```
import statsmodels
```

```
print(statsmodels.__version__)
```

```
0.13.2
```

```
import gc
import warnings
warnings.filterwarnings('ignore')
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```
df = pd.read_csv('/content/drive/MyDrive/df_daywise.csv')
```

```
df.head()
```

	Unnamed: 0	DateApproved	loans_approved
0	0	2020-04-03	10548
1	1	2020-04-04	18432
2	2	2020-04-05	21795
3	3	2020-04-06	31955
4	4	2020-04-07	43761

```
df.drop('Unnamed: 0',axis = 1,inplace = True)
```

Saved successfully!

	DateApproved	loans_approved
0	2020-04-03	10548
1	2020-04-04	18432
2	2020-04-05	21795
3	2020-04-06	31955
4	2020-04-07	43761

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 244 entries, 0 to 243
Data columns (total 2 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   DateApproved    244 non-null    object
 1   loans_approved  244 non-null    int64 
dtypes: int64(1), object(1)
memory usage: 3.9+ KB
```

```
df.DateApproved = pd.to_datetime(df.DateApproved)
```

```
df.set_index('DateApproved',inplace = True)
```

```
df.head()
```

DateApproved	loans_approved
2020-04-03	10548
2020-04-04	18432
2020-04-05	21795
2020-04-06	31955
2020-04-07	43761

```
df.isnull().sum()
```

```
loans_approved    0
dtype: int64
```

```
df.shape
```

```
(244, 1)
```

```
df.describe()
```

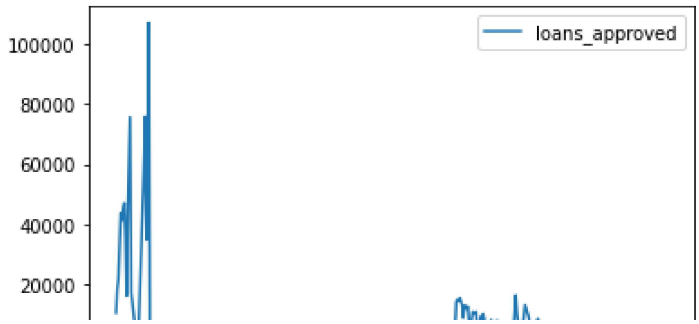
	loans_approved
std	13162.414653
min	1.000000
25%	838.000000
50%	2577.500000
75%	5565.000000
max	107111.000000

Saved successfully!

```
gc.collect()
```

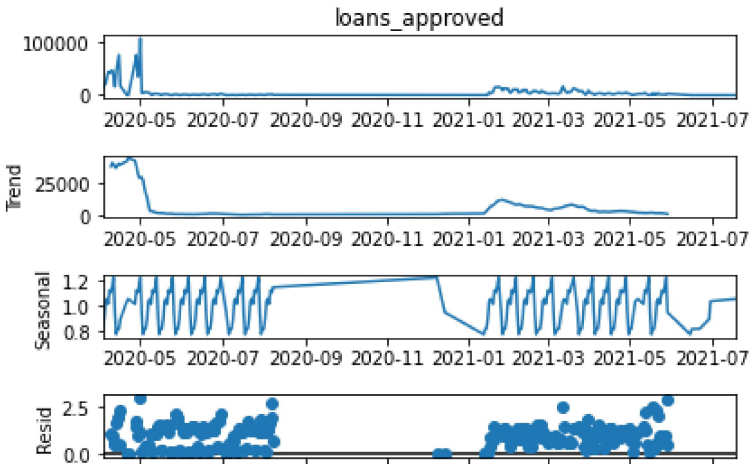
```
88
```

```
df.plot();
```




```
from statsmodels.tsa.seasonal import seasonal_decompose
```

```
result=seasonal_decompose(df['loans_approved'], model='multiplicative', period=12)
result.plot()
plt.tight_layout()
```




```
col = sns.color_palette()
col
```

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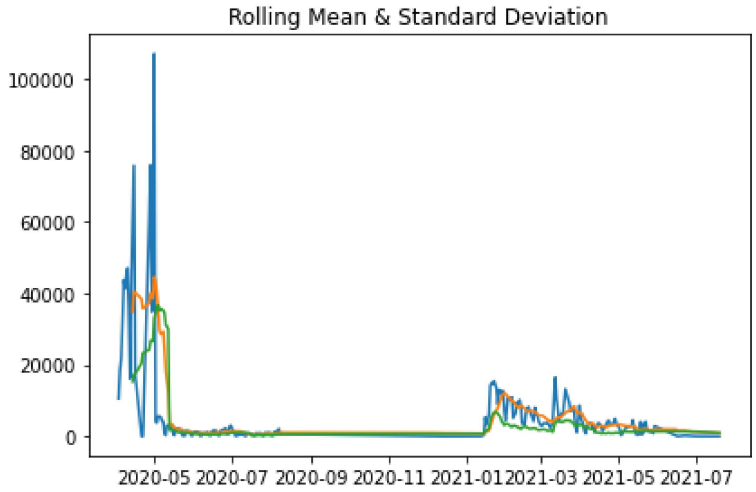
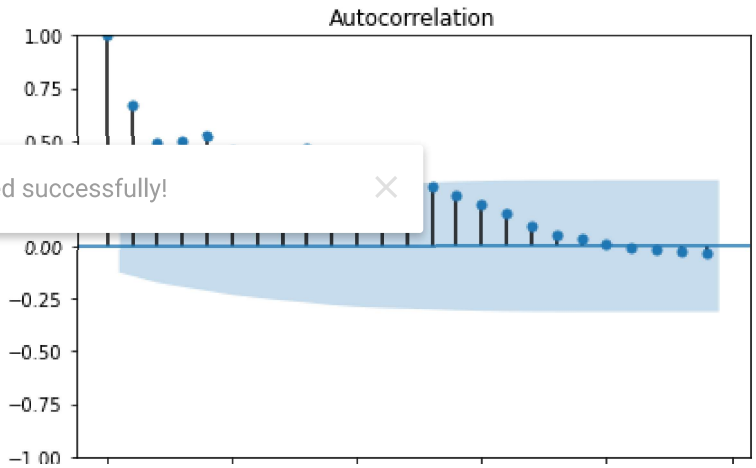
```
from statsmodels.tsa.stattools import adfuller
# rolling statistics
def stationary_check(data):
    mean = data.rolling(window=12).mean()
    std = data.rolling(window=12).std()
    plt.plot(data,color=col[0],label = 'Original Data');
    plt.plot(mean, color=col[1],label = 'mean');
    plt.plot(std, color=col[2],label = 'standard deviation');
    plt.title('Rolling Mean & Standard Deviation')
    plt.tight_layout()
    plt.show()

    # dickey-fuller test
    af = adfuller(data)
    op = pd.Series(af[0:4],index = ['Test Statistics','p-value','Lags used','No. of obs. used'])
    for key,value in af[4].items():
        op['Critical value (%s)'%key] = value
    print(op)
```

```
stationary_check(df.loans_approved)
```

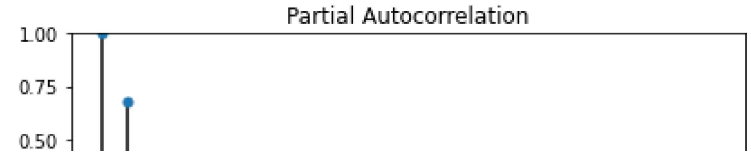



```
Test Statistics           -2.915453
p-value                    0.043580
Lags used                 15.000000
No. of obs. used         228.000000
Critical value (1%)       -3.459361
Critical value (5%)       -2.874302
Critical value (10%)      -2.573571
```

```
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

plot_acf(df['loans_approved'])
plt.tight_layout()
```




```
plot_pacf(df['loans_approved'])
plt.tight_layout()
```




```
import warnings

warnings.filterwarnings("ignore")
```

ARIMA

```
from statsmodels.tsa.arima.model import ARIMA
model = ARIMA(df.loans_approved, order=(3,2,0))


model_fit = model.fit()


print(model_fit.summary())
```

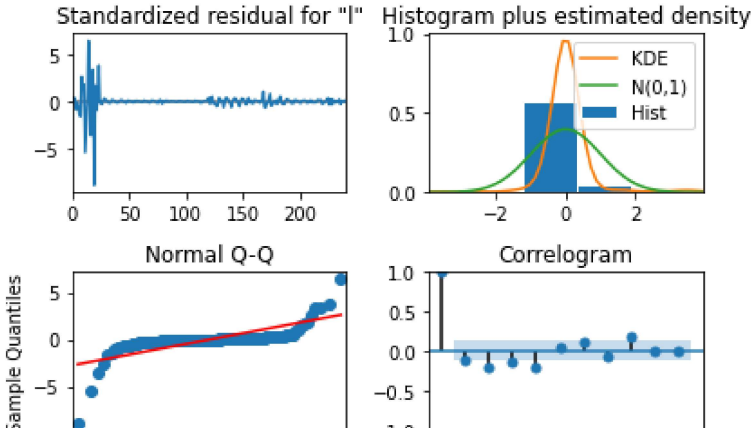
```
                               SARIMAX Results
==========================================================================================
Dep. Variable:         loans_approved   No. Observations:                  244
Model:                 ARIMA(3, 2, 0)   Log Likelihood               -2609.378
Date:                Sat, 01 Oct 2022   AIC                           5226.755
Time:                        15:02:54   BIC                           5240.711
Sample:                             0   HQIC                          5232.377
                                - 244
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.8869      0.019    -46.788      0.000      -0.924      -0.850
ar.L2         -0.7703      0.023    -33.495      0.000      -0.815      -0.725
ar.L3         -0.4375      0.018    -24.084      0.000      -0.473      -0.402
                    1   1.55e+18      0.000    1.37e+08    1.37e+08
===================================================================================
Ljung-Box (L1) (Q):                   2.94   Jarque-Bera (JB):             14418.00
Prob(Q):                              0.09   Prob(JB):                         0.00
Heteroskedasticity (H):               0.02   Skew:                            -2.07
Prob(H) (two-sided):                  0.00   Kurtosis:                        40.59
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 4.3e+32. Standard err
```

Saved successfully!

```
gc.collect()
```

```
19153
```

```
model_fit.plot_diagnostics()
plt.tight_layout()
```




```
#!pip install statsmodels==0.12.2


plt.figure(figsize=(10,8))
model_fit.plot_predict(dynamic=False)
plt.show()


gc.collect()
```

```
44
```

```
train = df[:195]
test = df[195:]


df.shape
```

```
(244, 1)
```

```
print(len(train))
print(len(test))
```

Saved successfully!

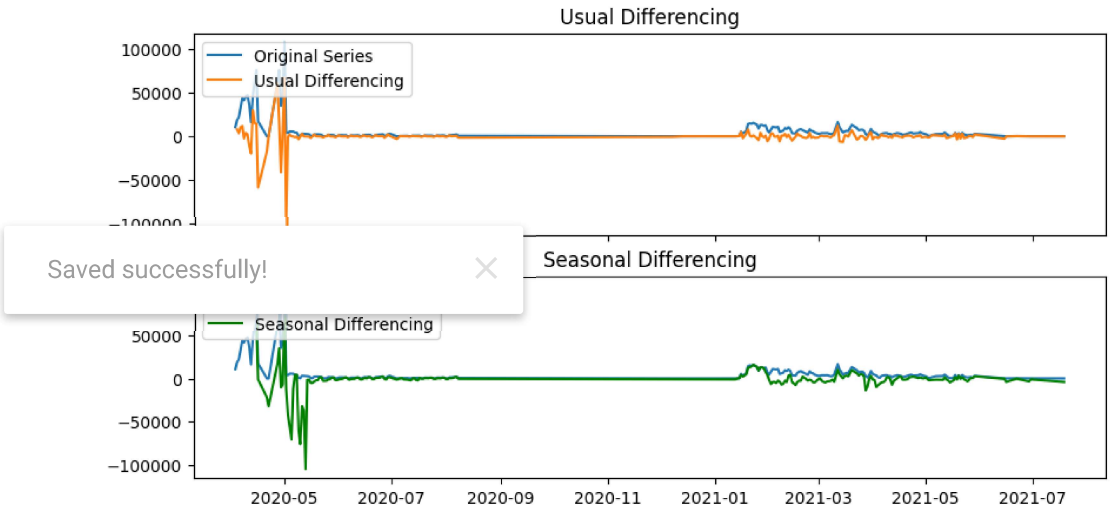
```
195
49
244
```

```
# Build Model
model = ARIMA(train, order=(2,2,1))
fitted = model.fit()

# Forecast
fc, se, conf = fitted.forecast(49, alpha=0.05)  # 95% conf

# Make as pandas series
fc_series = pd.Series(fc, index=test.index)
lower_series = pd.Series(conf[:, 0], index=test.index)
upper_series = pd.Series(conf[:, 1], index=test.index)

# Plot
plt.figure(figsize=(12,5), dpi=100)
plt.plot(train, label='training')
plt.plot(test, label='actual')
plt.plot(fc_series, label='forecast')
plt.fill_between(lower_series.index, lower_series, upper_series,
                 color='k', alpha=.15)
```

```
plt.title('Forecast vs Actuals')
plt.legend(loc='upper left', fontsize=8)
plt.show()
```

SARIMAX

```
import pmdarima


# Plot
fig, axes = plt.subplots(2, 1, figsize=(10,5), dpi=100, sharex=True)

# Usual Differencing
axes[0].plot(df[:], label='Original Series')
axes[0].plot(df[:].diff(1), label='Usual Differencing')
axes[0].set_title('Usual Differencing')
axes[0].legend(loc='upper left', fontsize=10)


# Seasonal Differencing
axes[1].plot(df[:], label='Original Series')
axes[1].plot(df[:].diff(12), label='Seasonal Differencing', color='green')
axes[1].set_title('Seasonal Differencing')
plt.legend(loc='upper left', fontsize=10)
plt.show()
```



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```
smodel = pmdarima.auto_arima(df, start_p=1, start_q=1,
                             test='adf',
                             max_p=3, max_q=3, m=12,
                             start_P=0, seasonal=True,
                             d=None, D=1, trace=True,
                             error_action='ignore',
                             suppress_warnings=True,
                             stepwise=True)
```

```
                                stepwise=True)

Performing stepwise search to minimize aic
 ARIMA(1,0,1)(0,1,1)[12] intercept   : AIC=4955.399, Time=0.47 sec
 ARIMA(0,0,0)(0,1,0)[12] intercept   : AIC=5103.930, Time=0.05 sec
 ARIMA(1,0,0)(1,1,0)[12] intercept   : AIC=5000.706, Time=0.34 sec
 ARIMA(0,0,1)(0,1,1)[12] intercept   : AIC=4964.217, Time=0.40 sec
 ARIMA(0,0,0)(0,1,0)[12]             : AIC=5105.690, Time=0.04 sec
 ARIMA(1,0,1)(0,1,0)[12] intercept   : AIC=5039.448, Time=0.16 sec
 ARIMA(1,0,1)(1,1,1)[12] intercept   : AIC=4957.398, Time=0.79 sec
 ARIMA(1,0,1)(0,1,2)[12] intercept   : AIC=4956.093, Time=1.49 sec
 ARIMA(1,0,1)(1,1,0)[12] intercept   : AIC=5000.872, Time=0.52 sec
 ARIMA(1,0,1)(1,1,2)[12] intercept   : AIC=4950.742, Time=2.19 sec
 ARIMA(1,0,1)(2,1,2)[12] intercept   : AIC=4951.168, Time=3.09 sec
 ARIMA(1,0,1)(2,1,1)[12] intercept   : AIC=4949.484, Time=1.99 sec
 ARIMA(1,0,1)(2,1,0)[12] intercept   : AIC=4956.183, Time=1.74 sec
 ARIMA(0,0,1)(2,1,1)[12] intercept   : AIC=4957.431, Time=1.49 sec
 ARIMA(1,0,0)(2,1,1)[12] intercept   : AIC=4953.075, Time=1.23 sec
 ARIMA(2,0,1)(2,1,1)[12] intercept   : AIC=4944.488, Time=2.85 sec
 ARIMA(2,0,1)(1,1,1)[12] intercept   : AIC=4946.460, Time=2.92 sec
 ARIMA(2,0,1)(2,1,0)[12] intercept   : AIC=4953.757, Time=2.22 sec
 ARIMA(2,0,1)(2,1,2)[12] intercept   : AIC=4946.361, Time=3.92 sec
 ARIMA(2,0,1)(1,1,0)[12] intercept   : AIC=5000.400, Time=1.02 sec
 ARIMA(2,0,1)(1,1,2)[12] intercept   : AIC=4945.591, Time=3.36 sec
 ARIMA(2,0,0)(2,1,1)[12] intercept   : AIC=4951.691, Time=1.54 sec
 ARIMA(3,0,1)(2,1,1)[12] intercept   : AIC=4938.568, Time=3.19 sec
 ARIMA(3,0,1)(1,1,1)[12] intercept   : AIC=4947.593, Time=1.23 sec
 ARIMA(3,0,1)(2,1,0)[12] intercept   : AIC=4942.758, Time=3.57 sec
 ARIMA(3,0,1)(2,1,2)[12] intercept   : AIC=4940.291, Time=6.83 sec
 ARIMA(3,0,1)(1,1,0)[12] intercept   : AIC=4989.122, Time=1.23 sec
 ARIMA(3,0,1)(1,1,2)[12] intercept   : AIC=inf, Time=7.78 sec
 ARIMA(3,0,0)(2,1,1)[12] intercept   : AIC=4940.044, Time=2.17 sec
 ARIMA(3,0,2)(2,1,1)[12] intercept   : AIC=4935.784, Time=4.57 sec
 ARIMA(3,0,2)(1,1,1)[12] intercept   : AIC=4943.327, Time=1.62 sec
 ARIMA(3,0,2)(2,1,0)[12] intercept   : AIC=4940.303, Time=3.98 sec
 ARIMA(3,0,2)(2,1,2)[12] intercept   : AIC=4937.495, Time=6.69 sec
 ARIMA(3,0,2)(1,1,0)[12] intercept   : AIC=4989.709, Time=1.46 sec
 ARIMA(3,0,2)(1,1,2)[12] intercept   : AIC=4939.092, Time=7.66 sec
 ARIMA(2,0,2)(2,1,1)[12] intercept   : AIC=4937.045, Time=2.65 sec
                         ept         : AIC=4899.433, Time=5.88 sec
                         ept         : AIC=4911.566, Time=2.79 sec
                         ept         : AIC=4912.068, Time=5.36 sec
 ARIMA(3,0,3)(2,1,2)[12] intercept   : AIC=4901.230, Time=6.88 sec
 ARIMA(3,0,3)(1,1,0)[12] intercept   : AIC=4981.279, Time=2.87 sec
 ARIMA(3,0,3)(1,1,2)[12] intercept   : AIC=inf, Time=7.59 sec
 ARIMA(2,0,3)(2,1,1)[12] intercept   : AIC=4913.271, Time=4.61 sec
 ARIMA(3,0,3)(2,1,1)[12]             : AIC=4892.630, Time=6.54 sec
 ARIMA(3,0,3)(1,1,1)[12]             : AIC=4896.424, Time=2.92 sec
 ARIMA(3,0,3)(2,1,0)[12]             : AIC=4911.439, Time=5.20 sec
 ARIMA(3,0,3)(2,1,2)[12]             : AIC=4894.461, Time=7.36 sec
 ARIMA(3,0,3)(1,1,0)[12]             : AIC=4981.196, Time=2.68 sec
 ARIMA(3,0,3)(1,1,2)[12]             : AIC=inf, Time=6.87 sec
 ARIMA(2,0,3)(2,1,1)[12]             : AIC=4899.868, Time=4.66 sec
 ARIMA(3,0,2)(2,1,1)[12]             : AIC=4925.919, Time=5.06 sec
 ARIMA(2,0,2)(2,1,1)[12]             : AIC=4926.357, Time=3.15 sec

Best model:  ARIMA(3,0,3)(2,1,1)[12]
Total fit time: 169.008 seconds
```

Saved successfully!

```
smodel.summary()
```

SARIMAX Results

Dep. Variable:	y	**No. Observations:**	244
Model:	SARIMAX(3, 0, 3)x(2, 1, [1], 12)	**Log Likelihood**	-2436.315
Date:	Sat, 01 Oct 2022	**AIC**	4892.630
Time:	15:06:22	**BIC**	4927.097
Sample:	0	**HQIC**	4906.530
	- 244		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	-0.3970	0.081	-4.893	0.000	-0.556	-0.238
ar.L2	0.8234	0.059	13.901	0.000	0.707	0.940
ar.L3	0.4454	0.070	6.360	0.000	0.308	0.583
ma.L1	0.9430	0.071	13.234	0.000	0.803	1.083
ma.L2	-0.4967	0.084	-5.940	0.000	-0.661	-0.333
ma.L3	-0.6546	0.038	-17.222	0.000	-0.729	-0.580
ar.S.L12	-0.1938	0.077	-2.525	0.012	-0.344	-0.043
ar.S.L24	-0.2466	0.055	-4.514	0.000	-0.354	-0.140
ma.S.L12	-0.7132	0.095	-7.513	0.000	-0.899	-0.527
sigma2	8.42e+07	1.15e-09	7.32e+16	0.000	8.42e+07	8.42e+07

Ljung-Box (L1) (Q):	0.64	**Jarque-Bera (JB):**	795.82
Prob(Q):	0.43	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.02	**Skew:**	0.60
Prob(H) (two-sided):	0.00	**Kurtosis:**	11.99

```
# crating the future dates
import datetime
a = pd.to_datetime('2021-08-01')
numdays = 31
futrue_dates = []
for x in range (0, numdays):
    futrue_dates.append(a + datetime.timedelta(days = x))
```

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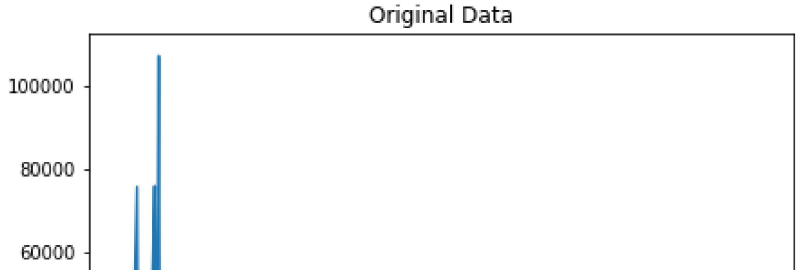
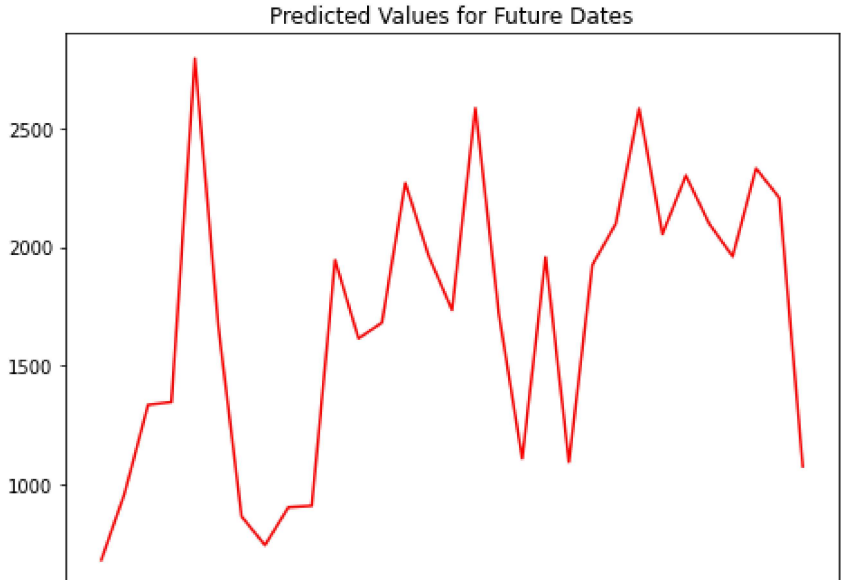
```
n_periods = 31
fitted, confint = smodel.predict(n_periods=n_periods, return_conf_int=True)
index_of_fc = futrue_dates


# make series for plotting purpose
fitted_series = pd.Series(np.array(fitted), index=index_of_fc)
lower_series = pd.Series(confint[:, 0], index=index_of_fc)
upper_series = pd.Series(confint[:, 1], index=index_of_fc)


plt.figure(figsize=(7,5));
plt.plot(df);
plt.title('Original Data')
```

```
Text(0.5, 1.0, 'Original Data')
```




```
plt.figure(figsize=(7,5));
plt.plot(fitted_series, color='r');
plt.title('Predicted Values for Future Dates')
plt.tight_layout()
```



ns approved for the august 2021 month.

Saved successfully!

```
pd.DataFrame(fitted_series,columns={'loan_approved':fitted_series})
```

	loan_approved
2021-08-01	682.896167
2021-08-02	964.540811
2021-08-03	1335.613889
2021-08-04	1347.268413
2021-08-05	2792.883365
2021-08-06	1670.804460
2021-08-07	865.974676
2021-08-08	745.125943
2021-08-09	904.714318
2021-08-10	910.945360
2021-08-11	1944.513106
2021-08-12	1614.946354
2021-08-13	1681.324953
2021-08-14	2269.176571
2021-08-15	1961.908130
2021-08-16	1734.630207
2021-08-17	2583.799618
2021-08-18	1720.273641
2021-08-19	1110.189557

```
pd.DataFrame(columns = {''})
```

Saved successfully!

2021-08-23	2097.284166
2021-08-24	2582.397327
2021-08-25	2054.568286
2021-08-26	2300.120101
2021-08-27	2097.732802
2021-08-28	1960.218260
2021-08-29	2330.514127
2021-08-30	2206.090930
2021-08-31	1076.577831

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