stock_notebook

February 11, 2025

Part1: Big Data Processing

Task 1: Data Cleaning and Exploration

[ ]:
```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.metrics import classification_report, accuracy_score
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
from sklearn.cluster import KMeans
import numpy as np
import seaborn as sns
from sklearn.preprocessing import MinMaxScaler
from sklearn.svm import SVR
from sklearn.metrics import r2_score
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.model_selection import RandomizedSearchCV, train_test_split
```

[2]:
```
df=pd.read_csv("../NVDA.csv")
```

[3]:
```
df.head()
```

[3]:

	Date	Open	High	Low	Close	Adj Close	Volume
0	2022/7/1	14.899	15.063000	14.392	14.523	14.506663	577610000.0
1	2022/7/5	14.175	14.971000	14.055	14.964	14.947166	651397000.0
2	2022/7/6	15.010	15.319000	14.789	15.130	15.112980	529066000.0
3	2022/7/7	15.456	15.945000	15.389	15.858	15.840160	492903000.0
4	2022/7/8	15.430	16.037001	15.389	15.838	15.820185	467972000.0

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 523 entries, 0 to 522
Data columns (total 7 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   Date       522 non-null    object
 1   Open       521 non-null    float64
```

```
 2   High       522 non-null    float64
 3   Low        523 non-null    float64
 4   Close      522 non-null    float64
 5   Adj Close  523 non-null    float64
 6   Volume     521 non-null    float64
dtypes: float64(6), object(1)
memory usage: 28.7+ KB
```

[5]:
```
df.isnull().sum()
```

[5]:
```
Date         1
Open         2
High         1
Low          0
Close        1
Adj Close    0
Volume       2
dtype: int64
```

[6]:
```
df.dropna(inplace=True)
```

[7]:
```
df.isnull().sum()
```

[7]:
```
Date         0
Open         0
High         0
Low          0
Close        0
Adj Close    0
Volume       0
dtype: int64
```

[8]:
```
# Convert the 'Date' column to datetime format, accounting for the use of␣
 ↪slashes
df['Date'] = pd.to_datetime(df['Date'], format='%Y/%m/%d')
```

[9]:
```
# Optionally change the format to another for display purposes
df['Date'] = df['Date'].dt.strftime('%d-%m-%Y')
```

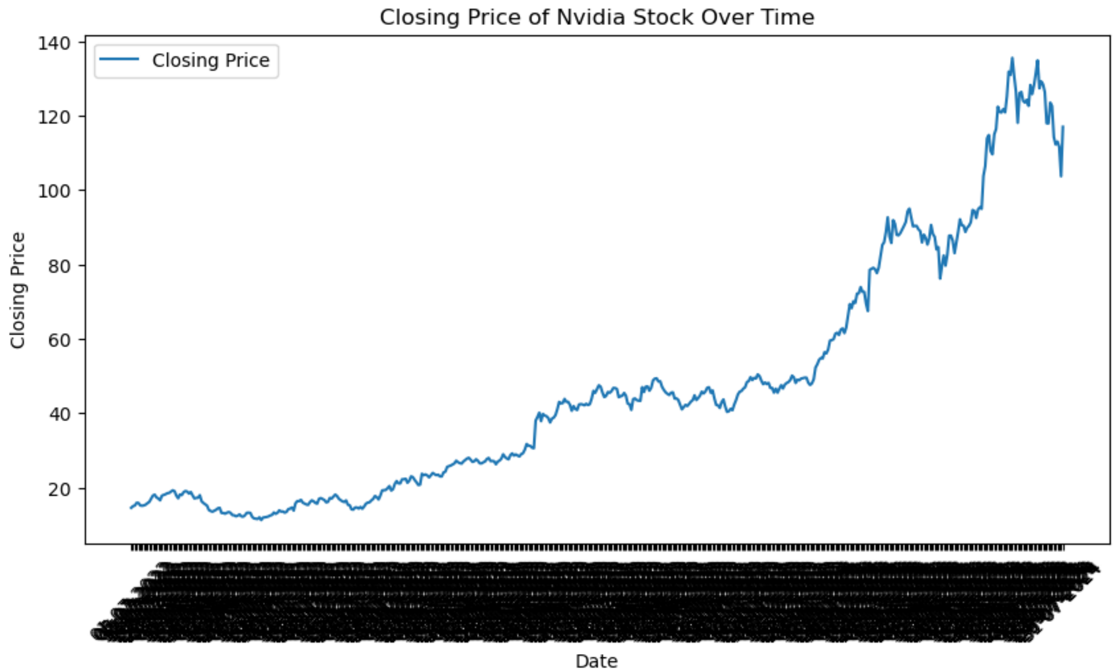
[10]:
```
# Print the transformed data
df['Date'].head()
```

[10]:
```
0    01-07-2022
1    05-07-2022
2    06-07-2022
3    07-07-2022
4    08-07-2022
Name: Date, dtype: object
```

[11]:
```
df.describe()
```

[11]:
```
             Open        High         Low       Close   Adj Close  \
count  517.000000  517.000000  517.000000  517.000000  517.000000
mean    46.601402   47.446458   45.700197   46.624110   46.613731
std     32.703247   33.282645   31.934308   32.602529   32.605493
min     10.971000   11.735000   10.813000   11.227000   11.217702
25%     18.160000   18.718000   17.875999   18.334999   18.314371
50%     42.252998   42.897999   41.648998   42.301998   42.289337
75%     57.988998   59.500000   57.224998   59.491001   59.483326
max    139.800003  140.759995  132.419998  135.580002  135.580002

