ARIMA model for time series forecasting

Aim:
To write a python program for implementing ARIMA model for time series forecasting.

Algorithm:

1. **Import and Setup:** The code starts by importing necessary libraries (such as pandas, matplotlib, and statsmodels) and defines helper functions for plotting time series data.
2. **Data Loading**: It then loads the Air Passengers dataset from a GitHub URL, converts the date column to datetime format, and sets it as the index to prepare the data for time series analysis.
3. **Raw Data Visualization**: The raw time series data is visualized to provide an initial view of the passenger counts over time.
4. **Differencing for Stationarity**: Next, the code computes the first difference of the series to observe and help confirm if the data has achieved stationarity after differencing.
5. **ACF and PACF Plots**: Autocorrelation (ACF) and Partial Autocorrelation (PACF) plots are generated to inspect the data's correlation structure and to assist in determining the appropriate ARIMA model parameters.
6. **Model Building**: An ARIMA model (with predetermined parameters like (1, 1, 1)) is constructed and fitted to the dataset, and a summary of the model's performance and diagnostics is printed.
7. **Forecasting**: The model is then used to forecast the future values (in this case, the next 12 months), and these forecasts are plotted alongside the observed data complete with confidence intervals.
8. **Residual and Seasonal Analysis**: Finally, the residuals from the ARIMA model are analyzed through line plots and histograms, and a seasonal decomposition of the original time series is performed to further understand its underlying components.

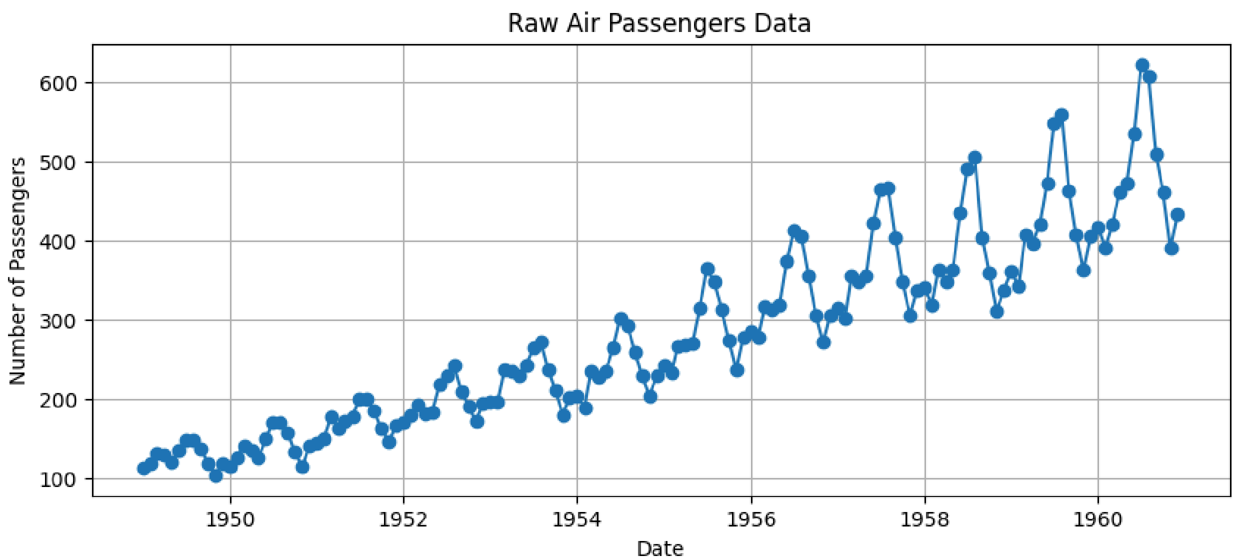
Program Code:

```
# Import necessary libraries
import warnings
warnings.filterwarnings("ignore")  # Suppress warning messages
```

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.seasonal import seasonal_decompose

# Function to plot time series with labels
def plot_timeseries(series, title, xlabel='Date', ylabel='Value', figsize=(10, 4)):
    plt.figure(figsize=figsize)
    plt.plot(series, marker='o')
    plt.title(title)
    plt.xlabel(xlabel)
    plt.ylabel(ylabel)
    plt.grid(True)
    plt.show()

# Load the Air Passengers dataset from GitHub
data_url = 'https://raw.githubusercontent.com/jbrownlee/Datasets/master/airline-passengers.csv'
df = pd.read_csv(data_url)

# Convert 'Month' column to datetime and set it as the index
df['Month'] = pd.to_datetime(df['Month'])
df.set_index('Month', inplace=True)
df.columns = ['Passengers']  # Rename the column for clarity

