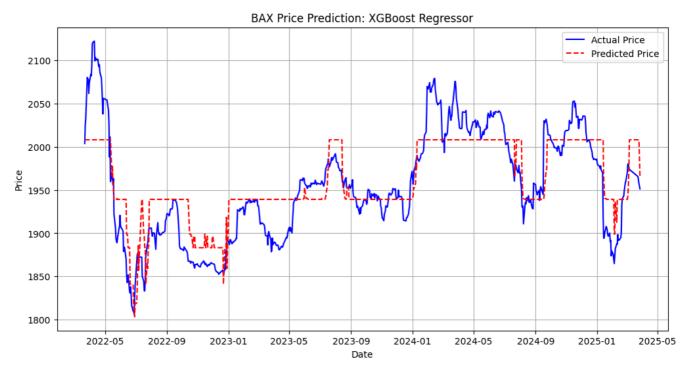
```
1 \# This Python 3 environment comes with many helpful analytics libraries installed
  2 # It is defined by the kaggle/python Docker image: https://github.com/kaggle/docker-python
  3 # For example, here's several helpful packages to load
  5 import numpy as np # linear algebra
  6 import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
  8 # Input data files are available in the read-only "../input/" directory
  9 # For example, running this (by clicking run or pressing Shift+Enter) will list all files under the input directory
 10
 11 import os
 12 for dirname, _, filenames in os.walk('/kaggle/input'):
 13
       for filename in filenames:
 14
            print(os.path.join(dirname, filename))
 15
 16 # You can write up to 20GB to the current directory (/kaggle/working/) that gets preserved as output when you create a version using
 17 # You can also write temporary files to <a href="kaggle/temp/">kaggle/temp/</a>, but they won't be saved outside of the current session
/kaggle/input/bax-for-xgb/df bax cleaned to view outliers.csv
  1 import pandas as pd
  2 import numpy as np
  3 import matplotlib.pyplot as plt
  4 import xgboost as xgb
  5 from sklearn.model_selection import train_test_split
  6 from sklearn.metrics import mean_squared_error, mean_absolute_error
  1 df = pd.read csv('/kaggle/input/bax-for-xgb/df bax cleaned to view outliers.csv')
  2 df
₹
                Date
                      Price
                                  0pen
                                          High
                                                    Low
                                                              Vol. Change %
           2010-05-24 1482.42 1491.98 1491.98 1482.42 926980.0
                                                                        -0.64
           2010-05-25 1454.85 1482.42 1482.42 1454.85 1660000.0
       1
                                                                       -1 86
       2
           2010-05-26 1472.29 1456.50 1472.29 1454.85 1500000.0
                                                                        1.20
           2010-05-27 1453.82 1472.29 1478.07 1453.82 2480000.0
                                                                       -1.25
       3
           2010-05-30 1455.16 1453.82 1462.04 1453.72 5910000.0
                                                                        0.09
       4
     3654 2025-03-05 1975.92 1980.24 1980.71 1974.02
                                                         818340.0
                                                                       -0.21
     3655 2025-03-06 1973.89 1975.92 1975.92 1973.89
                                                          294350.0
                                                                       -0.10
     3656 2025-03-23 1965.58 1962.09 1967.91 1955.49
                                                          611460 0
                                                                       -0.42
     3657 2025-03-25 1957.49 1951.62 1957.49 1942.88 1100000.0
                                                                       -0.41
     3658 2025-03-27 1951.36 1954.72 1954.72 1945.34 457910.0
                                                                       -0.31
    3659 rows × 7 columns
 1 # --- 1. Data Preprocessing and Feature Engineering ---
 3 # Convert 'Date' column to datetime objects and set it as the index
 4 df['Date'] = pd.to_datetime(df['Date'])
 5 df.set_index('Date', inplace=True)
 1 # Select only the 'Price' column for our forecasting task
 2 data = df[['Price']].copy()
 1 # Create lagged features to convert the time series problem into a supervised learning problem.
 2 # We will use the prices from the last 1, 2, 3, 5, and 10 days to predict the current day's price.
 3 \text{ lags} = [1, 2, 3, 5, 10]
 4 for lag in lags:
       data[f'Price_lag_{lag}'] = data['Price'].shift(lag)
 1 # Drop any rows with NaN values that were created by the lagging process.
 2 data.dropna(inplace=True)
 1 # Define the feature set (X) and the target variable (y)
 2 X = data.drop('Price', axis=1)
 3 y = data['Price']
```

```
1 # --- 2. Data Splitting ---
 3 # Split the data in a time-based manner.
 4 # We'll use the first 80% for training and the last 20% for testing.
 5 split_point = int(len(X) * 0.8)
 6 X_train, X_test = X[:split_point], X[split_point:]
 7 y_train, y_test = y[:split_point], y[split_point:]
 1 # Check the shapes of the splits
 2 print(f"Training data shape: {X_train.shape}, {y_train.shape}")
 3 print(f"Testing data shape: {X_test.shape}, {y_test.shape}")
Training data shape: (2919, 5), (2919,)
Testing data shape: (730, 5), (730,)
 1 # --- 3. Model Training ---
 3 # Initialize and train the XGBoost Regressor model.
 4\ \mbox{\#} The 'n_estimators' parameter is similar to the number of trees in Random Forest.
 5 # The 'objective' is set for regression.
 6 # The 'eval_metric' helps monitor performance during training.
 7 # random_state ensures reproducibility of results.
 8 xg_model = xgb.XGBRegressor(
 9
       n estimators=500,
10
       objective='reg:squarederror',
       eval_metric='rmse',
11
12
       random_state=42,
13
       n_jobs=-1
14)
16 print("\nTraining XGBoost model...")
17 xg_model.fit(X_train, y_train,
                early_stopping_rounds=50,
                eval_set=[(X_test, y_test)],
19
20
                verbose=False)
21 print("Training complete.")
<del>_</del>
    Training XGBoost model...
    /usr/local/lib/python3.11/dist-packages/xgboost/sklearn.py:889: UserWarning: `early_stopping_rounds` in `fit` method is deprecated 1
      warnings.warn(
    Training complete.
 2 # --- 4. Making Predictions ---
 4 # Use the trained model to make predictions on the test data.
 5 predictions = xg_model.predict(X_test)
 1 # --- 5. Model Evaluation ---
 3 \# Calculate and print the evaluation metrics.
 4 mae = mean_absolute_error(y_test, predictions)
 5 rmse = np.sqrt(mean_squared_error(y_test, predictions))
 7 print(f"\nMean Absolute Error (MAE): {mae:.2f}")
 8 print(f"Root Mean Squared Error (RMSE): {rmse:.2f}")
₹
    Mean Absolute Error (MAE): 26.01
    Root Mean Squared Error (RMSE): 33.26
 1 # --- 6. Visualization ---
 3 # Plot the actual vs. predicted prices
 4 plt.figure(figsize=(12, 6))
 5 plt.plot(y_test.index, y_test, label='Actual Price', color='blue')
  6 plt.plot(y_test.index, predictions, label='Predicted Price', color='red', linestyle='--')
 7 plt.title('BAX Price Prediction: XGBoost Regressor')
 8 plt.xlabel('Date')
 9 plt.ylabel('Price')
10 plt.legend()
 11 plt.grid(True)
12 plt.show()
```

∓*



 $^{{\}bf 1}$ Start coding or $\underline{\text{generate}}$ with AI.