Importing packages and reading dataset

[342]
```
import pandas as pd
import math
# Load the dataset
data = pd.read_csv('/content/^NSEI.csv')  # Replace 'path_to_your_dataset.csv' with the actual file path
```

Creating new columns for predictions

[343]
```
# Convert 'Date' column to datetime
data['Date'] = pd.to_datetime(data['Date'])

# Calculate Log Returns
data['Log Returns'] = data['Close'].pct_change().apply(lambda x: math.log(1 + x))  # Calculate log returns from 'Close'

# Calculate Moneyness
data['Moneyness'] = data['Close'] / data['Adj Close']  # Calculate moneyness using 'Close' and 'Adj Close'

# Assuming 'Date' column contains the contract's expiration date and today's date is used for the calculation
data['Time to Maturity'] =  data['Date'] + pd.DateOffset(days=30)  # Calculate time to maturity

# Assuming risk-free interest rate is constant, or you have another source
data['Risk-Free Interest Rate'] = 0.05  # Set a constant interest rate
```

lets have a look how the dataset actually looks

[344]
```
data.head(5)
```

	Date	Open	High	Low	Close	Adj Close	Volume	Log Returns	Moneyness	Time to Maturity	Risk-Free Interest Rate
0	2014-01-02	6301.250000	6358.299805	6211.299805	6221.149902	6221.149902	158100.0	NaN	1.0	2014-02-01	0.05
1	2014-01-03	6194.549805	6221.700195	6171.250000	6211.149902	6211.149902	139000.0	-0.001609	1.0	2014-02-02	0.05
2	2014-01-06	6220.850098	6224.700195	6170.250000	6191.450195	6191.450195	118300.0	-0.003177	1.0	2014-02-05	0.05
3	2014-01-07	6203.899902	6221.500000	6144.750000	6162.250000	6162.250000	138600.0	-0.004727	1.0	2014-02-06	0.05
4	2014-01-08	6178.049805	6192.100098	6160.350098	6174.600098	6174.600098	146900.0	0.002002	1.0	2014-02-07	0.05

