

153project

```
library(astsa)
library(TSA)

## Loading required package: leaps
## Loading required package: locfit
## locfit 1.5-9.1    2013-03-22
## Loading required package: mgcv
## Loading required package: nlme
## This is mgcv 1.8-22. For overview type 'help("mgcv-package")'.
## Loading required package: tseries

##
## Attaching package: 'TSA'

## The following objects are masked from 'package:stats':
##
##     acf, arima
## The following object is masked from 'package:utils':
##
##     tar
```

```
library(tsoutliers)
library(randtests)
```

```
##
## Attaching package: 'randtests'

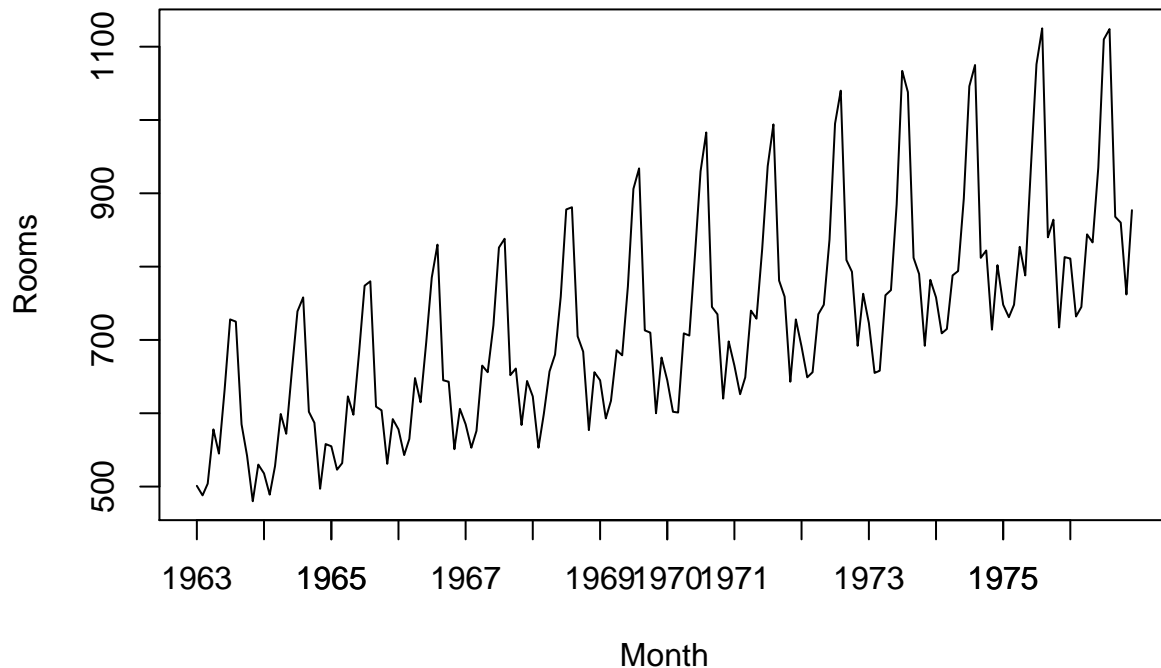
## The following object is masked from 'package:tseries':
##
##     runs.test
```

2.1 Set up and EDA

```
setwd("/Users/furonghuang/Documents/Study materials/Statistics/Time Series/Project")
hotel.raw = read.csv("monthly-hotel-occupied-room-av-6.csv")
colnames(hotel.raw)=c("Month", "Rooms")
hotel = hotel.raw[-169,]
hotel.ts = ts(hotel[,2], start=c(1963, 1), end = c(1976,12), frequency = 12)
hotel.train = ts(hotel[,2], start=c(1963, 1), end = c(1974,12), frequency = 12) # select 1963-1974 as training data
hotel.train.df = hotel[1:144, ]
hotel.test = ts(hotel[145:168, 2], start=c(1975, 1), end = c(1976,12), frequency = 12) # leave last 2 years as test data
hotel.test.df = hotel[145:168, ]
hotel$Month = as.Date(paste(as.character(hotel$Month), "-01", sep=""),
                      format = "%Y-%m-%d")

# in order to show yearly tick on the axis, have to use data.frame for plotting
plot(Rooms~Month, data= hotel, type="l",
      main="Time Series: Monthly data of hotel occupied room from 1963-01 to 1976-12")
axis.Date(side=1, at=seq.Date(min(hotel$Month),max(hotel$Month), by="1 year"))
```

Time Series: Monthly data of hotel occupied room from 1963-01 to 197



```
# add tick every year
```

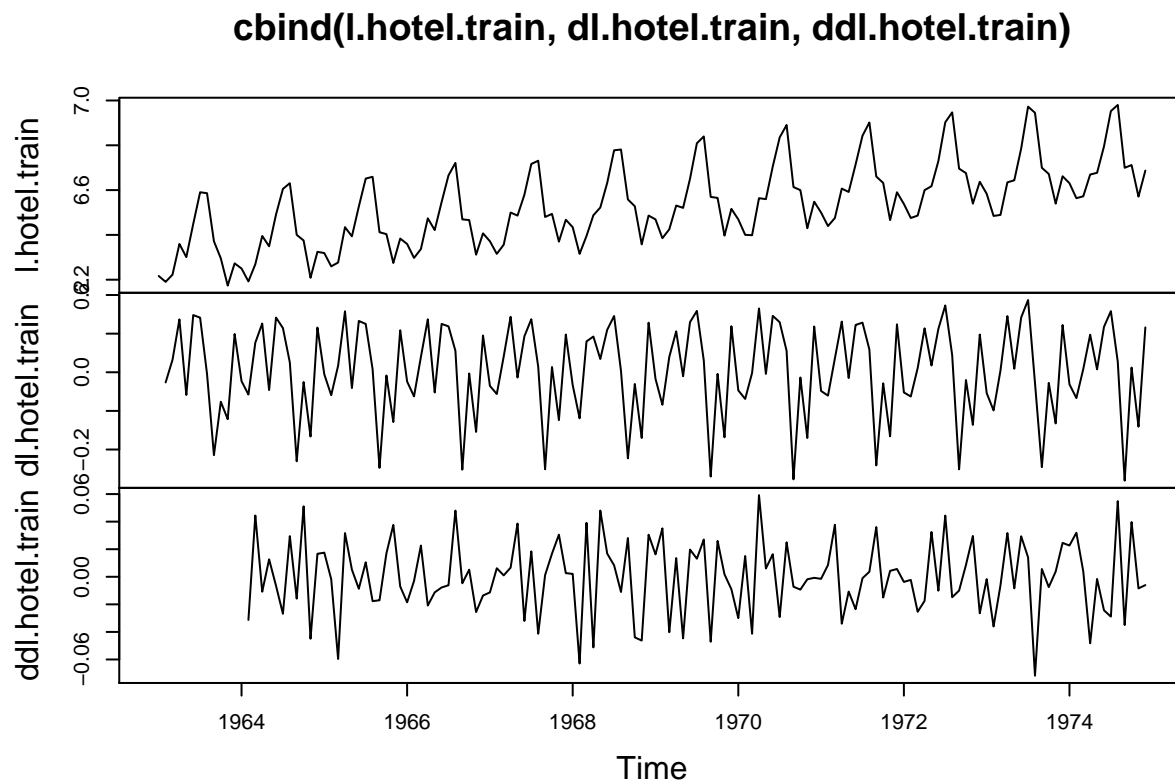
Test for outlier

```
tso(hotel.train, types = c("TC", "AO", "LS", "IO", "SLS"))
```

```
## Series: hotel.train
## Regression with ARIMA(2,0,0)(1,1,0)[12] errors
##
## Coefficients:
##          ar1      ar2      sar1      SLS80      SLS115
##          0.5685  0.3598 -0.4857  41.6283  48.3424
## s.e.      0.0811  0.0815   0.0822  11.3906  11.4903
##
## sigma^2 estimated as 240.6:  log likelihood=-548.92
## AIC=1109.84   AICc=1110.51   BIC=1127.14
##
## Outliers:
##   type ind    time coefhat tstat
## 1  SLS   80 1969:08   41.63 3.655
## 2  SLS  115 1972:07   48.34 4.207
```

Chasing stationarity

```
l.hotel = log(hotel[,2])
l.hotel.train = log(hotel.train)
dl.hotel.train = diff(l.hotel.train)
ddl.hotel.train = diff(dl.hotel.train,12)
plot.ts(cbind(l.hotel.train, dl.hotel.train, ddl.hotel.train))
```