             Volume
count  5.170000e+02
mean   4.831818e+08
std    1.574152e+08
min    1.679340e+08
25%    3.833870e+08
50%    4.573280e+08
75%    5.510110e+08
max    1.543911e+09
```

[12]:
```
# Plot the closing price over time
plt.figure(figsize=(10, 5))
plt.plot(df['Date'], df['Close'], label='Closing Price')
plt.title('Closing Price of Nvidia Stock Over Time')
plt.xlabel('Date')
plt.ylabel('Closing Price')
plt.xticks(rotation=45)
plt.legend()
plt.show()
```



Task 2 Feature Engineering

[13]:
```
# Calculate daily returns as the percentage change in adjusted close price
df['Daily_Returns'] = df['Adj Close'].pct_change() * 100


# Set the daily return for the first day to 0 since there's no previous day to␣
↪compare
# df[''].iloc[0] = 0

df.loc[0, "Daily_Returns"] = 0
```

[14]:
```
df.head()
```

[14]:
```
         Date    Open       High     Low   Close  Adj Close       Volume  \
0  01-07-2022  14.899  15.063000  14.392  14.523  14.506663  577610000.0
1  05-07-2022  14.175  14.971000  14.055  14.964  14.947166  651397000.0
2  06-07-2022  15.010  15.319000  14.789  15.130  15.112980  529066000.0
3  07-07-2022  15.456  15.945000  15.389  15.858  15.840160  492903000.0
4  08-07-2022  15.430  16.037001  15.389  15.838  15.820185  467972000.0

   Daily_Returns
0       0.000000
1       3.036556
2       1.109334
```

```
3       4.811626
4      -0.126104
```

[15]:
```
# Print the top 10 dates with the highest daily return
print(df.nlargest(10, 'Daily_Returns')[['Date', 'Daily_Returns']])
```

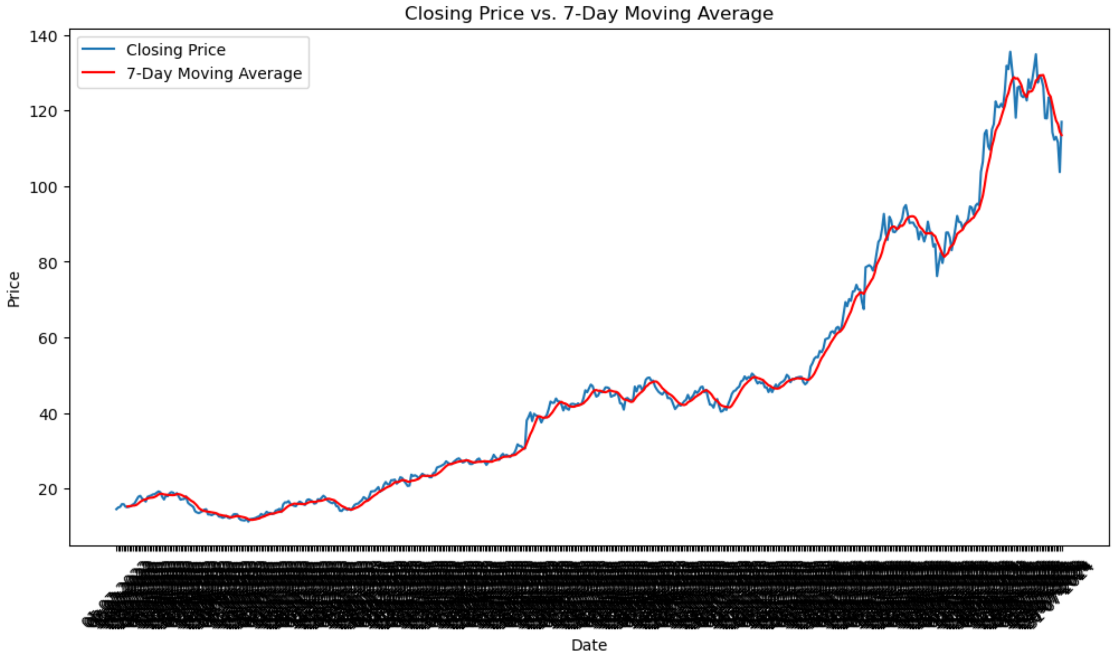
```
           Date  Daily_Returns
226  25-05-2023      24.369631
412  22-02-2024      16.400871
92   10-11-2022      14.329265
162  23-02-2023      14.021388
522  31-07-2024      12.812102
476  23-05-2024       9.319651
285  21-08-2023       8.471334
105  30-11-2022       8.237931
17   27-07-2022       7.603019
140  23-01-2023       7.590124
```

[16]:
```
# Calculate the 7-day moving average of the closing price
df['7_Day_MA'] = df['Close'].rolling(window=7).mean()
```

[17]:
```
df.tail()
```

[17]:
```
           Date        Open        High         Low       Close   Adj Close  \
518  25-07-2024  113.040001  116.629997  106.300003  112.279999  112.279999
519  26-07-2024  116.190002  116.199997  111.580002  113.059998  113.059998
520  29-07-2024  113.690002  116.279999  111.300003  111.589996  111.589996
521  30-07-2024  111.519997  111.989998  102.540001  103.730003  103.730003
522  31-07-2024  112.900002  118.339996  110.879997  117.019997  117.019997