[345]
```
data.head(50)
```

	Date	Open	High	Low	Close	Adj Close	Volume	Log Returns	Moneyness	Time to Maturity	Risk-Free Interest Rate
18	2014-01-28	6131.850098	6163.600098	6085.950195	6126.250000	6126.250000	184100.0	-0.001566	1.0	2014-02-27	0.05
19	2014-01-29	6161.000000	6170.450195	6109.799805	6120.250000	6120.250000	146700.0	-0.000980	1.0	2014-02-28	0.05
20	2014-01-30	6067.000000	6082.850098	6027.250000	6073.700195	6073.700195	208100.0	-0.007635	1.0	2014-03-01	0.05
21	2014-01-31	6082.750000	6097.850098	6067.350098	6089.500000	6089.500000	146700.0	0.002598	1.0	2014-03-02	0.05
22	2014-02-03	6058.799805	6074.850098	5994.450195	6001.799805	6001.799805	134900.0	-0.014507	1.0	2014-03-05	0.05
23	2014-02-04	5947.600098	6017.799805	5933.299805	6000.899902	6000.899902	183300.0	-0.000150	1.0	2014-03-06	0.05
24	2014-02-05	6004.250000	6028.049805	5962.049805	6022.399902	6022.399902	166600.0	0.003576	1.0	2014-03-07	0.05
25	2014-02-06	6028.350098	6048.350098	5965.399902	6036.299805	6036.299805	185500.0	0.002305	1.0	2014-03-08	0.05
26	2014-02-07	6077.649902	6079.950195	6030.899902	6063.200195	6063.200195	181900.0	0.004447	1.0	2014-03-09	0.05
27	2014-02-10	6072.799805	6083.049805	6046.399902	6053.450195	6053.450195	133100.0	-0.001609	1.0	2014-03-12	0.05
28	2014-02-11	6072.450195	6081.850098	6053.250000	6062.700195	6062.700195	150500.0	0.001527	1.0	2014-03-13	0.05
29	2014-02-12	6085.350098	6106.600098	6077.399902	6084.000000	6084.000000	138500.0	0.003507	1.0	2014-03-14	0.05
30	2014-02-13	6087.549805	6094.399902	5991.100098	6001.100098	6001.100098	153700.0	-0.013720	1.0	2014-03-15	0.05
31	2014-02-14	6023.750000	6056.399902	5984.600098	6048.350098	6048.350098	140200.0	0.007843	1.0	2014-03-16	0.05
32	2014-02-17	NaN	NaN	NaN	NaN	NaN	NaN	0.000000	NaN	2014-03-19	0.05
33	2014-02-18	6071.299805	6141.700195	6066.799805	6127.100098	6127.100098	126600.0	0.012936	1.0	2014-03-20	0.05
34	2014-02-19	6132.049805	6160.350098	6125.750000	6152.750000	6152.750000	95200.0	0.004178	1.0	2014-03-21	0.05
35	2014-02-20	6127.149902	6129.100098	6086.450195	6091.450195	6091.450195	132100.0	-0.010013	1.0	2014-03-22	0.05
36	2014-02-21	6108.299805	6159.649902	6108.000000	6155.450195	6155.450195	112600.0	0.010452	1.0	2014-03-23	0.05
37	2014-02-24	6140.950195	6191.850098	6130.799805	6186.100098	6186.100098	144900.0	0.004967	1.0	2014-03-26	0.05
38	2014-02-25	6205.700195	6216.850098	6176.600098	6200.049805	6200.049805	146300.0	0.002252	1.0	2014-03-27	0.05
39	2014-02-26	6202.450195	6245.950195	6202.100098	6238.799805	6238.799805	181700.0	0.006230	1.0	2014-03-28	0.05
40	2014-02-28	6228.450195	6282.700195	6228.100098	6276.950195	6276.950195	180600.0	0.006096	1.0	2014-03-30	0.05
41	2014-03-03	6264.350098	6277.750000	6212.250000	6221.450195	6221.450195	144600.0	-0.008881	1.0	2014-04-02	0.05
42	2014-03-04	6216.750000	6302.149902	6215.700195	6297.950195	6297.950195	166800.0	0.012221	1.0	2014-04-03	0.05
43	2014-03-05	6328.450195	6336.250000	6287.799805	6328.649902	6328.649902	160300.0	0.004863	1.0	2014-04-04	0.05
44	2014-03-06	6344.750000	6406.600098	6339.700195	6401.149902	6401.149902	180700.0	0.011391	1.0	2014-04-05	0.05

45	2014-03-07	6413.950195	6537.799805	6413.549805	6526.649902	6526.649902	284900.0	0.019416	1.0	2014-04-06	0.05
46	2014-03-10	6491.700195	6562.200195	6487.350098	6537.250000	6537.250000	242100.0	0.001623	1.0	2014-04-09	0.05
47	2014-03-11	6537.350098	6562.850098	6494.250000	6511.899902	6511.899902	239000.0	-0.003885	1.0	2014-04-10	0.05
48	2014-03-12	6497.500000	6546.149902	6487.299805	6516.899902	6516.899902	175000.0	0.000768	1.0	2014-04-11	0.05
49	2014-03-13	6491.750000	6561.450195	6476.649902	6493.100098	6493.100098	167900.0	-0.003659	1.0	2014-04-12	0.05

To check number of rows and columns:

[346]
```
print(data.shape)
```

```
(1230, 11)
```

Let's gather more information :

[347]
```
print(data.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1230 entries, 0 to 1229
Data columns (total 11 columns):
 #   Column                 Non-Null Count  Dtype         
---  ------                 --------------  -----         
 0   Date                   1230 non-null   datetime64[ns]
 1   Open                   1220 non-null   float64       
 2   High                   1220 non-null   float64       
 3   Low                    1220 non-null   float64       
 4   Close                  1220 non-null   float64       
 5   Adj Close              1220 non-null   float64       
 6   Volume                 1220 non-null   float64       
 7   Log Returns            1229 non-null   float64       
 8   Moneyness              1220 non-null   float64       
 9   Time to Maturity       1230 non-null   datetime64[ns]
 10  Risk-Free Interest Rate  1230 non-null   float64       
dtypes: datetime64[ns](2), float64(9)
memory usage: 105.8 KB
None
```

