INTERNSHIP PROJECT REPORT

ON

“STOCK MARKET ANALYSIS”

SUBMITTED BY:

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EXECUTIVE SUMMARY

The daily stock data for four significant technological companies—Apple (AAPL), Microsoft (MSFT), Netflix (NFLX), and Google (GOOG)—covering the period from February 7, 2023, to May 5, 2023, is quantitatively analyzed in this study. The project's main objectives were statistical testing, exploratory data analysis, and creating a highly precise linear regression model for price prediction.

Key Analytical Results

Market Volatility: Netflix (NFLX) showed the highest average daily volatility, while Apple (AAPL) showed the lowest, according to the examination of daily price ranges. Trading Volume and Trends: During the analysis window, AAPL had the greatest total trading volume out of the four tickers. Over the course of the period, its closing price movement demonstrated a steady and evident increasing trajectory.

Relationships in Statistics:

A statistically significant difference between the mean closing prices of AAPL and GOOG was confirmed using a two-sample t-test.
There was no statistically significant relationship between AAPL's daily closing price and trading volume, according to a Pearson correlation test.

Modeling Predictively (AAPL Focus)

To forecast the close price of AAPL, a Linear Regression model was used, utilizing features like Open, High, Low, and Volume. The model's outstanding performance confirmed these daily indicators' high predictive power:
R-Squared: 0.9854
This suggests that the input properties of the model account for about 98.54% of the closing price variance.
MSE: 1.0942
The model's forecasts closely match the actual observed closing prices, as indicated by the low MSE.

In summary, the information supports the different price patterns and trading patterns of the examined equities. Based on intraday market data, the created Linear Regression model for AAPL is very successful at short-term price predicting.

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OBJECTIVES

Conducting a thorough, data-driven examination of historical stock price and trade volume data for a few big technological companies (AAPL, MSFT, NFLX, and GOOG) covering the period from February 7, 2023, to May 5, 2023 is the main goal of this project module. Three main objectives are intended to be accomplished by this analysis:

Exploratory Data Insight: To conduct thorough Exploratory Data Analysis (EDA) in order to describe market dynamics, such as price distributions, total trading volume by ticker, volatility of the daily price range, and general price trends over the observation period.

Statistical Validation: To statistically validate observable market behaviors, such as substantial differences in mean closing prices of large stocks and the relationship between trading volume and price movements, by using hypothesis testing (e.g., Pearson correlation and two-sample t-test).

Predictive Model Development: To build, train, and assess a Linear Regression model that can reliably estimate daily closing prices using the knowledge gathered from the EDA and statistical validation. This will create a baseline for short-term forecasting abilities.

DATA ANALYSIS

```
# Importing librabries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
import math
%matplotlib inline
import mplfinance as mpf
from scipy import stats
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
```

```
# Importing data
data = pd.read_csv('stocks.csv')
```

```
# Checking the data
data.head(10)
```

	Ticker	Date	Open	High	Low	Close	Adj Close	Volume
0	AAPL	2023-02-07	150.639999	155.229996	150.639999	154.649994	154.414230	83322600
1	AAPL	2023-02-08	153.880005	154.580002	151.169998	151.919998	151.688400	64120100
2	AAPL	2023-02-09	153.779999	154.330002	150.419998	150.869995	150.639999	56007100
3	AAPL	2023-02-10	149.460007	151.339996	149.220001	151.009995	151.009995	57450700
4	AAPL	2023-02-13	150.949997	154.259995	150.919998	153.850006	153.850006	62199000
5	AAPL	2023-02-14	152.119995	153.770004	150.860001	153.199997	153.199997	61707600
6	AAPL	2023-02-15	153.110001	155.500000	152.880005	155.330002	155.330002	65573800
7	AAPL	2023-02-16	153.509995	156.330002	153.350006	153.710007	153.710007	68167900
8	AAPL	2023-02-17	152.350006	153.000000	150.850006	152.550003	152.550003	59144100
9	AAPL	2023-02-21	150.199997	151.300003	148.410004	148.479996	148.479996	58867200

```
data['Ticker'].unique()
```

```
array(['AAPL', 'MSFT', 'NFLX', 'GOOG'], dtype=object)
```

```
data.describe()
```

