simple-time-series-methods

December 27, 2023

[67]:
```
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
```

[68]:
```
data = pd.read_csv('/kaggle/input/air-passengers/AirPassengers.csv')
data.head()
```

[68]:

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

[69]:
```
data = data.rename(columns={"#Passengers": "Passengers"}, inplace=False)
data.head()
```

[69]:

	Month	Passengers
0	1949-01	112
1	1949-02	118
2	1949-03	132
3	1949-04	129
4	1949-05	121

[70]:
```
data.columns = ['Month','Passengers']
data['Month'] = pd.to_datetime(data['Month'], format='%Y-%m')
data = data.set_index('Month')
data.head()
```

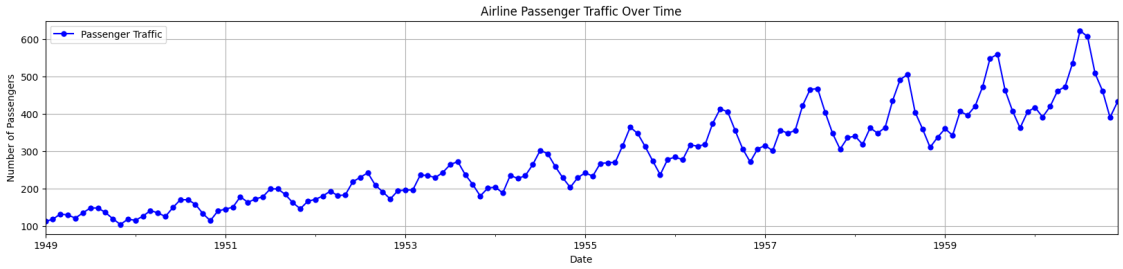
[70]:

Month	Passengers
1949-01-01	112
1949-02-01	118

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

0.1 Plot time series data

[71]:
```
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)
```

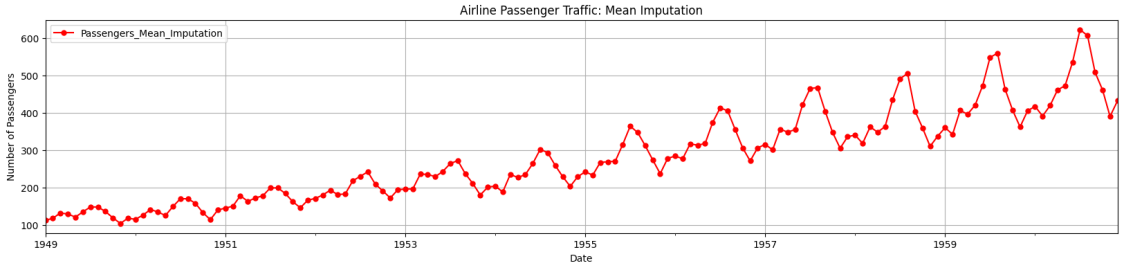


1 Missing value treatment

1.1 Mean imputation

[72]:
```
data['Passengers_Mean_Imputation'] = data['Passengers'].
 ↪fillna(data['Passengers'].mean())
```

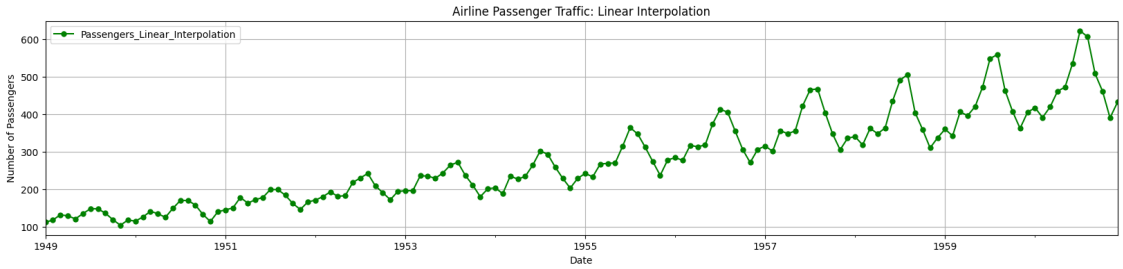
[73]:
```
data[['Passengers_Mean_Imputation']].plot(figsize=(20, 4), grid=True,␣
 ↪legend=True, color='red', linestyle='-', marker='o', markersize=5)
plt.title('Airline Passenger Traffic: Mean Imputation')
plt.xlabel('Date')
plt.ylabel('Number of Passengers')
plt.show(block=False)
```