          Volume  Daily_Returns    7_Day_MA
518  460067000.0      -1.724290  119.277142
519  293399100.0       0.694691  117.377142
520  248152100.0      -1.300196  116.462856
521  486833300.0      -7.043636  114.434285
522  473174200.0      12.812102  113.502856
```

[18]:
```
# Plot the closing price and the 7-day moving average
plt.figure(figsize=(12, 6))
plt.plot(df['Date'], df['Close'], label='Closing Price')
plt.plot(df['Date'], df['7_Day_MA'], label='7-Day Moving Average', color='red')
plt.title('Closing Price vs. 7-Day Moving Average')
plt.xlabel('Date')
plt.ylabel('Price')
plt.xticks(rotation=45)
plt.legend()
plt.show()
```



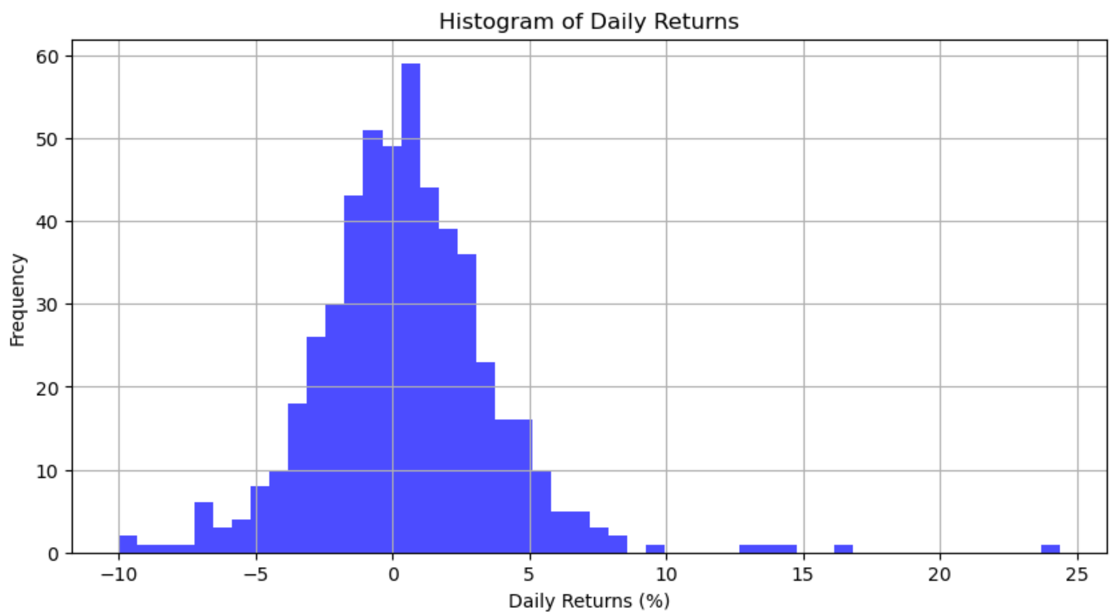
[19]:
```
# Initialize the MinMaxScaler
scaler = MinMaxScaler()

# Normalize the trading volume
df['Normalized_Volume'] = scaler.fit_transform(df[['Volume']])

# Print the top 10 dates with the highest normalized trading volume
print(df.nlargest(10, 'Normalized_Volume')[['Date', 'Normalized_Volume']])
```

```
           Date  Normalized_Volume
226  25-05-2023           1.000000
43   01-09-2022           0.734701
288  24-08-2023           0.718115
423  08-03-2024           0.708104
162  23-02-2023           0.690463
229  31-05-2023           0.606584
25   08-08-2022           0.591525
264  21-07-2023           0.578378
289  25-08-2023           0.550450
228  30-05-2023           0.549040
```

Task 3: Data Visualization

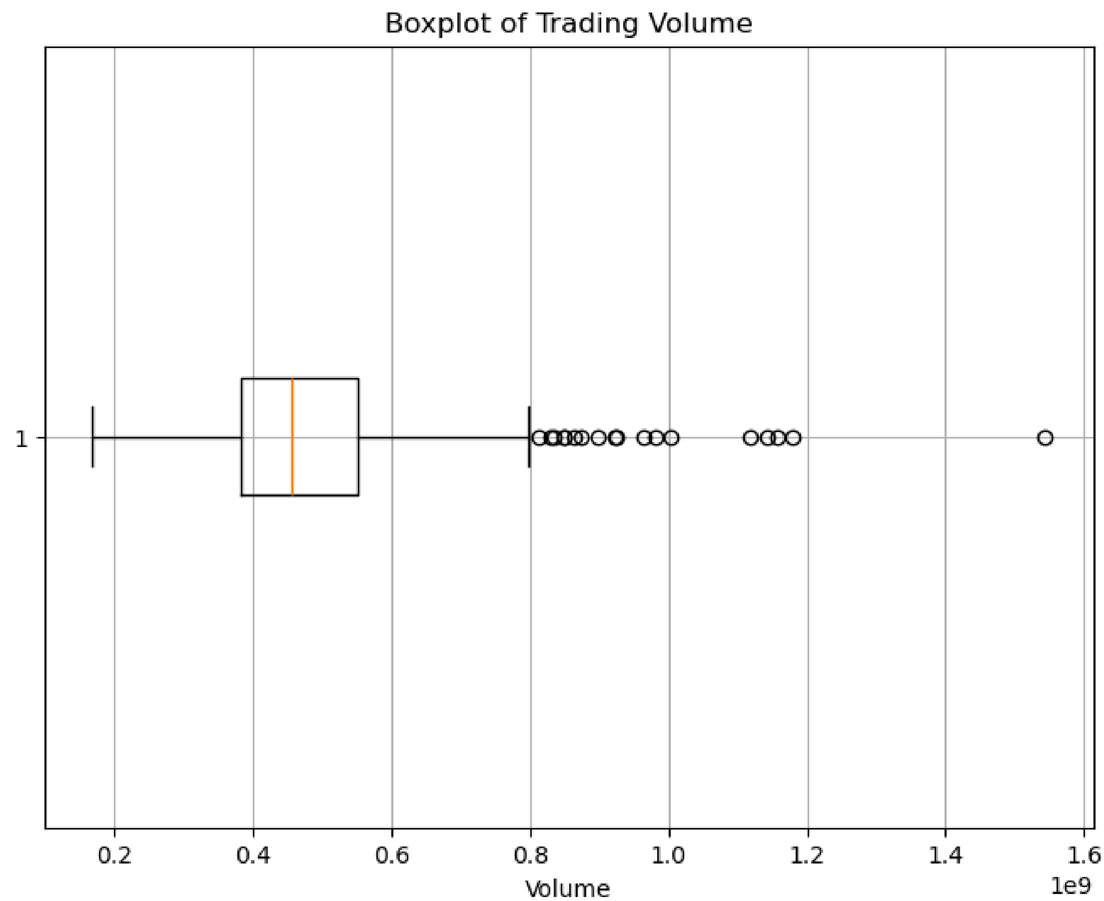
[20]:
```
# Create a histogram for daily returns
plt.figure(figsize=(10, 5))
plt.hist(df['Daily_Returns'], bins=50, color='blue', alpha=0.7)
```

