```
from google.colab import drive
drive.mount("/content/drive", force_remount=True)
```

```
Mounted at /content/drive
```

Importing "drive"module from the "google.colab' package and mounting google drive in the colab environment.

```
%cd /content/drive/MyDrive/ColabNotebooks/
!1s
```

```
/content/drive/MyDrive/ColabNotebooks
/bin/bash: line 1: 1s: command not found
```

Changing the current working directory to content/drive/MyDrive/u3269444_Capstone_Project

Introduction and Purposes

This project and the following analysis is based on the dataset of TESLA Stock Price Prediction built by A.Mohan Kumar, available from Kaggle repository (https://www.kaggle.com/datasets/amohankumar/tesla-stock-price-prediction-dataset)

- The dataset includes the stock price details of TESLA from the 29th of September, 2021 to the 29th of September, 2022.
- This project aims to create a machine learning model which can predict the future trend of TESLA stock price according to the characteristics of data.
- To resolve this issue, I will take a systematic approach, developing a data analysis and prediction model step by step. This model will implement various Python packages, modules, and classes (including machine learning and regression algorithms) to achieve the desired outcome.

Step 1: Reading Data by Using Python

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

# Reading the dataset
import pandas as pd
import numpy as np
TeslaData=pd.read_csv('/content/drive/MyDrive/ColabNotebooks/TESLA.csv', encoding='latin')
print('Shape before deleting duplicate values:', TeslaData.shape)

# Removing duplicate rows
TeslaData=TeslaData.drop_duplicates()
print('Shape After deleting duplicate values:', TeslaData.shape)

# Start observing the Quantitative/Qualitative variables
TeslaData.head(10)
```

```
Shape before deleting duplicate values: (253, 7)
Shape After deleting duplicate values: (253, 7)
```

	Date	Open	High	Low	Close	Adj Close	Volume
0	2021-09-29	259.933319	264.500000	256.893341	260.436676	260.436676	62828700
1	2021-09-30	260.333344	263.043335	258.333344	258.493347	258.493347	53868000
2	2021-10-01	259.466675	260.260010	254.529999	258.406677	258.406677	51094200
3	2021-10-04	265.500000	268.989990	258.706665	260.510010	260.510010	91449900
4	2021-10-05	261.600006	265.769989	258.066681	260.196655	260.196655	55297800
5	2021-10-06	258.733337	262.220001	257.739990	260.916656	260.916656	43898400
6	2021-10-07	261.820007	268.333344	261.126678	264.536682	264.536682	57587400
7	2021-10-08	265.403320	265.459991	260.303345	261.829987	261.829987	50215800
8	2021-10-11	262.549988	267.079987	261.833344	263.980011	263.980011	42600900
9	2021-10-12	266.976654	270.773346	265.523346	268.573334	268.573334	66060000

Next steps: Generate code with `TeslaData` View recommended plots

Key observations of the Data Description in Step 1

This dataset includes 253 valid data of the prices of TESLA stock from the 29th of September 2021 to 29th of September 2022.

There are 7 attributes contained in the file. They are outlined and explained below.

Date -- The specific date when the stock market data was recorded.

Open -- The price of a stock when the market opens for trading on a particular day.

High -- The highest price at which the stock traded during the trading day.

Low -- The lowest price at which the stock traded during the trading day.

Close -- The price of the stock at the end of the trading day.

Adj Close -- The closing price of the stock adjusted for any corporate actions, such as dividends, stock splits, or mergers, that may have occurred.

Volume -- The total number of shares of the stock that were traded during the trading day.

Step 2 : Define the Problem Statement

- Creating a prediction model to predict the volume of shares of TESLA stock market.
- Target Variable: Close
- Predictors: Date, Open, High, Low, Close, Adj Close, Volume.

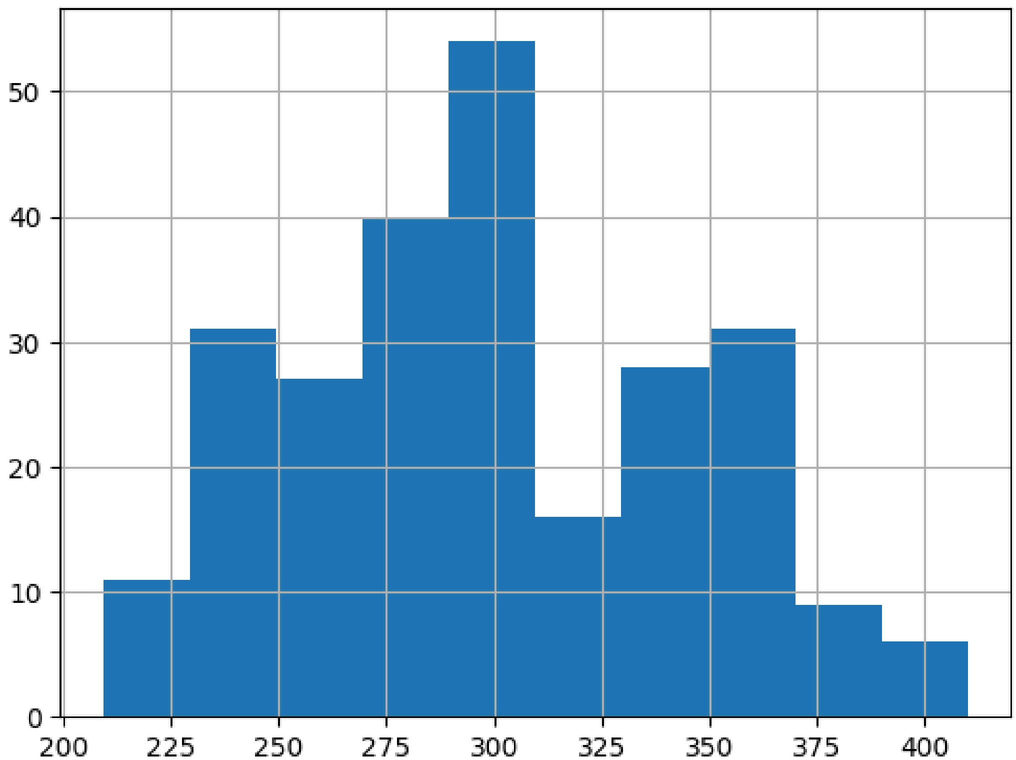
Step 3: Choosing the appropriate ML/AI Algorithm for Data Analysis.

- Based on the given problem description, a supervised Machine Learning (ML) Regression Model will be developed. The variable that it aims to predict is Volume, which variates continuously.

Step 4: Observe the Class Distribution

```
%matplotlib inline
# Creating histogram as the target variable is a Continuous variable
# Accesses the 'Volume' column of the TeslaData and calls the hist() function
TeslaData['Close'].hist()
```

```
<Axes: >
```



Observations from Step 4

- The data distribution of the target variable "Close" exhibits a bell curve.

- There's a noticeable decrease in data density around the values of 310 - 330, suggesting a slight negative skewness in that range. The decrease in data density may impact the model's ability to learn all scenarios accurately.
- It may not greatly affect predictions, but substantial decreases could lead to biased results.
- Further analysis and strategies such as data transformation will be conducted to address this issue and optimize model performance for predictive modeling tasks.

Step 5: Basic Exploratory Data Analysis

In this step of data analysis, the overall dataset is assessed to understand its structure and contents. The primary focus is on examining the volume of data and categorizing the columns as Quantitative, Categorical, or Qualitative. This initial evaluation serves as the foundation for identifying columns that may need further analysis or rejection.

Each column undergoes careful scrutiny to determine its impact on the target variable, which, in this report, is the stock price of Tesla. Columns that do not significantly affect the target variable are promptly removed from consideration, while others are retained for further analysis.

To conduct basic exploratory analysis, four commands are employed:

- head(): Displays a few sample rows of the data to provide a glimpse of its structure.
- info(): Summarizes the information contained in the dataset, including data types and missing values.
- describe(): Provides descriptive statistical details of the data, such as mean, median, and quartiles.
- nunique(): Identifies the number of unique values in each column, helping determine whether a column is categorical or continuous.

```
# Observes the first few rows of the dataset
TeslaData.head()
```

	Date	Open	High	Low	Close	Adj Close	Volume
0	2021-09-29	259.933319	264.500000	256.893341	260.436676	260.436676	62828700
1	2021-09-30	260.333344	263.043335	258.333344	258.493347	258.493347	53868000
2	2021-10-01	259.466675	260.260010	254.529999	258.406677	258.406677	51094200
3	2021-10-04	265.500000	268.989990	258.706665	260.510010	260.510010	91449900
4	2021-10-05	261.600006	265.769989	258.066681	260.196655	260.196655	55297800

Next steps: Generate code with TeslaData View recommended plots

```
# Observe the last few rows of the dataset
TeslaData.tail()
```

	Date	Open	High	Low	Close	Adj Close	Volume
248	2022-09-23	283.089996	284.500000	272.820007	275.329987	275.329987	63615400
249	2022-09-26	271.829987	284.089996	270.309998	276.010010	276.010010	58076900
250	2022-09-27	283.839996	288.670013	277.510010	282.940002	282.940002	61925200
251	2022-09-28	283.079987	289.000000	277.570007	287.809998	287.809998	54664800
252	2022-09-29	282.760010	283.649994	265.779999	268.209991	268.209991	77393100

```
# Provides summarized information about dataset
TeslaData.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 253 entries, 0 to 252
Data columns (total 7 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   Date       253 non-null    object
 1   Open       253 non-null    float64
 2   High       253 non-null    float64
 3   Low        253 non-null    float64
```

```
 4   Close      253 non-null    float64
 5   Adj Close  253 non-null    float64
 6   Volume     253 non-null    int64
dtypes: float64(5), int64(1), object(1)
memory usage: 14.0+ KB
```

```
# Provides the descriptive statistics
TeslaData.describe(include='all')
```

	Date	Open	High	Low	Close	Adj Close	Volume
count	253	253.000000	253.000000	253.000000	253.000000	253.000000	2.530000e+02
unique	253	NaN	NaN	NaN	NaN	NaN	NaN
top	2021-09-29	NaN	NaN	NaN	NaN	NaN	NaN
freq	1	NaN	NaN	NaN	NaN	NaN	NaN
mean	NaN	300.136008	307.486021	292.114058	299.709104	299.709104	8.050938e+07
std	NaN	46.139272	46.789896	44.685331	45.788283	45.788283	2.546595e+07
min	NaN	207.949997	217.973328	206.856674	209.386673	209.386673	3.504270e+07
25%	NaN	266.513336	273.166656	260.723328	266.923340	266.923340	6.255570e+07
50%	NaN	298.500000	303.709991	289.130005	296.666656	296.666656	7.695630e+07
75%	NaN	335.600006	344.950012	327.510010	336.336670	336.336670	9.347310e+07
max	NaN	411.470001	414.496674	405.666656	409.970001	409.970001	1.885563e+08