1.2 Linear interpolation

[74]:
```
data['Passengers_Linear_Interpolation'] = data['Passengers'].
↪interpolate(method='linear')
```

[75]:
```
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)
```



[76]:
```
data.head()
```

[76]:

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

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

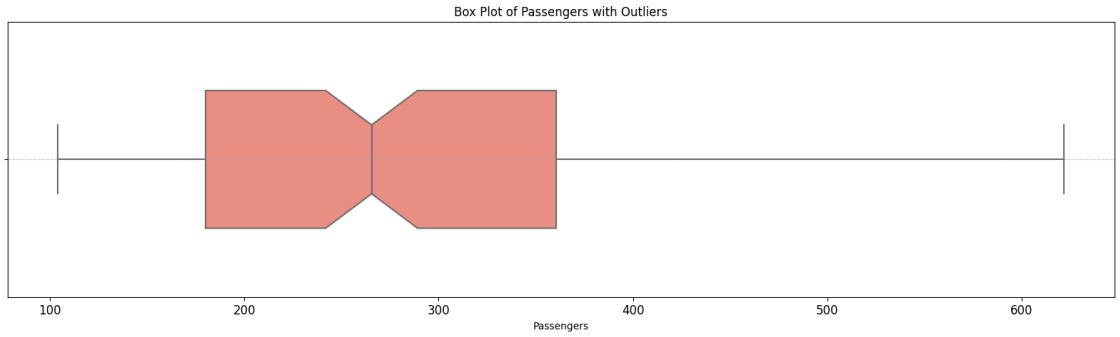
[77]:
```
data['Passengers'] = data['Passengers_Linear_Interpolation']
data.
  ↪drop(columns=['Passengers_Mean_Imputation','Passengers_Linear_Interpolation'],inplace=True)
data.head()
```

[77]:
```
            Passengers
Month
1949-01-01         112
1949-02-01         118
1949-03-01         132
1949-04-01         129
1949-05-01         121
```

