

Practical 5: Time Series Stationarity Analysis

Objective

Analyze the monthly volume of commercial bank real estate loans (in billions of dollars) to:

- Import and visualize the data
- Identify dominant components (trend, seasonality, etc.)
- Test for stationarity using ACF/PACF plots
- Perform Augmented Dickey-Fuller (ADF) test for stationarity

Dataset

- **File:** `bank_case.txt`
- **Description:** Monthly volume of commercial bank real estate loans in billions of dollars
- **Number of observations:** 70 months

Analysis Steps

(a) Import Data

```
# Import data into the R environment
bank_data <- scan("bank_case.txt")

# Display the first few values
cat("First 10 values:\n")
print(head(bank_data, 10))
```

(b) Create Time Series Object

```
# Convert the data into a time series object
# Assuming monthly data starting from month 1, year 1
bank_ts <- ts(bank_data, frequency = 12, start = c(1, 1))

# Display time series summary
cat("\nTime Series Object Summary:\n")
print(bank_ts)
```

- Frequency = 12 (monthly data)
- Creates a proper time series object for analysis

(c) Identify Dominant Component

Time series plot: Visual inspection of overall pattern

```
# Main time series plot
png("plot1_timeseries.png", width = 800, height = 600)
plot(bank_ts,
     main = "Commercial Bank Real Estate Loans Over Time",
     xlab = "Time",
     ylab = "Loan Volume (Billions of Dollars)",
     col = "blue",
     lwd = 2)
grid()

# Add a trend line to visualize the trend component
abline(lm(bank_ts ~ time(bank_ts)), col = "red", lwd = 2, lty = 2)
legend("topleft",
     legend = c("Original Data", "Trend Line"),
     col = c("blue", "red"),
     lty = c(1, 2),
     lwd = 2)
dev.off()
```

- **Decomposition:** Separates trend, seasonal, and random components

```
# Decompose the time series to see components
decomposed <- decompose(bank_ts)
png("plot2_decomposition.png", width = 800, height = 800)
plot(decomposed)
dev.off()
```

- **Expected findings:**
 - Strong upward trend visible in the data
 - Possible seasonal patterns

