Airline_Passengers_Timeseries_Forcasting

August 6, 2024

0.0.1 Time Series Forcasting

[10]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline

import warnings
warnings.filterwarnings("ignore")
```

[18]:
```
data = pd.read_csv('airline.csv')
print(data.head(10))
```

```
     Month  Thousands of Passengers
0  1949-01                    112.0
1  1949-02                    118.0
2  1949-03                    132.0
3  1949-04                    129.0
4  1949-05                    121.0
5  1949-06                    135.0
6  1949-07                    148.0
7  1949-08                    148.0
8  1949-09                    136.0
9  1949-10                    119.0
```

[40]:
```
data = pd.read_csv('airline.csv', skiprows=1)
data.columns = ['Month', 'Passengers']
data['Month'] = data['Month'].astype(str)
data['Month'] = pd.to_datetime(data['Month'], format='%Y-%m', errors='coerce')
data = data.dropna(subset=['Month'])
data['Passengers'] = data['Passengers'].astype(int)
data = data.set_index('Month')
```

[46]:
```
data.head()
```

[46]:

```
            Passengers
Month
1949-02-01         118
1949-03-01         132
```

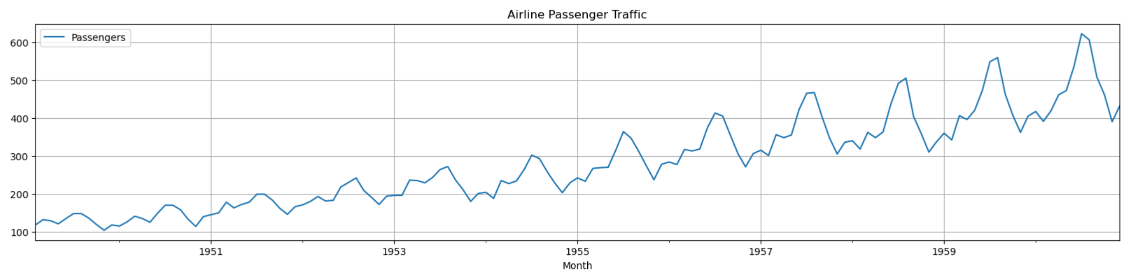
```
1949-04-01          129
1949-05-01          121
1949-06-01          135
```

[36]:
```
data.tail()
```

[36]:
```
            Passengers
Month
1960-08-01          606
1960-09-01          508
1960-10-01          461
1960-11-01          390
1960-12-01          432
```

0.0.2 Plotting the time series data

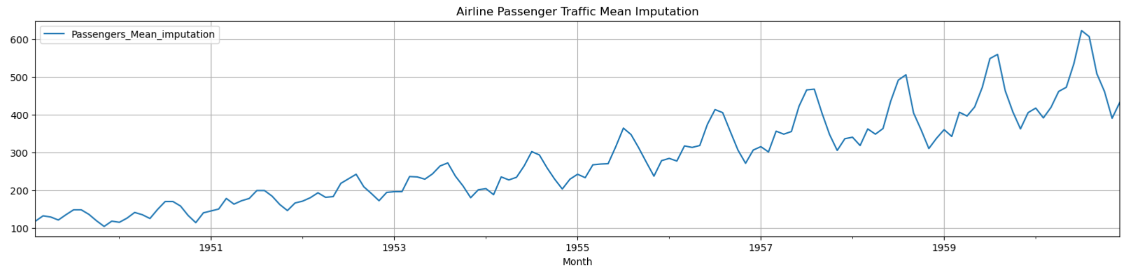
[50]:
```
data.plot(figsize=(20, 4))
plt.grid()
plt.legend(loc="best")
plt.title('Airline Passenger Traffic')
plt.show(block=False)
```



0.0.3 Treating Missing Value

Mean Imputation

[55]:
```
data= data.assign(Passengers_Mean_imputation = data.Passengers.fillna(data.
  ↪Passengers.mean()))
data[['Passengers_Mean_imputation']].plot(figsize=(20, 4))
plt.grid()
plt.legend(loc="best")
plt.title('Airline Passenger Traffic Mean Imputation')
plt.show(block=False)
```



Linear Interpolation

[64]:
```
# Checking if the 'Passengers_Linear_interpolation' column exists
if 'Passengers_Linear_interpolation' in data.columns:
    # Assigning the 'Passengers_Linear_interpolation' column to 'Passengers'
    data['Passengers'] = data['Passengers_Linear_interpolation']

    # Dropping the columns 'Passengers_Mean_imputation' and␣
 ↪'Passengers_Linear_interpolation'
    data.drop(columns=['Passengers_Mean_imputation',␣
 ↪'Passengers_Linear_interpolation'], inplace=True)
else:
    print("Column 'Passengers_Linear_interpolation' does not exist in the␣
 ↪dataframe.")