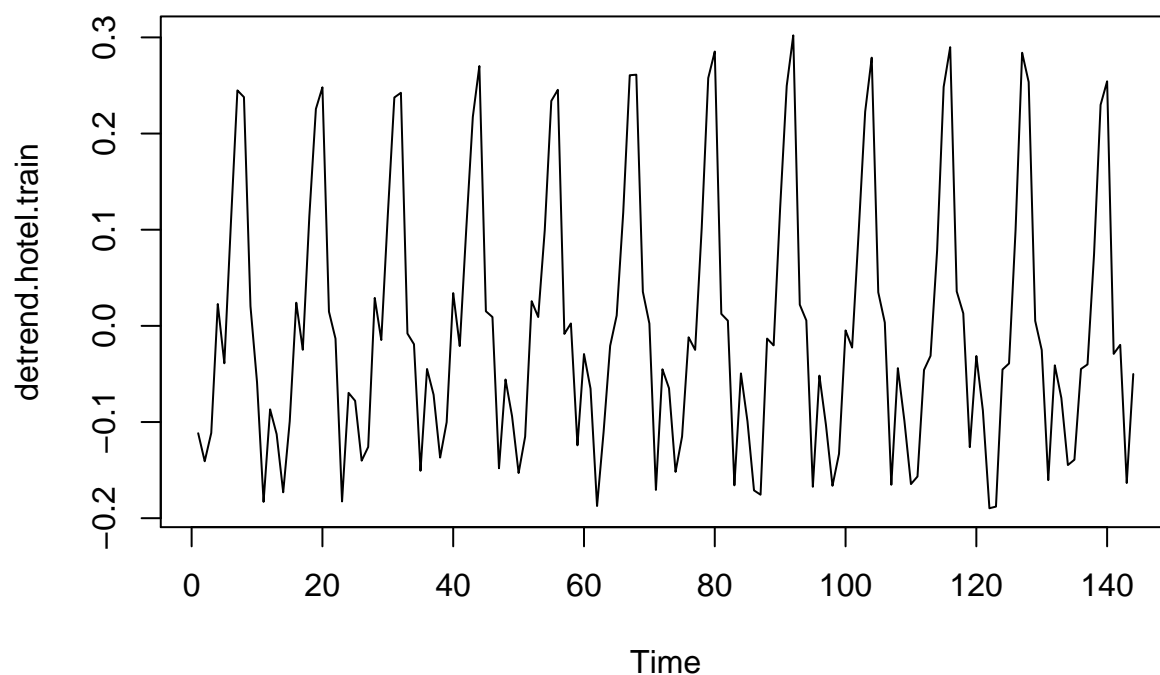


2.2 Spectral analysis

detrend by linear regression, residual plot

```
t = 1:length(l.hotel.train)
fit = lm(l.hotel.train ~ t)
detrend.hotel.train = fit$residuals
# to use spec.pgram() for periodogram, we need stationary, so use the detrend data. However, for spec.p
plot.ts(detrend.hotel.train, main="Detrend hotel")
```

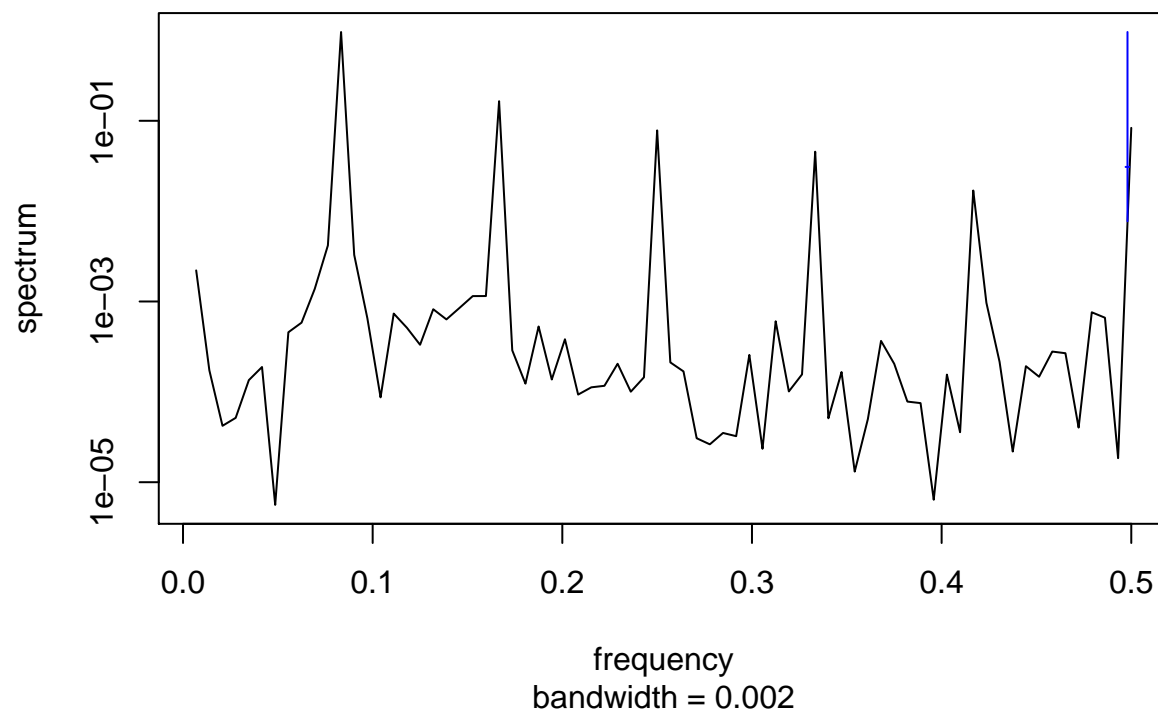
Detrend hotel



Periodogram without smoothing and tapering

```
spec.pgram(detrend.hotel.train, taper = 0)
```

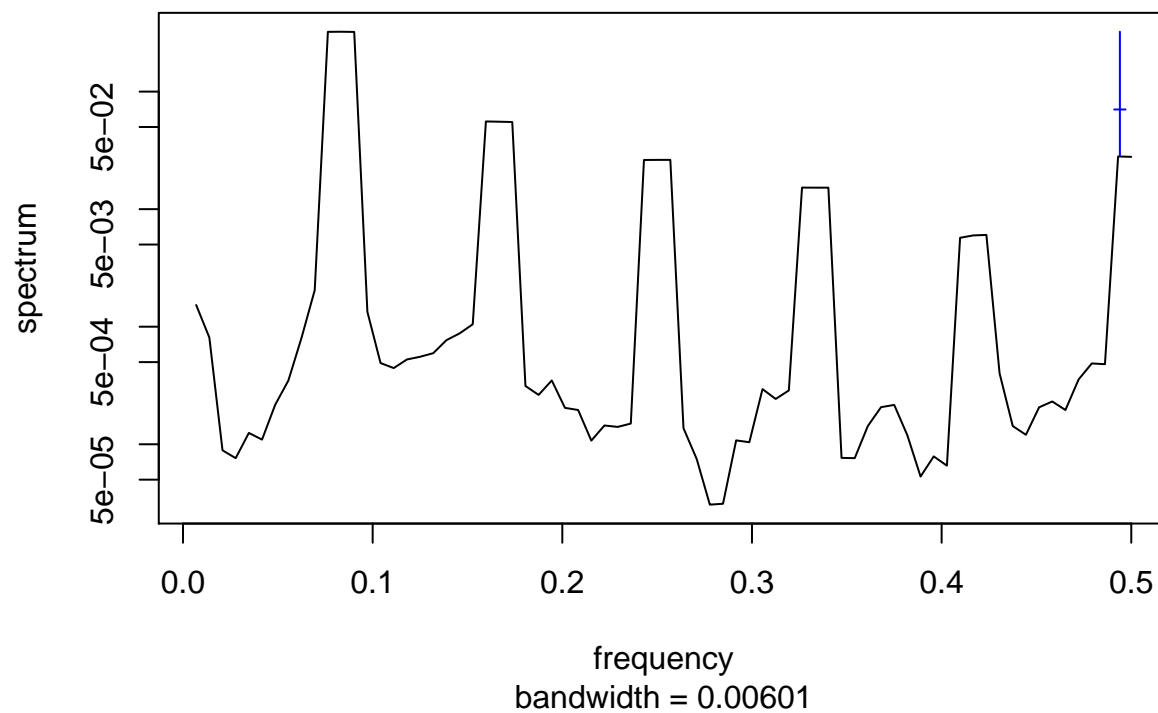
Series: detrend.hotel.train Raw Periodogram



Use daniell kernel to smooth the periodogram

```
spec.pgram(detrend.hotel.train, kernel("daniell", 1), taper=0)
```