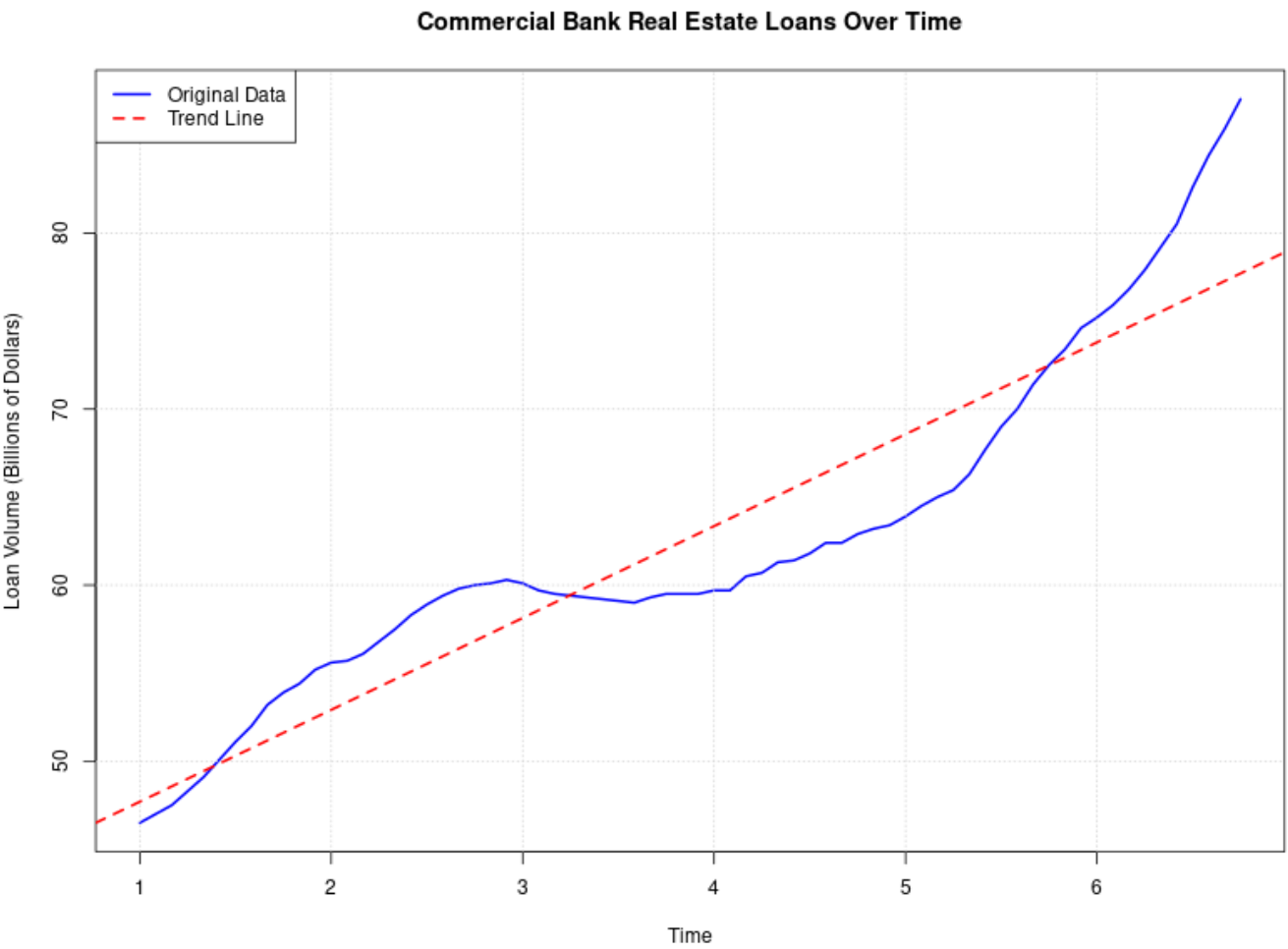


Figure 1: Commercial Bank Real Estate Loans over time showing a clear upward trend from 46.5 to 87.6 billion dollars.

