

S&P_500_Stock_Prices

February 1, 2025

1 S&P 500 Stock Prices: Case Study

About

Historical stock market data for current S&P 500 companies, from 2014-2017. Each record represents a single day of trading, and includes the ticker name, volume, high, low, open and close prices.

Recommended Analysis

1. Which date in the sample saw the largest overall trading volume? On that date, which two stocks were traded most?
2. On which day of the week does volume tend to be highest? Lowest?
3. On which date did Amazon (AMZN) see the most volatility, measured by the difference between the high and low price?
4. If you could go back in time and invest in one stock from 1/2/2014 - 12/29/2017, which would you choose? What % gain would you realize?

Want feedback on your solutions?

-> Share visualizations (and any applicable pivot tables, code, etc) on LinkedIn and mention @Maven Analytics. We would love to see your work and give our thoughts!

1.1 About S&P 500

The S&P 500 is like a snapshot of the US economy. It tracks the stock prices of 500 of the largest American companies, giving us a good idea of how the overall stock market is doing. [1] It's important because it's used as a benchmark for investments and reflects the health of the economy. [2]

1.2 The Purpose

I was hired on Fivver to help an entrepreneur understand which data in the sample saw the largest overall trading volume and which two stocks were traded the most due to the entrepreneur's time constraint.

The goal: Identify the date with the highest overall trading volume and the two most traded stocks on that date.

1.3 The Team

- Data Analyst
- Entrepreneur (Stakeholder)

1.4 The Data

The stock market data for companies that are currently in the S&P 500 composition changes. The dataset S&P 500 Stock Prices 2014-2017.csv, [3] contains a record that represents a single day of trading and includes the ticker name, volume, high, low, open, and close prices.

In this dataset, there are 497472 rows, 7 columns, and these variables. * *Disclaimer: I used Gemini to explain each variable description*

Variable	Description
symbol	ticker name: stock symbol
date	date of trading day
open	price of the stock at the beginning of the trading day
high	the highest price the stock reached during the trading day
low	the lowest price the stock reached during the trading day
close	The price of the stock at the end of the trading day (Most important price of the day)
volume	The total number of shares traded during that day. (High volume generally indicates more interest and activity in the stock.)

Open-Source * [1][Wikipedia](https://en.wikipedia.org/wiki/S%26P_500#:~:text=The%20Standard%20and%20)
* [2][The (Mis)uses of the S&P 500]([https://businesslawreview.uchicago.edu/print-archive/misuses-sp-500#:~:text=The%20S%26P%20500%20is%20widely,\(iii\)%20evaluate%20firm%20performance.](https://businesslawreview.uchicago.edu/print-archive/misuses-sp-500#:~:text=The%20S%26P%20500%20is%20widely,(iii)%20evaluate%20firm%20performance.))
* [3][Maven Analytics](<https://app.mavenanalytics.io/datasets?order=-fields.numberOfRecords>)

```
[3]: # For data manipulation
import numpy as np
import pandas as pd

# For data visualization
import matplotlib.pyplot as plt
import seaborn as sns

# For displaying all of the columns in dataframes
pd.set_option('display.max_columns', None)
```

```
[21]: df = pd.read_csv("S&P 500 Stock Prices 2014-2017.csv")
```

```
[22]: df.head()
```

```
# Format is good
```

```
[22]:
```

	symbol	date	open	high	low	close	volume
0	AAL	2014-01-02	25.0700	25.8200	25.0600	25.3600	8998943
1	AAPL	2014-01-02	79.3828	79.5756	78.8601	79.0185	58791957
2	AAP	2014-01-02	110.3600	111.8800	109.2900	109.7400	542711
3	ABBV	2014-01-02	52.1200	52.3300	51.5200	51.9800	4569061
4	ABC	2014-01-02	70.1100	70.2300	69.4800	69.8900	1148391

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

```
# 497472 entries / 7 columns  
# float(4) decimal numeric: open, high, low, close  
# int(1) numeric: volume  
# object(2) string/character: symbol and date
```

```
# I just noticed date needs to be changed datetime  
# There are missing values and potential duplications in entries
```

```
<class 'pandas.core.frame.DataFrame'>  
RangeIndex: 497472 entries, 0 to 497471  
Data columns (total 7 columns):  
#   Column  Non-Null Count  Dtype  
---  -  
0   symbol  497472 non-null   object  
1   date     497472 non-null   object  
2   open     497461 non-null   float64  
3   high     497464 non-null   float64  
4   low      497464 non-null   float64  
5   close    497472 non-null   float64  
6   volume   497472 non-null   int64  
dtypes: float64(4), int64(1), object(2)  
memory usage: 26.6+ MB
```

```
[24]: # Cleaning date to datetime
```

```
df['date'] = pd.to_datetime(df['date'])  
  
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>  
RangeIndex: 497472 entries, 0 to 497471  
Data columns (total 7 columns):  
#   Column  Non-Null Count  Dtype  
---  -  
0   symbol  497472 non-null   object  
1   date     497472 non-null   datetime64[ns]
```

```

2   open      497461 non-null float64
3   high      497464 non-null float64
4   low       497464 non-null float64
5   close     497472 non-null float64
6   volume    497472 non-null int64
dtypes: datetime64[ns](1), float64(4), int64(1), object(1)
memory usage: 26.6+ MB