# Displaying the first few rows of the dataframe.
data.head()
```

```
Column 'Passengers_Linear_interpolation' does not exist in the dataframe.
```

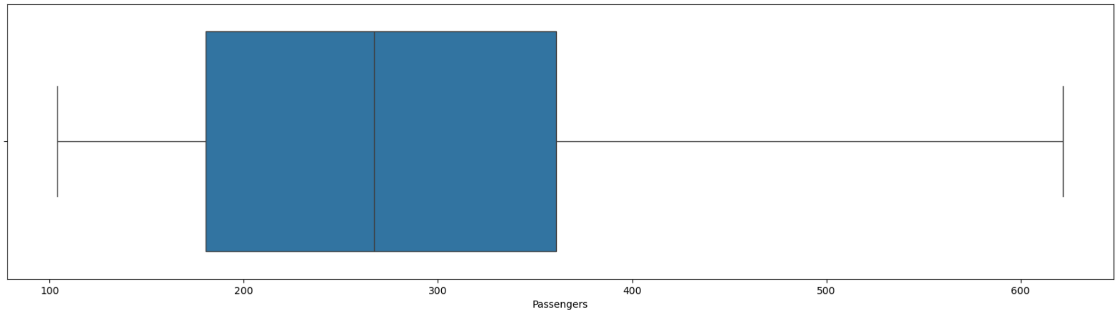
[64]:

	Passengers	Passengers_Mean_imputation
Month		
1949-02-01	118	118
1949-03-01	132	132
1949-04-01	129	129
1949-05-01	121	121
1949-06-01	135	135

Detecting Outlier

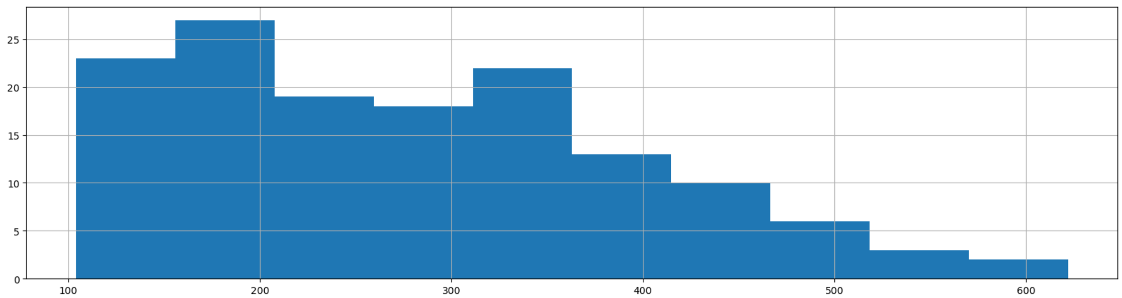
Box plot and interquartile range

[78]:
```
import seaborn as sns
fig = plt.subplots(figsize=(20, 5))
ax = sns.boxplot(x=data['Passengers'], whis=1.5)
plt.show()
```



Histogram plot

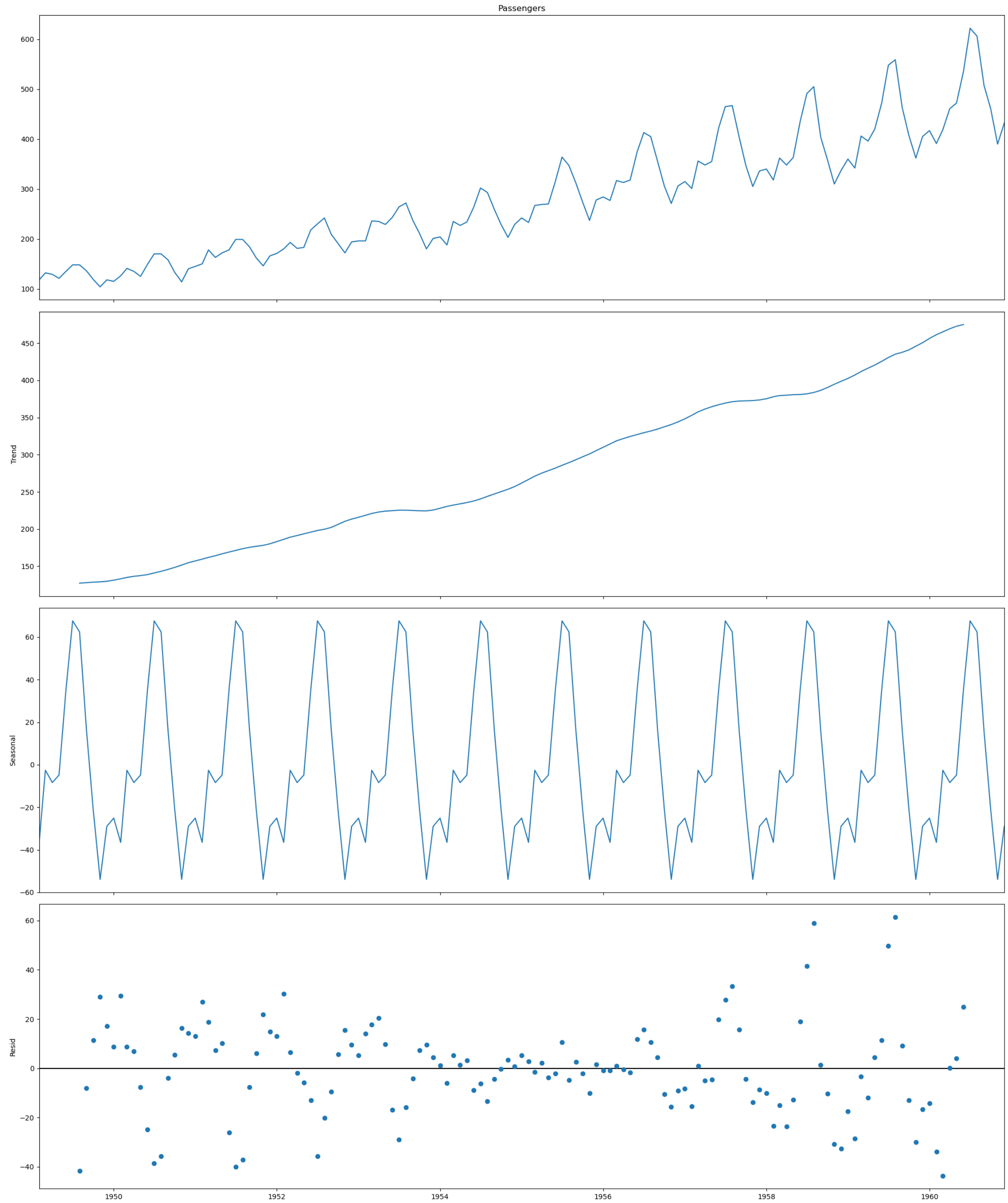
[84]:
```
fig, ax = plt.subplots(figsize=(20, 5))
data['Passengers'].hist(ax=ax)
plt.show()
```



Time Series Decomposition

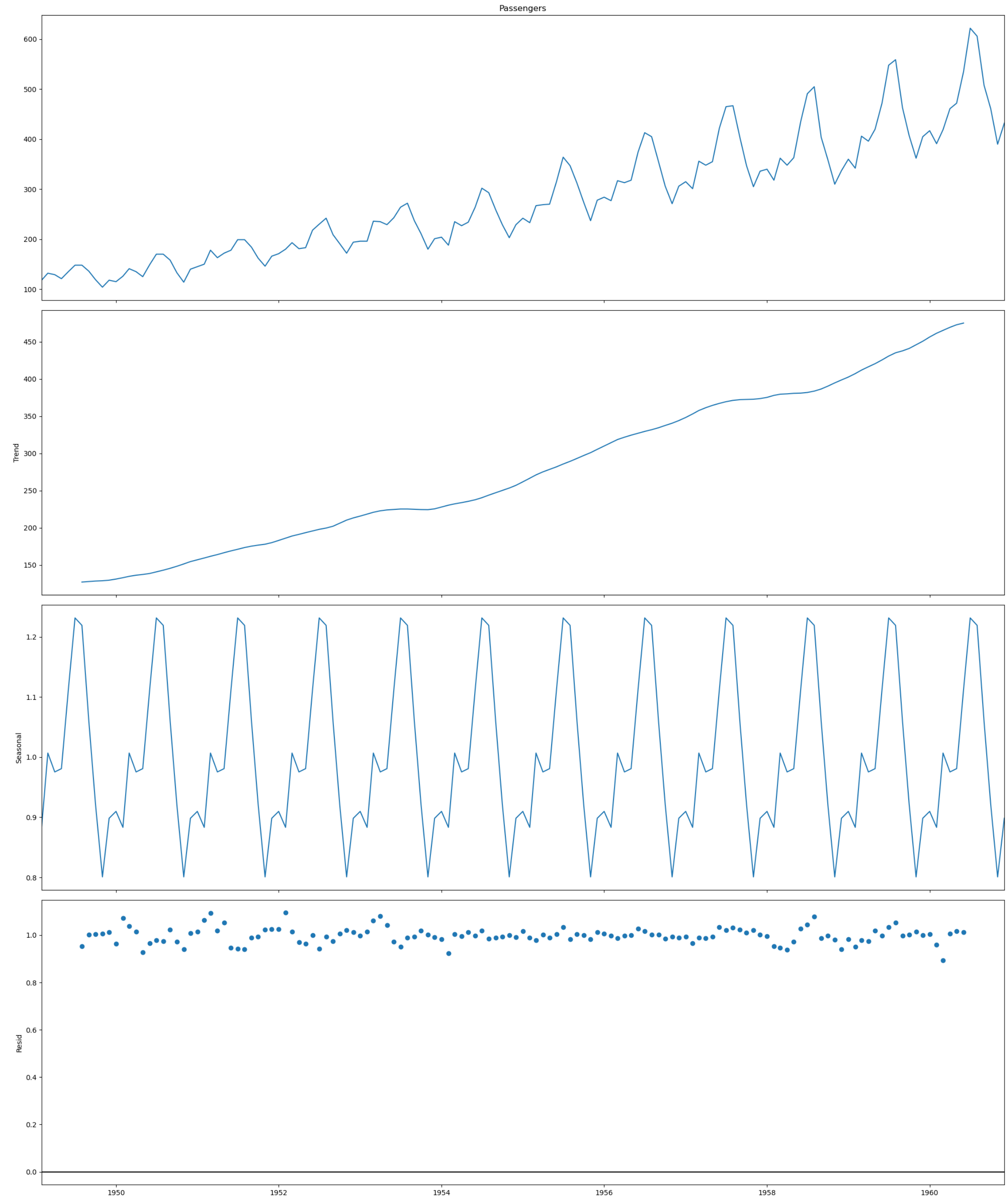
Additive Seasonal Decomposition

[96]:
```
from pylab import rcParams
import statsmodels.api as sm
rcParams['figure.figsize'] = 20, 24
decomposition = sm.tsa.seasonal_decompose(data['Passengers'], model='additive')␣
↪# additive seasonal index
fig = decomposition.plot()
plt.show()
```



Multiplicative Seasonal Decomposition

[100]:
```
decomposition = sm.tsa.seasonal_decompose(data['Passengers'],␣
    ↪model='multiplicative') # multiplicative seasonal index