	Open	High	Low	Close	Adj Close	Volume
count	248.000000	248.000000	248.000000	248.000000	248.000000	2.480000e+02
mean	215.252093	217.919662	212.697452	215.381674	215.362697	3.208210e+07
std	91.691315	92.863023	90.147881	91.461989	91.454750	2.233590e+07
min	89.540001	90.129997	88.860001	89.349998	89.349998	2.657900e+06
25%	135.235004	137.440004	134.822495	136.347498	136.347498	1.714180e+07
50%	208.764999	212.614998	208.184998	209.920006	209.920006	2.734000e+07
75%	304.177505	307.565002	295.437500	303.942505	303.942505	4.771772e+07
max	372.410004	373.829987	361.739990	366.829987	366.829987	1.133164e+08

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 248 entries, 0 to 247
Data columns (total 8 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   Ticker     248 non-null    object 
 1   Date       248 non-null    object 
 2   Open       248 non-null    float64
 3   High       248 non-null    float64
 4   Low        248 non-null    float64
 5   Close      248 non-null    float64
 6   Adj Close  248 non-null    float64
 7   Volume     248 non-null    int64  
dtypes: float64(5), int64(1), object(2)
memory usage: 15.6+ KB
```

```
data.shape
```

```
(248, 8)
```

```
data.dtypes
```

```
Ticker        object
Date          object
Open         float64
High         float64
Low          float64
Close        float64
Adj Close    float64
Volume         int64
dtype: object
```

```python
data.describe
```

```
<bound method NDFrame.describe of     Ticker        Date        Open        High         Low       Close  \
0     AAPL  2023-02-07  150.639999  155.229996  150.639999  154.649994
1     AAPL  2023-02-08  153.880005  154.580002  151.169998  151.919998
2     AAPL  2023-02-09  153.779999  154.330002  150.419998  150.869995
3     AAPL  2023-02-10  149.460007  151.339996  149.220001  151.009995
4     AAPL  2023-02-13  150.949997  154.259995  150.919998  153.850006
..     ...         ...         ...         ...         ...         ...
243   GOOG  2023-05-01  107.720001  108.680000  107.500000  107.709999
244   GOOG  2023-05-02  107.660004  107.730003  104.500000  105.980003
245   GOOG  2023-05-03  106.220001  108.129997  105.620003  106.120003
246   GOOG  2023-05-04  106.160004  106.300003  104.699997  105.209999
247   GOOG  2023-05-05  105.320000  106.440002  104.738998  106.214996

      Adj Close    Volume
0    154.414230  83322600
1    151.688400  64120100
2    150.639999  56007100
3    151.009995  57450700
4    153.850006  62199000
..          ...       ...
243  107.709999  20926300
244  105.980003  20343100
245  106.120003  17116300
246  105.209999  19780600
247  106.214996  20705300

[248 rows x 8 columns]>
```

```python
data.isnull().any()
```

```
Ticker       False
Date         False
Open         False
High         False
Low          False
Close        False
Adj Close    False
Volume       False
dtype: bool
```

```python
data.isnull().sum()
```

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

```python
# Check for duplicates
print('\nChecking for duplicate rows:')
print(f'Number of duplicate rows: {data.duplicated().sum()}')
```

```
Checking for duplicate rows:
Number of duplicate rows: 0
```

```python
# Convert 'Date' to datetime objects and analyze the time range
data['Date'] = pd.to_datetime(data['Date'])
print('\nDate Range:')
print(f"Start Date: {data['Date'].min()}")
print(f"End Date: {data['Date'].max()}")
```

```
Date Range:
Start Date: 2023-02-07 00:00:00
End Date: 2023-05-05 00:00:00
```

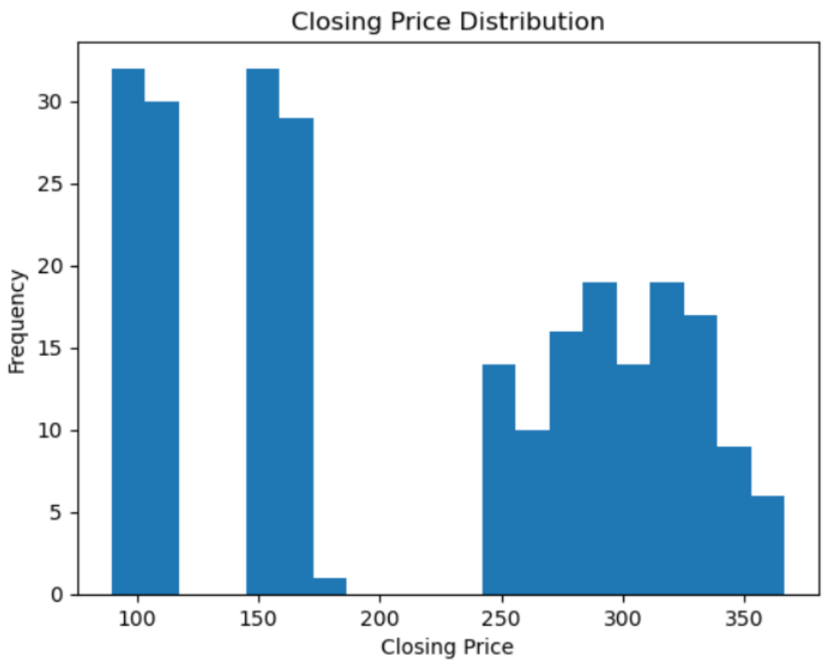
```python
# Analyze the Ticker column
print('\nTicker Counts:')
print(data['Ticker'].value_counts())
```