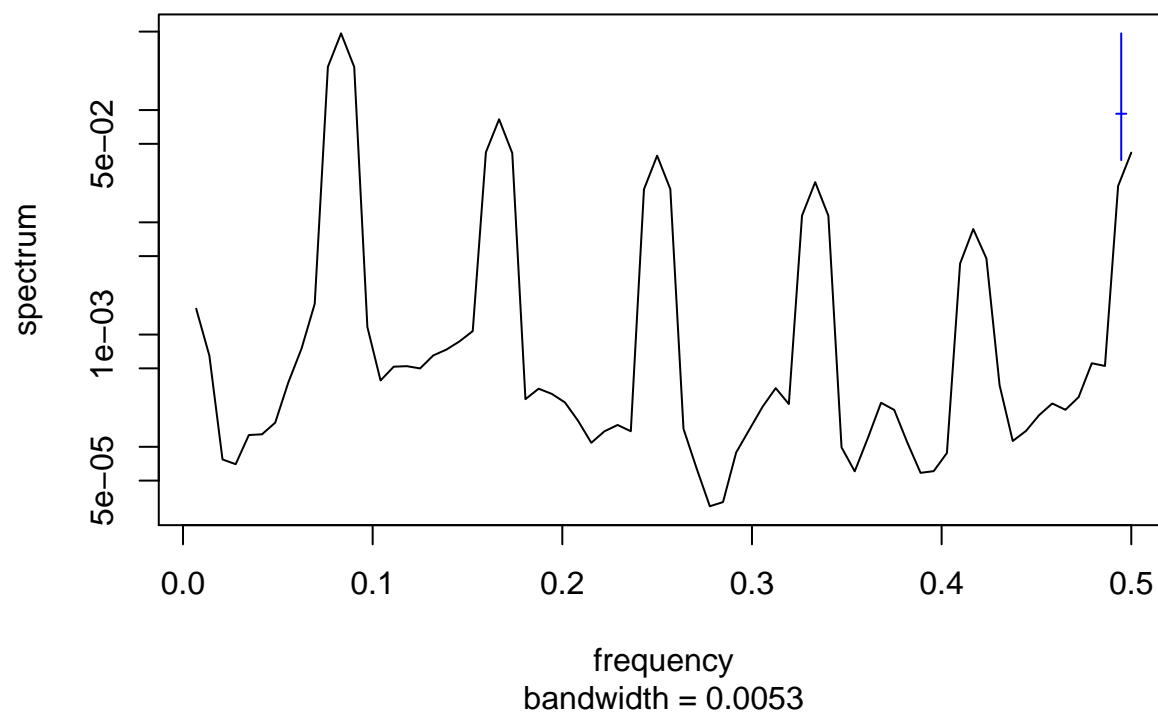
Series: detrend.hotel.train Smoothed Periodogram



To avoid the flat region at the peaks, use modified.daniell kernel

```
spec.pgram(detrend.hotel.train, kernel("modified.daniell", 1), taper=0)
```

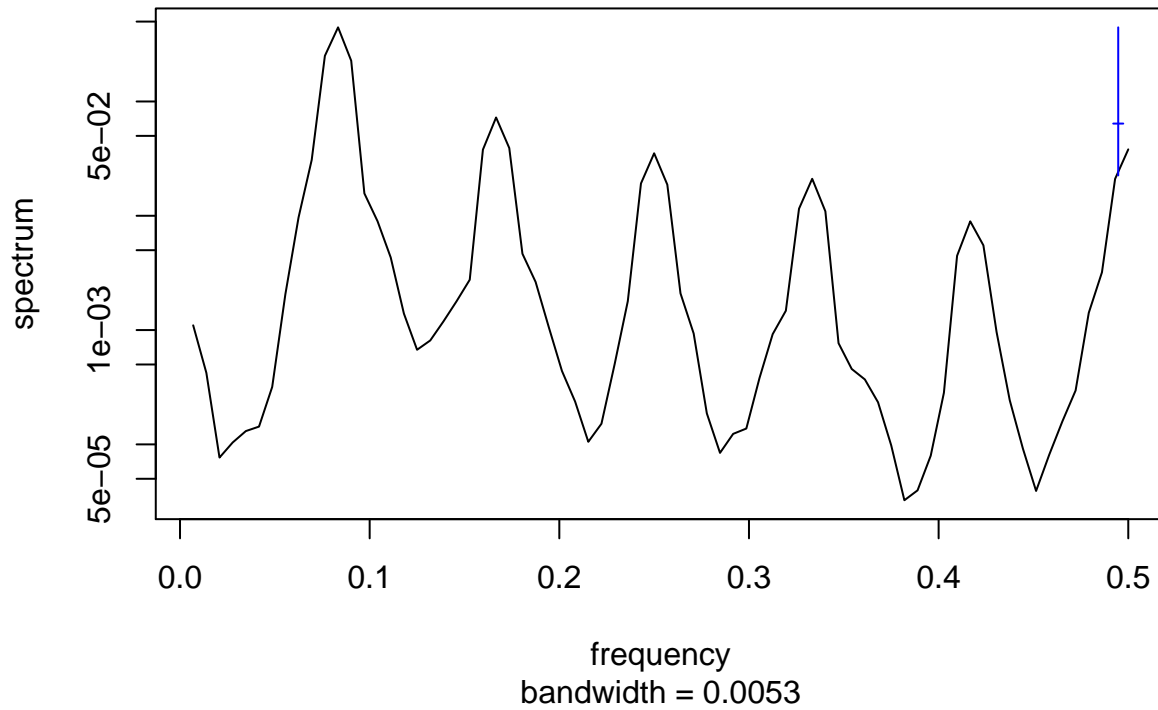
Series: detrend.hotel.train
Smoothed Periodogram



To reduce the side lobes, use tapering

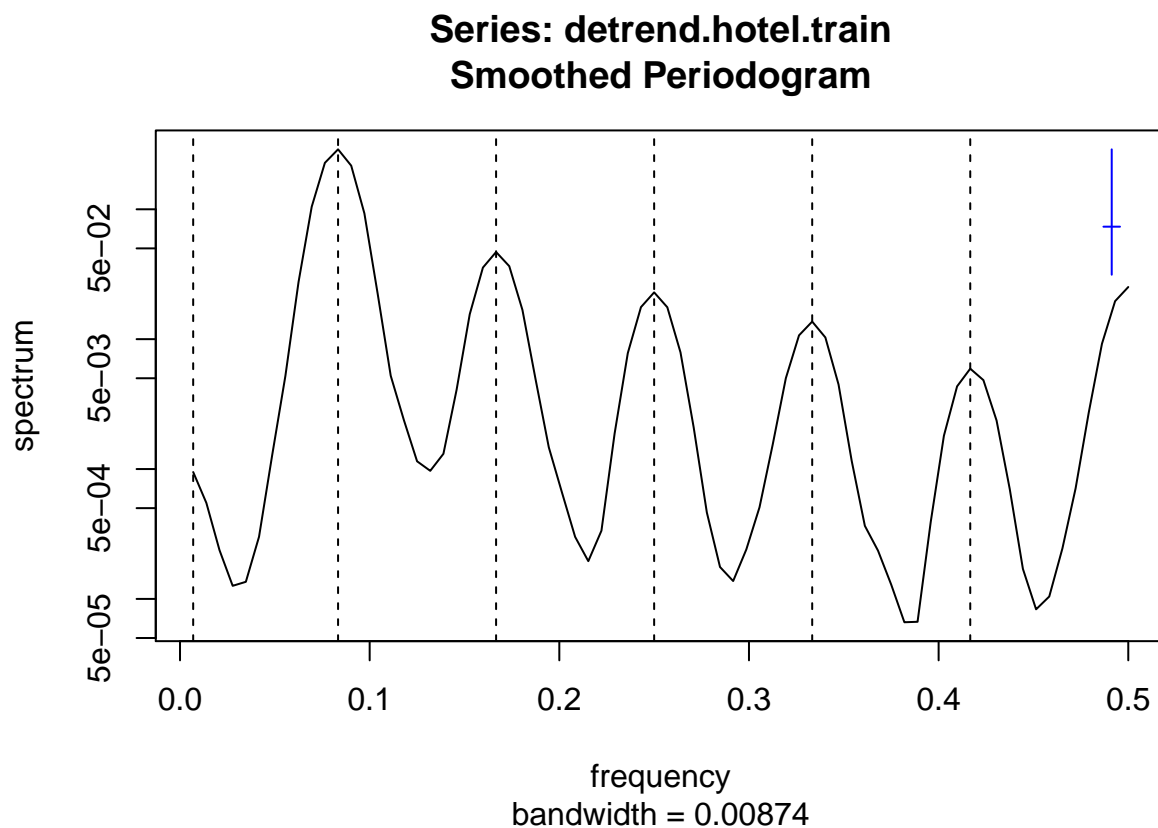
```
spec.pgram(detrend.hotel.train, kernel("modified.daniell", 1), taper=0.2)
```