```

```

[25]: # Cleaning missing values

df.isnull().sum()
print("\nMissing Values:\n", df.isnull().sum())

df.duplicated().sum()
print("\nDuplications:\n", df.duplicated().sum())

# There are no duplications in the dataset

```

Missing Values:

```

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

```

Duplications:

```
0
```

```

[26]: # Removing nulls in dataset

df= df.dropna()

# Summary of df
print("\nDataset after dropping rows w/nulls:\n", df)

# New total of rows: 497461 entries is only 5% less of the data

```

Dataset after dropping rows w/nulls:

	symbol	date	open	high	low	close	volume
0	AAL	2014-01-02	25.0700	25.8200	25.0600	25.3600	8998943
1	AAPL	2014-01-02	79.3828	79.5756	78.8601	79.0185	58791957
2	AAP	2014-01-02	110.3600	111.8800	109.2900	109.7400	542711
3	ABBV	2014-01-02	52.1200	52.3300	51.5200	51.9800	4569061
4	ABC	2014-01-02	70.1100	70.2300	69.4800	69.8900	1148391

...
497467	XYL	2017-12-29	68.5300	68.8000	67.9200	68.2000	1046677
497468	YUM	2017-12-29	82.6400	82.7100	81.5900	81.6100	1347613
497469	ZBH	2017-12-29	121.7500	121.9500	120.6200	120.6700	1023624
497470	ZION	2017-12-29	51.2800	51.5500	50.8100	50.8300	1261916
497471	ZTS	2017-12-29	72.5500	72.7600	72.0400	72.0400	1704122

[497461 rows x 7 columns]

Investigate the potential outliers on open, high, low, close, and volume. Understanding the why? * Why they are extreme values * Are they errors * Are they genuine * Domain expertise is often essential here

```
[28]: # Checking for outliers for open

plt.figure(figsize=(6,6))
plt.title('Boxplot to detect outliers for open', fontsize=12)
plt.xticks(fontsize=12)
plt.yticks(fontsize=12)
sns.boxplot(x=df['open'])
plt.show()

# Calculate Q1, Q3 and IQR
Q1 = df['open'].quantile(0.25)
Q3 = df['open'].quantile(0.75)

# Compute the interquartile range in `open`
IQR = Q3 - Q1

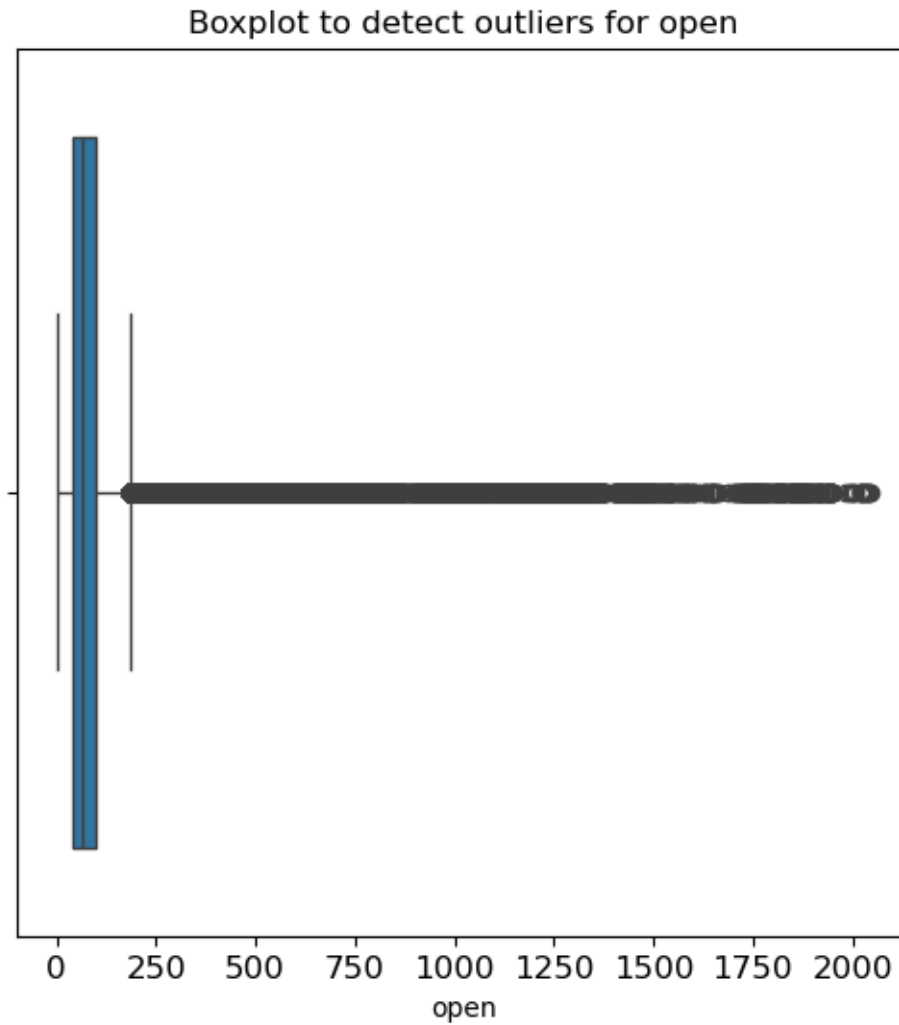
# Define outliers boundaries (using a multiplier of 1.5 is standard, but
↳adjustable)
open_upper_bound = Q3 + 1.5 * IQR
open_lower_bound = Q1 - 1.5 * IQR
print("Upper Bound:", open_upper_bound)
print("Lower Bound:", open_lower_bound)

# Identify subset of data containing outliers in `open`
outliers = df[(df['open'] < open_lower_bound) | (df['open'] > open_upper_bound)]

# Count how many rows in the data contain outliers in `open`
print("Number of outliers in 'open':", len(outliers))

if not outliers.empty: # Check if outliers is empty before printing to avoid
↳errors
    print("Outliers:\n", outliers)
else:
```

```
print("No outliers found")
```



