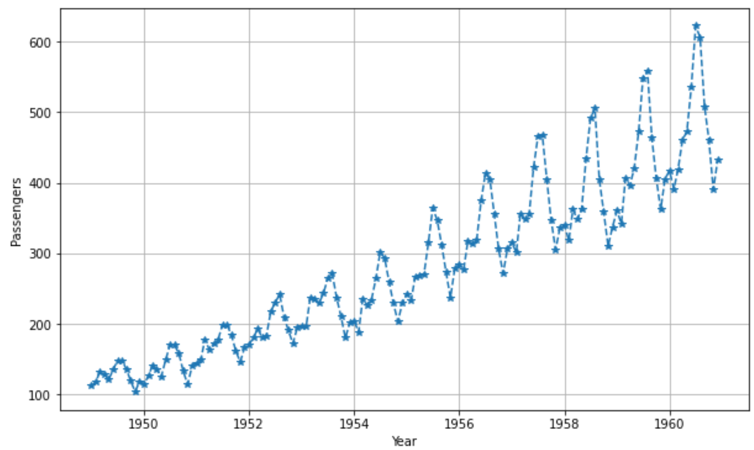
Lesson 2: Wrangling Time Series Data

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
df=pd.read_csv("https://raw.githubusercontent.com/jbrownlee/Datasets/master/airline-passenge
rs.csv")
df["Month"] = pd.to_datetime(df["Month"]) #convert column to datetime
df.set_index("Month", inplace=True)
plt.figure(figsize=(10,6))
plt.plot(df.index, df.Passengers, '--', marker='*', )
plt.grid()
plt.xlabel('Year')
plt.ylabel('Passengers')
```

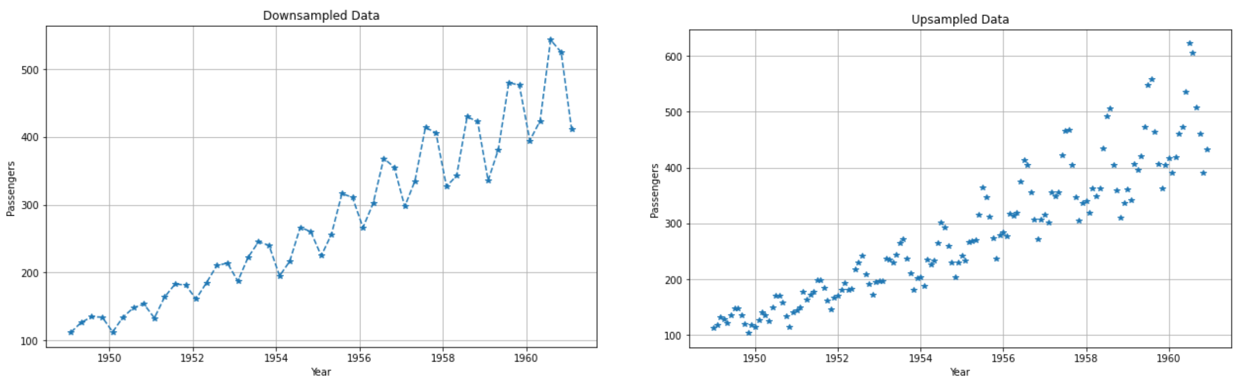



```
#check for missing values
df.isnull().values.any()
#There are no missing values in our dataset however, in bid to explain how we handle

#missing values, we will make a copy of our dataset and delete some values at random.
df_copy = df.copy()
rows = df_copy.sample(frac=0.1, random_state=0)
rows['Passengers'] = np.nan
df_copy.loc[rows.index, 'Passengers'] = rows['Passengers']
df_copy.isnull().sum()
#There are now 14 missing values in the dataset

#Filling missing data by imputation - Forward fill
df_copy_ffill = df_copy.fillna(method='ffill')
df_copy_ffill.isnull().sum()

#Filling missing data by imputation - Backward fill
df_copy_bfill = df_copy.fillna(method='bfill')
df_copy_bfill.isnull().sum()
```

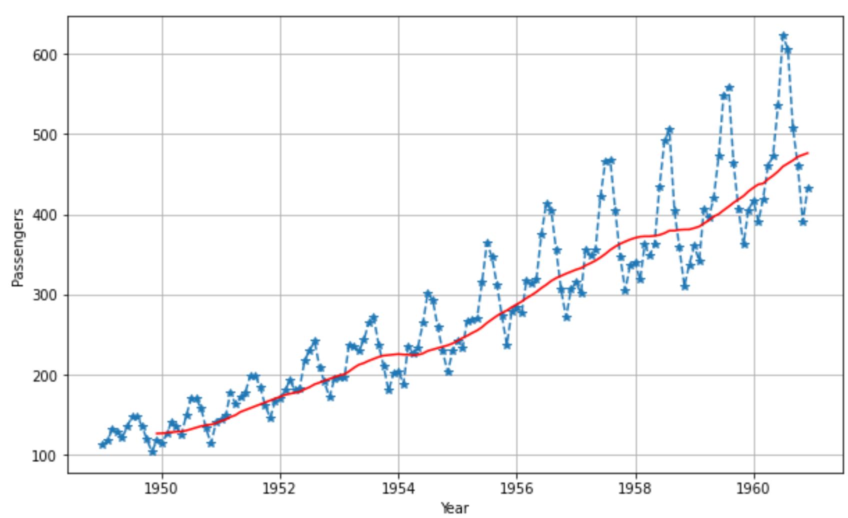
```
#Filling missing data by interpolation
df_copy_LIF = df_copy.interpolate(method='linear', limit_direction='forward')
df_copy_LIF.isnull().sum()
df_copy_LIB = df_copy.interpolate(method='linear', limit_direction='backward')
df_copy_LIB.isnull().sum()
```

Downsampling and Upsampling