Series: detrend.hotel.train Smoothed Periodogram



Find the key frequencies

```
pgram = spec.pgram(detrend.hotel.train, kernel("modified.daniell", c(1, 1, 1)), taper=0.2)
key_freq_ind = c(1, which(diff(sign(diff(pgram$spec)))== -2) + 1)
key_freq = pgram$freq[key_freq_ind]
abline(v=key_freq, lty=2)
```

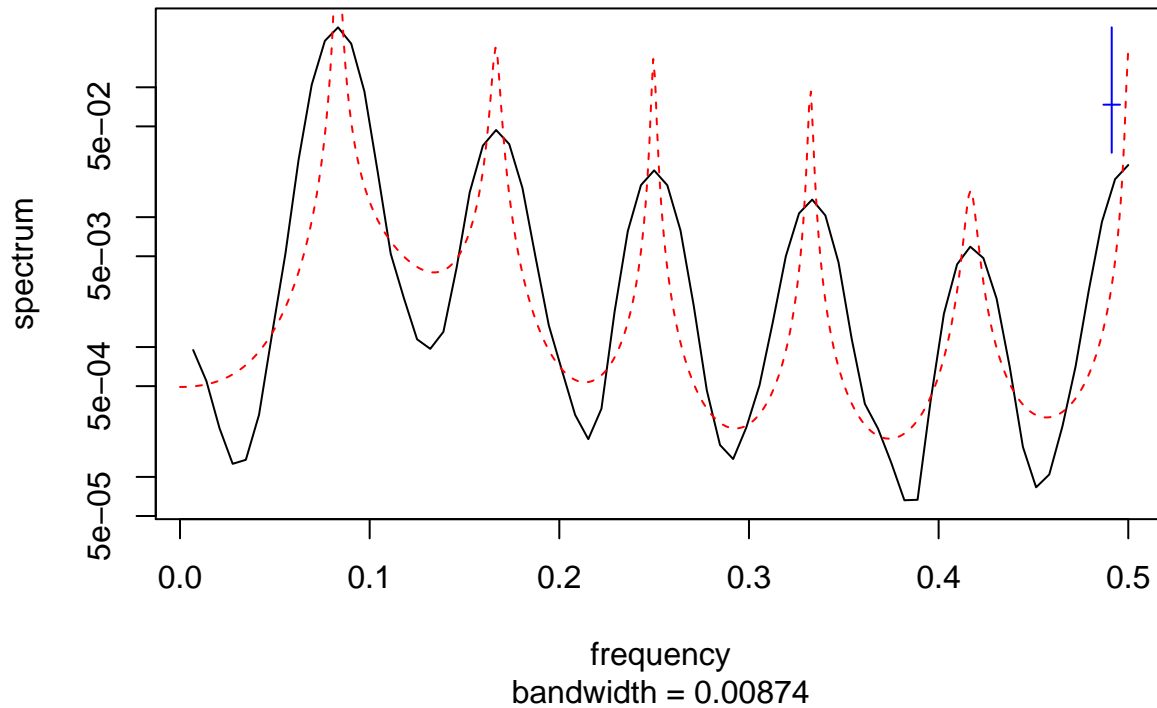


notice that the periodogram should range from $[0, 1/2]$, sometimes if you use the log data(which retains

Parametric way to find the periodogram and comparision to Nonparametric way.

```
spec.pgram(detrend.hotel.train, kernel("modified.daniell", c(1, 1, 1)), taper=0.2)
pgram_ar = spec.ar(detrend.hotel.train, plot=F) # plot the parametric spectral estimation as red, it ha
lines(pgram_ar$freq, pgram_ar$spec, lty=2, col="red")
```


Series: detrend.hotel.train Smoothed Periodogram



Para-

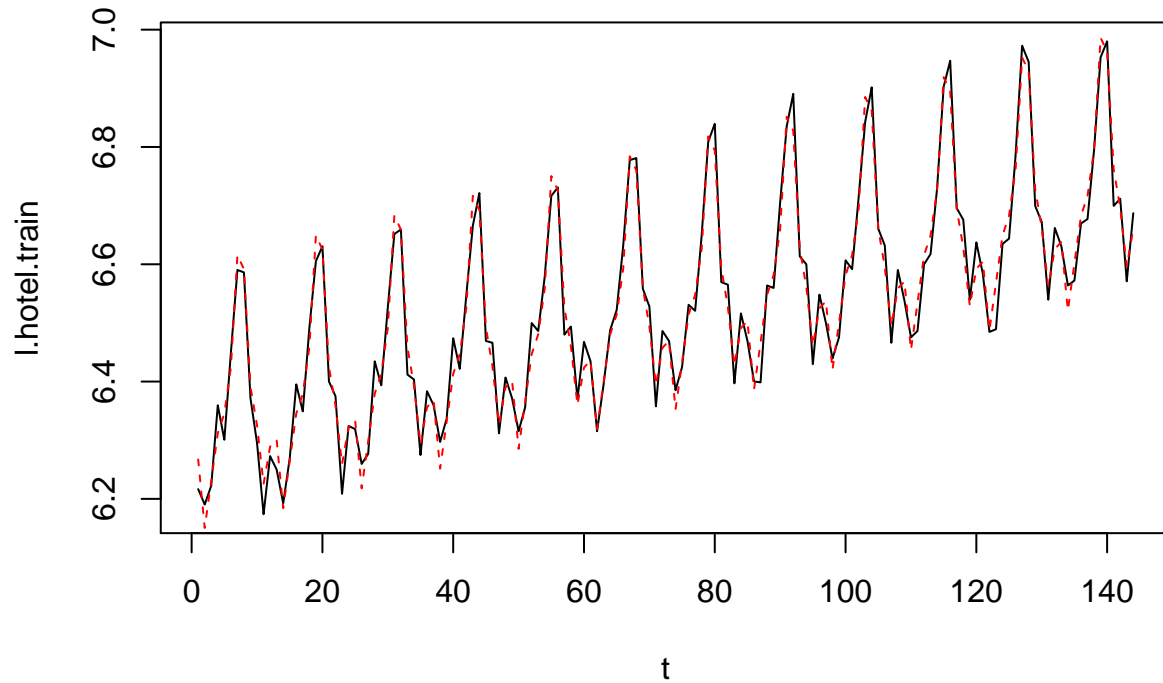
metric and Nonparametric yeild the same key frequencies

Check the model

```
top_freq = key_freq[order(pgram$spec[key_freq_ind], decreasing = T)][1:5]
periodic_terms = do.call(cbind, lapply(top_freq, function(freq) {
  cbind(cos(2 * pi * freq * t), sin(2 * pi * freq * t))
})) # no need to add columns of 1 and t because the fn lm() will accomodate the trend
df = data.frame(l.hotel.train, t, periodic_terms) # change: fit the original data instead of the log da
fit_final = lm(l.hotel.train ~ ., df) # first 2 cols are for linear trend, next cols are cos&sin terms,

plot(t, l.hotel.train, type="l", main="Original(black) and Fitted(red)") # plot the original time seri
lines(t, fit_final$fitted.values, lty=2, col="red")
```