```
# Checks the number of unique values and and inspects the distinct values present in each column.
# Determines if the a column is categorical or continuous.
# If the count of unique values equals 253, the variable is considered categorical. Otherwise, it's classified as continuous.
TeslaData.nunique()
```

```
Date          253
Open          249
High          251
Low           251
Close         252
```

```
Adj Close    252
Volume       253
dtype: int64
```

Observations from Step 5

Following the basic exploration outlined above, a simple data report will be presented, providing observations for each column.

This report serves as an instruction for subsequent analysis, guiding the direction of further examination. The columns selected at this stage represent a preliminary set, and additional scrutiny will be undertaken to compile a final list. This iterative process ensures a thorough understanding of the dataset's characteristics and facilitates informed decision-making in subsequent analytical steps.

- Date - Categorical. Selected.
- Open - Continuous. Selected.
- High - Continuous. Selected.
- Low - Continuous. Selected.
- Close - Continuous. Selected.
- Adj Close - Continuous. Selected.
- Volume - Continuous. Selected. (This is the Target Variable, which will be predicted by the proposed regression model.)

Step 7: Removing Unwanted columns

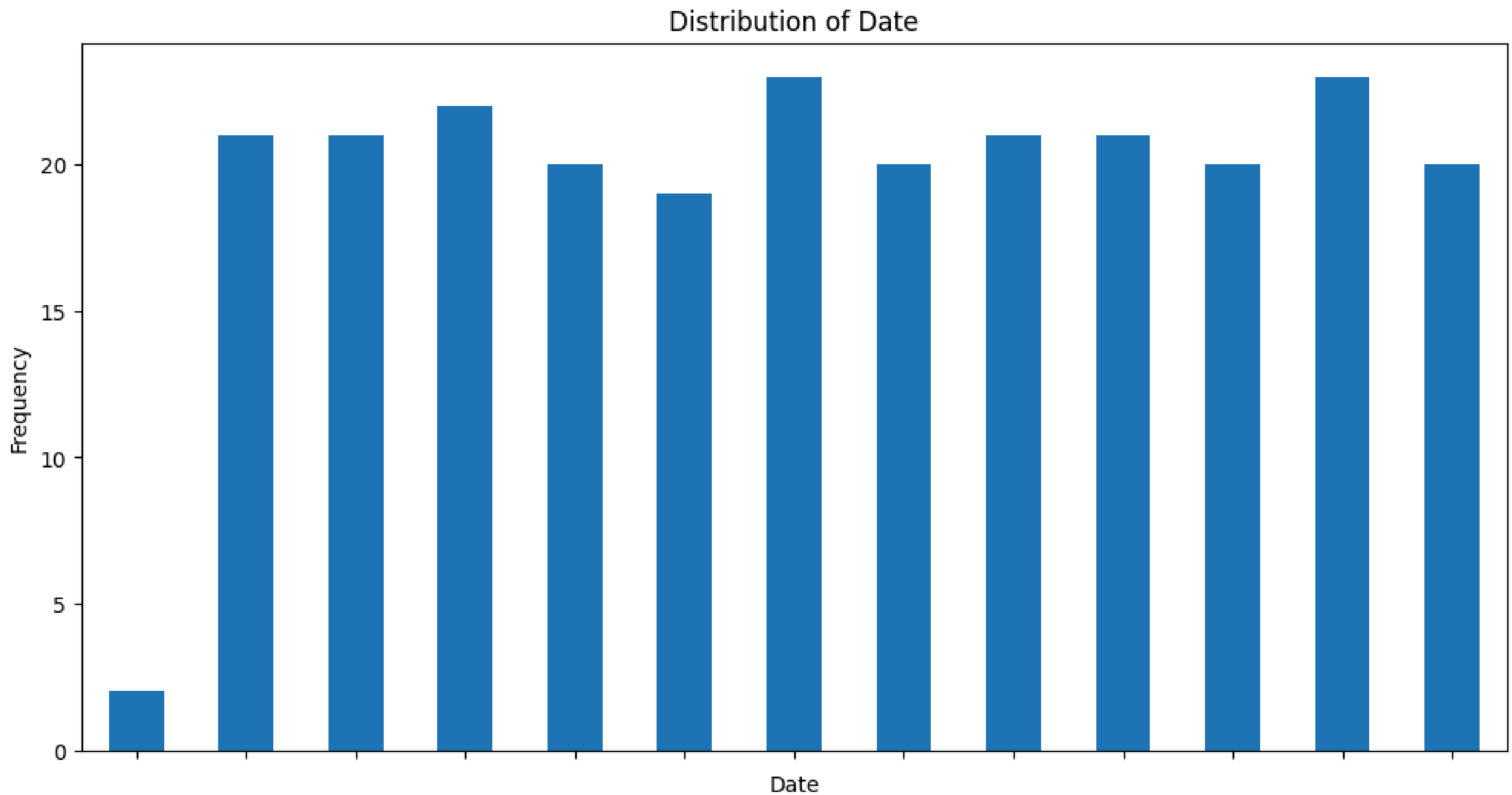
- There are no qualitative columns in the data.
- Hence no column will be removed

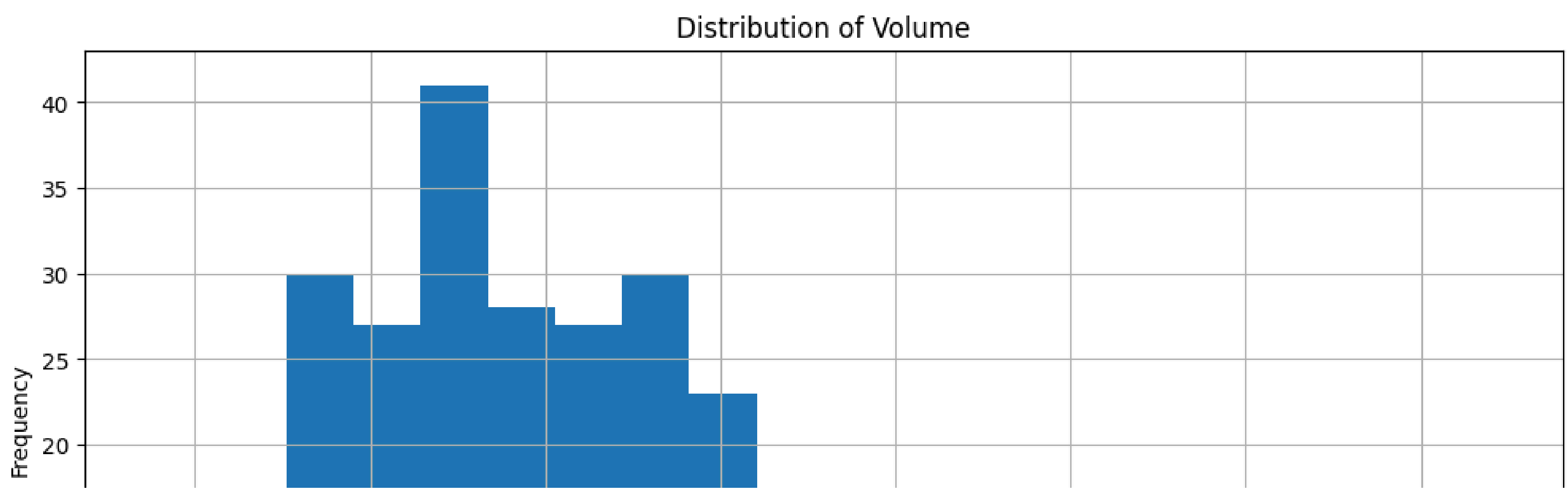
Step 8: Visual Exploratory Data Analysis

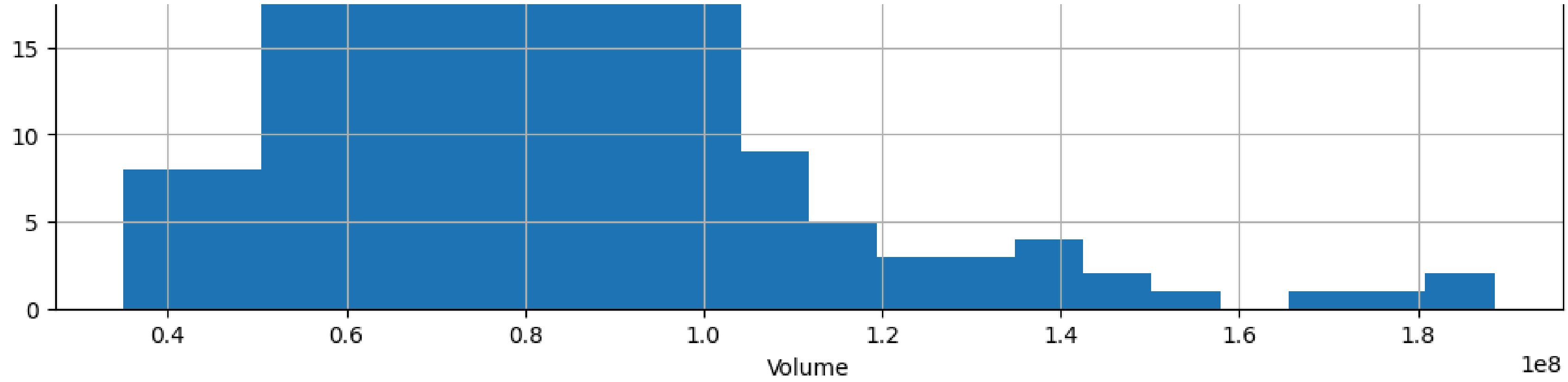
- Utilizing bar plots, the distribution of all Categorical Predictor variables in the dataset will be displayed.

- Categorical variables can be discerned by inspecting their unique values, which typically number around 253, fostering data grouping based on repetition.
- In the prior step of Basic Exploration Data Analysis, 'Date' and 'Volume' emerged as the identified categorical predictors in the dataset. To visualize the distribution of data for these categorical columns, bar charts will be employed.

