exponential-smoothing-methods

December 28, 2023

[89]:
```
import pandas as pd
import numpy as np
import seaborn as sns

import matplotlib.pyplot as plt
from statsmodels.tsa.seasonal import seasonal_decompose
from sklearn.metrics import mean_squared_error
```

[90]:
```
data = pd.read_csv('/kaggle/input/air-passengers/AirPassengers.csv')
data.head()
```

[90]:
```
     Month  #Passengers
0  1949-01          112
1  1949-02          118
2  1949-03          132
3  1949-04          129
4  1949-05          121
```

[91]:
```
data = data.rename(columns={"#Passengers": "Passengers"}, inplace=False)
data.head()
```

[91]:
```
     Month  Passengers
0  1949-01         112
1  1949-02         118
2  1949-03         132
3  1949-04         129
4  1949-05         121
```

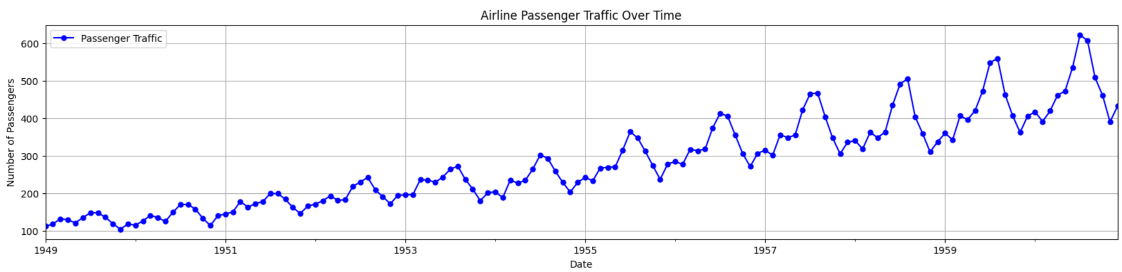
[92]:
```
data.columns = ['Month','Passengers']
data['Month'] = pd.to_datetime(data['Month'], format='%Y-%m')
data = data.set_index('Month')
data.head()
```

[92]:
```
            Passengers
Month
1949-01-01         112
1949-02-01         118
```

```
1949-03-01          132
1949-04-01          129
1949-05-01          121
```

1 Plot time series data

[93]:
```
data.plot(y='Passengers', figsize=(20, 4), color='blue', linestyle='-',
  ↪marker='o', markersize=5, label='Passenger Traffic')
plt.grid(True)
plt.legend(loc='best')
plt.title('Airline Passenger Traffic Over Time')
plt.xlabel('Date')
plt.ylabel('Number of Passengers')
plt.show(block=False)
```

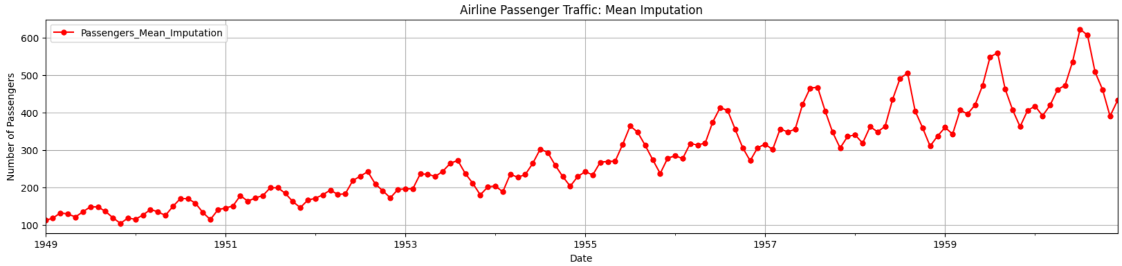


2 Missing value treatment

2.1 Mean imputation

[94]:
```
data['Passengers_Mean_Imputation'] = data['Passengers'].
  ↪fillna(data['Passengers'].mean())
```