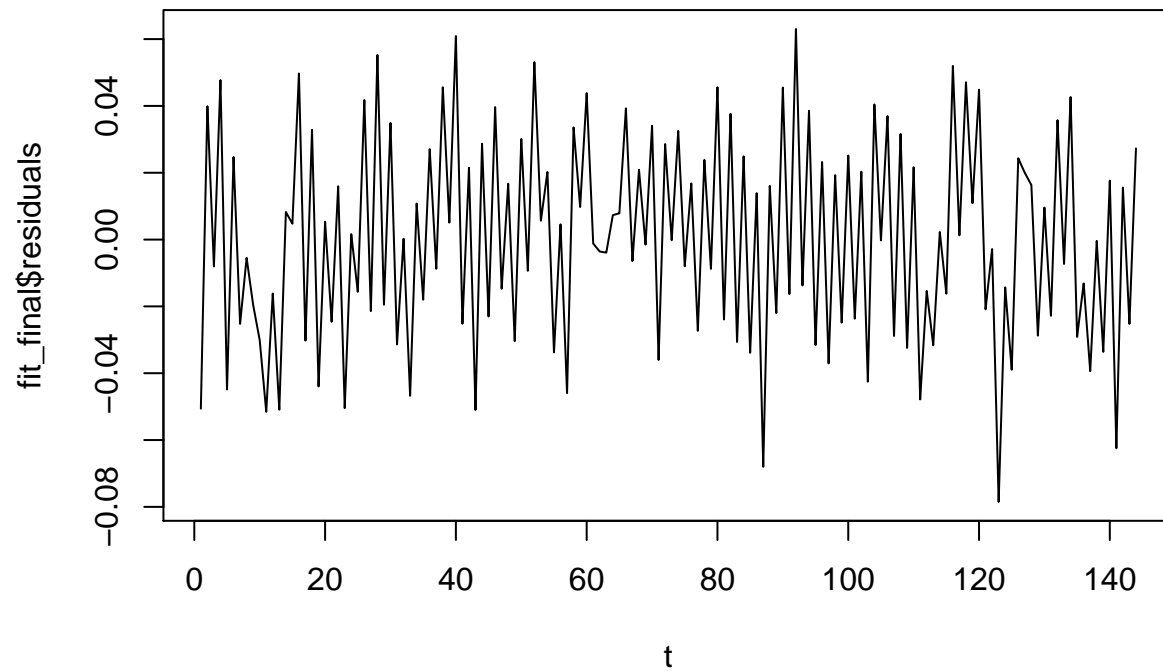
Original(black) and Fitted(red)



residual of the actual data and the model data

```
plot(t, fit_final$residuals, type = "l", main="Residues of model")
```

Residues of model



residuals are nearly equally spread on two sides of $y=0$ line and have a constant mean.

Predict the test set

The

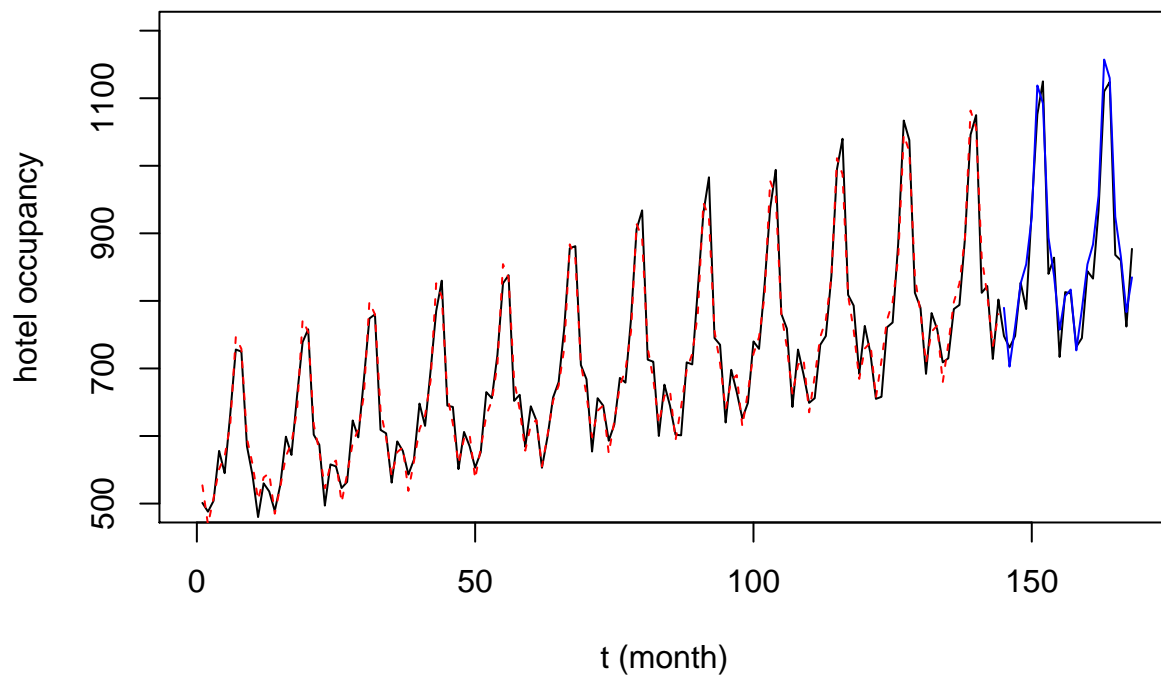
```

t_new = (tail(t, 1) + 1):(tail(t, 1) + 24)
periodic_terms_new = do.call(cbind, lapply(top_freq, function(freq) {
  cbind(cos(2 * pi * freq * t_new), sin(2 * pi * freq * t_new)) # key freqs are the same for the whole
})))
df_new = data.frame(t_new, periodic_terms_new)
colnames(df_new) = colnames(df)[-1]
hotel.pred.periogram = predict.lm(fit_final, newdata=df_new, interval="prediction", level=.95) # calc p

plot(c(t, t_new), hotel$Rooms, type="l", xlim=c(0, tail(t_new, 1)), ylim=c(500, 1200), xlab = "t (month",
lines(t, exp(fit_final$fitted.values), lty=2, col="red")
lines(t_new, exp(hotel.pred.periogram[, "fit"]), col="blue") # blue is prediction for test set

```

Prediction of test set (1975–1976)

