Ex No:1	Implement program for Time series Data cleaning,
Date:	Loading, Handling & Preprocessing Techniques

## AIM:

To implement program for time series data cleaning, loading, handling and preprocessing techniques on Air passenger dataset.

#### ALGORITHM:

- 1. Start
- 2. Import the required libraries
- 3. Load and visualize the dataset
- Analyze trends and seasonality
- 5. Data preprocessing
- 6. Splitting the data and ARIMA model implementation.
- 7. Evaluate the model and find the model accuracy.

# Program

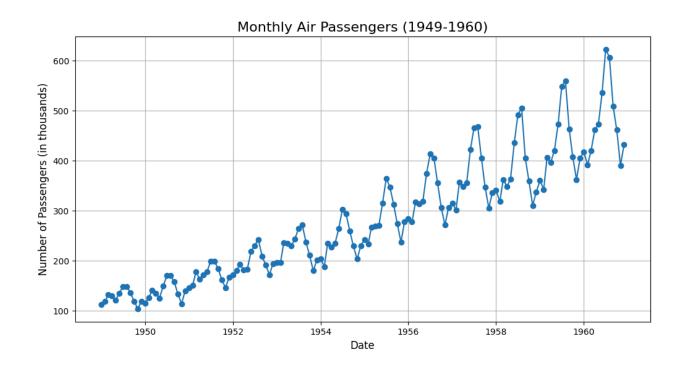
```
# Import required libraries
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
# Load the Air Passenger dataset
url = "/content/airline-passengers.csv"
data = pd.read csv(url, parse dates=['Month'], index col='Month')
# Display the first few rows of the dataset
print("Dataset Preview:")
print(data.head())
# Plot the time series data
plt.figure(figsize=(12, 6))
plt.plot(data.index, data['Passengers'], marker='o', linestyle='-')
plt.title('Monthly Air Passengers (1949-1960)', fontsize=16)
plt.xlabel('Date', fontsize=12)
plt.ylabel('Number of Passengers (in thousands)', fontsize=12)
plt.grid()
plt.show()
# Visualizing trends and seasonality using a rolling mean
```

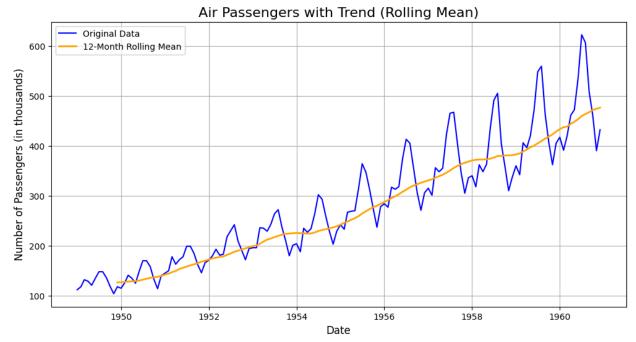
```
data['Passengers MA'] = data['Passengers'].rolling(window=12).mean()
12-month rolling mean
plt.figure(figsize=(12, 6))
plt.plot(data.index, data['Passengers'], label='Original Data',
color='blue')
plt.plot(data.index, data['Passengers_MA'], label='12-Month Rolling Mean',
color='orange', linewidth=2)
plt.title('Air Passengers with Trend (Rolling Mean)', fontsize=16)
plt.xlabel('Date', fontsize=12)
plt.ylabel('Number of Passengers (in thousands)', fontsize=12)
plt.legend()
plt.grid()
plt.show()
Dataset Preview:
```

# **Passengers**

## Month

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





```
# Import required libraries
from sklearn.preprocessing import MinMaxScaler
# Check for missing values
print("Checking for missing values:")
print(data.isnull().sum())
# Handle missing values (if any) - Filling with forward fill as an example
data['Passengers'] = data['Passengers'].fillna(method='ffill')
# Normalize the data using MinMaxScaler
scaler = MinMaxScaler(feature_range=(0, 1))
data['Passengers Normalized'] = scaler.fit transform(data[['Passengers']])
# Display the preprocessed data
print("\nPreprocessed Data (First 5 Rows):")
print(data.head())
# Visualize the normalized data
plt.figure(figsize=(12, 6))
plt.plot(data.index, data['Passengers Normalized'], color='green',
linestyle='-', marker='o')
plt.title('Normalized Air Passengers Data', fontsize=16)
plt.xlabel('Date', fontsize=12)
```

```
plt.ylabel('Normalized Passengers', fontsize=12)
plt.grid()
plt.show()
```

**Checking for missing values:** 

Passengers 0
Passengers\_MA 11

dtype: int64

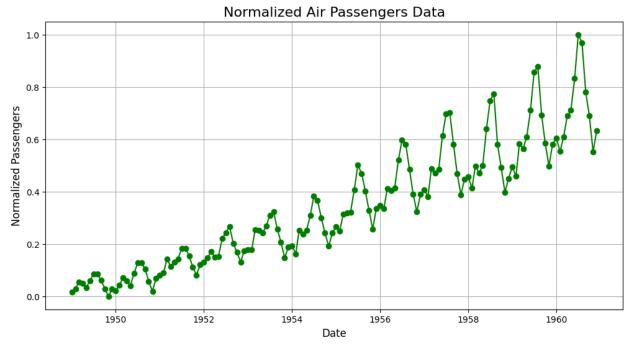
# **Preprocessed Data (First 5 Rows):**

Passengers Passengers\_MA Passengers\_Normalized

Month			
1949-01-01	112	NaN	0.015444
1949-02-01	118	NaN	0.027027
1949-03-01	132	NaN	0.054054
1949-04-01	129	NaN	0.048263
1949-05-01	121	NaN	0.032819