fig = decomposition.plot()
plt.show()
```



0.0.4 Building and Evaluating Time Series Forcast

Splitting the time series data into training and test set

[123]:
```
train_len = 120
train = data[0:train_len] # First 120 months as training set
test = data[train_len:] # Last 24 months as out_of_time test set
```

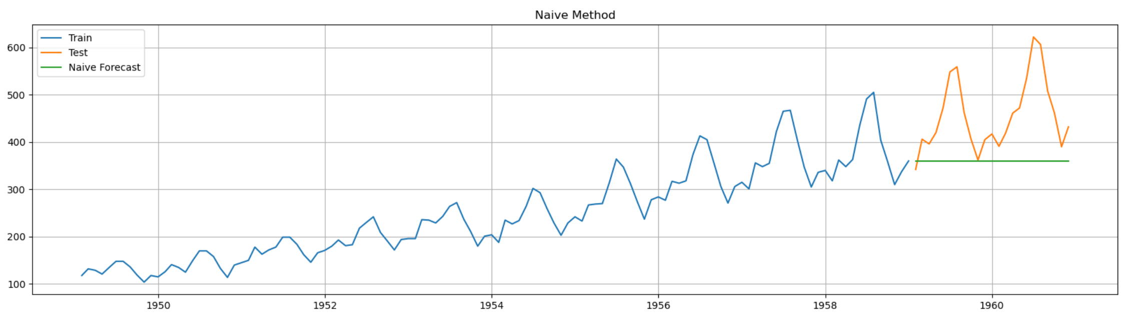
0.0.5 Simple Time Series Methods

0.0.6 1. Naive Method

[153]:
```
y_hat_naive = test.copy()
y_hat_naive['naive_forecast'] = train['Passengers'].iloc[-1]
```

Plotting train, test and forecast

[155]:
```
plt.figure(figsize=(20, 5))
plt.grid()
plt.plot(train['Passengers'], label='Train')
plt.plot(test['Passengers'], label='Test')
plt.plot(y_hat_naive['naive_forecast'], label='Naive Forecast')
plt.legend(loc="best")
plt.title('Naive Method')
plt.show()
```



0.0.7 Calculating the Performance of the Naive Method

Calculating Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE)

[159]:
```
from sklearn.metrics import mean_squared_error
rmse = np.sqrt(mean_squared_error(test['Passengers'],␣
↪y_hat_naive['naive_forecast'])).round(2)
mape = np.round(np.mean(np.abs((test['Passengers'] -␣
↪y_hat_naive['naive_forecast']) / test['Passengers'])) * 100, 2)