Handling NULL Values & Exploratory Data Analysis

[348]
```
null_count = data.isnull().sum()
```

[349]
```
print("Number of null values in each column:\n", null_count)
```

```
Number of null values in each column:
 Date                      0
Open                      10
High                      10
Low                       10
Close                     10
Adj Close                 10
Volume                    10
Log Returns                1
Moneyness                 10
Time to Maturity           0
Risk-Free Interest Rate    0
dtype: int64
```

[350]
```
# Remove rows with null values in any column
data.dropna(inplace=True)
```

Modeling

XGBoost

Applying XGBoost

[351]
```
import pandas as pd
import numpy as np
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from xgboost import XGBRegressor

# Load the dataset
data = pd.read_csv('/content/^NSEI.csv')

# Convert 'Date' column to datetime
data['Date'] = pd.to_datetime(data['Date'])

# Calculate Log Returns
data['Log Returns'] = data['Close'].pct_change().apply(lambda x: np.log(1 + x))  # Calculate log returns from 'Close'

# Calculate Moneyness
data['Moneyness'] = data['Close'] / data['Adj Close']  # Calculate moneyness using 'Close' and 'Adj Close'

# Assuming 'Date' column contains the contract's expiration date and today's date is used for the calculation
data['Time to Maturity'] = (data['Date'] - pd.to_datetime('today')).dt.days  # Calculate time to maturity in days

```

```python
# Assuming risk-free interest rate is constant, or you have another source
data['Risk-Free Interest Rate'] = 0.05  # Set a constant interest rate

# Assuming 'Close' as the target column
target_column = 'Close'

# Drop rows with missing values in the target column
data.dropna(subset=[target_column], inplace=True)

# Encode categorical columns using LabelEncoder
categorical_cols = ['Date']  # Add other categorical columns if needed
label_encoders = {}
for col in categorical_cols:
    label_encoders[col] = LabelEncoder()
    data[col] = label_encoders[col].fit_transform(data[col])

# Define features (excluding the target column)
features = ['Open', 'High', 'Low', 'Adj Close', 'Volume', 'Log Returns', 'Moneyness', 'Time to Maturity', 'Risk-Free Interest Rate']

# Splitting the data into train and test sets
X = data[features]
y = data[target_column]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Initialize XGBoost model
xgb = XGBRegressor()

# Fit the model
xgb.fit(X_train, y_train)

# Make predictions
predictions = xgb.predict(X_test)
```

Error metrics & Data Visualisation:

Mean Absolute Error:

[352] 0s

```python
# Evaluate the model (you can use regression evaluation metrics)
# For example, mean absolute error (MAE)
mae = np.mean(np.abs(predictions - y_test))
print(f"Mean Absolute Error: {mae}")
```

```
Mean Absolute Error: 14.227417004866817
```

Root Mean Square Error:

[353] 1m

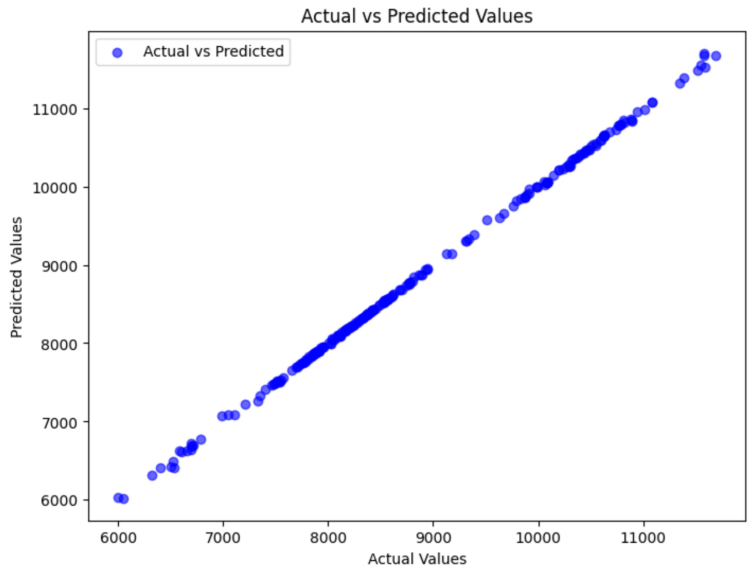
```python
from xgboost import XGBRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error

# Define the target column
target = 'Close'

# Select features and target
features = ['Open', 'High', 'Low', 'Close', 'Adj Close', 'Volume', 'Log Returns', 'Moneyness', 'Time to Maturity', 'Risk-Free Interest Rate']
X = data[features]
y = 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 the XGBoost regressor
xgb = XGBRegressor()

# Fit the model
xgb.fit(X_train, y_train)

# Make predictions
y_pred = xgb.predict(X_test)

# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
rmse = mse ** 0.5
print(f"Root Mean Squared Error (RMSE): {rmse}")

# Hyperparameter tuning (example, you might want to refine these)
params = {
    'learning_rate': [0.1, 0.3],
    'max_depth': [3, 5, 7],
    'min_child_weight': [1, 3, 5],
    'subsample': [0.5, 0.7],
    'colsample_bytree': [0.5, 0.7],
    'n_estimators': [100, 200, 300]
}

# Initialize the XGBoost regressor for hyperparameter tuning
xgb_tune = XGBRegressor()

# Perform GridSearchCV for hyperparameter tuning
from sklearn.model_selection import GridSearchCV
grid_search = GridSearchCV(estimator=xgb_tune, param_grid=params, cv=3, n_jobs=-1, verbose=2)
grid_search.fit(X_train, y_train)

# Get the best parameters
best_params = grid_search.best_params_
print(f"Best Hyperparameters: {best_params}")
```

```
print(f"Best Hyperparameters: {best_params}")

# Fit the model with the best parameters
best_xgb = XGBRegressor(**best_params)
best_xgb.fit(X_train, y_train)

# Make predictions with the tuned model
y_pred_tuned = best_xgb.predict(X_test)

# Evaluate the tuned model
mse_tuned = mean_squared_error(y_test, y_pred_tuned)
rmse_tuned = mse_tuned ** 0.5
print(f"Tuned Model RMSE: {rmse_tuned}")

```

```
Root Mean Squared Error (RMSE): 22.583838366232058
Fitting 3 folds for each of 216 candidates, totalling 648 fits
Best Hyperparameters: {'colsample_bytree': 0.7, 'learning_rate': 0.1, 'max_depth': 7, 'min_child_weight': 3, 'n_estimators': 300, 'subsample': 0.7}
Tuned Model RMSE: 16.033834928660898
```

Scatter plot

[354]
```
import matplotlib.pyplot as plt
plt.figure(figsize=(8, 6))
plt.scatter(y_test, y_pred, color='blue', label='Actual vs Predicted', alpha=0.6)
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.title('Actual vs Predicted Values')
plt.legend()
plt.show()

```



R2 Score:

[355]
```
from sklearn.metrics import r2_score

# Calculate R-squared (R2) score
r2 = r2_score(y_test, y_pred)
print(f"R-squared (R2) Score: {r2}")

```

```
R-squared (R2) Score: 0.999698469299721
```

Cross Validation Score:

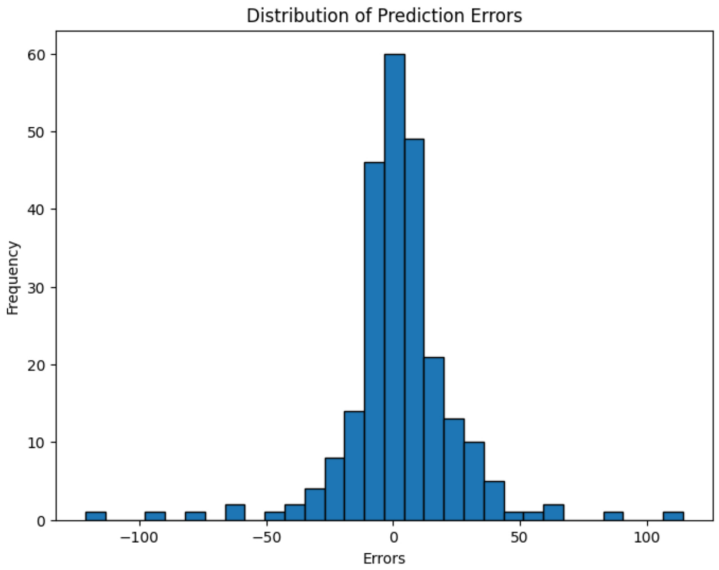
[356]
```
from sklearn.model_selection import cross_val_score

# Initialize XGBoost model
xgb = XGBRegressor()

# Perform K-fold cross-validation
cv_scores = cross_val_score(xgb, X, y, cv=5)  # Change cv value as needed
print("Cross Validation Scores:", cv_scores)
print("Mean Cross Validation Score:", np.mean(cv_scores))