Upper Bound: 183.49

Lower Bound: -43.39

Number of outliers in 'open': 30313

Outliers:

	symbol	date	open	high	low	close	volume
12	ADS	2014-01-02	262.44	262.680	258.78	262.34	547808
34	AMG	2014-01-02	215.92	216.690	211.79	213.38	285563
37	AMZN	2014-01-02	398.80	399.360	394.02	397.97	2140246
56	AZO	2014-01-02	477.67	479.700	472.51	474.11	151840
66	BIIB	2014-01-02	279.44	282.515	276.21	280.33	902226
...
497402	TDG	2017-12-29	276.61	279.500	274.62	274.62	251752
497408	TMO	2017-12-29	191.94	191.950	189.88	189.88	856644

497425	ULTA	2017-12-29	224.98	225.140	222.35	223.66	668078
497426	UNH	2017-12-29	223.95	223.950	220.46	220.46	2350169
497445	WAT	2017-12-29	195.52	195.660	193.16	193.19	205357

[30313 rows x 7 columns]

[29]: *# Checking for outliers for high*

```
plt.figure(figsize=(6,6))
plt.title('Boxplot to detect outliers for high', fontsize=12)
plt.xticks(fontsize=12)
plt.yticks(fontsize=12)
sns.boxplot(x=df['high'])
plt.show()

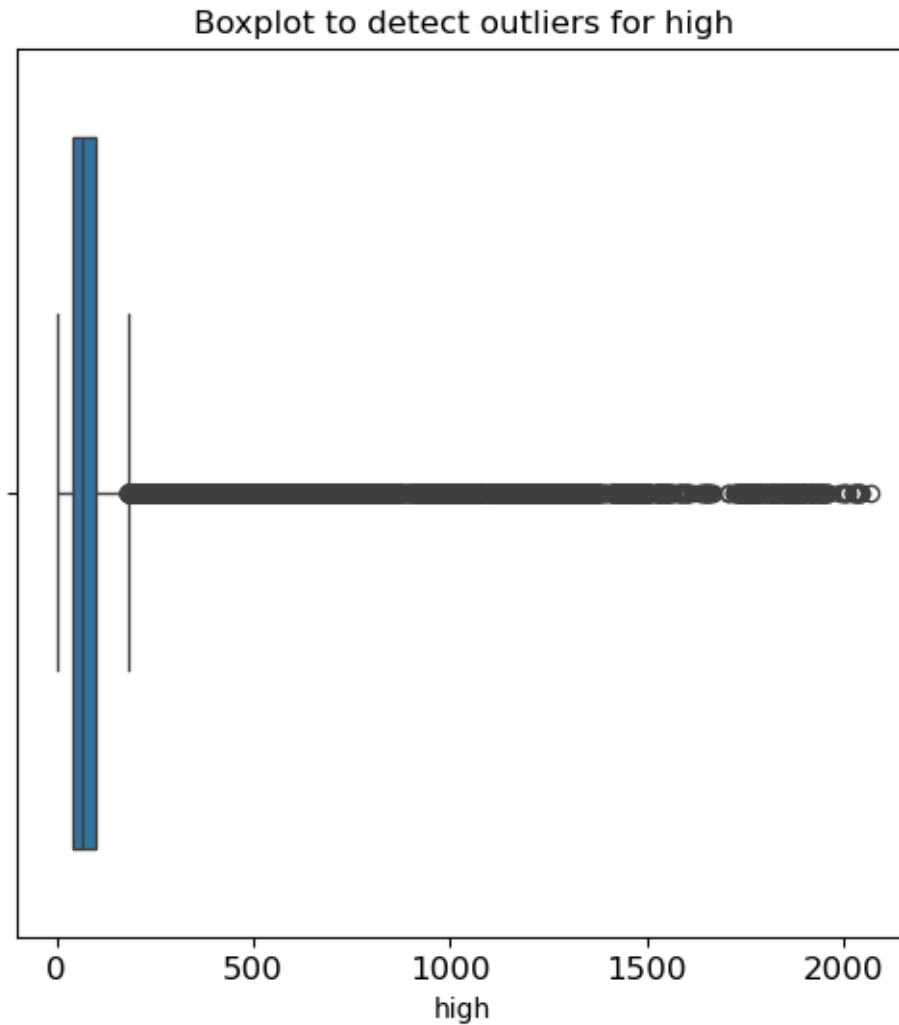
H_Q1 = df['high'].quantile(0.25)
H_Q3= df['high'].quantile(0.75)

H_IQR = H_Q3 - H_Q1

high_upper_bound = H_Q3 + 1.5 * H_IQR
high_lower_bound = H_Q1 - 1.5 * H_IQR
print("Upper Bound:", high_upper_bound)
print("Lower Bound:", high_lower_bound)

outliers = df[(df['high'] < high_lower_bound) | (df['high'] > high_upper_bound)]

print("Number of outliers in 'high':", len(outliers))
```



