 'PFE' 'PFG' 'PGR' 'PG' 'PHM' 'PH' 'PKG' 'PKI' 'PLD'
 'PM' 'PNC' 'PNR' 'PNW' 'PPG' 'PPL' 'PRGO' 'PRU' 'PSA' 'PSX' 'PVH' 'PWR'
 'PXD' 'PX' 'PYPL' 'QCOM' 'QRVO' 'RCL' 'REGN' 'REG' 'RE' 'RF' 'RHI' 'RHT'
 'RJF' 'RL' 'RMD' 'ROK' 'ROP' 'ROST' 'RRC' 'RSG' 'RTN' 'SBAC' 'SBUX' 'SCG'
 'SCHW' 'SEE' 'SHW' 'SIG' 'SJM' 'SLB' 'SLG' 'SNA' 'SNI' 'SNPS' 'SO' 'SPGI'
 'SPG' 'SRCL' 'SRE' 'STI' 'STT' 'STX' 'STZ' 'SWKS' 'SWK' 'SYF' 'SYK'
 'SYMC' 'SYY' 'TAP' 'TDG' 'TEL' 'TGT' 'TIF' 'TJX' 'TMK' 'TMO' 'TPR' 'TRIP'
 'TROW' 'TRV' 'TSCO' 'TSN' 'TSS' 'TWX' 'TXN' 'TXT' 'T' 'UAA' 'UAL' 'UA'
 'UDR' 'UHS' 'ULTA' 'UNH' 'UNM' 'UNP' 'UPS' 'URI' 'USB' 'UTX' 'VAR' 'VFC'
 'VIAB' 'VLO' 'VMC' 'VNO' 'VRSK' 'VRSN' 'VRTX' 'VTR' 'VZ' 'V' 'WAT' 'WBA'
 'WDC' 'WEC' 'WFC' 'WHR' 'WLTW' 'WMB' 'WMT' 'WM' 'WRK' 'WU' 'WYNN' 'WYN'
 'WY' 'XEC' 'XEL' 'XLNX' 'XL' 'XOM' 'XRAY' 'XRX' 'XYL' 'YUM' 'ZBH' 'ZION'
 'ZTS']
```

In [9]:

```
len(df['name'].unique())
```

Out[9]:

```
505
```

These are all the stocks included.

In [10]:

```
# checking for duplicate rows
df.duplicated().sum()
```

Out[10]:

```
0
```

Feature Engineering - making new features such as price change

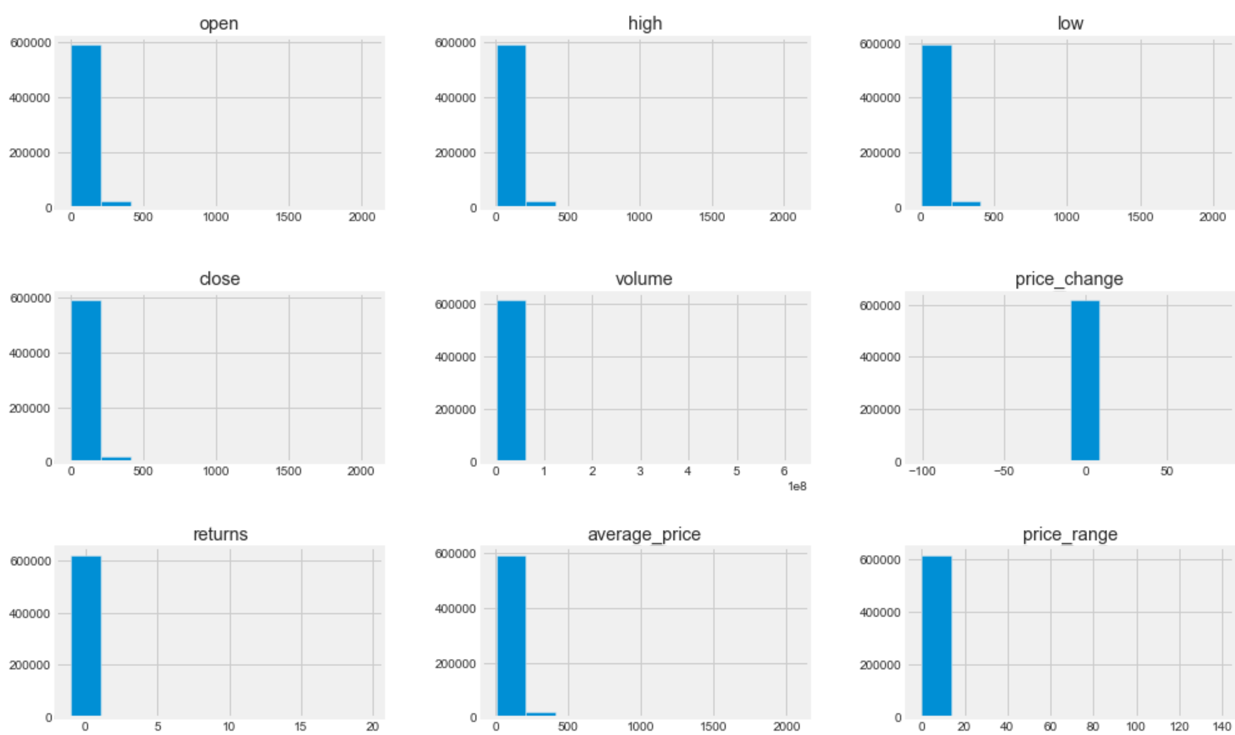
In [11]:
```
#https://www.kaggle.com/code/yassinesfaihi/preparing-the-data-for-stock-market-
#around line 59 there are more
df['price_change'] = df['close'] - df['open']
df['returns'] = df['close'].pct_change()
df['average_price'] = (df['close'] + df['open']) / 2
df['price_range'] = df['high'] - df['low']
```

In [12]:
```
df.describe()
```

Out[12]:

	open	high	low	close	volume	price_ch
count	619029.000000	619029.000000	619029.000000	619029.000000	6.190290e+05	619029.0(
mean	83.023334	83.778419	82.256200	83.043305	4.321892e+06	0.0
std	97.378769	98.207735	96.507634	97.388913	8.693671e+06	1.5
min	1.620000	1.690000	1.500000	1.590000	1.010000e+02	-100.9
25%	40.220000	40.620000	39.830000	40.240800	1.070351e+06	-0.3
50%	62.590000	63.150000	62.020000	62.620000	2.082165e+06	0.0
75%	94.370000	95.180000	93.540000	94.410000	4.284550e+06	0.4
max	2044.000000	2067.990000	2035.110000	2049.000000	6.182376e+08	81.3

In [13]:
```
#visualizing the data preliminarily
df.hist(figsize=(15,10))
plt.subplots_adjust(hspace=0.5);

#sns.pairplot(df)
#un-comment when it has time to load
```



Some are clustered towards zero, but maybe that's because of the scale/max being too high or an outlier. Let's visualize the outliers.

The IQR method is based on the interquartile range, or the difference between the 75th and 25th percentiles of the dataset. Data points that are outside of the range of 1.5IQR to 3IQR are considered outliers. I want to see the outliers of price range to consider getting rid of wildly fluctuating stocks in my training data.

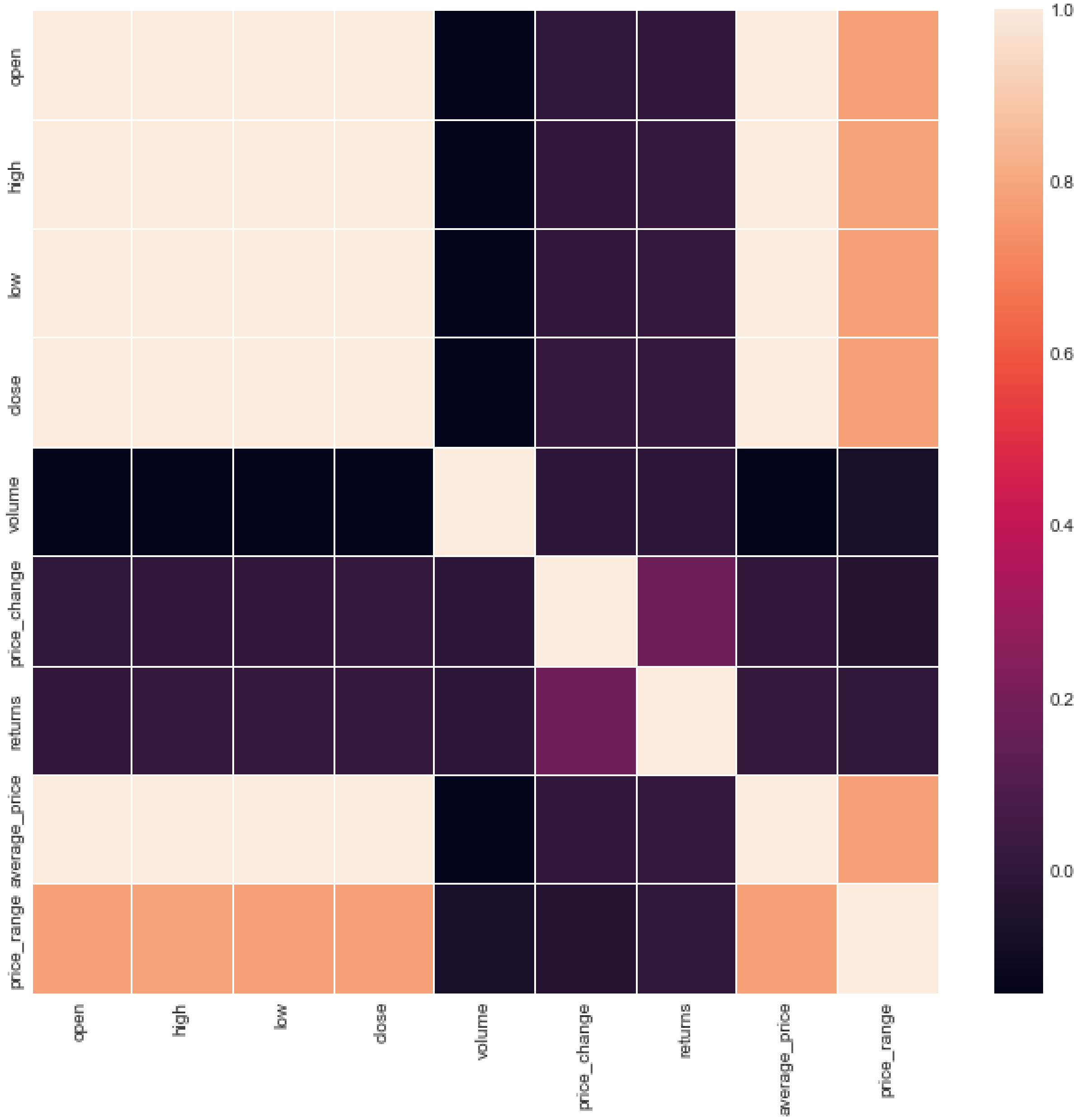
In [14]:
```
# Calculate the interquartile range (IQR) for the 'price' column
q1 = df['price_range'].quantile(0.25)
q3 = df['price_range'].quantile(0.75)
iqr = q3 - q1

# Calculate the lower and upper bounds for outliers
lower_bound = q1 - 1.5 * iqr
upper_bound = q3 + 1.5 * iqr

# Identify the outliers in the 'price' column
outliers = df[(df['price_range'] < lower_bound) | (df['price_range'] > upper_bo

# Print the outliers
print(outliers)
```

```
              date   open     high    low  close    volume name  price_change
\
422     2014-10-13  31.07  31.3900  28.10  28.58  34532913  AAL         -2.49
425     2014-10-16  30.63  33.4000  30.00  32.97  24987103  AAL          2.34
430     2014-10-23  37.43  40.1800  36.80  38.48  33292004  AAL          1.05
467     2014-12-16  51.01  51.1500  47.68  47.96  22053666  AAL         -3.05
468     2014-12-17  48.26  49.4900  46.05  48.80  24779800  AAL          0.54
...            ...    ...      ...    ...    ...       ...  ...           ...
618420  2015-08-24  42.51  44.9700  37.73  43.53   5725519  ZTS          1.02
618461  2015-10-21  43.38  43.5600  39.53  41.66   9780195  ZTS         -1.72
618847  2017-05-04  55.48  59.6025  55.48  58.87   6923157  ZTS          3.39
618974  2017-11-02  64.30  67.8450  64.30  67.31   5185564  ZTS          3.01
619037  2018-02-05  76.64  76.9200  73.18  73.83   2962031  ZTS         -2.81

         returns  average_price  price_range
422    -0.071475         29.825       3.2900
425     0.040391         31.800       3.4000
430     0.038877         37.955       3.3800
467    -0.056648         49.485       3.4700
468     0.017515         48.530       3.4400
...          ...            ...          ...
618420 -0.033096         43.020       7.2400
618461 -0.033186         42.520       4.0300
618847  0.059003         57.175       4.1225
618974  0.043404         65.805       3.5450
619037 -0.038421         75.235       3.7400