# Display the first few rows of the dataset
print("Dataset head:")
print(df.head())

# Visualization 1: Plot the raw time series data
plot_timeseries(df['Passengers'], title='Raw Air Passengers Data', ylabel='Number of
Passengers')
```

Dataset head:

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



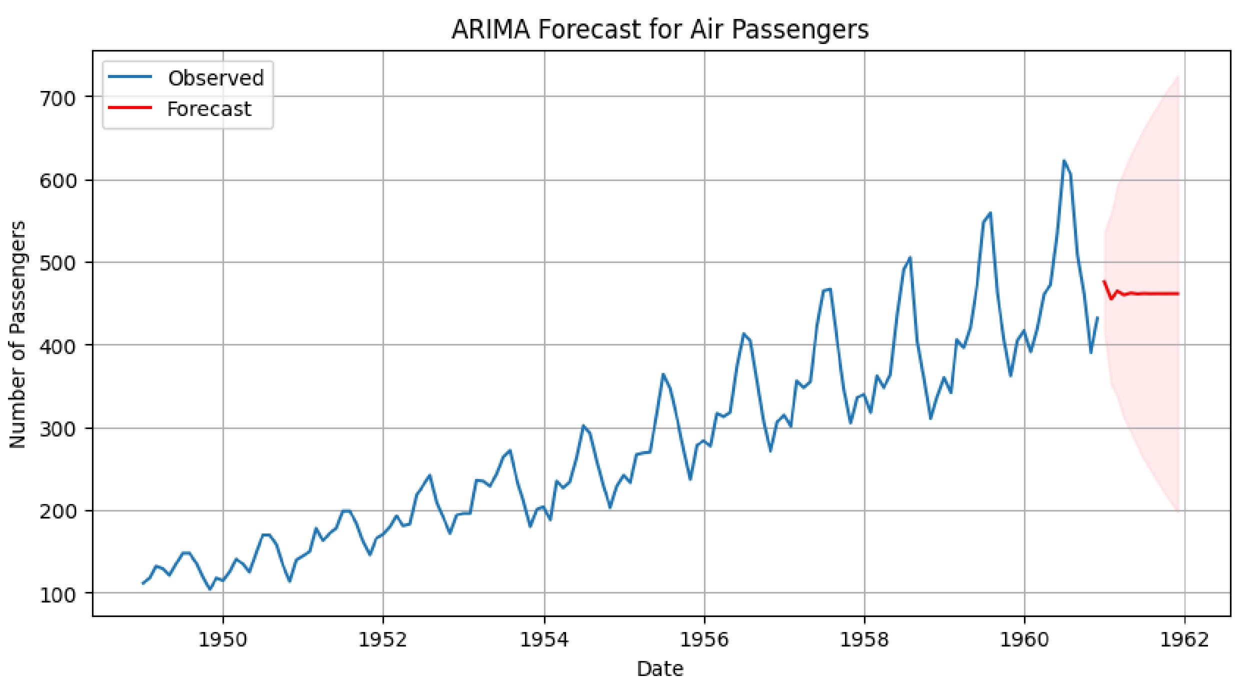

```
# Compute the first-order difference
diff_series = df['Passengers'].diff().dropna()
# Build and fit the ARIMA model
# Using ARIMA(1, 1, 1) as an example. In practice, use tests (ADF, ACF/PACF) to choose parameters.
arima_order = (1, 1, 1)
model = ARIMA(df['Passengers'], order=arima_order)
model_fit = model.fit()