Upper Bound: 184.94
 Lower Bound: -43.620000000000005
 Number of outliers in 'high': 30393

```
[30]: # Checking for outliers low

plt.figure(figsize=(6,6))
plt.title('Boxplot to detect outliers for low', fontsize=12)
plt.xticks(fontsize=12)
plt.yticks(fontsize=12)
sns.boxplot(x=df['low'])
plt.show()

Q1 = df['low'].quantile(0.25)
Q3= df['low'].quantile(0.75)
```



```

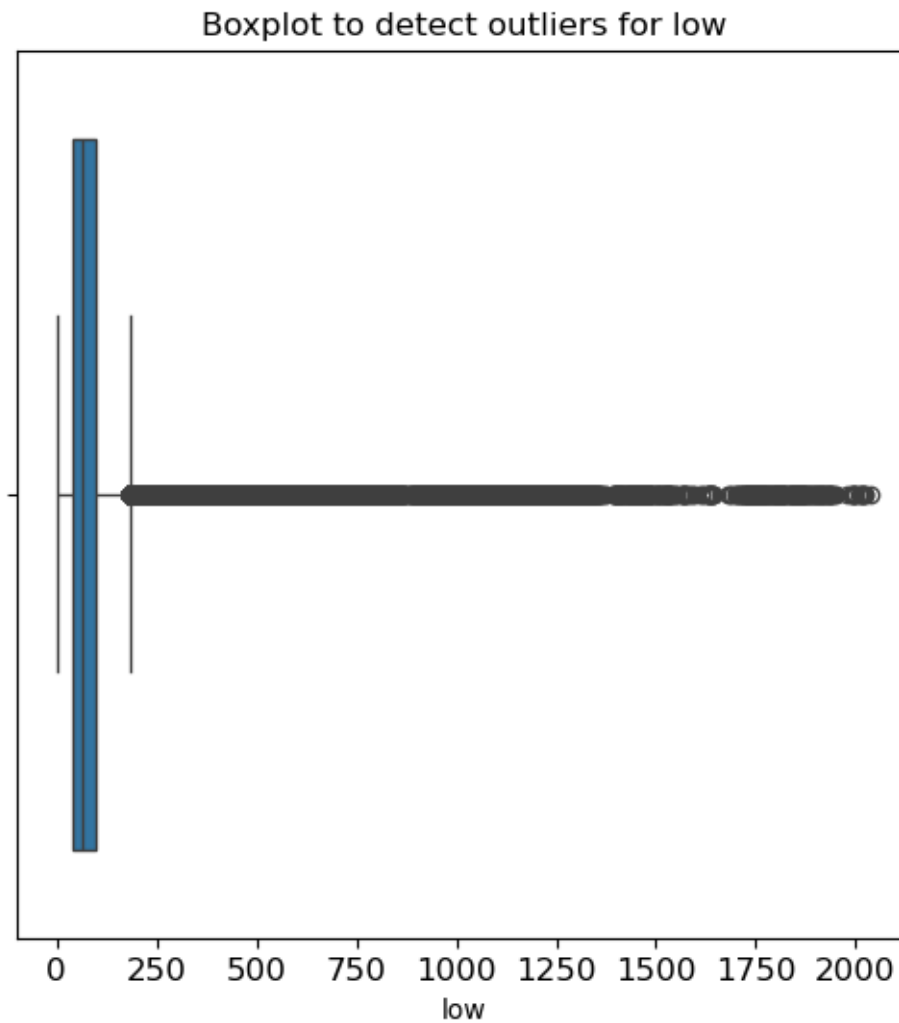
IQR = Q3 - Q1

upper_bound = Q3 + 1.5 * IQR
lower_bound = Q1 - 1.5 * IQR
print("Upper Bound:", upper_bound)
print("Lower Bound:", lower_bound)

outliers = df[(df['low'] < lower_bound) | (df['low'] > upper_bound)]

print("Number of outliers in 'low':", len(outliers))

```



```

Upper Bound: 182.02999999999997
Lower Bound: -43.16999999999999
Number of outliers in 'low': 30239