```
Ticker Counts:
Ticker
AAPL    62
MSFT    62
NFLX    62
GOOG    62
Name: count, dtype: int64
```

```python
# Analyze Daily Price Range
data['Daily_Range'] = data['High'] - data['Low']
print('\nDaily Price Range Statistics:')
print(data.groupby('Ticker')['Daily_Range'].describe())
```

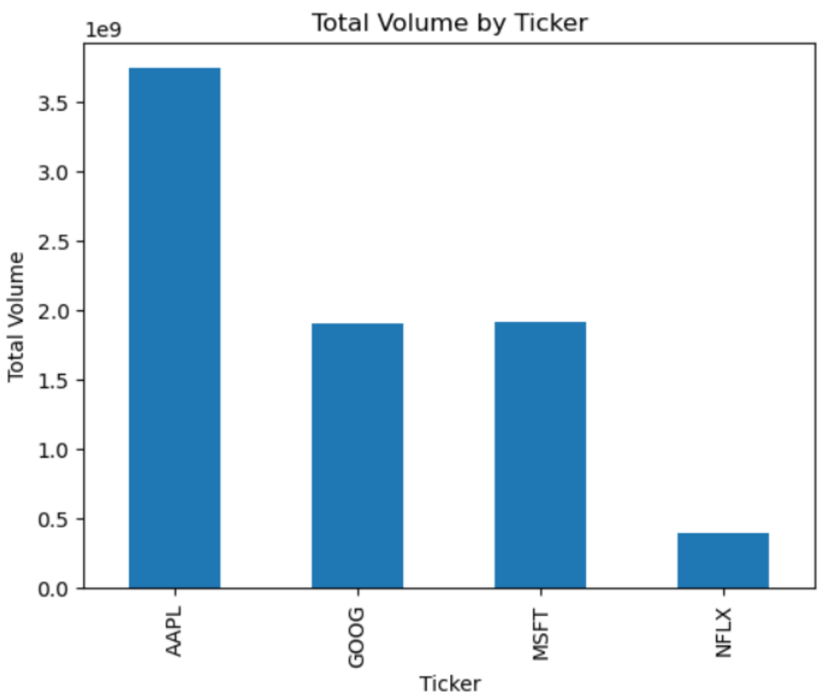
```
Daily Price Range Statistics:
        count      mean       std       min       25%       50%        75%  \
Ticker
AAPL     62.0  2.803065  0.904700  1.199997  2.127495  2.800003   3.330002
GOOG     62.0  2.529645  1.220019  0.839996  1.723253  2.260002   2.852505
MSFT     62.0  5.736614  2.323552  2.730011  4.229984  5.164993   6.637486
NFLX     62.0  9.819517  3.246085  4.709991  7.507515  9.134995  11.897499

              max
Ticker
AAPL     5.440002
GOOG     6.750000
MSFT    13.279999
NFLX    18.639984
```

```python
# The distribution of the closing prices to understand their range and frequency.
plt.hist(data['Close'], bins=20)
plt.xlabel('Closing Price')
plt.ylabel('Frequency')
plt.title('Closing Price Distribution')
plt.show()
```