results = pd.DataFrame({
    'Methods': ['Naive Method'],
    'RMSE': [rmse],
    'MAPE': [mape]
})
results = results[['Methods', 'RMSE', 'MAPE']]
results
```

[159]:

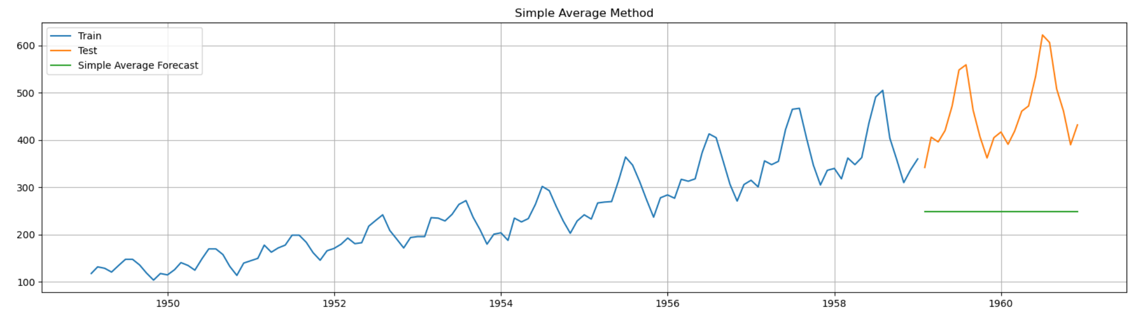
	Methods	RMSE	MAPE
0	Naive Method	121.24	19.62

0.0.8 2. Simple Average Method

[162]:
```
y_hat_avg = test.copy()
y_hat_avg['avg_forecast'] = train['Passengers'].mean()
```

Plot train, test and forecast

[165]:
```
plt.figure(figsize=(20, 5))
plt.grid()
plt.plot(train['Passengers'], label='Train')
plt.plot(test['Passengers'], label='Test')
plt.plot(y_hat_avg['avg_forecast'], label='Simple Average Forecast')
plt.legend(loc="best")
plt.title('Simple Average Method')
plt.show()
```



Calculating RMSE AND MAPE

[168]:
```
from sklearn.metrics import mean_squared_error
rmse = np.sqrt(mean_squared_error(test['Passengers'],␣
  ↪y_hat_avg['avg_forecast'])).round(2)
mape = np.round(np.mean(np.abs((test['Passengers'] - y_hat_avg['avg_forecast'])␣
  ↪/ test['Passengers'])) * 100, 2)

