Marriot Case Study Analysis (DBI001_IIMN)

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Section1: Introduction

Marriot Hamilton Hotel is the largest hotel chain in the world by the number of available rooms. In 1927, **J. Willard Marriott** opened the nine-stool root beer stand that grew into the Hot Shoppes Restaurant chain and evolved into today's Marriott International hotel company.

The Marriot Hamilton Hotel With a maximum capacity of **1,877 rooms** that is situated in the city and caters to business travelers as well as tourist visiting the city. The Hamilton's Hotel busiest days of the week tends to be in the middle of the work week such as Tuesday through Thursday. On the weekends, demand is less than the middle of the week and booking all the rooms in the hotel on a Saturday is a real plus for the hotel.

Linda Snow is the reservation manager of the Marriot Hamilton Hotel. As the reservation manager of this property, Snow is being required to identified the issue of overbooking reservations at this property as well as the request for an up-to sixty room request from a touring agency on a specific day.

While snow would be pleased to accept the sixty-room request, such request would put them over their maximum occupancy level. This hotel encounters a lot of no shows however which would make the hotel have additional reservations available to possibly accept all sixty-room request.

There are several tradeoffs involved in this which will be further explained below. As of now, Snow needs to figure out if her forecasting is accurate and if she should continue using her forecasting technique in the future as well as get back to the travelling agency about the sixty-room request in the short-term.

Section2: Situational Analysis

As of now the Hamilton Hotel has **1,839 rooms** already reserved with a maximum capacity of 1,877. It has also been stated that this hotel experiences a lot of "No Show" reservations which cannot be deemed as a "Head in bed." The goal of the Hotel is to Barrantes 3

Marriot Forecastsell out of all of the **1,877 rooms** available to maximize capacity without overbooking and rejecting individuals a room at the property. There are several factors that need to be taken into considerations before being able to accept this request. One of the variables is the cost of denying a room. This property only has 38 rooms available before reaching capacity and accepting the sixty-room request would have now 22 rooms overbooked.

The risk is greater than the profit, but the touring company could seek other hotels if the Hamilton hotel is not able to accommodate sixty rooms which could result in the lost opportunity of a steady client. Snows' forecasting might not be accurate as well, so it is vital to compute the forecast not only for this Saturday booking but for all other days to improve capacity utilization. The previous demand for the previous 13 weeks showed seasonality which is important to take into account.

Section3: Industrial Analysis

There have been several hospitality trends that have been occurring within the past couple of years. One of these trends is the direct bookings of customers and hotels focus on eliminating the middleman that do not have accurate information about the hotel and do not actively represent that chain.

Another trend that has been a competitor are private lodging companies **such as AirBnb and VRBO (JWU, 2019)**. These are cheaper and direct alternatives than traditional chain hotels.

Another very important trend is sustainability, this trend has demonstrated to customers that they are aware of their carbon footprint and are practicing environmentally friendly practices. This improves the hotels reputation as it keeps the future generations success in mind.

Marriot currently has 1.16 million international hotel rooms (Statista, 2019). The United States favorite hotel loyalty program is the Marriot reward programs which is shown due to their promise of recompensating guest due to overbookings. The revenue of the U.S. hotel industry is 218 billion USD which is dominated by Hilton and Marriot. The occupancy rate of hotels in the U.S is 66.1%, a pretty healthy percentage. Another important industry item is the average daily rate of hotels in the U.S. which is $131.21 USD.

Section4: Formulate Business Problem

A) How Discuss the hotel reservation systems work? What information do they provide to management?

Generally, the hotel reservation systems include variables such as **advance reservations**, **no-shows**, **occupancy rate**, and **customers' information**. Forecasting is the key to profit maximization because cancellations and no-shows always happen. According to this case, Snow will prepare a forecast on Tuesday about number of rooms that will be occupied each day of next week **(start Saturday)**. She will use the **historical data on demand**, calculated the **pickup ratios** and DOW to improve the forecasting. Overbooking is considered in case of the no-shows and cancellations.

B) It appears that there is no capacity for 60 additional rooms. Is this correct or could 60 additional reservations be taken?

After calculation, 60 additional reservations could be taken on Saturday. We calculated the adjusted pickup ratio by dividing pickup ratio by DOW index for each day in the previous weeks. Then, we can get the new adjusted pickup ratio on Saturday in week 14 by averaging the previous adjusted pickup ratios. Next, we can get the pickup ratio for that day and calculate the demand forecasting on that day. The forecast is about 1735 for that day, as a result, there are 83 more rooms available for that day which is enough for taking this order.

C) What ideas do you have to improve forecasting?

1) We have to build a forecasting model of demand curve and also develop over-booking rate or no-show rate recommendation, and use proper moving average to better measure the forecast error.

2) We have to build data base of the reservations, including data of reservation on hand (ROH) for different days before arrival (DBA).

3) Adjust the booking curve based on different business types of the hotel. For airport hotel, people usually make reservation a few days before arrival; for business hotel, reservations are often made 1-2 weeks before arrival; for resort hotel, people could plan a trip and reserve the hotel early.

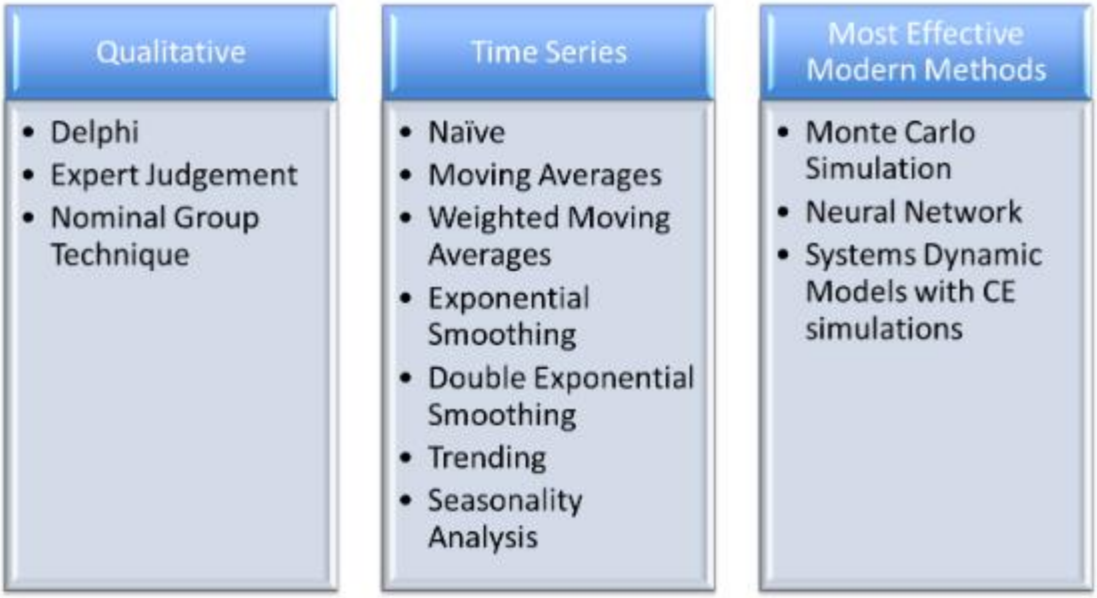
4) Consider the summer and winter break, and adopt strategies for hot season and cold season. o Hot season: restrict discounts and increase throughput of customers o Cold season: offer targeted promotions to increase number of customers.

Section2: Quantitative Support

For this section first we have to understood what is forecasting? As per my understanding regarding data analysis Forecasting is a technique that uses historical data as inputs to make informed estimates that are predictive in determining the direction of future trends.

And it has also some strategic Importance. Like in Every sector like Banking, Manufacturing, Healthcare everywhere we are using our Forecasting method,

In High Level Overview forcasting can be divided into following categories :-



In Marriot Case study dealing with Time series forecasting Models (Quantitative Methods).

The quantitative analysis was used to determine whether Snow should accept the request for the sixty-room reservation from the touring agency. The qualitative analytical approach is made on the basis of forecasting using Trend with seasonal Analysis, moving averages and exponential smoothing.