```

```

[31]: # Checking for outliers close

plt.figure(figsize=(6,6))
plt.title('Boxplot to detect outliers for close', fontsize=12)
plt.xticks(fontsize=12)
plt.yticks(fontsize=12)
sns.boxplot(x=df['close'])
plt.show()

Q1 = df['close'].quantile(0.25)
Q3 = df['close'].quantile(0.75)

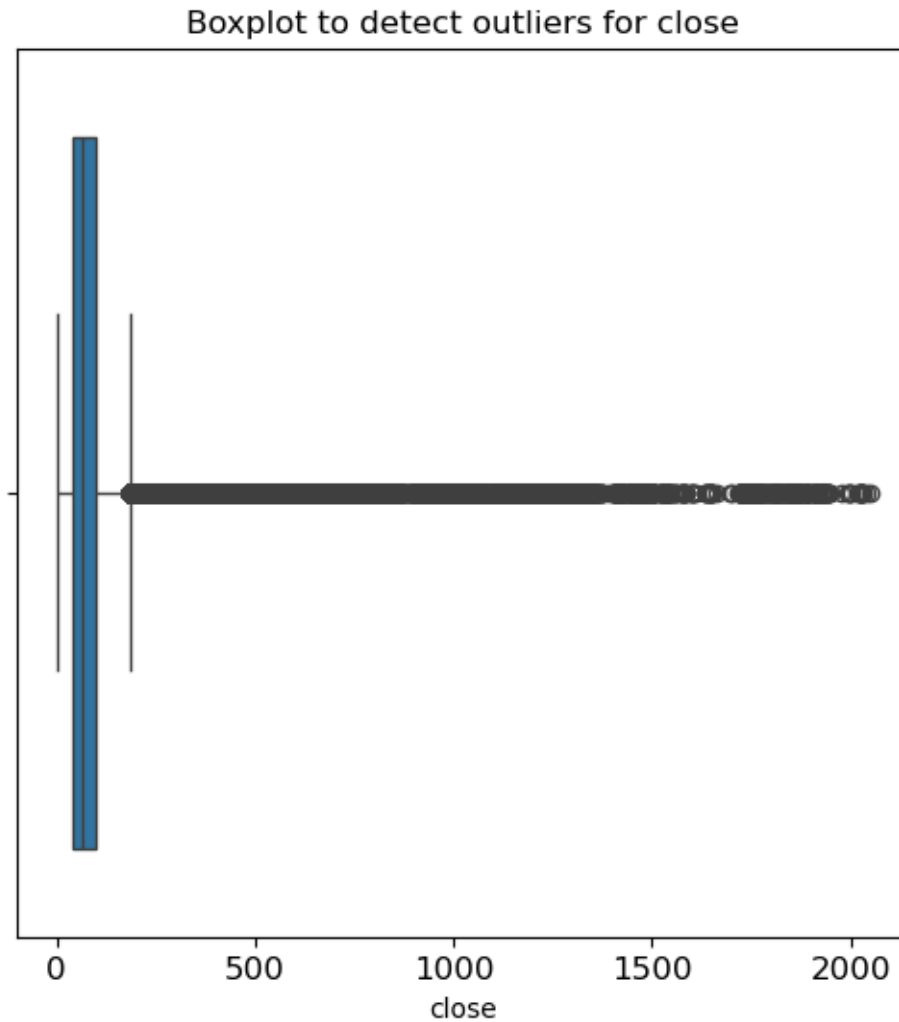
IQR = Q3 - Q1

upper_bound = Q3 + 1.5 * IQR
lower_bound = Q1 - 1.5 * IQR
print("Upper Bound:", upper_bound)
print("Lower Bound:", lower_bound)

outliers = df[(df['close'] < lower_bound) | (df['close'] > upper_bound)]

print("Number of outliers in 'close':", len(outliers))

```



Upper Bound: 183.5
 Lower Bound: -43.379999999999995
 Number of outliers in 'close': 30337

```
[32]: # Checking for outliers volume

plt.figure(figsize=(6,6))
plt.title('Boxplot to detect outliers for volume', fontsize=12)
plt.xticks(fontsize=12)
plt.yticks(fontsize=12)
sns.boxplot(x=df['volume'])
plt.show()

Q1 = df['volume'].quantile(0.25)
Q3= df['volume'].quantile(0.75)
```

```

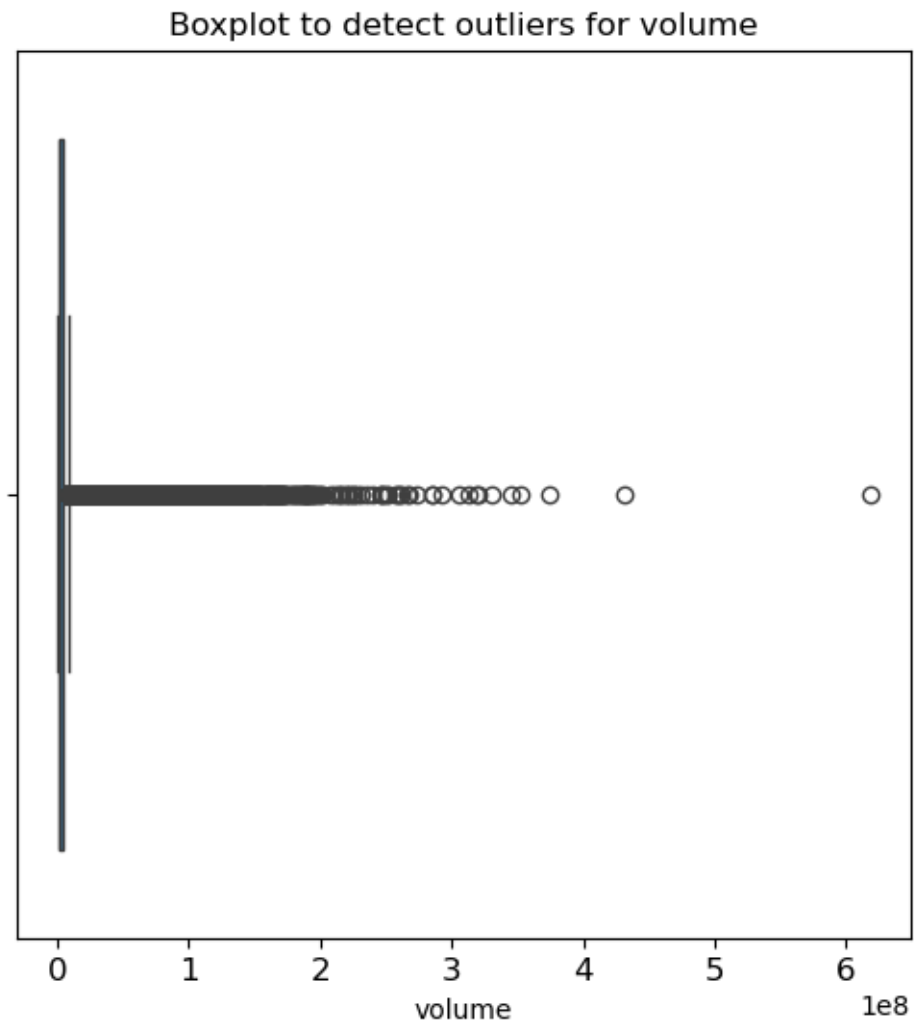
IQR = Q3 - Q1

upper_bound = Q3 + 1.5 * IQR
lower_bound = Q1 - 1.5 * IQR
print("Upper Bound:", upper_bound)
print("Lower Bound:", lower_bound)

outliers = df[(df['volume'] < lower_bound) | (df['volume'] > upper_bound)]

print("Number of outliers in 'volume':", len(outliers))