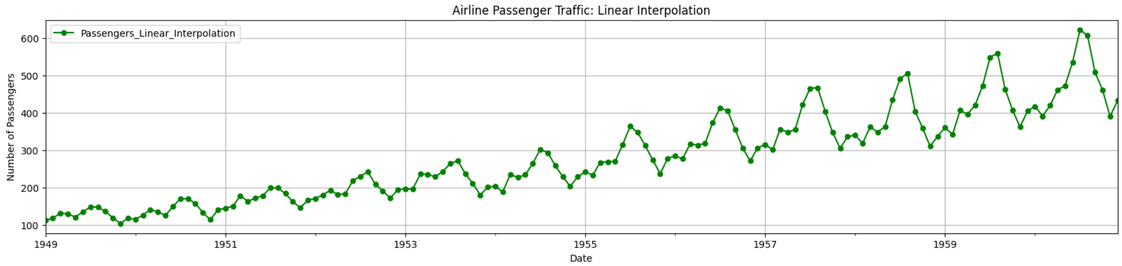
[95]:
```
data[['Passengers_Mean_Imputation']].plot(figsize=(20, 4), grid=True,
  ↪legend=True, color='red', linestyle='-', marker='o', markersize=5)
plt.title('Airline Passenger Traffic: Mean Imputation')
plt.xlabel('Date')
plt.ylabel('Number of Passengers')
plt.show(block=False)
```



2.2 Linear interpolation¶

[96]:
```
data['Passengers_Linear_Interpolation'] = data['Passengers'].
↪interpolate(method='linear')
```

[97]:
```
data[['Passengers_Linear_Interpolation']].plot(figsize=(20, 4), grid=True,␣
↪legend=True, color='green', linestyle='-', marker='o', markersize=5)
plt.title('Airline Passenger Traffic: Linear Interpolation')
plt.xlabel('Date')
plt.ylabel('Number of Passengers')
plt.show(block=False)
```



[98]:
```
data.head()
```

[98]:
```
            Passengers  Passengers_Mean_Imputation  \
Month
1949-01-01         112                         112
1949-02-01         118                         118
1949-03-01         132                         132
1949-04-01         129                         129
1949-05-01         121                         121

            Passengers_Linear_Interpolation
Month
1949-01-01                              112
```

```
1949-02-01                              118
1949-03-01                              132
1949-04-01                              129
1949-05-01                              121
```

[99]:

```python
data['Passengers'] = data['Passengers_Linear_Interpolation']
data.
 ↪drop(columns=['Passengers_Mean_Imputation','Passengers_Linear_Interpolation'],inplace=True)
data.head()
```

[99]:

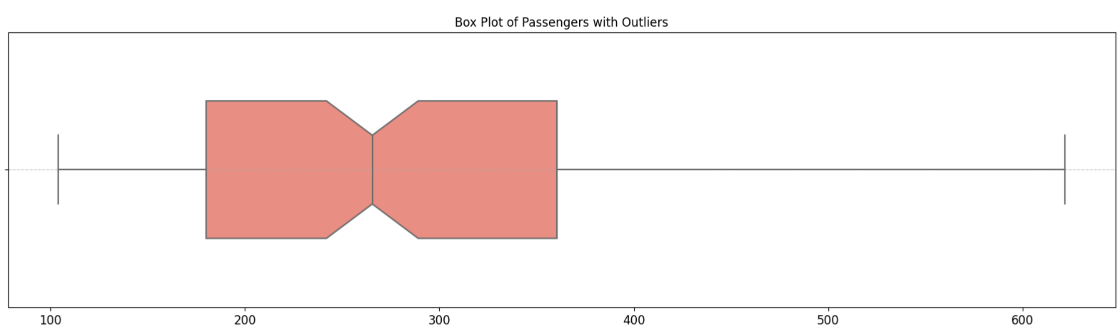
```
            Passengers
Month
1949-01-01         112
1949-02-01         118
1949-03-01         132
1949-04-01         129
1949-05-01         121
```

