]:	<pre>from io import StringIO import requests import matplotlib.pyplot as plt %matplotlib inline plt.style.use('bmh') Analysis of Rural & Urban wages wages = pd.read_excel("C:\\Users\\bahirwal\\Desktop\\Balaji\\Advanced ECotrix\\Task-3\\Wages_rural & urba wages.head()</pre>
]: [Date Rural Urban 0 2013-01-01 105.1 104.0 1 2013-02-01 105.8 104.7 2 2013-03-01 106.0 105.0 3 2013-04-01 106.4 105.7 4 2013-05-01 107.2 106.6 wages['Date'] = pd.to_datetime(wages['Date'])
	<pre>wages.set_index('Date', inplace=True) wages.head() Rural Urban Date 2013-01-01 105.1 104.0 2013-02-01 105.8 104.7</pre>
]:	2013-04-01 106.0 105.0 2013-04-01 106.4 105.7 2013-05-01 107.2 106.6 For Rural # extract out the time-series wages_ts = wages['Rural']
	<pre># Plot the time series plt.figure(figsize=(10,5)) plt.plot(wages_ts) plt.xlabel('Date') plt.ylabel('Rural wages');</pre>
	120 120 110 2013 2014 2015 2016 2017 2018 2019 2020 2021 2022 Date
]:	<pre>random_df = wages fig, axes = plt.subplots(1, 2, sharey=False, sharex=False) 10 0.8 0.6 0.6</pre>
]:	0.4 0.2 0.0 0.2 0.4 0.0 0.2 0.4 0.0 0.2 0.4 0.6 0.8 10 fig, axes = plt.subplots(1, 2, sharey=False, sharex=False) fig.set_figwidth(12) fig.set_figheight(4)
	<pre>axes[0].plot(random_df.index, random_df['Rural']) axes[0].set_xlabel('Date') axes[0].set_ylabel('Rural') axes[0].set_title('wages in Rural') axes[1].plot(random_df.index, random_df['Rural'].diff(periods=1)) axes[1].set_xlabel('Date') axes[1].set_ylabel('Differenced') axes[1].set_title('1\$^(st)\$ order Differenced Data') plt.tight_layout() plt.show()</pre> <pre> wages in Rural</pre> <pre> 1(st) order Differenced Data</pre>
	160 - 150 - 140 - 150 -
]:	# Generate white noise np.random.seed(1) # Plot of discrete white noise plt.figure(figsize=(10, 5)) white_noise = np.random.normal(size = 1000) plt.plot(white_noise) plt.xlabel('Data') plt.ylabel('Time_index')
	plt.show()
]:	# there is no autocorrelation as it is a noise a no pattern can be drawn plt.figure() smt.graphics.plot_acf(white_noise, alpha=0.5)
	<pre>plt.show() <</pre>
]:	# plot autocorrelation for rural wages data plt.figure() smt.graphics.plot_acf(wages_ts, alpha=0.5) plt.show()
	Autocorrelation 10 0.8 0.6 0.4 0.2 0.0
]:	# when variance is not stationary we took log transformation to find differentiation # Now time series become stationary by making mean and variance constant plt.figure(figsize=(10, 5)) plt.plot(np.log10(wages_ts).diff(periods=1)) plt.xlabel('Date') plt.ylabel('Differenced log (Rural)');
	0.0100 - 0.0075 - 0.0050 - 0.0005 - 0.0000 - 0.0000 - 0.0005 - 0.0
]:	-0.0050 -0.0075 2013 2014 2015 2016 2017 2018 2019 2020 2021 2022 wages_ts_log = np.log10 (wages_ts) wages_ts_log.dropna(inplace=True) wages_ts_log_diff = wages_ts_log.diff(periods=1) wages_ts_log_diff.dropna(inplace=True)
]:	<pre># ACF plot fig, axes = plt.subplots(1, 2, sharey=False, sharex=False) fig.set_figwidth(12) fig.set_figheight(4) smt.graphics.plot_acf(wages_ts_log_diff, lags=30, ax=axes[0], alpha=0.5) smt.graphics.plot_acf(wages_ts_log_diff, lags=30, ax=axes[1], alpha=0.5) plt.tight_layout()</pre> Autocorrelation Autocorrelation
	0.8 0.6 0.4 0.2 0.0 -0.2 -0.4