```
plt.title('Histogram of Daily Returns')
plt.xlabel('Daily Returns (%)')
plt.ylabel('Frequency')
plt.grid(True)
plt.show()
```

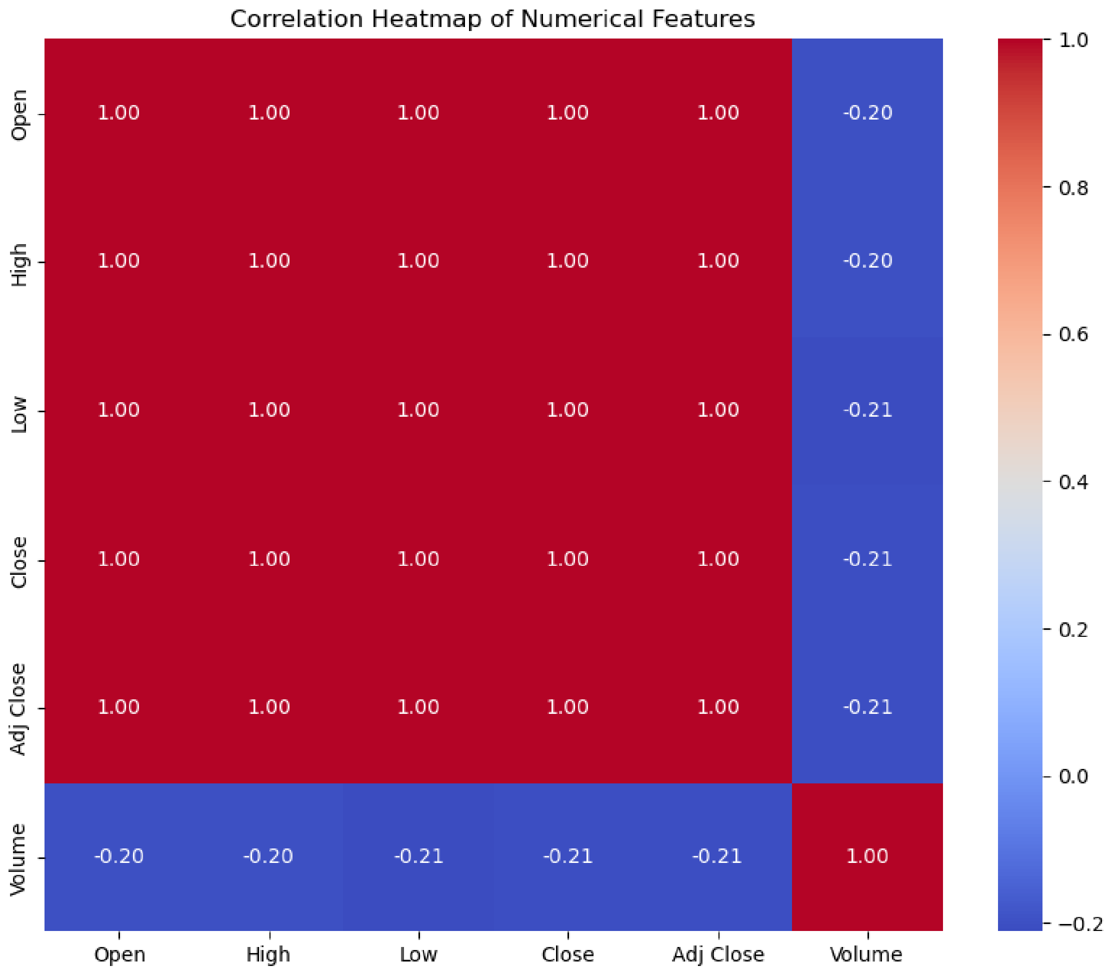


[21]:

```
# Generate a boxplot for the trading volume
plt.figure(figsize=(8, 6))
plt.boxplot(df['Volume'], vert=False)
plt.title('Boxplot of Trading Volume')
plt.xlabel('Volume')
plt.grid(True)
plt.show()
```



[22]:
```
# Calculate the correlation matrix excluding the newly added columns
correlation_matrix = df[['Open', 'High', 'Low', 'Close', 'Adj Close',␣
↪'Volume']].corr()