[49358 rows x 11 columns]
```

There are a lot of outliers because of the way I defined it with the IQR. I will choose to keep them in because it's a lot of valuable data.

In [15]:
```
corr = df.corr()
fig, ax = plt.subplots(figsize=(10,10))
sns.heatmap(corr, linewidths=.5, ax=ax)
```

Out[15]: <AxesSubplot:>



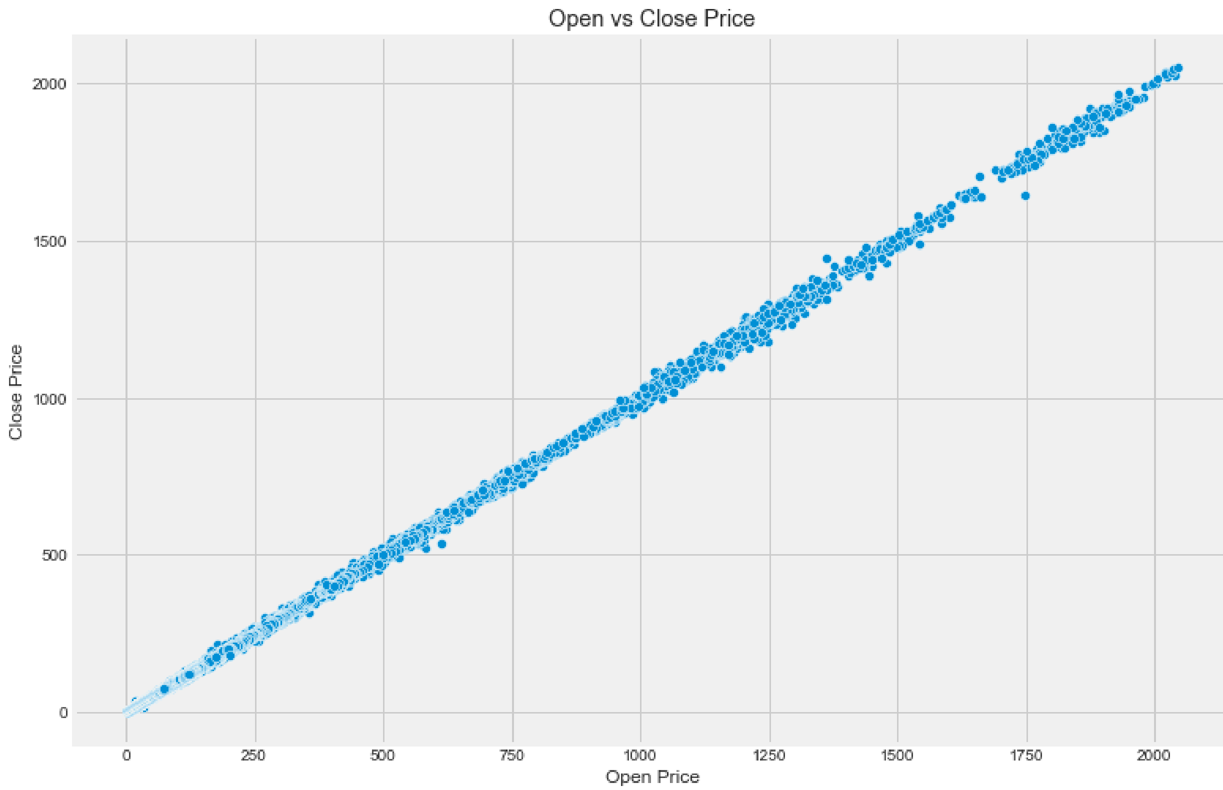
The stock prices are correlated with themselves in a predictable way - the open and close for a single stock would be expected to be similar values.

3) Exploratory data analysis

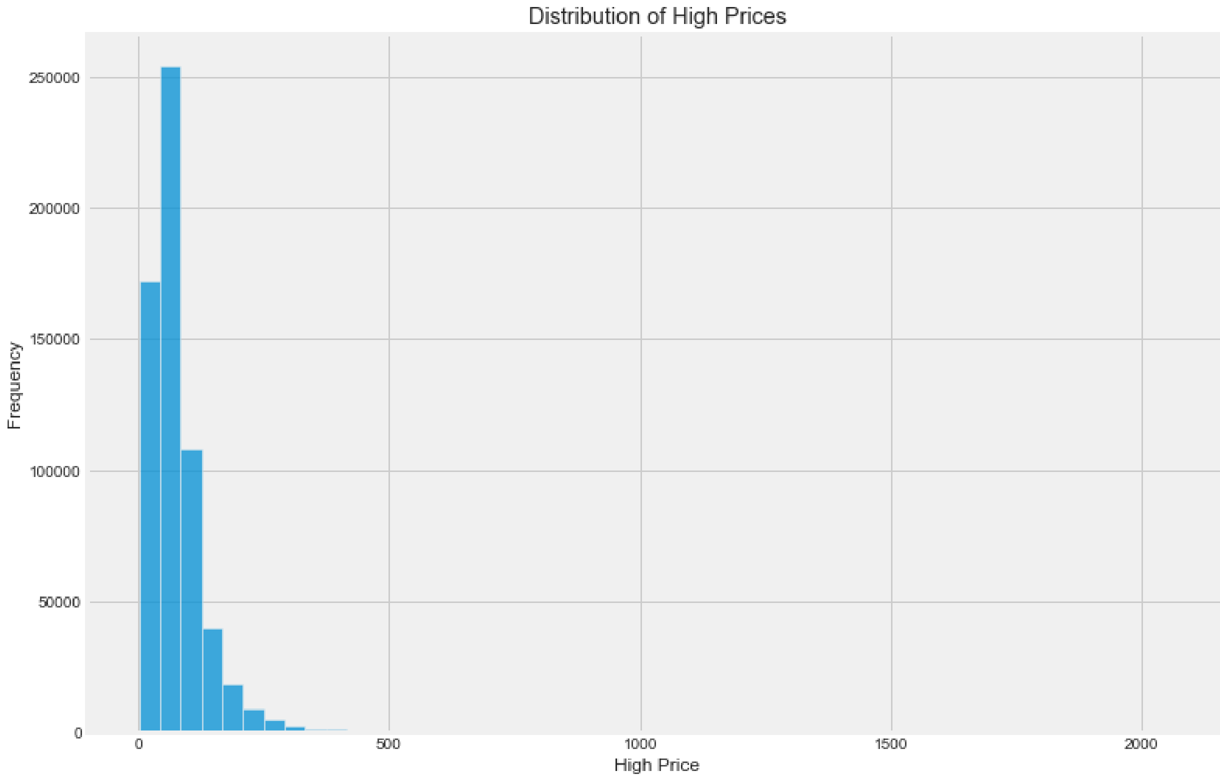
We already did some EDA with pairplots and corr, but let's see some of the data more in depth.

In [16]:
```
# set figure size
plt.figure(figsize=(11.7,8.27))

# create scatter plot
sns.scatterplot(x='open', y='close', data=df)

# add labels and title
plt.xlabel('Open Price')
plt.ylabel('Close Price')
plt.title('Open vs Close Price')
```

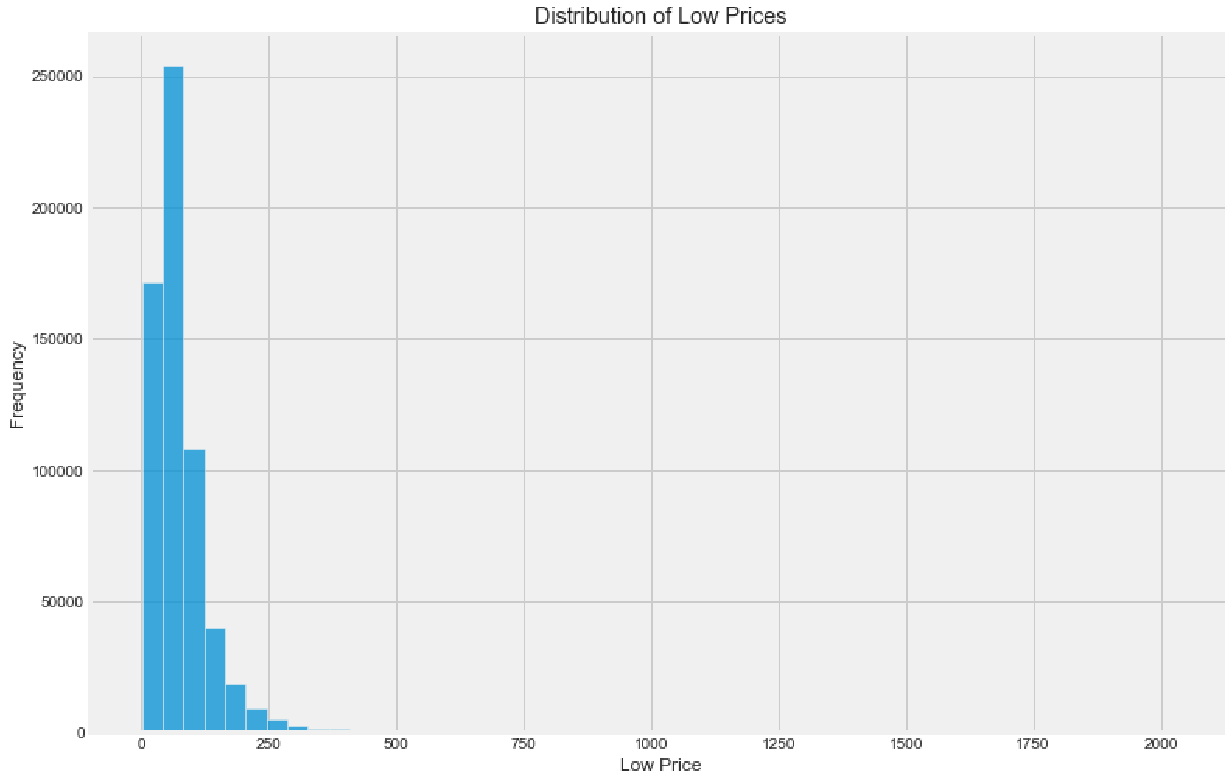
```
# show plot
plt.show()
```



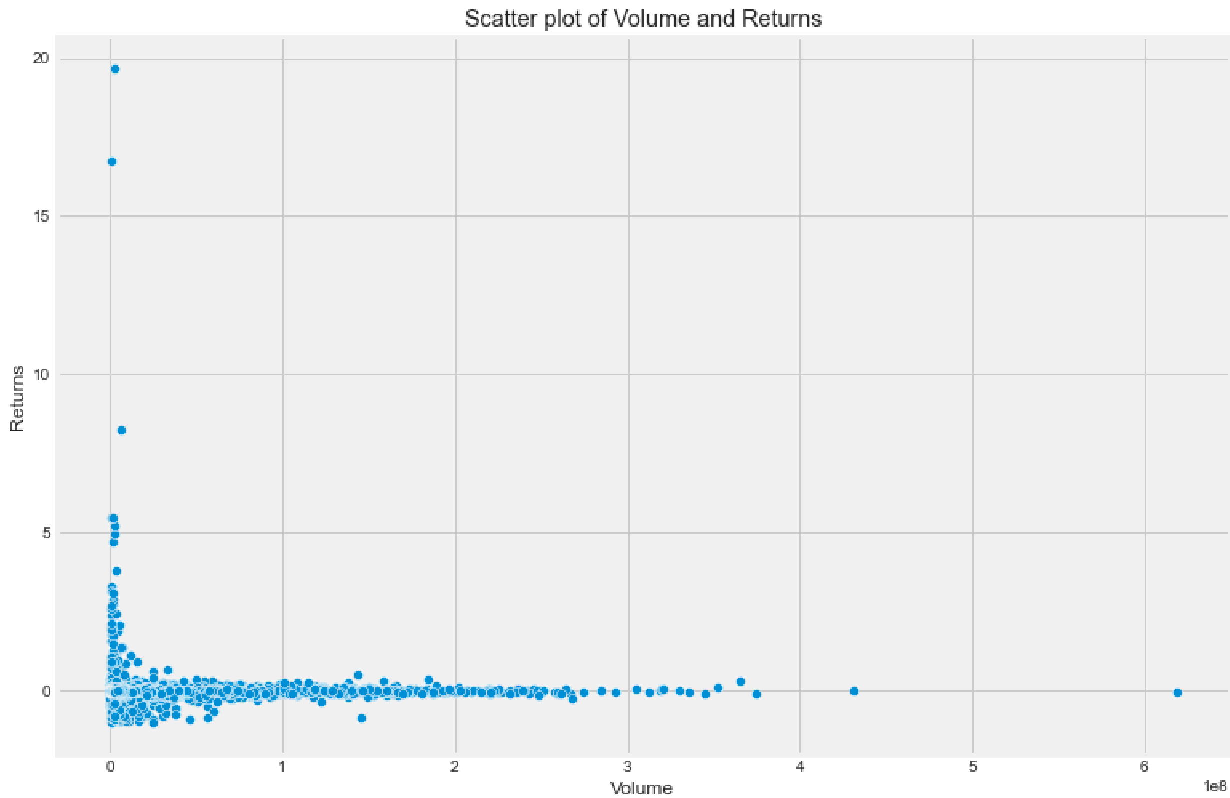
In [17]:
```
# import necessary libraries
import seaborn as sns
import matplotlib.pyplot as plt