```
# Plotting multiple bar charts at once for categorical variables
import pandas as pd
import matplotlib.pyplot as plt

# Visualizing the distribution of the categorical variable 'Date'
TeslaData['Date'] = pd.to_datetime(TeslaData['Date'])

# Aggregate data into larger time intervals
date_counts = TeslaData.resample('M', on='Date').size()
plt.figure(figsize=(12, 6))
date_counts.plot(kind='bar')

plt.title('Distribution of Date')
plt.xlabel('Date')
plt.ylabel('Frequency')
plt.xticks(rotation=45)
plt.gca().set_xticklabels([])
plt.show()

# Visualizing the distribution of the continuous variable 'Volume'
plt.figure(figsize=(12, 6))
plt.hist(TeslaData['Volume'], bins=20)
plt.title('Distribution of Volume')
plt.xlabel('Volume')
plt.ylabel('Frequency')
plt.grid(True)
# Displaying the plot
plt.show()
```


Distribution of Date
Frequency
0
5
10
15
20
Date


Distribution of Volume
Frequency
20
25
30
35
40



Observations from Step 8 - Visual Exploratory Data Analysis

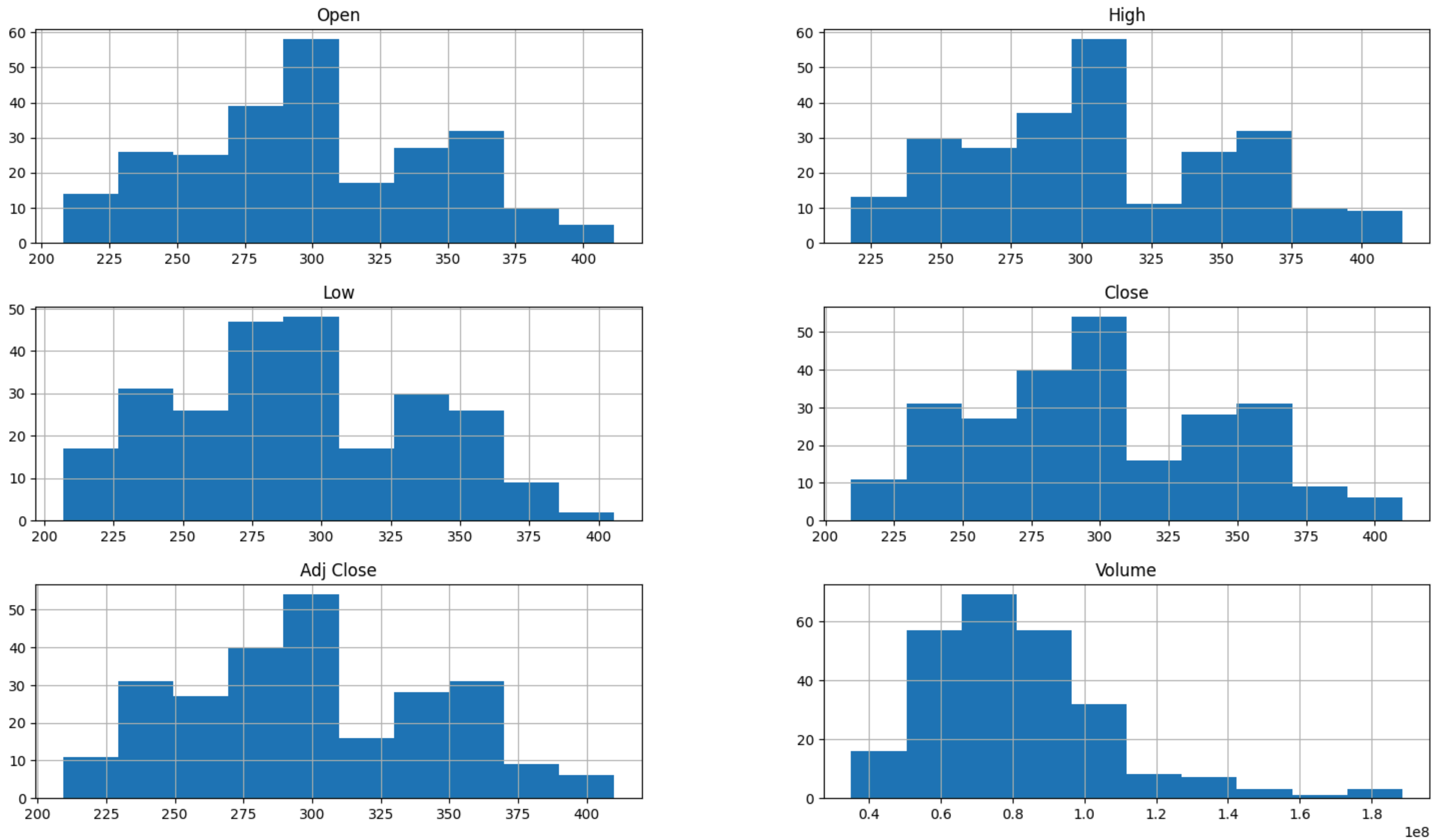
- The Volume bar chart exhibits a positively skewed distribution, indicating that one category has significantly higher frequency compared to others.
- The Date bar chart shows a low frequency for the first category and relatively higher frequencies for the rest.
- Ideally, categories should have comparable frequencies for effective learning by ML/AI regression algorithms. However, the skewed distributions suggest that this may not be the case.
- The presence of highly skewed distributions, where one category dominates, can hinder the effectiveness of ML model development. In Date chart, one category dominates, while in the other, the first category has low frequency compared to the rest.
- The hypothesis suggests that highly skewed columns may lack correlation with the target variable due to limited information.
- Confirmation of this hypothesis through correlation analysis can guide decisions on whether to retain or discard such columns.
- Columns exhibiting uncertain characteristics, such as highly skewed distributions, warrant further investigation to understand their impact on the dataset and ML model development.

Step 9: Visualizing the distribution of all the Continuous Predictor variables in the data using histograms

- Based on the Basic Exploratory Data Analysis, there are six continuous predictor variables 'Open', 'High', 'Low', 'Close', 'Adj Close', and 'Volume'.

```
# Plotting histograms of multiple columns together
TeslaData.hist(['Open', 'High', 'Low', 'Close', 'Adj Close', 'Volume'], figsize=(18,10))
```

```
array([[<Axes: title={'center': 'Open'}>,
        <Axes: title={'center': 'High'}>],
       [<Axes: title={'center': 'Low'}>,
        <Axes: title={'center': 'Close'}>],
       [<Axes: title={'center': 'Adj Close'}>,
        <Axes: title={'center': 'Volume'}>]], dtype=object)
```



Observations from Step 9

- Each histogram visualizes the data distribution for a single continuous variable.
- The X-axis represents the range of values, while the Y-axis indicates the frequency of values within each range.
- In the histograms of 'Open', 'High', 'Low', 'Close', and 'Adj Close', the distribution closely resembles a bell curve. However, there consistently appears to be a lower column around 310 to 325, leading to a less than ideal distribution.
- Selected Continuous Variables:
- Open : Selected. The distribution is good.
- High : Selected. The distribution is good.
- Low : Selected. The distribution is good.
- Close : Selected. The distribution is good.
- Adj Close : Selected. The distribution is good.
- Volume : Selected. The distribution is good.

Step 10: Outlier Analysis

- Outliers are the extreme values in the dataset, significantly different from the majority of values.
- It's necessary to address outliers individually for each column or data attribute, as the treatment approach varies slightly for each. Outliers can skew machine learning model development, as the algorithm may prioritize fitting the extreme values rather than the bulk of the data.
- In the histogram of High, it's noticeable that the columns around the range 315 to 340 are relatively lower. Therefore, it's necessary to replace the outliers for High.

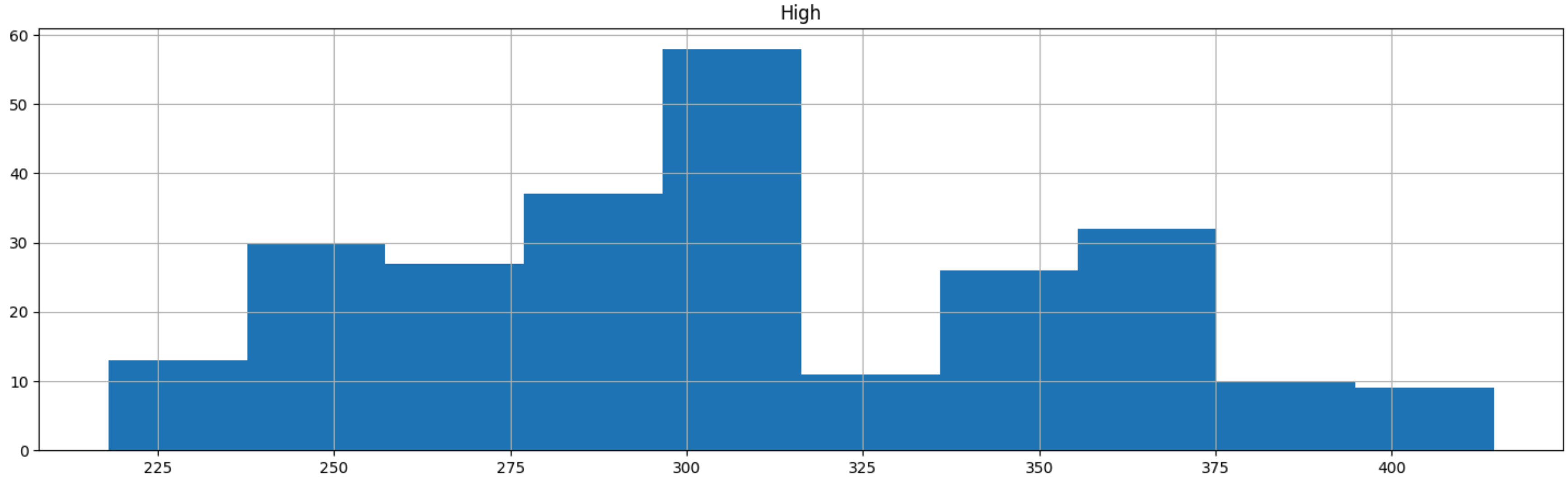
```
#Replacing outliers for 'High'
# Finding nearest values to 340 mark
TeslaData['High'][TeslaData['High']<340].sort_values(ascending=False)
```

```
59     338.553345
138    338.306671
137    337.570007
143    336.206665
134    336.156677
          ...
178    226.330002
180    225.166672
165    223.106674
181    220.970001
164    217.973328
Name: High, Length: 181, dtype: float64
```

Step 11:Visualising Data Distribution after outlier removal

```
TeslaData.hist(['High'], figsize=(18,5))
```

```
array([[<Axes: title={'center': 'High'}>]], dtype=object)
```



Observation from Step 11

- The distribution exhibits improvement post-outlier treatment.
- Although a tail remains, it appears thickened, indicating a substantial concentration of values within that range. Hence, this distribution is deemed acceptable.

Step 12: Missing Values Analysis

- Missing values in each column are handled individually.
- If a column has over 30% missing data, addressing them becomes impractical, leading to significant information loss, and consequently, the column is usually discarded.
- Below are various options for handling missing values:

- Removal of rows containing missing values, especially if only a few records are affected.
- Imputation of missing values with the median for continuous variables.
- Imputation of missing values with the mode for categorical variables.
- Interpolation of values based on neighboring data points.
- Interpolation of values according to established business logic.