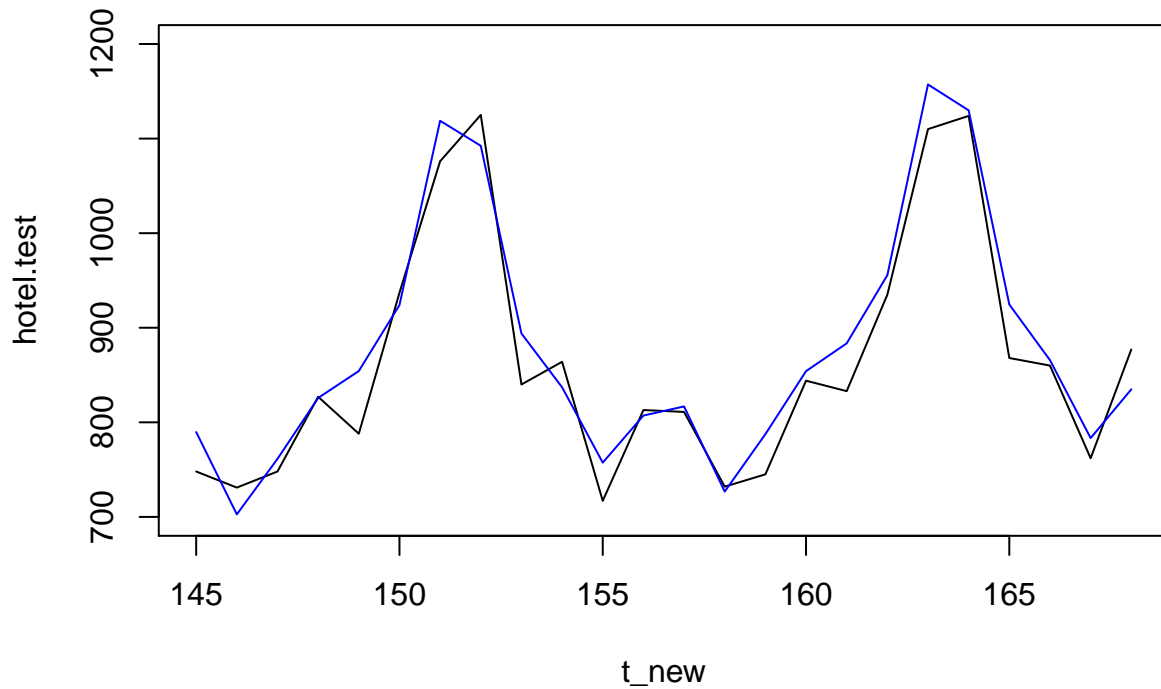


Real test value compared to predicted value

```

plot(t_new, hotel.test, type = "l", ylim = c(700,1200))
lines(t_new, exp(hotel.pred.periogram[, "fit"]), col="blue") # blue is prediction for test set

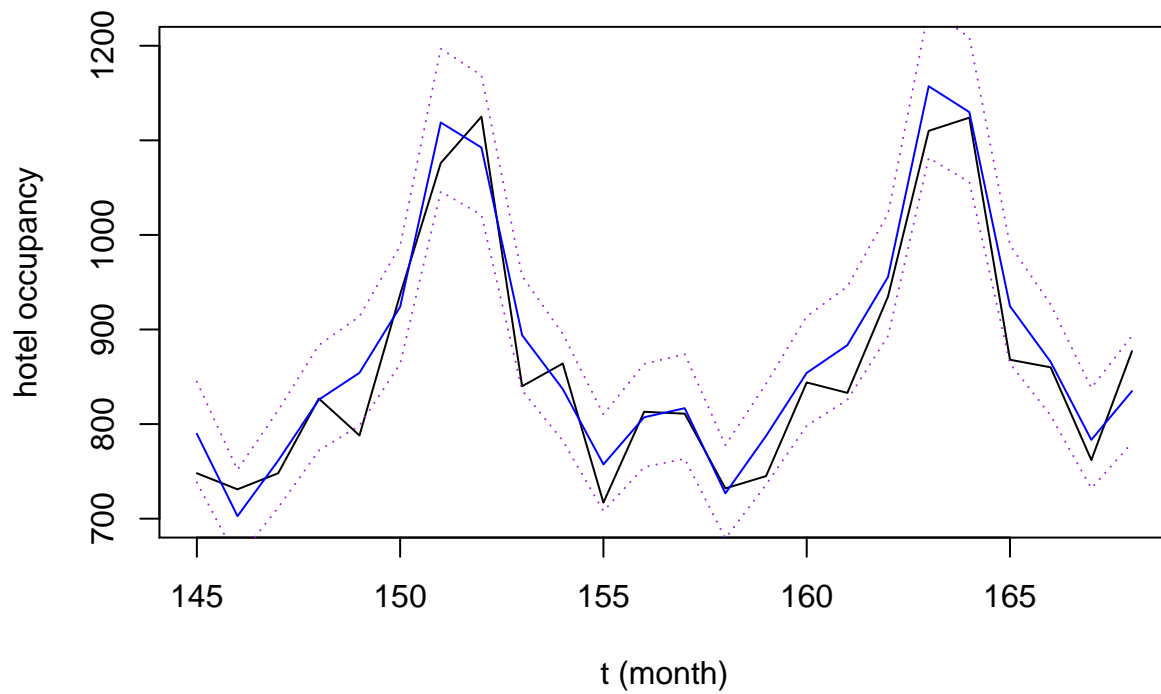
```



add CI

```
plot(t_new, hotel.test, type = "l", ylim = c(700,1200), main="Zoom in the prediction of test set", xlab=
lines(t_new, exp(hotel.pred.periogram[, "fit"]), col="blue") # blue is prediction for test set
matlines(t_new, exp(hotel.pred.periogram[, 2:3]), col = "purple", lty=3) #purple is CI
```

Zoom in the prediction of test set



MSE of the test set

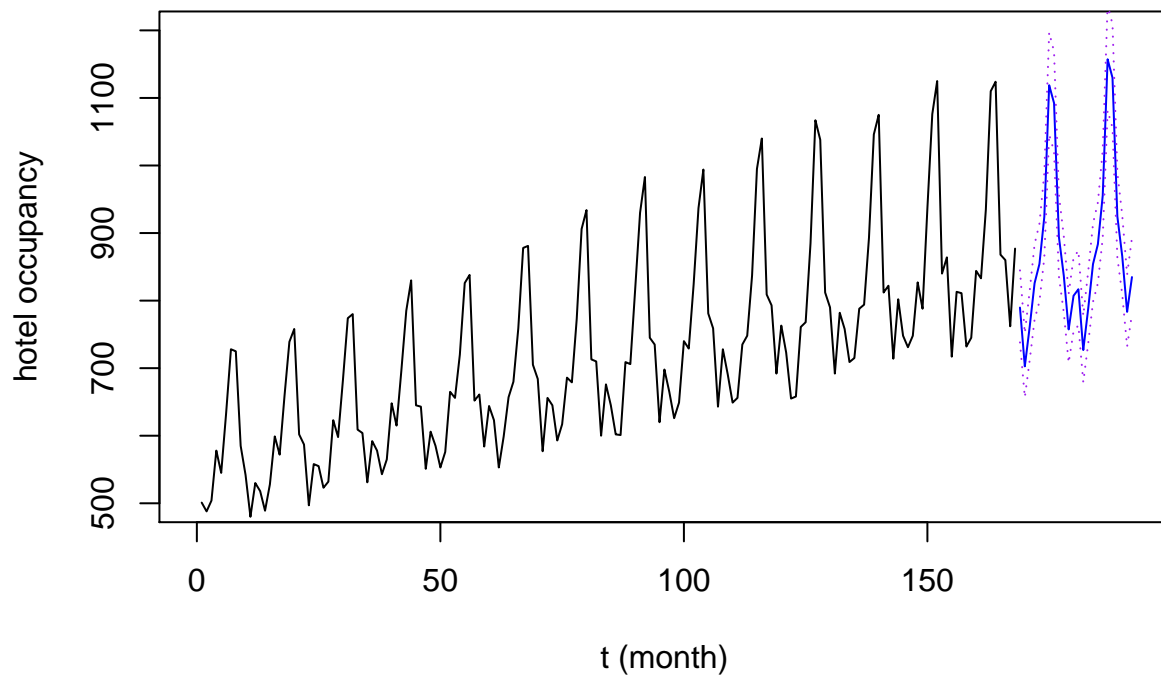
```
mean((exp(hotel.pred.periogram[, "fit"])-hotel.test)^2)
```

```
## [1] 1173.298
```

Predict the future 2 years (1977-1978)

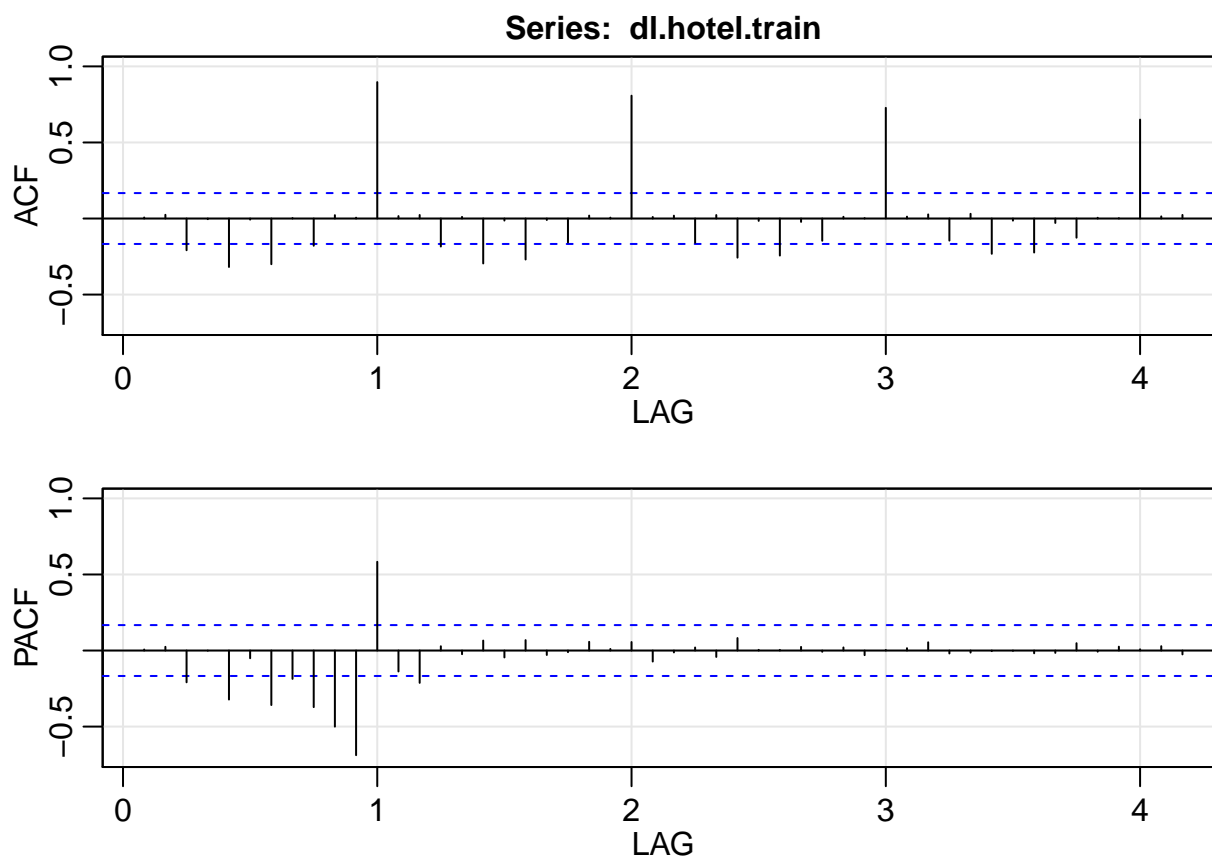
```
t_pred = (tail(t_new, 1) + 1):(tail(t_new, 1) + 24)
plot(c(t, t_new), hotel$Rooms, type = "l", xlim = c(0, tail(t_pred,1)), ylim = c(500,1200), xlab = "t (month)", ylab = "hotel occupancy")
lines(t_pred, exp(hotel.pred.periogram[, "fit"]), col="blue")
matlines(t_pred, exp(hotel.pred.periogram[,2:3]), col='purple', lty = 3)
```