# set figure size
plt.figure(figsize=(11.7,8.27))

# create histogram
sns.histplot(data=df['high'], bins=50)

# add labels and title
plt.xlabel('High Price')
plt.ylabel('Frequency')
plt.title('Distribution of High Prices')

# show plot
plt.show()
```



In [18]:
```
# set figure size
plt.figure(figsize=(11.7,8.27))

# create histogram
sns.histplot(data=df['low'], bins=50)

# add labels and title
plt.xlabel('Low Price')
plt.ylabel('Frequency')
plt.title('Distribution of Low Prices')

# show plot
plt.show()
```



In [19]:
```
# set figure size
plt.figure(figsize=(11.7,8.27))

# create scatter plot
sns.scatterplot(x='volume', y='returns', data=df)

# add labels and title
plt.xlabel('Volume')
plt.ylabel('Returns')
plt.title('Scatter plot of Volume and Returns')

# show plot
plt.show()
```



In [20]:
```
#choosing 5 stocks to work with
# Create a list of the 5 stocks you want to include
selected_stocks = ['AAL', 'AAPL', 'AAP', 'ABBV', 'ABC']

# Filter the dataframe to only include rows where the 'Stock' column is in the
df = df.loc[df['name'].isin(selected_stocks)]

#there are 6295 rows now. everything works on the entire set too and if it wasn
```

Now it's time to train test split so we can work with the data to model.

In [21]:
```
df.describe()
```

Out[21]:

	open	high	low	close	volume	price_change	
count	6295.000000	6295.000000	6295.000000	6295.000000	6.295000e+03	6295.000000	62
mean	84.550957	85.396175	83.706077	84.570166	1.487854e+07	0.019209	
std	40.196676	40.511310	39.861328	40.192771	2.518825e+07	1.214912	
min	13.140000	13.420000	12.700000	13.020000	1.307120e+05	-9.110000	
25%	52.760000	53.375000	52.220000	52.765000	1.584827e+06	-0.520000	
50%	77.200000	77.840000	76.590000	77.150000	5.269007e+06	0.030000	
75%	110.625000	111.875000	109.490000	110.410000	1.316181e+07	0.590000	
max	201.240000	201.240000	198.160000	200.380000	2.668336e+08	13.890000	

In [22]:
```
df['date'] = pd.to_datetime(df['date']) #Convert the date column to datetime fo

df_train = df[df['date'] < '2017-06-01']
```

```
df_test = df[df['date'] >= '2017-06-01']
#change all df to df_train

df_train = df_train.set_index('date') #set the date column as the index

df_train = df_train.sort_index() #sort the dataframe by the index

# Normalize the data (this is optional, but it can help improve the performance
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()
df_train[['open','high','low','close','volume', 'price_change', 'returns', 'ave
```

I didn't use train test split because it would have made the training random dates and not be helpful with predicting more random test set dates.

4) Pre-processing and training data

In [23]:
```
df_train.columns
```

Out[23]:
```
Index(['open', 'high', 'low', 'close', 'volume', 'name', 'price_change',
       'returns', 'average_price', 'price_range'],
      dtype='object')
```

In [24]:
```
df_test.columns
```

Out[24]:
```
Index(['date', 'open', 'high', 'low', 'close', 'volume', 'name',
       'price_change', 'returns', 'average_price', 'price_range'],
      dtype='object')
```

In [25]:
```
df
```

Out[25]:

	date	open	high	low	close	volume	name	price_change	returns	average
0	2013-02-08	15.07	15.12	14.6300	14.75	8407500	AAL	-0.32	NaN	
1	2013-02-11	14.89	15.01	14.2600	14.46	8882000	AAL	-0.43	-0.019661	
2	2013-02-12	14.45	14.51	14.1000	14.27	8126000	AAL	-0.18	-0.013140	
3	2013-02-13	14.30	14.94	14.2500	14.66	10259500	AAL	0.36	0.027330	
4	2013-02-14	14.94	14.96	13.1600	13.99	31879900	AAL	-0.95	-0.045703	
...	...	...	...	...	...	...	...	...	...	
6290	2018-02-01	97.74	99.81	95.7300	99.29	2786798	ABC	1.55	-0.003813	
6291	2018-02-02	99.09	99.09	95.9100	96.02	1660267	ABC	-3.07	-0.032934	
6292	2018-02-05	95.62	96.52	91.6900	91.90	2278534	ABC	-3.72	-0.042908	
6293	2018-02-06	92.58	93.37	86.9403	91.54	4574997	ABC	-1.04	-0.003917	
6294	2018-02-07	91.60	95.34	91.1000	94.22	2509484	ABC	2.62	0.029277	

6295 rows × 11 columns

In [26]:

```
df_train
```

Out[26]:

date	open	high	low	close	volume	name	price_change	returns	aver
2013-02-08	0.010260	0.009051	0.010407	0.009234	0.031034	AAL	0.382174	NaN	
2013-02-08	0.290134	0.292735	0.292207	0.292668	0.592561	AAPL	0.402174	1.000000	
2013-02-08	0.177459	0.178229	0.182034	0.180775	0.004132	ABC	0.412174	0.083743	
2013-02-08	0.346624	0.352998	0.352151	0.351623	0.004377	AAP	0.420435	0.166395	
2013-02-08	0.123498	0.122458	0.124690	0.123986	0.051473	ABBV	0.390870	0.000000	
...	...	...	...	...	...	...	...	...	
2017-05-31	0.643275	0.649452	0.641216	0.643734	0.007453	AAP	0.373913	0.681624	
2017-05-31	0.748698	0.749388	0.753154	0.745837	0.091189	AAPL	0.343478	0.670786	
2017-05-31	0.186390	0.186668	0.187803	0.188888	0.016331	AAL	0.405217	0.686239	
2017-05-31	0.282297	0.282132	0.285291	0.282878	0.025516	ABBV	0.386522	0.676765	
2017-05-31	0.415683	0.417261	0.420845	0.420314	0.006522	ABC	0.415217	0.684973	

5425 rows × 10 columns

In [27]:

```
df_test
```

Out[27]:

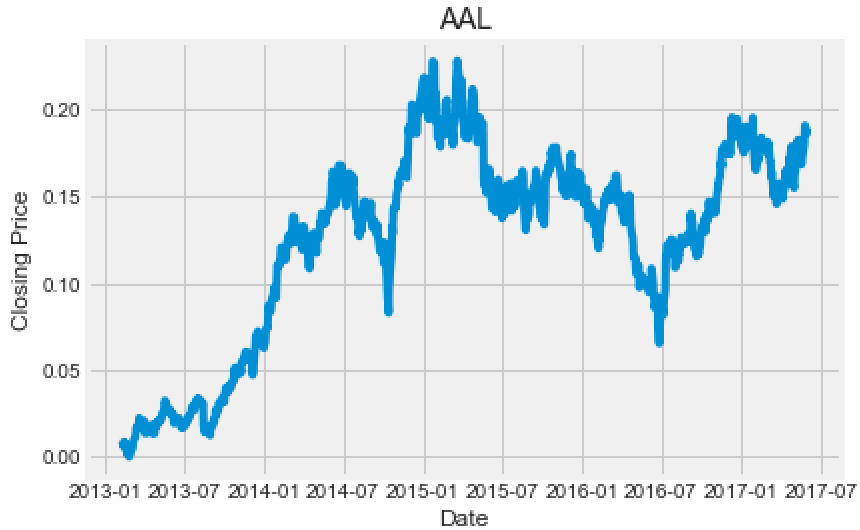
	date	open	high	low	close	volume	name	price_change	returns	average_
1085	2017-06-01	48.50	49.36	48.3000	49.05	4421404	AAL	0.55	0.013220	4
1086	2017-06-02	49.56	50.47	49.3700	49.52	7708567	AAL	-0.04	0.009582	4
1087	2017-06-05	49.53	49.95	49.4000	49.74	5466685	AAL	0.21	0.004443	4
1088	2017-06-06	49.47	50.10	49.3200	49.74	4473456	AAL	0.27	0.000000	4
1089	2017-06-07	49.44	50.91	48.8000	50.86	7078405	AAL	1.42	0.022517	5
...	...	...	...	...	...	...	...	...	...	
6290	2018-02-01	97.74	99.81	95.7300	99.29	2786798	ABC	1.55	-0.003813	9
6291	2018-02-02	99.09	99.09	95.9100	96.02	1660267	ABC	-3.07	-0.032934	9
6292	2018-02-05	95.62	96.52	91.6900	91.90	2278534	ABC	-3.72	-0.042908	9
6293	2018-02-06	92.58	93.37	86.9403	91.54	4574997	ABC	-1.04	-0.003917	9
6294	2018-02-07	91.60	95.34	91.1000	94.22	2509484	ABC	2.62	0.029277	9

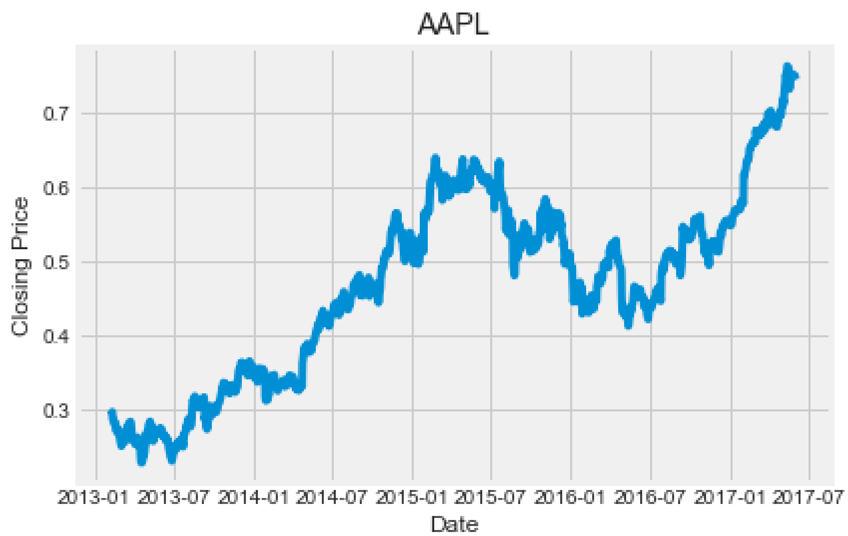
870 rows × 11 columns

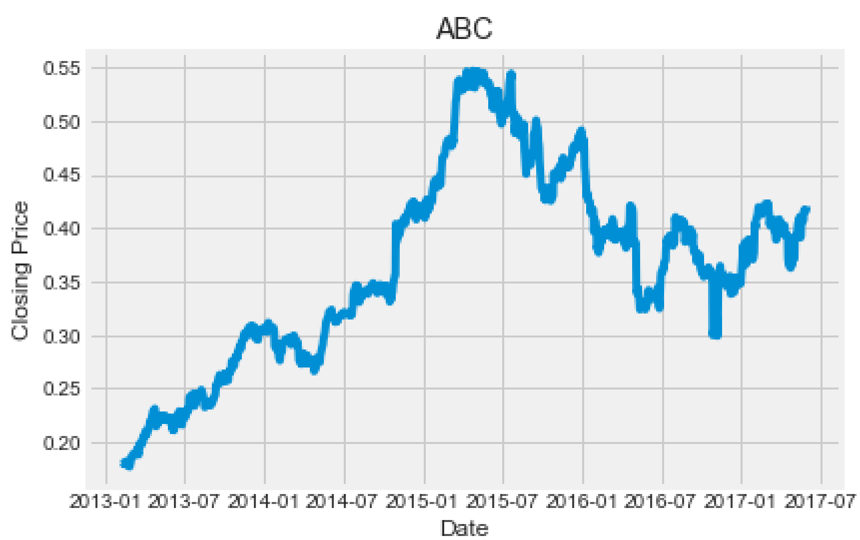
The X will be all the columns besides close, and close is the y. Here is each of the stocks in the training data plotted (should I be plotting for all time with df instead of df_train)?

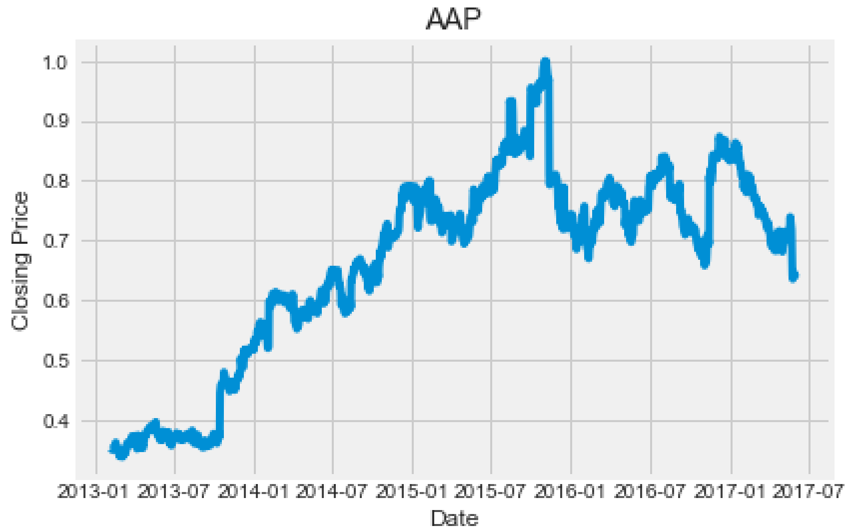
In [28]:

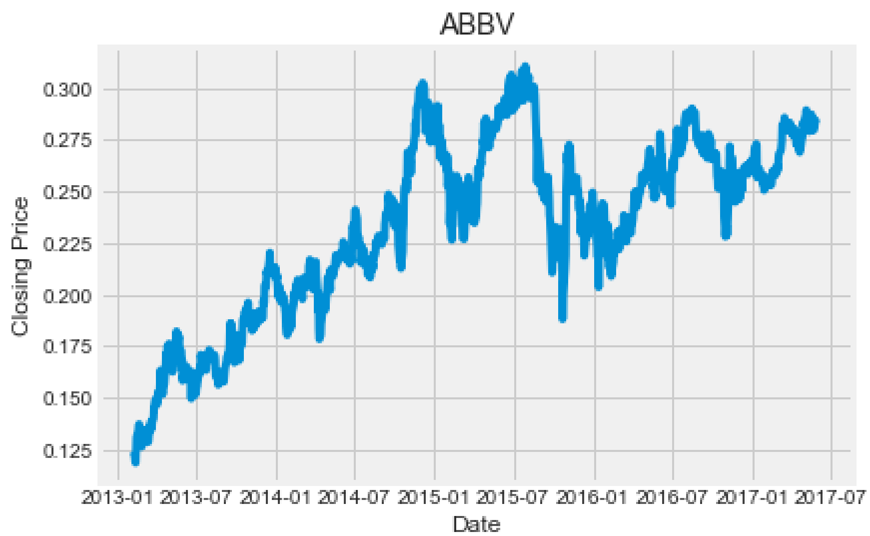
```
names = df_train['name'].unique() # get unique list of stock names
for name in names:
    # filter dataframe for each stock
    stock_df = df_train[df_train['name'] == name]