tempResults = pd.DataFrame({
    'Methods': ['Simple Average Method'],
    'RMSE': [rmse],
    'MAPE': [mape]
})
results = pd.concat([results, tempResults])
results = results[['Methods', 'RMSE', 'MAPE']]
results
```

[168]:

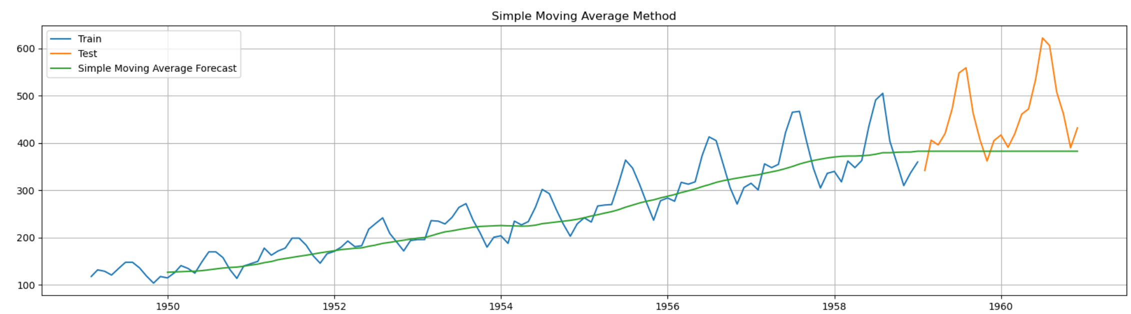
	Methods	RMSE	MAPE
0	Naive Method	121.24	19.62
0	Simple Average Method	220.94	44.32

0.0.9 3. Simple Moving Average Method

[206]:
```
y_hat_sma = data.copy()
ma_window = 12
y_hat_sma['sma_forecast'] = y_hat_sma['Passengers'].rolling(window=ma_window).mean()
y_hat_sma['sma_forecast'].iloc[train_len:] = y_hat_sma['sma_forecast'].iloc[train_len-1]
```

Plot Train, Test and Forecast

[208]:
```
plt.figure(figsize=(20, 5))
plt.grid()
plt.plot(train['Passengers'], label='Train')
plt.plot(test['Passengers'], label='Test')
plt.plot(y_hat_sma['sma_forecast'], label='Simple Moving Average Forecast')
plt.legend(loc="best")
plt.title('Simple Moving Average Method')
plt.show()
```



Calculating RMSE AND MAPE

[212]:
```
from sklearn.metrics import mean_squared_error
y_hat_sma_forecast = y_hat_sma['sma_forecast'].iloc[train_len:]
test = data.iloc[train_len:]
rmse = np.sqrt(mean_squared_error(test['Passengers'], y_hat_sma_forecast)).round(2)
mape = np.round(np.mean(np.abs((test['Passengers'] - y_hat_sma_forecast) / test['Passengers'])) * 100, 2)
tempResults = pd.DataFrame({
    'Methods': ['Simple Moving Average Forecast'],
    'RMSE': [rmse],
```