```
# Finding how many missing values are there for each column
TeslaData.isnull().sum()
```

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

Observations from Step 12: Missing Value Analysis

- The data contains no missing values.
- Therefore, there is no need to remove any data rows.

Step 13: Feature Selection (Attribute Selection)

- The following parts will select the most relevant columns (features) that correlate with the Target variable.
- This selection process can be achieved through direct measurement of correlation values, ANOVA analysis, or Chi-Square tests.
- However, it's beneficial to visually assess the relationship between the Target variable/class variable and each predictor (feature) to gain a deeper understanding of the data.

- Below are techniques used for visualizing relationships between variables and statistically measuring their strength:

Visual Exploration of Relationship between Variables

- Continuous Vs Continuous ---- Scatter Plot
- Categorical Vs Continuous ---- Box Plot
- Categorical Vs Categorical ---- Grouped Bar Plots

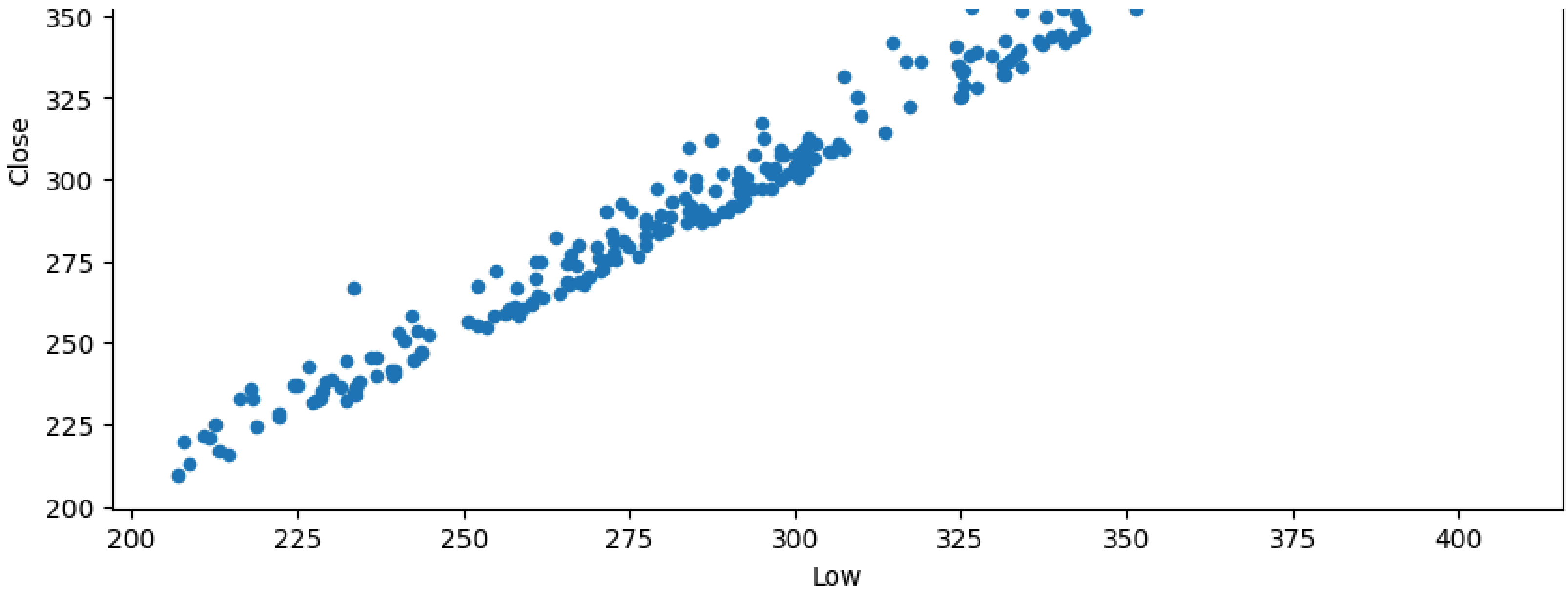
Statistical Measurement of Relationship Strength between Variables

- Continuous Vs Continuous ---- Correlation matrix
- Categorical Vs Continuous ---- ANOVA test
- Categorical Vs Categorical ---- Chi-Square test
- In the case of this dataset, the Target variable is Continuous, thus requiring attention to the following two scenarios:
- Continuous Target Variable Vs Continuous Predictor
- Continuous Target Variable Vs Categorical Predictor

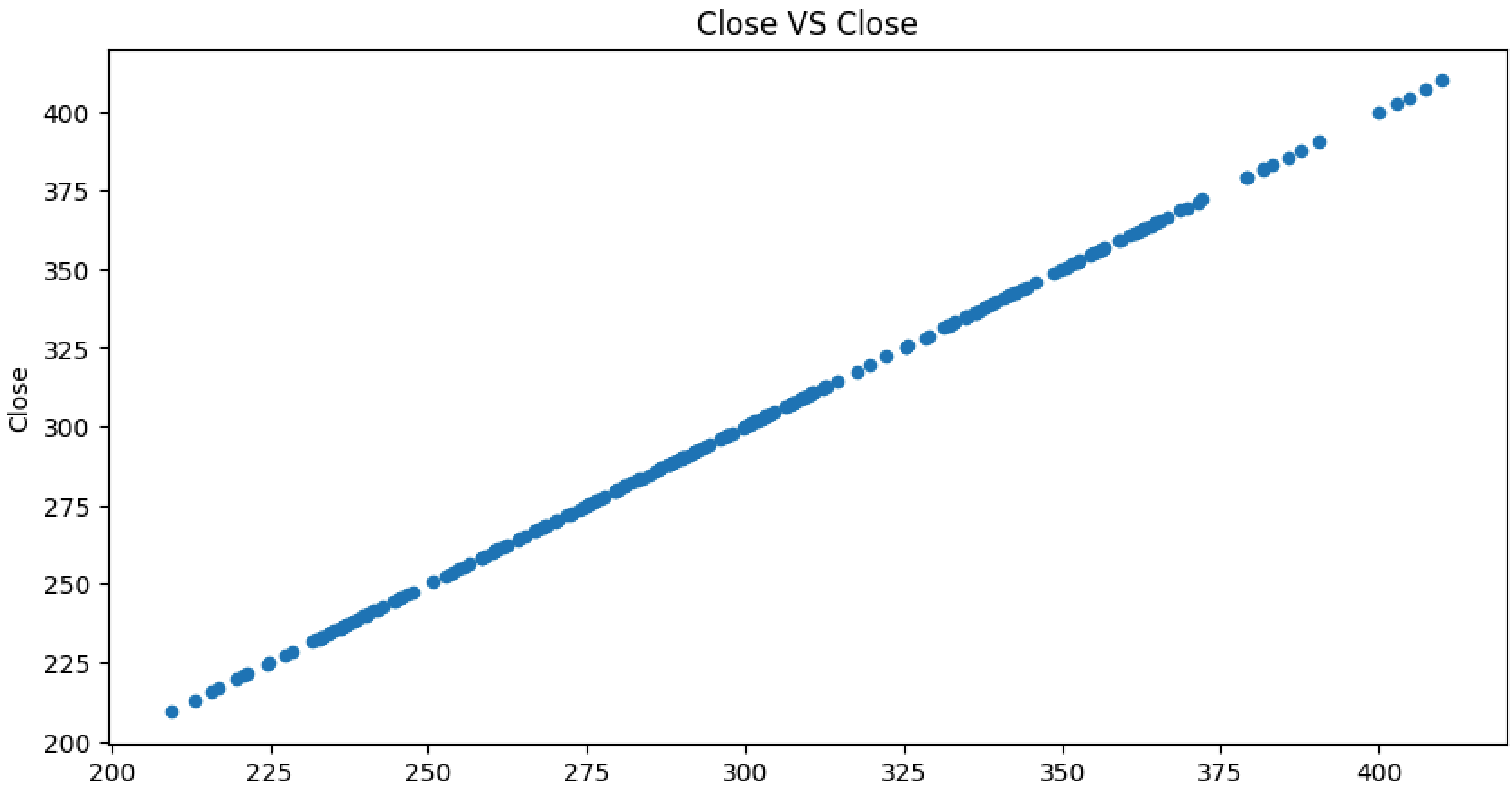
Relationship exploration: Continuous Vs Continuous -- Scatter Charts

- When both the Target variable and the predictor are continuous, it's available depict their relationship through a scatter plot and quantify the strength of their association using Pearson's correlation coefficient.

```
ContinuousCols=['Open', 'High', 'Low', 'Close', 'Adj Close', 'Volume']