A) Exponential Smoothing Model

Exponential Smoothing: Before any calculations were done, a line graph was made using the historic demand figures to determine what kind of forecasting should be made. The graph revealed a cyclical/seasonal demand pattern with peaks and valleys. Exponential smoothing is considered an appropriate forecasting technique for time series data, so it was good to start with Exponential Smoothing. Two dampening factors were used for this forecast, one of them being .05 and the other one being .8. The first Alpha of .05 represents the deferral of the demand, which in some cases can be overlooked due to certain unconditional instances. The alpha of .8 which proved to be the best alpha was used to keep in mind the past factors, the demand of the historic data figures and of course, the expectation to increase the reservation at the Hamilton Hotel. Alphas are to be taken between zero and one depending on the deviation and fluctuation of data points and to decide if Snow should accept the reservation for sixty tourist or not. With the alpha of .8, the demand was much smoother than with the alpha of .05. Also, the mape for the alpha of .8 was below 20% at 17%.

B) moving average model

The 3-period and 5-period moving average was used with the period timetable to smoothen the short-term fluctuations in the repeated seasonal demand. Also, since it was necessary to forecast long term trends. The deviation was calculated as well as the absolute deviation from the demand. The Absolute percentage error was calculated for the all the data points. The calculated MFE was 8 which meant Snows' method was Barrantes 85 Marriot Forecast under forecasted. The MAPE was then calculated and came out to be 12% which is not bad.

C) Decomposition of time series

Time series decomposition involves thinking of **a series** as a combination of level, trend, seasonality, and noise components. Decomposition provides a useful abstract model for thinking about time series generally and for better understanding problems during time series analysis and forecasting. We have two kind of decomposition like additive and multiplicative.

D) Saturday Demand Forecasting

TO calculate Saturday demand forecasting we have to calculate the critical ratio and mean with standard deviation formula. And as per the model my Saturday demand forecast is **1736**. 1736 rooms are mandatory to cover fluctuation in demand (based on historical demand pattern).However, hotel already has capacity of 1877 rooms.1736 rooms are already covering cost of underage(probability of 66%). Hamilton hotels have total room capacity of 1877. Also based on the forecasted demand for 22nd August 1987 Saturday, the room reservation stands at **1736**. Rooms remaining vacant are 141. Therefore Ms. Snow can comfortably accept the bookings for Tour Company. Contribution margin for each room, $90 Therefore, total profit contribution by accepting the order, $5400.

G) Naïve Method Forecasting

Naïve forecasting is the **technique in which the last period's sales are used for the next period's forecast without predictions or adjusting the factors**. Forecasts produced using a naïve approach are equal to the final observed value. The MAPE was then calculated and came out to be **10%** which is not bad.

Note: (All the calculation part is showing in screenshot in Section 7: Technical Solution part)

Section6: Managerial Insights from this problem

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Maximizing revenue by means of utilizing full capacity can be quite the challenge. This can be broken down a few ways. In one scenario, the hotel can decide to underbook the amount of rooms available, guaranteeing a loss in potential maximization of revenue. In another, they can overbook the hotel and hope exactly enough people cancel in order to have the rooms at full capacity, which would guarantee maximum revenue. The likely scenarios from this case show little probability of the latter occurring. The other problem faced by the hotel is customer satisfaction. There lies a fine balance between being able to maximize revenue and maintain a high customer satisfaction. Specifically, if the hotel decides to turn down the tour in fear of overbooking and "X" amount of people cancel, they just lost $90*(X+60) in revenue. Not only that but they just lost customer satisfaction as well. On the other hand, if they decide to overbook and not enough people cancel, they now have to spend more money relocating a dissatisfied customer

Based on the analysis of our decision tree, Linda Snow should book the reservation for 60. All EV's which include accepting the reservation, are greater than the EV of not accepting it. This means that even if they fell into the worst case scenario of overbooking 22 guests and paying $8360 to relocate them, it would be the better financial choice to make. This is backed by using the historical data as a probabilistic measure of how many people will end up cancelling their reservations and being confident that it will hold true.

Moving forward, Snow should use exponential smoothing to smoothen out and forecast the demand for the upcoming reservations and determine whether to accept the reservation for this request and any other future request. Exponential Smoothing revealed the lowest Mape result. With the alpha of 80 perfect, the forecast was able to trace the demand values the best. The alpha of 80% and 5% were key in generating the forecast for future fluctuations of demand and to decide if Snow should accept the reservation for the sixty rooms or not.

Section 8: Conclusion

It can be said that Snow should accept the request for all of the 60 rooms. This Will prevent a negative reputation and given the mape scores, regression and exponential smoothing calculations, the demand is meeting up with the forecast. Based on the forecasted demand for week 14, the demand will be high. The future demand for the hotel past that Saturday also seems to be higher in the forecasted values. The values suggest that the people who have a booking will check in and meet the forecasted demand. In the long run, the Hamilton hotel management should expand their capacity to fulfill the upcoming increase in demand and actual reservations. It is indicative for Snow and her management to realize the importance of maximizing capacity to increase revenues

Section 7 : Technical Solution in R Language

Library Setup

```
library(ggplot2)

library(forecast)

library(TTR)

library(dplyr)

library(readxl)
```

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library(tidyverse)

library(DT)

library(plotly)

library(lubridate)

library(tseries)

Data Description

WEEK = Week number

DOW INDICATOR1 = Day of the week where 1 represents Sat, 2 represent Sun and going on..

DEMAND = Historical Demand Data

UESDAY BOOKINGS = Tuesday Booking

PICKUP RATIO = DEMAND / TUESDAY BOOKINGS

DOW INDEX = Average PICKUP RATIO of the day of the week / Average daily PICKUP RATIO

Detailed Programming ScreenShot

```
#read csv file
library(readxl)
file_path <- paste(getwd(), "mariot_data.xlsx", sep ="/")
marriot_data_set<-read_excel(file_path)
#view csv file
View(marriot_data_set)
```

Filter

	WEEK	Dates	Day	DOW INDICATOR1	DEMAND	TUESDAY BOOKINGS	PICKUP RATIO	DOW INDEX
1	1	1987-05-23	Saturday	1	1470	1512	0.972	0.865
2	1	1987-05-24	Sunday	2	870	864	1.007	0.911
3	1	1987-05-25	Monday	3	986	827	1.192	0.973
4	1	1987-05-26	Tuesday	4	1247	952	1.310	1.013
5	1	1987-05-27	Wednesday	5	1109	740	1.499	1.068
6	1	1987-05-28	Thursday	6	1197	908	1.318	1.123

Showing 1 to 8 of 98 entries, 8 total columns

```
#summary of the dataset
summary(marriot_data_set)
```

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```
      WEEK                Dates                              Day
 Min.   : 1.000   Min.   :1987-05-23 00:00:00   Length:98
 1st Qu.: 4.000   1st Qu.:1987-06-16 06:00:00   Class :character
 Median : 7.000   Median :1987-07-10 12:00:00   Mode  :character
 Mean   : 7.076   Mean   :1987-07-10 12:00:00
 3rd Qu.:10.000   3rd Qu.:1987-08-03 18:00:00
 Max.   :14.000   Max.   :1987-08-28 00:00:00
 NA's   :6
 DOW INDICATOR1      DEMAND      TUESDAY BOOKINGS  PICKUP RATIO
 Min.   :1       Min.   : 722   Min.   : 599      Min.   :0.8460
 1st Qu.:2       1st Qu.:1268   1st Qu.:1010      1st Qu.:0.9615
 Median :4       Median :1600   Median :1478      Median :1.0755
 Mean   :4       Mean   :1506   Mean   :1413      Mean   :1.0987
 3rd Qu.:6       3rd Qu.:1773   3rd Qu.:1746      3rd Qu.:1.1952
 Max.   :7       Max.   :1924   Max.   :2105      Max.   :1.5510
                 NA's   :10                       NA's   :10
```