```



```

Upper Bound: 9059723.0
Lower Bound: -3707541.0
Number of outliers in 'volume': 47680

```

In this observation of outliers in float variable the number of outliers is the amount of entries, potentially showing it could be genuine. The lower bound is relatively the same but in the left skew. A closer scope on upper bound are right skewed.

Total of outliers in each float variable: * open outliers-30313 (of 497461 entries) * high outliers-30239 * close outliers-30337 * volume outliers-47680

Definitions of Bounds[1]: * Lower bound: a value that is less than or equal to every element of a set of data. * Upper bound: a value that is greater than or equal to every element of a set of data.

[1][Math is fun](<https://www.mathsisfun.com/definitions/bounds.html>)

[34]: `df.describe()`

```
# Pandas datetime or datetime64[ns] will show up that way
# It seems there is no fluctuation between the open, high, low, and close
# However, volume show fluctuation on total shares traded during the days
# It seems 2016-2017 has the most volumes
```

```
[34]:
```

	date	open	high \
count	497461	497461.000000	497461.000000
mean	2016-01-06 17:16:56.524310016	86.352275	87.132717
min	2014-01-02 00:00:00	1.620000	1.690000
25%	2015-01-08 00:00:00	41.690000	42.090000
50%	2016-01-11 00:00:00	64.970000	65.560000
75%	2017-01-06 00:00:00	98.410000	99.230000
max	2017-12-29 00:00:00	2044.000000	2067.990000
std	NaN	101.471228	102.312340

	low	close	volume
count	497461.000000	497461.000000	4.974610e+05
mean	85.552616	86.368586	4.253695e+06
min	1.500000	1.590000	1.010000e+02
25%	41.280000	41.700000	1.080183e+06
50%	64.357400	64.980000	2.085013e+06
75%	97.580000	98.420000	4.271999e+06
max	2035.110000	2049.000000	6.182376e+08
std	100.571231	101.471516	8.232210e+06

Now that the data is cleaned and prepared, I will begin analyzing and process.

Reflection: * The relationship between the float variable are genuine. * The distributions of the data has a right skew

```
[45]: # Identify the date with the highest overall trading volume

# Calculating total trading volume for each date
daily_volume = df.groupby('date')['volume'].sum()

# Find the date with the largest overall trading volume
```

```

max_volume_date = daily_volume.idxmax()
max_volume = daily_volume.max()

# Filter the DataFrame for the date with the maximum volume
max_volume_df = df[df['date'] == max_volume_date]

# Find the top two traded stocks on that date
top_two_stocks = max_volume_df.nlargest(2, 'volume')

print(f"\nThe date with the largest overall trading volume was:␣
↪{max_volume_date.strftime('%Y-%m-%d')}")
print(f"The total trading volume on that date was: {max_volume}")
print("\nThe two stocks with the highest trading volume on that date were:")
print(top_two_stocks[['symbol', 'volume']])