# Plotting scatter chart for each predictor vs the target variable
for predictor in ContinuousCols:
    TeslaData.plot.scatter(x=predictor, y='Close', figsize=(10,5), title=predictor+" VS "+ 'Close')
```

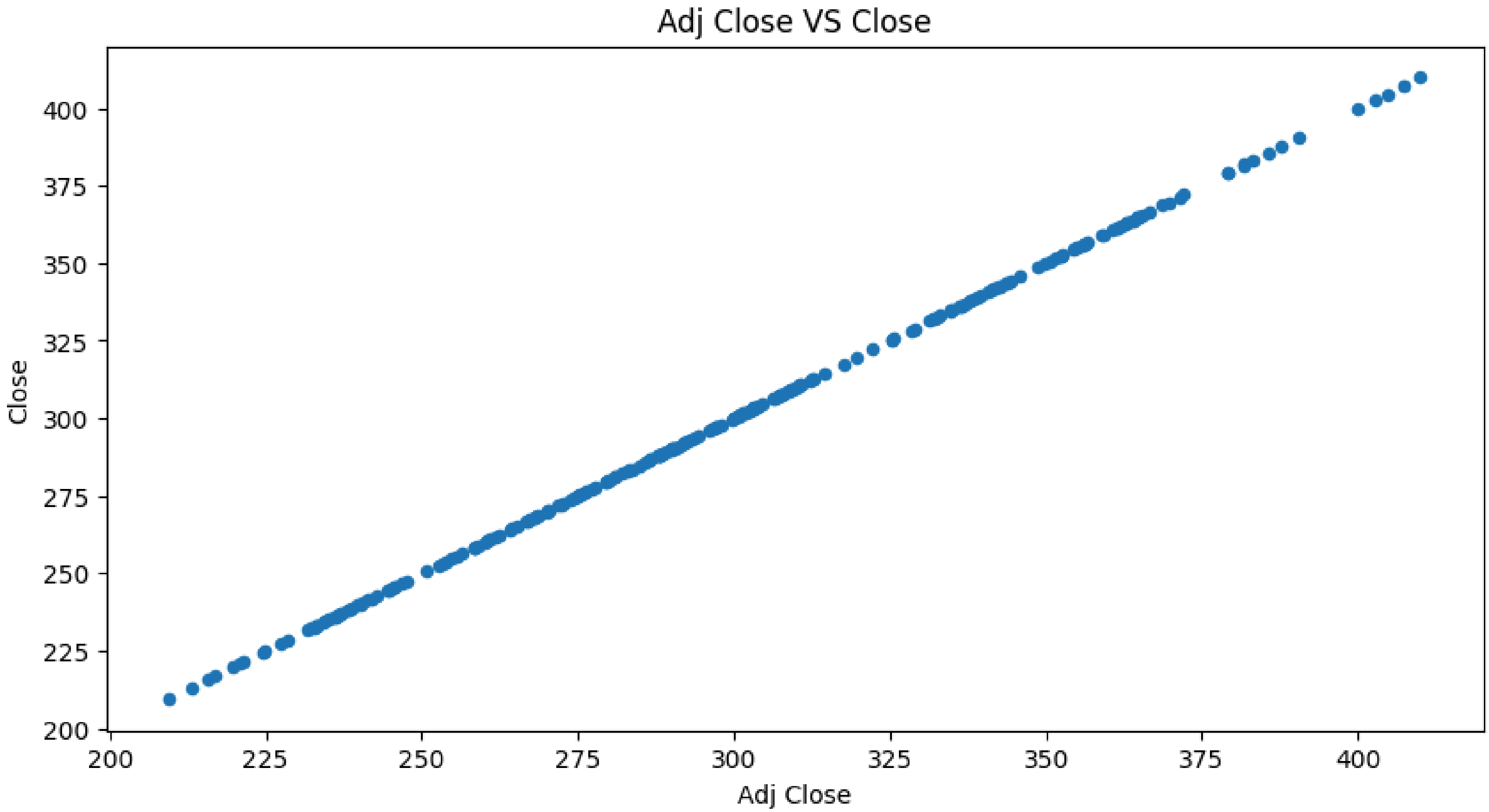


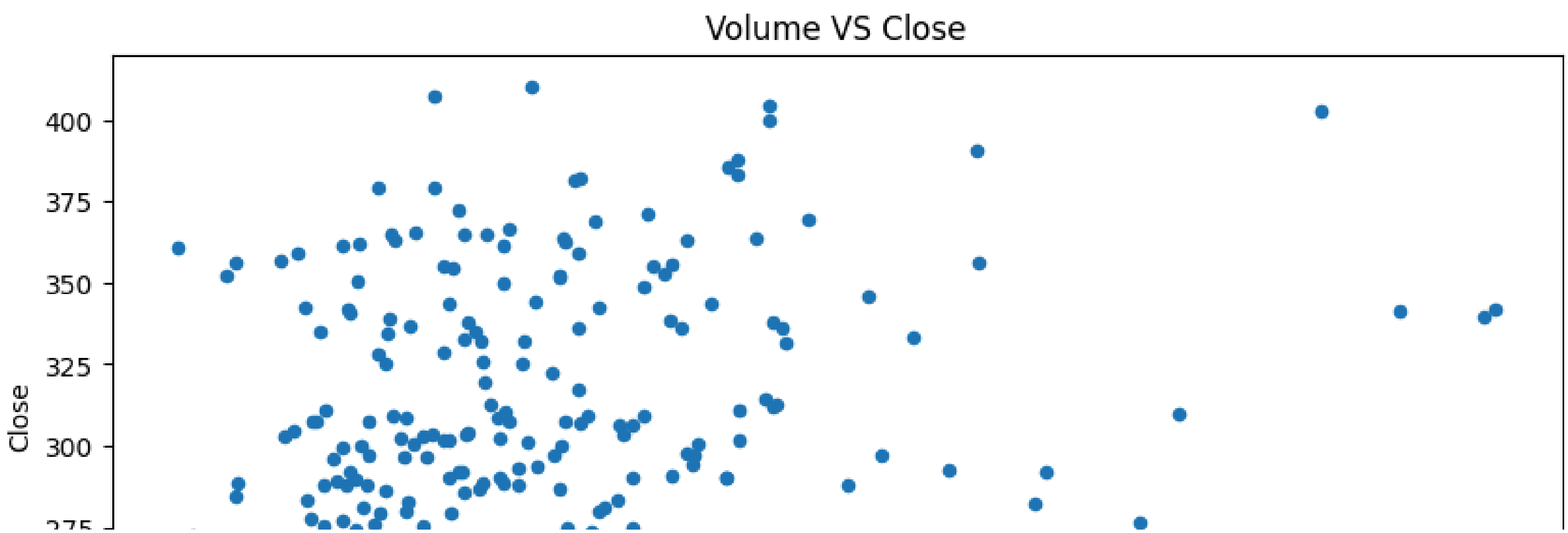
Close
Low

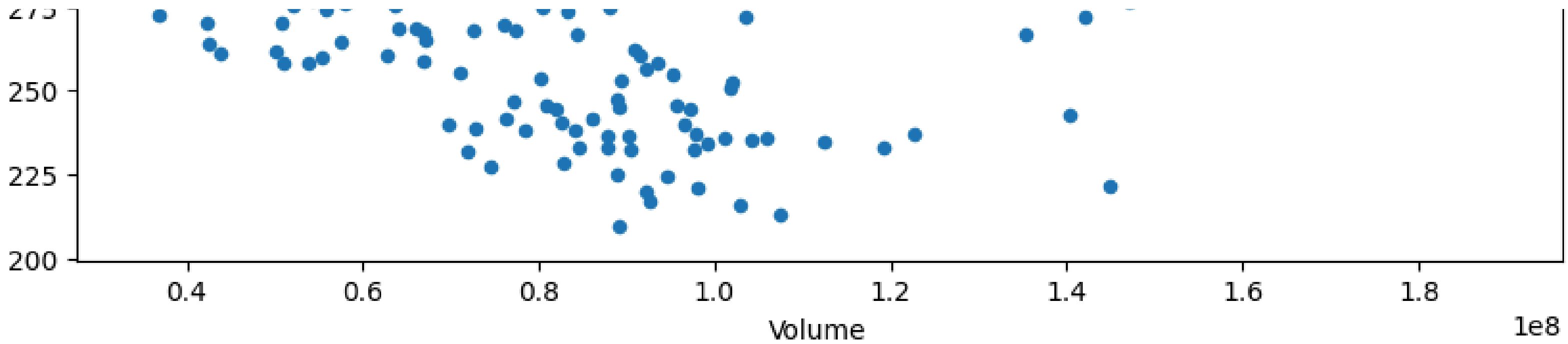


Close VS Close
Close

Close


Adj Close VS Close
Close
400
375
350
325
300
275
250
225
200
200
225
250
275
300
325
350
375
400
Adj Close


Volume VS Close
Close
400
375
350
325
300


275
250
225
200
0.4
0.6
0.8
1.0
1.2
1.4
1.6
1.8
Volume
1e8

Scatter charts interpretation

1. **Open Vs Close**: This graph presents dots mainly on the left-hand side and less on the right-hand side, with some scatter and a few outliers. Despite this, it still suggests an increasing trend, indicating a positive correlation between open and close prices, which could be beneficial for ML model building.

2. **High Vs Close**: This graph presents dots mainly on the left-hand side and less on the right-hand side, with some scatter and a few outliers. The data dots are closer to each other compare to "Open Vs Close". It shows an increasing trend, indicating a positive correlation between High and Close values, which could be beneficial for ML model building.

3. **Low Vs Close**: The scatter of data dots shows a slightly less organized increasing trend compared to "Close Vs Close" and "Adj Close Vs Close". Nevertheless, it still demonstrates an increasing trend, indicating a positive correlation between low and close prices, which can be useful for ML model building.

4. **Close Vs Close and Adj Close Vs Close**: Both of these graphs exhibit an increasing trend, with values being directly proportional to each other. This indicates a positive correlation between the variables, making them potentially useful for ML model building.

5. **Volume Vs Close**: The graph shows a decreasing trend, with data dots scattered mainly on the left-hand side and fewer dots on the right-hand side. This suggests a negative correlation between volume and close price, making them inversely proportional to each other. This decreasing trend makes them suitable for ML model building.

Step 14: Statistical Feature Selection (Continuous Vs Continuous) using Correlation value

- Pearson's correlation coefficient serves as a robust measure for this purpose.
- It can be computed straightforwardly by dividing the covariance between two features (x) and (y) (numerator) by the product of their standard deviations (denominator).

$$r_{xy} = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}}$$

- This calculation is applicable only to numeric columns.
- A correlation between [-1,0) signifies an inverse relationship, where the scatter plot depicts a downward trend.
- A correlation between (0,1] indicates a direct relationship, with the scatter plot displaying an upward trend.
- A correlation close to {0} suggests no discernible relationship, and the scatter plot shows no clear trend.
- If the correlation value between two variables exceeds 0.5 in magnitude, it indicates a strong relationship, regardless of the sign.
- The correlations between the Target variable and all other predictor variables have been assessed to determine which columns/features/predictors are genuinely associated with the target variable under consideration.

```
# Calculating correlation matrix
ContinuousCols=['Open', 'High', 'Low', 'Close', 'Adj Close', 'Volume']

# Creating the correlation matrix
CorrelationData=TeslaData[ContinuousCols].corr()
CorrelationData
```

	Open	High	Low	Close	Adj Close	Volume
Open	1.000000	0.991269	0.986364	0.971783	0.971783	-0.047793
High	0.991269	1.000000	0.988299	0.986715	0.986715	0.008397
Low	0.986364	0.988299	1.000000	0.990137	0.990137	-0.104980
Close	0.971783	0.986715	0.990137	1.000000	1.000000	-0.047791
Adj Close	0.971783	0.986715	0.990137	1.000000	1.000000	-0.047791
Volume	-0.047793	0.008397	-0.104980	-0.047791	-0.047791	1.000000

Next steps: Generate code with CorrelationData View recommended plots

```
# Filtering only those columns where absolute correlation > 0.5 with Target Variable
# reduce the 0.5 threshold if no variable is selected
CorrelationData['Close'][abs(CorrelationData['Close']) > 0.5 ]
```