2 Outlier detection

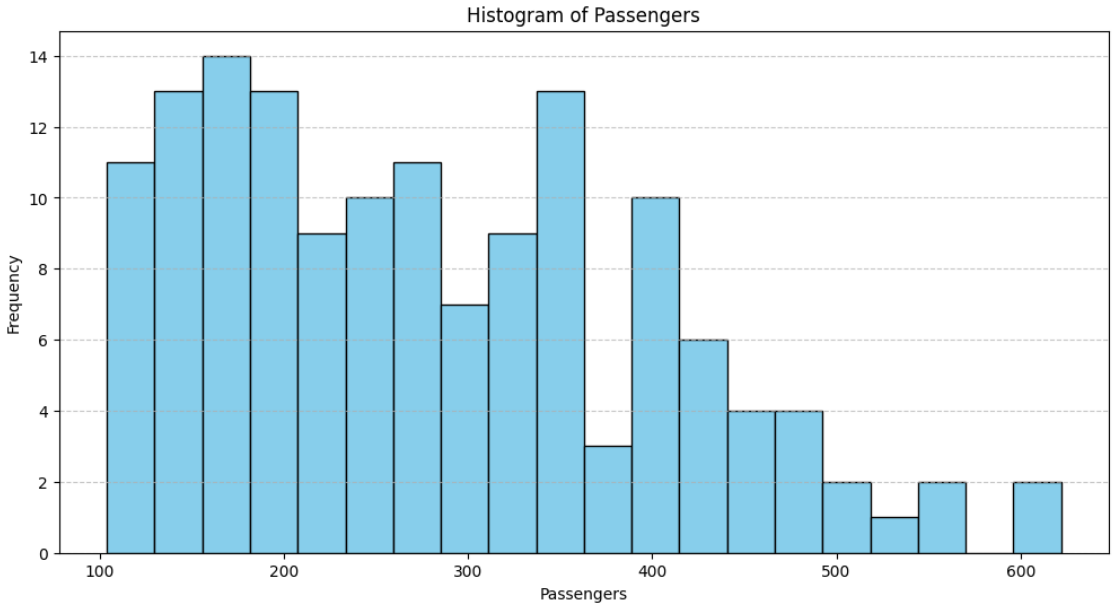
2.1 Box plot and interquartile range

[78]:
```
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()
```



2.2 Histogram plot

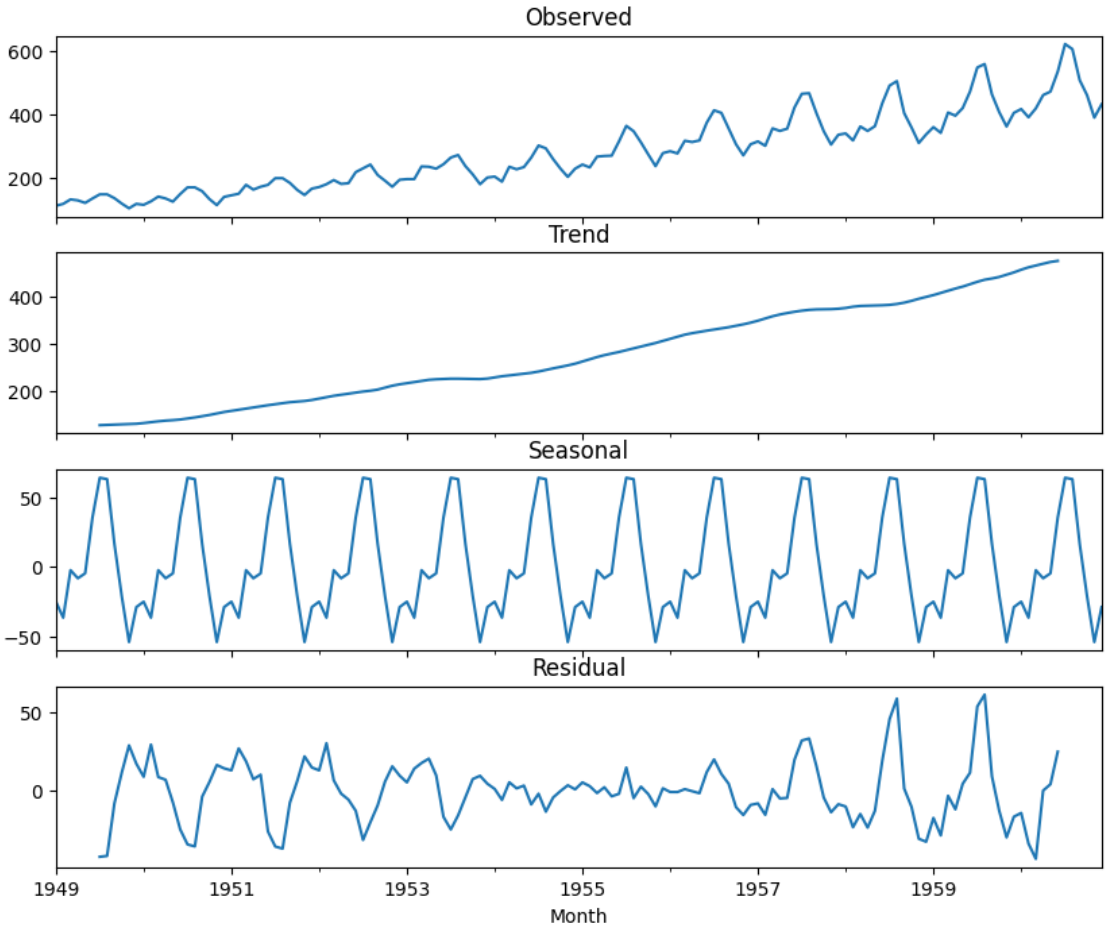
[79]:
```
plt.figure(figsize=(12, 6))
plt.hist(data['Passengers'], bins=20, color='skyblue', edgecolor='black')

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



3 Time series Decomposition

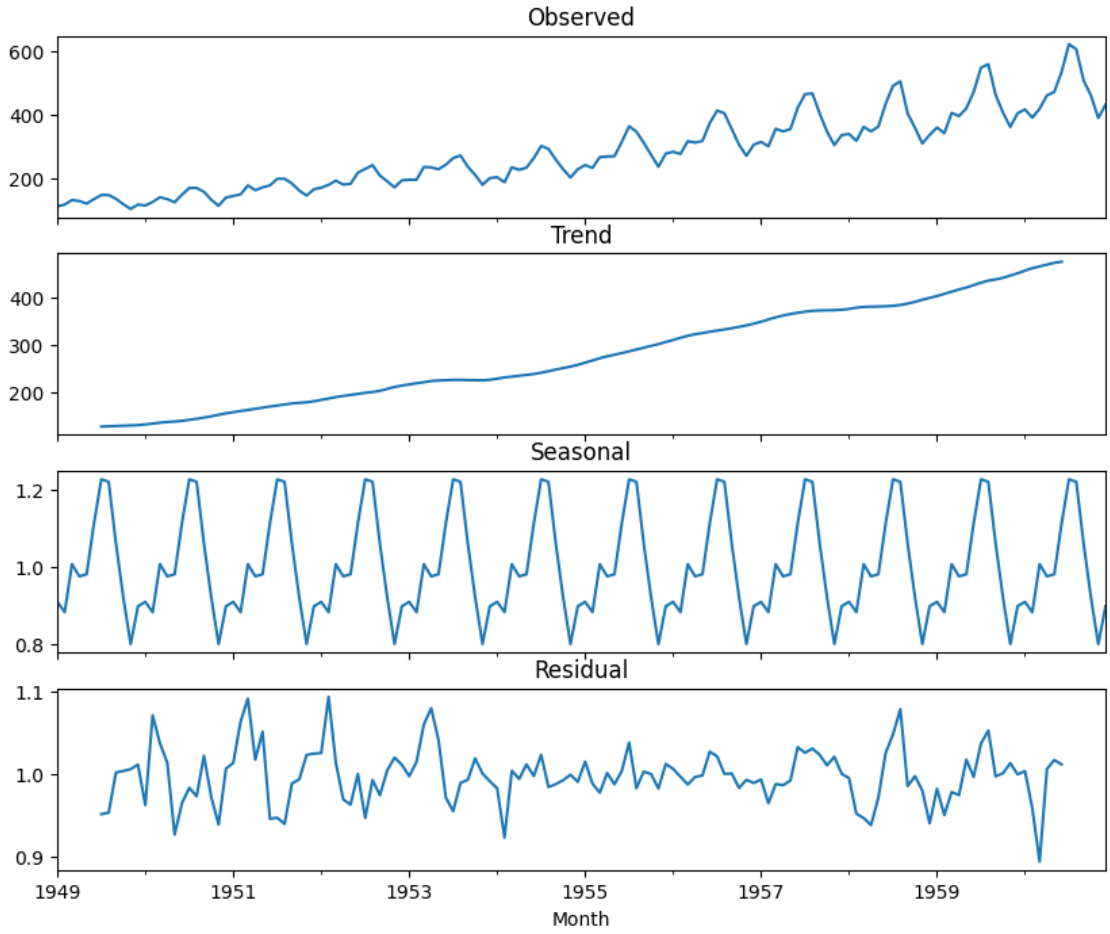
3.1 Additive seasonal decomposition

[80]:
```
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()
```



3.2 Multiplicative seasonal decomposition

[81]:
```
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()
```



4 Build and evaluate time series forecast

4.1 Split time series data into training and test set

[82]:
```
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
```

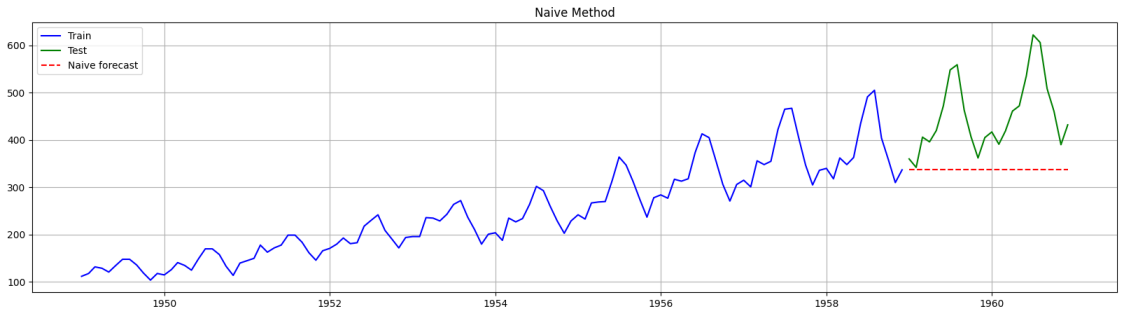
5 Simple time series methods

5.1 Naive method

[83]:
```
y_hat_naive = test.copy()
y_hat_naive['naive_forecast'] = train['Passengers'].iloc[-1]
```

5.1.1 Plot train, test and forecas

[84]:
```
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_naive['naive_forecast'], label='Naive forecast', linestyle='--',␣