```python
# The cumulative volume traded over time to observe any trends or spikes.
ticker_volume = data.groupby('Ticker')['Volume'].sum()
ticker_volume.plot(kind='bar')
plt.xlabel('Ticker')
plt.ylabel('Total Volume')
plt.title('Total Volume by Ticker')
```

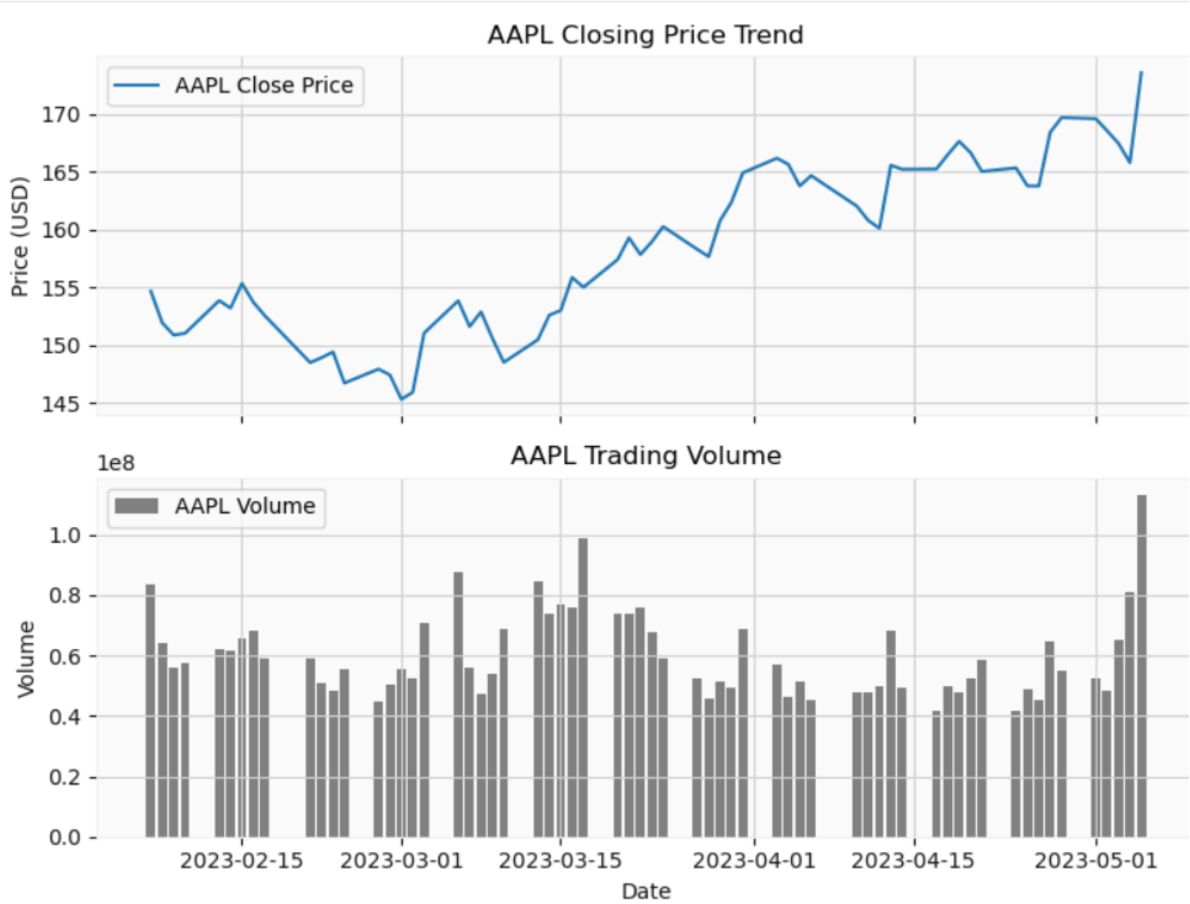
```
Text(0.5, 1.0, 'Total Volume by Ticker')
```



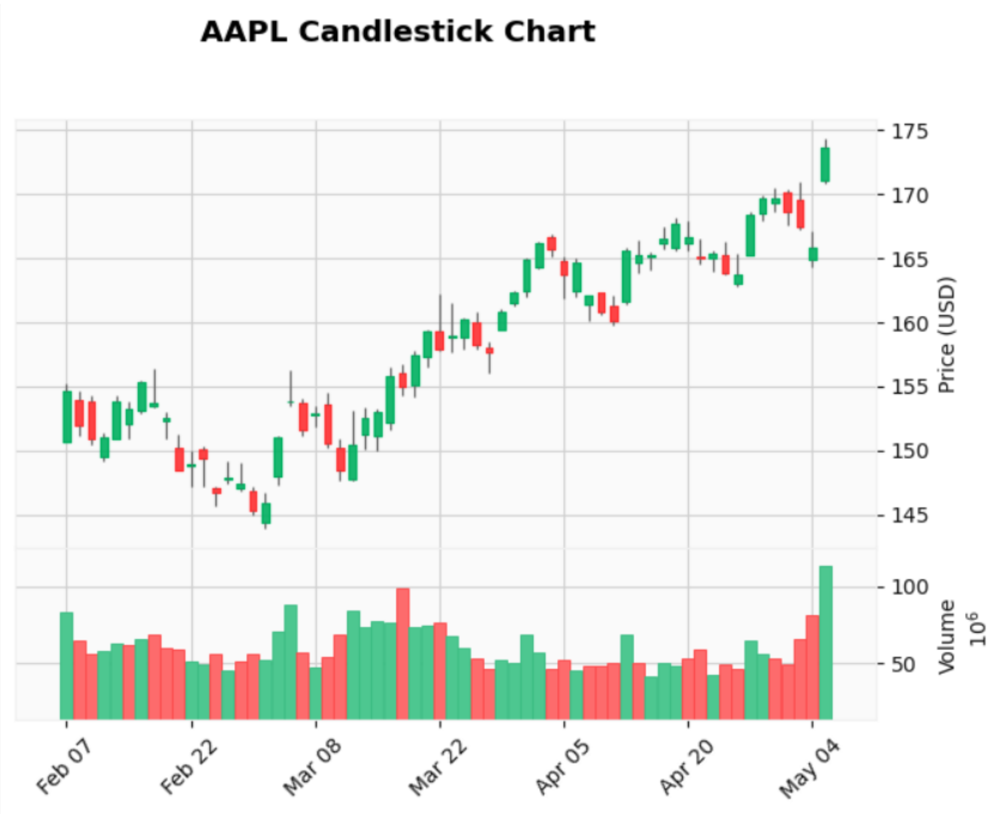
```python
# Exploring the relationship between volume and closing prices, to identify any correlations.
plt.scatter(data['Volume'], data['Close'])
plt.xlabel('Volume')
plt.ylabel('Closing Price')
plt.title('Volume vs. Closing Price')
plt.show()
```