```

The date with the largest overall trading volume was: 2015-08-24

The total trading volume on that date was: 4607945196

The two stocks with the highest trading volume on that date were:

	symbol	volume
201266	BAC	214649482
201209	AAPL	162206292

[47]: *# Creating a bar chart to show dates of volumes of price in high and low*

```

daily_high_price = df.groupby('date')['high'].sum()
daily_low_price = df.groupby('date')['low'].sum()

plt.figure(figsize=(12, 6))

plt.bar(daily_volume.index, daily_volume.values, label='Daily Volume',␣
↪color='skyblue')

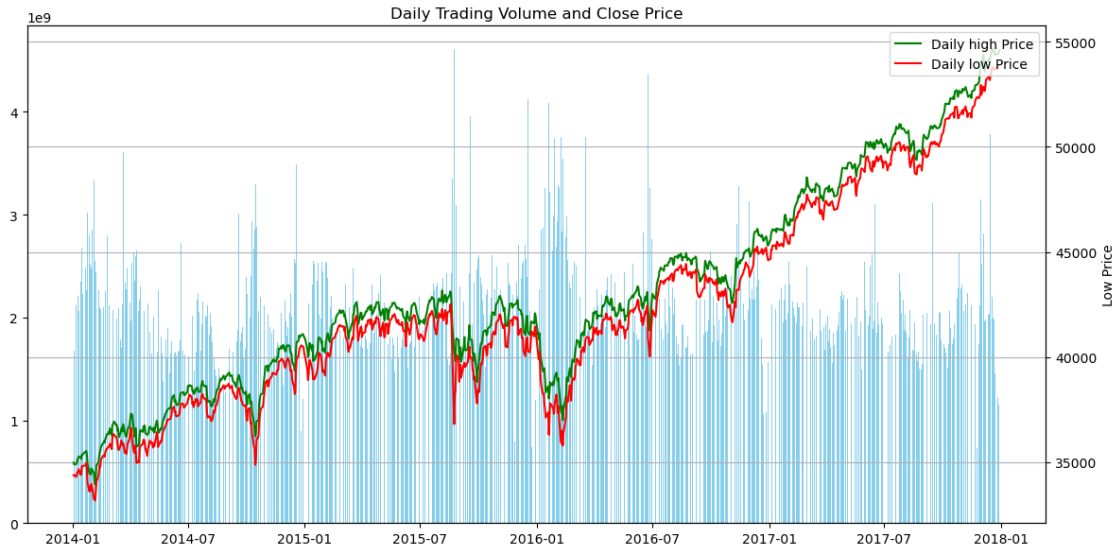
ax2 = plt.gca().twinx() # Use gca() to get the current axes

ax2.plot(daily_high_price.index, daily_high_price.values, color='green',␣
↪label='Daily high Price')
ax2.plot(daily_low_price.index, daily_low_price.values, color='red',␣
↪label='Daily low Price')

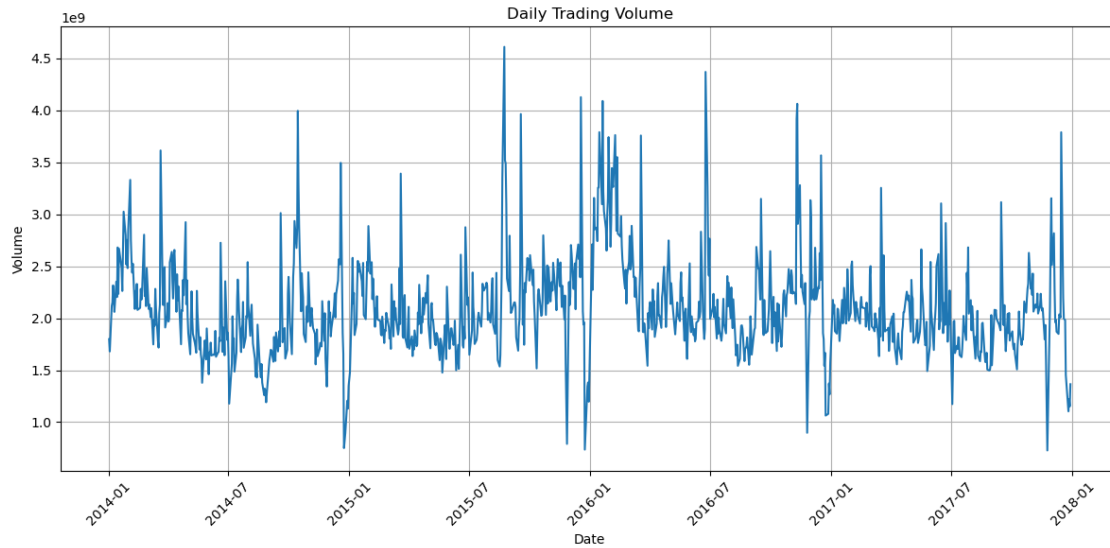
plt.title('Daily Trading Volume and Close Price')
plt.xlabel('Date')
plt.ylabel('Trading Volume')
ax2.set_ylabel('High Price')
ax2.set_ylabel('Low Price')
plt.grid(True)

```

```
plt.xticks(rotation=45)
plt.legend(loc='upper left') # Adjust legend location as needed
ax2.legend(loc='upper right') # Legend for the second y-axis
plt.tight_layout()
plt.show()
```



```
[49]: # Up close visual on the daily trading volume
plt.figure(figsize=(12, 6))
plt.plot(daily_low_price.index, daily_volume.values)
plt.title('Daily Trading Volume')
plt.xlabel('Date')
plt.ylabel('Volume')
plt.grid(True)
plt.xticks(rotation=45) # Rotate x-axis labels for readability
plt.tight_layout() # Adjust layout to prevent labels from overlapping
plt.show()
```