 ↪color='red')
plt.legend(loc='best')
plt.title('Naive Method')
plt.show()
```



[85]:
```
# Calculate RMSE and MAPE
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)
```

[86]:
```
results = pd.DataFrame({'Method':['Naive method'], 'MAPE': [mape], 'RMSE':␣
↪[rmse]})
results = results[['Method', 'RMSE', 'MAPE']]
results
```

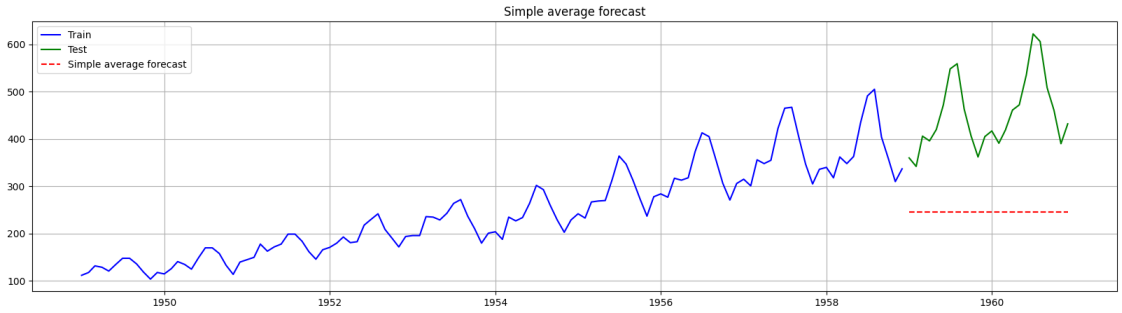
[86]:

	Method	RMSE	MAPE
0	Naive method	137.33	23.58

5.2 Simple average method

[87]:
```
y_hat_avg = test.copy()
y_hat_avg['avg_forecast'] = train['Passengers'].mean()
```

[88]:
```
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_avg['avg_forecast'], label='Simple average forecast',␣
↪linestyle='--', color='red')
plt.legend(loc='best')
plt.title('Simple average forecast')
plt.show()
```



[89]:
```
# Calculate RMSE and MAPE
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)
```

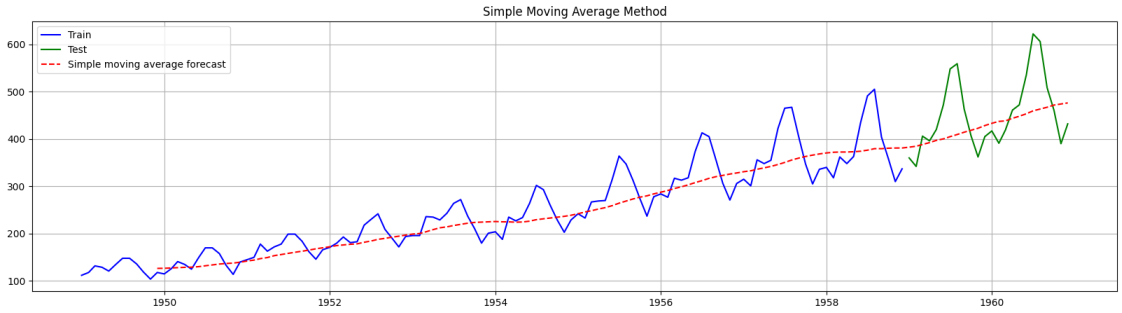
[90]:
```
tempResults = pd.DataFrame({'Method':['Simple average method'], 'RMSE':␣
↪[rmse],'MAPE': [mape] })
results = pd.concat([results, tempResults])
results = results[['Method', 'RMSE', 'MAPE']]
results
```

[90]:
```
