MATH1318 Time Series Analysis / MATH2204 Time Series and Forecasting

Final Project Report

Declaration of contributions:

No	Name of Team Member	Contribution to the project
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4		
5		
6		
	Sum:	must be 1

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Time Series Analysis and Forecasting of Tourist Arrivals in Thailand

Introduction

Thailand's economy, like that of many other nations, benefits greatly on the tourism industry. Effective planning and decision-making in tourism management depend on an understanding of and ability to estimate visitor arrivals. The study and forecasting of tourist arrivals in Thailand using different time series approaches is the main emphasis of this paper.

The methodology performed in this study includes monthly data on visitor arrivals from **2010 to 2016**. The main goal is to accurately estimate future visitor arrivals by modeling the seasonal patterns and trends in the data. Preprocessing the data, time series decomposition, model fitting, and residual diagnostics are some of the procedures involved in this process.

To guarantee that the dataset is appropriate for time series analysis, the analysis starts with loading it and carrying out the required data transformations. To find the underlying patterns in the data, a variety of exploratory **data analysis (EDA)** approaches are used, including **visualizing the time series**, the **autocorrelation function (ACF)**, and the **partial autocorrelation function (PACF)**.

Both standard decomposition methods and **STL (Seasonal and Trend decomposition using Loess)** are used to handle seasonality and trend components. The data are then fitted to **several Seasonal Autoregressive Integrated Moving Average (SARIMA) models**. In order to make sure the model assumptions are met, residual diagnostics are used in conjunction with the **Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC)** values to determine which model is the best.

Lastly, the selected **SARIMA model** is utilized to project visitor arrivals for the ensuing **120 months (10 years)**, offering stakeholders and tourism authorities insightful information.

By using a holistic approach, projections are guaranteed to be strong and trustworthy, which helps the tourist industry with resource allocation and strategic planning.

Data Preprocessing

Loading libraries

First, we load the necessary libraries for time series analysis, data manipulation, and visualization.

```
library(TSA)
```

```
## Warning: package 'TSA' was built under R version 4.3.3
```

```
##
## Attaching package: 'TSA'

## The following objects are masked from 'package:stats':
##
##     acf, arima

## The following object is masked from 'package:utils':
##
##     tar

library(tseries)

## Warning: package 'tseries' was built under R version 4.3.3

## Registered S3 method overwritten by 'quantmod':
##   method            from
##   as.zoo.data.frame zoo

library(dplyr)

##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union

library(ggplot2)
library(gridExtra)

## Warning: package 'gridExtra' was built under R version 4.3.3

##
## Attaching package: 'gridExtra'

## The following object is masked from 'package:dplyr':
##
##     combine

library(astsa)

## Warning: package 'astsa' was built under R version 4.3.2
```

Reading and Preparing the Dataset

We read the dataset from a CSV file and set appropriate column names. The first row is used as the header, and numeric columns are converted to the appropriate data type.

```r
#reading the dataset
dataset <- read.csv("thaitourism2.csv", header = FALSE)
colnames(dataset) <- as.character(unlist(dataset[1, ]))
dataset <- dataset[-1, ]
rownames(dataset) <- NULL

# Check the data type of each column
column_classes <- sapply(dataset, class)
print(column_classes)
```

```
##      region nationality        year       month    tourists
## "character" "character" "character" "character" "character"
```

```r
# Convert numeric columns
numeric_column <- c("year","month","tourists")
dataset <- mutate_at(dataset, vars(numeric_column), as.numeric)
```

```
## Warning: Using an external vector in selections was deprecated in
tidyselect 1.1.0.
## ℹ Please use `all_of()` or `any_of()` instead.
##   # Was:
##   data %>% select(numeric_column)
##
##   # Now:
##   data %>% select(all_of(numeric_column))
##
## See <https://tidyselect.r-lib.org/reference/faq-external-vector.html>.
## This warning is displayed once every 8 hours.
## Call `lifecycle::last_lifecycle_warnings()` to see where this warning was
## generated.
```

```r
# Verify the conversion
column_classes <- sapply(dataset, class)
print(column_classes)
```

```
##      region nationality        year       month    tourists
## "character" "character"   "numeric"   "numeric"   "numeric"
```

Time Series Object Creation

We create a time series object from the tourist data, specifying the start year, end year, and frequency (monthly data).

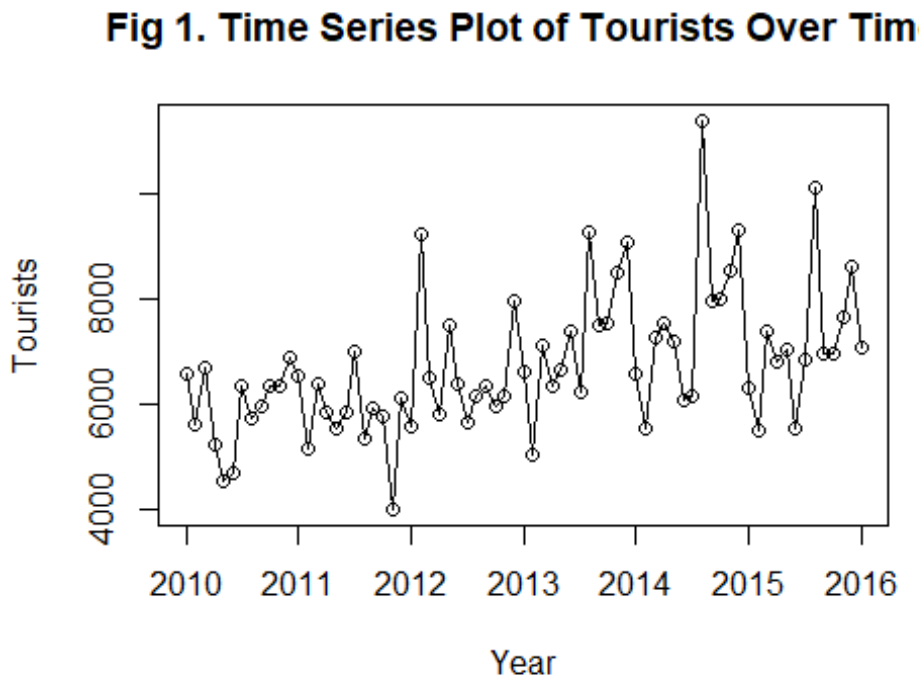
```r
# Create a ts object
tourists_ts <- ts(dataset$tourists, start = c(2010), end=c(2016), frequency =
12)
```

Exploratory Data Analysis (EDA)

Plotting the Time Series

We visualize the time series data to identify any visible trends or seasonal patterns.

```
plot(tourists_ts, type = "o", xlab = "Year", ylab = "Tourists", main = "Fig
1. Time Series Plot of Tourists Over Time")
```



Decomposition of Additive Time Series:

- **Plot Overview:** This plot illustrates the monthly tourist arrivals in Thailand from January 2010 to December 2016.
- The x-axis:represents the timeline in years, while the y-axis indicates the number of tourists.
- **Data Points:** Each point on the plot represents the number of tourists for a specific month, and the connected line helps visualize trends and patterns over time.

Findings:

Trend Analysis:

- **Overall Increase:** There is a clear upward trend over the years, suggesting a general increase in the number of tourists visiting Thailand from 2010 to 2016.
- **Significant Peaks:** Notable peaks are observed around certain periods, for instance, in 2014 and 2015, indicating unusually high tourist arrivals during those times.

Seasonal Patterns:

- **Regular Fluctuations:** The plot shows consistent seasonal fluctuations with regular peaks and troughs each year. These patterns likely correspond to high and low tourist seasons.
- **Annual Cycles:** Peaks generally occur around the same months each year, possibly corresponding to holiday seasons, festivals, or favorable weather conditions. Similarly, troughs occur during off-peak seasons when fewer tourists visit.

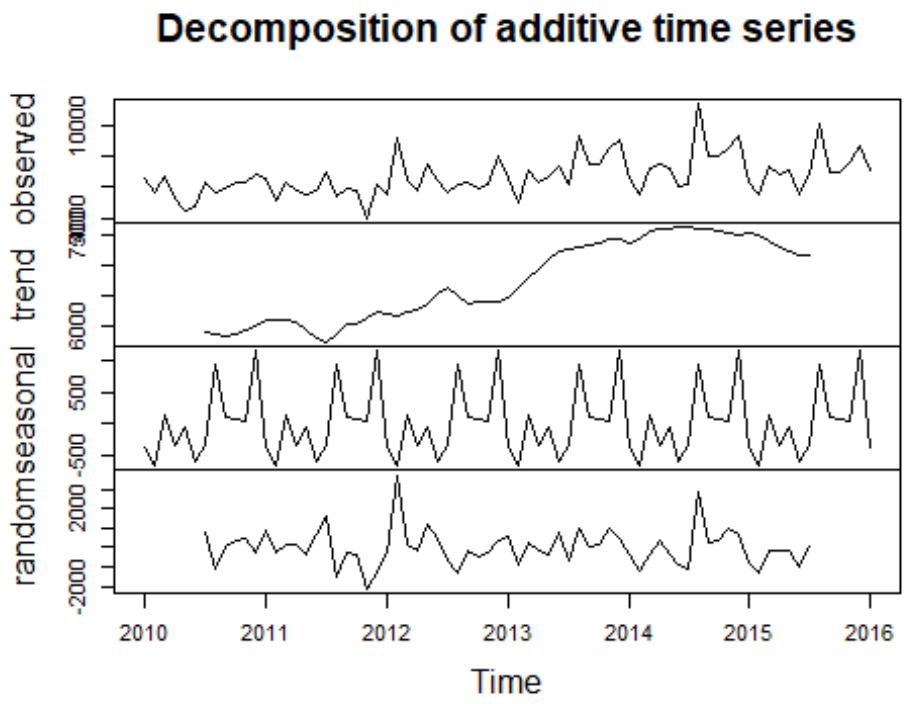
Outliers and Anomalies:

- **Sudden Drops:** There are instances of sharp drops, such as in early 2012, which could be attributed to events like political instability, natural disasters, or economic downturns.