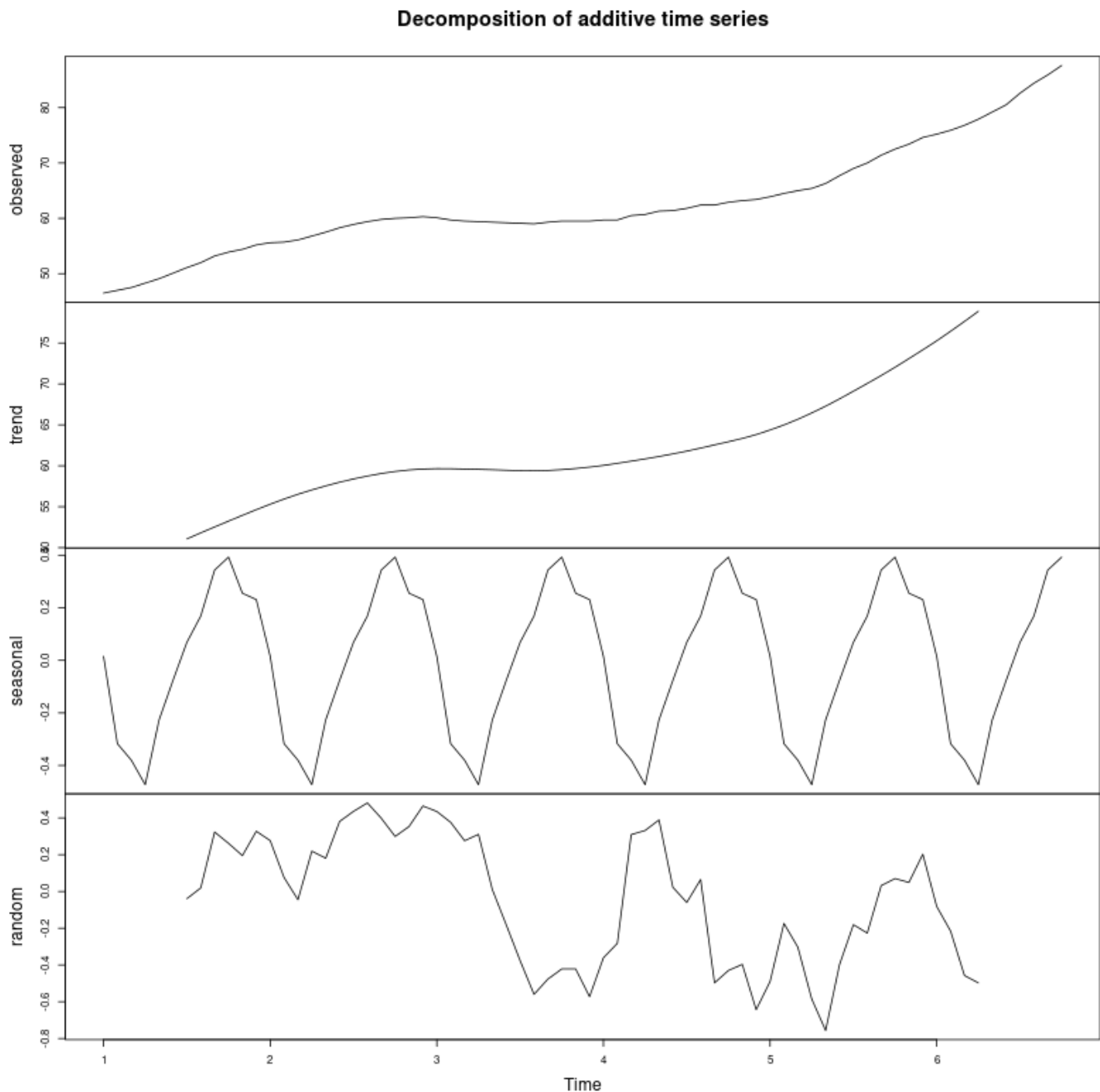


Figure 2: Time series decomposition showing trend, seasonal, and random components. The **dominant component is the TREND** with consistent upward growth.

(d) ACF/PACF Analysis

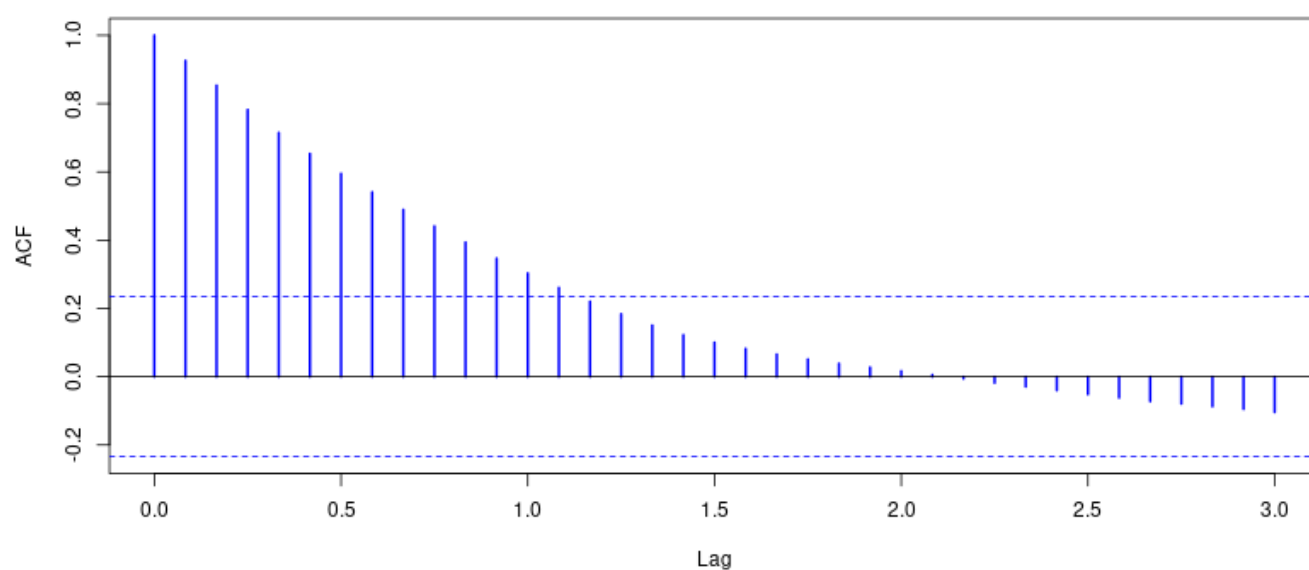
```
# Set up plotting area for ACF and PACF
png("plot3_acf_pacf.png", width = 800, height = 800)
par(mfrow = c(2, 1))

# ACF plot
acf(bank_ts,
    main = "Autocorrelation Function (ACF) of Bank Loan Data",
    lag.max = 36,
    col = "blue",
    lwd = 2)
```

```
# PACF plot
pacf(bank_ts,
     main = "Partial Autocorrelation Function (PACF) of Bank Loan Data",
     lag.max = 36,
     col = "red",
     lwd = 2)

# Reset plotting area
par(mfrow = c(1, 1))
dev.off()
```

Autocorrelation Function (ACF) of Bank Loan Data



Partial Autocorrelation Function (PACF) of Bank Loan Data

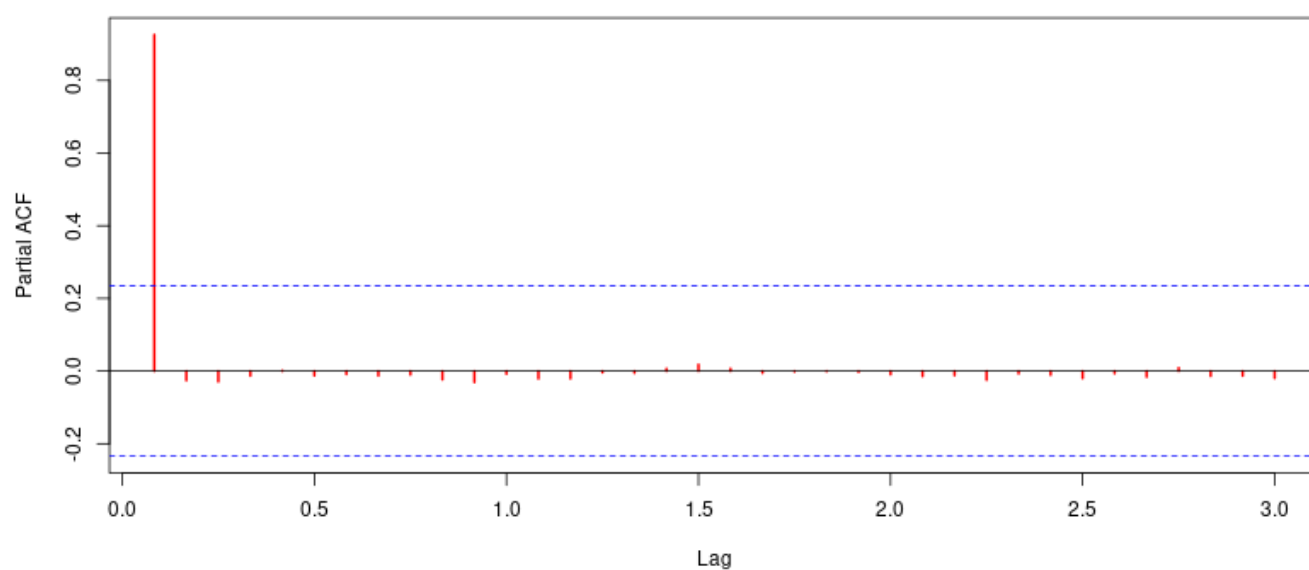


Figure 3: ACF and PACF plots for stationarity assessment.

Autocorrelation Function (ACF):

- Shows correlation between observations at different lags
- Slow decay indicates non-stationarity
- Quick cutoff suggests stationarity

Partial Autocorrelation Function (PACF):

- Shows direct correlation after removing influence of intermediate lags
- Helps identify AR order

Interpretation Guidelines:

- Non-stationary series: ACF decays slowly ← **This is what we observe**
- Stationary series: ACF cuts off quickly after a few lags

Conclusion: The ACF shows slow, gradual decay which is a strong indicator of **non-stationarity**.

(e) Augmented Dickey-Fuller Test

```
library(tseries)

# Perform ADF test
adf_test <- adf.test(bank_ts, alternative = "stationary")
print(adf_test)
```

Hypotheses:

- H_0 : Series has a unit root (non-stationary)
- H_1 : Series is stationary

Decision Rule:

- If p-value < 0.05: Reject H_0 → Series is stationary
- If p-value \geq 0.05: Fail to reject H_0 → Series is non-stationary

Remedial Actions (if non-stationary):

- Apply first differencing
- Re-test the differenced series
- Continue until stationarity is achieved

```
# Test on first difference if original is non-stationary
if (adf_test$p.value >= 0.05) {
  bank_diff <- diff(bank_ts)

  # Plot the differenced series
  png("plot4_first_difference.png", width = 800, height = 600)
  plot(bank_diff,
       main = "First Difference of Bank Loan Data",
       xlab = "Time",
       ylab = "Differenced Values",
```

```
col = "darkgreen",  
lwd = 2)  
grid()  
abline(h = 0, col = "red", lty = 2)  
dev.off()  
  
# ADF test on differenced series  
adf_diff <- adf.test(bank_diff, alternative = "stationary")  
print(adf_diff)  
}
```