                    Method    RMSE   MAPE
0            Naive method  137.33  23.58
0  Simple average method  219.44  44.23
```

5.3 Simple moving average method

[91]:
```
y_hat_sma = data.copy()
ma_window = 12
y_hat_sma['sma_forecast'] = data['Passengers'].rolling(ma_window).mean()
```

[92]:
```
#Plot train, test and forecast
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_sma['sma_forecast'], label='Simple moving average␣
 ↪forecast',linestyle='--', color='red')
plt.legend(loc='best')
plt.title('Simple Moving Average Method')
plt.show()
```



[93]:
```
#Calculate RMSE and MAPE
rmse = np.sqrt(mean_squared_error(test['Passengers'],␣
 ↪y_hat_sma['sma_forecast'][train_len:])).round(2)
mape = np.round(np.mean(np.
 ↪abs(test['Passengers']-y_hat_sma['sma_forecast'][train_len:])/
 ↪test['Passengers'])*100,2)
```

[94]:
```
tempResults = pd.DataFrame({'Method':['Simple moving average forecast'], 'RMSE':
 ↪ [rmse],'MAPE': [mape] })
results = pd.concat([results, tempResults])
results = results[['Method', 'RMSE', 'MAPE']]
results
```

[94]:

	Method	RMSE	MAPE
0	Naive method	137.33	23.58
0	Simple average method	219.44	44.23
0	Simple moving average forecast	72.40	11.23