```
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-5y-sarima/df bax cleaned to view outliers 5y.csv
SARIMAX: PRATHIK MOHAN
```

```
1 import pandas as pd
 2 from statsmodels.tsa.statespace.sarimax import SARIMAX
 3 from sklearn.metrics import mean_squared_error
 4 import numpy as np
 5 import matplotlib.pyplot as plt
 6 import warnings
 7 warnings.filterwarnings("ignore")
 9 # Load 5-year data
10 df = pd.read_csv('/kaggle/input/bax-5y-sarima/df_bax_cleaned_to_view_outliers_5y.csv', index_col=0, parse_dates=True)
11 df.index = pd.to_datetime(df.index)
13 # Slice last 4 years
14 df_4y = df.last('4YE')
15 print(f"Rows in 4 years: {len(df 4y)}")
16
17 # Preview
18 df 4y.head()
→ Rows in 4 years: 786
                  Price
                           0pen
                                    High
                                             Low
                                                       Vol. Change %
           Date
     2022-01-03 1792.24 1797.10 1797.10 1792.24
                                                   635180.0
                                                                 -0.28
     2022-01-04 1796.49 1790.33 1796.49 1789.90 2440000.0
                                                                 0.24
     2022-01-05 1796.08 1797.20 1799.26 1795.84 2130000.0
                                                                 -0.02
     2022-01-06 1788.93 1796.08 1796.08 1788.93
                                                   974210.0
                                                                 -0.40
     2022-01-09 1794.47 1788.38 1795.43 1788.14 1350000.0
                                                                 0.31
 1 # Check correlation with Price
 2 correlations = df_4y.corr()
 3 price_corr = correlations['Price'].sort_values(ascending=False)
 4 print(price_corr)
→ Price
                1,000000
                0.995698
    Low
    High
                0.995506
                0.990376
    0pen
                0.052195
    Vol.
    Change %
                0.044944
    Name: Price, dtype: float64
 1 df_4y['Vol.'] = np.log1p(df_4y['Vol.']) # log(1 + volume)
 2 df_4y.head()
```

```
₹
                   Price
                                                         Vol. Change %
                            0pen
                                     High
                                               Low
           Date
     2022-01-03 1792.24 1797.10 1797.10 1792.24 13.361665
                                                                   -0.28
     2022-01-04 1796.49 1790.33 1796.49 1789.90 14.707509
                                                                   0.24
     2022-01-05 1796.08 1797.20 1799.26 1795.84 14.571633
                                                                   -0.02
     2022-01-06 1788.93 1796.08 1796.08 1788.93 13.789383
                                                                   -0.40
     2022-01-09 1794.47 1788.38 1795.43 1788.14 14.115616
                                                                   0.31
 1 # Target
 2 target = df_4y['Price']
 4 # Exogenous variables - based on your correlation decision
 5 exog = df_4y[['Vol.', 'Change %']] # ✓ adjust based on previous step
 7 # Train-test split (80/20)
 8 train_size = int(len(target) * 0.8)
 9 train_y, test_y = target[:train_size], target[train_size:]
10 train_X, test_X = exog[:train_size], exog[train_size:]
11
12 # Define SARIMAX model
13 model = SARIMAX(train_y,
14
                    exog=train_X,
15
                    order=(2, 0, 1),
16
                    seasonal_order=(1, 1, 1, 252),
17
                    enforce stationarity=False,
                    enforce_invertibility=False)
18
19
20 # Fit model
21 model_fit = model.fit()
23 # Forecast with exog input
24 preds = model_fit.forecast(steps=len(test_y), exog=test_X)
26 # Evaluate
27 rmse = np.sqrt(mean_squared_error(test_y, preds))
28 print(f"\nSARIMAX RMSE: {rmse:.2f}")
    SARIMAX RMSE: 79.94
 1 print(df_4y[['Vol.', 'Change %']].dtypes)
2 print(df_4y[['Vol.', 'Change %']].isna().sum())
                float64

→ Vol.
    Change %
                float64
    dtype: object
    Vol.
                0
    Change %
                0
    dtype: int64
  1 plt.figure(figsize=(12, 5))
  2 plt.plot(train_y.index, train_y, label='Train')
  3 plt.plot(test_y.index, test_y, label='Actual')
  4 plt.plot(test_y.index, preds, label='Forecast')
  5 plt.title('SARIMAX Forecast')
  6 plt.xlabel('Date')
  7 plt.ylabel('Price')
  8 plt.legend()
  9 plt.grid(True)
 10 plt.tight_layout()
 11 plt.show()
 12
```