# Create a heatmap to visualize the correlation matrix
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, fmt=".2f", cmap='coolwarm',␣
↪cbar=True)
plt.title('Correlation Heatmap of Numerical Features')
plt.show()
```



Part 2: Machine Learning

Task 1: Clustering with KMeans

[23]:
```
# Select features for clustering
features = df[['Daily_Returns', 'Normalized_Volume', 'Adj Close']]
```

[24]:
```
# Calculate the inertia for a range of k values
inertia = []
k_values = range(1, 11)  # Testing 1 to 10 clusters
for k in k_values:
    kmeans = KMeans(n_clusters=k, random_state=0)
    kmeans.fit(features)
    inertia.append(kmeans.inertia_)

# Plot the elbow curve
plt.figure(figsize=(10, 6))
```

```
plt.plot(k_values, inertia, marker='o')
plt.title('Elbow Method For Optimal k')
plt.xlabel('Number of Clusters')
plt.ylabel('Inertia')
plt.grid(True)
plt.show()
```

```
c:\Users\domma\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1446:
UserWarning: KMeans is known to have a memory leak on Windows with MKL, when
there are less chunks than available threads. You can avoid it by setting the
environment variable OMP_NUM_THREADS=3.
  warnings.warn(
c:\Users\domma\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1446:
UserWarning: KMeans is known to have a memory leak on Windows with MKL, when
there are less chunks than available threads. You can avoid it by setting the
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c:\Users\domma\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1446:
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there are less chunks than available threads. You can avoid it by setting the
environment variable OMP_NUM_THREADS=3.
  warnings.warn(
c:\Users\domma\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1446:
```
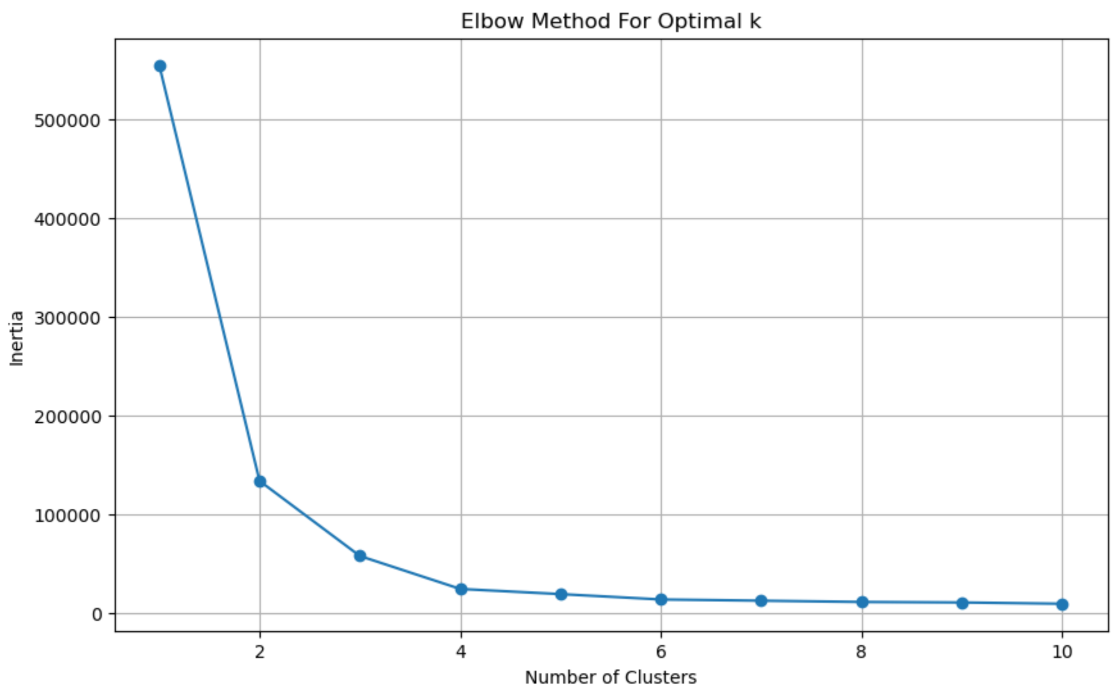

```
UserWarning: KMeans is known to have a memory leak on Windows with MKL, when
there are less chunks than available threads. You can avoid it by setting the
environment variable OMP_NUM_THREADS=3.
  warnings.warn(
c:\Users\domma\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1446:
UserWarning: KMeans is known to have a memory leak on Windows with MKL, when
there are less chunks than available threads. You can avoid it by setting the
environment variable OMP_NUM_THREADS=3.
  warnings.warn(
```



[25]:
```
# Choose the number of clusters (for example, k=3 based on the elbow method␣
↪output)
k = 3
kmeans = KMeans(n_clusters=k, random_state=0)
df['Cluster'] = kmeans.fit_predict(features)

# Visualize the clusters
plt.figure(figsize=(12, 8))
plt.scatter(df['Daily_Returns'], df['Adj Close'], c=df['Cluster'],␣
↪cmap='viridis', marker='o', alpha=0.7)
plt.title('Clusters by Daily Returns and Adjusted Close Price')
plt.xlabel('Daily Returns (%)')
plt.ylabel('Adjusted Close Price')
plt.grid(True)
plt.colorbar(label='Cluster')
```