```
    'MAPE': [mape]
})
results = pd.concat([results, tempResults])
results = results[['Methods', 'RMSE', 'MAPE']]
results
```

[212]:

	Methods	RMSE	MAPE
0	Naive Method	121.24	19.62
0	Simple Average Method	220.94	44.32
0	Simple Moving Average Forecast	104.16	15.60

0.0.10 Exponential Smoothing Method

4. Simple Exponential Smoothing

[227]:
```
data.index = pd.to_datetime(data.index)
data.index.freq = 'MS'
from statsmodels.tsa.holtwinters import SimpleExpSmoothing
model = SimpleExpSmoothing(train['Passengers'])
model_fit = model.fit(smoothing_level=0.2, optimized=False)
model_fit.params
y_hat_ses = test.copy()
y_hat_ses['ses_forecast'] = model_fit.forecast(24)
y_hat_ses.head()
```

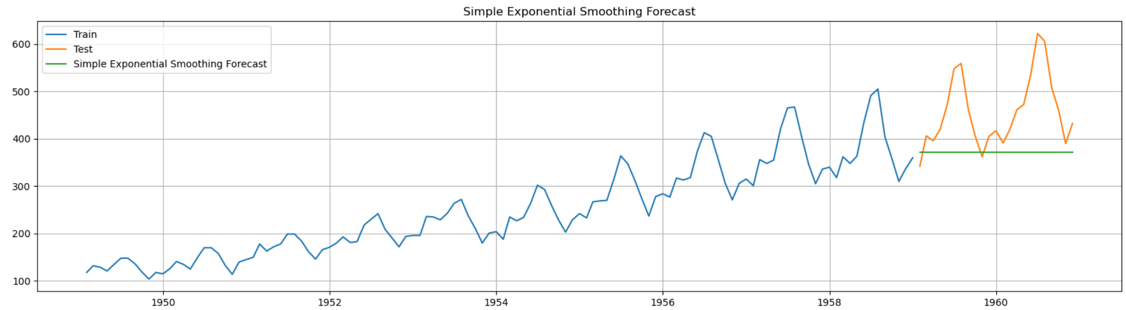
```
C:\Users\user\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473:
ValueWarning: No frequency information was provided, so inferred frequency MS
will be used.
  self._init_dates(dates, freq)
```

[227]:

	Passengers	Passengers_Mean_imputation	ses_forecast
Month			
1959-02-01	342	342	371.917858
1959-03-01	406	406	371.917858
1959-04-01	396	396	371.917858
1959-05-01	420	420	371.917858
1959-06-01	472	472	371.917858

Plot, Train and Forecast

[233]:
```
plt.figure(figsize=(20, 5))
plt.grid()
plt.plot(train['Passengers'], label='Train')
plt.plot(test['Passengers'], label='Test')
plt.plot(y_hat_ses['ses_forecast'], label='Simple Exponential Smoothing␣
 ↪Forecast')
plt.legend(loc="best")
plt.title('Simple Exponential Smoothing Forecast')
plt.show()
```



Calculating RSME and MAPE

[237]:
```
rmse = np.
↪sqrt(mean_squared_error(test['Passengers'],y_hat_ses['ses_forecast'])).
↪round(2)
mape = np.round(np.mean(np.abs((test['Passengers'] - y_hat_ses['ses_forecast'])/
↪ test['Passengers'])) * 100, 2)
tempResults = pd.DataFrame({
    'Methods': ['Simple Exponential Smoothing Forecast'],
    'RMSE': [rmse],
    'MAPE': [mape]
})
results = pd.concat([results, tempResults])
results = results[['Methods', 'RMSE', 'MAPE']]
results
```

[237]:

	Methods	RMSE	MAPE
0	Naive Method	121.24	19.62
0	Simple Average Method	220.94	44.32
0	Simple Moving Average Forecast	104.16	15.60
0	Simple Exponential Smoothing Forecast	112.01	17.48

0.0.11 5. Holt's Method With Trend

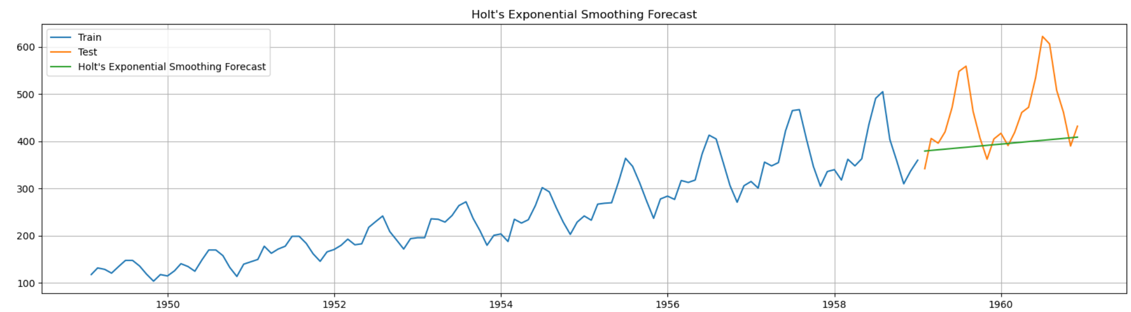
[243]:
```
from statsmodels.tsa.holtwinters import ExponentialSmoothing
model = ExponentialSmoothing(np.
↪asarray(train['Passengers']),seasonal_periods=12, trend='additive',␣
↪seasonal=None)
model_fit = model.fit(smoothing_level=0.2, smoothing_slope=0.01,␣
↪optimized=False)
print(model_fit.params)
y_hat_holt = test.copy()
y_hat_holt['holt_forecast'] = model_fit.forecast(len(test))
```