3 Outlier detection

3.1 Box plot and interquartile range

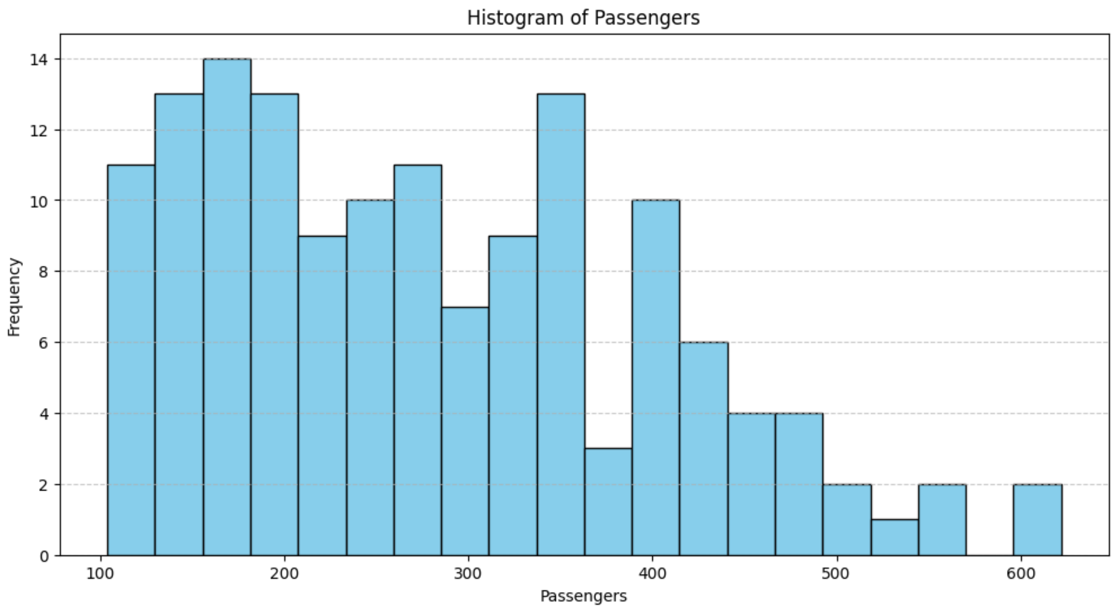
[100]:

```python
import seaborn as sns
plt.figure(figsize=(20, 5))

sns.boxplot(x=data['Passengers'], color='salmon', width=0.5, notch=True)

plt.title('Box Plot of Passengers with Outliers')
plt.xlabel('Passengers')
plt.xticks(fontsize=12)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```



3.2 Histogram plot

[101]:
```
plt.figure(figsize=(12, 6))
plt.hist(data['Passengers'], bins=20, color='skyblue', edgecolor='black')

plt.title('Histogram of Passengers')
plt.xlabel('Passengers')
plt.ylabel('Frequency')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```