Prediction of future 2 years (1977-1978)



2.3 Fit SARIMA ACF

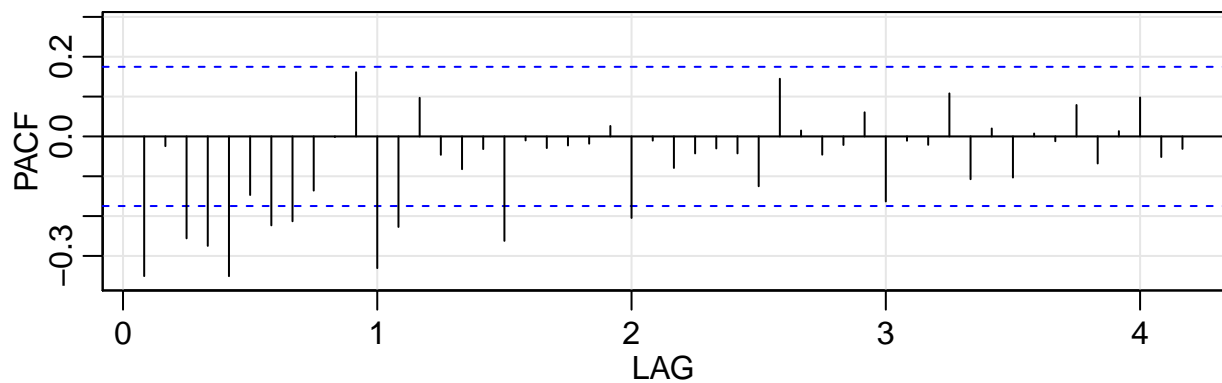
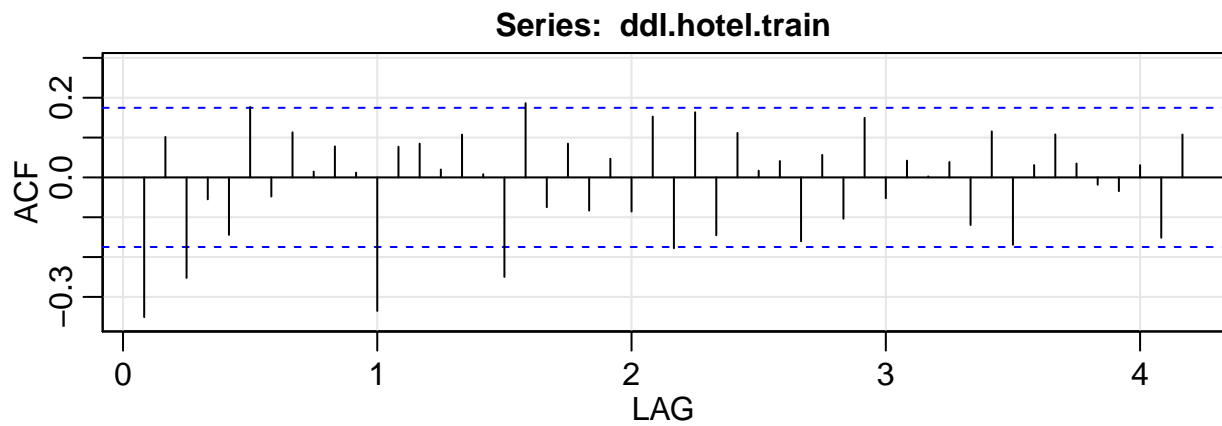
```
acf2(dl.hotel.train,50) # see a seasonal pattern every 12 months
```



##		ACF	PACF
##	[1,]	0.01	0.01
##	[2,]	0.02	0.02
##	[3,]	-0.21	-0.21
##	[4,]	0.00	0.00
##	[5,]	-0.32	-0.32
##	[6,]	-0.01	-0.05
##	[7,]	-0.30	-0.36
##	[8,]	0.00	-0.19
##	[9,]	-0.18	-0.37
##	[10,]	0.02	-0.50
##	[11,]	0.01	-0.69
##	[12,]	0.90	0.58
##	[13,]	0.02	-0.14
##	[14,]	0.02	-0.21
##	[15,]	-0.18	0.03
##	[16,]	0.01	-0.02
##	[17,]	-0.30	0.07
##	[18,]	-0.01	-0.05
##	[19,]	-0.27	0.07
##	[20,]	-0.01	-0.03
##	[21,]	-0.16	-0.01
##	[22,]	0.02	0.06
##	[23,]	0.01	0.01
##	[24,]	0.81	0.06
##	[25,]	0.01	-0.07
##	[26,]	0.02	-0.01

```
## [27,] -0.16  0.02
## [28,]  0.02 -0.04
## [29,] -0.26  0.08
## [30,] -0.02  0.00
## [31,] -0.24  0.00
## [32,] -0.02  0.02
## [33,] -0.15 -0.01
## [34,]  0.01  0.02
## [35,]  0.00 -0.03
## [36,]  0.73  0.00
## [37,]  0.01  0.02
## [38,]  0.03  0.05
## [39,] -0.15 -0.02
## [40,]  0.03 -0.01
## [41,] -0.23  0.00
## [42,] -0.01  0.00
## [43,] -0.22 -0.02
## [44,] -0.03 -0.02
## [45,] -0.13  0.05
## [46,]  0.01 -0.01
## [47,]  0.00  0.03
## [48,]  0.65  0.01
## [49,]  0.01  0.03
## [50,]  0.02 -0.03
```

```
acf2(ddl.hotel.train, 50)
```



```
##          ACF  PACF
```

```

## [1,] -0.35 -0.35
## [2,]  0.10 -0.02
## [3,] -0.25 -0.26
## [4,] -0.05 -0.27
## [5,] -0.14 -0.35
## [6,]  0.18 -0.15
## [7,] -0.05 -0.22
## [8,]  0.11 -0.21
## [9,]  0.01 -0.14
## [10,] 0.08  0.00
## [11,] 0.01  0.16
## [12,] -0.34 -0.33
## [13,] 0.08 -0.23
## [14,] 0.08  0.10
## [15,] 0.02 -0.05
## [16,] 0.11 -0.08
## [17,] 0.01 -0.03
## [18,] -0.25 -0.26
## [19,] 0.19 -0.01
## [20,] -0.07 -0.03
## [21,] 0.08 -0.02
## [22,] -0.08 -0.02
## [23,] 0.05  0.03
## [24,] -0.09 -0.20
## [25,] 0.15 -0.01
## [26,] -0.18 -0.08
## [27,] 0.16 -0.04
## [28,] -0.15 -0.03
## [29,] 0.11 -0.04
## [30,] 0.02 -0.13
## [31,] 0.04  0.14
## [32,] -0.16  0.01
## [33,] 0.06 -0.05
## [34,] -0.10 -0.02
## [35,] 0.15  0.06
## [36,] -0.05 -0.16
## [37,] 0.04 -0.01
## [38,] 0.00 -0.02
## [39,] 0.04  0.11
## [40,] -0.12 -0.11
## [41,] 0.12  0.02
## [42,] -0.17 -0.10
## [43,] 0.03  0.01
## [44,] 0.11 -0.01
## [45,] 0.03  0.08
## [46,] -0.02 -0.07
## [47,] -0.03  0.01
## [48,] 0.03  0.10
## [49,] -0.15 -0.05
## [50,] 0.11 -0.03

```

From the ACF of the first differencing data, see a yearly seasonal pattern

Estimate parameter


```
eacf(dl.hotel.train)
```

```
## AR/MA
##   0 1 2 3 4 5 6 7 8 9 10 11 12 13
## 0 o o x o x o x o x o o x o o
## 1 x o x o x o x o x o o x x o
## 2 o o o o o o o o x o o x o o
## 3 o x o o o o o o o o o x o x
## 4 o x o x o o o o o o o x o x
## 5 o x o x o o o o o o o x o x
## 6 o x o x o o o o o o o x o x
## 7 x x x x o o o o o o o x x x
```

