


```

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
4
5 import numpy as np # linear algebra
6 import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
7
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 /kaggle/temp/, but they won't be saved outside of the current session

```

 /kaggle/input/bax-5y/df_bax_cleaned_to_view_outliers_5y.csv


Kaggle Run of SARIMA: Prathik Mohan

```

1 import pandas as pd
2 import numpy as np
3 import matplotlib.pyplot as plt
4 from statsmodels.tsa.statespace.sarimax import SARIMAX
5 from sklearn.metrics import mean_squared_error
6 import itertools
7 import warnings
8 warnings.filterwarnings("ignore")

1 # Picking 4 years of data for SARIMA - If 3 years of daily data = 726 rows, that's only about 2.8 seasonal cycles (assuming ~252 tr
2 # For SARIMA to learn seasonal patterns well, you should ideally have at least 3 full cycles, i.e. ~750+ rows for yearly seasonality
3
4 # Load data (same as you did)
5 df = pd.read_csv('/kaggle/input/bax-5y/df_bax_cleaned_to_view_outliers_5y.csv', index_col=0, parse_dates=True)
6
7 # Make sure index is datetime
8 df.index = pd.to_datetime(df.index)
9
10 # Slice last 4 years of data
11 df_4y = df.last('4Y')
12
13 # Check result
14 print(f"Rows in 4 years of data: {len(df_4y)}")
15 df_4y

```

 Rows in 4 years of data: 786

	Price	Open	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
...
2025-03-05	1975.92	1980.24	1980.71	1974.02	818340.0	-0.21
2025-03-06	1973.89	1975.92	1975.92	1973.89	294350.0	-0.10
2025-03-23	1965.58	1962.09	1967.91	1955.49	611460.0	-0.42
2025-03-25	1957.49	1951.62	1957.49	1942.88	1100000.0	-0.41
2025-03-27	1951.36	1954.72	1954.72	1945.34	457910.0	-0.31

786 rows × 6 columns

```

1 series = df_4y['Price'] # Assuming 'Price' column exists

1 # Train-test split (80% train, 20% test)
2 train_size = int(len(series) * 0.8)
3 train, test = series[:train_size], series[train_size:]

```

```

1 # ☒ Manually set SARIMA orders here:
2 p, d, q = 2, 0, 1          # ARIMA part
3 P, D, Q, s = 1, 1, 1, 252 # Seasonal part – try 252, 273, 365

1 # Fit SARIMA model
2 model = SARIMAX(train,
3                 order=(p, d, q),
4                 seasonal_order=(P, D, Q, s),
5                 enforce_stationarity=False,
6                 enforce_invertibility=False)
7
8 model_fit = model.fit()

1 # Forecast
2 preds = model_fit.forecast(steps=len(test))

1 # Evaluate
2 rmse = np.sqrt(mean_squared_error(test, preds))
3 print(f"\nSARIMA({p},{d},{q}) x ({P},{D},{Q},{s}) RMSE: {rmse:.2f}")

```

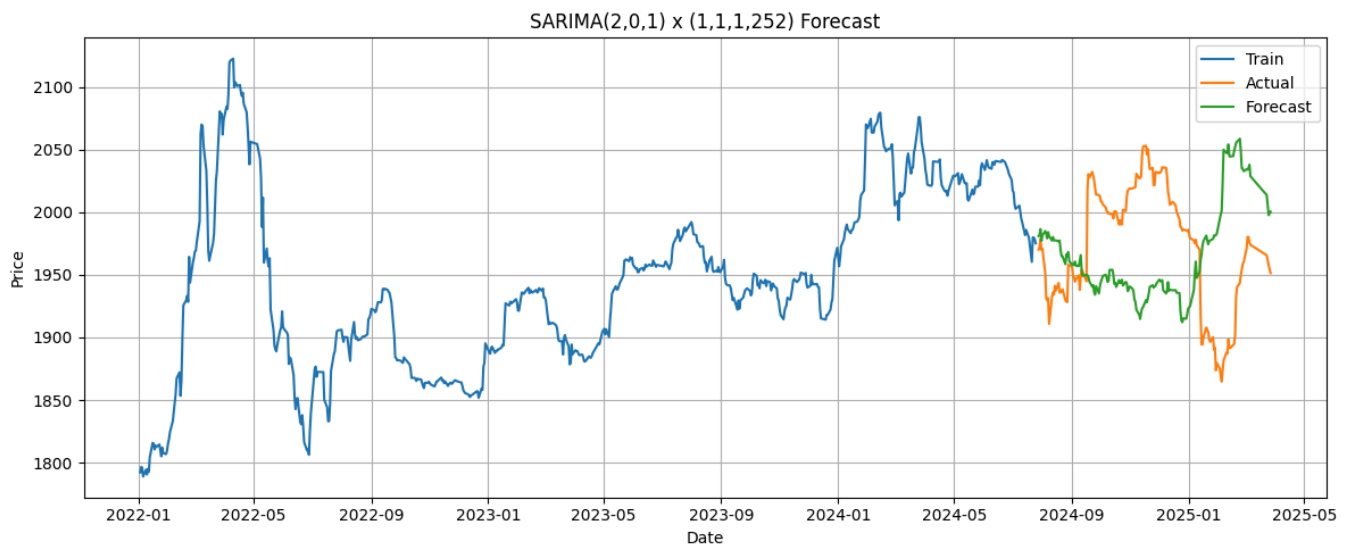


SARIMA(2,0,1) x (1,1,1,252) RMSE: 79.40

```

1 # Plot
2 plt.figure(figsize=(12, 5))
3 plt.plot(train.index, train, label='Train')
4 plt.plot(test.index, test, label='Actual')
5 plt.plot(test.index, preds, label='Forecast')
6 plt.title(f"SARIMA({p},{d},{q}) x ({P},{D},{Q},{s}) Forecast")
7 plt.xlabel("Date")
8 plt.ylabel("Price")
9 plt.legend()
10 plt.grid(True)
11 plt.tight_layout()
12 plt.show()

```



1 Start coding or [generate](#) with AI.