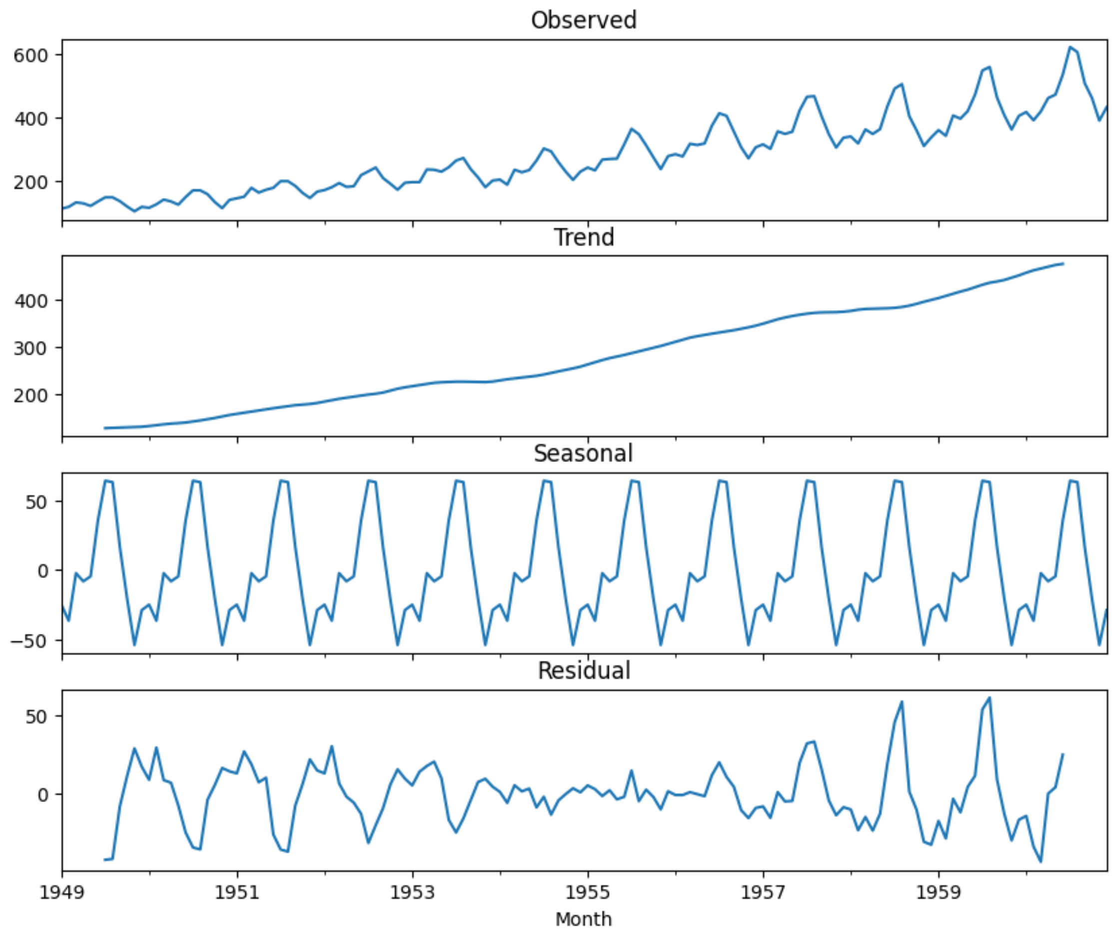


4 Time series Decomposition

4.1 Additive seasonal decomposition

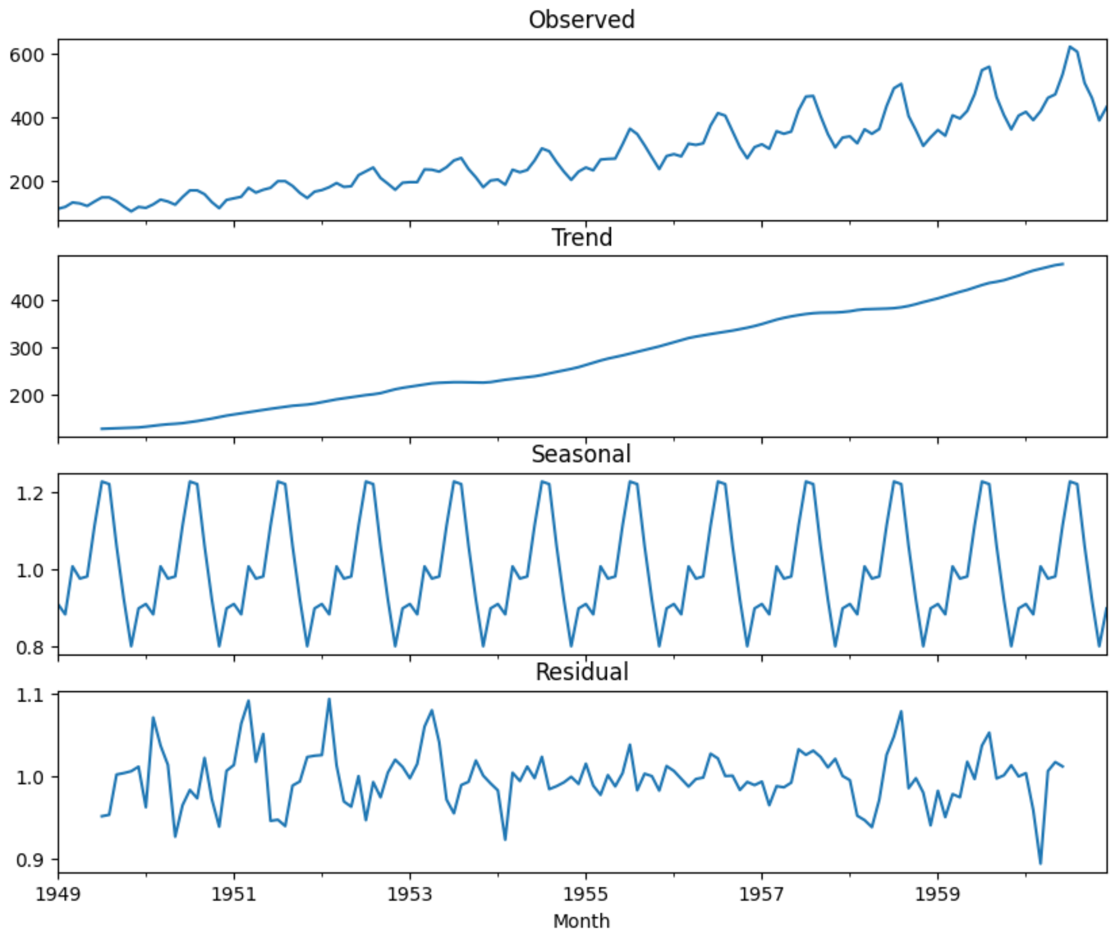
[102]:

```
from statsmodels.tsa.seasonal import seasonal_decompose

# Perform decomposition
result = seasonal_decompose(data['Passengers'], model='additive')
fig, (ax1, ax2, ax3, ax4) = plt.subplots(4, 1, figsize=(10, 8), sharex=True)

result.observed.plot(ax=ax1, title='Observed')
result.trend.plot(ax=ax2, title='Trend')
result.seasonal.plot(ax=ax3, title='Seasonal')
result.resid.plot(ax=ax4, title='Residual')

plt.show()
```