]:	-0.4 0 5 10 15 20 25 30 0 5 10 15 20 25 3 # Determing rolling statistics rolmean = wages_ts.rolling(window=6).mean() rolstd = wages_ts.rolling(window=6).std() # plot rolling statistics orig = plt.plot(wages_ts, label='Original') mean = plt.plot(rolmean, label='Rollong mean') std = plt.plot(rolstd, label='Rollong std') plt.legend(loc='best') plt.title('Rolling Mean & Standard deviation') plt.show(block=False)
]: [decomposition = sm.tsa.seasonal_decompose(wages_ts, model = 'multiplicative') fig = decomposition.plot() fig.set_figwidth(12) fig.set_figheight(8)
	fig.set_figheight(8) fig.suptitle('Decomposition of multiplicative time series') plt.show() Decomposition of multiplicative time series Rural 150 125 2013 2014 2015 2016 2017 2018 2019 2020 2021
	160 140 120 2013 2014 2015 2016 2017 2018 2019 2020 2021
	2013 2014 2015 2016 2017 2018 2019 2020 2021
9	<pre># extract out the time-series wages_ts_ur = wages['Urban'] # Plot the time series plt.figure(figsize=(10,5)) plt.plot(wages_ts_ur) plt.xlabel('Date') plt.ylabel('Urban wages');</pre>
	160 - 150 - 140 - 130 - 120 -
]:	# First order differenced data to make mean and variance constant and converting time series into station
	<pre># First order differenced data to make mean and variance constant and converting time series into station fig, axes = plt.subplots(1, 2, sharey=False, sharex=False) fig.set_figwidth(12) fig.set_figheight(4) axes[0].plot(random_df.index, random_df['Urban']) axes[0].set_xlabel('Date') axes[0].set_ylabel('Urban') axes[0].set_title('wages in Urban') axes[1].plot(random_df.index, random_df['Urban'].diff(periods=1)) axes[1].set_xlabel('Date') axes[1].set_ylabel('Differenced') axes[1].set_title('1\$^(st)\$ order Differenced Data') plt.tight_layout() plt.show()</pre>
	wages in Urban $1^{(st)}$ order Differenced Data $\frac{1}{150}$ $\frac{1}{120}$ 1
]:	# plot autocorrelation for uban wages data plt.figure() smt.graphics.plot_acf(wages_ts_ur, alpha=0.5) plt.show() <figure 0="" 432x288="" axes="" size="" with=""></figure>
	Autocorrelation 1.0 0.8 0.6 0.4 0.2 0.0
]:	# we will also try making time series stationary by taking its log transformation plt.figure(figsize=(10, 5)) plt.plot(np.log10(wages_ts_ur).diff(periods=1)) plt.xlabel('Date') plt.ylabel('Differenced log (Urban)');
	0.0100 (up 0.0075 0.0050 0.0025 -0.0025 -0.0050
]: [<pre>wages_ts_log_ur = np.log10(wages_ts_ur) wages_ts_log_ur.dropna(inplace=True) wages_ts_log_diff_ur = wages_ts_log_ur.diff(periods=1) wages_ts_log_diff_ur.dropna(inplace=True) # ACF plot</pre>
	# ACF plot fig, axes = plt.subplots(1, 2, sharey=False, sharex=False) fig.set_figwidth(12) fig.set_figheight(4) smt.graphics.plot_acf(wages_ts_log_diff_ur, lags=30, ax=axes[0], alpha=0.5) smt.graphics.plot_acf(wages_ts_log_diff_ur, lags=30, ax=axes[1], alpha=0.5) plt.tight_layout() Autocorrelation Autocorrelation Autocorrelation Autocorrelation 0.8 0.6
]:	0.4 0.2 0.0 -0.2 0 5 10 15 20 25 30 0 5 10 15 20 25 3
	<pre># Determing rolling statistics rolmean_ur = wages_ts_ur.rolling(window=6).mean() rolstd_ur = wages_ts_ur.rolling(window=6).std() # plot rolling statistics orig = plt.plot(wages_ts_ur, label='Original') mean = plt.plot(rolmean_ur, label='Rollong mean') std = plt.plot(rolstd_ur, label='Rollong std') plt.legend(loc='best') plt.title('Rolling Mean & Standard deviation') plt.show(block=False)</pre> Rolling Mean & Standard deviation