```
plt.show()
```

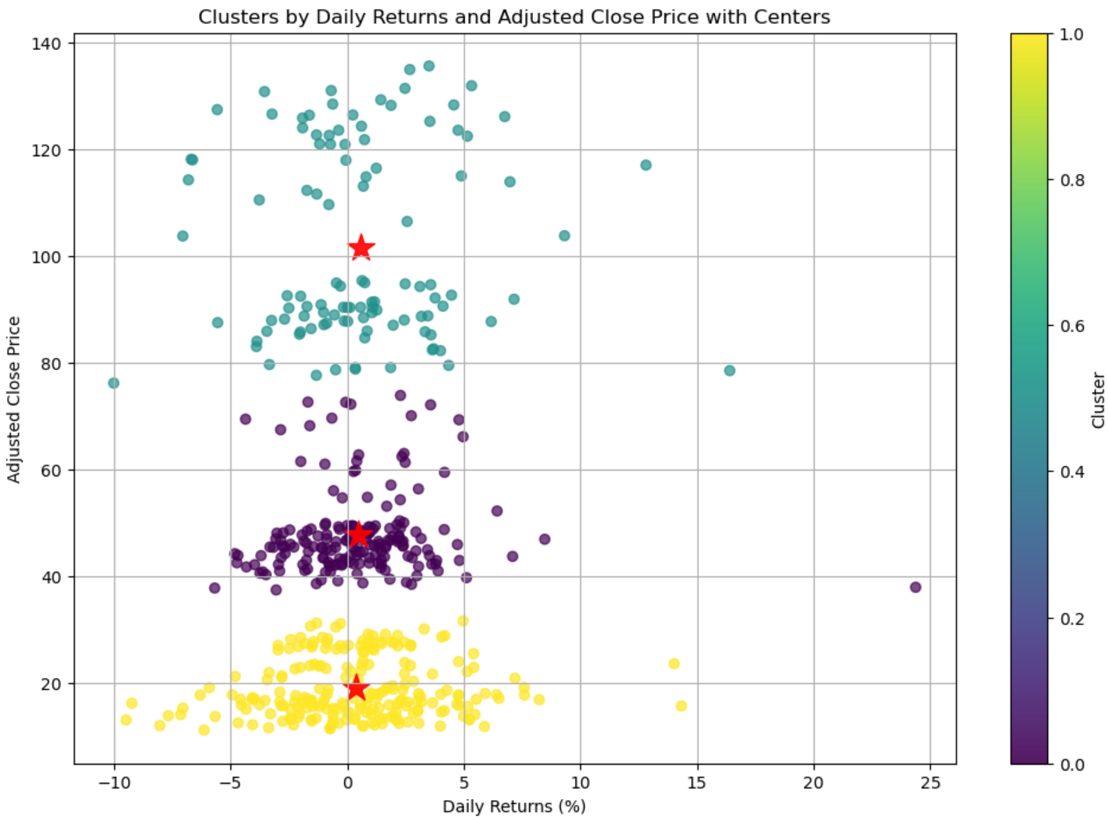
```
c:\Users\domma\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1446:
UserWarning: KMeans is known to have a memory leak on Windows with MKL, when
there are less chunks than available threads. You can avoid it by setting the
environment variable OMP_NUM_THREADS=3.
  warnings.warn(
```

[26]:
```
# Get the cluster centers
centers = kmeans.cluster_centers_

# Print the cluster centers
print("Cluster centers:")
for i, center in enumerate(centers):
    print(f"Cluster {i}: Daily Returns = {center[0]:.2f}%, Normalized Volume =␣
 ↪{center[1]:.2f}, Adjusted Close Price = {center[2]:.2f}")
```

```
Cluster centers:
Cluster 0: Daily Returns = 0.47%, Normalized Volume = 0.23, Adjusted Close Price
= 47.80
Cluster 1: Daily Returns = 0.58%, Normalized Volume = 0.20, Adjusted Close Price
= 101.62
```