4.2 Multiplicative seasonal decomposition

[103]:
```
result = seasonal_decompose(data['Passengers'], model='multiplicative')
fig, (ax1, ax2, ax3, ax4) = plt.subplots(4, 1, figsize=(10, 8), sharex=True)

result.observed.plot(ax=ax1, title='Observed')
result.trend.plot(ax=ax2, title='Trend')
result.seasonal.plot(ax=ax3, title='Seasonal')
result.resid.plot(ax=ax4, title='Residual')

plt.show()
```



5 Build and evaluate time series forecas

5.1 Split time series data into training and test set

[104]:
```
train_len = 120
train = data[:train_len]  # first 120 months as the training set
test = data[train_len:]  # last 24 months as the out-of-time test set
```

6 Exponential smoothing methods

6.1 Simple exponential smoothing

[105]:
```
from statsmodels.tsa.holtwinters import SimpleExpSmoothing
model = SimpleExpSmoothing(train['Passengers'])
model_fit = model.fit(smoothing_level=0.2,optimized=False)
model_fit.params
```

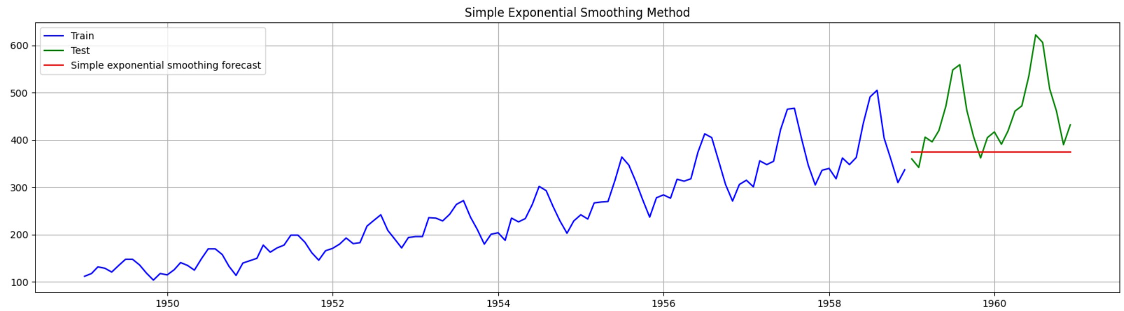
```
/opt/conda/lib/python3.10/site-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: No frequency information was provided, so inferred frequency MS
will be used.
  self._init_dates(dates, freq)
```