    # create plot
    plt.plot(stock_df.index, stock_df['close'])
    plt.title(name)
    plt.xlabel('Date')
    plt.ylabel('Closing Price')
    plt.show()
```


AAL
Closing Price
0.00
0.05
0.10
0.15
0.20
2013-01 2013-07 2014-01 2014-07 2015-01 2015-07 2016-01 2016-07 2017-01 2017-07
Date


AAPL
Closing Price
0.3
0.4
0.5
0.6
0.7
2013-01 2013-07 2014-01 2014-07 2015-01 2015-07 2016-01 2016-07 2017-01 2017-07
Date


ABC
Closing Price
0.20
0.25
0.30
0.35
0.40
0.45
0.50
0.55
2013-01 2013-07 2014-01 2014-07 2015-01 2015-07 2016-01 2016-07 2017-01 2017-07
Date





In these graphs the trend is mostly upward and non-stationary, but there is variation between the graphs. some seasonal fluctations? there is also noise. additive or multiplicative?

5) Modelling

Model 1 - ARMA

In [29]:
```
import statsmodels.api as sm
import itertools
from sklearn.metrics import mean_squared_error


import warnings
from statsmodels.tools.sm_exceptions import ConvergenceWarning
warnings.simplefilter('ignore', ConvergenceWarning)
warnings.filterwarnings("ignore")

# Create a dictionary to store the ARMA models for each stock
arma_models = {}

# Define the orders to test for the ARMA model
p = range(0, 3)
```

```
q = range(0, 3)
orders = list(itertools.product(p, q))

# Loop through each stock in the dataframe
for stock in df_train['name'].unique():

    # Filter the dataframe to only include the current stock
    stock_df = df_train[df_train['name'] == stock]['close']

    # Train multiple ARMA models with different orders
    best_aic = float('inf')
    best_order = None
    best_model = None

    for order in orders:
        try:
            arma_model = sm.tsa.SARIMAX(stock_df, order=(order[0], 0, order[1])
            if arma_model.aic < best_aic:
                best_aic = arma_model.aic
                best_order = order
                best_model = arma_model
        except Exception as e:
            print(f"Error fitting ARMA model for {stock} with order {order}: {e
            continue

    # Store the best model in the dictionary with the stock name as the key
    arma_models[stock] = best_model

    # Print the summary of the best model
    if best_model is not None:
        print(f"Summary of best ARMA model for {stock}:")
        print(best_model.summary())

    # Predict the test data using the best model
    if stock in df_test['name'].unique():
        test_stock_df = df_test[df_test['name'] == stock]['close']
        pred = best_model.predict(start=len(df_train), end=len(df_train)+len(te
        mse_score = mean_squared_error(test_stock_df, pred)
        print(f"MSE score for {stock}: {mse_score}")
```

```
This problem is unconstrained.

Warning:  more than 10 function and gradient
  evaluations in the last line search.  Termination
  may possibly be caused by a bad search direction.
This problem is unconstrained.
```

```
RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =            1     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f= -5.63177D-01    |proj g|=  5.26734D-04

           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    1      1     15      1     0     0   5.267D-04  -5.632D-01
  F = -0.56317684922351330

CONVERGENCE: REL_REDUCTION_OF_F_<=_FACTR*EPSMCH
RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =            2     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f= -5.63175D-01    |proj g|=  9.96082D-01

At iterate    5    f= -1.21033D+00    |proj g|=  3.25768D-01

At iterate   10    f= -1.23144D+00    |proj g|=  7.43214D-03

           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    2     13     25      1     0     0   3.146D-08  -1.231D+00
  F =  -1.2314519411011695

CONVERGENCE: NORM_OF_PROJECTED_GRADIENT_<=_PGTOL
```

```
RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =            3     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f= -5.63171D-01    |proj g|=  9.93770D-01

At iterate    5    f= -1.73383D+00    |proj g|=  3.39349D+00

At iterate   10    f= -1.80066D+00    |proj g|=  9.12714D-03
 This problem is unconstrained.
At iterate   15    f= -1.80085D+00    |proj g|=  1.45080D-01

At iterate   20    f= -1.80150D+00    |proj g|=  2.91669D-03

           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    3     23     32      1     0     0   7.017D-07  -1.802D+00
  F =  -1.8015038721509726

CONVERGENCE: NORM_OF_PROJECTED_GRADIENT_<=_PGTOL
RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =            2     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  4.45109D+02    |proj g|=  1.94835D+05
 This problem is unconstrained.
```

```
At iterate    5    f= -2.21919D+00    |proj g|=  1.00354D+01

At iterate   10    f= -3.20703D+00    |proj g|=  9.18208D+00

At iterate   15    f= -3.89313D+00    |proj g|=  3.47092D+01

At iterate   20    f= -3.95637D+00    |proj g|=  1.29596D+00

At iterate   25    f= -3.96072D+00    |proj g|=  7.62511D-01

At iterate   30    f= -3.96089D+00    |proj g|=  2.24243D-05

           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    2     32     71      1     0     0   2.776D-03  -3.961D+00
  F =  -3.9608871899371181

CONVERGENCE: REL_REDUCTION_OF_F_<=_FACTR*EPSMCH
RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =            3     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  3.96620D+02    |proj g|=  1.73892D+05

At iterate    5    f= -2.10116D+00    |proj g|=  6.54147D+00
```

```
 This problem is unconstrained.
```

```
At iterate   10    f= -3.01409D+00    |proj g|=  8.21307D+00

At iterate   15    f= -3.01719D+00    |proj g|=  5.28515D-01

At iterate   20    f= -3.69171D+00    |proj g|=  3.10711D+01

At iterate   25    f= -3.93886D+00    |proj g|=  1.25370D+01

At iterate   30    f= -3.96008D+00    |proj g|=  4.24147D-01

At iterate   35    f= -3.96266D+00    |proj g|=  3.04308D-01

           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    3     39     96      1     0     0   2.354D-02  -3.963D+00
  F =  -3.9626799650870326

CONVERGENCE: REL_REDUCTION_OF_F_<=_FACTR*EPSMCH
RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =            4     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  3.68898D+02    |proj g|=  1.61850D+05
```

```
 Warning:  more than 10 function and gradient
   evaluations in the last line search.  Termination
   may possibly be caused by a bad search direction.
 This problem is unconstrained.
```

```
At iterate    5    f= -2.01905D+00    |proj g|=  5.46834D+00

At iterate   10    f= -2.88812D+00    |proj g|=  5.47683D+00

At iterate   15    f= -3.01584D+00    |proj g|=  2.35858D+01

At iterate   20    f= -3.75926D+00    |proj g|=  4.27289D+00

At iterate   25    f= -3.76487D+00    |proj g|=  2.53707D+00

At iterate   30    f= -3.80299D+00    |proj g|=  2.40521D+01

At iterate   35    f= -3.92165D+00    |proj g|=  2.04802D+01

At iterate   40    f= -3.93757D+00    |proj g|=  1.88793D+01

At iterate   45    f= -3.96200D+00    |proj g|=  2.72766D+00

At iterate   50    f= -3.96338D+00    |proj g|=  3.83997D-01

           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    4     50     85      1     0     0   3.840D-01  -3.963D+00
  F =  -3.9633840949170689

STOP: TOTAL NO. of ITERATIONS REACHED LIMIT
RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =            3     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  4.46438D+02    |proj g|=  1.95700D+05
 This problem is unconstrained.
```

```
At iterate    5    f= -2.32297D+00    |proj g|=  9.53873D+00

At iterate   10    f= -3.47017D+00    |proj g|=  2.57549D+01

At iterate   15    f= -3.61146D+00    |proj g|=  7.79588D-01

At iterate   20    f= -3.61217D+00    |proj g|=  1.46978D-02

At iterate   25    f= -3.61517D+00    |proj g|=  3.63556D+00

At iterate   30    f= -3.95417D+00    |proj g|=  7.02066D-01

At iterate   35    f= -3.96232D+00    |proj g|=  3.49144D-01

At iterate   40    f= -3.96280D+00    |proj g|=  1.27008D-01

At iterate   45    f= -3.96281D+00    |proj g|=  6.41147D-05

           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    3     45     84      1     0     0   6.411D-05  -3.963D+00
  F =  -3.9628080378647197

CONVERGENCE: REL_REDUCTION_OF_F_<=_FACTR*EPSMCH
RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =            4     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  1.94402D+03    |proj g|=  8.46153D+05
```

```
 This problem is unconstrained.
```

```
  ys=-5.286E-01  -gs= 1.113E+00 BFGS update SKIPPED

At iterate    5    f= -3.88486D-01    |proj g|=  2.34549D+00
  ys=-7.792E+00  -gs= 1.337E+00 BFGS update SKIPPED

At iterate   10    f= -3.65523D+00    |proj g|=  1.91960D+00

At iterate   15    f= -3.94174D+00    |proj g|=  4.35151D+00

At iterate   20    f= -3.96018D+00    |proj g|=  2.62834D-01

At iterate   25    f= -3.96078D+00    |proj g|=  1.51888D-01

At iterate   30    f= -3.96078D+00    |proj g|=  4.73424D-03

At iterate   35    f= -3.96078D+00    |proj g|=  7.62542D-02

At iterate   40    f= -3.96079D+00    |proj g|=  7.82758D-01

At iterate   45    f= -3.96089D+00    |proj g|=  1.66703D-01

           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    4     48    104      1     2     0   1.233D-03  -3.961D+00
  F =  -3.9608892824787967

CONVERGENCE: REL_REDUCTION_OF_F_<=_FACTR*EPSMCH
RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =            5     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  2.08335D+02    |proj g|=  9.21649D+04
```

```
 Warning:  more than 10 function and gradient
   evaluations in the last line search.  Termination
   may possibly be caused by a bad search direction.
 This problem is unconstrained.
```

```
  ys=-1.617E+00  -gs= 8.840E-01 BFGS update SKIPPED

At iterate    5    f= -1.03966D+00    |proj g|=  4.11516D+00

At iterate   10    f= -3.22850D+00    |proj g|=  1.52645D+00

At iterate   15    f= -3.53216D+00    |proj g|=  1.99493D+01

At iterate   20    f= -3.53663D+00    |proj g|=  1.36531D+00

At iterate   25    f= -3.54562D+00    |proj g|=  1.58203D+01

At iterate   30    f= -3.94877D+00    |proj g|=  1.43810D+01

At iterate   35    f= -3.95078D+00    |proj g|=  1.43779D+00

At iterate   40    f= -3.95465D+00    |proj g|=  2.52533D+00

At iterate   45    f= -3.95840D+00    |proj g|=  6.06711D-01

At iterate   50    f= -3.95849D+00    |proj g|=  2.60106D-03

           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    5     50     91      1     1     0   2.601D-03  -3.958D+00
  F =  -3.9584937690586632

STOP: TOTAL NO. of ITERATIONS REACHED LIMIT
Summary of best ARMA model for AAL:
                               SARIMAX Results
==============================================================================
Dep. Variable:                  close   No. Observations:                 1085
Model:               SARIMAX(2, 0, 0)   Log Likelihood                4299.647
Date:                Sun, 26 Mar 2023   AIC                          -8593.293
Time:                        15:52:43   BIC                          -8578.325
Sample:                             0   HQIC                         -8587.627
                               - 1085
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          1.0613      0.027     39.869      0.000       1.009       1.113
ar.L2         -0.0619      0.027     -2.325      0.020      -0.114      -0.010
sigma2      2.098e-05   6.22e-07     33.721      0.000    1.98e-05    2.22e-05
==============================================================================
=====
Ljung-Box (L1) (Q):                   0.01   Jarque-Bera (JB):              2
52.97
Prob(Q):                              0.91   Prob(JB):
```

```
0.00
Heteroskedasticity (H):               2.04   Skew:
-0.26
Prob(H) (two-sided):                  0.00   Kurtosis:
5.31
===============================================================================
=====

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex
-step).
MSE score for AAL: 2500.3323356590035
RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =            1     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  6.95168D-01    |proj g|=  4.25250D-05
```

```
 This problem is unconstrained.