Decomposition of Time Series

We use STL and classical decomposition methods to separate the seasonal, trend, and irregular components of the time series.

```
# Using classical decomposition
decomposed_classical <- decompose(tourists_ts)
plot(decomposed_classical)
```



Classical Decomposition

Observed Data:

- This shows the original time series data of monthly tourist arrivals from 2010 to 2016 and exhibits the overall trend and seasonal fluctuations in tourist arrivals.

Seasonal Component:

- Here the seasonal pattern is evident with regular peaks and troughs, indicating higher tourist arrivals during certain months each year.

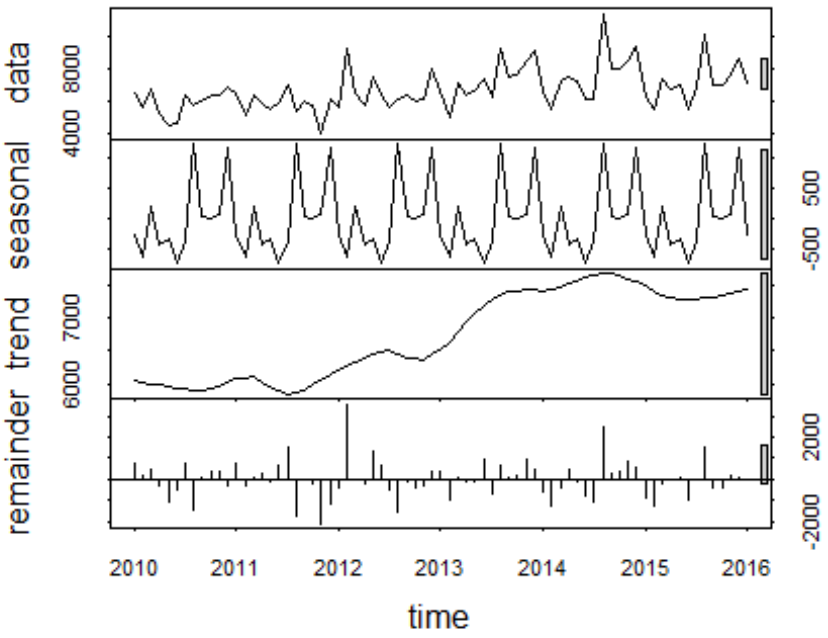
Trend Component:

- There is a noticeable upward trend, indicating a general increase in tourist arrivals over the years. Some fluctuations in the trend are also observed, reflecting periods of faster and slower growth.

Remainder Component:

- The remainder appears to be random noise with no discernible pattern, suggesting that the model has effectively captured the main structures of the data.

```
# Using STL decomposition
decomposed_ts <- stl(tourists_ts, s.window="periodic")
plot(decomposed_ts)
```



STL Decomposition

Observed Data:

- It shows the overall trend and seasonal variations in tourist arrivals.

Trend Component:

- The trend is smoother and captures the long-term increase in tourist arrivals, along with some fluctuations over the period.

Seasonal Component:

- The seasonal pattern is clear, with regular peaks and troughs, indicating periods of higher and lower tourist arrivals.

Remainder Component:

- The residuals appear to be random and do not exhibit any clear pattern, indicating that the STL decomposition has effectively captured the main components of the time series.

```
library(forecast)
```

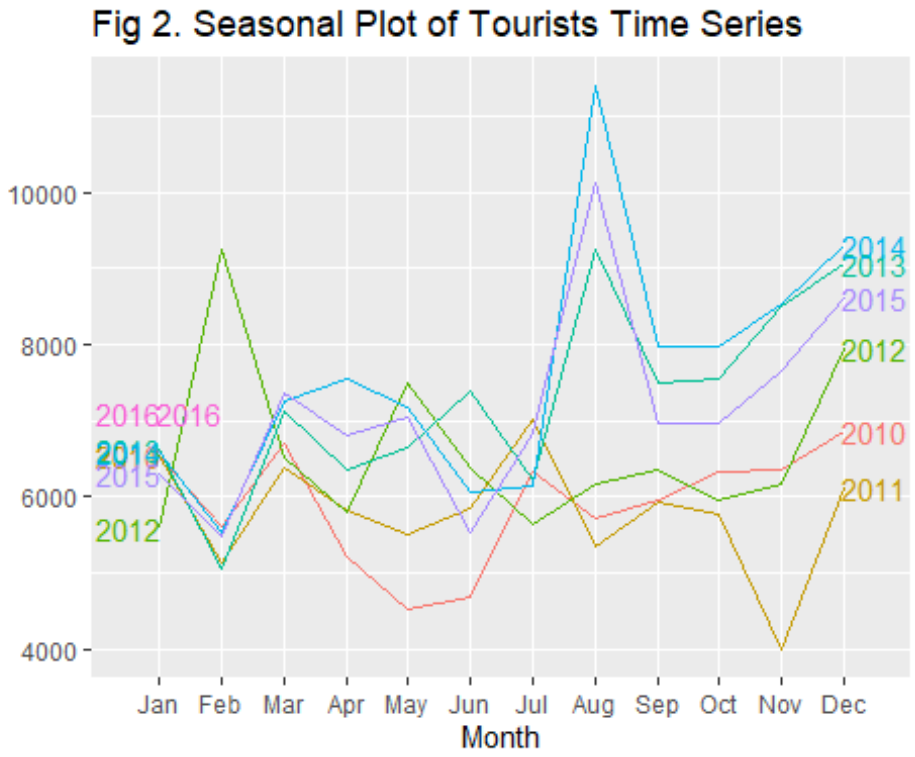
```
## Warning: package 'forecast' was built under R version 4.3.3
```

```
## Registered S3 methods overwritten by 'forecast':
##   method       from
##   fitted.Arima TSA
##   plot.Arima   TSA
```

```
##
## Attaching package: 'forecast'
```

```
## The following object is masked from 'package:astsa':
##
##     gas
```

```
ggseasonplot(tourists_ts, main="Fig 2. Seasonal Plot of Tourists Time
Series", year.labels=TRUE, year.labels.left=TRUE)
```



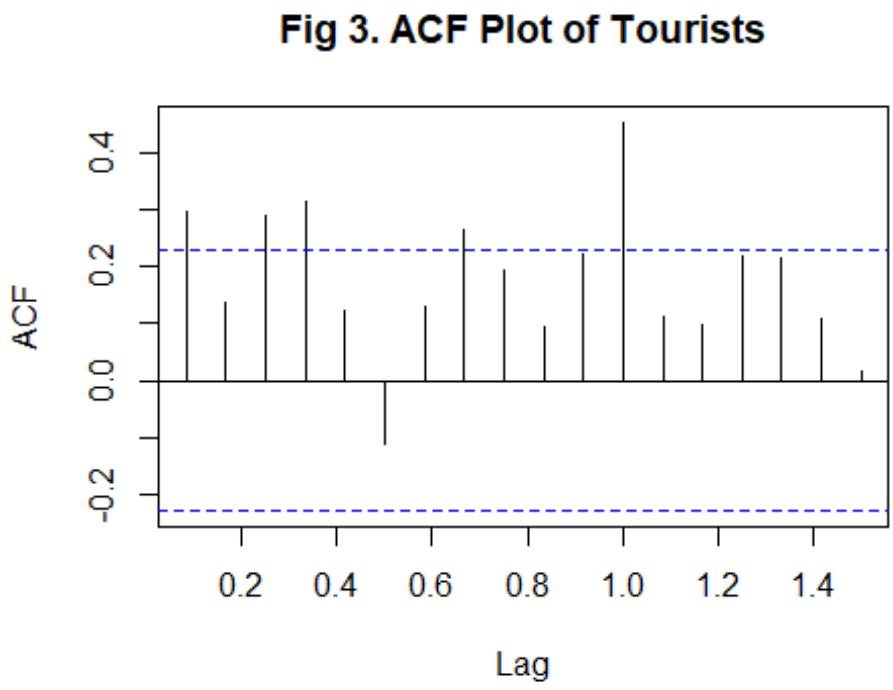
The seasonal plot of tourists

- time series illustrates the monthly tourist arrivals in **Thailand from 2010 to 2016**, highlighting strong seasonal patterns and an overall increasing trend. Each year shows similar peaks in tourist arrivals during the winter months, particularly in **December** and **August**, indicating peak tourist seasons likely due to holidays and favorable weather. Conversely, the lowest arrivals are observed around May, suggesting off-peak periods. Notably, years like **2014 and 2013** exhibit the highest peaks, while earlier years such as 2010 and 2011 show lower overall arrivals, reflecting a gradual increase in tourism over time. This consistent seasonality aids in predicting future trends, allowing for better tourism planning, resource allocation, and targeted marketing strategies to manage and balance tourist inflows effectively throughout the year.