```
Open         0.971783
High         0.986715
Low          0.990137
Close        1.000000
Adj Close    1.000000
Name: Close, dtype: float64
```

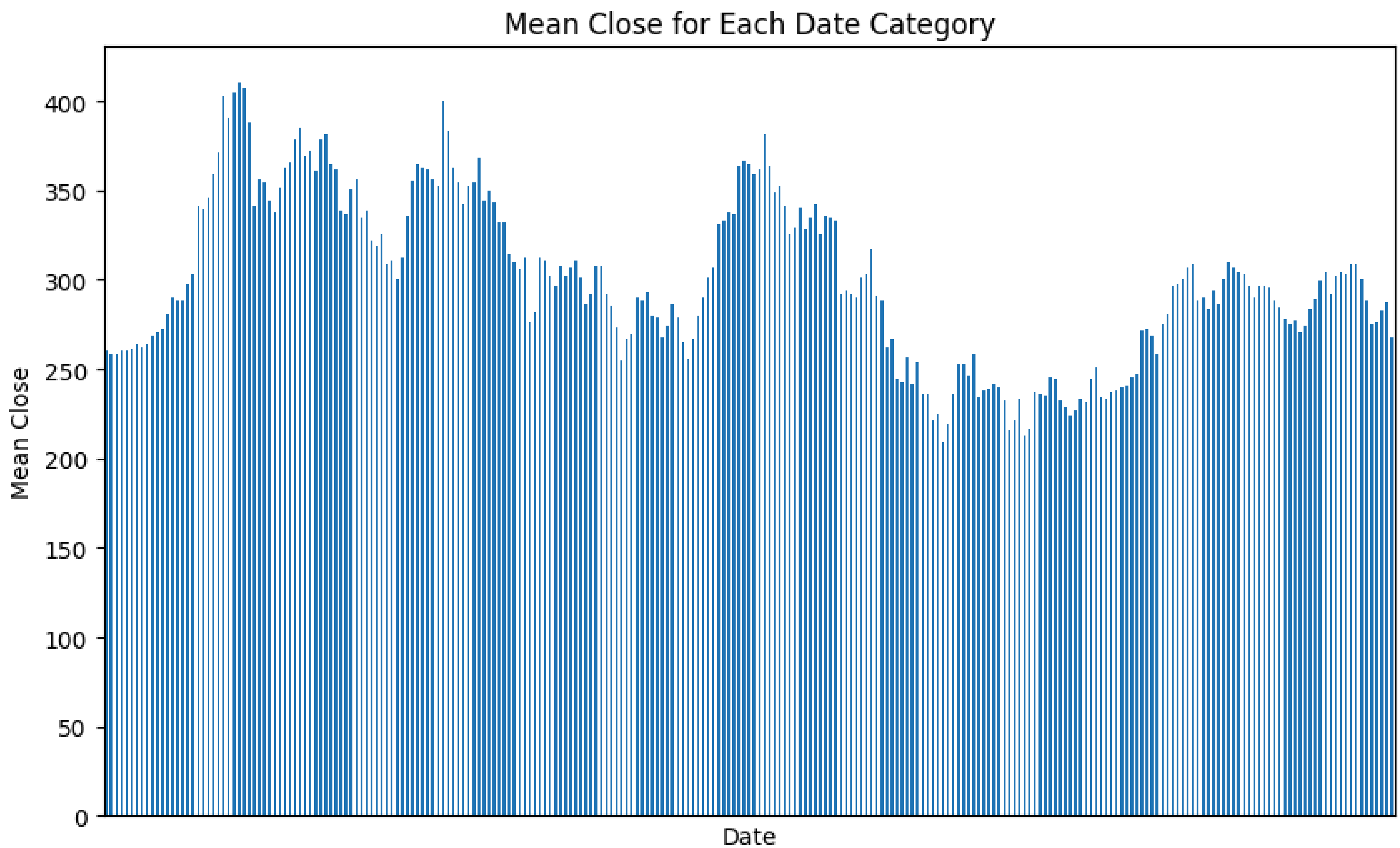
Observations from Step 14

- Final selected Continuous columns: volume

Step 15: Relationship exploration: Categorical Vs Continuous -- Box Plots

- In scenarios where the target variable is Continuous and the predictor variable is Categorical, the relationship will be examined using Boxplots.
- Evaluate the strength of the relationship using an ANOVA test.

```
# Calculate the mean volume for each date category
mean_volume = TeslaData.groupby('Date')['Close'].mean()

# Create a bar plot
mean_volume.plot(kind='bar', figsize=(10, 6))
plt.xlabel('Date')
plt.ylabel('Mean Close')
plt.title('Mean Close for Each Date Category')
plt.xticks(rotation=45)
plt.xticks([])  # Hide x-axis labels
plt.show()
```



Observations from Step 15: Box-Plots interpretation

- These plots illustrate how the continuous predictor variable changes across various categories, with the Y-axis representing its distribution and the X-axis depicting each category.
- When the distributions of the continuous variable appear similar for each category (aligned boxes), it likely indicates minimal influence on the target variable, suggesting a weak correlation.
- Conversely, if the distributions differ across categories (unaligned boxes), it suggests a potential correlation with the target variable.

- Within our dataset, both categorical predictors appear to exhibit correlations with the target variable.

Step 16: Statistical Feature Selection (Categorical Vs Continuous) using ANOVA test

- ANOVA (Analysis of Variance) assesses the relationship between a continuous variable and a categorical one. It compares means across multiple groups, akin to a t-test but applicable to more than two groups. ANOVA evaluates variation between data samples against variation within each sample. High between-group variance and low within-group variance suggest significant differences in group means.
- The Null Hypothesis (H0) assumes no association between variables, suggesting equal average values of the numeric Target variable across all groups of the categorical Predictor variable. In statistical hypothesis testing, rejecting the null hypothesis indicates statistically significant effects, supported by evidence from the sample.
- The ANOVA test outcome reflects the probability of the Null Hypothesis being true, indicating the likelihood of no relationship between the variables.

```
# Defining a function to find the statistical relationship with all the categorical variables
def FunctionAnova(inpData, TargetVariable, CategoricalPredictorList):
    from scipy.stats import f_oneway

    # Creating an empty list of final selected predictors
    SelectedPredictors=[]

    print('##### ANOVA Results ##### \n')
    for predictor in CategoricalPredictorList:
        CategoryGroupLists=inpData.groupby(predictor)[TargetVariable].apply(list)
        AnovaResults = f_oneway(*CategoryGroupLists)

        # If the ANOVA P-Value is <0.05, that means we reject H0
        if (AnovaResults[1] < 0.05):
            print(predictor, 'is correlated with', TargetVariable, '| P-Value:', AnovaResults[1])
            SelectedPredictors.append(predictor)
        else:
            print(predictor, 'is NOT correlated with', TargetVariable, '| P-Value:', AnovaResults[1])
```

```
    return(SelectedPredictors)


#Calling the function to check which categorical variables are correlated with target
CategoricalPredictorList=['Date']
FunctionAnova(inpData=TeslaData,
              TargetVariable='Close',
              CategoricalPredictorList=CategoricalPredictorList)
```

```
##### ANOVA Results #####

Date is NOT correlated with Close | P-Value: nan
[]
```

Observations from Step 16

- The ANOVA results substantiate the earlier visual examination conducted via box plots.
- All categorical variables demonstrate correlation with the Target variable.
- This alignment can be anticipated by merely observing the box plots.
- The selected categorical column for further analysis is 'Date'.

Selecting final Predictors/Features for building Machine Learning/AI model.

- After conducting thorough exploratory data analysis, the following parts will finalize the features/predictors/columns for machine learning model construction as:
- 'Open', 'High', 'Low', 'Close','Adj Close', and 'Volume'.

```
SelectedColumns=['Open', 'High', 'Low', 'Close', 'Adj Close', 'Volume']

# Selecting final columns
DataForML=TeslaData[SelectedColumns]
DataForML.head()
```

	Open	High	Low	Close	Adj Close	Volume
0	259.933319	264.500000	256.893341	260.436676	260.436676	62828700
1	260.333344	263.043335	258.333344	258.493347	258.493347	53868000
2	259.466675	260.260010	254.529999	258.406677	258.406677	51094200
3	265.500000	268.989990	258.706665	260.510010	260.510010	91449900
4	261.600006	265.769989	258.066681	260.196655	260.196655	55297800

Next steps: Generate code with DataForML View recommended plots

```
# Saving this final data subset for reference during deployment
DataForML.to_pickle('DataForML.pkl')
```

Step 17: Data Pre-processing for Machine Learning Model Building or Model Development

Below are the necessary steps to prepare predictor variables for machine learning:

1. Ordinal categorical columns are converted to numeric values.
2. Binary nominal categorical columns are transformed into numeric format using a 1/0 mapping.
3. All other nominal categorical columns are converted to numeric using the `pd.get_dummies()` function.

Data transformation is a critical process in modern organizations. By manipulating raw data, it becomes more meaningful and useful. This transformation enhances decision-making by providing valuable insights. Moreover, improved data quality ensures accuracy and reliability. Efficiently structured data streamlines operations, leading to faster reporting and better resource allocation.

Converting the nominal variable to numeric using get_dummies()

```
# Treating all the nominal variables at once using dummy variables
DataForML_Numeric=pd.get_dummies(DataForML)

# Adding Target Variable to the data
DataForML_Numeric['Close']=TeslaData['Close']

# Printing sample rows
DataForML_Numeric.head()
```

	Open	High	Low	Close	Adj Close	Volume
0	259.933319	264.500000	256.893341	260.436676	260.436676	62828700
1	260.333344	263.043335	258.333344	258.493347	258.493347	53868000
2	259.466675	260.260010	254.529999	258.406677	258.406677	51094200
3	265.500000	268.989990	258.706665	260.510010	260.510010	91449900
4	261.600006	265.769989	258.066681	260.196655	260.196655	55297800

Next steps: Generate code with `DataForML_Numeric` View recommended plots

Step 18: Machine Learning Model Development:

The data is divided into Training and Testing sets to facilitate model development and evaluation. Not all of the dataset is used for creating the model (training data). Instead, a portion is randomly reserved to evaluate the model's performance. This reserved portion is termed Testing Data, while the rest is designated as Training Data, utilized for constructing the model. Typically, around 70% of the data serves as Training Data, with the remaining 30% allocated for Testing Data.

```
# Printing all the column names for our reference
DataForML_Numeric.columns
```

```
Index(['Open', 'High', 'Low', 'Close', 'Adj Close', 'Volume'], dtype='object')
```

```
#Separate Target Variable and Predictor Variables
TargetVariable='Close'
Predictors=['Open', 'High', 'Low', 'Close', 'Adj Close']

X=DataForML_Numeric[Predictors].values
y=DataForML_Numeric[TargetVariable].values

# Split the data into training and testing set
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=428)
```

Step 19: Standardization/Normalization of data

- This step compares the resulting accuracy of this transformation with the accuracy of raw data.

```
#Sandardization
from sklearn.preprocessing import StandardScaler, MinMaxScaler

#PredictorScaler=StandardScaler()
PredictorScaler=MinMaxScaler()

# Storing the fit object for later reference
PredictorScalerFit=PredictorScaler.fit(X)

# Generating the standardized values of X
X=PredictorScalerFit.transform(X)

# Split the data into training and testing set
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
```

```
# Sanity check for the sampled data
print(X_train.shape)
print(y_train.shape)
print(X_test.shape)
print(y_test.shape)
```

```
(177, 5)
(177,)
(76, 5)
(76,)
```

Step 20: Multiple Linear Regression Algorithm For ML/AI model building

```
#Multiple Linear Regression
from sklearn.linear_model import LinearRegression
RegModel = LinearRegression()

# Printing all the parameters of Linear regression
print(RegModel)

# Creating the model on Training Data
LREG=RegModel.fit(X_train,y_train)
prediction=LREG.predict(X_test)

from sklearn import metrics
# Measuring Goodness of fit in Training data
print('R2 Value:',metrics.r2_score(y_train, LREG.predict(X_train)))
print('\n##### Model Validation and Accuracy Calculations ##########')

# Printing some sample values of prediction
TestingDataResults=pd.DataFrame(data=X_test, columns=Predictors)
TestingDataResults[TargetVariable]=y_test
TestingDataResults[('Predicted'+TargetVariable)]=np.round(prediction)

# Printing sample prediction values
print(TestingDataResults.head())

# Calculating the error for each row
TestingDataResults['APE']=100 * ((abs(
TestingDataResults['Close']-TestingDataResults['PredictedClose']))/TestingDataResults['Close'])

MAPE=np.mean(TestingDataResults['APE'])
MedianMAPE=np.median(TestingDataResults['APE'])