 Warning:  more than 10 function and gradient
   evaluations in the last line search.  Termination
   may possibly be caused by a bad search direction.
 This problem is unconstrained.
```

```
           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    1      1     16      1     0     0   4.251D-05   6.952D-01
  F =  0.69516781542909423

CONVERGENCE: REL_REDUCTION_OF_F_<=_FACTR*EPSMCH
RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =            2     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  6.95169D-01    |proj g|=  9.96564D-01

At iterate    5    f=  7.81857D-02    |proj g|=  2.81223D-01

At iterate   10    f=  1.73546D-02    |proj g|=  6.21207D-02

At iterate   15    f=  1.40729D-02    |proj g|=  5.31804D-03

           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    2     17     26      1     0     0   1.577D-05   1.407D-02
  F =   1.4072072105632067E-002

CONVERGENCE: REL_REDUCTION_OF_F_<=_FACTR*EPSMCH
RUNNING THE L-BFGS-B CODE

           * * *
```

```
 This problem is unconstrained.
```

```
Machine precision = 2.220D-16
 N =            3     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  6.95172D-01    |proj g|=  9.94408D-01

At iterate    5    f= -5.39876D-01    |proj g|=  4.58850D-01

At iterate   10    f= -5.90641D-01    |proj g|=  2.16742D-03

At iterate   15    f= -5.90676D-01    |proj g|=  4.16572D-02
```

```
 Bad direction in the line search;
   refresh the lbfgs memory and restart the iteration.

 Warning:  more than 10 function and gradient
   evaluations in the last line search.  Termination
   may possibly be caused by a bad search direction.
 This problem is unconstrained.
```

```
           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    3     19     63      2     0     0   2.681D-04  -5.907D-01
  F = -0.59068791256200581

CONVERGENCE: REL_REDUCTION_OF_F_<=_FACTR*EPSMCH
RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =            2     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  1.89770D+03    |proj g|=  4.82636D+05

At iterate    5    f=  9.61300D-04    |proj g|=  1.26399D+00
  ys=-2.566E-01  -gs= 7.977E-01 BFGS update SKIPPED

At iterate   10    f= -3.40228D+00    |proj g|=  3.75506D+00

At iterate   15    f= -3.41186D+00    |proj g|=  7.95623D+00

At iterate   20    f= -3.42078D+00    |proj g|=  1.56461D+00

At iterate   25    f= -3.42152D+00    |proj g|=  1.87582D-01

           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    2     29     65      1     1     0   2.743D-04  -3.422D+00
  F =  -3.4215358296276110

CONVERGENCE: REL_REDUCTION_OF_F_<=_FACTR*EPSMCH
RUNNING THE L-BFGS-B CODE

           * * *
```

```
Machine precision = 2.220D-16
 N =            3     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  1.82465D+03    |proj g|=  4.63887D+05
```

```
 Warning:  more than 10 function and gradient
   evaluations in the last line search.  Termination
   may possibly be caused by a bad search direction.
 This problem is unconstrained.
```

```
At iterate    5    f= -1.25719D+00    |proj g|=  3.10693D+00

At iterate   10    f= -2.47564D+00    |proj g|=  1.23983D+01

At iterate   15    f= -2.60557D+00    |proj g|=  2.25598D+00

At iterate   20    f= -3.33351D+00    |proj g|=  6.52266D+01

At iterate   25    f= -3.41358D+00    |proj g|=  5.79943D-01

At iterate   30    f= -3.42050D+00    |proj g|=  3.72798D-01

At iterate   35    f= -3.42170D+00    |proj g|=  2.66385D-02

At iterate   40    f= -3.42178D+00    |proj g|=  5.70236D-04

           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    3     40     78      1     0     0   5.702D-04  -3.422D+00
  F =  -3.4217782475748235

CONVERGENCE: REL_REDUCTION_OF_F_<=_FACTR*EPSMCH
RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =            4     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  1.87401D+03    |proj g|=  4.75944D+05
```

```
 This problem is unconstrained.
```

```
At iterate    5    f= -6.78481D-01    |proj g|=  4.91206D+00

At iterate   10    f= -2.18645D+00    |proj g|=  5.32706D+00

At iterate   15    f= -2.83060D+00    |proj g|=  2.82817D+00

At iterate   20    f= -3.32333D+00    |proj g|=  4.82425D+00

At iterate   25    f= -3.40366D+00    |proj g|=  2.52109D+00

At iterate   30    f= -3.41227D+00    |proj g|=  2.64470D-01

At iterate   35    f= -3.41737D+00    |proj g|=  8.88475D+00

At iterate   40    f= -3.42156D+00    |proj g|=  1.64763D+00

At iterate   45    f= -3.42183D+00    |proj g|=  2.25526D-01
```

```
Warning:  more than 10 function and gradient
  evaluations in the last line search.  Termination
  may possibly be caused by a bad search direction.
This problem is unconstrained.
```

```
           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    4     48    100      1     0     0   2.450D-02  -3.422D+00
  F =  -3.4218294294125817

CONVERGENCE: REL_REDUCTION_OF_F_<=_FACTR*EPSMCH
RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =            3     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  1.89696D+03    |proj g|=  4.82354D+05

At iterate    5    f= -1.03181D+00    |proj g|=  3.31669D+00

At iterate   10    f= -2.65325D+00    |proj g|=  2.58064D+01

At iterate   15    f= -3.06888D+00    |proj g|=  3.68620D+00

At iterate   20    f= -3.07548D+00    |proj g|=  1.15273D-02

At iterate   25    f= -3.07555D+00    |proj g|=  3.77603D-01

At iterate   30    f= -3.35754D+00    |proj g|=  3.67246D+01

At iterate   35    f= -3.41826D+00    |proj g|=  2.30300D+00

At iterate   40    f= -3.42163D+00    |proj g|=  4.15878D-02

At iterate   45    f= -3.42177D+00    |proj g|=  7.65864D-03
```

```
 Warning:  more than 10 function and gradient
   evaluations in the last line search.  Termination
   may possibly be caused by a bad search direction.
 This problem is unconstrained.
```

```
           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    3     46    104      1     0     0   7.659D-03  -3.422D+00
  F =  -3.4217731597268064

CONVERGENCE: REL_REDUCTION_OF_F_<=_FACTR*EPSMCH
RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =            4     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  6.04586D+02    |proj g|=  1.54302D+05

At iterate    5    f= -1.50301D+00    |proj g|=  1.17936D+00

At iterate   10    f= -3.13580D+00    |proj g|=  2.58615D+01

At iterate   15    f= -3.36572D+00    |proj g|=  1.75047D+00

At iterate   20    f= -3.37806D+00    |proj g|=  1.30514D-01

At iterate   25    f= -3.39449D+00    |proj g|=  1.14040D+00

At iterate   30    f= -3.41439D+00    |proj g|=  1.64324D+00
  ys=-2.833E-01  -gs= 1.790E-04 BFGS update SKIPPED

At iterate   35    f= -3.41460D+00    |proj g|=  3.76100D-02
```

```
 Bad direction in the line search;
   refresh the lbfgs memory and restart the iteration.

 Line search cannot locate an adequate point after MAXLS
  function and gradient evaluations.
  Previous x, f and g restored.
 Possible causes: 1 error in function or gradient evaluation;
                  2 rounding error dominate computation.
```

```
           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    4     36    142      2     1     0   3.761D-02  -3.415D+00
  F =  -3.4145957632653183

ABNORMAL_TERMINATION_IN_LNSRCH
RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =            5     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  3.67485D+06    |proj g|=  9.31810D+08
 This problem is unconstrained.
```

```
At iterate    5    f=  1.69197D+01    |proj g|=  3.96336D+01

At iterate   10    f=  1.93757D+00    |proj g|=  1.34899D+00

At iterate   15    f= -7.38877D-01    |proj g|=  8.86517D-01

At iterate   20    f= -1.26155D+00    |proj g|=  5.59920D+00
  ys=-1.364E+00  -gs= 8.036E-01 BFGS update SKIPPED

At iterate   25    f= -3.34339D+00    |proj g|=  9.39311D+00

At iterate   30    f= -3.37319D+00    |proj g|=  5.10216D+00

At iterate   35    f= -3.41420D+00    |proj g|=  1.62455D-01

At iterate   40    f= -3.41757D+00    |proj g|=  5.75209D-01

At iterate   45    f= -3.41769D+00    |proj g|=  3.06491D-01

           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    5     47     93      1     1     0   1.186D-01  -3.418D+00
  F =  -3.4176971114059382

CONVERGENCE: REL_REDUCTION_OF_F_<=_FACTR*EPSMCH
Summary of best ARMA model for AAPL:
                               SARIMAX Results
==============================================================================
Dep. Variable:                  close   No. Observations:                 1085
Model:               SARIMAX(1, 0, 0)   Log Likelihood                3712.366
Date:                Sun, 26 Mar 2023   AIC                          -7420.733
Time:                        15:52:50   BIC                          -7410.754
Sample:                             0   HQIC                         -7416.955
                               - 1085
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.9999      0.000   4235.288      0.000       0.999       1.000
sigma2      6.189e-05   1.59e-06     38.812      0.000    5.88e-05     6.5e-05
==============================================================================
=====
Ljung-Box (L1) (Q):                   0.40   Jarque-Bera (JB):                5
86.54
Prob(Q):                              0.53   Prob(JB):
0.00
Heteroskedasticity (H):               1.85   Skew:
-0.12
Prob(H) (two-sided):                  0.00   Kurtosis:
```

```
6.59
==============================================================================
=====

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex
-step).
MSE score for AAPL: 25897.155535940266
RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =            1     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  4.39471D-01    |proj g|=  7.09145D-05

           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    1      1     17      1     0     0   7.091D-05   4.395D-01
  F =  0.43947114509010526

CONVERGENCE: REL_REDUCTION_OF_F_<=_FACTR*EPSMCH
RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =            2     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  7.34704D-02    |proj g|=  1.95942D+00

At iterate    5    f= -2.26670D-01    |proj g|=  2.24359D-01

At iterate   10    f= -2.41771D-01    |proj g|=  5.63611D-02
```

```
 This problem is unconstrained.

 Warning:  more than 10 function and gradient
   evaluations in the last line search.  Termination
   may possibly be caused by a bad search direction.
 This problem is unconstrained.
```

```
At iterate   15    f= -2.42608D-01    |proj g|=  1.14770D-02

           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    2     19     27      1     0     0   7.349D-06  -2.426D-01
  F = -0.24262004509623164

CONVERGENCE: NORM_OF_PROJECTED_GRADIENT_<=_PGTOL
RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =            3     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  4.74293D-03    |proj g|=  2.34037D+00

At iterate    5    f= -6.40629D-01    |proj g|=  2.25224D-01
 This problem is unconstrained.
At iterate   10    f= -6.82793D-01    |proj g|=  2.72141D+00

At iterate   15    f= -7.56126D-01    |proj g|=  6.67397D-04

At iterate   20    f= -7.56128D-01    |proj g|=  2.50484D-02

At iterate   25    f= -7.56322D-01    |proj g|=  1.64471D-01

At iterate   30    f= -7.56514D-01    |proj g|=  7.45930D-04
 Bad direction in the line search;
   refresh the lbfgs memory and restart the iteration.

 Line search cannot locate an adequate point after MAXLS
  function and gradient evaluations.
  Previous x, f and g restored.
 Possible causes: 1 error in function or gradient evaluation;
                  2 rounding error dominate computation.
 This problem is unconstrained.
```

```
           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    3     32     89      2     0     0   1.146D-04  -7.565D-01
  F = -0.75651389655353907

ABNORMAL_TERMINATION_IN_LNSRCH
RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =            2     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  2.06724D+03    |proj g|=  7.08137D+05

At iterate    5    f= -2.58322D+00    |proj g|=  2.38301D+01

At iterate   10    f= -3.47577D+00    |proj g|=  1.15388D+02

At iterate   15    f= -3.68612D+00    |proj g|=  3.77684D+00

At iterate   20    f= -3.71852D+00    |proj g|=  4.57479D-01

At iterate   25    f= -3.72099D+00    |proj g|=  4.62438D-01

At iterate   30    f= -3.72118D+00    |proj g|=  4.78361D-04

           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    2     31     72      1     0     0   2.397D-05  -3.721D+00
  F =  -3.7211789417505607

CONVERGENCE: REL_REDUCTION_OF_F_<=_FACTR*EPSMCH
RUNNING THE L-BFGS-B CODE

           * * *
```

```
Machine precision = 2.220D-16
 N =            3     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  2.09754D+03    |proj g|=  7.17576D+05
 This problem is unconstrained.
At iterate    5    f= -1.28467D+00    |proj g|=  1.16640D+00

At iterate   10    f= -2.70103D+00    |proj g|=  5.12051D+00

At iterate   15    f= -3.16217D+00    |proj g|=  3.41660D+00

At iterate   20    f= -3.18779D+00    |proj g|=  8.57610D+00

At iterate   25    f= -3.70973D+00    |proj g|=  2.12382D+01

At iterate   30    f= -3.71944D+00    |proj g|=  3.76619D-01

At iterate   35    f= -3.72056D+00    |proj g|=  3.73904D+00

At iterate   40    f= -3.72120D+00    |proj g|=  7.87553D-01

           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    3     44     97      1     0     0   8.070D-03  -3.721D+00
  F =  -3.7212082416370458