```python
# Illustrating the distribution of the closing prices, including the median, quartiles, and outliers.
plt.boxplot(data['Close'])
plt.ylabel('Closing Price')
plt.title('Closing Price Distribution')
plt.show()
```

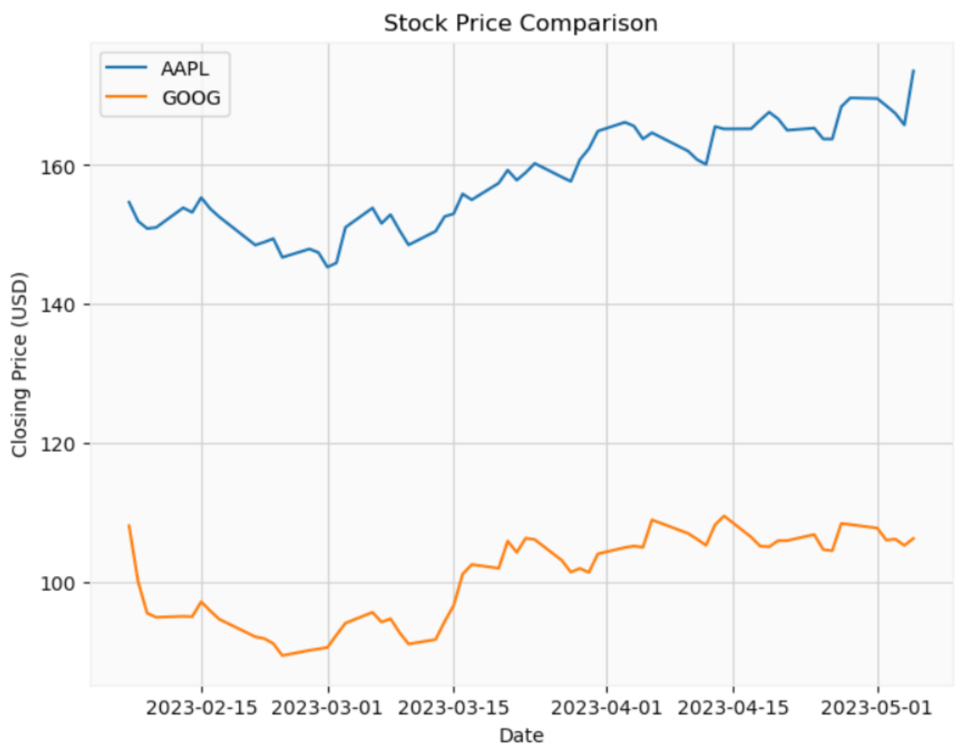
```python
# Line Chart for Closing Price and Volume
aapl_data = data[data['Ticker'] == 'AAPL'].sort_values('Date')

fig, (ax1, ax2) = plt.subplots(2, 1, figsize=(8, 8), sharex=True)