Accuracy =100 - MAPE
MedianAccuracy=100- MedianMAPE
print('Mean Accuracy on test data:', Accuracy) # Can be negative sometimes due to outlier
print('Median Accuracy on test data:', MedianAccuracy)

# Defining a custom function to calculate accuracy
# Make sure there are no zeros in the Target variable if you are using MAPE
def Accuracy_Score(orig,pred):
    MAPE = np.mean(100 * (np.abs(orig-pred)/orig))
```

```
    #print('#'*70,'Accuracy:', 100-MAPE)
    return(100-MAPE)

# Custom Scoring MAPE calculation
from sklearn.metrics import make_scorer
custom_Scoring=make_scorer(Accuracy_Score, greater_is_better=True)

# Importing cross validation function from sklearn
from sklearn.model_selection import cross_val_score

# Running 10-Fold Cross validation on a given algorithm
# Passing full data X and y because the K-fold will split the data and automatically choose train/test
Accuracy_Values=cross_val_score(RegModel, X , y, cv=10, scoring=custom_Scoring)
print('\nAccuracy values for 10-fold Cross Validation:\n',Accuracy_Values)
print('\nFinal Average Accuracy of the model:', round(Accuracy_Values.mean(),2))
```

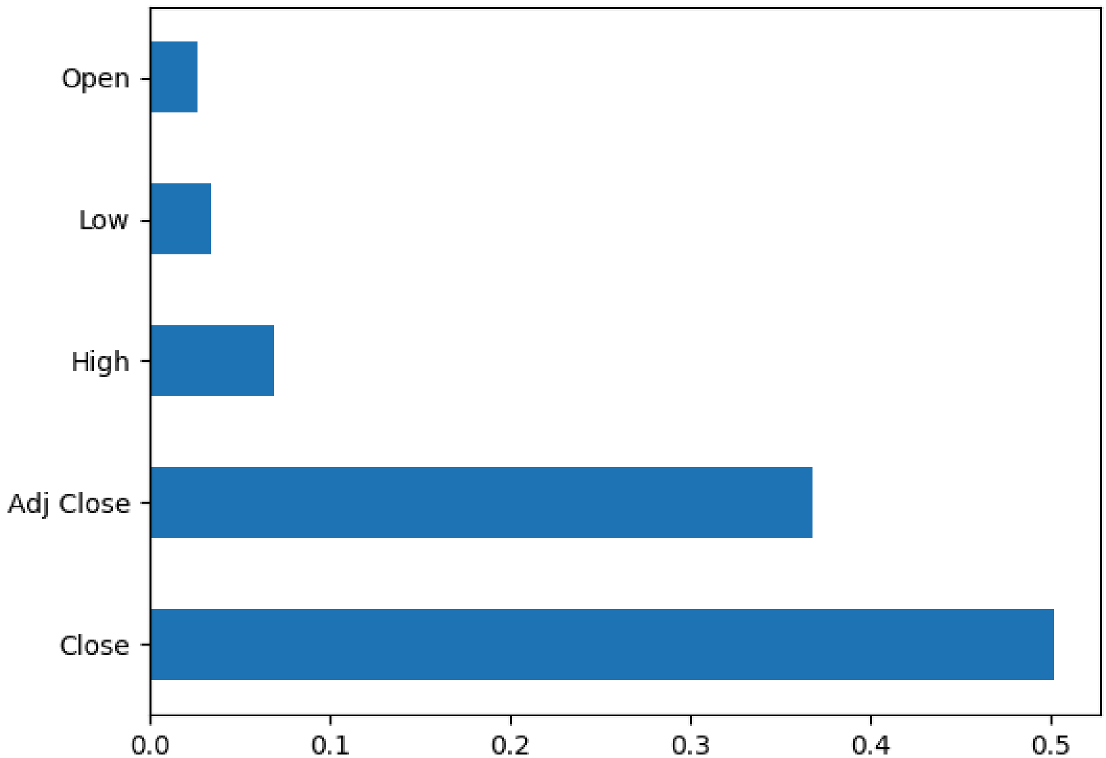
```
LinearRegression()
R2 Value: 1.0

##### Model Validation and Accuracy Calculations ##########
       Open      High       Low       Close  Adj Close  PredictedClose
0  0.354347  0.332412  0.331690  280.899994   0.356527           281.0
1  0.264691  0.256255  0.272974  264.536682   0.274948           265.0
2  0.610079  0.594722  0.536408  314.633331   0.524703           315.0
3  0.335446  0.319623  0.321194  272.243347   0.313369           272.0
4  0.339262  0.374985  0.343963  290.533325   0.404553           291.0
Mean Accuracy on test data: 99.9146696203498
Median Accuracy on test data: 99.9091453235422

Accuracy values for 10-fold Cross Validation:
 [100. 100. 100. 100. 100. 100. 100. 100. 100. 100.]

Final Average Accuracy of the model: 100.0
```

Step 21: AdaBoost Algorithm For ML/AI model building

```
# Adaboost (Boosting of multiple Decision Trees)
from sklearn.ensemble import AdaBoostRegressor
from sklearn.tree import DecisionTreeRegressor

# Choosing Decision Tree with 6 level as the weak learner
DTR=DecisionTreeRegressor(max_depth=3)
RegModel = AdaBoostRegressor(n_estimators=100, base_estimator=DTR ,learning_rate=0.04)

# Printing all the parameters of Adaboost
print(RegModel)

# Creating the model on Training Data
AB=RegModel.fit(X_train,y_train)
prediction=AB.predict(X_test)

from sklearn import metrics
# Measuring Goodness of fit in Training data
print('R2 Value:',metrics.r2_score(y_train, AB.predict(X_train)))

# Plotting the feature importance for Top 10 most important columns
%matplotlib inline
feature_importances = pd.Series(AB.feature_importances_, index=Predictors)
feature_importances.nlargest(10).plot(kind='barh')

print('\n##### Model Validation and Accuracy Calculations ##########')

# Printing some sample values of prediction
TestingDataResults=pd.DataFrame(data=X_test, columns=Predictors)
TestingDataResults[TargetVariable]=y_test
TestingDataResults[('Predicted'+TargetVariable)]=np.round(prediction)

# Printing sample prediction values
print(TestingDataResults.head())

# Calculating the error for each row
TestingDataResults['APE']=100 * ((abs(
TestingDataResults['Close']-TestingDataResults['PredictedClose']))/TestingDataResults['Close'])

MAPE=np.mean(TestingDataResults['APE'])
MedianMAPE=np.median(TestingDataResults['APE'])
```

```
Accuracy =100 - MAPE
MedianAccuracy=100- MedianMAPE
print('Mean Accuracy on test data:', Accuracy) # Can be negative sometimes due to outlier
print('Median Accuracy on test data:', MedianAccuracy)


# Defining a custom function to calculate accuracy
# Make sure there are no zeros in the Target variable if you are using MAPE
def Accuracy_Score(orig,pred):
    MAPE = np.mean(100 * (np.abs(orig-pred)/orig))
    #print('#'*70,'Accuracy:', 100-MAPE)
    return(100-MAPE)

# Custom Scoring MAPE calculation
from sklearn.metrics import make_scorer
custom_Scoring=make_scorer(Accuracy_Score, greater_is_better=True)

# Importing cross validation function from sklearn
from sklearn.model_selection import cross_val_score

# Running 10-Fold Cross validation on a given algorithm
# Passing full data X and y because the K-fold will split the data and automatically choose train/test
Accuracy_Values=cross_val_score(RegModel, X , y, cv=10, scoring=custom_Scoring)
print('\nAccuracy values for 10-fold Cross Validation:\n',Accuracy_Values)
print('\nFinal Average Accuracy of the model:', round(Accuracy_Values.mean(),2))
```

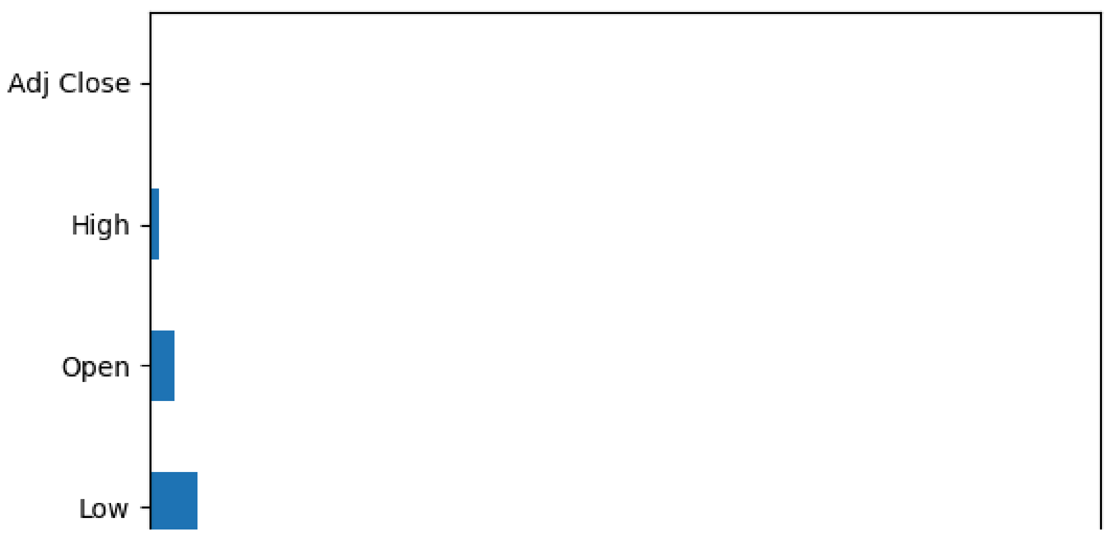
```
AdaBoostRegressor(base_estimator=DecisionTreeRegressor(max_depth=3),
                  learning_rate=0.04, n_estimators=100)
R2 Value: 0.9949681049917504

##### Model Validation and Accuracy Calculations ##########
       Open      High       Low       Close  Adj Close  PredictedClose
0  0.354347  0.332412  0.331690  280.899994   0.356527           282.0
1  0.264691  0.256255  0.272974  264.536682   0.274948           265.0
2  0.610079  0.594722  0.536408  314.633331   0.524703           311.0
3  0.335446  0.319623  0.321194  272.243347   0.313369           275.0
4  0.339262  0.374985  0.343963  290.533325   0.404553           288.0
Mean Accuracy on test data: 99.10472865809139
Median Accuracy on test data: 99.28411198950009

Accuracy values for 10-fold Cross Validation:
 [98.40035034 98.67849481 98.81915361 98.56525336 99.2918884  98.94678098
 97.70540413 97.75406865 99.21617248 99.36029078]