```
{'smoothing_level': 0.2, 'smoothing_trend': 0.01, 'smoothing_seasonal': None,
'damping_trend': nan, 'initial_level': 131.93333333333322, 'initial_trend':
```

```
-0.5333333333333254, 'initial_seasons': array([], dtype=float64), 'use_boxcox':
False, 'lamda': None, 'remove_bias': False}
```

Plot Train, Test And Forecast

[260]:
```
plt.figure(figsize=(20, 5))
plt.grid()
plt.plot(train['Passengers'], label='Train')
plt.plot(test['Passengers'], label='Test')
plt.plot(y_hat_holt['holt_forecast'],label='Holt\'s Exponential Smoothing␣
↪Forecast')
plt.legend(loc="best")
plt.title('Holt\'s Exponential Smoothing Forecast')
plt.show()
```



Calculating RSME And MAPE

[263]:
```
rmse = np.sqrt(mean_squared_error(test['Passengers'],␣
↪y_hat_holt['holt_forecast'])).round(2)
mape = np.round(np.mean(np.abs((test['Passengers'] -␣
↪y_hat_holt['holt_forecast'])/ test['Passengers'])) * 100, 2)
tempResults = pd.DataFrame({
    'Methods': ['Holt\'s Exponential Smoothing Forecast'],
    'RMSE': [rmse],
    'MAPE': [mape]
})
results = pd.concat([results, tempResults])
results = results[['Methods', 'RMSE', 'MAPE']]
results
```

[263]:

	Methods	RMSE	MAPE
0	Naive Method	121.24	19.62
0	Simple Average Method	220.94	44.32
0	Simple Moving Average Forecast	104.16	15.60
0	Simple Exponential Smoothing Forecast	112.01	17.48
0	Holt's Exponential Smoothing Forecast	94.59	13.75

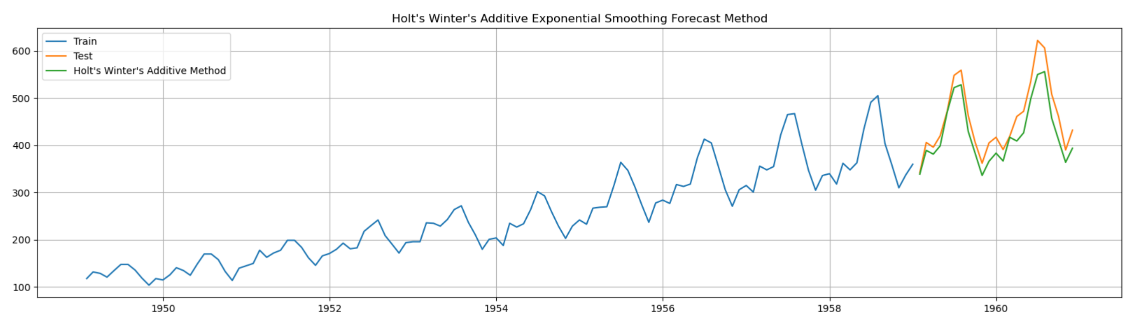
0.0.12 6. Holt's Winter's Additive Method With Trend And Seasonality

[268]:
```
y_hat_hwa = test.copy()
model = ExponentialSmoothing(np.
 ↪asarray(train['Passengers']),seasonal_periods=12, trend='add',␣
 ↪seasonal='add')
model_fit = model.fit(optimized=True)
print(model_fit.params)
y_hat_hwa['hwa_forecast'] = model_fit.forecast(23)
```

```
{'smoothing_level': 0.23664628690277897, 'smoothing_trend':
2.4639036251860125e-10, 'smoothing_seasonal': 0.7633537119162593,
'damping_trend': nan, 'initial_level': 119.06349141540223, 'initial_trend':
2.312032346049103, 'initial_seasons': array([ -3.38865685,   9.2043327 ,
4.17358947,  -4.45329457,
         9.7479721 ,  21.97831612,  19.65034468,   5.5158419 ,
       -13.3715079 , -28.08000703, -11.93849861, -15.05081336]), 'use_boxcox':
False, 'lamda': None, 'remove_bias': False}
```

Plot Train, Test And Forecast

[275]:
```
plt.figure(figsize=(20, 5))
plt.grid()
plt.plot(train['Passengers'], label='Train')
plt.plot(test['Passengers'], label='Test')
plt.plot(y_hat_hwa['hwa_forecast'],label='Holt\'s Winter\'s Additive Method')
plt.legend(loc="best")
plt.title('Holt\'s Winter\'s Additive Exponential Smoothing Forecast Method')
plt.show()
```



Calculating RSME And MAPE

[280]:
```
rmse = np.sqrt(mean_squared_error(test['Passengers'],␣
 ↪y_hat_hwa['hwa_forecast'])).round(2)
mape = np.round(np.mean(np.abs((test['Passengers'] - y_hat_hwa['hwa_forecast'])/
 ↪ test['Passengers'])) * 100, 2)
tempResults = pd.DataFrame({
```