```

```
Cross Validation Scores: [ 0.74725589  0.99843148  0.99594051  0.62247023 -0.40191009]
Mean Cross Validation Score: 0.5924376040514125
```

Error distribution:

[357]
```
# Calculate errors
errors = y_test - y_pred
```

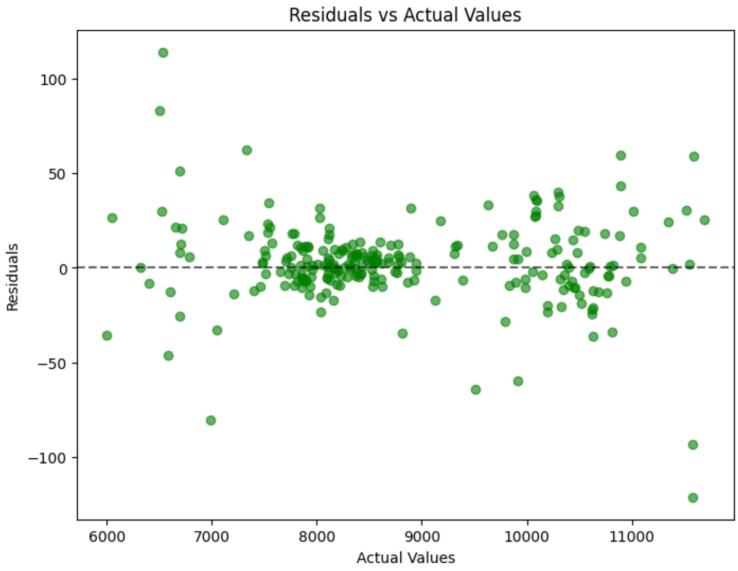
```
# Plotting the error distribution
plt.figure(figsize=(8, 6))
plt.hist(errors, bins=30, edgecolor='black')
plt.xlabel('Errors')
plt.ylabel('Frequency')
plt.title('Distribution of Prediction Errors')
plt.show()
```



The shape of the histogram provides insights into the distribution of errors. A symmetric distribution around zero implies that the model's errors are evenly distributed above and below the actual values. If the histogram is skewed towards either end (positive or negative), it indicates a bias in the predictions.

Residual plot

```
import matplotlib.pyplot as plt

plt.figure(figsize=(8, 6))
plt.scatter(y_test, y_test - y_pred, color='green', marker='o', alpha=0.6)
plt.axhline(y=0, color='black', linestyle='--', alpha=0.6)
plt.xlabel('Actual Values')
plt.ylabel('Residuals')
plt.title('Residuals vs Actual Values')
plt.show()
```



This plot helps visualize the relationship between the actual values and their corresponding residuals. The horizontal line at y=0 indicates where residuals equal zero, allowing you to see how much the predictions deviate from the actual values across the dataset.