CONVERGENCE: REL_REDUCTION_OF_F_<=_FACTR*EPSMCH
RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =            4     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  1.96666D+03    |proj g|=  6.72170D+05
 Warning:  more than 10 function and gradient
   evaluations in the last line search.  Termination
   may possibly be caused by a bad search direction.
 This problem is unconstrained.
```

```
At iterate    5    f= -1.49474D+00    |proj g|=  5.28693D+00

At iterate   10    f= -2.88671D+00    |proj g|=  2.51914D+00

At iterate   15    f= -2.96518D+00    |proj g|=  4.22387D-01

At iterate   20    f= -3.26474D+00    |proj g|=  2.20388D+01

At iterate   25    f= -3.61798D+00    |proj g|=  8.64903D-01

At iterate   30    f= -3.63013D+00    |proj g|=  1.31105D+00

At iterate   35    f= -3.64888D+00    |proj g|=  8.89536D+00

At iterate   40    f= -3.71264D+00    |proj g|=  8.64835D+00

At iterate   45    f= -3.72092D+00    |proj g|=  4.25377D-01

At iterate   50    f= -3.72172D+00    |proj g|=  1.26806D-01

           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    4     50     91      1     0     0   1.268D-01  -3.722D+00
  F =  -3.7217246946379170

STOP: TOTAL NO. of ITERATIONS REACHED LIMIT
RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =            3     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  2.06552D+03    |proj g|=  7.07257D+05
 This problem is unconstrained.
At iterate    5    f= -8.96283D-01    |proj g|=  4.85152D+00

At iterate   10    f= -3.02319D+00    |proj g|=  3.76053D+00

At iterate   15    f= -3.37693D+00    |proj g|=  1.60420D+01

At iterate   20    f= -3.39220D+00    |proj g|=  3.20094D-01

At iterate   25    f= -3.39258D+00    |proj g|=  3.31674D-02
```

```
 Warning:  more than 10 function and gradient
   evaluations in the last line search.  Termination
   may possibly be caused by a bad search direction.
 This problem is unconstrained.
           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    3     28     76      1     0     0   7.452D-02  -3.393D+00
  F =  -3.3926002321547912

CONVERGENCE: REL_REDUCTION_OF_F_<=_FACTR*EPSMCH
RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =            4     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  2.06396D+03    |proj g|=  7.06456D+05

At iterate    5    f= -1.54811D+00    |proj g|=  1.15989D+01

At iterate   10    f= -3.52712D+00    |proj g|=  2.35663D+00

At iterate   15    f= -3.70347D+00    |proj g|=  4.59811D+00

At iterate   20    f= -3.71810D+00    |proj g|=  2.86669D-01

At iterate   25    f= -3.71975D+00    |proj g|=  2.99539D-01

At iterate   30    f= -3.71976D+00    |proj g|=  1.79169D-01
  ys=-3.197E-04  -gs= 3.565E-08 BFGS update SKIPPED
 Bad direction in the line search;
   refresh the lbfgs memory and restart the iteration.

 Warning:  more than 10 function and gradient
   evaluations in the last line search.  Termination
   may possibly be caused by a bad search direction.
 This problem is unconstrained.
```

```
           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    4     31    135      2     1     0   1.792D-01  -3.720D+00
  F =  -3.7197590437067625

CONVERGENCE: REL_REDUCTION_OF_F_<=_FACTR*EPSMCH
RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =            5     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  2.16971D+03    |proj g|=  7.41441D+05
  ys=-3.430E-01  -gs= 1.111E+00 BFGS update SKIPPED

At iterate    5    f= -4.93525D-01    |proj g|=  2.88149D+00
  ys=-5.171E+00  -gs= 9.919E-01 BFGS update SKIPPED

At iterate   10    f= -3.25051D+00    |proj g|=  3.12147D+01

At iterate   15    f= -3.30131D+00    |proj g|=  2.41104D+00

At iterate   20    f= -3.69097D+00    |proj g|=  2.01094D+01

At iterate   25    f= -3.70209D+00    |proj g|=  2.94193D+00

At iterate   30    f= -3.72044D+00    |proj g|=  1.22724D+00

At iterate   35    f= -3.72142D+00    |proj g|=  8.69372D-03

           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    5     35     94      1     2     0   8.694D-03  -3.721D+00
  F =  -3.7214177954169956
```

```
CONVERGENCE: REL_REDUCTION_OF_F_<=_FACTR*EPSMCH
Summary of best ARMA model for ABC:
                               SARIMAX Results
==============================================================================
Dep. Variable:                  close   No. Observations:                 1085
Model:               SARIMAX(1, 0, 0)   Log Likelihood                4037.479
Date:                Sun, 26 Mar 2023   AIC                          -8070.958
Time:                        15:52:55   BIC                          -8060.980
Sample:                             0   HQIC                         -8067.181
                               - 1085
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.9998      0.000   3169.397      0.000       0.999       1.000
sigma2      3.399e-05   4.89e-07     69.451      0.000     3.3e-05     3.5e-05
==============================================================================
=====
Ljung-Box (L1) (Q):                   0.10   Jarque-Bera (JB):             114
74.03
Prob(Q):                              0.75   Prob(JB):
0.00
Heteroskedasticity (H):               5.79   Skew:
-0.35
Prob(H) (two-sided):                  0.00   Kurtosis:
18.92
==============================================================================
=====

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex
-step).
MSE score for ABC: 7647.104895228071
RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =            1     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  1.03696D+00    |proj g|=  2.14672D-05

           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    1      1     11      1     0     0   2.145D-05   1.037D+00
  F =   1.0369568733519654
```

```
CONVERGENCE: REL_REDUCTION_OF_F_<=_FACTR*EPSMCH
 Warning:  more than 10 function and gradient
   evaluations in the last line search.  Termination
   may possibly be caused by a bad search direction.
 This problem is unconstrained.
 This problem is unconstrained.
 This problem is unconstrained.
RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =            2     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  1.03696D+00    |proj g|=  9.96913D-01

At iterate    5    f=  3.84556D-01    |proj g|=  2.75650D-02

At iterate   10    f=  3.59754D-01    |proj g|=  4.65689D-03

At iterate   15    f=  3.57967D-01    |proj g|=  1.80161D-03

           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    2     17     24      1     0     0   3.366D-07   3.580D-01
  F =  0.35796719152715345

CONVERGENCE: NORM_OF_PROJECTED_GRADIENT_<=_PGTOL
RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =            3     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  5.99922D-01    |proj g|=  1.29192D+00

At iterate    5    f= -1.74274D-01    |proj g|=  2.06233D+00

At iterate   10    f= -2.31865D-01    |proj g|=  6.77435D-02

At iterate   15    f= -2.32848D-01    |proj g|=  3.17593D-03
```

```
Bad direction in the line search;
  refresh the lbfgs memory and restart the iteration.

Line search cannot locate an adequate point after MAXLS
 function and gradient evaluations.
 Previous x, f and g restored.
Possible causes: 1 error in function or gradient evaluation;
                 2 rounding error dominate computation.
This problem is unconstrained.
```

```
           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    3     18     64      2     0     0   1.378D-04  -2.329D-01
  F = -0.23285267762358666

ABNORMAL_TERMINATION_IN_LNSRCH
RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =            2     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  1.43470D+03    |proj g|=  2.25674D+05

At iterate    5    f= -1.28235D+00    |proj g|=  2.89243D+00

At iterate   10    f= -2.60585D+00    |proj g|=  1.60212D+00

At iterate   15    f= -2.89850D+00    |proj g|=  1.65832D+00

At iterate   20    f= -2.93842D+00    |proj g|=  3.22398D-01

At iterate   25    f= -2.94163D+00    |proj g|=  2.93106D-01

At iterate   30    f= -2.94177D+00    |proj g|=  6.20897D-04

           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    2     32     62      1     0     0   1.359D-06  -2.942D+00
  F =  -2.9417651716849273

CONVERGENCE: NORM_OF_PROJECTED_GRADIENT_<=_PGTOL
RUNNING THE L-BFGS-B CODE

           * * *
```

```
Machine precision = 2.220D-16
 N =            3     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  1.38190D+03    |proj g|=  2.17125D+05
 This problem is unconstrained.
At iterate    5    f= -1.58573D+00    |proj g|=  9.08294D+00

At iterate   10    f= -2.34375D+00    |proj g|=  4.34504D+00

At iterate   15    f= -2.74455D+00    |proj g|=  3.19169D+01

At iterate   20    f= -2.92021D+00    |proj g|=  3.99404D+00

At iterate   25    f= -2.94025D+00    |proj g|=  7.25078D-01

At iterate   30    f= -2.94184D+00    |proj g|=  1.93504D-01

At iterate   35    f= -2.94193D+00    |proj g|=  1.10083D-02

           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    3     36     63      1     0     0   8.967D-03  -2.942D+00
  F =  -2.9419272077431575

CONVERGENCE: REL_REDUCTION_OF_F_<=_FACTR*EPSMCH
RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =            4     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  1.58913D+03    |proj g|=  2.49815D+05
 This problem is unconstrained.
```

```
At iterate    5    f= -9.45637D-01    |proj g|=  7.85781D+00

At iterate   10    f= -1.64220D+00    |proj g|=  6.52824D-01

At iterate   15    f= -2.43758D+00    |proj g|=  2.43580D+01

At iterate   20    f= -2.53114D+00    |proj g|=  8.18867D-01

At iterate   25    f= -2.56314D+00    |proj g|=  5.38525D+00

At iterate   30    f= -2.93188D+00    |proj g|=  1.05862D+01

At iterate   35    f= -2.93856D+00    |proj g|=  1.18276D+00

At iterate   40    f= -2.94056D+00    |proj g|=  1.93773D+00

At iterate   45    f= -2.94125D+00    |proj g|=  2.29668D+00

At iterate   50    f= -2.94412D+00    |proj g|=  3.20240D-01

           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    4     50     77      1     0     0   3.202D-01  -2.944D+00
  F =  -2.9441204535127010

STOP: TOTAL NO. of ITERATIONS REACHED LIMIT
RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =            3     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  1.43383D+03    |proj g|=  2.25468D+05

At iterate    5    f= -1.82243D+00    |proj g|=  4.85574D+00
 This problem is unconstrained.
```

```
At iterate   10    f= -2.59310D+00    |proj g|=  1.14735D+00

At iterate   15    f= -2.60434D+00    |proj g|=  8.23307D-03

At iterate   20    f= -2.60449D+00    |proj g|=  4.45710D-01

At iterate   25    f= -2.88607D+00    |proj g|=  2.33475D+01

At iterate   30    f= -2.93752D+00    |proj g|=  7.99435D-01

At iterate   35    f= -2.94177D+00    |proj g|=  1.27566D-02
```

```
Warning:  more than 10 function and gradient
  evaluations in the last line search.  Termination
  may possibly be caused by a bad search direction.
This problem is unconstrained.
```

```
At iterate   40    f= -2.94190D+00    |proj g|=  6.75818D-03

           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    3     40     95      1     0     0   6.758D-03  -2.942D+00
  F =  -2.9419032219365810

CONVERGENCE: REL_REDUCTION_OF_F_<=_FACTR*EPSMCH
RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =            4     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  1.43868D+03    |proj g|=  2.26610D+05

At iterate    5    f= -1.36299D+00    |proj g|=  2.16641D+01

At iterate   10    f= -2.81795D+00    |proj g|=  3.12833D+01

At iterate   15    f= -2.91403D+00    |proj g|=  1.56683D+00

At iterate   20    f= -2.93353D+00    |proj g|=  6.60428D-01

At iterate   25    f= -2.93732D+00    |proj g|=  6.06072D-02

           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    4     27     61      1     0     0   3.113D-02  -2.937D+00
  F =  -2.9374348334511433

CONVERGENCE: REL_REDUCTION_OF_F_<=_FACTR*EPSMCH
RUNNING THE L-BFGS-B CODE

           * * *
```

```
Machine precision = 2.220D-16
 N =            5     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  1.70866D+03    |proj g|=  2.68572D+05
```

```
 This problem is unconstrained.
```

```
  ys=-1.606E+00  -gs= 9.784E-01 BFGS update SKIPPED

At iterate    5    f= -2.35801D+00    |proj g|=  5.37861D-01

At iterate   10    f= -2.76840D+00    |proj g|=  4.16295D+00

At iterate   15    f= -2.92387D+00    |proj g|=  1.44228D-01

At iterate   20    f= -2.92394D+00    |proj g|=  1.02472D+00

At iterate   25    f= -2.92881D+00    |proj g|=  7.03905D+00

At iterate   30    f= -2.93725D+00    |proj g|=  1.43219D+00

           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    5     31     57      1     1     0   1.432D+00  -2.937D+00
  F =  -2.9372527918357996

CONVERGENCE: REL_REDUCTION_OF_F_<=_FACTR*EPSMCH
Summary of best ARMA model for AAP:
                               SARIMAX Results
==============================================================================
Dep. Variable:                  close   No. Observations:                 1085
Model:               SARIMAX(1, 0, 2)   Log Likelihood                3194.371
Date:                Sun, 26 Mar 2023   AIC                          -6380.741
Time:                        15:52:59   BIC                          -6360.784
Sample:                             0   HQIC                         -6373.186
                               - 1085
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.9997      0.000   2120.353      0.000       0.999       1.001
ma.L1          0.0133      0.033      0.404      0.687      -0.051       0.078
ma.L2         -0.0635      0.027     -2.345      0.019      -0.117      -0.010
sigma2         0.0002   1.63e-06     99.241      0.000       0.000       0.000
==============================================================================
=====
Ljung-Box (L1) (Q):                   0.01   Jarque-Bera (JB):               601
79.77
Prob(Q):                              0.92   Prob(JB):
0.00
Heteroskedasticity (H):               2.21   Skew:
-0.30
Prob(H) (two-sided):                  0.00   Kurtosis:
39.48
==============================================================================
=====
```

```
Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex
-step).
MSE score for AAP: 10768.315414664408
RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =            1     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f= -1.91402D-02    |proj g|=  1.77447D-04

           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    1      1     15      1     0     0   1.774D-04  -1.914D-02
  F =  -1.9140238166426338E-002

CONVERGENCE: REL_REDUCTION_OF_F_<=_FACTR*EPSMCH
RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =            2     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f= -3.87943D-01    |proj g|=  3.12543D+00

At iterate    5    f= -6.95944D-01    |proj g|=  1.93678D-01
```

```
 This problem is unconstrained.