	160 Original Rollong mean Rollong std 120 - Rollong std 100 - Rollong std 20 - Rollong std 20 - Rollong std 20 - Rollong std
]:	decomposition_ur = sm.tsa.seasonal_decompose(wages_ts_ur, model = 'multiplicative') fig = decomposition_ur.plot() fig.set_figwidth(12) fig.set_figheight(8) fig.suptitle('Decomposition of multiplicative time series') plt.show()
	Decomposition of multiplicative time series Urban 150 125 2013 2014 2015 2016 2017 2018 2019 2020 2021
	Temporary 100 2013 2014 2015 2016 2017 2018 2019 2020 2021 2021 2013 2014 2015 2016 2017 2018 2019 2020 2021
	0.99 2013 2014 2015 2016 2017 2018 2019 2020 2021 10 0.59 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5
	<pre>cell continue of starting of year.</pre> <pre>CPI & WPI</pre> <pre>pd.read_excel("C:\\Users\\bahirwal\\Desktop\\Balaji\\Advanced ECotrix\\Task-3\\WPI annually.xlsx")</pre>
	<pre>WPI.head() Year wpi 0 1960 3.068381 1 1961 3.141976 2 1962 3.255201</pre>
]:	3 1963 3.374086 4 1964 3.725082 WPI.tail() Year wpi 56 2016 122.940363 57 2017 127.167193
]:	58 2018 132.592399 59 2019 135.091338 60 2020 146.345357 WPI.set_index('Year', inplace=True) WPI.head() wpi
	Year 1960 3.068381 1961 3.141976 1962 3.255201 1963 3.374086 1964 3.725082
]: [<pre>plt.figure(figsize=(10,5)) plt.plot(WPI) [<matplotlib.lines.line2d 0x1e3f41e96d0="" at="">] 140 120 100</matplotlib.lines.line2d></pre>
1	80 60 40 20 1960 1970 1980 1990 2000 2010 2020
]:	<pre>random_df = WPI fig, axes = plt.subplots(1, 2, sharey=False, sharex=False) fig.set_figwidth(12) fig.set_figheight(4) axes[0].plot(random_df.index, random_df['wpi']) axes[0].set_xlabel('Year') axes[0].set_ylabel('wpi') axes[0].set_title('Origin data') axes[1].plot(random_df.index, random_df['wpi'].diff(periods=1)) axes[1].set_xlabel('Year') axes[1].set_ylabel('Differenced cpi') axes[1].set_title('1\$^(st)\$ order Differenced Data') plt.tight_layout()</pre>
	Origin data Origin data Origin data 1(st) order Differenced Data
;	wholesale price index shows a continuous increase from 1960 till 2020. the time series is no stationary and trend is clearly visible. 1st order differenced data is also not stationary and we have to go for log transformation to make time series stationary.
]: [<pre># plot autocorrelation for cpi data plt.figure() smt.graphics.plot_acf(random_df, alpha=0.5) plt.show() <figure 0="" 432x288="" axes="" size="" with=""></figure></pre>
]:	0.4 0.2 0.0 -0.2 0.0 2.5 5.0 7.5 10.0 12.5 15.0 17.5 # extract out the time-series
]:	<pre># extract out the time-series WPI_ts = WPI['wpi'] # when variance is not stationary we took log transformation to find differentiation # Now time series become stationary by making mean and variance constant plt.figure(figsize=(10, 5)) plt.plot(np.log10(WPI_ts).diff(periods=1)) plt.xlabel('Years') plt.ylabel('Differenced log (wpi)');</pre>
	0.10 -
]:	# Determing rolling statistics for both cpi and wpi rolmean = random_df.rolling(window=6).mean() rolstd = random_df.rolling(window=6).std() # plot rolling statistics orig = plt.plot(random_df, label='Original') mean = plt.plot(rolmean, label='Rollong mean')
3	
3	<pre>ValueError</pre>
	<pre>ValueError</pre>