```
Cluster 2: Daily Returns = 0.39%, Normalized Volume = 0.24, Adjusted Close Price
= 19.11
```

[27]:
```
# Plot the clusters along with the cluster centers
plt.figure(figsize=(12, 8))
plt.scatter(df['Daily_Returns'], df['Adj Close'], c=df['Cluster'],␣
 ↪cmap='viridis', alpha=0.7)
plt.scatter(centers[:, 0], centers[:, 2], c='red', s=300, alpha=0.9,␣
 ↪marker='*')  # centers[:, 0] and centers[:, 2] for Daily Returns and Adj␣
 ↪Close respectively
plt.title('Clusters by Daily Returns and Adjusted Close Price with Centers')
plt.xlabel('Daily Returns (%)')
plt.ylabel('Adjusted Close Price')
plt.colorbar(label='Cluster')
plt.grid(True)
plt.show()
```



[28]:
```
# Prepare the features and target variable
X = df[['Open', 'High', 'Low', 'Volume']]  # Features
y = df['Close']  # Target variable
```

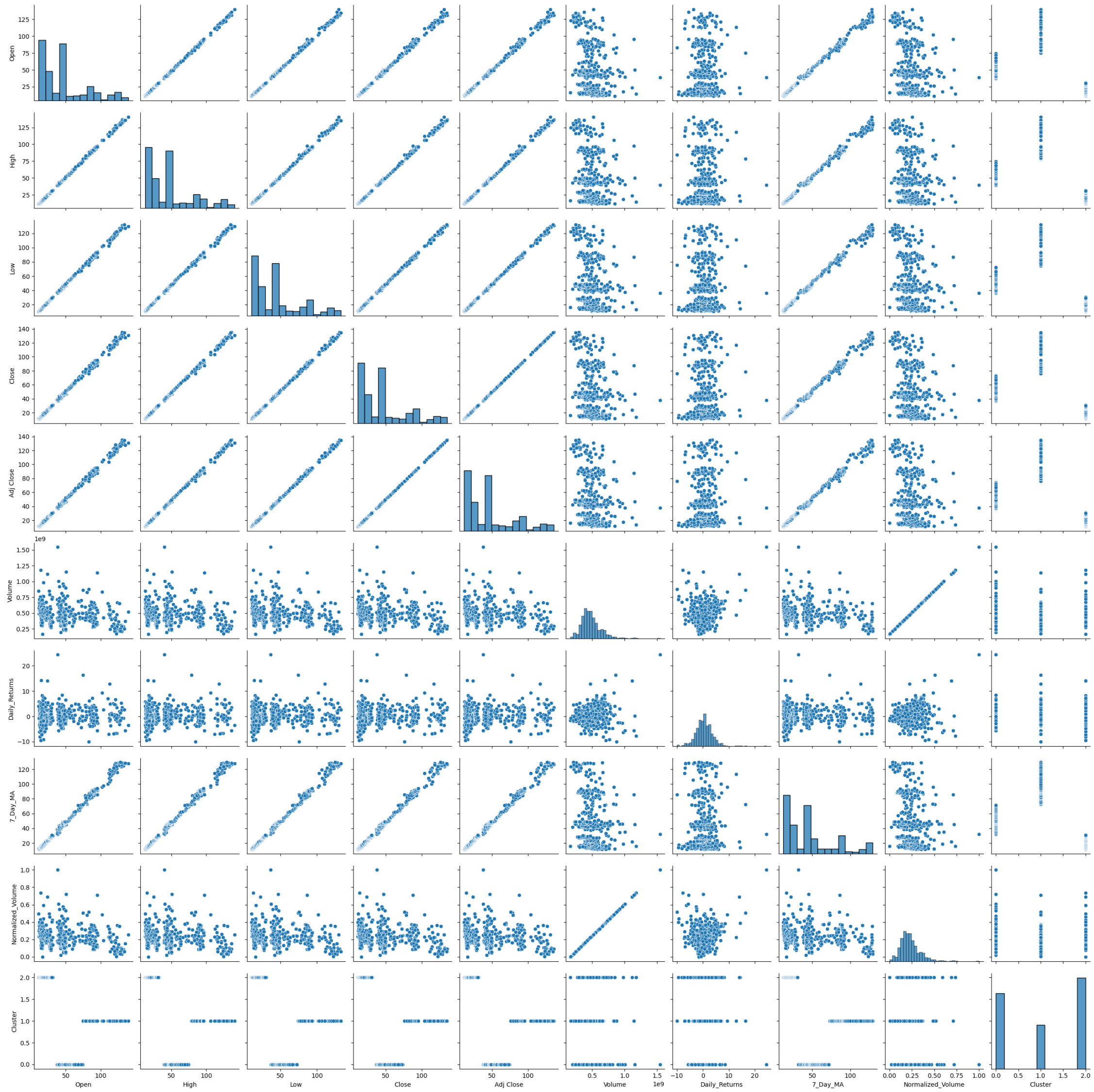
```
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=0)
```

[29]:
```
df["Close"]
```

[29]:
```
0       14.523000
1       14.964000
2       15.130000
3       15.858000
4       15.838000
          …
518    112.279999
519    113.059998
520    111.589996
521    103.730003
522    117.019997
Name: Close, Length: 517, dtype: float64
```

[30]:
```
sns.pairplot(df)
```

[30]: <seaborn.axisgrid.PairGrid at 0x22760cfbc50>



Task 2: Other machine learning methods

[48]:
```python
# Create 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)

# Calculate the root mean squared error (RMSE)
rmse = mean_squared_error(y_test, predictions, squared=False)
print(f"Root Mean Squared Error: {rmse}")
```

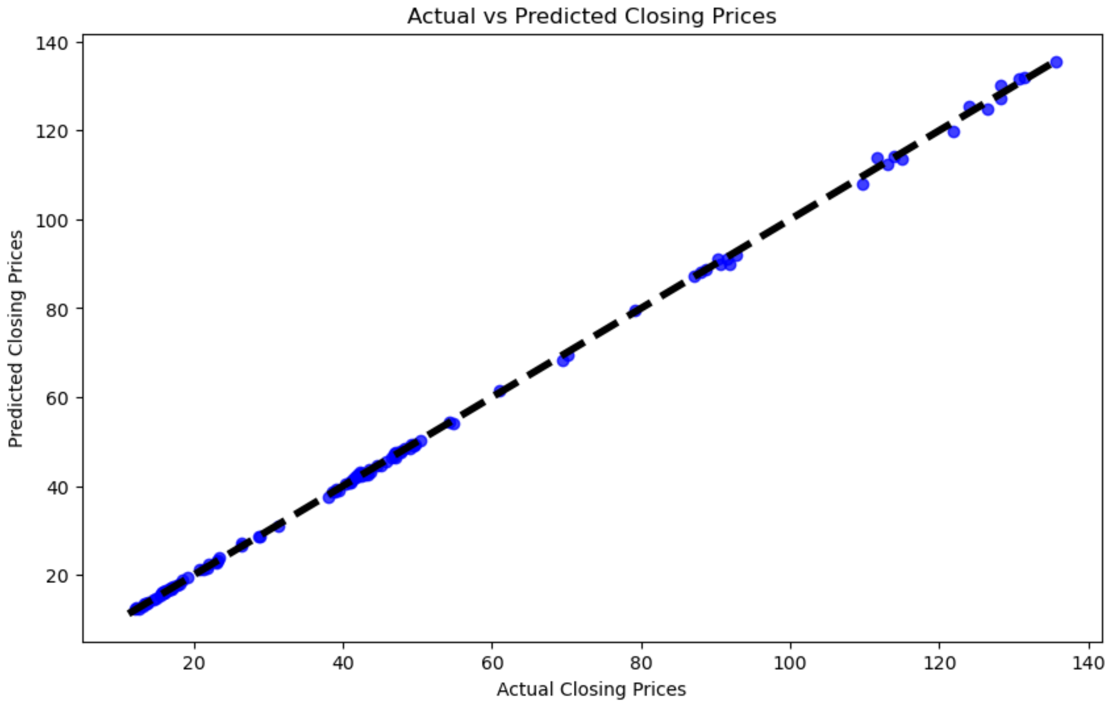
```
Root Mean Squared Error: 0.62794816494417
```