<ipython-input-2-c0f3d9447aaf>:9: FutureWarning: Series.fillna with 'method' is deprecated and will raise in a future version. Use obj.ffill() or obj.bfill() instead.

data['Passengers'] = data['Passengers'].fillna(method='ffill')



```
# Import required libraries

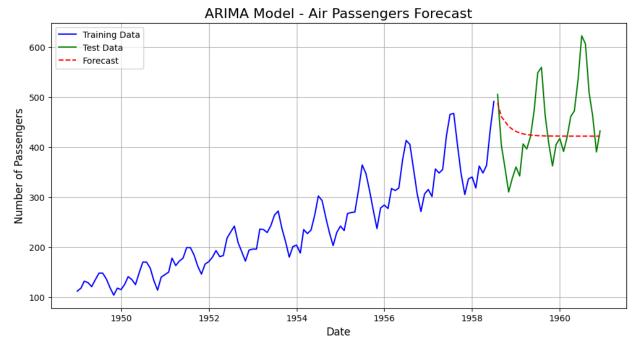
from statsmodels.tsa.arima.model import ARIMA

from sklearn.metrics import mean_squared_error

import numpy as np
```

```
train size = int(len(data) * 0.8) # 80% training, 20% testing
train, test = data['Passengers'][:train size],
data['Passengers'][train size:]
# Fit the ARIMA model (parameters can be tuned for better performance)
model = ARIMA(train, order=(2, 1, 2)) # ARIMA(p, d, q)
arima model = model.fit()
# Forecast on the test data
forecast = arima model.forecast(steps=len(test))
forecast index = test.index
# Evaluate model performance
mse = mean squared error(test, forecast)
print(f"Mean Squared Error (MSE): {mse}")
print(f"Root Mean Squared Error (RMSE): {np.sqrt(mse)}")
# Plot the results
plt.figure(figsize=(12, 6))
plt.plot(train.index, train, label='Training Data', color='blue')
plt.plot(test.index, test, label='Test Data', color='green')
plt.plot(forecast index, forecast, label='Forecast', color='red',
linestyle='--')
plt.title('ARIMA Model - Air Passengers Forecast', fontsize=16)
plt.xlabel('Date', fontsize=12)
plt.ylabel('Number of Passengers', fontsize=12)
plt.legend()
plt.grid()
plt.show()
/usr/local/lib/python3.11/dist-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)
/usr/local/lib/python3.11/dist-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)
/usr/local/lib/python3.11/dist-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)
```

# Split the dataset into training and testing sets



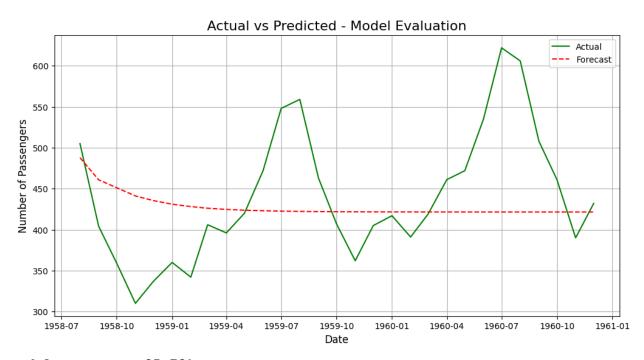
```
from sklearn.metrics import mean absolute error, mean squared error,
r2_score
import numpy as np
# Calculate performance metrics
mae = mean absolute error(test, forecast)
mse = mean squared error(test, forecast)
rmse = np.sqrt(mse)
r2 = r2 score(test, forecast)
# Print the metrics
print("Model Performance Metrics:")
print(f"Mean Absolute Error (MAE): {mae}")
print(f"Mean Squared Error (MSE): {mse}")
print(f"Root Mean Squared Error (RMSE): {rmse}")
print(f"R-squared (R2): {r2}")
# Visualize Actual vs Predicted
plt.figure(figsize=(12, 6))
plt.plot(test.index, test, label='Actual', color='green')
```

```
plt.plot(forecast_index, forecast, label='Forecast', color='red',
linestyle='--')
plt.title('Actual vs Predicted - Model Evaluation', fontsize=16)
plt.xlabel('Date', fontsize=12)
plt.ylabel('Number of Passengers', fontsize=12)
plt.legend()
plt.grid()
plt.show()
```

# **Model Performance Metrics:**

Mean Absolute Error (MAE): 63.545311250127014 Mean Squared Error (MSE): 6808.3970474928465 Root Mean Squared Error (RMSE): 82.51301138301066

R-squared (R2): -0.11530974198470823



Model Accuracy: 85.78%