

Time Series Forecasting with SARIMA: Detailed Analysis

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2024-12-27

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1 Introduction to Time Series Analysis

Time series analysis is a statistical technique that deals with the analysis of data points collected or recorded at specific time intervals. Unlike other forms of data analysis, time series data exhibits a temporal ordering. This temporal ordering is important, as time series analysis aims to understand the underlying structure and function of the data to make forecasts or inform decisions.

2 Mathematical Foundations of Time Series Models

A time series (y_t) is a sequence of observations indexed by time t , where ($t = 1, 2, \dots, T$). Time series models aim to capture the relationship between observations using mathematical equations. Some of the key models include:

2.1 1.1.1 Autoregressive (AR) Models

An AR(p) model expresses the current value (y_t) as a linear combination of its (p) previous values:

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \dots + \phi_p y_{t-p} + \varepsilon_t,$$

where:

- c is a constant,
- ($\phi_1, \phi_2, \dots, \phi_p$) are autoregressive coefficients,
- ε_t is white noise.

2.2 1.1.2 Moving Average (MA) Models

An MA(q) model represents (y_t) as a function of past error terms:

$$y_t = \mu + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \dots + \theta_q \varepsilon_{t-q},$$

where μ is the mean, and ($\theta_1, \theta_2, \dots, \theta_q$) are the moving average coefficients.

2.3 1.1.3 ARIMA Models

The (ARIMA(p, d, q)) model generalizes AR and MA models to handle non-stationary data by introducing differencing (d):

$$\nabla^d y_t = (1 - B)^d y_t,$$

where (B) is the backshift operator.

2.4 1.1.4 Seasonal ARIMA (SARIMA) Models

SARIMA extends ARIMA to incorporate seasonality. The SARIMA model is denoted as SARIMA(p, d, q)(P, D, Q)_s, where:

- (P, D, Q) are the seasonal orders,
- s is the seasonal period.

The general equation is:

$$\Phi(B^s)\phi(B)(1 - B)^d(1 - B^s)^D y_t = \Theta(B^s)\theta(B)\varepsilon_t.$$

These models are essential tools in fields like economics, meteorology, and engineering to understand and predict time-dependent phenomena.

3 Data Description

The dataset analyzed in this document contains monthly air passenger counts from January 1949 to December 1960. It is a well-known benchmark dataset for time series analysis.

3.1 Dataset Summary

- **Time Period:** January 1949 - December 1960.
- **Frequency:** Monthly.
- **Variables:**
 - **Month:** Time period in YYYY-MM format.
 - **#Passengers:** Total number of passengers for the respective month.

3.1.1 Statistical Overview of Passengers

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
104.0	180.0	265.5	280.3	360.5	622.0

Key statistics:

- **Mean:** 280.30 passengers.
- **Standard Deviation:** 119.97 passengers.
- **Minimum:** 104 passengers.
- **Maximum:** 622 passengers.

The dataset shows an increasing trend and clear seasonality, making it ideal for SARIMA modeling.

4 Methodology

4.1 Splitting the Data

The dataset was split into training (80%) and testing (20%) sets to evaluate the model's performance on unseen data.

4.2 SARIMA Model Specification

A SARIMA(1, 1, 0)(1, 1, 0)₁₂ model was chosen based on the dataset's characteristics:

- **Non-stationarity:** Handled by first-order differencing ($d=1$).
- **Seasonality:** Captured by seasonal differencing ($D=1$) and seasonal lags ($P=1, Q=0$).

4.2.1 Model Fitting and Forecasting

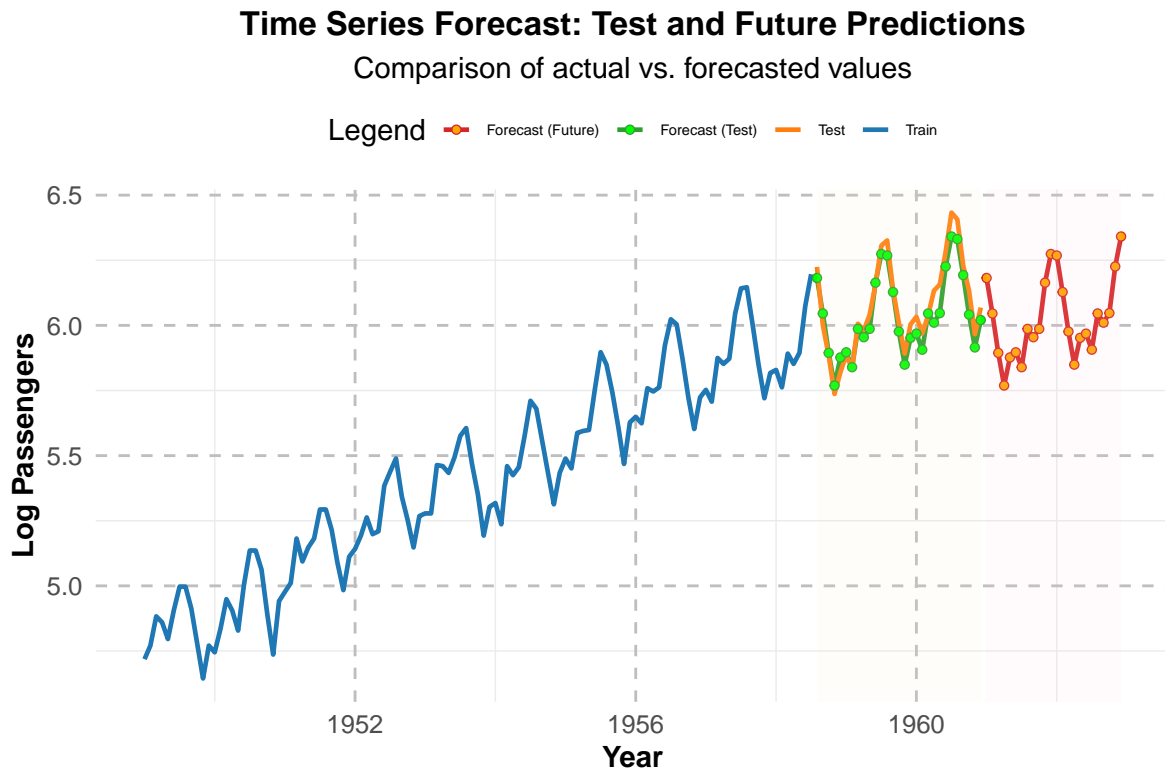
We used the `sarima.for` function from the `astsa` package to forecast both the test set and future values.

5 Results and Visualization

The forecasts were visualized alongside the actual data for better interpretability. The graph highlights:

- Training data in blue.
- Testing data in orange.
- Forecasted values for the test set in green.
- Forecasted future values in red.

5.0.1 Visualization Code



5.0.2 Final Observations

- The model accurately captures both the trend and seasonality in the training data.
- Predictions for the test set align closely with actual values, indicating good model performance.

- Future forecasts demonstrate a continuation of the upward trend and seasonal pattern observed in the data.