# Plotting Closing Price
ax1.plot(aapl_data['Date'], aapl_data['Close'], label='AAPL Close Price')
ax1.set_title('AAPL Closing Price Trend')
ax1.set_ylabel('Price (USD)')
ax1.grid(True)
ax1.legend()

# Plotting Volume
ax2.bar(aapl_data['Date'], aapl_data['Volume'], color='gray', label='AAPL Volume')
ax2.set_title('AAPL Trading Volume')
ax2.set_xlabel('Date')
ax2.set_ylabel('Volume')
ax2.grid(True)
ax2.legend()

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



```
# mplfinance requires a DataFrame with a DatetimeIndex
aapl_data = data[data['Ticker'] == 'AAPL'].sort_values('Date')
aapl_data = aapl_data.set_index(pd.DatetimeIndex(aapl_data['Date']))

mpf.plot(aapl_data,
         type='candle',
         style='yahoo',
         title='AAPL Candlestick Chart',
         ylabel='Price (USD)',
         volume=True,
         ylabel_lower='Volume')
```

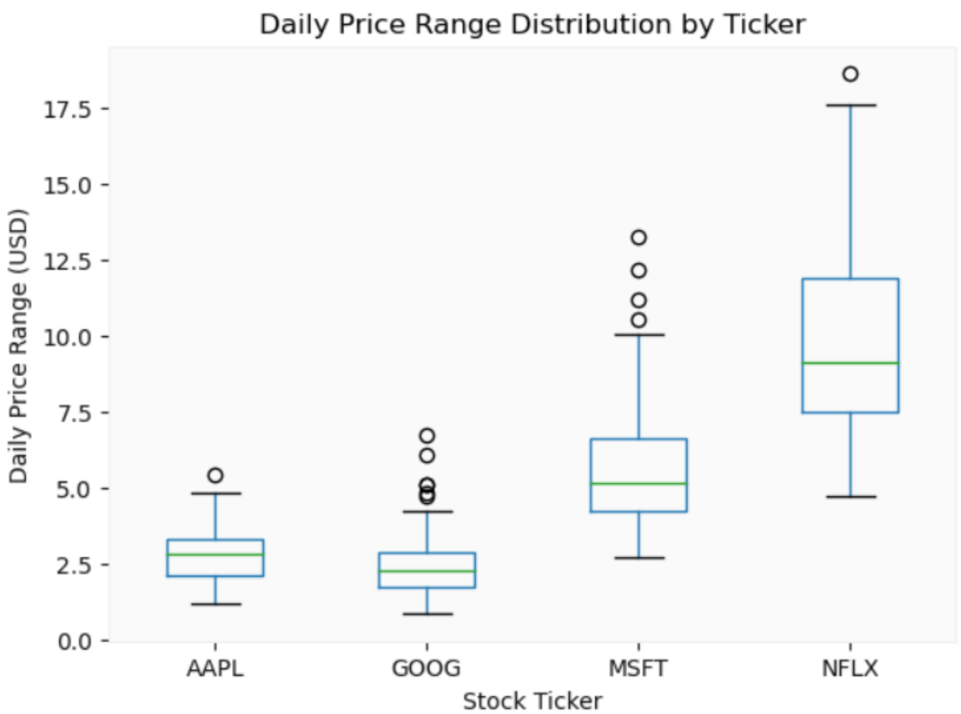



```
# Filter data for two tickers, e.g., 'AAPL' and 'GOOG'
aapl_data = data[data['Ticker'] == 'AAPL'].sort_values('Date')
goog_data = data[data['Ticker'] == 'GOOG'].sort_values('Date')

plt.figure(figsize=(8, 6))
plt.plot(aapl_data['Date'], aapl_data['Close'], label='AAPL')
plt.plot(goog_data['Date'], goog_data['Close'], label='GOOG')
plt.title('Stock Price Comparison')
plt.xlabel('Date')
plt.ylabel('Closing Price (USD)')
plt.grid(True)
plt.legend()
plt.show()
```




```python
# First, calculate the daily range
data['Daily_Range'] = data['High'] - data['Low']
plt.figure(figsize=(8, 5))
data.boxplot(column='Daily_Range', by='Ticker', grid=False)
plt.suptitle('') # Suppress the default title
plt.title('Daily Price Range Distribution by Ticker')
plt.xlabel('Stock Ticker')
plt.ylabel('Daily Price Range (USD)')
plt.show()
```

```
<Figure size 800x500 with 0 Axes>
```



```python
# Two-Sample T-Test for Mean Closing Prices
# Filter the data for two different stocks
aapl_close = data[data['Ticker'] == 'AAPL']['Close']
goog_close = data[data['Ticker'] == 'GOOG']['Close']

# Perform a two-sample t-test
t_statistic, p_value = stats.ttest_ind(aapl_close, goog_close, equal_var=False)

print(f"T-statistic: {t_statistic:.4f}")
print(f"P-value: {p_value:.4f}")

# Interpret the results
alpha = 0.05
if p_value < alpha:
    print("Conclusion: Reject the null hypothesis. There is a statistically significant difference in the mean closing prices.")
else:
    print("Conclusion: Fail to reject the null hypothesis. There is no statistically significant difference in the mean closing prices.")
```

```
T-statistic: 46.8845
P-value: 0.0000
Conclusion: Reject the null hypothesis. There is a statistically significant difference in the mean closing prices.
```