[105]:
```
{'smoothing_level': 0.2,
 'smoothing_trend': None,
 'smoothing_seasonal': None,
 'damping_trend': nan,
 'initial_level': 112.0,
 'initial_trend': nan,
 'initial_seasons': array([], dtype=float64),
 'use_boxcox': False,
 'lamda': None,
 'remove_bias': False}
```

[106]:
```
y_hat_ses = test.copy()
y_hat_ses['ses_forecast'] = model_fit.forecast(24)
```

6.1.1 Plot train, test and forecast

[107]:
```
plt.figure(figsize=(20,5))
plt.grid()
plt.plot(train['Passengers'], label='Train', color='blue')
plt.plot(test['Passengers'], label='Test',color='green')
plt.plot(y_hat_ses['ses_forecast'], label='Simple exponential smoothing␣
  ↪forecast',color='red')
plt.legend(loc='best')
plt.title('Simple Exponential Smoothing Method')
plt.show()
```



6.1.2 Calculate RMSE and MAPE

[108]:
```
results = pd.DataFrame(columns=['Method', 'RMSE', 'MAPE'])
```

[109]:
```
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)
```

[110]:
```
tempResults = pd.DataFrame({'Method':['Simple exponential smoothing forecast'],␣
  ↪'RMSE': [rmse],'MAPE': [mape] })
results = pd.concat([results, tempResults])
results
```

[110]:

	Method	RMSE	MAPE
0	Simple exponential smoothing forecast	107.52	16.43

6.2 Holt's method with trend

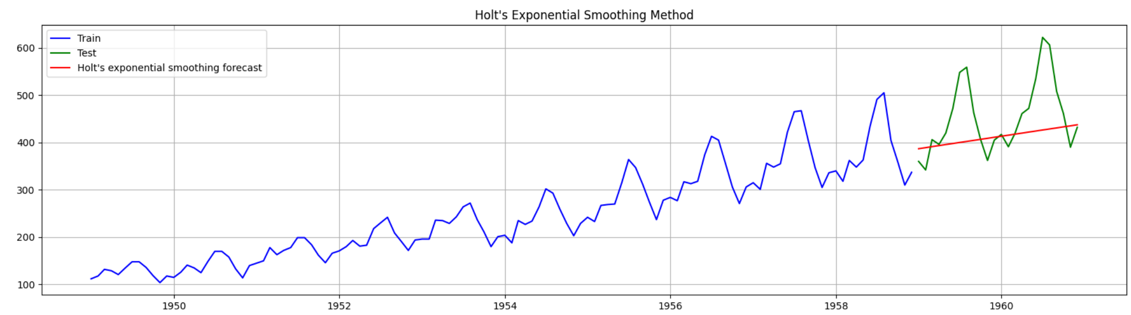
[111]:
```
from statsmodels.tsa.holtwinters import ExponentialSmoothing
model = ExponentialSmoothing(np.asarray(train['Passengers'])␣
  ↪,seasonal_periods=12 ,trend='additive', seasonal=None)
model_fit = model.fit(smoothing_level=0.2, smoothing_slope=0.01,␣
  ↪optimized=False)
print(model_fit.params)
```

```
{'smoothing_level': 0.2, 'smoothing_trend': 0.01, 'smoothing_seasonal': None,
'damping_trend': nan, 'initial_level': 118.46666666666661, 'initial_trend':
2.0606060606060677, 'initial_seasons': array([], dtype=float64), 'use_boxcox':
False, 'lamda': None, 'remove_bias': False}
```

```
/tmp/ipykernel_43/3162401862.py:3: FutureWarning: the 'smoothing_slope' keyword
is deprecated, use 'smoothing_trend' instead.
  model_fit = model.fit(smoothing_level=0.2, smoothing_slope=0.01,
optimized=False)
```