```
  DOW INDEX
Min.   :0.8650
1st Qu.:0.9110
Median :1.0130
Mean   :0.9974
3rd Qu.:1.0680
Max.   :1.1230
NA's   :11
```

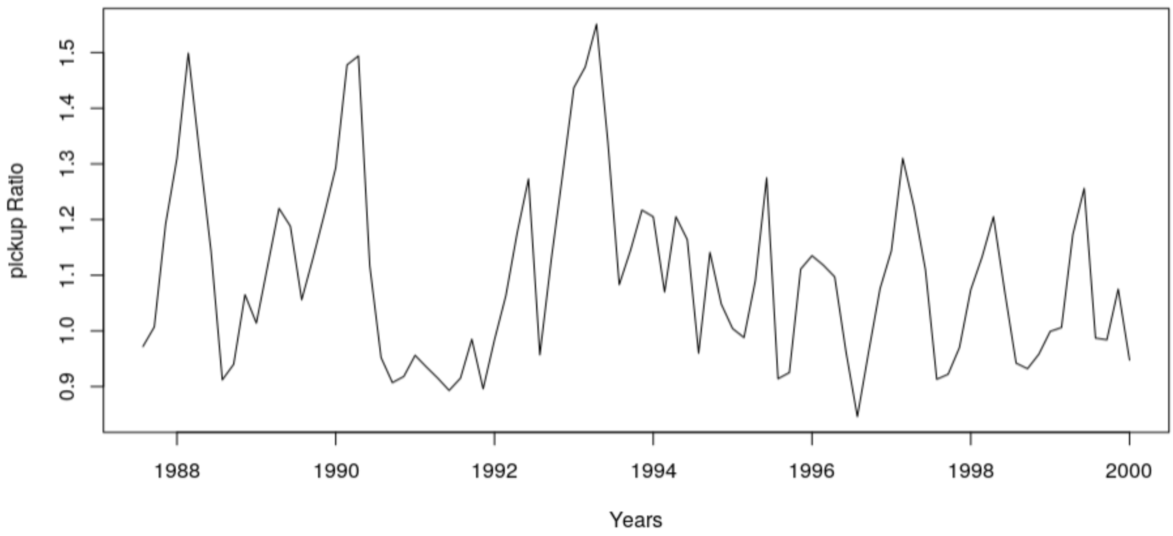
```
#calculate the saturday demand
Sat_Demand_forcasting <- marriot_data_set %>%
  filter(`DOW INDICATOR1`==1 & `DEMAND` != 'NA') %>%
  select(`DOW INDICATOR1`,`DEMAND`)
#view the saturday demand caulative dataset
```

Marriot Case Study Analysis (DBI001_IIMN)

```r
#find out the critical ratio
Cost_of_shortage <- 180
Cost_of_coverge <- 90
Critical_ratio <- Cost_of_shortage/(Cost_of_coverge+Cost_of_shortage)
Critical_ratio
#find out the saturday demand calculations
Sat_demand_Size <-length(Sat_Demand_forcasting$DEMAND)
Sat_demand_Size
Sat_demand_Mean_value <- mean(Sat_Demand_forcasting$DEMAND)
Sat_demand_Mean_value
Sat_demand_Sd <- sd(Sat_Demand_forcasting$DEMAND)
Sat_demand_Sd
#find out the forecast value for Saturay based on demand
Sat_forecasting_value <- qnorm(
  p = Critical_ratio,
  mean = Sat_demand_Mean_value,
  sd = Sat_demand_Sd
)
Sat_forecasting_value
paste0('Saturday demand calculations can be predicted' ," : ",Sat_forecasting_value)
```

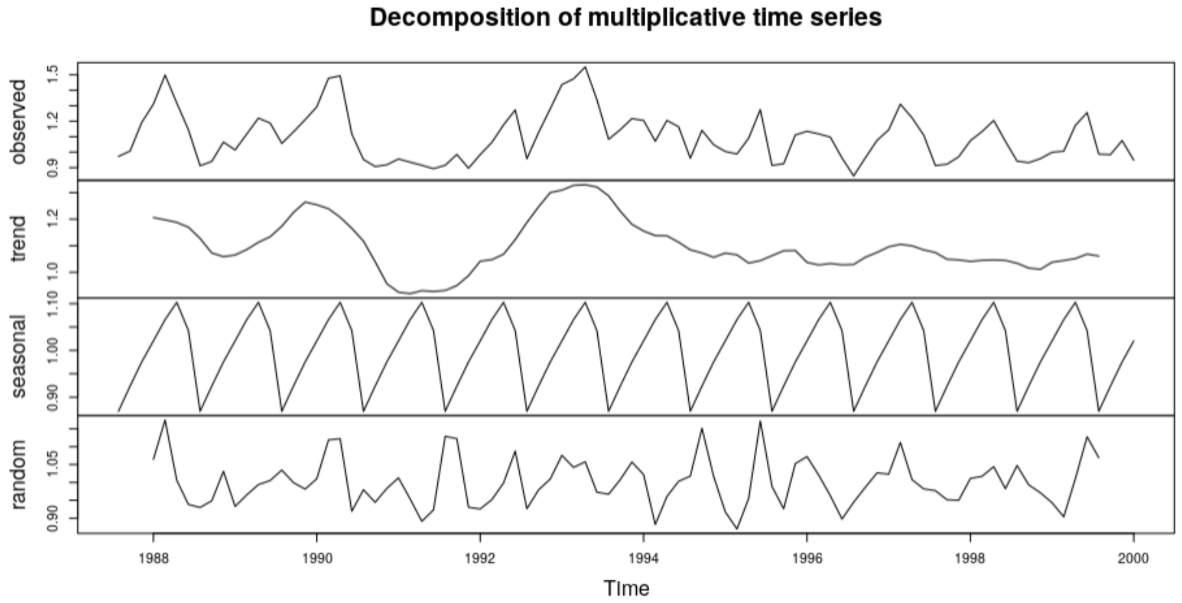
```
> paste0('Saturday demand calculations can be predicted' ," : ",Sat_forecasting_v
alue)
[1] "Saturday demand calculations can be predicted : 1735.05605020744"
```

```r
#now we have to find out the calculations as time series dataset.
Predicted_TimeSeries <- marriot_data_set %>%
  filter(`PICKUP RATIO` != 'NA') %>%
  select(Dates,`PICKUP RATIO`)

Predicted_TimeSeries$Dates =ymd(Predicted_TimeSeries$Dates)
Predicted_TimeSeries
#convert predicted time series data into TS actual Conversion with seasonality
TimeSeries_ts = ts(Predicted_TimeSeries[,2],start = c(1987,05,23),frequency=7)
plot(TimeSeries_ts, xlab='Years', ylab='pickup Ratio')

#decompostion time series model(multiplicative)
TimeSeries_ts_decompose_multiple = decompose(TimeSeries_ts, type=c("multiplicative")
summary(TimeSeries_ts_decompose_multiple)
plot(TimeSeries_ts_decompose_multiple)
```

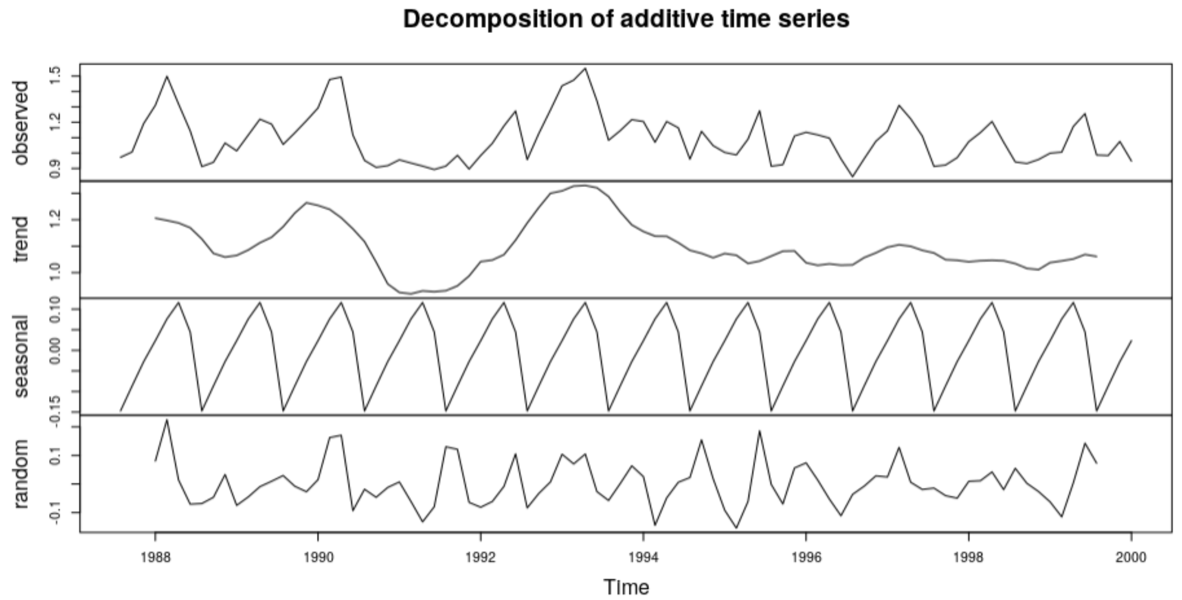