# Print summary of the model for diagnostics
print("ARIMA Model Summary:")
```

```
print(model_fit.summary())
```

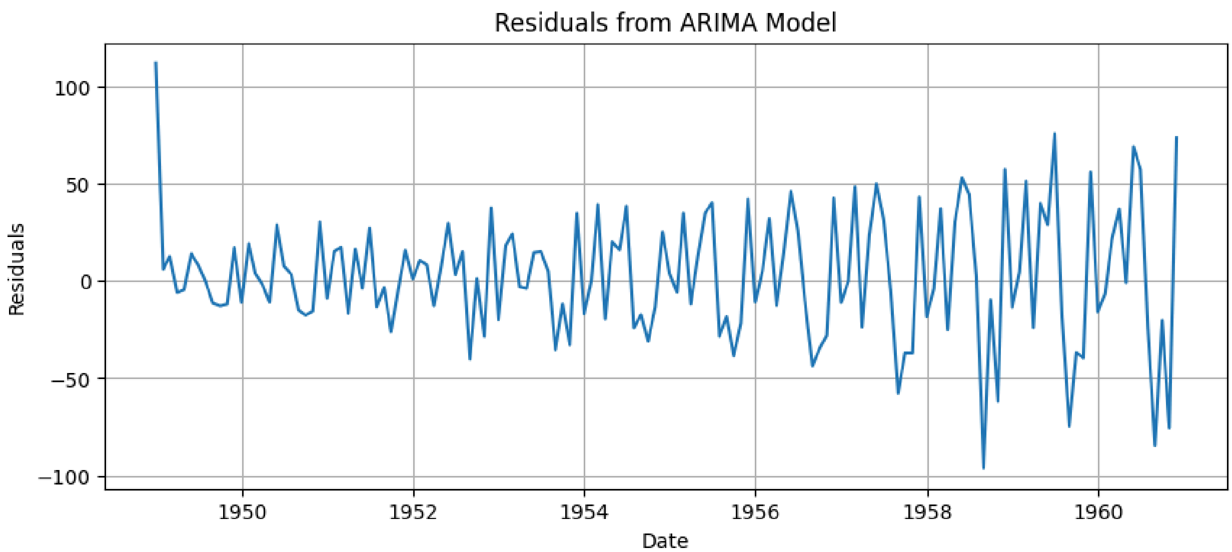
```
ARIMA Model Summary:
                               SARIMAX Results
==============================================================================
Dep. Variable:            Passengers   No. Observations:                  144
Model:                ARIMA(1, 1, 1)   Log Likelihood                -694.341
Date:               Tue, 15 Apr 2025   AIC                           1394.683
Time:                       08:34:26   BIC                           1403.571
Sample:                   01-01-1949   HQIC                          1398.294
                        - 12-01-1960
Covariance Type:                 opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.4742      0.123     -3.847      0.000      -0.716      -0.233
ma.L1          0.8635      0.078     11.051      0.000       0.710       1.017
sigma2       961.9270    107.433      8.954      0.000     751.362    1172.492
===================================================================================
Ljung-Box (L1) (Q):                   0.21   Jarque-Bera (JB):                 2.14
Prob(Q):                              0.65   Prob(JB):                         0.34
Heteroskedasticity (H):               7.00   Skew:                            -0.21
Prob(H) (two-sided):                  0.00   Kurtosis:                         3.43
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
```

```
# Forecast the next 12 months (1 year)
forecast_steps = 12
forecast_result = model_fit.get_forecast(steps=forecast_steps)
forecast_mean = forecast_result.predicted_mean
forecast_conf_int = forecast_result.conf_int()
```

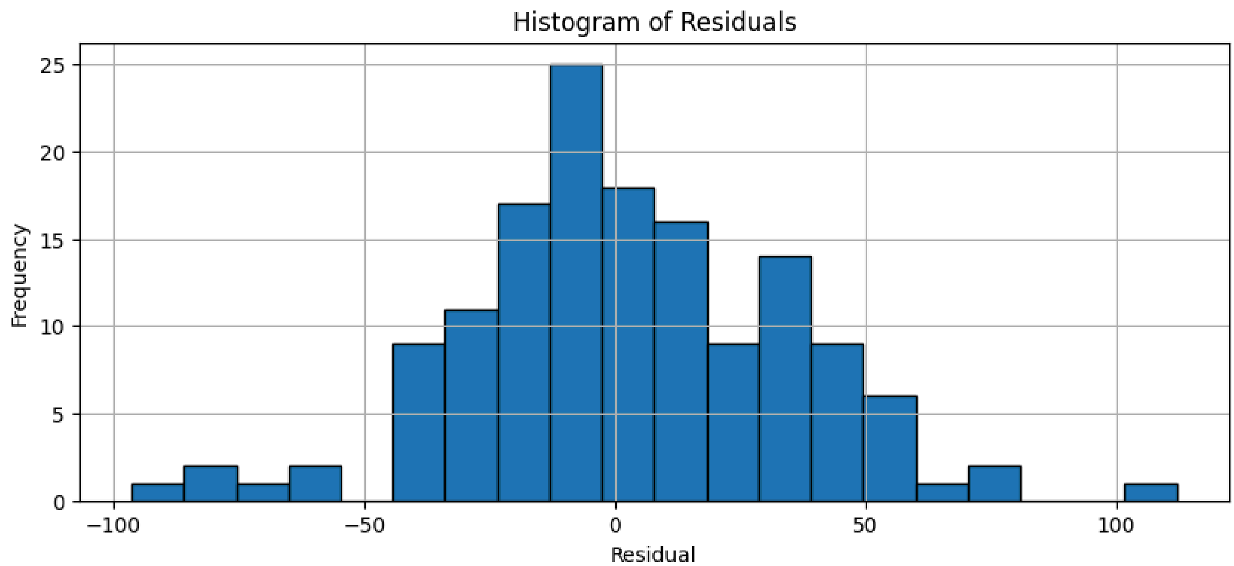
```
# Create an index for the forecasted period
forecast_index = pd.date_range(start=df.index[-1] + pd.DateOffset(months=1), periods=forecast_steps, freq='MS')
forecast_mean.index = forecast_index
forecast_conf_int.index = forecast_index

# Visualization 4: Plot observed data and forecasts together with confidence intervals
plt.figure(figsize=(10, 5))
plt.plot(df['Passengers'], label='Observed')
plt.plot(forecast_mean, label='Forecast', color='red')
plt.fill_between(forecast_conf_int.index,
                 forecast_conf_int.iloc[:, 0],
                 forecast_conf_int.iloc[:, 1],
                 color='pink', alpha=0.3)
plt.title('ARIMA Forecast for Air Passengers')
plt.xlabel('Date')
plt.ylabel('Number of Passengers')
plt.legend()
plt.grid(True)
plt.show()
```



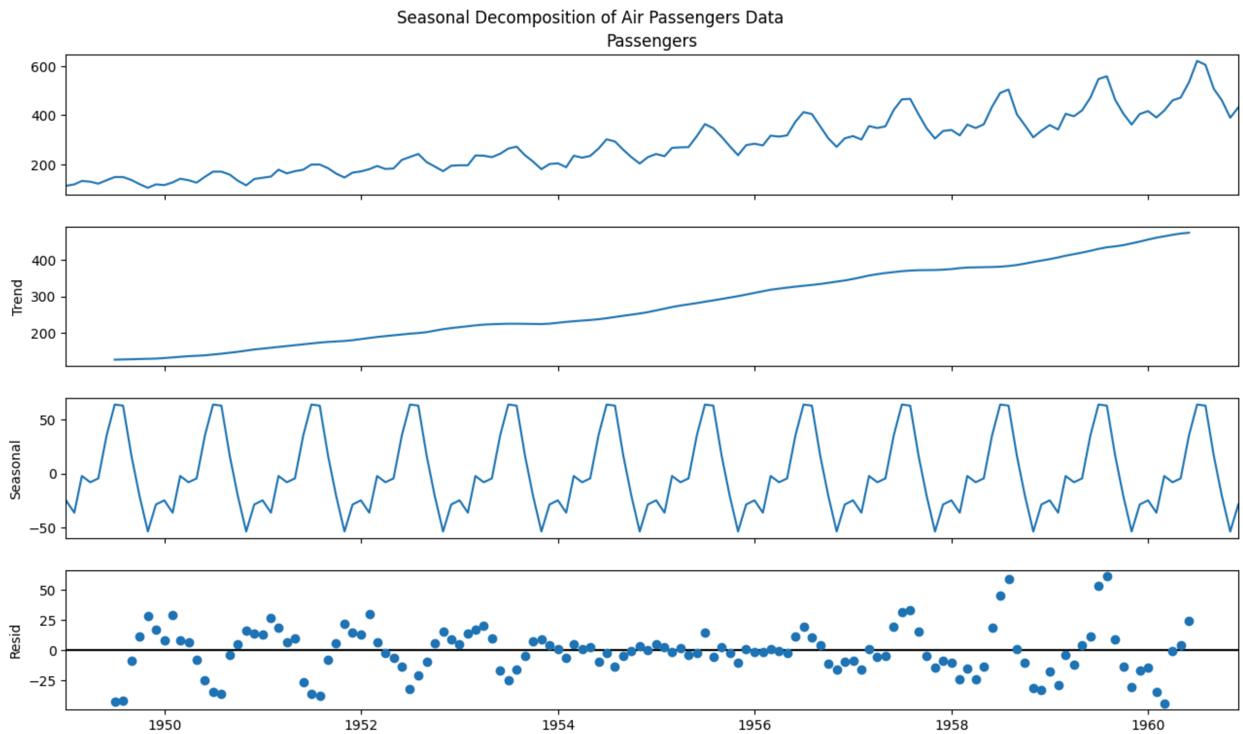
```
# Visualization 5: Residual Analysis
residuals = model_fit.resid

plt.figure(figsize=(10, 4))
plt.plot(residuals)
plt.title('Residuals from ARIMA Model')
plt.xlabel('Date')
plt.ylabel('Residuals')
plt.grid(True)
plt.show()
```




```
# Histogram of residuals
plt.figure(figsize=(10, 4))
plt.hist(residuals, bins=20, edgecolor='k')
plt.title('Histogram of Residuals')
plt.xlabel('Residual')
plt.ylabel('Frequency')
plt.grid(True)
plt.show()
```




```
# Visualization 6: Seasonal Decomposition Plot
# Decompose the time series using an additive model.
decomposition = seasonal_decompose(df['Passengers'], model='additive', period=12)
fig = decomposition.plot()
fig.set_size_inches(14, 8)
plt.suptitle('Seasonal Decomposition of Air Passengers Data')
plt.show()
```



RESULTS:

The program has been created and implemented successfully for creating a ARIMA model for time series forecasting.