[112]:
```
y_hat_holt = test.copy()
y_hat_holt['holt_forecast'] = model_fit.forecast(len(test))
```

[113]:
```
plt.figure(figsize=(20,5))
plt.grid()
plt.plot( train['Passengers'], label='Train',color='blue')
plt.plot(test['Passengers'], label='Test',color='green')
plt.plot(y_hat_holt['holt_forecast'], label='Holt\'s exponential smoothing␣
↪forecast',color='red')
plt.legend(loc='best')
plt.title('Holt\'s Exponential Smoothing Method')
plt.show()
```



[114]:
```
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)
```

[115]:
```
tempResults = pd.DataFrame({'Method':['Holt\'s exponential smoothing method'],␣
↪'RMSE': [rmse],'MAPE': [mape] })
results = pd.concat([results, tempResults])
results = results[['Method', 'RMSE', 'MAPE']]
results
```

[115]:

	Method	RMSE	MAPE
0	Simple exponential smoothing forecast	107.52	16.43
0	Holt's exponential smoothing method	80.90	11.32

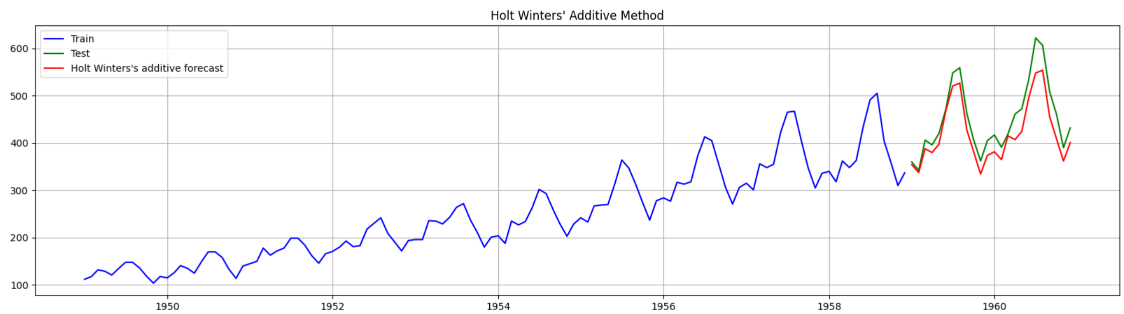
6.3 Holt Winters' additive method with trend and seasonality

[116]:
```
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 = test.copy()
```

```
forecast_values = model_fit.forecast(len(test))
y_hat_hwa['hw_forecast'] = forecast_values
```

```
{'smoothing_level': 0.23678678235712566, 'smoothing_trend':
1.8055668382578714e-09, 'smoothing_seasonal': 0.7632132086415252,
'damping_trend': nan, 'initial_level': 119.1876680939318, 'initial_trend':
2.2768394955266533, 'initial_seasons': array([ -9.42424719,  -3.87104168,
8.69002781,   3.6678027 ,
        -4.94701962,   9.26652064,  21.53444859,  19.2001798 ,
         5.07181472, -13.80997707, -28.51179942, -12.37245268]), 'use_boxcox':
False, 'lamda': None, 'remove_bias': False}
```

[117]:
```
plt.figure(figsize=(20,5))
plt.grid()
plt.plot( train['Passengers'], label='Train',color='blue')
plt.plot(test['Passengers'], label='Test',color='green')
plt.plot(y_hat_hwa['hw_forecast'], label='Holt Winters\'s additive␣
 ↪forecast',color='red')
plt.legend(loc='best')
plt.title('Holt Winters\' Additive Method')
plt.show()
```



[118]:
```
rmse = np.sqrt(mean_squared_error(test['Passengers'],␣
 ↪y_hat_hwa['hw_forecast'])).round(2)
mape = np.round(np.mean(np.abs(test['Passengers']-y_hat_hwa['hw_forecast'])/
 ↪test['Passengers'])*100,2)
```

[119]:
```
tempResults = pd.DataFrame({'Method':['Holt Winters\' additive method'], 'RMSE':
 ↪ [rmse],'MAPE': [mape] })
results = pd.concat([results, tempResults])
results = results[['Method', 'RMSE', 'MAPE']]
results
```