Final Average Accuracy of the model: 98.67
```

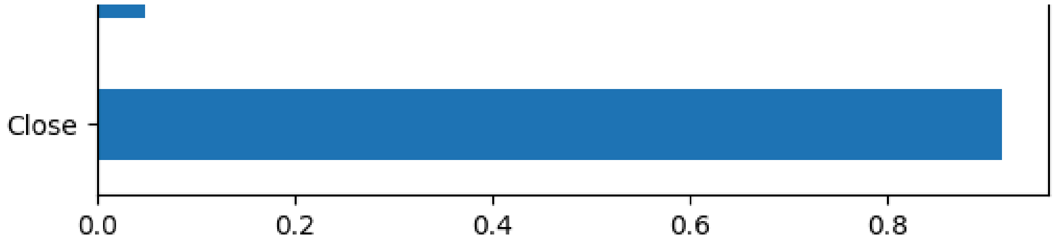


```
# Xtreme Gradient Boosting (XGBoost)
from xgboost import XGBRegressor
RegModel=XGBRegressor(max_depth=2,
                      learning_rate=0.1,
                      n_estimators=1000,
                      objective='reg:linear',
                      booster='gbtree')

# Printing all the parameters of XGBoost
print(RegModel)

# Creating the model on Training Data
XGB=RegModel.fit(X_train,y_train)
prediction=XGB.predict(X_test)

from sklearn import metrics
# Measuring Goodness of fit in Training data
print('R2 Value:',metrics.r2_score(y_train, XGB.predict(X_train)))

# Plotting the feature importance for Top 10 most important columns
%matplotlib inline
feature_importances = pd.Series(XGB.feature_importances_, index=Predictors)
feature_importances.nlargest(10).plot(kind='barh')

print('\n##### Model Validation and Accuracy Calculations ##########')

# Printing some sample values of prediction
TestingDataResults=pd.DataFrame(data=X_test, columns=Predictors)
TestingDataResults[TargetVariable]=y_test
TestingDataResults[('Predicted'+TargetVariable)]=np.round(prediction)

# Printing sample prediction values
print(TestingDataResults.head())

# Calculating the error for each row
TestingDataResults['APE']=100 * ((abs(
TestingDataResults['Close']-TestingDataResults['PredictedClose']))/TestingDataResults['Close'])


MAPE=np.mean(TestingDataResults['APE'])
```

```
MedianMAPE=np.median(TestingDataResults['APE'])

Accuracy =100 - MAPE
MedianAccuracy=100- MedianMAPE
print('Mean Accuracy on test data:', Accuracy) # Can be negative sometimes due to outlier
print('Median Accuracy on test data:', MedianAccuracy)


# Defining a custom function to calculate accuracy
# Make sure there are no zeros in the Target variable if you are using MAPE
def Accuracy_Score(orig,pred):
    MAPE = np.mean(100 * (np.abs(orig-pred)/orig))
    #print('#'*70,'Accuracy:', 100-MAPE)
    return(100-MAPE)

# Custom Scoring MAPE calculation
from sklearn.metrics import make_scorer
custom_Scoring=make_scorer(Accuracy_Score, greater_is_better=True)

# Importing cross validation function from sklearn
from sklearn.model_selection import cross_val_score

# Running 10-Fold Cross validation on a given algorithm
# Passing full data X and y because the K-fold will split the data and automatically choose train/test
Accuracy_Values=cross_val_score(RegModel, X , y, cv=10, scoring=custom_Scoring)
print('\nAccuracy values for 10-fold Cross Validation:\n',Accuracy_Values)
print('\nFinal Average Accuracy of the model:', round(Accuracy_Values.mean(),2))
```

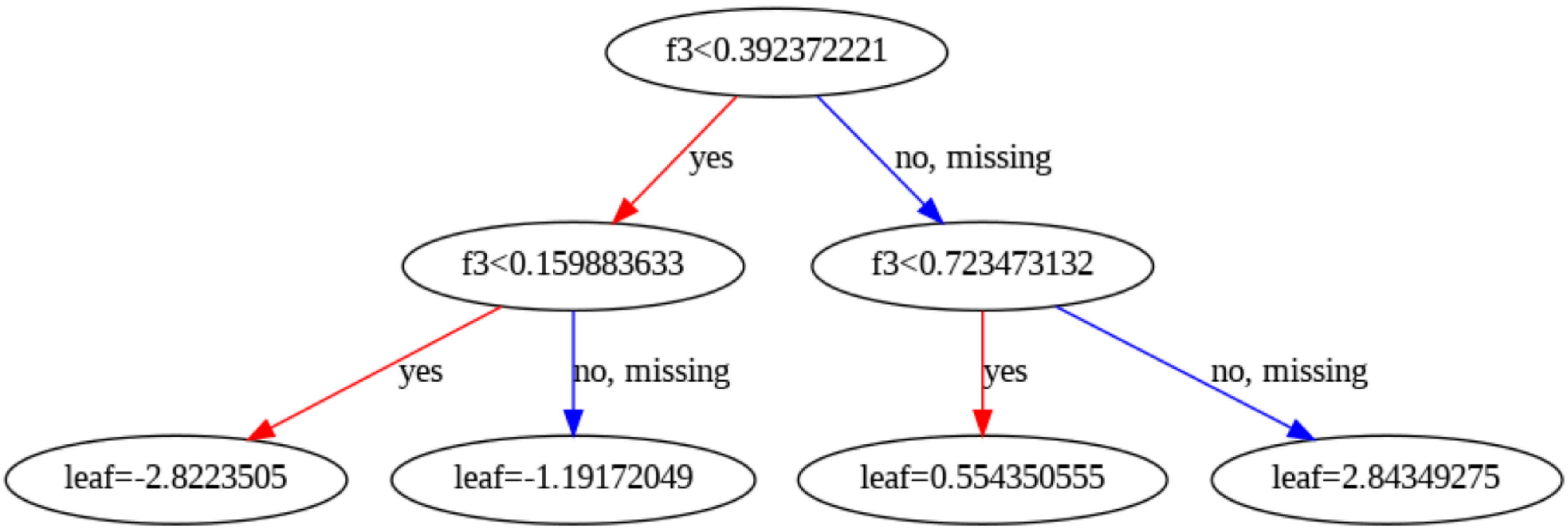
```
XGBRegressor(base_score=None, booster='gbtree', callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, device=None, early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None, feature_types=None,
             gamma=None, grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=0.1, max_bin=None,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max_delta_step=None, max_depth=2, max_leaves=None,
             min_child_weight=None, missing=nan, monotone_constraints=None,
             multi_strategy=None, n_estimators=1000, n_jobs=None,
             num_parallel_tree=None, objective='reg:linear', ...)
R2 Value: 0.9999990638342287

##### Model Validation and Accuracy Calculations ##########
       Open      High       Low       Close  Adj Close  PredictedClose
0  0.354347  0.332412  0.331690  280.899994   0.356527           280.0
1  0.264691  0.256255  0.272974  264.536682   0.274948           263.0
2  0.610079  0.594722  0.536408  314.633331   0.524703           319.0
3  0.335446  0.319623  0.321194  272.243347   0.313369           270.0
4  0.339262  0.374985  0.343963  290.533325   0.404553           290.0
Mean Accuracy on test data: 99.32927342698288
Median Accuracy on test data: 99.61738518703801

Accuracy values for 10-fold Cross Validation:
 [99.23044059 99.4096969  99.55073903 99.53192857 99.57342264 99.45398034
 98.8665202  99.14383024 99.74474465 99.65644276]

Final Average Accuracy of the model: 99.42
```






```
#Plotting a single Decision tree out of XGBoost
from xgboost import plot_tree
import matplotlib.pyplot as plt
fig, ax = plt.subplots(figsize=(20, 8))
plot_tree(XGB, num_trees=10, ax=ax)
```

<Axes: >



```
#kNN
# K-Nearest Neighbor(KNN)
from sklearn.neighbors import KNeighborsRegressor
RegModel = KNeighborsRegressor(n_neighbors=3)

# Printing all the parameters of KNN
print(RegModel)

# Creating the model on Training Data
KNN=RegModel.fit(X_train,y_train)
prediction=KNN.predict(X_test)

from sklearn import metrics
# Measuring Goodness of fit in Training data
print('R2 Value:',metrics.r2_score(y_train, KNN.predict(X_train)))

# Plotting the feature importance for Top 10 most important columns
# The variable importance chart is not available for KNN

print('\n##### Model Validation and Accuracy Calculations ##########')

# Printing some sample values of prediction
TestingDataResults=pd.DataFrame(data=X_test, columns=Predictors)
TestingDataResults[TargetVariable]=y_test
TestingDataResults[('Predicted'+TargetVariable)]=np.round(prediction)

# Printing sample prediction values
print(TestingDataResults.head())

# Calculating the error for each row
TestingDataResults['APE']=100 * ((abs(
  TestingDataResults['Close']-TestingDataResults['PredictedClose']))/TestingDataResults['Close'])

MAPE=np.mean(TestingDataResults['APE'])
MedianMAPE=np.median(TestingDataResults['APE'])

Accuracy =100 - MAPE
MedianAccuracy=100- MedianMAPE
print('Mean Accuracy on test data:', Accuracy) # Can be negative sometimes due to outlier
print('Median Accuracy on test data:', MedianAccuracy)
```

```
# Defining a custom function to calculate accuracy
# Make sure there are no zeros in the Target variable if you are using MAPE
def Accuracy_Score(orig,pred):
    MAPE = np.mean(100 * (np.abs(orig-pred)/orig))
    #print('#'*70,'Accuracy:', 100-MAPE)
    return(100-MAPE)

# Custom Scoring MAPE calculation
from sklearn.metrics import make_scorer
custom_Scoring=make_scorer(Accuracy_Score, greater_is_better=True)

# Importing cross validation function from sklearn
from sklearn.model_selection import cross_val_score

# Running 10-Fold Cross validation on a given algorithm
# Passing full data X and y because the K-fold will split the data and automatically choose train/test
Accuracy_Values=cross_val_score(RegModel, X , y, cv=10, scoring=custom_Scoring)
print('\nAccuracy values for 10-fold Cross Validation:\n',Accuracy_Values)
print('\nFinal Average Accuracy of the model:', round(Accuracy_Values.mean(),2))
```

```
KNeighborsRegressor(n_neighbors=3)
R2 Value: 0.9979298143337859

##### Model Validation and Accuracy Calculations ##########
       Open      High       Low       Close  Adj Close  PredictedClose
0  0.354347  0.332412  0.331690  280.899994   0.356527           279.0
1  0.264691  0.256255  0.272974  264.536682   0.274948           262.0
2  0.610079  0.594722  0.536408  314.633331   0.524703           320.0
3  0.335446  0.319623  0.321194  272.243347   0.313369           273.0
4  0.339262  0.374985  0.343963  290.533325   0.404553           289.0
Mean Accuracy on test data: 99.14929491384004
Median Accuracy on test data: 99.30312208095485

Accuracy values for 10-fold Cross Validation:
 [99.3611643  99.07070812 99.29435435 99.13219824 99.42953293 99.07267453
 99.10232821 99.06393465 99.59834539 99.59601864]

Final Average Accuracy of the model: 99.27
```