```
c:\Users\domma\anaconda3\Lib\site-packages\sklearn\metrics\_regression.py:483:
FutureWarning: 'squared' is deprecated in version 1.4 and will be removed in
1.6. To calculate the root mean squared error, use the
function'root_mean_squared_error'.
  warnings.warn(
```

[53]:
```
score = r2_score(y_test, predictions)
print(f"R-Squared: {score}")
```

```
R-Squared: 0.9996738122564774
```

[54]:
```
# Plotting the predictions against the actual values
plt.figure(figsize=(10, 6))
plt.scatter(y_test, predictions, alpha=0.75, color='b')
plt.xlabel('Actual Closing Prices')
plt.ylabel('Predicted Closing Prices')
plt.title('Actual vs Predicted Closing Prices')
plt.plot([y.min(), y.max()], [y.min(), y.max()], 'k--', lw=4)
plt.show()
```



Gradient Boosting Regressor With Randomized Search

[55]:
```
# Prepare data
X = df[['Open', 'High', 'Low', 'Volume']]  # Features
y = df['Close']  # Target variable
```

```
# Split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=0)

# Set up the parameter distribution
param_dist = {
    'n_estimators': [100, 200, 300],
    'learning_rate': [0.01, 0.05, 0.1],
    'max_depth': [3, 4, 5],
    'min_samples_split': [2, 4],
    'min_samples_leaf': [1, 2]
}

# Initialize RandomizedSearchCV
random_search =␣
↪RandomizedSearchCV(estimator=GradientBoostingRegressor(random_state=0),␣
↪param_distributions=param_dist, n_iter=10, cv=3, n_jobs=-1, verbose=2)

# Fit RandomizedSearchCV
random_search.fit(X_train, y_train)

# Best parameters and RMSE
best_gbm = random_search.best_estimator_
predictions = best_gbm.predict(X_test)
rmse = np.sqrt(mean_squared_error(y_test, predictions))

print(f"Best Parameters: {random_search.best_params_}")
print(f"Improved RMSE: {rmse}")
```

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits
Best Parameters: {'n_estimators': 200, 'min_samples_split': 2,
'min_samples_leaf': 2, 'max_depth': 5, 'learning_rate': 0.05}
Improved RMSE: 1.0915679296037941
```

[56]:
```
score = r2_score(y_test, predictions)
print(f"R-Squared: {score}")
```

```
R-Squared: 0.9990143525962691
```

Logistic Regression

[78]:
```
# Create a binary target variable indicating whether the price will go up the␣
↪next day
df['Price_Up'] = (df['Close'].shift(-1) > df['Close']).astype(int)

# Prepare the data for classification
X = df[['Open', 'High', 'Low', 'Close', 'Volume']]  # Features
```

```
y = df['Price_Up'][:-1]  # Target, excluding the last day since there's no next␣
↪day to compare
```

[79]:
```
df.head()
```

[79]:
```
         Date    Open       High     Low   Close  Adj Close       Volume  \
0  01-07-2022  14.899  15.063000  14.392  14.523  14.506663  577610000.0
1  05-07-2022  14.175  14.971000  14.055  14.964  14.947166  651397000.0
2  06-07-2022  15.010  15.319000  14.789  15.130  15.112980  529066000.0
3  07-07-2022  15.456  15.945000  15.389  15.858  15.840160  492903000.0
4  08-07-2022  15.430  16.037001  15.389  15.838  15.820185  467972000.0

   Daily_Returns  7_Day_MA  Normalized_Volume  Cluster  Price_Up
0       0.000000       NaN           0.297735        2         1
1       3.036556       NaN           0.351360        2         1
2       1.109334       NaN           0.262455        2         1
3       4.811626       NaN           0.236173        2         0
4      -0.126104       NaN           0.218055        2         0
```

[66]:
```
# Split the data
X_train, X_test, y_train, y_test = train_test_split(X[:-1], y, test_size=0.2,␣
↪random_state=0)

# Initialize and train the logistic regression model
from sklearn.linear_model import LogisticRegression
classifier = LogisticRegression()
classifier.fit(X_train, y_train)

# Predict on the test set
predictions = classifier.predict(X_test)
```

[ ]:
```
# Print classification report and accuracy
print(classification_report(y_test, predictions))
print(f"Accuracy: {accuracy_score(y_test, predictions)}")
```

```
              precision    recall  f1-score   support

           0       0.00      0.00      0.00        52
           1       0.50      1.00      0.67        52

    accuracy                           0.50       104
   macro avg       0.25      0.50      0.33       104
weighted avg       0.25      0.50      0.33       104

Accuracy: 0.5
```

```
c:\Users\domma\anaconda3\Lib\site-
packages\sklearn\metrics\_classification.py:1509: UndefinedMetricWarning:
```

```
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
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