```
#decompostion time series model(multiplicative)
TimeSeries_ts_decompose_multiple = decompose(TimeSeries_ts, type=c("multipli
summary(TimeSeries_ts_decompose_multiple)
plot(TimeSeries_ts_decompose_multiple)
```

```
          Length Class  Mode
x         88     ts     numeric
seasonal  88     ts     numeric
trend     88     ts     numeric
random    88     ts     numeric
figure     7     -none- numeric
type       1     -none- character
>
```

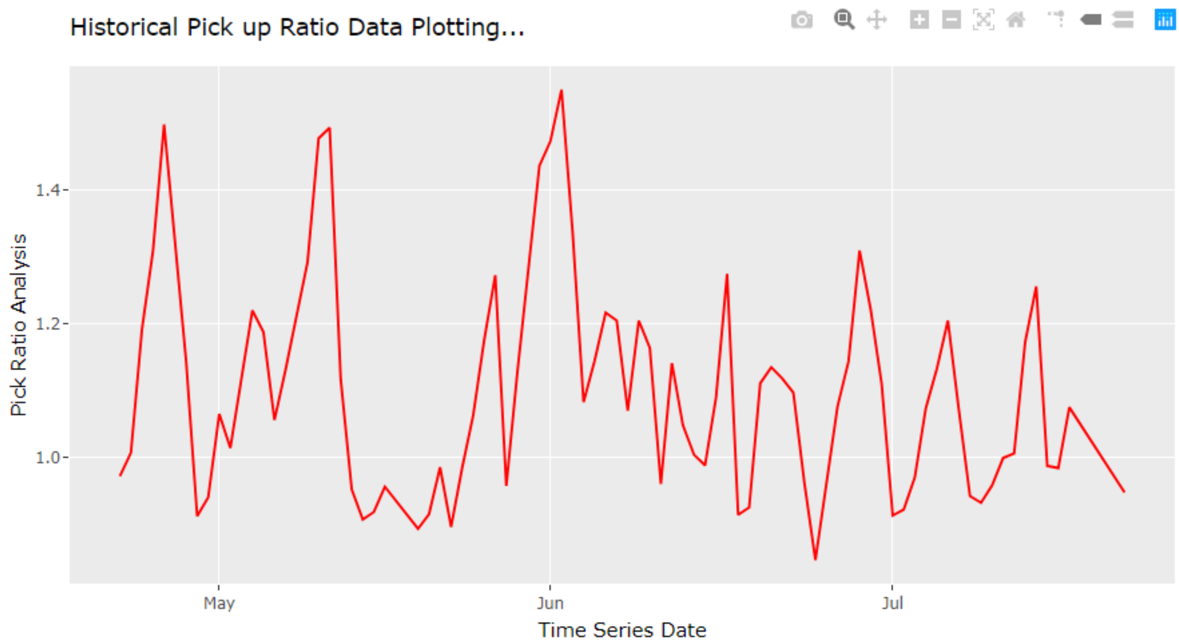



```
#decompostion time series model(additive)
TimeSeries_ts_decompose_additive = decompose(TimeSeries_ts, type=c("additive
summary(TimeSeries_ts_decompose_additive)
plot(TimeSeries_ts_decompose_additive)
```

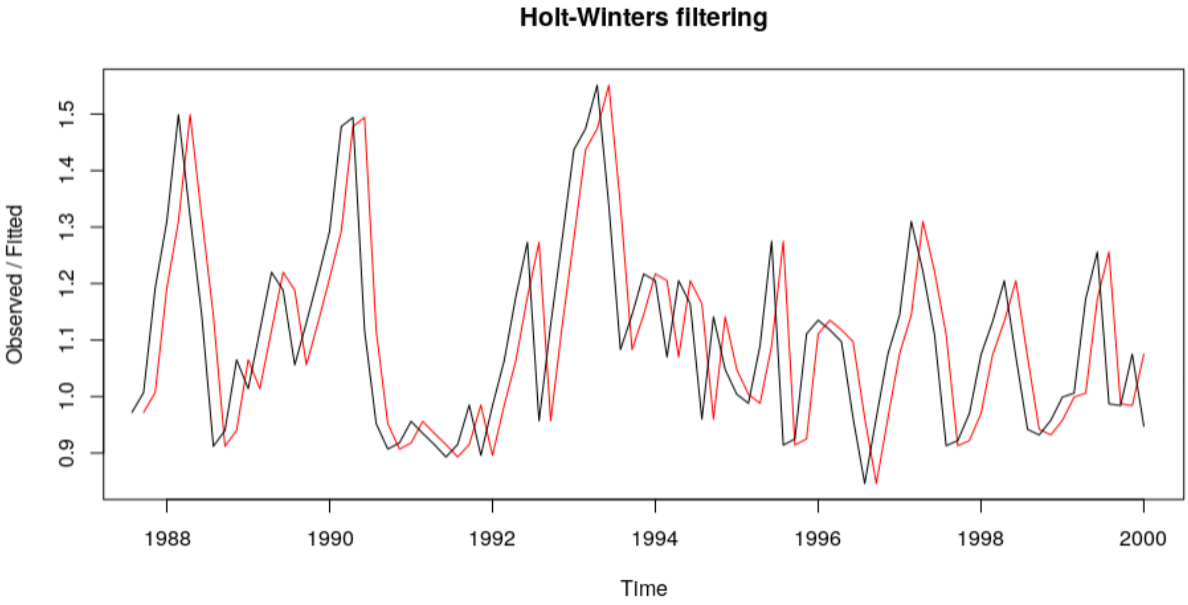


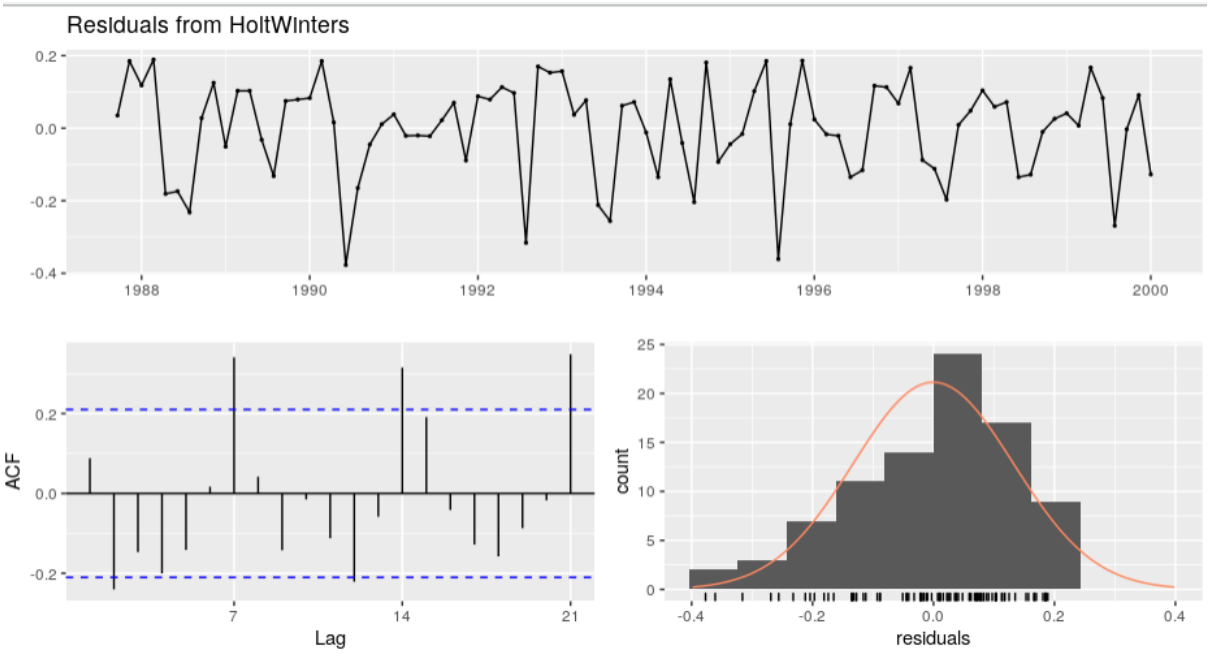
Marriot Case Study Analysis (DBI001_IIMN)