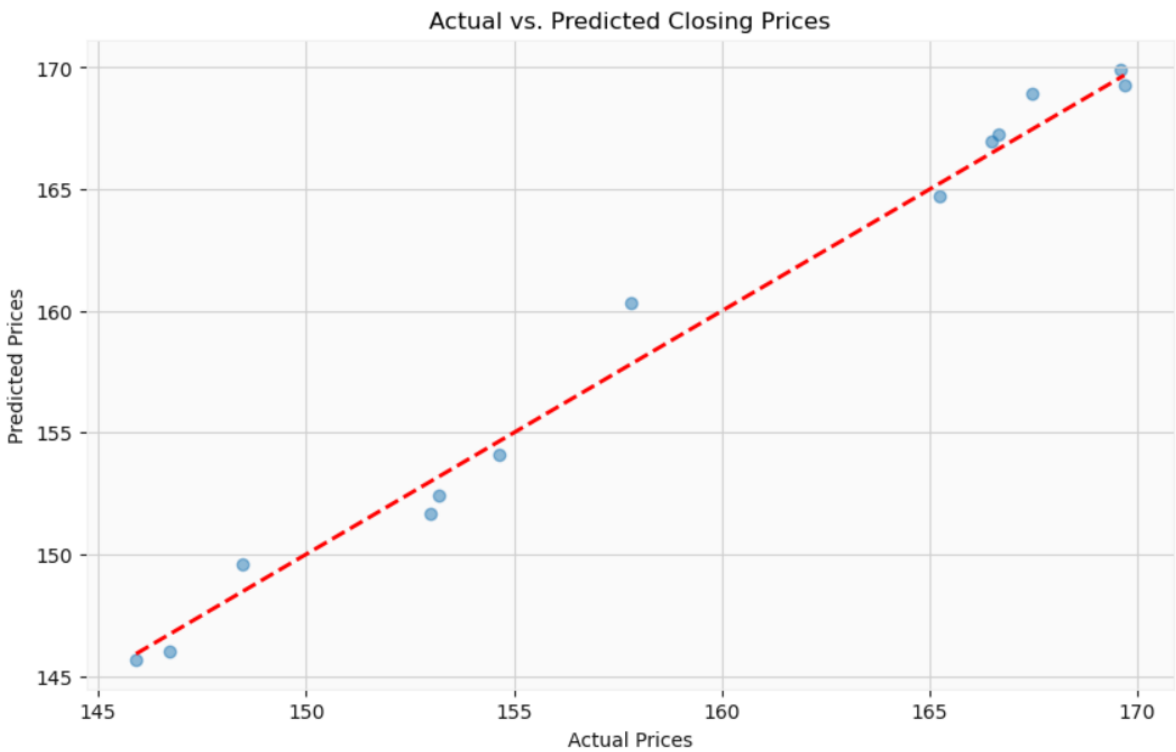
```python
# Pearson Correlation for Price and Volume
# Select a single stock for this analysis
aapl_data = data[data['Ticker'] == 'AAPL']

# Perform Pearson correlation test
correlation, p_value = stats.pearsonr(aapl_data['Close'], aapl_data['Volume'])

print(f"Pearson Correlation Coefficient: {correlation:.4f}")
print(f"P-value: {p_value:.4f}")

# Interpret the results
alpha = 0.05
if p_value < alpha:
    print("Conclusion: Reject the null hypothesis. There is a statistically significant correlation between price and volume.")
else:
    print("Conclusion: Fail to reject the null hypothesis. There is no statistically significant correlation between price and volume.")
```

```
Pearson Correlation Coefficient: -0.0563
P-value: 0.6638
Conclusion: Fail to reject the null hypothesis. There is no statistically significant correlation between price and volume.
```

```python
data['Date'] = pd.to_datetime(data['Date'])

aapl_data = data[data['Ticker'] == 'AAPL'].copy()
aapl_data = aapl_data.sort_values('Date')

# Feature Engineering: Create a numerical feature for the date
# Using the number of days since the first date in the dataset
aapl_data['Days_Since_Start'] = (aapl_data['Date'] - aapl_data['Date'].min()).dt.days

# Define the features (X) and target (y)
features = ['Days_Since_Start', 'Open', 'High', 'Low', 'Volume']
target = 'Close'

X = aapl_data[features]
y = aapl_data[target]

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Initialize and train the Linear Regression model
model = LinearRegression()
model.fit(X_train, y_train)

# Make predictions on the test set
predictions = model.predict(X_test)

# Evaluate the model's performance
mse = mean_squared_error(y_test, predictions)
r2 = r2_score(y_test, predictions)

print(f"Mean Squared Error (MSE): {mse:.4f}")
print(f"R-squared (R²): {r2:.4f}")
```

```python
# Printing the model coefficients to see the weight of each feature
print("\nModel Coefficients:")
for feature, coef in zip(features, model.coef_):
    print(f"{feature}: {coef:.4f}")

print(f"Intercept: {model.intercept_:.4f}")

plt.figure(figsize=(10, 6))
plt.scatter(y_test, predictions, alpha=0.5)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--', lw=2)
plt.title('Actual vs. Predicted Closing Prices')
plt.xlabel('Actual Prices')
plt.ylabel('Predicted Prices')
plt.grid(True)
plt.show()
```

```
Mean Squared Error (MSE): 1.0942
R-squared (R²): 0.9854

Model Coefficients:
Days_Since_Start: -0.0016
Open: -0.5489
High: 0.7733
Low: 0.7944
Volume: -0.0000
Intercept: -2.5707
```