```
    'Methods': ['Holt\'s Winter\'s Additive Method'],
    'RMSE': [rmse],
    'MAPE': [mape]
})
results = pd.concat([results, tempResults])
results = results[['Methods', 'RMSE', 'MAPE']]
results
```

[280]:

	Methods	RMSE	MAPE
0	Naive Method	121.24	19.62
0	Simple Average Method	220.94	44.32
0	Simple Moving Average Forecast	104.16	15.60
0	Simple Exponential Smoothing Forecast	112.01	17.48
0	Holt's Exponential Smoothing Forecast	94.59	13.75
0	Holt's Winter's Additive Method	35.60	6.64

0.0.13 7. Holt's Winter's Multiplicative Method With Trend And Seasonality

[283]:

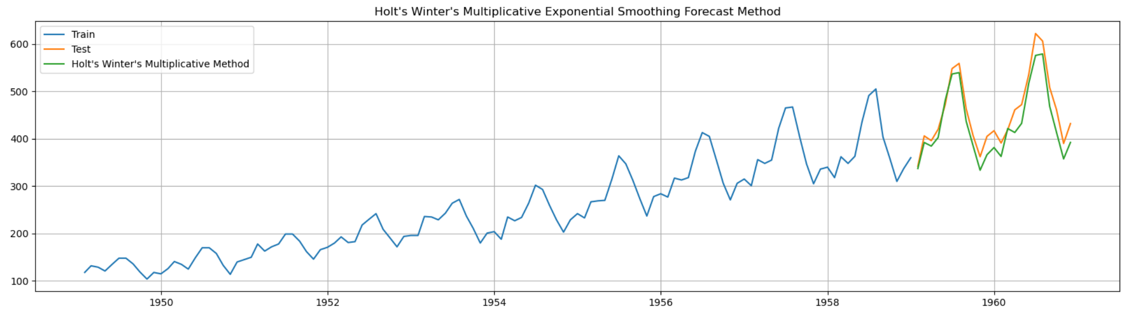
```
y_hat_hwm = test.copy()
model = ExponentialSmoothing(np.
  ↪asarray(train['Passengers']),seasonal_periods=12, trend='add',␣
  ↪seasonal='mul')
model_fit = model.fit(optimized=True)
print(model_fit.params)
y_hat_hwm['hwm_forecast'] = model_fit.forecast(23)
```

```
{'smoothing_level': 0.37452555210761707, 'smoothing_trend':
3.0577682760149587e-10, 'smoothing_seasonal': 0.6254744478197194,
'damping_trend': nan, 'initial_level': 121.0336171247121, 'initial_trend':
2.6712360653608336, 'initial_seasons': array([0.95388001, 1.05119075,
0.99974301, 0.9241966 , 1.01270795,
       1.10372749, 1.08979856, 0.99346317, 0.86527977, 0.76883907,
       0.88753233, 0.88519045]), 'use_boxcox': False, 'lamda': None,
'remove_bias': False}
```

Plot Train, Test And Forecast

[287]:

```
plt.figure(figsize=(20, 5))
plt.grid()
plt.plot(train['Passengers'], label='Train')
plt.plot(test['Passengers'], label='Test')
plt.plot(y_hat_hwm['hwm_forecast'],label='Holt\'s Winter\'s Multiplicative␣
  ↪Method')
plt.legend(loc="best")
plt.title('Holt\'s Winter\'s Multiplicative Exponential Smoothing Forecast␣
  ↪Method')
plt.show()
```



Calculating RSME And MAPE

[290]:
```python
rmse = np.sqrt(mean_squared_error(test['Passengers'],␣
↪y_hat_hwm['hwm_forecast'])).round(2)
mape = np.round(np.mean(np.abs((test['Passengers'] - y_hat_hwm['hwm_forecast'])/
↪ test['Passengers'])) * 100, 2)
tempResults = pd.DataFrame({
    'Methods': ['Holt\'s Winter\'s Multiplicative Method'],
    'RMSE': [rmse],
    'MAPE': [mape]
})
results = pd.concat([results, tempResults])
results = results[['Methods', 'RMSE', 'MAPE']]
results
```

[290]:

	Methods	RMSE	MAPE
0	Naive Method	121.24	19.62
0	Simple Average Method	220.94	44.32
0	Simple Moving Average Forecast	104.16	15.60
0	Simple Exponential Smoothing Forecast	112.01	17.48
0	Holt's Exponential Smoothing Forecast	94.59	13.75
0	Holt's Winter's Additive Method	35.60	6.64
0	Holt's Winter's Multiplicative Method	29.72	5.82

Hence it is recommended to use Holt's Winter's Multiplicative Method for accurate prediction for time series as it has the least RSME and MAPE for this data set

[ ]:
```

```