```
#Downsample to quarterly data points
df_quarterly = df.resample('3M').mean()

#Upsample to daily data points
df_daily = df.resample('D').mean()
```

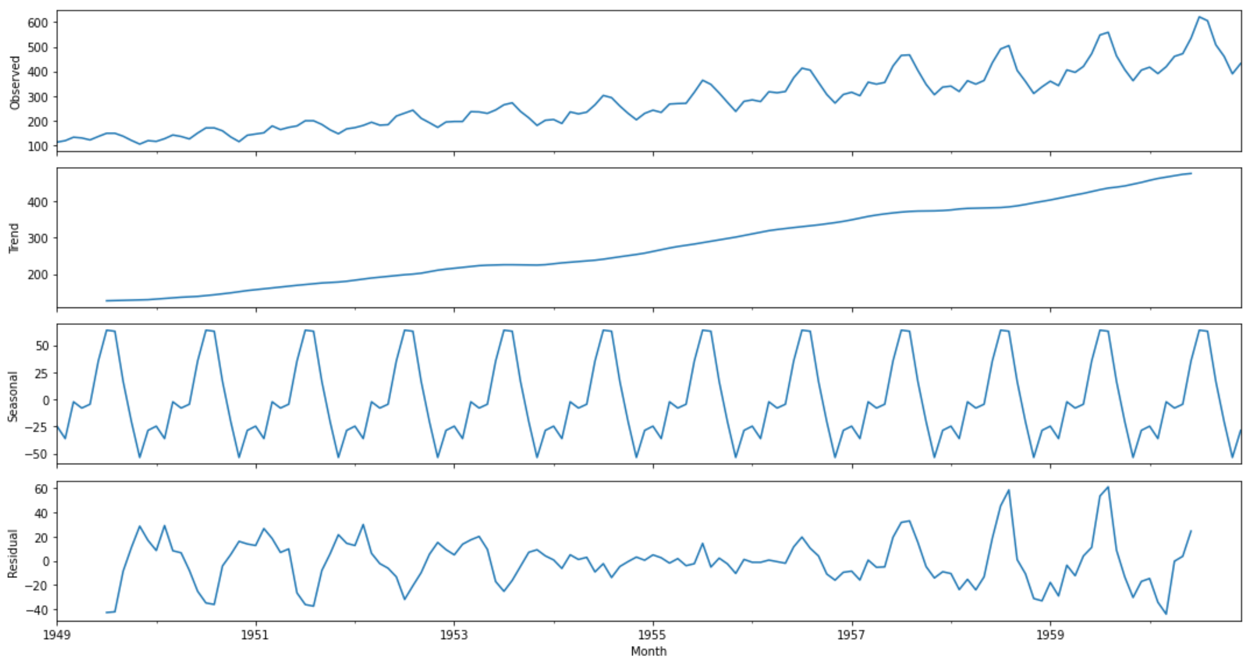



```
df_MA = df.copy()
MA = df_MA['Passengers'].rolling(12).mean()
```



Time Series Specific Exploratory Methods

```
import statsmodels.api as sm
from pylab import rcParams
rcParams['figure.figsize'] = 15, 8
decompose_series = sm.tsa.seasonal_decompose(df['Passengers'], model='additive')
decompose_series.plot()
plt.show()
```




```
#The decomposed time series show an obvious increasing trend and seasonality variations.
Recall that we have initially plotted the moving average on the last 12 months which showed
that it varies with time. This suggests that the data is not stationary. We will now perform
an ADF test to confirm this speculation
```

```
from statsmodels.tsa.stattools import adfuller
adf_result = adfuller(df['Passengers'])
print(f'ADF Statistic: {adf_result[0]}')
print(f'p-value: {adf_result[1]}')
print(f'No. of lags used: {adf_result[2]}')
print(f'No. of observations used : {adf_result[3]}')
print('Critical Values:')
for k, v in adf_result[4].items():
    print(f'   {k}: {v}')

#results in
```

```
ADF Statistic: 0.815368879206047
p-value: 0.991880243437641
No. of lags used: 13
No. of observations used : 130
Critical Values:
   1%: -3.4816817173418295
   5%: -2.8840418343195267
   10%: -2.578770059171598

#From the results obtained, the p-value is greater than the critical value at a 5%
#significance level and, the ADF statistic is greater that any of the critical values
obtain. #This confirms that the series is indeed non-stationary.


#Convert time series to stationary by removing trend and seasonality
#Transformation and Differencing
df_log = np.log(df)
df_diff = df_log.diff(periods=1)
plt.plot(df_diff.index, df_diff.Passengers, '-')
plt.plot(df_diff.rolling(12).mean(), color='red')
```