CONCLUSION

By creating a very effective baseline predictive model and offering a thorough quantitative analysis of stock data for AAPL, GOOG, MSFT, and NFLX, the analysis module effectively met its goals.

Summary of Key Findings

Exploratory Data Analysis (EDA) allowed us to identify significant variations in market behavior:

Volatility: Compared to the other tickers, especially Apple (AAPL), which showed the least amount of volatility, Netflix (NFLX) showed the biggest mean daily price range, indicating higher intraday volatility.

Price Trends: Throughout the observation period, AAPL's closing price trend showed a steady and robust increasing trajectory, in contrast to Google's somewhat flat trend.

Statistical Differences: The mean closing prices of AAPL and GOOG showed a statistically significant difference (alpha = 0.05) according to a two-sample t-test, confirming that both stocks have different pricing mechanisms. On the other hand, there was no statistically significant linear link between AAPL's closing price and trading volume over this time frame, according to the Pearson correlation test.

Model Outcomes and Consequences

A Mean Squared Error (MSE) of 1.0942 and a R-Square score of 0.9854 were two outstanding performance indicators for the constructed Linear Regression model used to forecast AAPL closing prices. The model's selected features (Open, High, Low, and Days_Since_Start) are very good predictors of the closing price, as seen by this remarkably high R^2 value, which makes the model a trustworthy instrument for short-term price estimation. Additionally, the coefficient analysis showed that the Low and High prices had the most influence on the Close price.

Future Work

Although the linear regression model has a high degree of short-term predictive power, future research should concentrate on expanding this analysis to include more complex methods in order to account for non-linear market dynamics:

Time Series Modeling: Use sophisticated time series models, like Prophet or ARIMA, to predict future prices that take into account temporal relationships and go beyond a single trading day.

Feature Engineering: To potentially increase model robustness and forecast accuracy, particularly for equities with higher volatility like NFLX, investigate other technical indicators (such as moving averages and RSI) as input features.

Comparative Predictive Analysis: To offer a performance comparison of the various stock types, apply the Linear Regression modeling to MSFT, NFLX, and GOOG.