```r
#plot the pickup ratio data
title_bar <- "Historical Pick up Ratio Data Plotting..."
x_bar <- "Time Series Date"
y_bar <- "Pick Ratio Analysis"
graph_plotting<-ggplot(Predicted_TimeSeries) +
  aes(x = Dates, y = `PICKUP RATIO`) +
  geom_line(size = 0.5, colour = "red") +
  labs(x = x_bar, y = y_bar,title = title_bar) +
  theme_gray()
ggplotly(graph_plotting)
```




```r
#HoltWinter Exponential Smoothing method
marriot_holt_expo <- HoltWinters(TimeSeries_ts, gamma = FALSE, beta = FALSE)
summary(marriot_holt_expo)
plot(marriot_holt_expo)
checkresiduals(marriot_holt_expo)
```



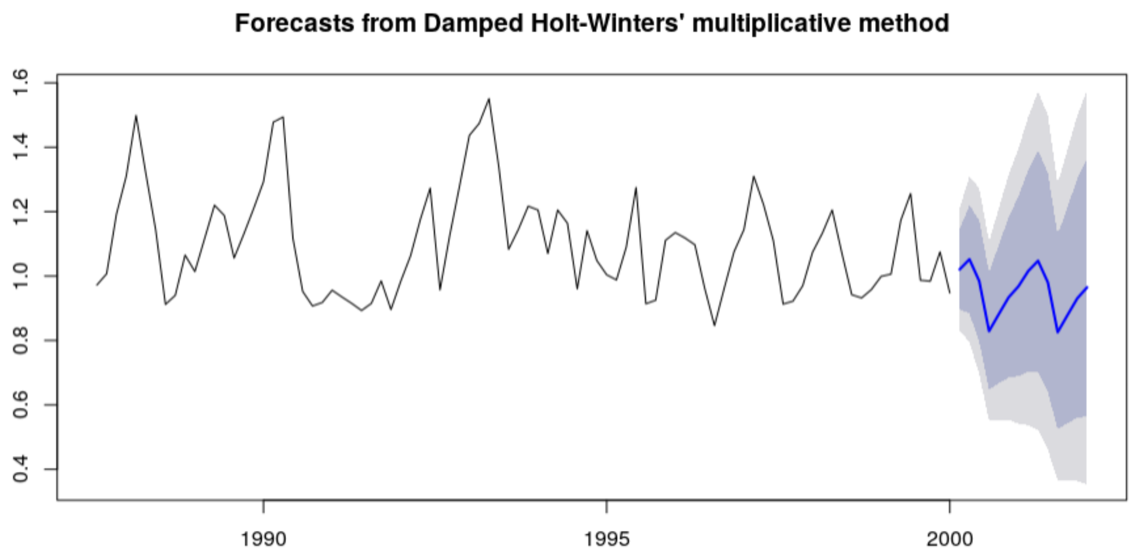



```
#HoltWinter's Multiplecative model
marriot_HoltWinter_multi <- hw(TimeSeries_ts,seasonal= "multiplicative",damp
summary(marriot_HoltWinter_multi)
plot(marriot_HoltWinter_multi)
checkresiduals(marriot_HoltWinter_multi)
```

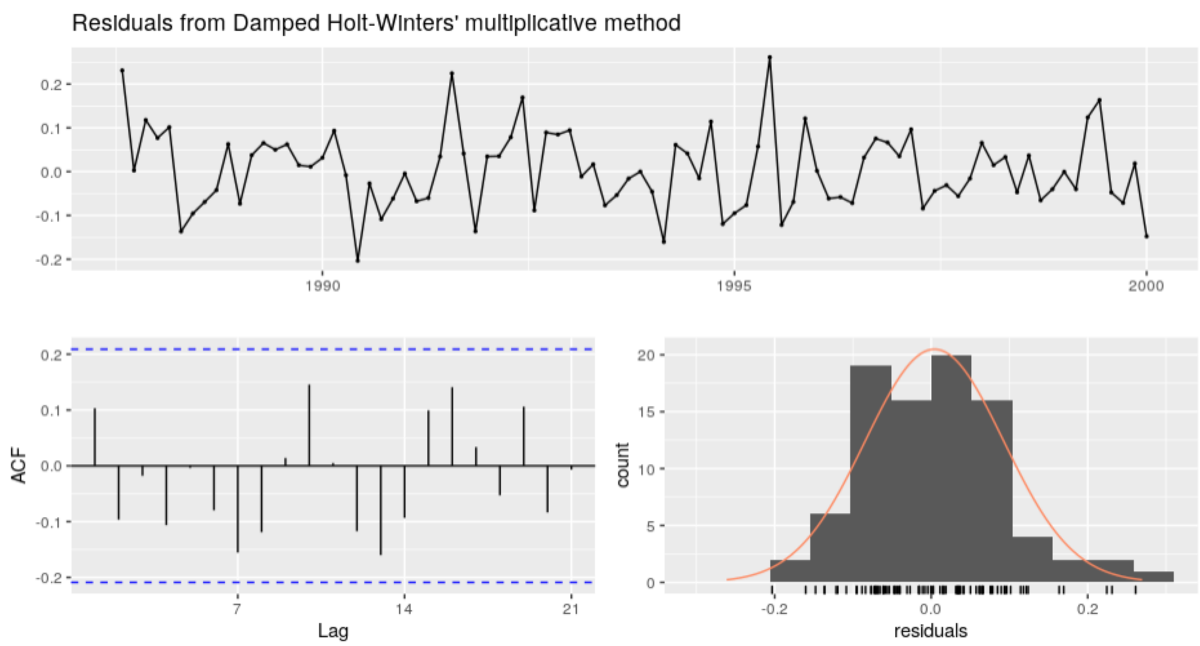
```
Forecast method: Damped Holt-Winters' multiplicative met
hod
```

```
Model Information:
Damped Holt-Winters' multiplicative method

Call:
 hw(y = TimeSeries_ts, seasonal = "multiplicative", damp
ed = TRUE)

  Smoothing parameters:
    alpha = 0.8444
    beta  = 0.0065
    gamma = 1e-04
    phi   = 0.9363

  Initial states:
    l = 0.9091
    b = -0.0018
    s = 1.0324 1.1026 1.0687 1.0181 0.9817 0.9264
           0.8702

  sigma:  0.0948

      AIC      AICc       BIC
 7.141574 12.060493 39.346952

Error measures:
                       ME        RMSE         MAE          M
PE      MAPE      MASE
Training set 0.0008299464 0.09634119 0.07705806 -0.34838
41 7.027699 0.4956324
                 ACF1
Training set 0.107738

Forecasts:
         Point Forecast     Lo 80    Hi 80     Lo 95     
Hi 95
2000.143      1.0205662 0.8966049 1.144528 0.8309837 1.2
10149
2000.286      1.0520496 0.8838908 1.220208 0.7948730 1.3
09226
```

```
2000.429       0.9843373 0.7960599 1.172615 0.6963919 1.2
72283
2000.571       0.8290106 0.6476559 1.010365 0.5516525 1.1
06369
2000.714       0.8819252 0.6670662 1.096784 0.5533267 1.2
10524
2000.857       0.9339900 0.6849989 1.182981 0.5531910 1.3
14789
2001.000       0.9680887 0.6891874 1.246990 0.5415460 1.3
94631
2001.143       1.0155882 0.7023373 1.328839 0.5365123 1.4
94664
2001.286       1.0472409 0.7039226 1.390559 0.5221808 1.5
72301
2001.429       0.9801215 0.6405902 1.319653 0.4608532 1.4
99390
2001.571       0.8256839 0.5248729 1.126495 0.3656332 1.2
85735
2001.714       0.8786094 0.5433135 1.213905 0.3658185 1.3
91400
2001.857       0.9307002 0.5599081 1.301492 0.3636227 1.4
97778
2002.000       0.9648942 0.5647370 1.365051 0.3529066 1.5
76882
```



```
> checkresiduals(marriot_HoltWinter_multi)