 Warning:  more than 10 function and gradient
   evaluations in the last line search.  Termination
   may possibly be caused by a bad search direction.
 This problem is unconstrained.
```

```
At iterate   10    f= -6.98657D-01    |proj g|=  1.41320D-02

           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    2     14     26      1     0     0   3.607D-04  -6.987D-01
  F = -0.69866026150373650

CONVERGENCE: REL_REDUCTION_OF_F_<=_FACTR*EPSMCH
RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =            3     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f= -4.54065D-01    |proj g|=  3.69505D+00

At iterate    5    f= -1.21580D+00    |proj g|=  5.30011D+00
```

```
 This problem is unconstrained.
```

```
At iterate   10    f= -1.28521D+00    |proj g|=  1.56756D-01

At iterate   15    f= -1.28527D+00    |proj g|=  5.63986D-02

At iterate   20    f= -1.28589D+00    |proj g|=  6.63548D-01

At iterate   25    f= -1.28768D+00    |proj g|=  9.61065D-02

At iterate   30    f= -1.29070D+00    |proj g|=  2.04264D+00

At iterate   35    f= -1.30609D+00    |proj g|=  7.09093D-02

           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    3     39     54      1     0     0   1.208D-06  -1.306D+00
  F =  -1.3061005256212552

CONVERGENCE: NORM_OF_PROJECTED_GRADIENT_<=_PGTOL
RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =            2     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  1.12697D+03    |proj g|=  4.51851D+05

At iterate    5    f= -2.13262D+00    |proj g|=  3.42494D+01
 This problem is unconstrained.
```

```
At iterate   10    f= -3.42147D+00    |proj g|=  4.02662D+01

At iterate   15    f= -3.85206D+00    |proj g|=  1.46903D+01

At iterate   20    f= -3.87572D+00    |proj g|=  5.21264D-01

At iterate   25    f= -3.87764D+00    |proj g|=  7.09505D-02

At iterate   30    f= -3.87776D+00    |proj g|=  1.33695D-04

           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    2     31     64      1     0     0   9.041D-05  -3.878D+00
  F =  -3.8777611827802900

CONVERGENCE: REL_REDUCTION_OF_F_<=_FACTR*EPSMCH
RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =            3     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  1.18037D+03    |proj g|=  4.72760D+05
 This problem is unconstrained.
```

```
  ys=-6.762E-02  -gs= 7.131E-01 BFGS update SKIPPED

At iterate    5    f= -3.10550D-01    |proj g|=  6.48206D+00

At iterate   10    f= -3.13491D+00    |proj g|=  3.31099D+01

At iterate   15    f= -3.38530D+00    |proj g|=  1.36927D+01

At iterate   20    f= -3.77008D+00    |proj g|=  2.20387D+01

At iterate   25    f= -3.86901D+00    |proj g|=  3.06482D+00

At iterate   30    f= -3.87710D+00    |proj g|=  1.40526D+00

At iterate   35    f= -3.87800D+00    |proj g|=  6.36884D-02

At iterate   40    f= -3.87802D+00    |proj g|=  6.09147D-02

           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    3     40     75      1     1     0   6.091D-02  -3.878D+00
  F =  -3.8780210437723523

CONVERGENCE: REL_REDUCTION_OF_F_<=_FACTR*EPSMCH
RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =            4     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  1.24945D+03    |proj g|=  5.00477D+05
 This problem is unconstrained.
```

```
At iterate    5    f= -1.04323D+00    |proj g|=  1.33284D+00

At iterate   10    f= -2.73702D+00    |proj g|=  1.72254D+01

At iterate   15    f= -2.78273D+00    |proj g|=  2.95495D+00

At iterate   20    f= -3.33571D+00    |proj g|=  1.40761D+01

At iterate   25    f= -3.82294D+00    |proj g|=  1.04256D+01

At iterate   30    f= -3.84325D+00    |proj g|=  6.91221D-01

At iterate   35    f= -3.84846D+00    |proj g|=  3.40007D+00

At iterate   40    f= -3.87825D+00    |proj g|=  4.20006D-01

At iterate   45    f= -3.87831D+00    |proj g|=  8.28653D-01

At iterate   50    f= -3.87839D+00    |proj g|=  1.13850D-02

           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    4     50     95      1     0     0   1.138D-02  -3.878D+00
  F =  -3.8783850840965286

STOP: TOTAL NO. of ITERATIONS REACHED LIMIT
RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =            3     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  1.12672D+03    |proj g|=  4.51698D+05
  ys=-7.228E+00  -gs= 1.834E+00 BFGS update SKIPPED
 This problem is unconstrained.
```

```
At iterate    5    f= -2.48001D+00    |proj g|=  9.07147D+00

At iterate   10    f= -3.49994D+00    |proj g|=  5.91187D+00

At iterate   15    f= -3.55941D+00    |proj g|=  4.86307D-01

At iterate   20    f= -3.56000D+00    |proj g|=  2.28403D-02

At iterate   25    f= -3.56012D+00    |proj g|=  2.87268D-01

At iterate   30    f= -3.84374D+00    |proj g|=  4.95196D+01

At iterate   35    f= -3.87245D+00    |proj g|=  2.27184D+00

At iterate   40    f= -3.87749D+00    |proj g|=  9.56717D-01

At iterate   45    f= -3.87800D+00    |proj g|=  3.29201D-02
```

```
Warning:  more than 10 function and gradient
  evaluations in the last line search.  Termination
  may possibly be caused by a bad search direction.
This problem is unconstrained.
```

```
           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    3     47    103      1     1     0   2.769D-01  -3.878D+00
  F =  -3.8780073923270884

CONVERGENCE: REL_REDUCTION_OF_F_<=_FACTR*EPSMCH
RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =            4     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  1.12587D+03    |proj g|=  4.51193D+05

At iterate    5    f= -1.65889D+00    |proj g|=  3.02171D+00

At iterate   10    f= -3.12174D+00    |proj g|=  2.84949D+01

At iterate   15    f= -3.71812D+00    |proj g|=  2.82372D+01

At iterate   20    f= -3.86495D+00    |proj g|=  1.84096D+00

At iterate   25    f= -3.87527D+00    |proj g|=  2.00387D+00

At iterate   30    f= -3.87831D+00    |proj g|=  7.39882D-01

At iterate   35    f= -3.87838D+00    |proj g|=  1.27649D-01

           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    4     36    107      1     0     0   1.250D-01  -3.878D+00
  F =  -3.8783841963015897

CONVERGENCE: REL_REDUCTION_OF_F_<=_FACTR*EPSMCH
RUNNING THE L-BFGS-B CODE
```

```
           * * *

Machine precision = 2.220D-16
 N =            5     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  1.12855D+03    |proj g|=  4.52799D+05
```

```
 Warning:  more than 10 function and gradient
   evaluations in the last line search.  Termination
   may possibly be caused by a bad search direction.
 This problem is unconstrained.
```

```
At iterate    5    f= -1.34035D+00    |proj g|=  1.22484D+01

At iterate   10    f= -3.13153D+00    |proj g|=  3.17954D+01

At iterate   15    f= -3.32140D+00    |proj g|=  4.03264D-01

At iterate   20    f= -3.33449D+00    |proj g|=  1.16754D+01

At iterate   25    f= -3.86968D+00    |proj g|=  3.57769D+00

At iterate   30    f= -3.87016D+00    |proj g|=  4.21245D-01

At iterate   35    f= -3.87393D+00    |proj g|=  3.04728D-01

At iterate   40    f= -3.87431D+00    |proj g|=  3.60578D-01

At iterate   45    f= -3.87431D+00    |proj g|=  6.10923D-02

           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    5     47    100      1     0     0   5.422D-02  -3.874D+00
  F =  -3.8743102397723996

CONVERGENCE: REL_REDUCTION_OF_F_<=_FACTR*EPSMCH
Summary of best ARMA model for ABBV:
                               SARIMAX Results
==============================================================================
Dep. Variable:                  close   No. Observations:                 1085
Model:               SARIMAX(1, 0, 0)   Log Likelihood                4207.371
Date:                Sun, 26 Mar 2023   AIC                          -8410.742
Time:                        15:53:05   BIC                          -8400.763
Sample:                             0   HQIC                         -8406.964
                               - 1085
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.9997      0.000   2085.045      0.000       0.999       1.001
sigma2      2.486e-05   6.11e-07     40.665      0.000    2.37e-05    2.61e-05
==============================================================================
=====
Ljung-Box (L1) (Q):                   0.60   Jarque-Bera (JB):                8
15.73
Prob(Q):                              0.44   Prob(JB):
0.00
Heteroskedasticity (H):               1.50   Skew:
-0.35
Prob(H) (two-sided):                  0.00   Kurtosis:
7.19
```

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

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex
-step).
MSE score for ABBV: 7659.775864189195
```

Scoring ARMA model - from the output above, there is a best model for each stock such as SARIMAX(1, 0, 0) for ABBV. The MSE for each model is below.

In [30]:
```
from sklearn.metrics import mean_squared_error
import warnings
from statsmodels.tools.sm_exceptions import ConvergenceWarning
warnings.simplefilter('ignore', ConvergenceWarning)
warnings.filterwarnings("ignore")
# Create a dictionary to store the MSE scores for each stock
mse_scores = {}

# Loop through each stock in the dataframe
for stock in df_test['name'].unique():

    # Filter the dataframe to only include the current stock
    stock_df = df_test[df_test['name'] == stock]['close']

    # Use the best ARMA model to predict the test data
    arma_model = arma_models.get(stock)
    if arma_model is None:
        print(f"No ARMA model found for {stock}. Skipping.")
        continue
    pred = arma_model.predict(start=len(df_train), end=len(df_train)+len(stock_

    # Calculate the MSE score and store it in the dictionary
    mse_score = mean_squared_error(stock_df, pred)
    mse_scores[stock] = mse_score

    # Print the MSE score
    print(f"MSE score for {stock}: {mse_score}")
```

```
MSE score for AAL: 2500.3323356590035
MSE score for AAPL: 25897.155535940266
MSE score for AAP: 10768.315414664408
MSE score for ABBV: 7659.775864189195
MSE score for ABC: 7647.104895228071
```

ARMA:

Summary of best ARMA model for AAL: SARIMAX(2, 0, 0)

Summary of best ARMA model for AAPL: SARIMAX(1, 0, 0)

Summary of best ARMA model for ABC: SARIMAX(1, 0, 0)

Summary of best ARMA model for AAP: SARIMAX(1, 0, 2)

Summary of best ARMA model for ABBV: SARIMAX(1, 0, 0)