[119]:

	Method	RMSE	MAPE
0	Simple exponential smoothing forecast	107.52	16.43

```
0    Holt's exponential smoothing method   80.90  11.32
0          Holt Winters' additive method   35.76   6.64
```

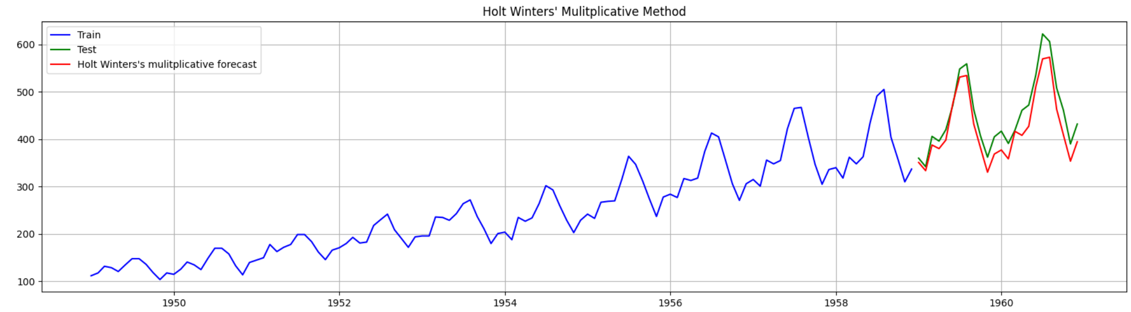
6.4 Holt Winter's multiplicative method with trend and seasonality

[120]:
```
model = ExponentialSmoothing(np.asarray(train['Passengers'])␣
↪,seasonal_periods=12 ,trend='add', seasonal='mul')
model_fit = model.fit(optimized=True)
print(model_fit.params)
```

```
{'smoothing_level': 0.364208357460606, 'smoothing_trend': 4.191162581733996e-09,
'smoothing_seasonal': 0.6357916412612594, 'damping_trend': nan, 'initial_level':
110.89386078445895, 'initial_trend': 2.389331198805944, 'initial_seasons':
array([0.98867675, 1.03912176, 1.14217091, 1.08689584, 1.00612809,
       1.10442233, 1.20431631, 1.18998306, 1.08561792, 0.94580897,
       0.84005265, 0.96819086]), 'use_boxcox': False, 'lamda': None,
'remove_bias': False}
```

[121]:
```
y_hat_hwm = test.copy()
forecast_values = model_fit.forecast(len(test))
y_hat_hwm['hw_forecast'] = forecast_values
```

[122]:
```
plt.figure(figsize=(20,5))
plt.grid()
plt.plot( train['Passengers'], label='Train',color='blue')
plt.plot(test['Passengers'], label='Test',color='green')
plt.plot(y_hat_hwm['hw_forecast'], label='Holt Winters\'s mulitplicative␣
↪forecast',color='red')
plt.legend(loc='best')
plt.title('Holt Winters\' Mulitplicative Method')
plt.show()
```



[123]:
```
rmse = np.sqrt(mean_squared_error(test['Passengers'],␣
↪y_hat_hwm['hw_forecast'])).round(2)
```

```
mape = np.round(np.mean(np.abs(test['Passengers']-y_hat_hwm['hw_forecast'])/
 ↪test['Passengers'])*100,2)
```

[124]:

```
tempResults = pd.DataFrame({'Method':['Holt Winters\' multiplicative method'],␣
 ↪'RMSE': [rmse],'MAPE': [mape] })
results = pd.concat([results, tempResults])
results = results[['Method', 'RMSE', 'MAPE']]
results
```

[124]:

	Method	RMSE	MAPE
0	Simple exponential smoothing forecast	107.52	16.43
0	Holt's exponential smoothing method	80.90	11.32
0	Holt Winters' additive method	35.76	6.64
0	Holt Winters' multiplicative method	32.49	6.39

i recommend to use Holt Winters' multiplicative method for accurate prediction for time series as it has least RMSE among all.