      Ljung-Box test

data:  Residuals from Damped Holt-Winters' multiplicativ
e method
Q* = 15.621, df = 3, p-value = 0.001356

Model df: 12.   Total lags used: 15
```

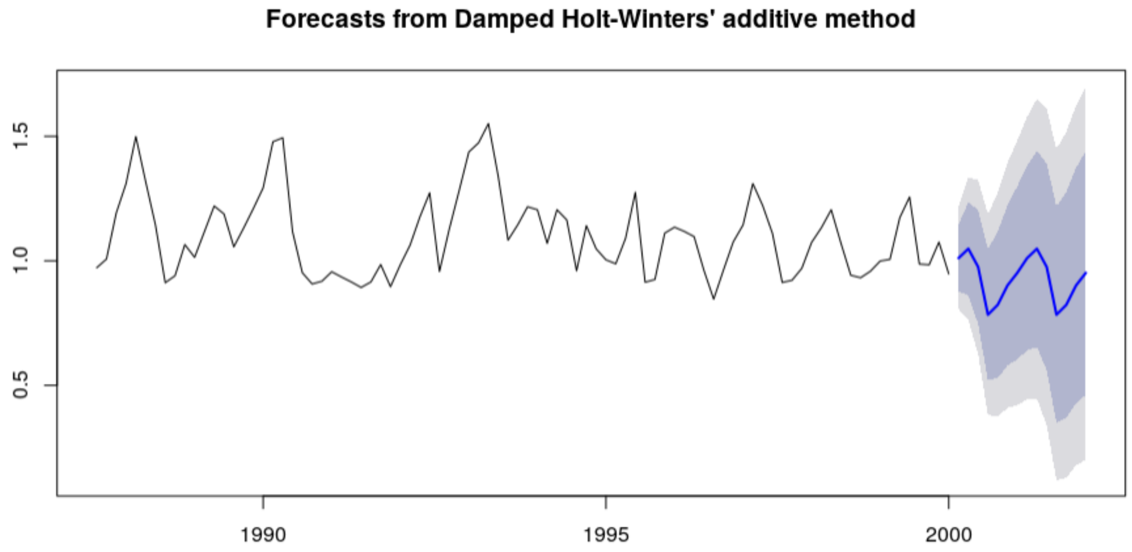



```
#HoltWinter's additive model
marriot_HoltWinter_additive <- hw(TimeSeries_ts,seasonal= "additive",damped
summary(marriot_HoltWinter_additive)
plot(marriot_HoltWinter_additive)
summary(TimeSeries_HoltWinter)
checkresiduals(marriot_HoltWinter_additive)
```

```
Forecast method: Damped Holt-Winters' additive method

Model Information:
Damped Holt-Winters' additive method

Call:
 hw(y = TimeSeries_ts, seasonal = "additive", damped = T
RUE)
```

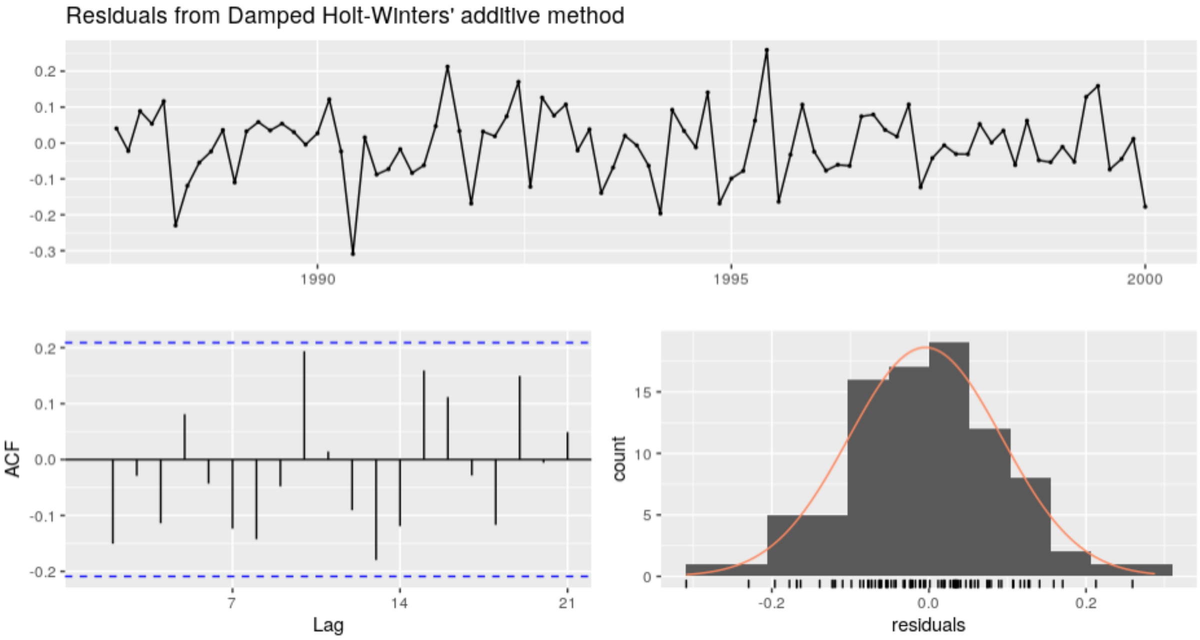
```
  Smoothing parameters:
    alpha = 0.9763
    beta  = 3e-04
    gamma = 1e-04
    phi   = 0.9257

  Initial states:
    l = 1.0556
    b = 0.0218
    s = 0.0476 0.1206 0.083 0.024 -0.0264 -0.1047
           -0.1441

  sigma:  0.1044

      AIC      AICc       BIC
 9.370585 14.289504 41.575963

Error measures:
                      ME        RMSE         MAE         MP
E      MAPE      MASE
Training set -0.00463337 0.09698939 0.07570768 -0.785790
4 6.937284 0.4869468
                     ACF1
Training set 0.0001200237

Forecasts:
         Point Forecast     Lo 80    Hi 80     Lo 95
Hi 95
2000.143      1.0108334 0.8770831 1.144584 0.8062799 1.2
15387
2000.286      1.0483757 0.8614269 1.235325 0.7624622 1.3
34289
2000.429      0.9754155 0.7473406 1.203490 0.6266051 1.3
24226
2000.571      0.7836411 0.5207849 1.046497 0.3816372 1.1
85645
2000.714      0.8230933 0.5295373 1.116649 0.3741382 1.2
72048
```

```
2000.857       0.9013231 0.5799778 1.222668 0.4098678 1.3
92778
2001.000       0.9517071 0.6047834 1.298631 0.4211331 1.4
82281
2001.143       1.0107741 0.6400208 1.381527 0.4437559 1.5
77792
2001.286       1.0483208 0.6551782 1.441463 0.4470611 1.6
49581
2001.429       0.9753647 0.5610355 1.389694 0.3417030 1.6
09026
2001.571       0.7835941 0.3491056 1.218083 0.1191013 1.4
48087
2001.714       0.8230497 0.3692925 1.276807 0.1290880 1.5
17011
2001.857       0.9012827 0.4290387 1.373527 0.1790478 1.6
23518
2002.000       0.9516698 0.4616325 1.441707 0.2022224 1.7
01117
```




```
> checkresiduals(marriot_HoltWinter_additive)