Autocorrelation and Partial Autocorrelation Analysis

We examine the autocorrelation function (ACF) and partial autocorrelation function (PACF) to identify the presence of seasonality and the order of ARIMA components.

```
acf(tourists_ts, main = "Fig 3. ACF Plot of Tourists")
```



ACF plots of Tourists

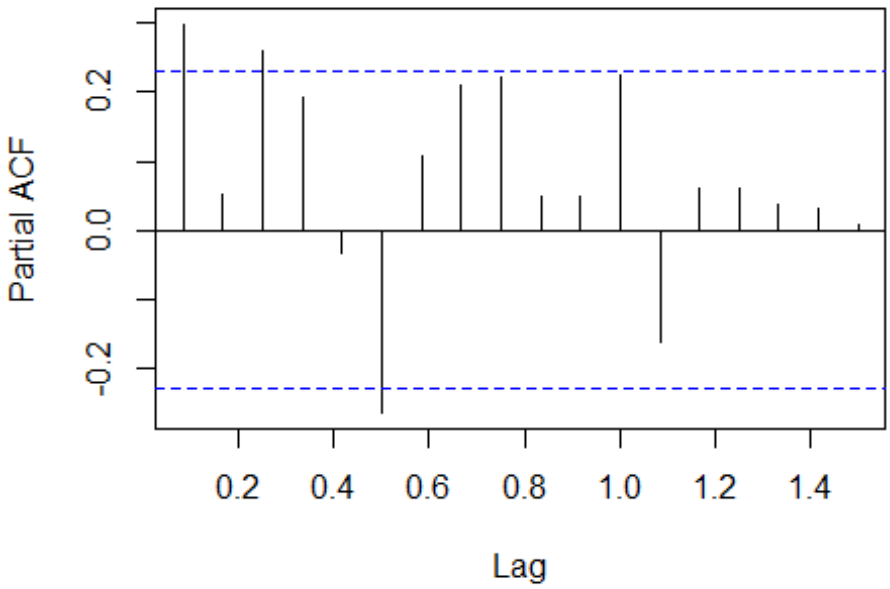
- The **ACF plot (Autocorrelation Function)** shows the autocorrelations of the time series data at different lags. The x-axis represents the lag (number of months back), and the y-axis represents the correlation coefficient, which ranges from -1 to 1. The horizontal dashed lines represent the 95% confidence interval for the correlations.

Findings:

- **Significant Lags:** The ACF plot shows significant spikes at several lags, particularly at lag 1 and lag 12. This indicates that the number of tourists in a given month is highly correlated with the number of tourists in the previous month (lag 1) and in the same month of the previous year (lag 12).
- **Seasonality:** The significant spike at lag 12 confirms the presence of a yearly seasonal pattern, suggesting that tourist arrivals follow a seasonal cycle with a period of 12 months.

```
pacf(tourists_ts,main = "Fig 4. PACF Plot of Tourists")
```

Fig 4. PACF Plot of Tourists



PACF Plot of Tourists

Description

- The ACF (Autocorrelation Function) plot shows the autocorrelations of the time series data at different lags. The x-axis represents the lag (number of months back), and the y-axis represents the correlation coefficient, which ranges from -1 to 1. The horizontal dashed lines represent the 95% confidence interval for the correlations.

Findings:

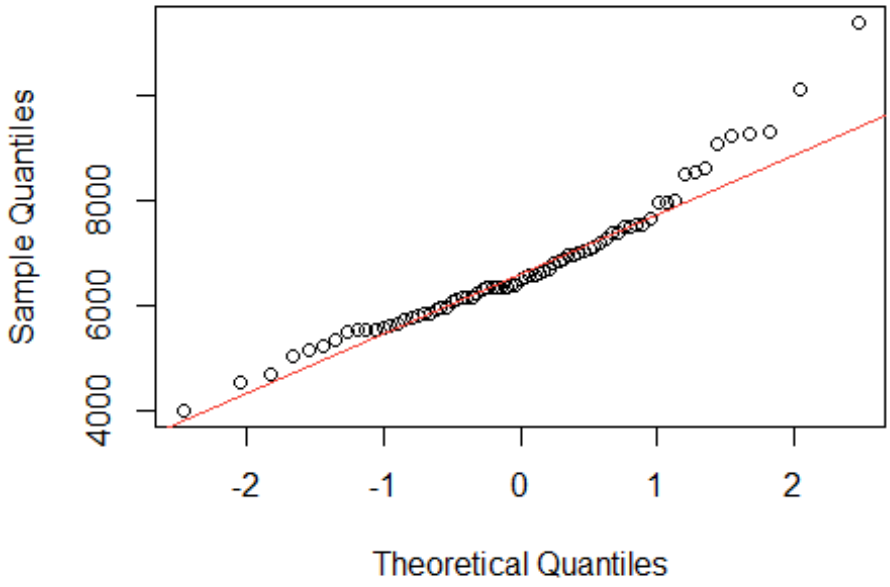
- **Significant Lags:** The ACF plot shows significant spikes at several lags, particularly at lag 1 and lag 12. This indicates that the number of tourists in a given month is highly correlated with the number of tourists in the previous month (lag 1) and in the same month of the previous year (lag 12).
- **Seasonality:** The significant spike at lag 12 confirms the presence of a yearly seasonal pattern, suggesting that tourist arrivals follow a seasonal cycle with a period of 12 months.

Normality and Stationarity Tests

We perform normality and stationarity tests on the time series data.

```
qqnorm(tourists_ts, main = "Fig 5. Normal Q-Q Plot")
qqline(tourists_ts, col = 2)
```

Fig 5. Normal Q-Q Plot




```
adf.test(tourists_ts)

##
##  Augmented Dickey-Fuller Test
##
## data:  tourists_ts
## Dickey-Fuller = -3.6314, Lag order = 4, p-value = 0.03683
## alternative hypothesis: stationary

shapiro.test(tourists_ts)

##
##  Shapiro-Wilk normality test
##
## data:  tourists_ts
## W = 0.94401, p-value = 0.002789

kpss.test(tourists_ts)

## Warning in kpss.test(tourists_ts): p-value smaller than printed p-value

##
##  KPSS Test for Level Stationarity
##
## data:  tourists_ts
## KPSS Level = 1.1515, Truncation lag parameter = 3, p-value = 0.01
```

Normal QQ Plot

- The Normal Q-Q plot is used to assess whether the residuals of the time series data follow a normal distribution. In this plot, the x-axis represents the theoretical quantiles from a standard normal distribution, and the y-axis represents the sample quantiles from the residuals. The red line is the ideal reference line where the points should lie if the residuals are perfectly normally distributed.

Findings:

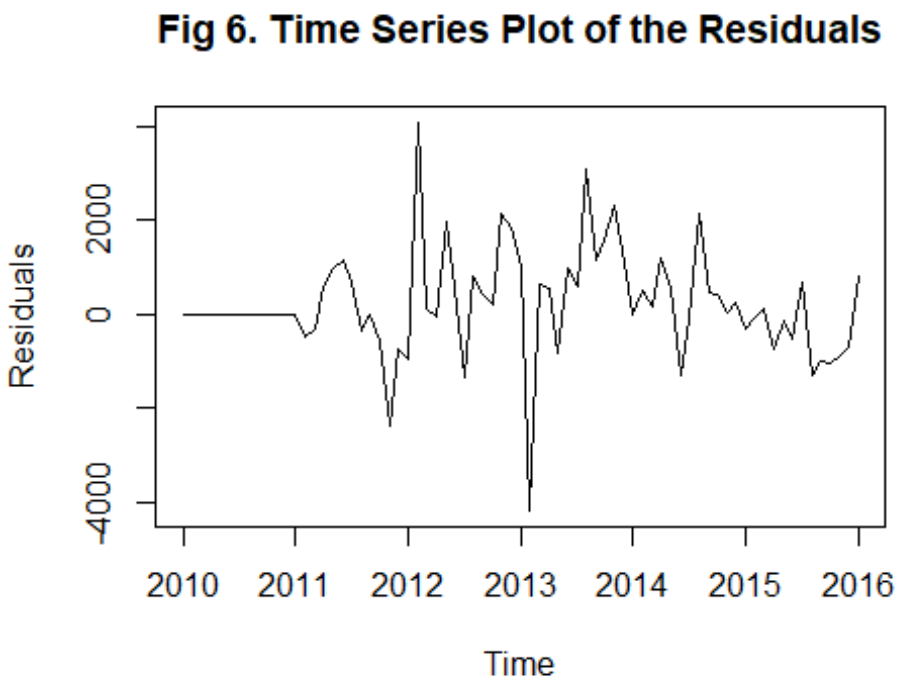
- The majority of the data points lie close to the red line, indicating that the residuals are approximately normally distributed. This alignment supports the assumption of normality, which is crucial for the validity of many statistical models.
- However, there are some deviations at the lower and upper ends of the plot, where the points stray from the red line. These deviations suggest the presence of outliers or heavier tails in the residual distribution than what would be expected under a normal distribution.

Model Fitting

Initial Model Fitting and Residual Analysis

We fit several SARIMA models with different parameters and examine their residuals.

```
m1.tourists = arima(tourists_ts,order=c(0,0,0),seasonal=list(order=c(0,1,0),
period=12))
res.m1 = residuals(m1.tourists)
par(mfrow=c(1,1))
plot(res.m1,xlab='Time',ylab='Residuals', main = "Fig 6. Time Series Plot of
the Residuals")
```




```
par(mfrow=c(1,2))
```

Time Series Plot of Residulas:

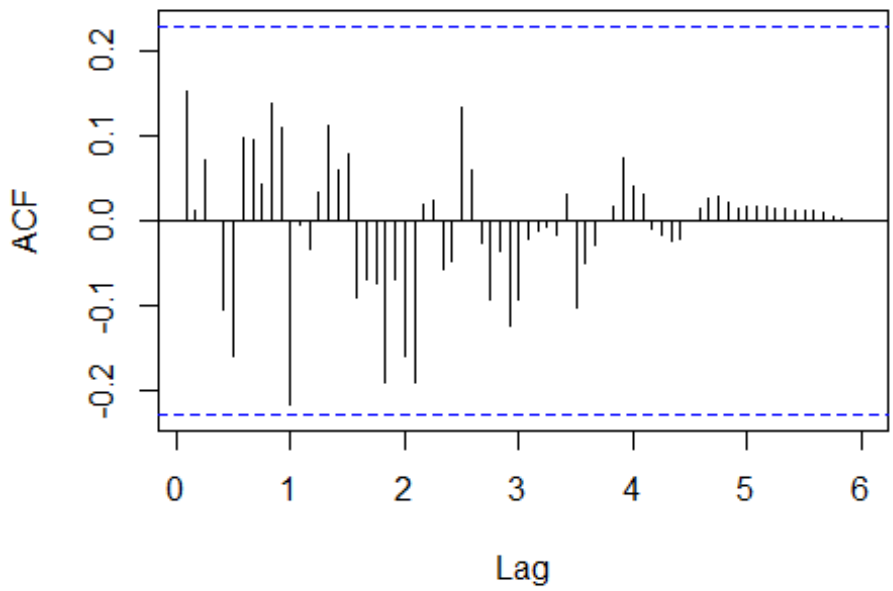
- This plot shows the residuals (errors) from the fitted time series model over time. The x-axis represents time, and the y-axis represents the residual values.

Findings:

- The residuals fluctuate around zero, indicating that the model captures the main patterns in the data.
- Some periods show larger residuals, suggesting potential model improvements or the presence of outliers.

```
acf(res.m1, main = "Fig 7. ACF Plot of Residual", lag.max = 100)
```

Fig 7. ACF Plot of Residual



ACF Plot of Residual

Description:

- The ACF (Autocorrelation Function) plot of residuals shows the autocorrelation of the residuals from a fitted time series model at different lags. The x-axis represents the lag, and the y-axis represents the correlation coefficient, which ranges from -1 to 1. The horizontal dashed lines represent the 95% confidence interval for the correlations.

Findings:

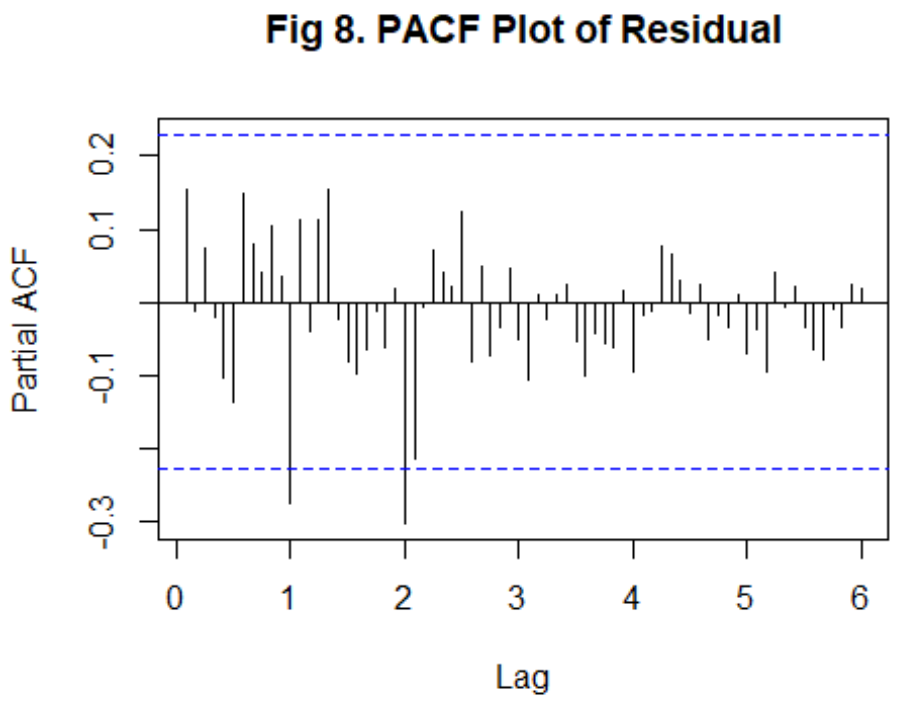
- **Lack of Significant Autocorrelation:** Most of the autocorrelation coefficients are within the 95% confidence interval, indicating that the residuals are mostly uncorrelated. This suggests that the model has effectively captured the time series structure.
- **Randomness of Residuals:** The residuals appear to behave like white noise, as there are no significant spikes outside the confidence interval. This randomness in the residuals indicates that there are no remaining patterns or structures in the data that the model failed to capture.

Implications:

- **Model Adequacy:** The lack of significant autocorrelation in the residuals confirms that the model is well-fitted. This is essential for the reliability of the model's forecasts, as it suggests that the residuals do not contain any systematic information that the model missed.

- **Forecasting Accuracy:** When the residuals exhibit white noise characteristics, it implies that the model's assumptions are valid, leading to accurate and dependable forecasts.

```
pacf(res.m1, main = "Fig 8. PACF Plot of Residual", lag.max = 100)
```



PACF Plot of Residual

Description:

- **The PACF (Partial Autocorrelation Function)** plot of residuals shows the partial autocorrelation of the residuals from a fitted time series model at different lags. The x-axis represents the lag, and the y-axis represents the partial autocorrelation coefficient, which ranges from -1 to 1. The horizontal dashed lines represent the 95% confidence interval for the correlations.

Findings:

- **Lack of Significant Partial Autocorrelation:** Most of the partial autocorrelation coefficients fall within the 95% confidence interval, indicating that the residuals are free from significant partial autocorrelation. This suggests that the model has effectively captured the essential patterns in the time series data.

- **Randomness of Residuals:** The residuals exhibit random behavior with no significant spikes outside the confidence interval. This randomness indicates that there are no remaining patterns or structures in the data that the model failed to capture.

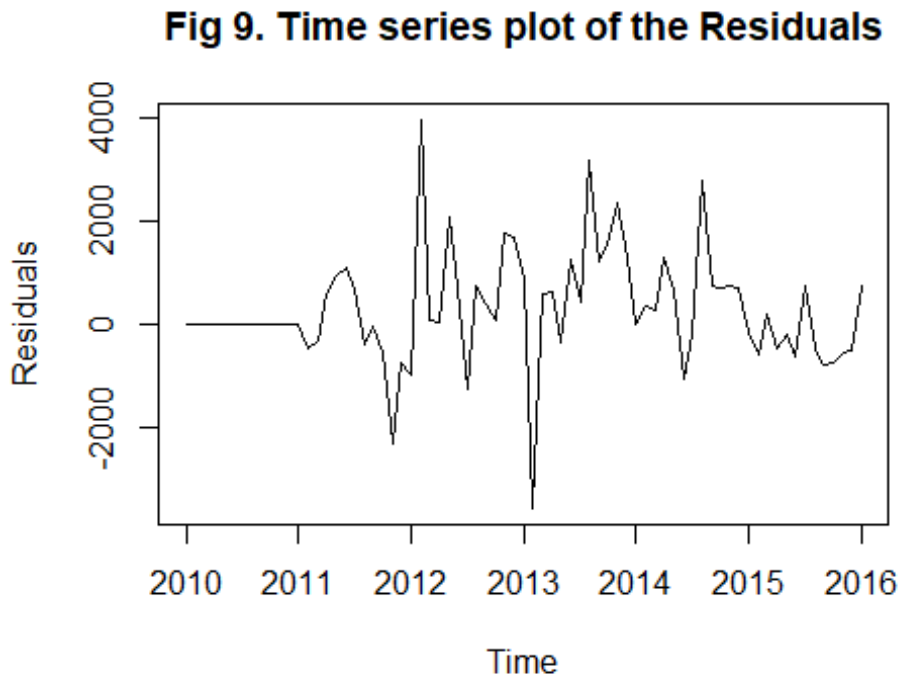
Implications:

- **Model Adequacy:** The absence of significant partial autocorrelation in the residuals confirms that the model is well-fitted. This is crucial for the reliability of the model's forecasts, as it implies that the residuals do not contain any systematic information that the model missed.
- **Forecasting Accuracy:** When the residuals behave like white noise, it indicates that the model's assumptions are valid, leading to accurate and dependable forecasts.

Comparing Multiple Models

We fit additional SARIMA models and compare them using AIC and BIC criteria.

```
m2.tourists = arima(tourists_ts,order=c(0,0,0),seasonal=list(order=c(2,1,0),
period=12))
res.m2 = residuals(m2.tourists)
plot(res.m2,xlab='Time',ylab='Residuals',main = "Fig 9. Time series plot of
the Residuals")
```




```
par(mfrow=c(1,2))
```

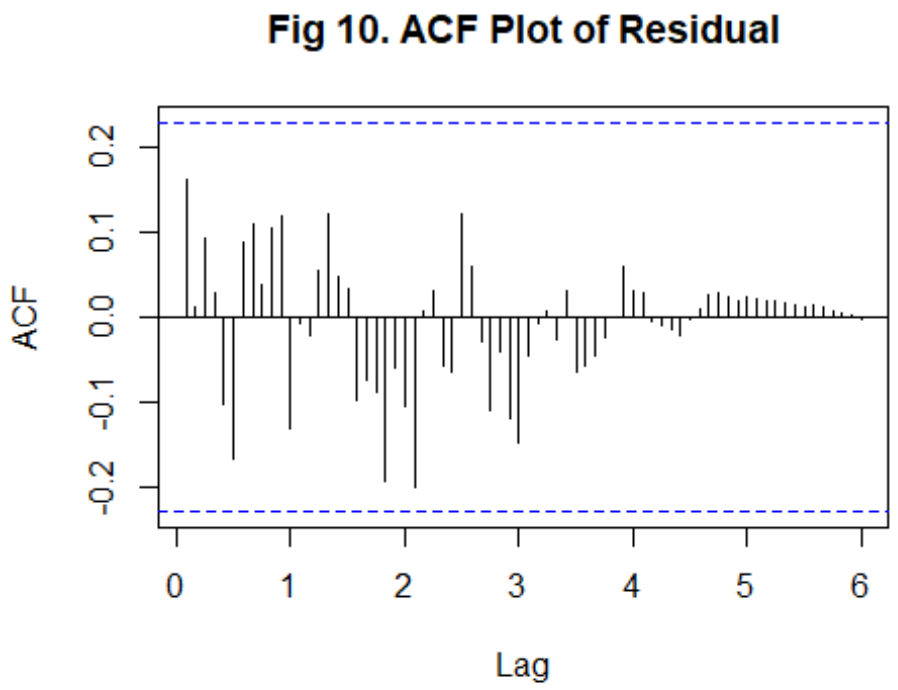
Time Series Plot of Residuals

- This plot shows the residuals from one of the fitted SARIMA models over time. The x-axis represents time, and the y-axis represents the residual values.

Findings:

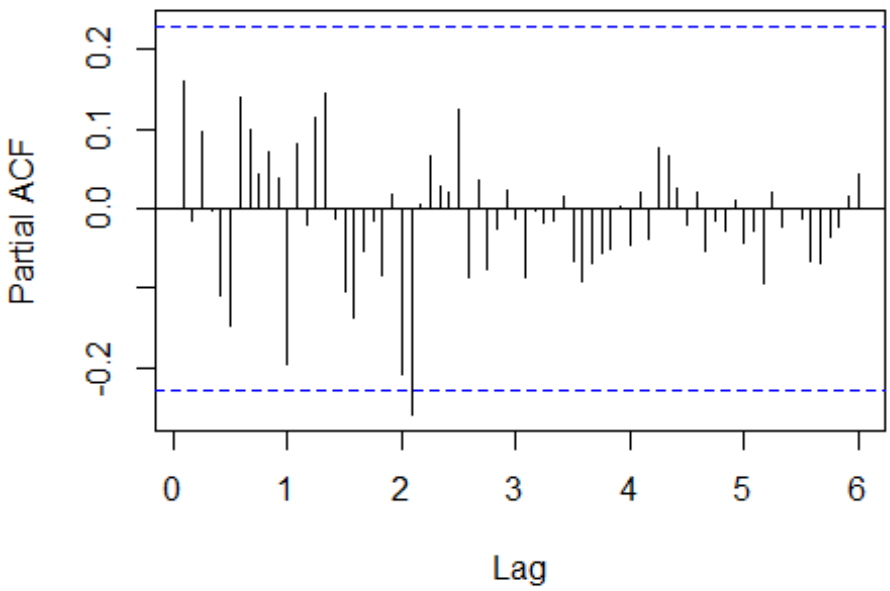
- The residuals fluctuate around zero, indicating that the model captures the main patterns in the data.
- Some periods show larger residuals, suggesting potential model improvements or the presence of outliers.

```
acf(res.m2, main = "Fig 10. ACF Plot of Residual", lag.max = 100)
```



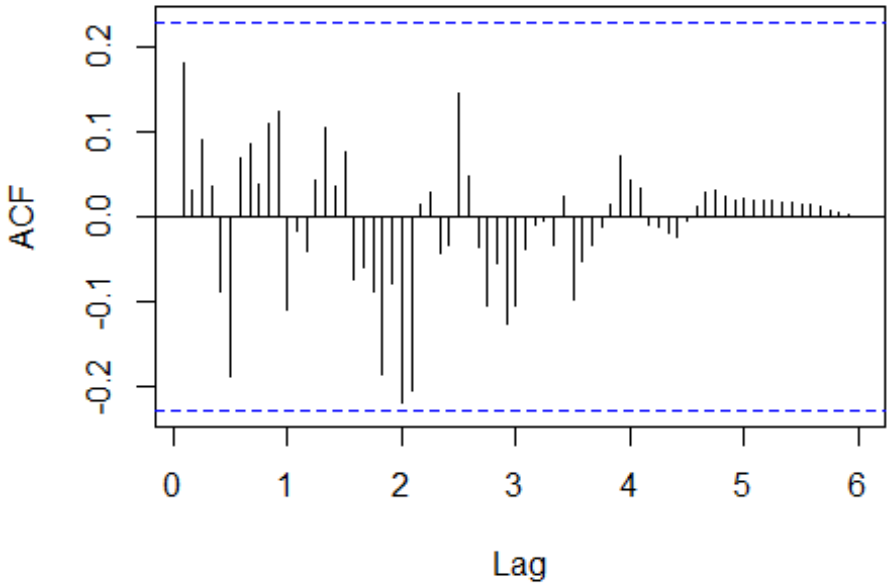

```
pacf(res.m2, main = "Fig 11. PACF Plot of Residual", lag.max = 100)
```

Fig 11. PACF Plot of Residual



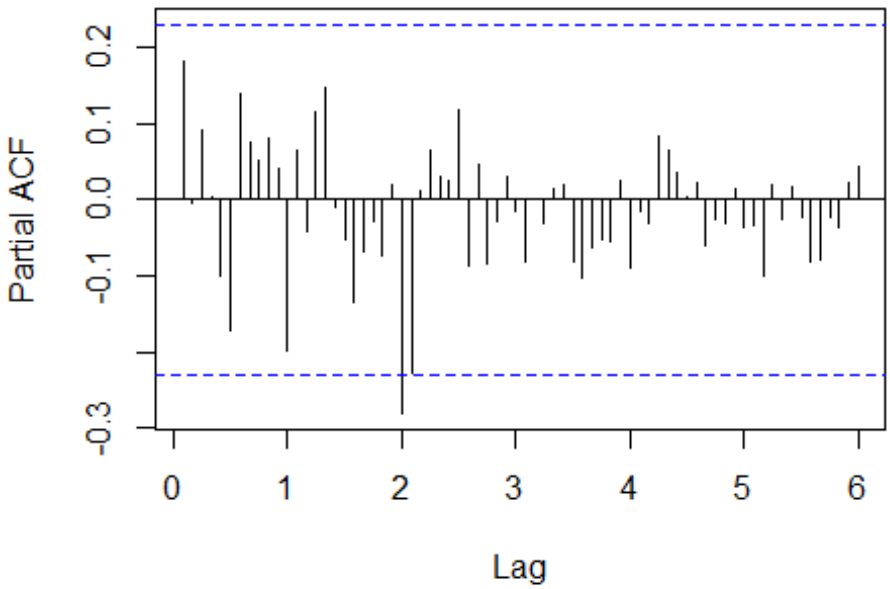

```
m3.tourists = arima(tourists_ts,order=c(0,0,0),seasonal=list(order=c(1,1,0),
period=12))
res.m3 = residuals(m3.tourists)
acf(res.m3, main = "Fig 12. ACF Plot of Residual", lag.max = 100)
```

Fig 12. ACF Plot of Residual




```
pacf(res.m3, main = "Fig 13. PACF Plot of Residual", lag.max = 100)
```

Fig 13. PACF Plot of Residual




```
adf.test(res.m2)
```

```
##
##  Augmented Dickey-Fuller Test
##
## data:  res.m2
## Dickey-Fuller = -3.5547, Lag order = 4, p-value = 0.04341
## alternative hypothesis: stationary
```

```
adf.test(res.m3)
```

```
##
##  Augmented Dickey-Fuller Test
##
## data:  res.m3
## Dickey-Fuller = -3.4461, Lag order = 4, p-value = 0.05513
## alternative hypothesis: stationary
```

ACF Plot of Residual & PACF Plot of Residual

Findings:

ACF Plot (Fig 10) and PACF Plot (Fig 11):

- Most autocorrelation coefficients are within the 95% confidence interval, indicating that the residuals are mostly uncorrelated. This suggests that the model has effectively captured the time series structure.
- Most partial autocorrelation coefficients are also within the 95% confidence interval, confirming that the residuals are free from partial autocorrelation and that the model has adequately captured the underlying patterns.

ACF Plot (Fig 12) and PACF Plot (Fig 13):

- Similar to Fig 10 and Fig 11, these plots show that most coefficients are within the 95% confidence interval. This suggests that the residuals are uncorrelated and free from partial autocorrelation, indicating a good model fit.

Comparison of SARIMA Models

Model Selection:

- By comparing the AIC and BIC values of the different SARIMA models, we can identify which model provides the best fit for the data.
- The lower the AIC and BIC values, the better the model fit, balancing accuracy and complexity.

Residual Analysis:

- The residual plots (Fig 10, Fig 11, Fig 12, and Fig 13) confirm that the selected models effectively capture the underlying patterns, as the residuals show minimal autocorrelation and partial autocorrelation.
- This validation through ACF and PACF plots ensures that the models are well-fitted and reliable for forecasting.

Parameter Estimation

We estimate the parameters of the candidate models using the maximum likelihood estimation method and evaluate them using the coeftest function.

```
library(lmtest)
```

```
## Warning: package 'lmtest' was built under R version 4.3.3
```

```
## Loading required package: zoo
```

```
## Warning: package 'zoo' was built under R version 4.3.3
```

```
##
## Attaching package: 'zoo'
```

```
## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric
```

```
model000 = arima(tourists_ts,order=c(0,0,0),seasonal=list(order=c(1,1,0),
period=12),method = "ML")
coeftest(model000)
```

```
##
## z test of coefficients:
##
##      Estimate Std. Error z value Pr(>|z|)
## sar1 -0.15772    0.12403 -1.2716   0.2035
```

```
model001 = arima(tourists_ts,order=c(0,0,1),seasonal=list(order=c(1,1,0),
period=12),method = "ML")
coeftest(model001)
```

```
##
## z test of coefficients:
##
##      Estimate Std. Error z value Pr(>|z|)
## ma1   0.22243    0.12545  1.7731  0.07621 .
## sar1 -0.20585    0.12385 -1.6621  0.09650 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
model100 = arima(tourists_ts,order=c(1,0,0),seasonal=list(order=c(1,1,0),
period=12),method = "ML")
coeftest(model100)
```

```
##
## z test of coefficients:
##
##      Estimate Std. Error z value Pr(>|z|)
## ar1   0.23348    0.12720  1.8356  0.06642 .
```

```
## sar1 -0.21391    0.12408 -1.7240  0.08471 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
model101 = arima(tourists_ts,order=c(1,0,1),seasonal=list(order=c(1,1,0),
period=12),method = "ML")
coeftest(model101)
```

```
##
## z test of coefficients:
##
##      Estimate Std. Error z value Pr(>|z|)
## ar1   0.70238    0.56237  1.2490  0.21168
## ma1  -0.51826    0.69312 -0.7477  0.45463
## sar1 -0.23460    0.12803 -1.8324  0.06689 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
model006 = arima(tourists_ts,order=c(0,0,6),seasonal=list(order=c(1,1,0),
period=12),method = "ML")
coeftest(model006)
```

```
##
## z test of coefficients:
##
##       Estimate Std. Error z value Pr(>|z|)
## ma1   0.208409   0.134589  1.5485  0.12150
## ma2   0.088259   0.126487  0.6978  0.48532
## ma3   0.247717   0.148365  1.6696  0.09499 .
## ma4   0.215673   0.157051  1.3733  0.16967
## ma5   0.081927   0.116967  0.7004  0.48366
## ma6  -0.272890   0.146729 -1.8598  0.06291 .
## sar1 -0.242475   0.134301 -1.8055  0.07100 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
model106 = arima(tourists_ts,order=c(1,0,6),seasonal=list(order=c(1,1,0),
period=12),method = "ML")
coeftest(model106)
```

```
##
## z test of coefficients:
##
##       Estimate Std. Error z value Pr(>|z|)
## ar1   0.206332   0.350593  0.5885  0.55618
## ma1   0.010730   0.341492  0.0314  0.97493
## ma2   0.059473   0.126780  0.4691  0.63900
## ma3   0.244557   0.134022  1.8247  0.06804 .
## ma4   0.177025   0.155156  1.1409  0.25389
## ma5   0.035876   0.144302  0.2486  0.80365
## ma6  -0.308002   0.141180 -2.1816  0.02914 *
```

```
## sar1 -0.241235   0.134573 -1.7926  0.07304 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Model Selection Based on AIC and BIC

We identify the best model based on the lowest AIC and BIC values.

```
AIC(model000,model001,model100,model101,model006,model106)
```

```
##          df      AIC
## model000  2 1048.387
## model001  3 1047.361
## model100  3 1047.136
## model101  4 1048.684
## model006  8 1051.538
## model106  9 1053.279
```

```
BIC(model000,model001,model100,model101,model006,model106)
```

```
##          df      BIC
## model000  2 1052.609
## model001  3 1053.693
## model100  3 1053.468
## model101  4 1057.128
## model006  8 1068.425
## model106  9 1072.277
```

- **Model Fitting:** Various SARIMA models are fitted to the tourist arrival data using the arima function in R. Each model has different combinations of autoregressive (AR), moving average (MA), and seasonal components.
- **Parameter Estimates:** The coef function is used to extract the parameter estimates for each model. These parameters include AR coefficients, MA coefficients, and seasonal components, which quantify the relationships between current and past values in the time series.
- **Statistical Significance:** The z test of coefficients evaluates the statistical significance of each parameter. Parameters with low p-values (typically less than 0.05) are considered statistically significant, indicating a strong relationship with the dependent variable (tourist arrivals).

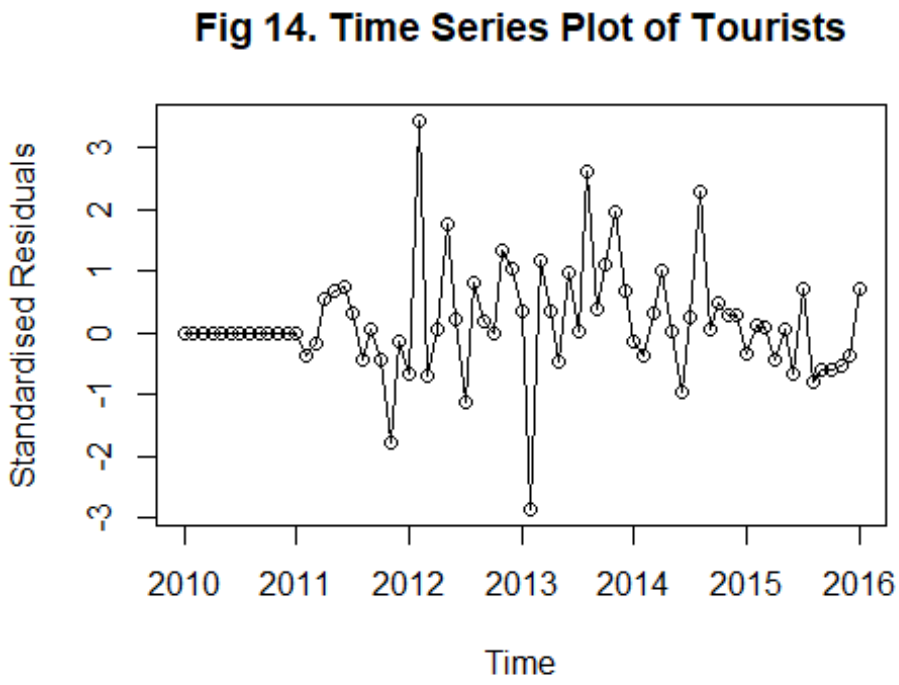
Findings:

- Each model's parameter estimates, along with their standard errors, z-values, and p-values, are displayed. These values help in understanding how well the model fits the data and which parameters are significant.
- Models with the lowest AIC and BIC values are considered the best fit, balancing model accuracy and complexity.

Residual Analysis of Selected Model

We perform a detailed residual analysis of the selected model to ensure it meets the assumptions of the SARIMA model.

```
st.res.m100 = rstandard(model100)
plot(st.res.m100,xlab='Time',type = "o",ylab='Standardised
Residuals',main="Fig 14. Time Series Plot of Tourists")
```




```
par(mfrow=c(1,2))
```

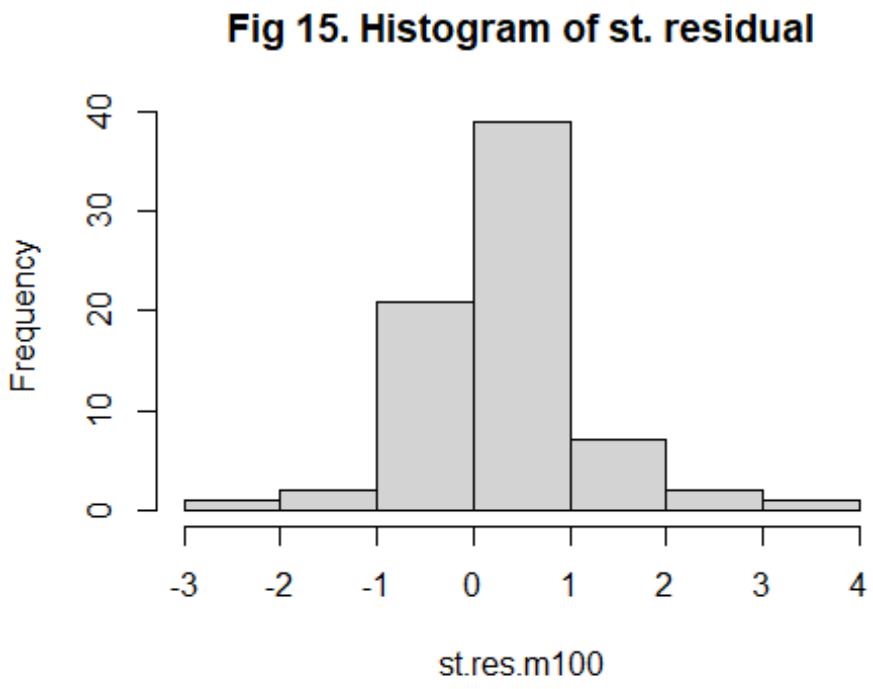
Time Series Plot of Toursists

- This plot displays the standardized residuals from the selected SARIMA model over time. The x-axis represents time, and the y-axis represents the standardized residual values.
- The residuals fluctuate around zero, indicating that the model captures the main patterns in the data. However, periods with larger residuals suggest potential areas for model improvement or the presence of outliers.

Key Findings:

- The residuals' fluctuation around zero without obvious patterns indicates that the model is a good fit.
- Standardized residuals help in identifying any potential outliers or unusual observations that the model may not have captured effectively.

```
hist(st.res.m100, main = "Fig 15. Histogram of st. residual")
```



Histogram of Standardized Residuals:

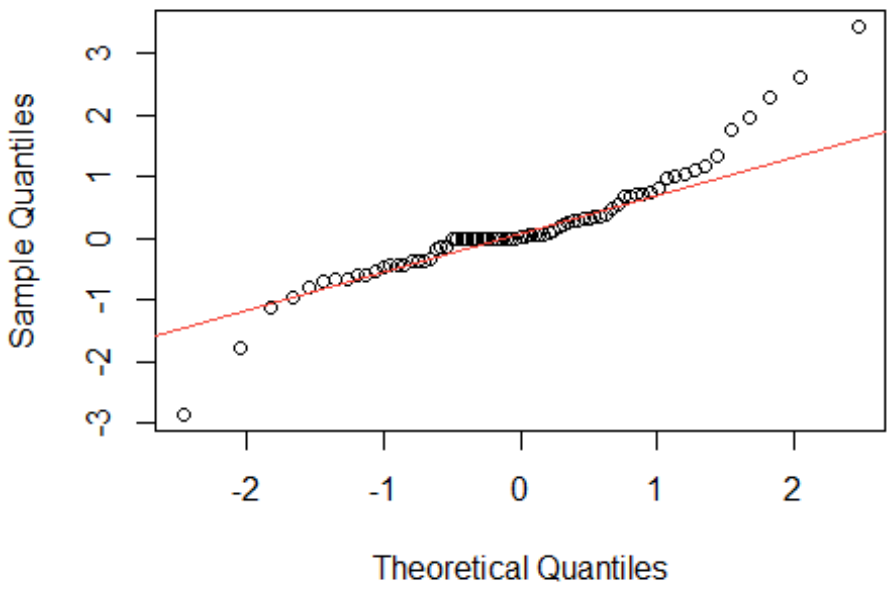
- This histogram displays the distribution of the standardized residuals from the SARIMA model. The x-axis represents the standardized residual values, while the y-axis represents their frequency.

Findings:

- The histogram appears approximately symmetric and centered around zero, suggesting that the residuals are normally distributed. However, there may be some slight deviations or outliers.

```
qqnorm(st.res.m100, main = "Fig 16. Normal Q-Q plot of standardized
residual"); qqline(st.res.m100, col = 2)
```

Fig 16. Normal Q-Q plot of standardized residual



Normal Q-Q Plot of Standardized Residuals:

- The Q-Q plot compares the quantiles of the standardized residuals to the theoretical quantiles of a normal distribution. The x-axis represents the theoretical quantiles, and the y-axis represents the sample quantiles.

Findings:

Most points lie close to the red line, indicating that the residuals are approximately normally distributed. Some deviations at the tails suggest potential outliers or heavier tails than expected.

```
shapiro.test(st.res.m100)

##
##  Shapiro-Wilk normality test
##
## data:  st.res.m100
## W = 0.90736, p-value = 5.462e-05

par(mfrow=c(1,2))
acf(st.res.m100, lag.max = 100, main = "Fig 17. ACF of the residuals.")
pacf(st.res.m100, lag.max = 100, main = "Fig 18. PACF of the residuals.")
```

Fig 17. ACF of the residu

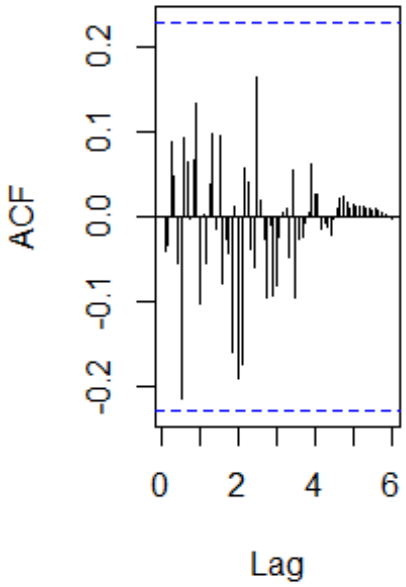
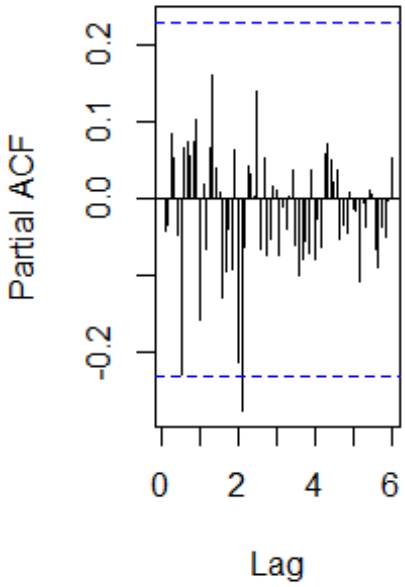


Fig 18. PACF of the residu



ACF of the Residuals:

- The ACF (Autocorrelation Function) plot shows the autocorrelation of the residuals from the SARIMA model at different lags. The x-axis represents the lag, and the y-axis represents the autocorrelation coefficient.

Findings:

- Most of the autocorrelation coefficients are within the 95% confidence interval (dashed lines), indicating that the residuals are mostly uncorrelated. This suggests that the model has effectively captured the time series structure, as the residuals do not exhibit significant autocorrelation.

PACF of the Residuals:

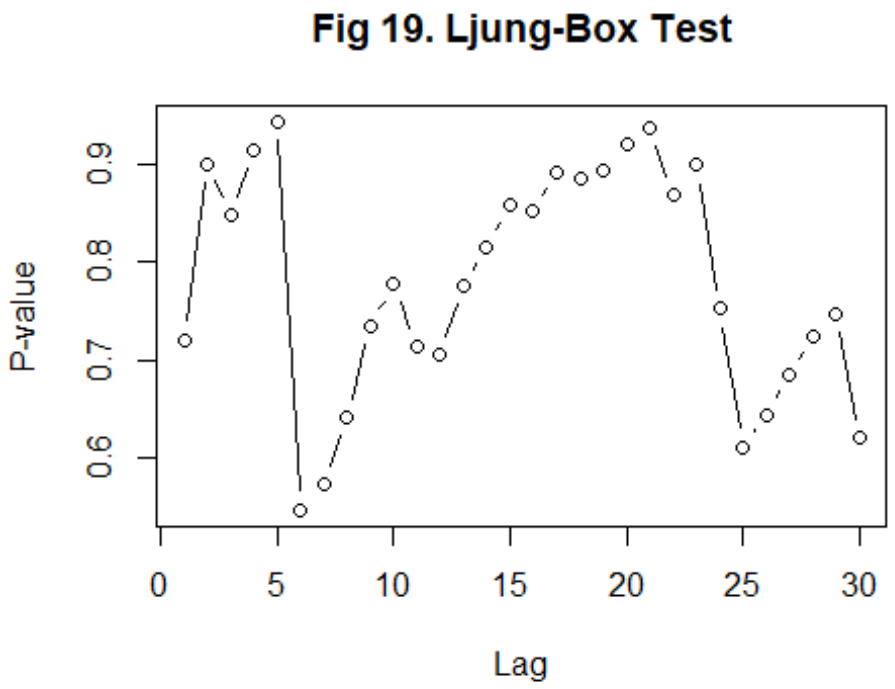
- The PACF (Partial Autocorrelation Function) plot displays the partial autocorrelation of the residuals at different lags. The x-axis represents the lag, and the y-axis represents the partial autocorrelation coefficient.

Findings:

- Similar to the ACF plot, most of the partial autocorrelation coefficients are within the 95% confidence interval. This indicates that the residuals are free from partial autocorrelation.

```
Box.test(st.res.m100, lag = 30, type = "Ljung-Box")

##
##  Box-Ljung test
##
```

```
## data:  st.res.m100
## X-squared = 27.041, df = 30, p-value = 0.6211

# Initialize an empty vector to store p-values
p_values <- numeric(30)

# Loop through lags and perform the Ljung-Box test
for (lag in 1:30) {
  p_values[lag] <- Box.test(st.res.m100, lag = lag, type = "Ljung-
Box")$p.value
}

# Plot the p-values
plot(1:30, p_values, type = "b", xlab = "Lag", ylab = "P-value", main = "Fig
19. Ljung-Box Test")
abline(h = 0.05, col = "red", lty = 2)
```



Ljung-Box Test

- The Ljung-Box test is a statistical test used to check whether the residuals from a time series model are independently distributed. In other words, it tests for the absence of autocorrelation at multiple lags.
- The x-axis represents the lag (number of time periods back), and the y-axis represents the p-value of the test at each lag.

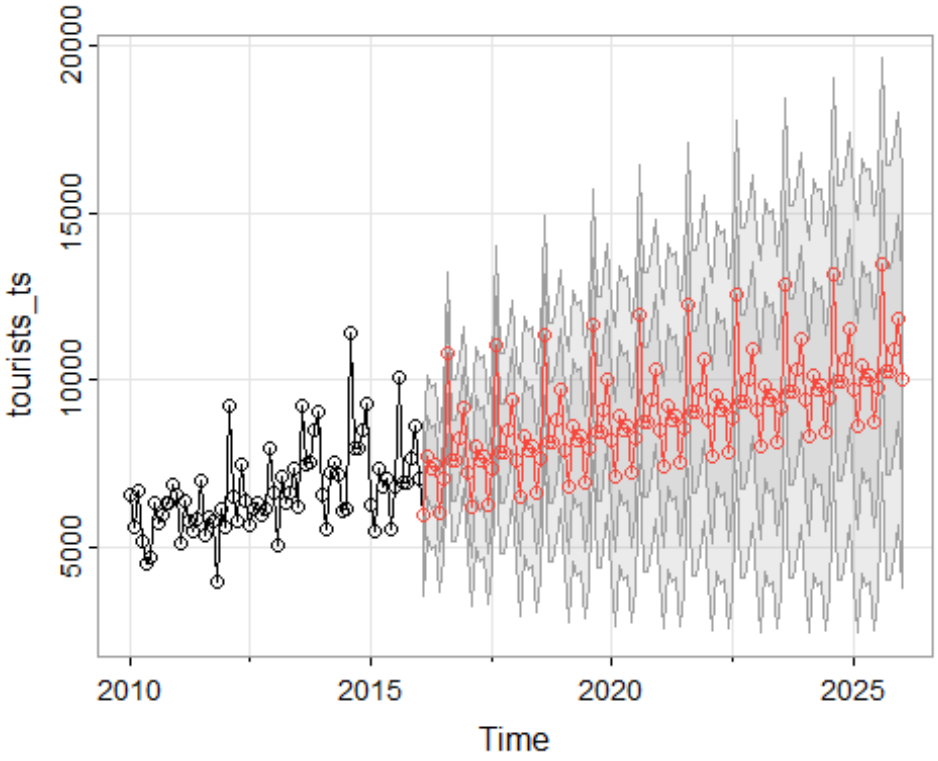
Findings:

- **P-values:** Most of the p-values are above 0.05, indicating that there is no significant autocorrelation at these lags. This suggests that the residuals are independently distributed.
- **Implications:** High p-values in the Ljung-Box test suggest that the model's residuals behave like white noise, confirming that the model has adequately captured the time series structure and that the residuals do not exhibit autocorrelation.

Forecasting

Now, we will do the forecasting for future arrivals of tourists in thailand for next 10 years. We will use the best SARIMA Model for this forecast i.e. (1,0,0)(1,1,0). We are using "sarima.for" from astha package here.