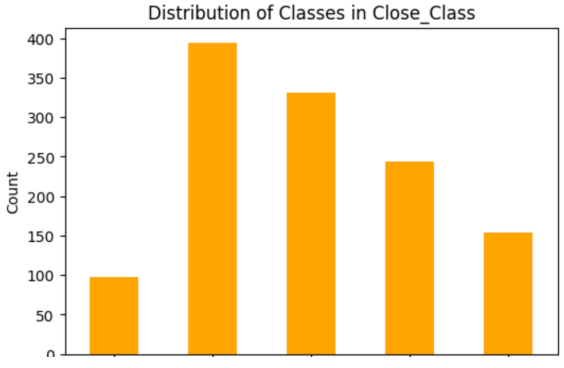
Predicting range of prices by classifying "Close" price

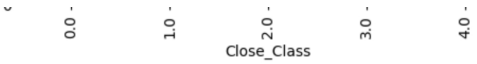
[365]
```python
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from xgboost import XGBClassifier

# Load the dataset
data = pd.read_csv('/content/^NSEI.csv')

# Assuming 'Close' as the target column
target_column = 'Close'

# Calculate the range and intervals for creating classes
min_value = data[target_column].min()
max_value = data[target_column].max()
interval = (max_value - min_value) / 5

# Function to map the 'Close' values to classes
def classify_close(value):
    if value <= min_value + interval:
        return 0
    elif value <= min_value + 2 * interval:
        return 1
    elif value <= min_value + 3 * interval:
        return 2
    elif value <= min_value + 4 * interval:
        return 3
    else:
        return 4

# Create a new column 'Close_Class' representing the classes
data['Close_Class'] = data[target_column].apply(classify_close)

# Define features (X) and target variable (y)
features = ['Open', 'High', 'Low', 'Adj Close', 'Volume']
X = data[features]
y = data['Close_Class']

# Splitting the data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Initialize XGBoost classifier
xgb_classifier = XGBClassifier()

# Fit the model
xgb_classifier.fit(X_train, y_train)

# Make predictions
predictions = xgb_classifier.predict(X_test)

```

[360]
```python
import pandas as pd

# Load the dataset
data = pd.read_csv('/content/^NSEI.csv')  # Load your dataset here

# Set the bins for classifying 'Close' values
num_classes = 5
bin_edges = pd.cut(data['Close'], bins=num_classes, labels=False)
data['Close_Class'] = bin_edges

# Check the distribution of classes
class_distribution = data['Close_Class'].value_counts()
print(class_distribution)

```

```
1.0    394
2.0    331
3.0    244
4.0    154
0.0     97
Name: Close_Class, dtype: int64
```

[361]
```python
# Plotting the distribution of classes in Close_Class
plt.figure(figsize=(6, 4))
data['Close_Class'].value_counts().sort_index().plot(kind='bar', color='orange')
plt.xlabel('Close_Class')
plt.ylabel('Count')
plt.title('Distribution of Classes in Close_Class')
plt.show()
```





The above graph says that frequency of closing price lies more CLASS-1.

[366]
```
# Define features (X) and target variable (y)
features = ['Open', 'High', 'Low', 'Adj Close', 'Volume']  # Update features based on available columns

X = data[features]
y = data['Close_Class']  # 'Close_Class' contains the classes for the 'Close' column
```

[367]
```
class_ranges = data.groupby('Close_Class')['Close'].describe()
print(class_ranges)
```

```
                count          mean         std           min           25%  \
Close_Class
0                97.0   6497.495877  331.934519   6000.899902   6191.450195
1               394.0   7866.962181  279.858355   7162.950195   7671.562378
2               331.0   8681.216325  281.781613   8296.299805   8464.824707
3               244.0  10139.928079  312.889060   9445.400391   9907.074952
4               154.0  10959.558124  315.826947  10593.150391  10715.762451

                        50%           75%           max
Close_Class
0              6511.899902   6736.100098   7123.149902
1              7889.274902   8111.350098   8295.450195
2              8629.150391   8808.650391   9438.250000
3             10185.724609  10412.462891  10589.099609
4             10847.875000  11133.724854  11738.500000
```

Let's look at range of price:

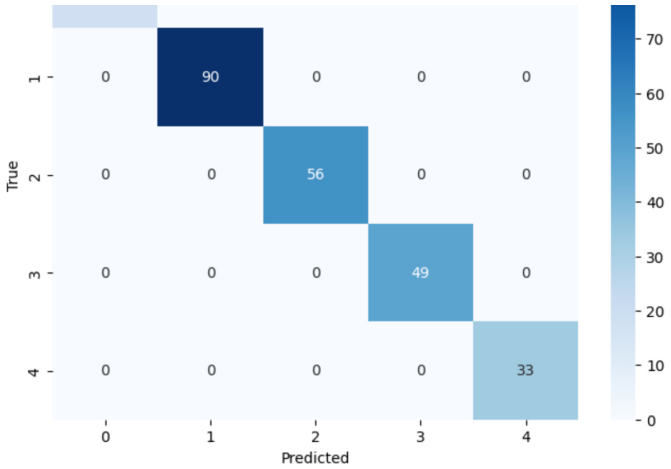
[368]
```
import pandas as pd

# Sample DataFrame
data = {
    'Class': [0.0, 1.0, 2.0, 3.0, 4.0],
    'Count': [97, 394, 331, 244, 154],
    'Mean': [6497.495877, 7866.962181, 8681.216325, 10139.928079, 10959.558124],
    'Std': [331.934519, 279.858355, 281.781613, 312.889060, 315.826947],
    'Min': [6000.899902, 7162.950195, 8296.299805, 9445.400391, 10593.150391],
    'Max': [7123.149902, 8295.450195, 9438.25, 10589.099609, 11738.5]
}

df = pd.DataFrame(data)

# Select only the necessary columns
result = df[['Class', 'Min', 'Max']]
print(result)

```

```
   Class           Min           Max
0    0.0   6000.899902   7123.149902
1    1.0   7162.950195   8295.450195
2    2.0   8296.299805   9438.250000
3    3.0   9445.400391  10589.099609
4    4.0  10593.150391  11738.500000
```

[369]
```
print(pd.unique(y_train))
```

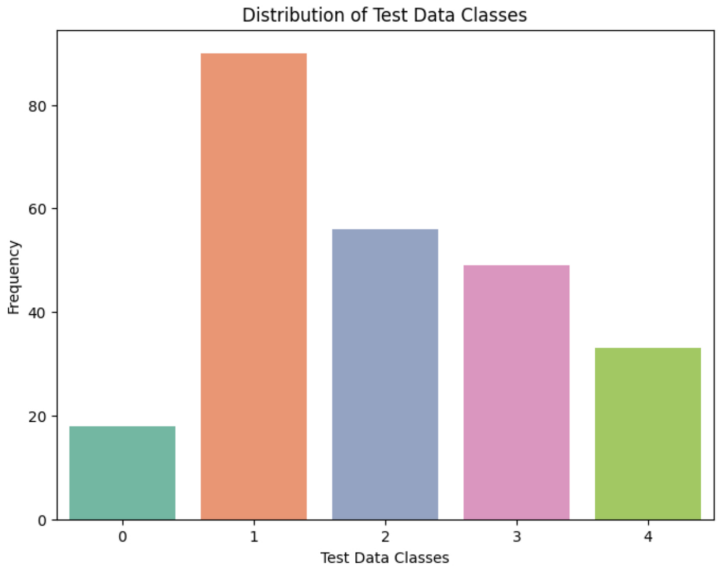
```
[2 4 3 1 0]
```

[370]
```
import pandas as pd
from sklearn.model_selection import train_test_split
from xgboost import XGBClassifier
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt

# Initialize the XGBoost classifier
xgb = XGBClassifier()

# Fit the model
xgb.fit(X_train, y_train)

# Make predictions
y_pred = xgb.predict(X_test)

# Get the confusion matrix
conf_mat = confusion_matrix(y_test, y_pred)

# Plot confusion matrix as a heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(conf_mat, annot=True, cmap='Blues', fmt='d', cbar=True)
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()
```



Above plot says that Close prices lying in Class-1 are more accurately predicted by our Model.

[371]
```
import seaborn as sns
import matplotlib.pyplot as plt

# Plotting the distribution of classes in the test data
plt.figure(figsize=(8, 6))
sns.countplot(x=y_test, palette='Set2')  # Assuming y_test contains the true class labels
plt.xlabel('Test Data Classes')
plt.ylabel('Frequency')
plt.title('Distribution of Test Data Classes')
plt.show()

```

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