	Ljung-Box test

data:  Residuals from Damped Holt-Winters' additive meth
od
```

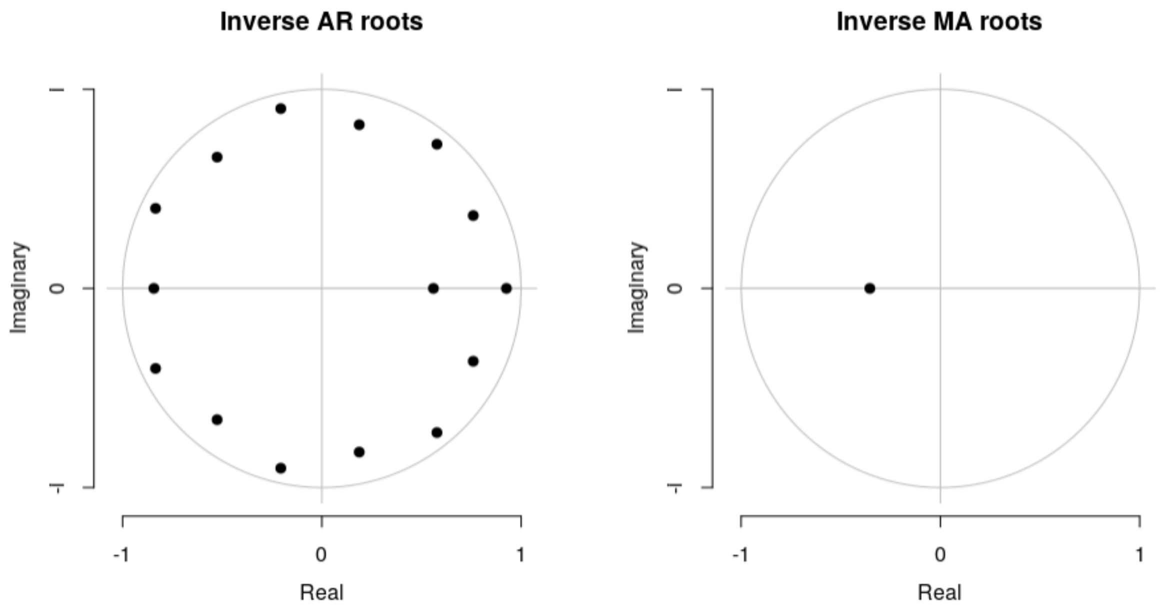
```
Q* = 20.283, df = 3, p-value = 0.0001483

Model df: 12.   Total lags used: 15
```



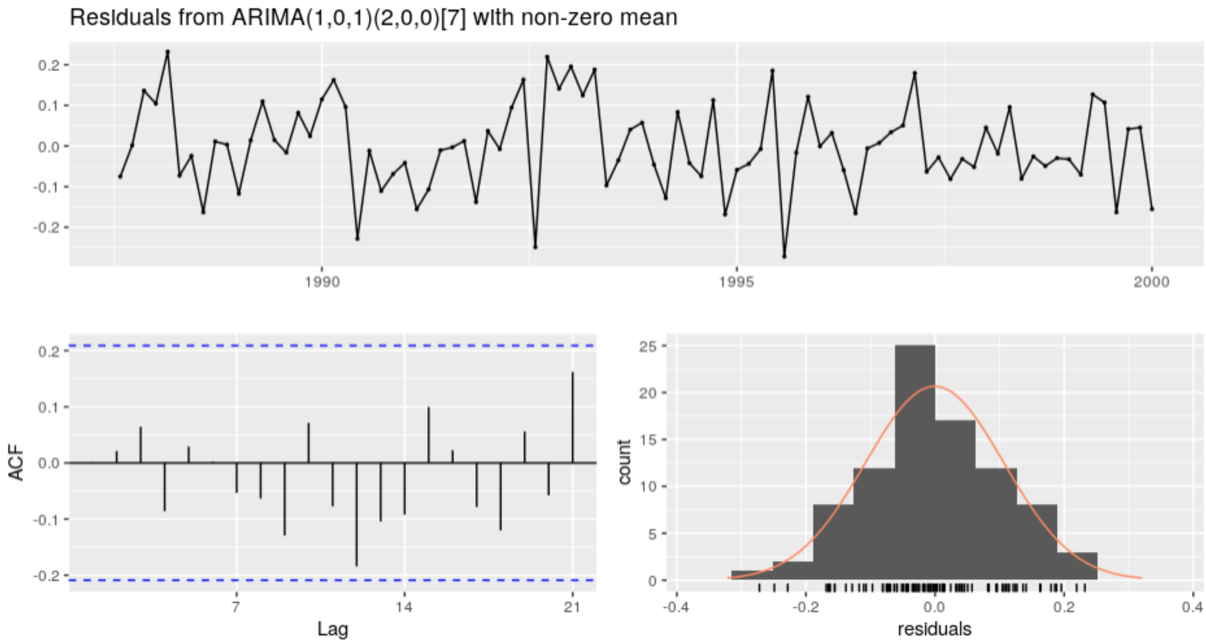

```
#arima Model analysis
marriot_Arima <- auto.arima(TimeSeries_ts)
summary(marriot_Arima)
plot(marriot_Arima)
checkresiduals(marriot_Arima)
```

```
> summary(marriot_Arima)
Series: TimeSeries_ts
ARIMA(1,0,1)(2,0,0)[7] with non-zero mean

Coefficients:
         ar1    ma1    sar1    sar2    mean
      0.5598  0.354  0.2813  0.1769  1.0942
s.e.  0.1248  0.151  0.1091  0.1128  0.0584

sigma^2 estimated as 0.01203:  log likelihood=71.11
AIC=-130.23   AICc=-129.19   BIC=-115.36
```

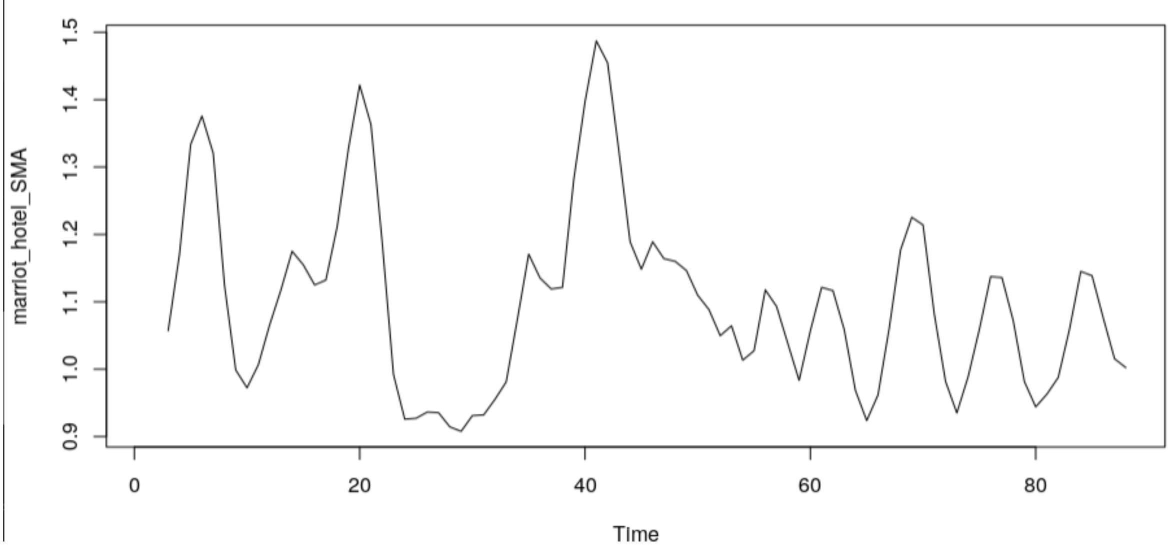
```
Training set error measures:
                        ME      RMSE        MAE          MP
E      MAPE      MASE
Training set -0.0006670875 0.106508 0.08357688 -0.948067
9 7.526225 0.537561
                    ACF1
Training set 0.001073771
```




```
> checkresiduals(marriot_Arima)

      Ljung-Box test

data:  Residuals from ARIMA(1,0,1)(2,0,0)[7] with non-ze
ro mean
Q* = 10.272, df = 9, p-value = 0.3289