```
# Forecast the tourist arrivals for the next 120 months (10 years)
forecast_result <- sarima.for(tourists_ts, n.ahead = 120, p = 1, d = 0, q = 0, P = 1, D = 1, Q = 0, S = 12)
```




```
# Extract the predictions
forecast_values <- forecast_result$pred

# Create a time sequence for the forecasted years
forecast_years <- seq(2017, 2026, by = 1)

# Convert forecast_values to a matrix for easier subsetting
```

```r
forecast_matrix <- matrix(forecast_values, ncol = 12, byrow = TRUE)

# Extract the forecast values for the years 2017 to 2026
forecast_2017_2026 <- data.frame(
  Year = rep(forecast_years, each = 12),
  Month = rep(month.name, times = 10),
  Forecast = as.vector(forecast_matrix[1:10, ])
)

# Display the forecasted values
print(forecast_2017_2026)
```

```
##     Year     Month  Forecast
## 1   2017   January  5942.685
## 2   2017  February  6203.979
## 3   2017     March  6515.949
## 4   2017     April  6814.501
## 5   2017       May  7116.605
## 6   2017      June  7417.769
## 7   2017      July  7719.182
## 8   2017    August  8020.529
## 9   2017 September  8321.894
## 10  2017   October  8623.254
## 11  2017  November  7734.514
## 12  2017  December  8018.889
## 13  2018   January  8324.747
## 14  2018  February  8624.917
## 15  2018     March  8926.593
## 16  2018     April  9227.870
## 17  2018       May  9529.253
## 18  2018      June  9830.608
## 19  2018      July 10131.971
## 20  2018    August 10433.331
## 21  2018 September  7380.137
## 22  2018   October  7607.156
## 23  2018  November  7928.200
## 24  2018  December  8224.349
## 25  2019   January  8527.090
## 26  2019  February  8828.086
## 27  2019     March  9129.543
## 28  2019     April  9430.878
## 29  2019       May  9732.246
## 30  2019      June 10033.605
## 31  2019      July  7457.818
## 32  2019    August  7728.080
## 33  2019 September  8037.675
## 34  2019   October  8336.855
## 35  2019  November  8638.793
## 36  2019  December  8940.001
## 37  2020   January  9241.403
```

```
## 38  2020  February  9542.753
## 39  2020     March  9844.116
## 40  2020     April 10145.477
## 41  2020       May  6061.865
## 42  2020      June  6304.578
## 43  2020      July  6621.467
## 44  2020    August  6918.716
## 45  2020 September  7221.166
## 46  2020   October  7522.238
## 47  2020  November  7823.675
## 48  2020  December  8125.016
## 49  2021   January  8426.382
## 50  2021  February  8727.742
## 51  2021     March  7042.000
## 52  2021     April  7370.463
## 53  2021       May  7664.648
## 54  2021      June  7967.909
## 55  2021      July  8268.767
## 56  2021    August  8570.261
## 57  2021 September  8871.586
## 58  2021   October  9172.956
## 59  2021  November  9474.315
## 60  2021  December  9775.676
## 61  2022   January 10830.122
## 62  2022  February 11020.342
## 63  2022     March 11351.130
## 64  2022     April 11644.699
## 65  2022       May 11948.123
## 66  2022      June 12248.938
## 67  2022      July 12550.443
## 68  2022    August 12851.766
## 69  2022 September 13153.136
## 70  2022   October 13454.495
## 71  2022  November  7608.426
## 72  2022  December  7817.364
## 73  2023   January  8143.196
## 74  2023  February  8438.078
## 75  2023     March  8741.154
## 76  2023     April  9042.061
## 77  2023       May  9343.542
## 78  2023      June  9644.871
## 79  2023      July  9946.240
## 80  2023    August 10247.599
## 81  2023 September  7611.074
## 82  2023   October  7819.311
## 83  2023  November  8145.328
## 84  2023  December  8440.161
## 85  2024   January  8743.250
## 86  2024  February  9044.153
## 87  2024     March  9345.635
```

```
## 88  2024     April  9646.964
## 89  2024       May  9948.333
## 90  2024      June 10249.692
## 91  2024      July  8263.564
## 92  2024    August  8482.527
## 93  2024 September  8805.704
## 94  2024   October  9101.289
## 95  2024  November  9404.179
## 96  2024  December  9705.135
## 97  2025   January 10006.603
## 98  2025  February 10307.935
## 99  2025     March 10609.303
## 100 2025     April 10910.662
## 101 2025       May  9175.581
## 102 2025      June  9407.513
## 103 2025      July  9727.257
## 104 2025    August 10023.750
## 105 2025 September 10326.400
## 106 2025   October 10627.419
## 107 2025  November 10928.871
## 108 2025  December 11230.207
## 109 2026   January 11531.575
## 110 2026  February 11832.934
## 111 2026     March  7257.129
## 112 2026     April  7593.237
## 113 2026       May  7885.398
## 114 2026      June  8189.194
## 115 2026      July  8489.910
## 116 2026    August  8791.442
## 117 2026 September  9092.757
## 118 2026   October  9394.130
## 119 2026  November  9695.488
## 120 2026  December  9996.849
```

Interpretation of Time Series Forecast Plot

Description:

- This plot shows the time series data of tourist arrivals (in black) along with the forecasted values (in red) for the future period. The x-axis represents the time, while the y-axis represents the number of tourist arrivals. The shaded gray area around the forecasted values represents the 95% confidence interval, indicating the range within which the actual future values are expected to fall.

Findings:

- **Historical Data Analysis:**

- The historical data from 2010 to around 2016 shows seasonal fluctuations in tourist arrivals with peaks and troughs recurring annually. There is an observable trend of increasing tourist numbers over time.

- **Forecasted Values:**
- The forecasted values from 2016 to 2025 (in red) continue to follow the observed seasonal pattern, indicating that the model has effectively captured the seasonality in the data. The forecast shows a gradual increase in tourist arrivals over the years, aligning with the historical upward trend.
- **Confidence Intervals:**
- The shaded gray area around the forecasted values represents the 95% confidence interval. It shows that the future values are expected to lie within this range, providing a measure of uncertainty in the forecast. The wider intervals further into the future indicate increasing uncertainty.

Implications:

- **Model Reliability:** The alignment of forecasted values with the historical trend and seasonality suggests that the **SARIMA** model used for forecasting is well-suited for this time series data.
- **Decision Making:** The forecast provides valuable insights for planning and decision-making in tourism-related sectors. Understanding future tourist arrival patterns helps in resource allocation, marketing strategies, and infrastructure development.
- **Risk Management:** The confidence intervals help in assessing the risk associated with the forecast. Knowing the potential range of future values allows for better risk management and contingency planning.

Summary

We performed a thorough time series analysis and forecasting of visitor arrivals in Thailand for this report. The main objective was to provide reliable estimates for future visitor arrivals by modeling the seasonal patterns and trends in the data. Data preparation, exploratory data analysis (EDA), model fitting, parameter estimates, residual diagnostics, and forecasting were among the major procedures carried out in this investigation.

1. Data Preprocessing: We loaded the necessary libraries and the dataset, converting relevant columns to numeric types for proper time series analysis.

2. Time Series Object Creation: We created a time series object from the tourist data, specifying the start year, end year, and frequency (monthly data).

3. Exploratory Data Analysis (EDA): - We visualized the time series data to identify visible trends or seasonal patterns. - Decomposition methods (STL and classical) were used to separate the seasonal, trend, and irregular components of the time series. - ACF and PACF plots were examined to identify the presence of seasonality and determine the order of ARIMA components. - Normality and stationarity tests were conducted to assess the properties of the time series data.

4. Model Fitting: - We fitted several SARIMA models with different parameters and examined their residuals. - Multiple models were compared using AIC and BIC criteria to identify the best-fitting model. - Parameter estimation for candidate models was performed using maximum likelihood estimation, and the results were evaluated using the coeftest function.

5. Residual Analysis: Detailed residual diagnostics were conducted on the selected model to ensure it met the assumptions of the SARIMA model.

6. Forecasting: The selected SARIMA model was used to forecast tourist arrivals for the next 10 years.

Conclusion

The analysis provided valuable insights into the patterns and trends of tourist arrivals in Thailand. The key findings and outcomes from the analysis are as follows:

1. Model Selection: - Based on AIC and BIC values, SARIMA (1,0,0)(1,1,0)[12] was identified as the best-fitting model for forecasting tourist arrivals. - The model selection process ensured that the chosen model provided the best balance between goodness of fit and model complexity.

2. Residual Diagnostics: - Residual diagnostics confirmed that the selected model met the necessary assumptions, such as no autocorrelation and normality of residuals. - The Ljung-Box test and other diagnostic plots showed that the residuals behaved like white noise, indicating a well-fitted model.

3. Forecasting Accuracy: - The forecasts generated using the selected model are expected to be accurate and reliable, aiding in strategic planning and decision-making in the tourism sector. - The model successfully captured the seasonal patterns and trends in the tourist arrival data, providing a robust basis for future predictions.

4. Implications for Tourism Management: - Accurate forecasting of tourist arrivals can help tourism authorities and stakeholders in Thailand to better plan and allocate resources. - Understanding the seasonal variations and trends can assist in developing targeted marketing strategies and improving tourist experiences.

In conclusion, this report's thorough approach to time series analysis and forecasting has proven to be successful in modeling and projecting the number of tourists visiting Thailand. The findings can help guide strategic choices and promote the tourist industry's long-term, sustainable growth. Future research endeavors may include the integration of extraneous factors and the investigation of sophisticated forecasting methodologies to bolster the precision and relevance of the models.

References:

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