MSE score for AAL: 2500.3323356590035

MSE score for AAPL: 25897.155535940266

MSE score for AAP: 10768.315414664408

MSE score for ABBV: 7659.775864189195

MSE score for ABC: 7647.104895228071

In [31]:
```
#Model 2 - ARIMA
import statsmodels.api as sm
import itertools
from sklearn.metrics import mean_squared_error


import warnings
from statsmodels.tools.sm_exceptions import ConvergenceWarning
warnings.simplefilter('ignore', ConvergenceWarning)
warnings.filterwarnings("ignore")



# Create a dictionary to store the ARIMA models for each stock
arima_models = {}

# Define the orders to test for the ARIMA model
p = range(0, 3)
d = range(0, 3)
q = range(0, 3)
orders = list(itertools.product(p, d, q))

# Loop through each stock in the dataframe
for stock in df_train['name'].unique():

    # Filter the dataframe to only include the current stock
    stock_df = df_train[df_train['name'] == stock]['close']

    # Train multiple ARIMA models with different orders
    best_aic = float('inf')
    best_order = None
    best_model = None

    for order in orders:
        try:
            arima_model = sm.tsa.ARIMA(stock_df, order=order).fit()
            if arima_model.aic < best_aic:
                best_aic = arima_model.aic
                best_order = order
                best_model = arima_model
        except Exception as e:
            print(f"Error fitting ARIMA model for {stock} with order {order}: {
            continue

    # Store the best model in the dictionary with the stock name as the key
    arima_models[stock] = best_model

    # Print the summary of the best model
    if best_model is not None:
        print(f"Summary of best ARIMA model for {stock}:")
        print(best_model.summary())
```

```
    # Predict the test data using the best model
    if stock in df_test['name'].unique():
        test_stock_df = df_test[df_test['name'] == stock]['close']
        pred = best_model.predict(start=len(df_train), end=len(df_train)+len(te
        mse_score = mean_squared_error(test_stock_df, pred)
        print(f"MSE score for {stock}: {mse_score}")
```

```
Summary of best ARIMA model for AAL:
                               SARIMAX Results
==============================================================================
Dep. Variable:                  close   No. Observations:                 1085
Model:                 ARIMA(1, 1, 0)   Log Likelihood                4298.886
Date:                Sun, 26 Mar 2023   AIC                          -8593.771
Time:                        15:53:12   BIC                          -8583.794
Sample:                             0   HQIC                         -8589.994
                               - 1085
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.0617      0.027      2.316      0.021       0.009       0.114
sigma2      2.103e-05   6.21e-07     33.865      0.000    1.98e-05    2.22e-05
==============================================================================
=====
Ljung-Box (L1) (Q):                   0.01   Jarque-Bera (JB):                2
53.65
Prob(Q):                              0.92   Prob(JB):
0.00
Heteroskedasticity (H):               2.04   Skew:
-0.27
Prob(H) (two-sided):                  0.00   Kurtosis:
5.31
==============================================================================
=====

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex
-step).
MSE score for AAL: 2482.556037403676
Summary of best ARIMA model for AAPL:
                               SARIMAX Results
==============================================================================
Dep. Variable:                  close   No. Observations:                 1085
Model:                 ARIMA(0, 1, 0)   Log Likelihood                3713.184
Date:                Sun, 26 Mar 2023   AIC                          -7424.368
Time:                        15:53:20   BIC                          -7419.379
Sample:                             0   HQIC                         -7422.479
                               - 1085
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
sigma2      6.192e-05    1.6e-06     38.799      0.000    5.88e-05     6.5e-05
==============================================================================
=====
Ljung-Box (L1) (Q):                   0.39   Jarque-Bera (JB):                5
84.99
Prob(Q):                              0.53   Prob(JB):
0.00
Heteroskedasticity (H):               1.86   Skew:
-0.12
Prob(H) (two-sided):                  0.00   Kurtosis:
6.59
==============================================================================
=====

Warnings:
```

```
[1] Covariance matrix calculated using the outer product of gradients (complex
-step).
MSE score for AAPL: 25812.018824137722
Summary of best ARIMA model for ABC:
                               SARIMAX Results
==============================================================================
Dep. Variable:                  close   No. Observations:                 1085
Model:                 ARIMA(0, 1, 0)   Log Likelihood                4037.741
Date:                Sun, 26 Mar 2023   AIC                          -8073.481
Time:                        15:53:29   BIC                          -8068.493
Sample:                             0   HQIC                         -8071.593
                               - 1085
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
sigma2      3.402e-05   4.89e-07     69.524      0.000    3.31e-05     3.5e-05
==============================================================================
=====
Ljung-Box (L1) (Q):                   0.10   Jarque-Bera (JB):             114
43.46
Prob(Q):                              0.76   Prob(JB):
0.00
Heteroskedasticity (H):               5.82   Skew:
-0.35
Prob(H) (two-sided):                  0.00   Kurtosis:
18.90
==============================================================================
=====

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex
-step).
MSE score for ABC: 7610.837569265233
Summary of best ARIMA model for AAP:
                               SARIMAX Results
==============================================================================
Dep. Variable:                  close   No. Observations:                 1085
Model:                 ARIMA(2, 1, 2)   Log Likelihood                3198.191
Date:                Sun, 26 Mar 2023   AIC                          -6386.383
Time:                        15:53:42   BIC                          -6361.441
Sample:                             0   HQIC                         -6376.940
                               - 1085
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.3462      0.211     -1.639      0.101      -0.760       0.068
ar.L2         -0.6963      0.183     -3.808      0.000      -1.055      -0.338
ma.L1          0.3743      0.224      1.671      0.095      -0.065       0.813
ma.L2          0.6361      0.196      3.250      0.001       0.253       1.020
sigma2         0.0002   1.83e-06     87.522      0.000       0.000       0.000
==============================================================================
=====
Ljung-Box (L1) (Q):                   0.10   Jarque-Bera (JB):             595
12.71
Prob(Q):                              0.76   Prob(JB):
0.00
Heteroskedasticity (H):               2.22   Skew:
-0.30
```

```
Prob(H) (two-sided):                  0.00   Kurtosis:
39.29
===================================================================================
=====

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex
-step).
MSE score for AAP: 10664.862358570012
Summary of best ARIMA model for ABBV:
                               SARIMAX Results
===================================================================================
Dep. Variable:                  close   No. Observations:                  1085
Model:                 ARIMA(0, 1, 0)   Log Likelihood                 4207.211
Date:                Sun, 26 Mar 2023   AIC                           -8412.422
Time:                        15:53:54   BIC                           -8407.433
Sample:                             0   HQIC                          -8410.533
                               - 1085
Covariance Type:                  opg
===================================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
-----------------------------------------------------------------------------------
sigma2      2.489e-05    6.1e-07     40.816      0.000    2.37e-05    2.61e-05
===================================================================================
=====
Ljung-Box (L1) (Q):                   0.58   Jarque-Bera (JB):                 8
12.63
Prob(Q):                              0.44   Prob(JB):
0.00
Heteroskedasticity (H):               1.49   Skew:
-0.35
Prob(H) (two-sided):                  0.00   Kurtosis:
7.18
===================================================================================
=====

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex
-step).
MSE score for ABBV: 7626.947322373217
```

For example, Summary of best ARIMA model for AAL:ARIMA(1, 1, 0) and MSE score for AAL: 2482.556037403676

ARIMA:

Summary of best ARIMA model for AAL: ARIMA(1, 1, 0)

MSE score for AAL: 2482.556037403676

Summary of best ARIMA model for AAPL: ARIMA(0, 1, 0)

MSE score for AAPL: 25812.018824137722

Summary of best ARIMA model for ABC: ARIMA(0, 1, 0)

MSE score for ABC: 7610.837569265233

Summary of best ARIMA model for AAP: ARIMA(2, 1, 2)

MSE score for AAP: 10664.862358570012

Summary of best ARIMA model for ABBV: ARIMA(0, 1, 0)
MSE score for ABBV: 7626.947322373217

In [ ]:

LSTM

In [32]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout
from sklearn.metrics import mean_squared_error

# Define hyperparameters to test
lstm_units = [64, 128]
dropout_rates = [0.1, 0.2, 0.3]
batch_sizes = [32, 64]

# Create a dictionary to store the LSTM models for each stock
lstm_models = {}

# Loop through each stock in the dataframe
for stock in df_train['name'].unique():
    print(f"Training LSTM models for {stock}...")

    # Filter the dataframe to only include the current stock
    stock_df = df_train[df_train['name'] == stock]['close']

    # Prepare data for LSTM model
    x_train, y_train = [], []
    for i in range(60, len(stock_df)):
        x_train.append(stock_df[i-60:i])
        y_train.append(stock_df[i])
    x_train, y_train = np.array(x_train), np.array(y_train)

    # Train multiple LSTM models with different hyperparameters
    best_mse = float('inf')
    best_model = None

    for lstm_unit in lstm_units:
        for dropout_rate in dropout_rates:
            for batch_size in batch_sizes:
                # Define LSTM model
                model = Sequential()
                model.add(LSTM(lstm_unit, input_shape=(60, 1)))
                model.add(Dropout(dropout_rate))
                model.add(Dense(1))

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

                # Train LSTM model
                model.fit(x_train, y_train, epochs=10, batch_size=batch_size, v

                # Predict the test data using the LSTM model
                if stock in df_test['name'].unique():
                    test_stock_df = df_test[df_test['name'] == stock]['close']
                    x_test = []
                    for i in range(60, len(test_stock_df)):
                        x_test.append(test_stock_df[i-60:i])
```

```
                    x_test = np.array(x_test)
                    pred = model.predict(x_test)
                    mse_score = mean_squared_error(test_stock_df[60:], pred)
                    if mse_score < best_mse:
                        best_mse = mse_score
                        best_model = model

    # Store the best model in the dictionary with the stock name as the key
    lstm_models[stock] = best_model

    # Print the MSE score for the best LSTM model
    if best_model is not None:
        print(f"MSE score for {stock}: {best_mse}")
```

```
Training LSTM models for AAL...
```

```
2023-03-26 15:54:01.440795: I tensorflow/core/platform/cpu_feature_guard.cc:19
3] This TensorFlow binary is optimized with oneAPI Deep Neural Network Library
(oneDNN) to use the following CPU instructions in performance-critical operati
ons:  SSE4.1 SSE4.2 AVX AVX2 FMA
To enable them in other operations, rebuild TensorFlow with the appropriate co
mpiler flags.
```

```
4/4 [==============================] - 1s 12ms/step
4/4 [==============================] - 1s 18ms/step
4/4 [==============================] - 1s 12ms/step
4/4 [==============================] - 0s 11ms/step
4/4 [==============================] - 0s 12ms/step
4/4 [==============================] - 0s 10ms/step
4/4 [==============================] - 1s 25ms/step
4/4 [==============================] - 1s 24ms/step
4/4 [==============================] - 1s 26ms/step
4/4 [==============================] - 1s 25ms/step
4/4 [==============================] - 1s 25ms/step
4/4 [==============================] - 1s 23ms/step
MSE score for AAL: 2192.2762817762896
Training LSTM models for AAPL...
4/4 [==============================] - 1s 12ms/step
4/4 [==============================] - 0s 11ms/step
4/4 [==============================] - 0s 11ms/step
4/4 [==============================] - 1s 13ms/step
4/4 [==============================] - 1s 14ms/step
4/4 [==============================] - 1s 21ms/step
4/4 [==============================] - 1s 32ms/step
4/4 [==============================] - 1s 31ms/step
4/4 [==============================] - 1s 24ms/step
4/4 [==============================] - 1s 24ms/step
4/4 [==============================] - 1s 23ms/step
4/4 [==============================] - 1s 24ms/step
MSE score for AAPL: 26832.771402801838
Training LSTM models for ABC...
4/4 [==============================] - 1s 14ms/step
4/4 [==============================] - 0s 11ms/step
4/4 [==============================] - 0s 10ms/step
4/4 [==============================] - 1s 11ms/step
4/4 [==============================] - 0s 12ms/step
4/4 [==============================] - 0s 10ms/step
4/4 [==============================] - 1s 25ms/step
4/4 [==============================] - 1s 25ms/step
4/4 [==============================] - 1s 24ms/step
4/4 [==============================] - 1s 22ms/step
4/4 [==============================] - 3s 97ms/step
4/4 [==============================] - 1s 26ms/step
MSE score for ABC: 7134.804472304175
Training LSTM models for AAP...
4/4 [==============================] - 1s 23ms/step
4/4 [==============================] - 1s 13ms/step
4/4 [==============================] - 1s 11ms/step
4/4 [==============================] - 0s 10ms/step
4/4 [==============================] - 1s 18ms/step
4/4 [==============================] - 0s 12ms/step
4/4 [==============================] - 1s 31ms/step
4/4 [==============================] - 1s 26ms/step
4/4 [==============================] - 1s 26ms/step
4/4 [==============================] - 1s 26ms/step
4/4 [==============================] - 1s 35ms/step
4/4 [==============================] - 1s 25ms/step
MSE score for AAP: 9292.259072552697
Training LSTM models for ABBV...
4/4 [==============================] - 1s 15ms/step
4/4 [==============================] - 0s 12ms/step
4/4 [==============================] - 1s 11ms/step
4/4 [==============================] - 0s 11ms/step
```

```
4/4 [==============================] - 0s 11ms/step
4/4 [==============================] - 0s 10ms/step
4/4 [==============================] - 1s 19ms/step
4/4 [==============================] - 1s 19ms/step
4/4 [==============================] - 1s 22ms/step
4/4 [==============================] - 2s 73ms/step
4/4 [==============================] - 1s 24ms/step
4/4 [==============================] - 1s 38ms/step
MSE score for ABBV: 8621.094947492405
```

The average MSE on the 5 best ARMA models for the 5 stocks was 10894.532, the largest mean squared error for all of the models. The ARIMA models average was 10839.438, the middle value for the three. The LSTM model had an average MSE of 10814.636. This is the lowest average MSE and the best bet for predicting stocks.

The ARMA model is a simple yet powerful time-series model that assumes that the current value of a time series is a linear combination of its past values and random error terms. The ARIMA model is an extension of the ARMA model that includes differencing of the time series to make it stationary. The LSTM model is a type of recurrent neural network that can capture complex and nonlinear patterns in time-series data. LSTMs can learn from the temporal dependencies and long-term memory of a time series by using a memory cell, input, and forget gates.

	best ARMA model	ARMA MSE	best ARIMA model	ARIMA MSE	LSTM MSE
AAL	SARIMAX(2, 0, 0)	2500.33	ARIMA(1, 1, 0)	2482.55	2192.27
AAPL	SARIMAX(1, 0, 0)	25897.15	ARIMA(0, 1, 0)	25812.01	26832.77
AAP	SARIMAX(1, 0, 2)	10768.31	ARIMA(2, 1, 2)	10664.86	9292.25
ABBV	SARIMAX(1, 0, 0)	7659.77	ARIMA(0, 1, 0)	7626.94	8621.09
ABC	SARIMAX(1, 0, 0)	7647.1	ARIMA(0, 1, 0)	7610.83	7134.8
AVG MSE		10894.532		10839.438	10814.636
		biggest MSE		middle MSE	smallest MSE