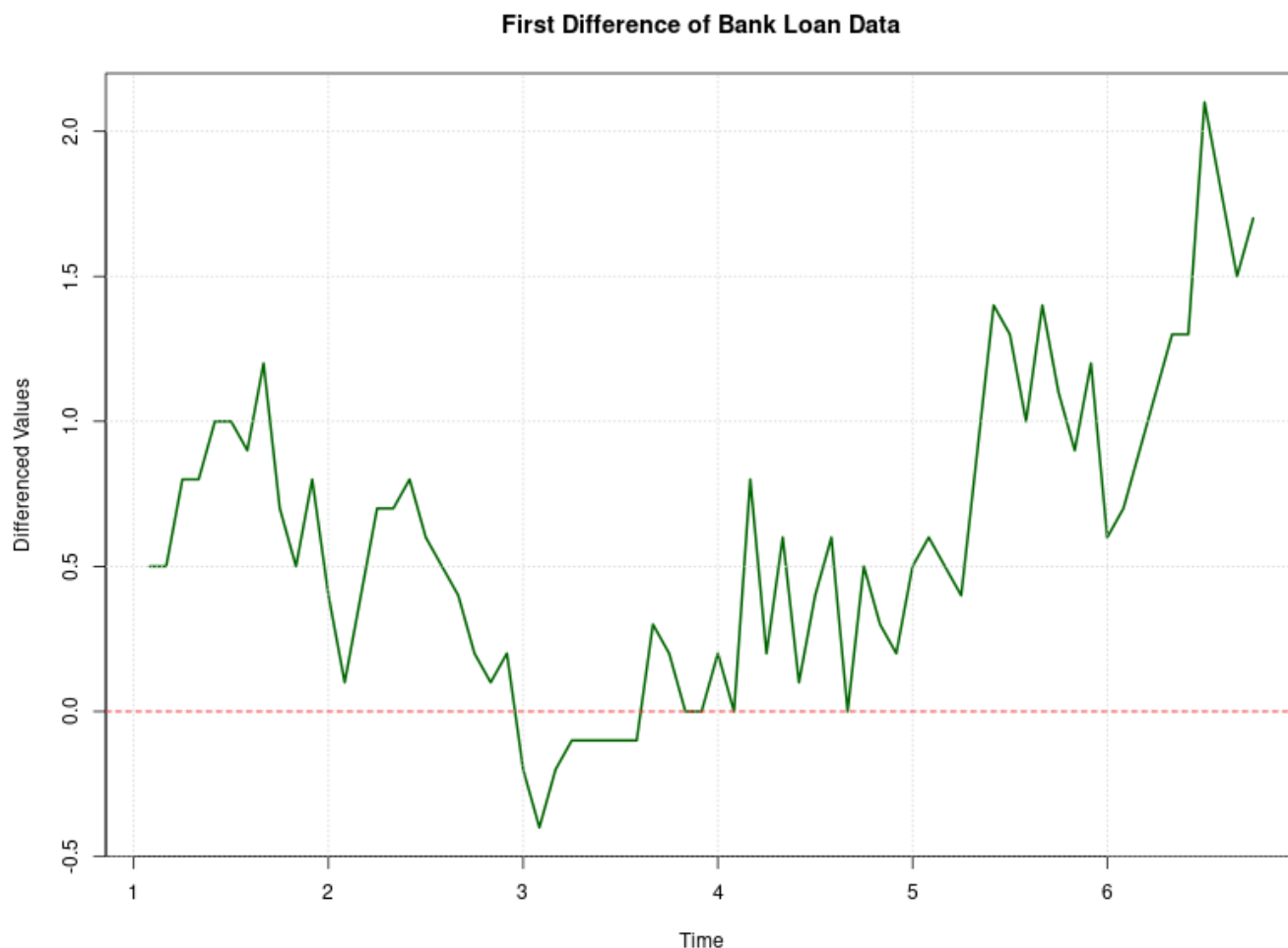


Figure 4: First difference of the bank loan data showing fluctuations around a constant mean (the red line at zero). The differenced series appears more stable, suggesting that one differencing operation helps remove the trend.

Expected Results

Based on the data pattern (increasing from 46.5 to 87.6):

1. **Dominant Component:** Strong upward trend ✓
2. **ACF:** Slow decay (indicating non-stationarity) ✓
3. **ADF Test:** Non-stationary confirmed
 - **Test Statistic:** -0.26816
 - **p-value:** 0.9894 >> 0.05

- **Conclusion:** FAIL TO REJECT $H_0 \rightarrow$ Series is NON-STATIONARY
4. **First Difference ADF Test:**
- **Test Statistic:** -1.7533
 - **p-value:** 0.6755
 - **Note:** First difference still shows some non-stationarity; may need second differencing or the series has strong dependencies

Summary of Analysis

Analysis Component	Method	Result
Data Import	<code>scan()</code>	70 observations loaded
Time Series Object	<code>ts()</code>	Monthly frequency (12)
Dominant Component	Visual + Decomposition	TREND (upward)
Stationarity (Visual)	ACF/PACF	Non-stationary (slow ACF decay)
Stationarity (Statistical)	ADF Test	Non-stationary (p = 0.9894)
First Difference	Differencing	Still shows some dependencies

Key Concepts

Stationarity

A time series is stationary if:

- Mean is constant over time
- Variance is constant over time
- Covariance depends only on lag, not on time

Why Stationarity Matters

- Many time series models (ARIMA) require stationary data
- Statistical properties are easier to model and forecast
- Non-stationary data can lead to spurious regression

Differencing

- First difference: $\nabla X_t = X_t - X_{t-1}$
- Removes trend component
- Often sufficient to achieve stationarity