Model df: 5.   Total lags used: 14
```



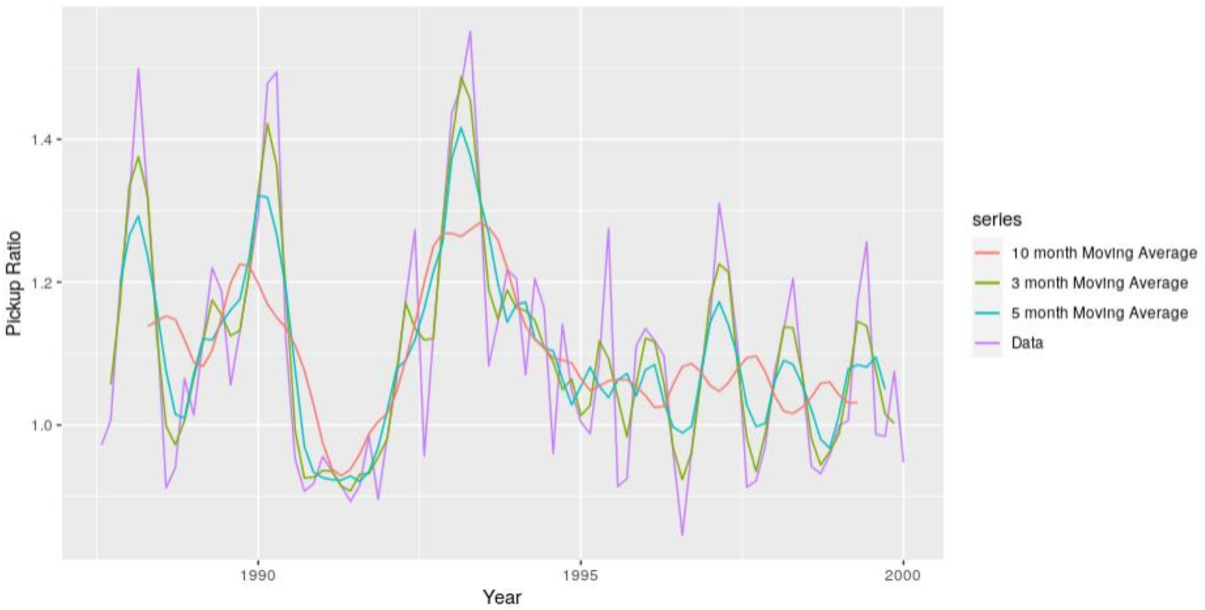

```
#Simple moving average model
marriot_hotel_SMA <- SMA(TimeSeries_ts,n=3)
plot.ts(marriot_hotel_SMA)
summary(marriot_hotel_SMA)
```




```
  Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
0.9077  0.9895  1.0850  1.1013  1.1630  1.4873       2
```

Marriot Case Study Analysis (DBI001_IIMN)

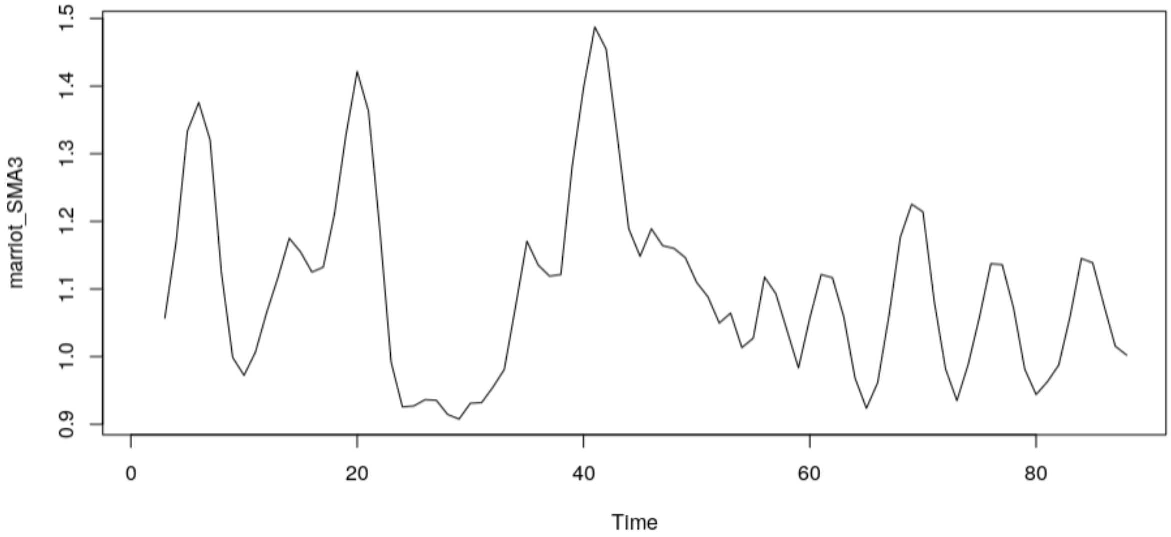
```
#Simple moving average model of mulitple MA
autoplot(TimeSeries_ts, series = "Data") +
  autolayer(ma(TimeSeries_ts, 3), series = "3 month Moving Average") +
  autolayer(ma(TimeSeries_ts, 5), series = "5 month Moving Average") +
  autolayer(ma(TimeSeries_ts, 10), series = "10 month Moving Average") +
  xlab("Year") +  ylab("Pickup Ratio") +
  theme_gray()
```



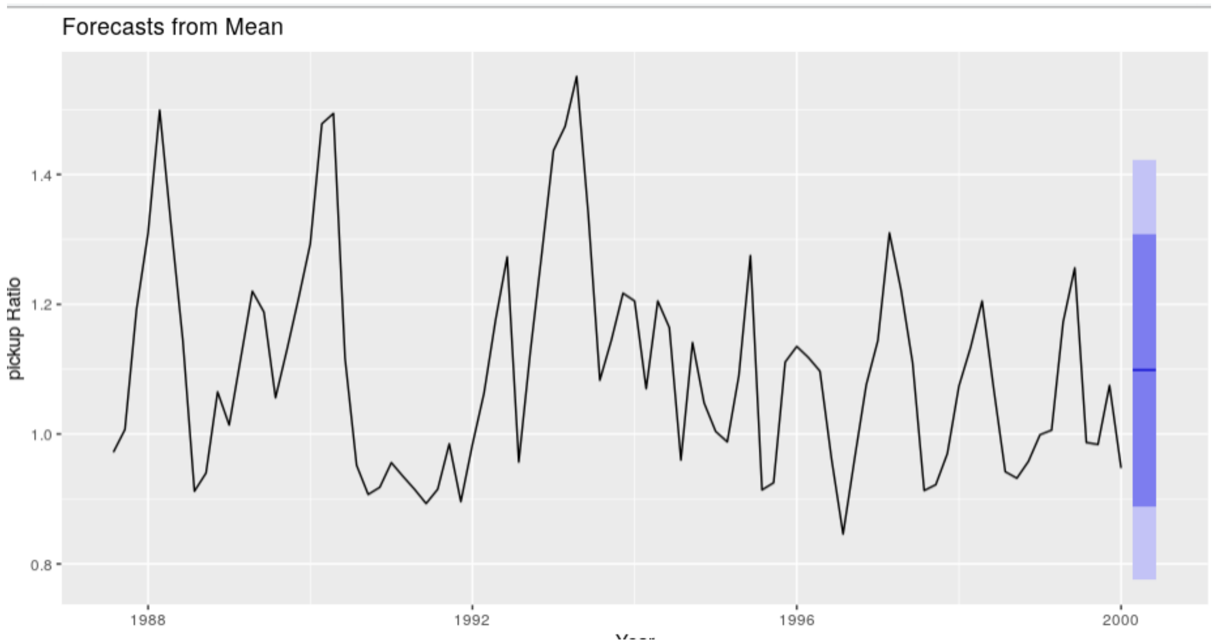

```
#3 months moving average
marriot_SMA3 <- SMA(TimeSeries_ts, n=3)
summary(marriot_SMA3)
plot.ts(marriot_SMA3)
```

```
Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
 0.9077  0.9895  1.0850  1.1013  1.1630  1.4873       2
```

Marriot Case Study Analysis (DBI001_IIMN)




```
#Mean method
marriot_MA3 <- meanf(TimeSeries_ts, h=3)
autoplot(marriot_MA3,xlab = "Year", ylab = "pickup Ratio")
summary(marriot_MA3)
checkresiduals(marriot_MA3)
```




```
Forecast method: Mean

Model Information:
$mu
[1] 1.098688
```

```
$mu.se
[1] 0.01723028

$sd
[1] 0.1616344

$bootstrap
[1] FALSE

$call
meanf(y = TimeSeries_ts, h = 3)

attr(,"class")
[1] "meanf"

Error measures:
                        ME      RMSE       MAE       MPE
MAPE      MASE
Training set -1.059789e-16 0.1607134 0.1293059 -1.995675
11.69516 0.8316871
                  ACF1
Training set 0.6580118

Forecasts:
         Point Forecast    Lo 80    Hi 80     Lo 95    H
i 95
2000.143       1.098688 0.888778 1.308599 0.7756025 1.42
1775
2000.286       1.098688 0.888778 1.308599 0.7756025 1.42
1775
2000.429       1.098688 0.888778 1.308599 0.7756025 1.42
1775
```