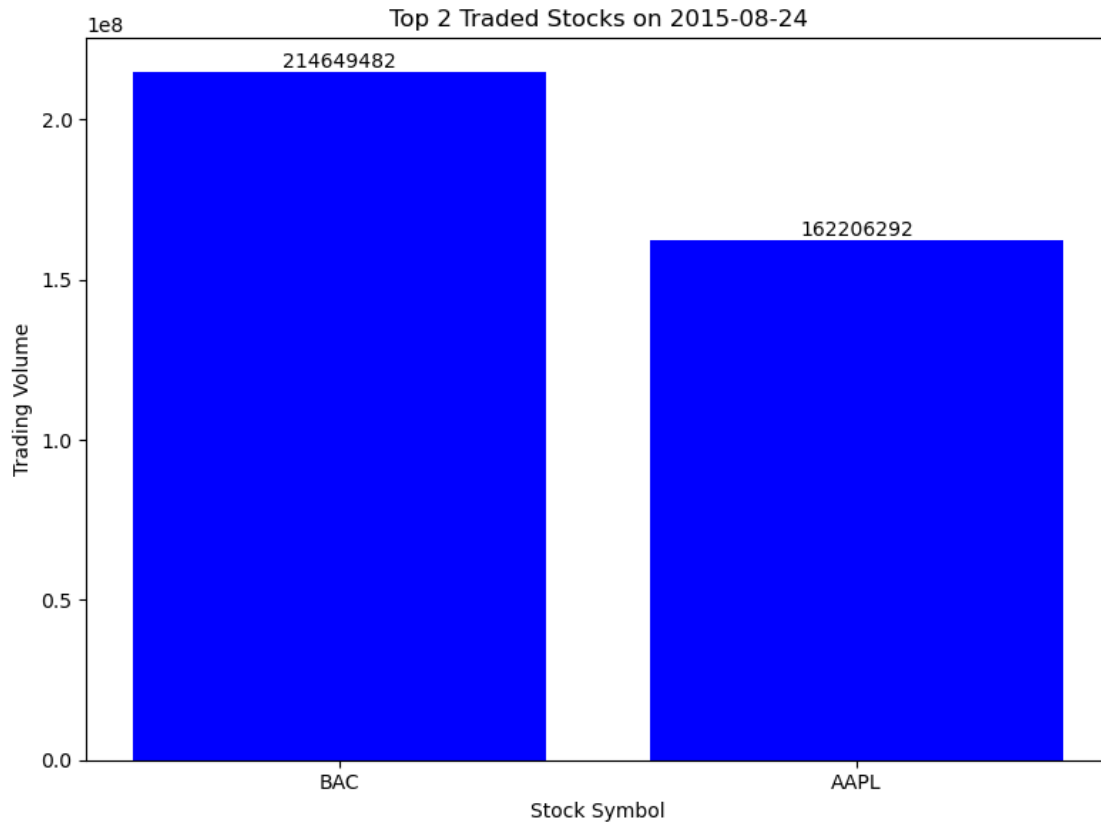


```
[51]: # Create the bar chart comparing the 2 top ticker name
plt.figure(figsize=(8, 6)) # Adjust figure size if needed
plt.bar(top_two_stocks['symbol'], top_two_stocks['volume'], color='blue')

plt.title(f'Top 2 Traded Stocks on {max_volume_date.strftime("%Y-%m-%d")}')
plt.xlabel('Stock Symbol')
plt.ylabel('Trading Volume')

# Add volume labels on top of bars for better readability
for i, v in enumerate(top_two_stocks['volume']):
    plt.text(i, v, str(v), ha='center', va='bottom') # ha and va adjust the
    ↪ position of the text

plt.tight_layout()
plt.show()
```

1.5 Insight

Recap, the goal: Identify the date with the highest overall trading volume and the two most traded stocks on that date.

I have identified the date with the highest overall trading volume at 2015-08-24. I include the maximum volume, and date to search for the top two stocks which are BAC and AAPL in the S&P 500. I learned BAC or Bank of America and AAPL or Apple were at it's lowest of the day which created volume.

It is good to check the US economy and other factors during the date of 2015-08-24 on why it dipped so low. Based on my research: Bank of America (BAC) stock dipped low in August 2015 due to a large drop in equities in Asia, which triggered a drop in index futures in Europe and the U.S.[1][2] The stock closed at \$46.72, falling short of the S&P 500's gain of 0.39%3.[3] Apple (APPLE), stock price was significantly lower than the highest priced reached in the past year which could me apple would most likley rise in the future. [4]

Open-Source * [1][CNBC](<https://www.bing.com/search?q=why%20did%20BAC%20stock%20dipped%20so%2008-24&q=n&form=seinsb&sp=-1&lq=0&pq=why%20did%20bac%20stock%20dipped%20so%20low%20of%202015-08-24&sc=12-45&sk=&cvid=02B0BF588FEA43FC8CCA8F6F83E05195&ghsh=0&ghacc=0&ghpl=>)
 * [2][Yahoo](<https://finance.yahoo.com/news/aug-24-2015-flash-crash-142252551.html>) *
 [3][Yahoo](<https://finance.yahoo.com/news/bank-america-bac-stock-sinks-224518306.html>) *

[4][MacRumors](<https://www.macrumors.com/2015/08/24/aapl-below-100-dow-jones-downturn/>)

[]: