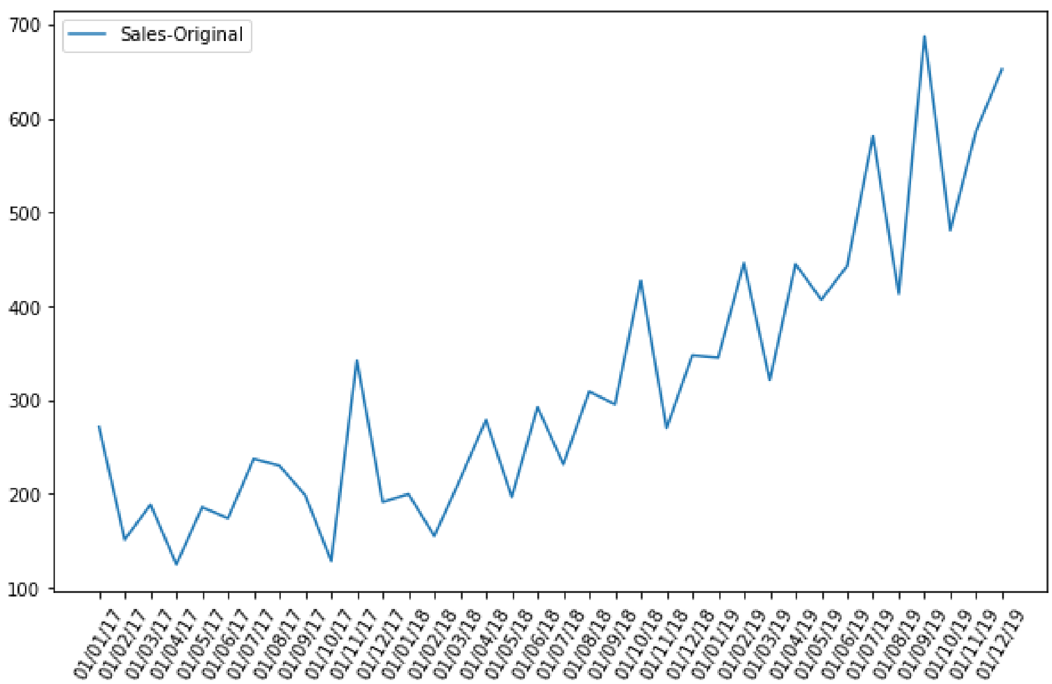
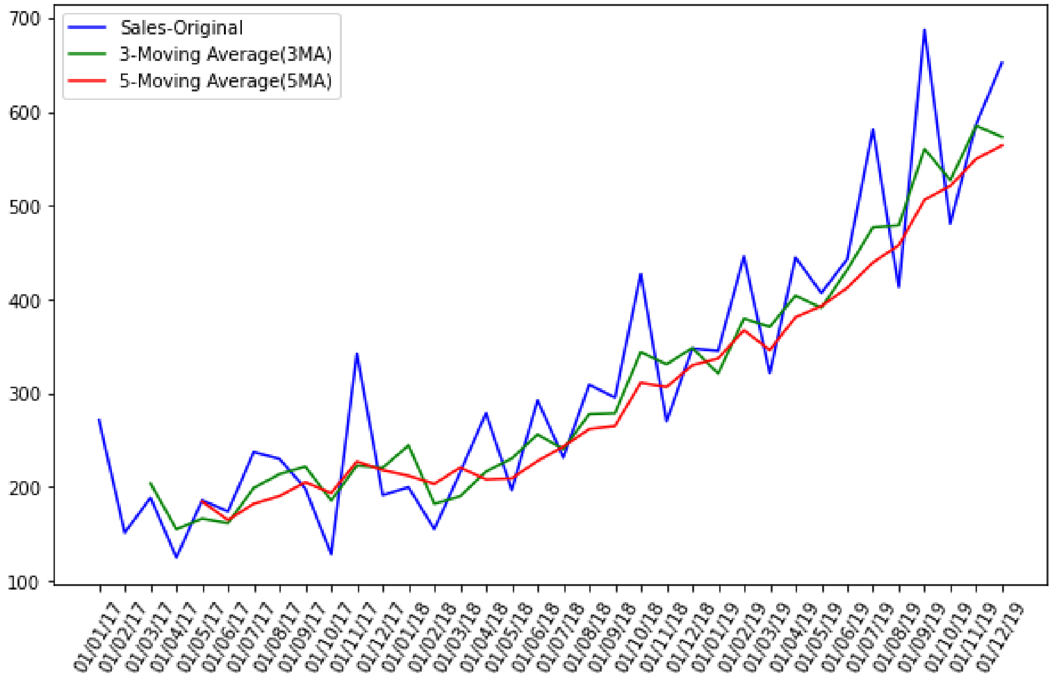
Moving averages

```
# import needful libraries
import pandas as pd
import statsmodels.api as sm
import matplotlib.pyplot as plt

# Read dataset
sales_data = pd.read_csv('sales.csv')

# Setting figure size
plt.figure(figsize=(10,6))
# Plot original sales data
plt.plot(sales_data['Time'], sales_data['Sales'], label="Sales-Original")
# Rotate xlabels
plt.xticks(rotation=60)
# Add legends
plt.legend()
#display the plot
plt.show()
```




```
# Moving average with window 3
sales_data['3MA']=sales_data['Sales'].rolling(window=3).mean()
# Moving average with window 5
sales_data['5MA']=sales_data['Sales'].rolling(window=5).mean()
# Setting figure size
plt.figure(figsize=(10,6))
# Plot original sales data
plt.plot(sales_data['Time'], sales_data['Sales'], label="Sales-Original", color="blue")
# Plot 3-Moving Average of sales data
plt.plot(sales_data['Time'], sales_data['3MA'], label="3-Moving Average(3MA)", color="green")
# Plot 5-Moving Average of sales data
plt.plot(sales_data['Time'], sales_data['5MA'], label="5-Moving Average(5MA)", color="red")
# Rotate xlabels
plt.xticks(rotation=60)
# Add legends
plt.legend()
```

```
#display the plot
plt.show()
```



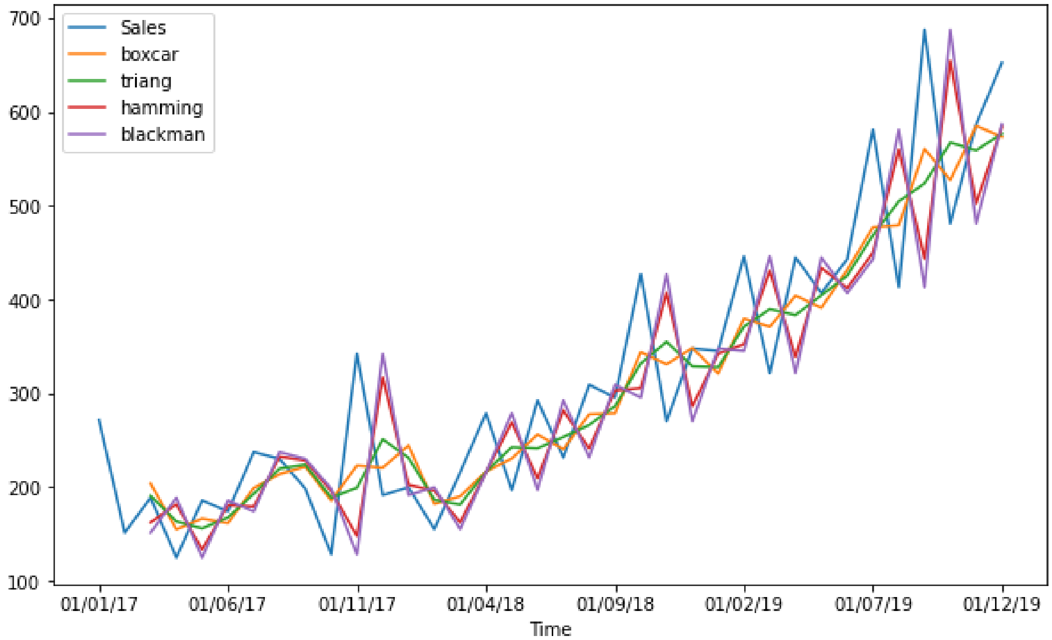
Window Function

```
# import needful libraries
import pandas as pd
import statsmodels.api as sm
import matplotlib.pyplot as plt

# Read dataset
sales_data = pd.read_csv('sales.csv', index_col ="Time")

# Show initial 5 records
sales_data.head()
```

	Sales
Time	
01/01/17	271.5
01/02/17	151.4
01/03/17	188.6
01/04/17	124.8
01/05/17	185.8

```
# Apply all the windows on given DataFrame
sales_data['boxcar']=sales_data.Sales.rolling(3, win_type ='boxcar').mean()
sales_data['triang']=sales_data.Sales.rolling(3, win_type ='triang').mean()
sales_data['hamming']=sales_data.Sales.rolling(3, win_type ='hamming').mean()
sales_data['blackman']=sales_data.Sales.rolling(3, win_type ='blackman').mean()
#Plot the rolling mean of all the windows
sales_data.plot(kind='line',figsize=(10,6))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f7f69669610>
```



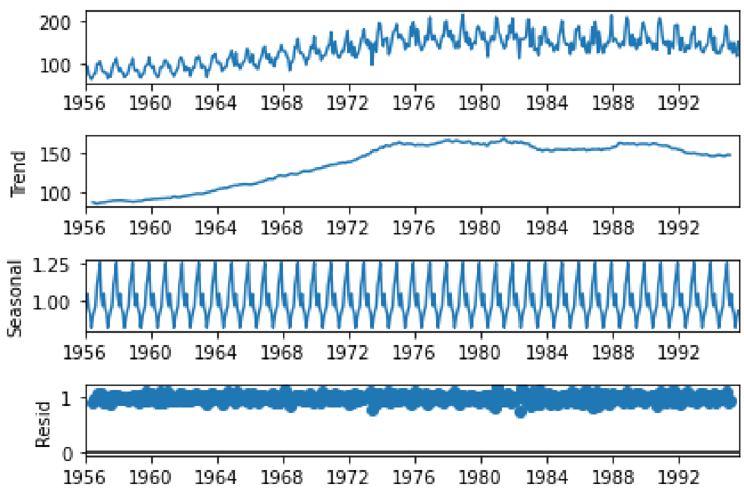
Defining cointegration

```python
# Import required library
import statsmodels.api as sm
import pandas as pd
import statsmodels.tsa.stattools as ts
import numpy as np

# Calculate ADF function
def calc_adf(x, y):
    result = sm.OLS(x, y).fit()
    return ts.adfuller(result.resid)

# Read the Dataset
data = sm.datasets.sunspots.load_pandas().data.values
N = len(data)

# Create Sine wave and apply ADF test
t = np.linspace(-2 * np.pi, 2 * np.pi, N)
sine = np.sin(np.sin(t))
print("Self ADF", calc_adf(sine, sine))

# Apply ADF test on Sine and Sine with noise
noise = np.random.normal(0, .01, N)
print("ADF sine with noise", calc_adf(sine, sine + noise))

# Apply ADF test on Sine and Cosine with noise
cosine = 100 * np.cos(t) + 10
print("ADF sine vs cosine with noise", calc_adf(sine, cosine + noise))

# Apply ADF test on Sine and sunspots dataset
print("Sine vs sunspots", calc_adf(sine, data))
```

```
Self ADF (-6.896689349349742e-16, 0.9585320860600559, 0, 308, {'1%': -3.45176116018037, '5%': -2.870970093607691, '10%': -2.57
ADF sine with noise (-4.091294292410859, 0.0010011179783234881, 12, 296, {'1%': -3.452636878592149, '5%': -2.871354395433143
ADF sine vs cosine with noise (-19.959621318125926, 0.0, 16, 292, {'1%': -3.4529449243622383, '5%': -2.871489553425686, '10%': -2.
Sine vs sunspots (-6.724269181070102, 3.4210811915549028e-09, 16, 292, {'1%': -3.4529449243622383, '5%': -2.871489553425686, '
```

Decomposing time series

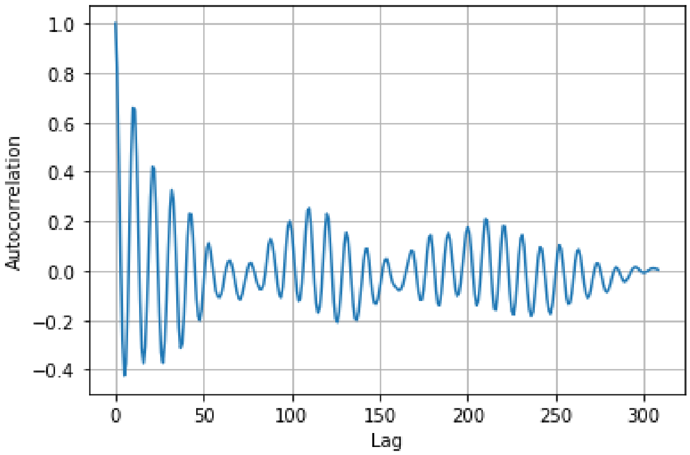
```
# import needful libraries
import pandas as pd
import matplotlib.pyplot as plt
from statsmodels.tsa.seasonal import seasonal_decompose

# Read the dataset
data = pd.read_csv('beer_production.csv')
data.columns= ['date','data']
# Change datatype to pandas datetime
data['date'] = pd.to_datetime(data['date'])
data=data.set_index('date')

# Decompose the data
decomposed_data = seasonal_decompose(data, model='multiplicative')
# Plot decomposed data
decomposed_data.plot()
# Display the plot
plt.show()
```



Autocorrelation

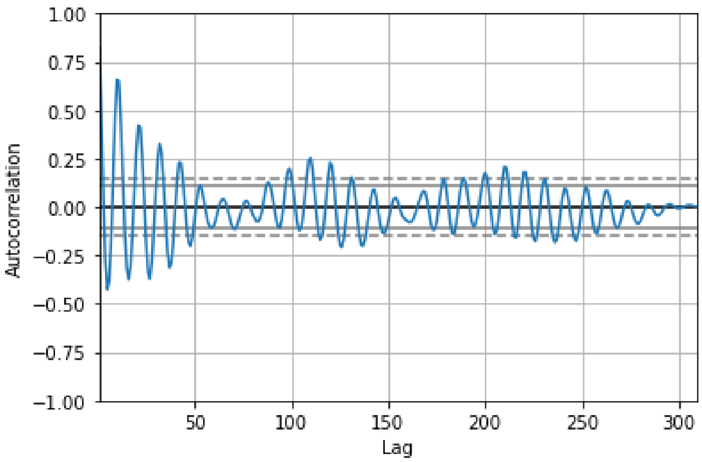
```
# import needful libraries
import pandas as pd
import numpy as np
import statsmodels.api as sm
import matplotlib.pyplot as plt

# Read the dataset
data = sm.datasets.sunspots.load_pandas().data

# Calculate autocorrelation using numpy
dy = data.SUNACTIVITY - np.mean(data.SUNACTIVITY)
dy_square = np.sum(dy ** 2)

# Cross-correlation
sun_correlated = np.correlate(dy, dy, mode='full')/dy_square
result = sun_correlated[int(len(sun_correlated)/2):]

# Diplay the Chart
```

```
plt.plot(result)
# Display grid
plt.grid(True)
# Add labels
plt.xlabel("Lag")
plt.ylabel("Autocorrelation")
# Display the chart
plt.show()
```




```
from pandas.plotting import autocorrelation_plot
# Plot using pandas function
autocorrelation_plot(data.SUNACTIVITY)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f7f621ec910>
```



Auto Regression

```
# import needful libraries
from statsmodels.tsa.ar_model import AR
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import mean_squared_error
import matplotlib.pyplot as plt
import statsmodels.api as sm
from math import sqrt

# Read the dataset
data = sm.datasets.sunspots.load_pandas().data

# Split data into train and test set
train_ratio=0.8
train=data[:int(train_ratio*len(data))]
```

```
test=data[int(train_ratio*len(data)):]


# AutoRegression Model training
ar_model = AR(train.SUNACTIVITY)
ar_model = ar_model.fit()

# print lags and
print("Number of Lags:", ar_model.k_ar)
print("Model Coefficients:\n", ar_model.params)
```

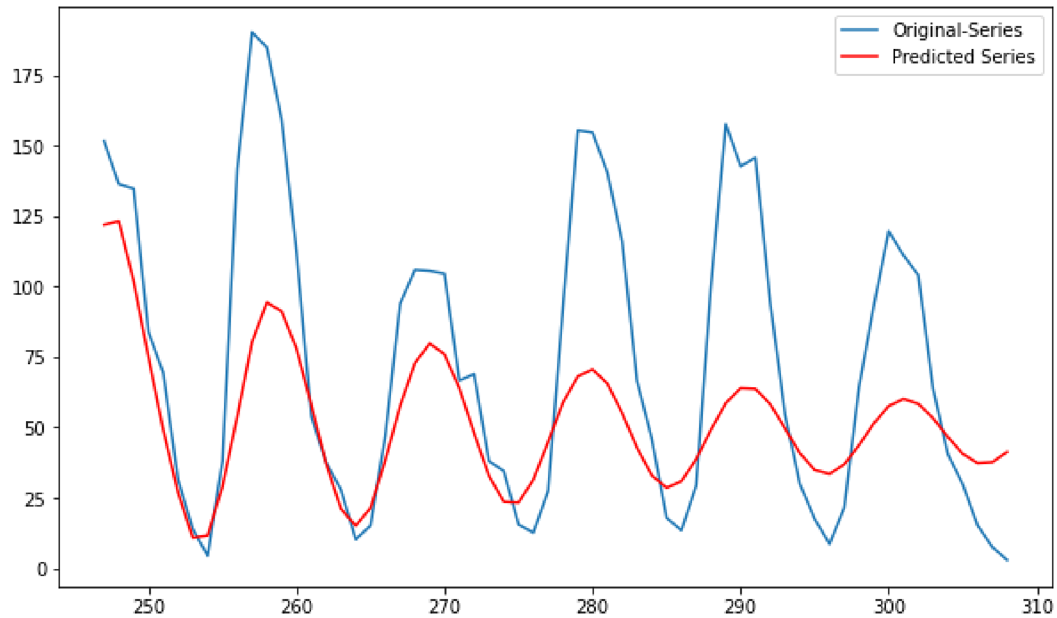
```
Number of Lags: 15
Model Coefficients:
 const              9.382322
L1.SUNACTIVITY     1.225684
L2.SUNACTIVITY    -0.512193
L3.SUNACTIVITY    -0.130695
L4.SUNACTIVITY     0.193492
L5.SUNACTIVITY    -0.168907
L6.SUNACTIVITY     0.054594
L7.SUNACTIVITY    -0.056725
L8.SUNACTIVITY     0.109404
L9.SUNACTIVITY     0.108993
L10.SUNACTIVITY   -0.117063
L11.SUNACTIVITY    0.200454
L12.SUNACTIVITY   -0.075111
L13.SUNACTIVITY   -0.114437
L14.SUNACTIVITY    0.177516
L15.SUNACTIVITY   -0.091978
dtype: float64
/home/avinash/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/ar_model.py:691: FutureWarning:
statsmodels.tsa.AR has been deprecated in favor of statsmodels.tsa.AutoReg and
statsmodels.tsa.SARIMAX.

AutoReg adds the ability to specify exogenous variables, include time trends,
and add seasonal dummies. The AutoReg API differs from AR since the model is
treated as immutable, and so the entire specification including the lag
length must be specified when creating the model. This change is too
substantial to incorporate into the existing AR api. The function
ar_select_order performs lag length selection for AutoReg models.

AutoReg only estimates parameters using conditional MLE (OLS). Use SARIMAX to
estimate ARX and related models using full MLE via the Kalman Filter.

To silence this warning and continue using AR until it is removed, use:

import warnings
warnings.filterwarnings('ignore', 'statsmodels.tsa.ar_model.AR', FutureWarning)

  warnings.warn(AR_DEPRECATION_WARN, FutureWarning)
```

```
# make predictions
start_point = len(train)
end_point = start_point + len(test)-1
pred = ar_model.predict(start=start_point, end=end_point, dynamic=False)

# Calculate erros
mae = mean_absolute_error(test.SUNACTIVITY, pred)
mse = mean_squared_error(test.SUNACTIVITY, pred)
rmse = sqrt(mse)
print("MAE:",mae)
print("MSE:",mse)
print("EMSE:",rmse)
```

```
MAE: 31.178460983500255
```

```
MSE: 1776.9463826165686
EMSE: 42.15384184883471
```

```python
# Setting figure size
plt.figure(figsize=(10,6))
# Plot test data
plt.plot(test.SUNACTIVITY, label='Original-Series')
# Plot predictions
plt.plot(pred, color='red', label='Predicted Series')
# Add legends
plt.legend()
# Display the plot
plt.show()
```

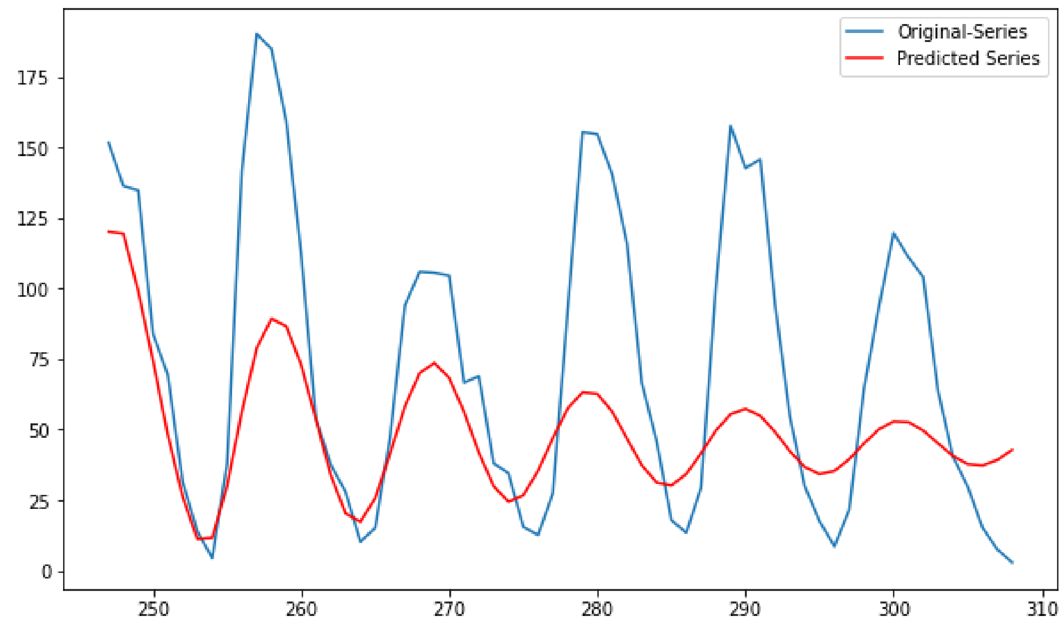


ARMA

```python
# import needful libraries
import statsmodels.api as sm
from statsmodels.tsa.arima_model import ARMA
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import mean_squared_error
import matplotlib.pyplot as plt
from math import sqrt

# Read the dataset
data = sm.datasets.sunspots.load_pandas().data
data.drop('YEAR',axis=1,inplace=True)

# Split data into train and test set
train_ratio=0.8
train=data[:int(train_ratio*len(data))]
test=data[int(train_ratio*len(data)):]

# AutoRegression Model training
arma_model = ARMA(train, order=(10,1))
arma_model = arma_model.fit()

# make predictions
start_point = len(train)
end_point = start_point + len(test)-1
```

```
end_point = start_point + len(test)-1
pred = arma_model.predict(start_point,end_point)

# Calculate erros
mae = mean_absolute_error(test.SUNACTIVITY, pred)
mse = mean_squared_error(test.SUNACTIVITY, pred)
rmse = sqrt(mse)
print("MAE:",mae)
print("MSE:",mse)
print("EMSE:",rmse)

# Setting figure size
plt.figure(figsize=(10,6))
# Plot test data
plt.plot(test, label='Original-Series')
# Plot predictions
plt.plot(pred, color='red', label='Predicted Series')
# Add legends
plt.legend()
# Display the plot
plt.show()
```

```
MAE: 33.95456896482045
MSE: 2041.3852298217791
EMSE: 45.18169131209874
```

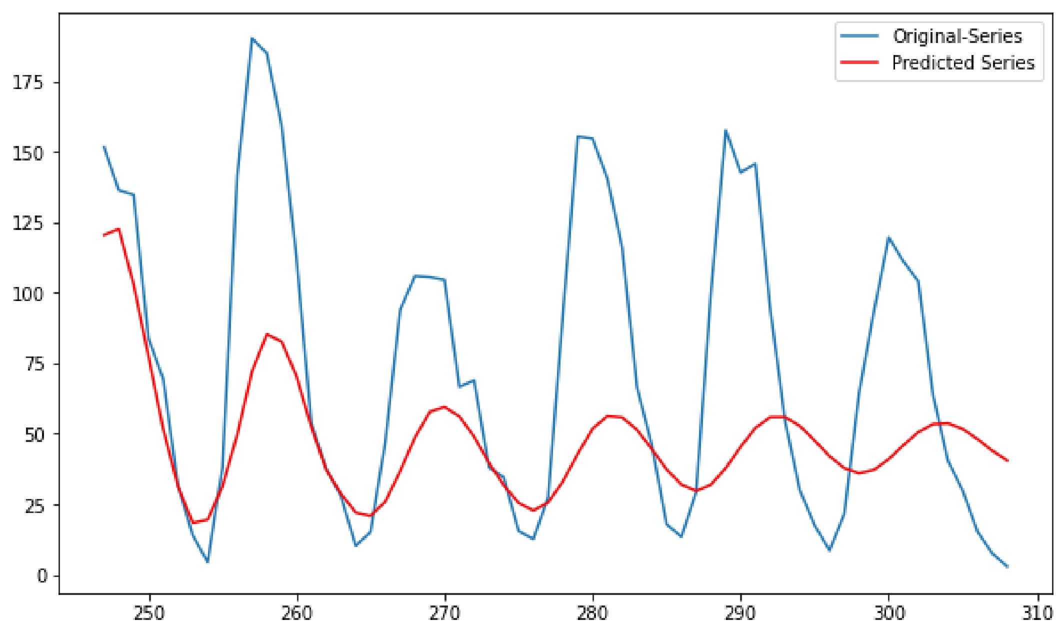


ARIMA

```
# import needful libraries
import statsmodels.api as sm
from statsmodels.tsa.arima_model import ARIMA
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import mean_squared_error
import matplotlib.pyplot as plt
from math import sqrt

# Read the dataset
data = sm.datasets.sunspots.load_pandas().data
data.drop('YEAR',axis=1,inplace=True)

# Split data into train and test set
train_ratio=0.8
```

```
train=data[:int(train_ratio*len(data))]
test=data[int(train_ratio*len(data)):]

# AutoRegression Model training
arima_model = ARIMA(train, order=(20,0,1))
arima_model = arima_model.fit()

# make predictions
start_point = len(train)
end_point = start_point + len(test)-1
pred = arima_model.predict(start_point,end_point)

# Calculate erros
mae = mean_absolute_error(test.SUNACTIVITY, pred)
mse = mean_squared_error(test.SUNACTIVITY, pred)
rmse = sqrt(mse)
print("MAE:",mae)
print("MSE:",mse)
print("EMSE:",rmse)

# Setting figure size
plt.figure(figsize=(10,6))
# Plot test data
plt.plot(test, label='Original-Series')
# Plot predictions
plt.plot(pred, color='red', label='Predicted Series')
# Add legends
plt.legend()
# Display the plot
plt.show()
```

```
MAE: 36.934332860115326
MSE: 2527.6415003516413
EMSE: 50.27565514592168
```

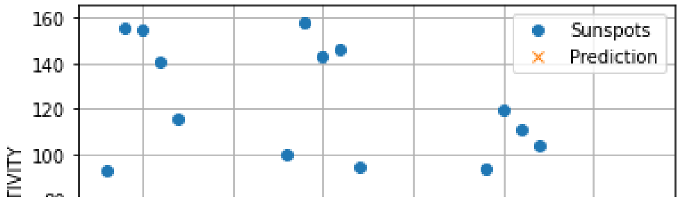


Generating Periodic Signals

```
# Import required libraries
import numpy as np
import statsmodels.api as sm
from scipy.optimize import leastsq
```

```
import matplotlib.pyplot as plt


# Create model function
def model(p, t):
    C, p1, f1, phi1 , p2, f2, phi2, p3, f3, phi3 = p
    return C + p1 * np.sin(f1 * t + phi1) + p2 * np.sin(f2 * t + phi2) +p3 * np.sin(f3 * t + phi3)

# Create error function
def error(p, y, t):
    return y - model(p, t)

# Create fit function
def fit(y, t):
    p0 = [y.mean(), 0, 2 * np.pi/11, 0, 0, 2 * np.pi/22, 0, 0, 2 * np.pi/100, 0]
    params = leastsq(error, p0, args=(y, t))[0]
    return params

# Load the dataset
data_loader = sm.datasets.sunspots.load_pandas()
sunspots = data_loader.data["SUNACTIVITY"].values
years = data_loader.data["YEAR"].values

# Apply and fit the model
cutoff = int(.9 * len(sunspots))
params = fit(sunspots[:cutoff], years[:cutoff])
print("Params", params)

pred = model(params, years[cutoff:])
actual = sunspots[cutoff:]
print("Root mean square error", np.sqrt(np.mean((actual - pred) **
2)))
print("Mean absolute error", np.mean(np.abs(actual - pred)))
print("Mean absolute percentage error", 100 *
np.mean(np.abs(actual - pred)/actual))
mid = (actual + pred)/2
print("Symmetric Mean absolute percentage error", 100 *
np.mean(np.abs(actual - pred)/mid))
print("Coefficient of determination", 1 - ((actual - pred) **
2).sum()/ ((actual - actual.mean()) ** 2).sum())
year_range = data_loader.data["YEAR"].values[cutoff:]

# Plot the actual and predicted data points
plt.plot(year_range, actual, 'o', label="Sunspots")
plt.plot(year_range, pred, 'x', label="Prediction")
plt.grid(True)
# Add labels
plt.xlabel("YEAR")
plt.ylabel("SUNACTIVITY")
# Add legend
plt.legend()
# Display the chart
plt.show()
```

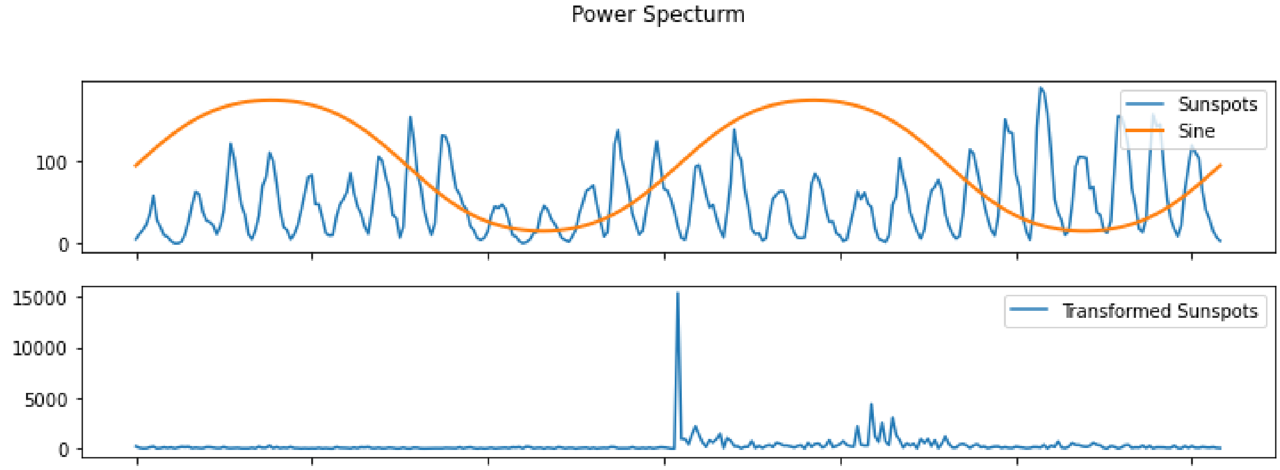
```
Params [ 47.1880006   28.89947462   0.56827279   6.51178464   4.55214564
  0.29372076 -14.30924768 -18.16524123   0.06574835  -4.37789476]
Root mean square error 59.56205597915569
Mean absolute error 44.58158470150657
Mean absolute percentage error 65.16458348768887
Symmetric Mean absolute percentage error 78.4480696873044
Coefficient of determination -0.3635315489903188
```



Fourier Analysis

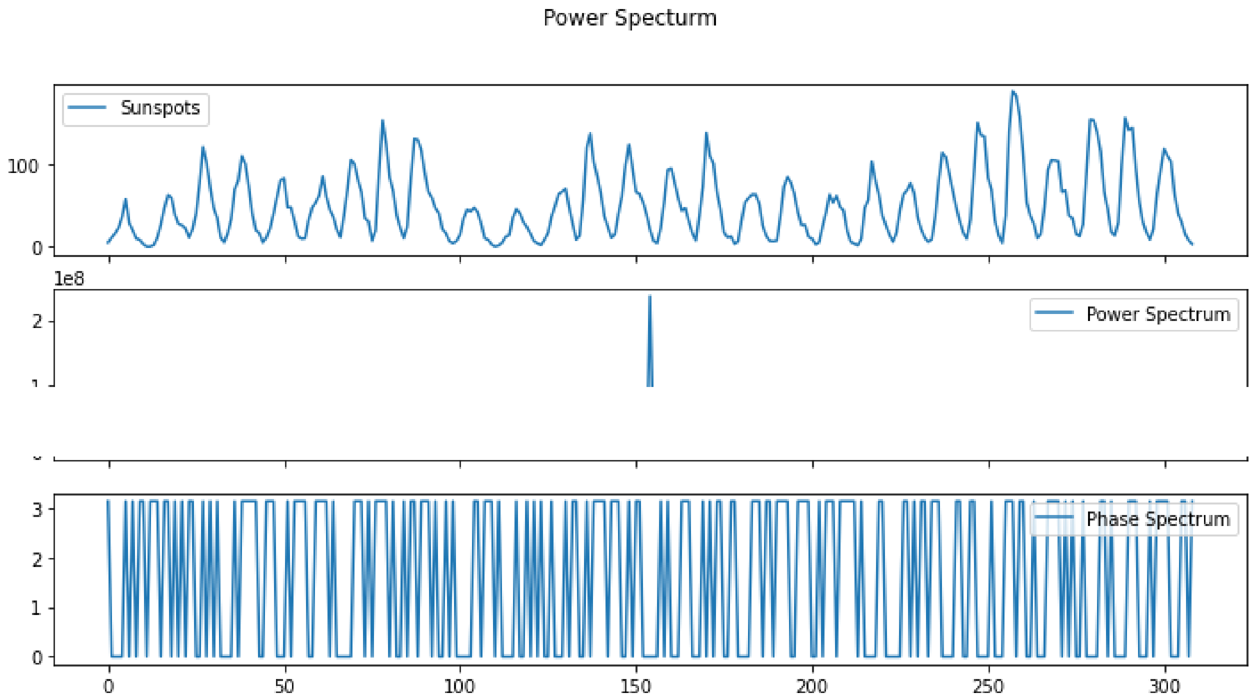
```python
# Import required library
import numpy as np
import statsmodels.api as sm
import matplotlib.pyplot as plt
from scipy.fftpack import rfft
from scipy.fftpack import fftshift


# Read the dataset
data = sm.datasets.sunspots.load_pandas().data

# Create Sine wave
t = np.linspace(-2 * np.pi, 2 * np.pi, len(data.SUNACTIVITY.values))
mid = np.ptp(data.SUNACTIVITY.values)/2
sine = mid + mid * np.sin(np.sin(t))

# Compute FFT for Sine wave
sine_fft = np.abs(fftshift(rfft(sine)))
print("Index of max sine FFT", np.argsort(sine_fft)[-5:])

# Compute FFT for sunspots dataset
transformed = np.abs(fftshift(rfft(data.SUNACTIVITY.values)))
print("Indices of max sunspots FFT", np.argsort(transformed)[-5:])

# Create subplots
fig, axs = plt.subplots(3,figsize=(12,6),sharex=True)
fig.suptitle('Power Specturm')
axs[0].plot(data.SUNACTIVITY.values, label="Sunspots")
axs[0].plot(sine, lw=2, label="Sine")
axs[0].legend() # Set legends
axs[1].plot(transformed, label="Transformed Sunspots")
axs[1].legend() # Set legends
axs[2].plot(sine_fft, lw=2, label="Transformed Sine")
axs[2].legend() # Set legends

# Display the chart
plt.show()
```

Index of max sine FFT [160 157 166 158 154]
Indices of max sunspots FFT [205 212 215 209 154]



Spectral Analysis Filtering


```
# Import required library
import numpy as np
import statsmodels.api as sm
from scipy.fftpack import rfft
from scipy.fftpack import fftshift
import matplotlib.pyplot as plt

# Read the dataset
data = sm.datasets.sunspots.load_pandas().data

# Compute FFT
transformed = fftshift(rfft(data.SUNACTIVITY.values))
# Compute Power Spectrum
power=transformed ** 2
# Compute Phase
phase=np.angle(transformed)

# Create subplots
fig, axs = plt.subplots(3,figsize=(12,6),sharex=True)
fig.suptitle('Power Specturm')
axs[0].plot(data.SUNACTIVITY.values, label="Sunspots")
axs[0].legend() # Set legends
axs[1].plot(power, label="Power Spectrum")
axs[1].legend() # Set legends
axs[2].plot(phase, label="Phase Spectrum")
axs[2].legend() # Set legends

# Display the chart
plt.show()
```


Power Specturm
Sunspots
100
0
1e8
2
Power Spectrum
Phase Spectrum
3
2
1
0
0
50
100
150
200
250
300

1