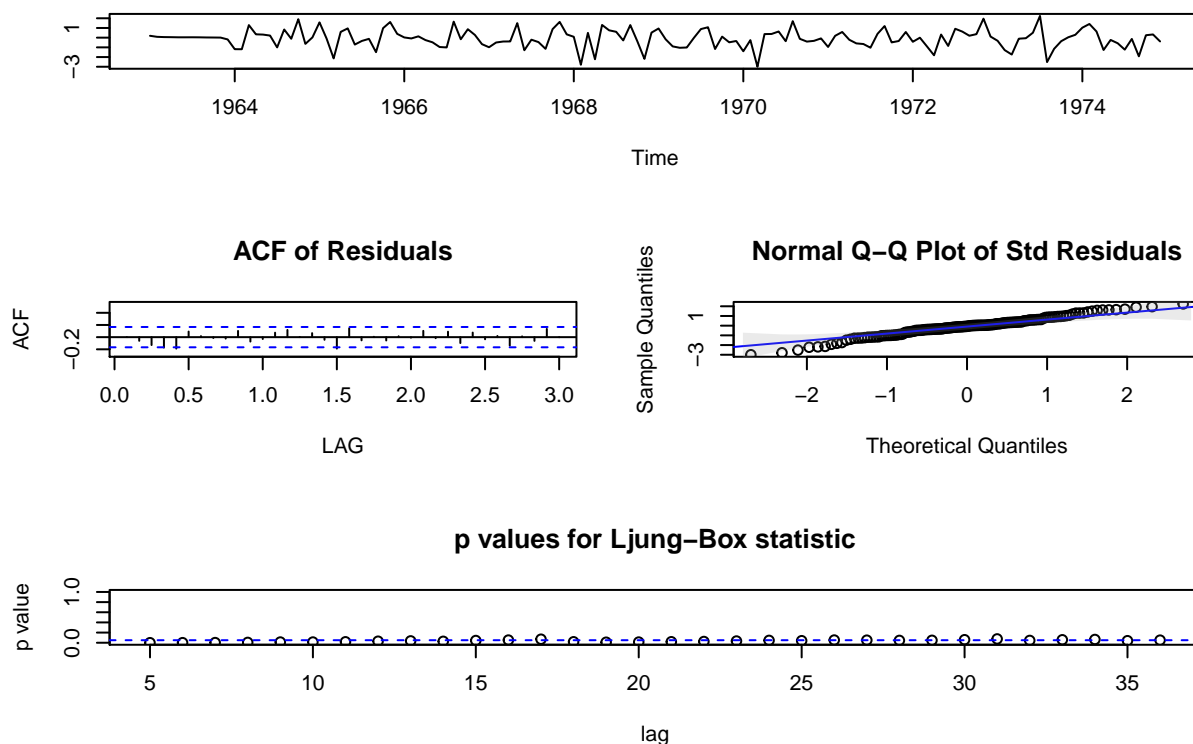
eacf of the first differencing data gives no information, check the eacf of the seasonal differencing data to get further guess of the model parameter(seasonal)

Fit model Tests several possible parameter

```
sarima(l.hotel.train, 0,1,3, 0,1,1, 12) # AIC -6.92
```

```
## initial value -3.618183
## iter 2 value -3.846594
## iter 3 value -3.934272
## iter 4 value -3.961719
## iter 5 value -3.965279
## iter 6 value -3.967273
## iter 7 value -3.967794
## iter 8 value -3.968131
## iter 9 value -3.969699
## iter 10 value -3.969757
## iter 11 value -3.969955
## iter 12 value -3.970799
## iter 13 value -3.970998
## iter 14 value -3.971009
## iter 15 value -3.971015
## iter 16 value -3.971015
## iter 16 value -3.971015
## iter 16 value -3.971015
## final value -3.971015
## converged
## initial value -3.953875
## iter 2 value -3.956691
## iter 3 value -3.957362
## iter 4 value -3.958505
## iter 5 value -3.958568
## iter 6 value -3.958578
## iter 7 value -3.958581
## iter 7 value -3.958581
## iter 7 value -3.958581
## final value -3.958581
## converged
```

Model: (0,1,3) (0,1,1) [12] Standardized Residuals



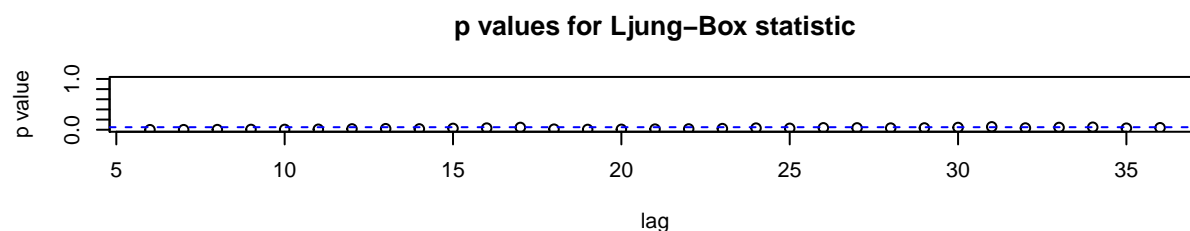
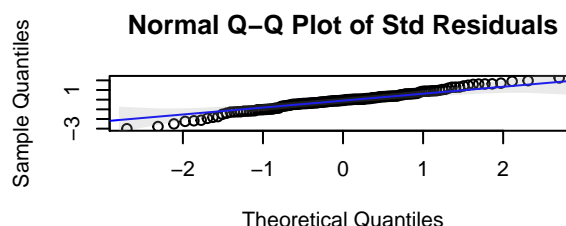
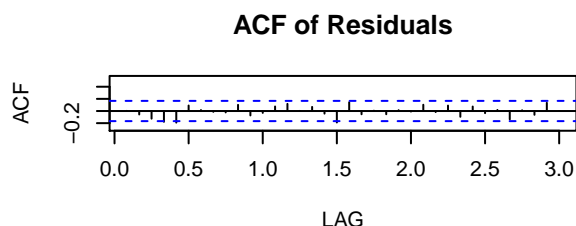
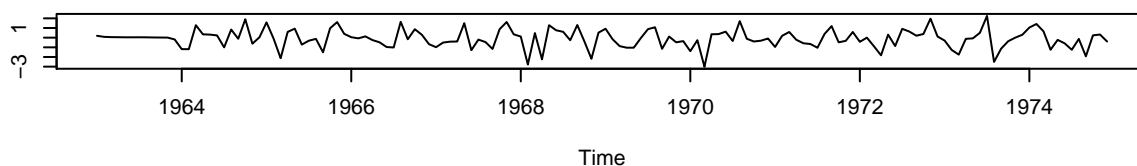
```
## $fit
##
## Call:
## stats::arima(x = xdata, order = c(p, d, q), seasonal = list(order = c(P, D,
##     Q), period = S), include.mean = !no.constant, optim.control = list(trace = trc,
##     REPORT = 1, reltol = tol))
##
## Coefficients:
##          ma1      ma2      ma3      sma1
##      -0.6436  0.0277 -0.3306 -0.5699
## s.e.   0.0840  0.1109  0.0821  0.0869
##
## sigma^2 estimated as 0.0003435:  log likelihood = 332.69,  aic = -655.39
##
## $degrees_of_freedom
## [1] 127
##
## $ttable
##      Estimate      SE t.value p.value
## ma1   -0.6436  0.0840 -7.6581  0.0000
## ma2    0.0277  0.1109  0.2499  0.8031
## ma3   -0.3306  0.0821 -4.0268  0.0001
## sma1  -0.5699  0.0869 -6.5567  0.0000
##
## $AIC
## [1] -6.920911
##
## $AICc
```

```
## [1] -6.904003
##
## $BIC
## [1] -7.838416
```

```
sarima(l.hotel.train, 0,1,4, 0,1,1, 12) # AIC -6.9
```

```
## initial value -3.618183
## iter 2 value -3.856307
## iter 3 value -3.952109
## iter 4 value -3.956633
## iter 5 value -3.960929
## iter 6 value -3.963759
## iter 7 value -3.965321
## iter 8 value -3.966128
## iter 9 value -3.966845
## iter 10 value -3.970863
## iter 11 value -3.970890
## iter 12 value -3.971197
## iter 13 value -3.971208
## iter 14 value -3.971233
## iter 15 value -3.971234
## iter 16 value -3.971234
## iter 16 value -3.971234
## iter 16 value -3.971234
## final value -3.971234
## converged
## initial value -3.954142
## iter 2 value -3.957055
## iter 3 value -3.957412
## iter 4 value -3.958481
## iter 5 value -3.958570
## iter 6 value -3.958598
## iter 7 value -3.958606
## iter 8 value -3.958606
## iter 9 value -3.958606
## iter 9 value -3.958606
## iter 9 value -3.958606
## final value -3.958606
## converged
```

Model: (0,1,4) (0,1,1) [12] Standardized Residuals



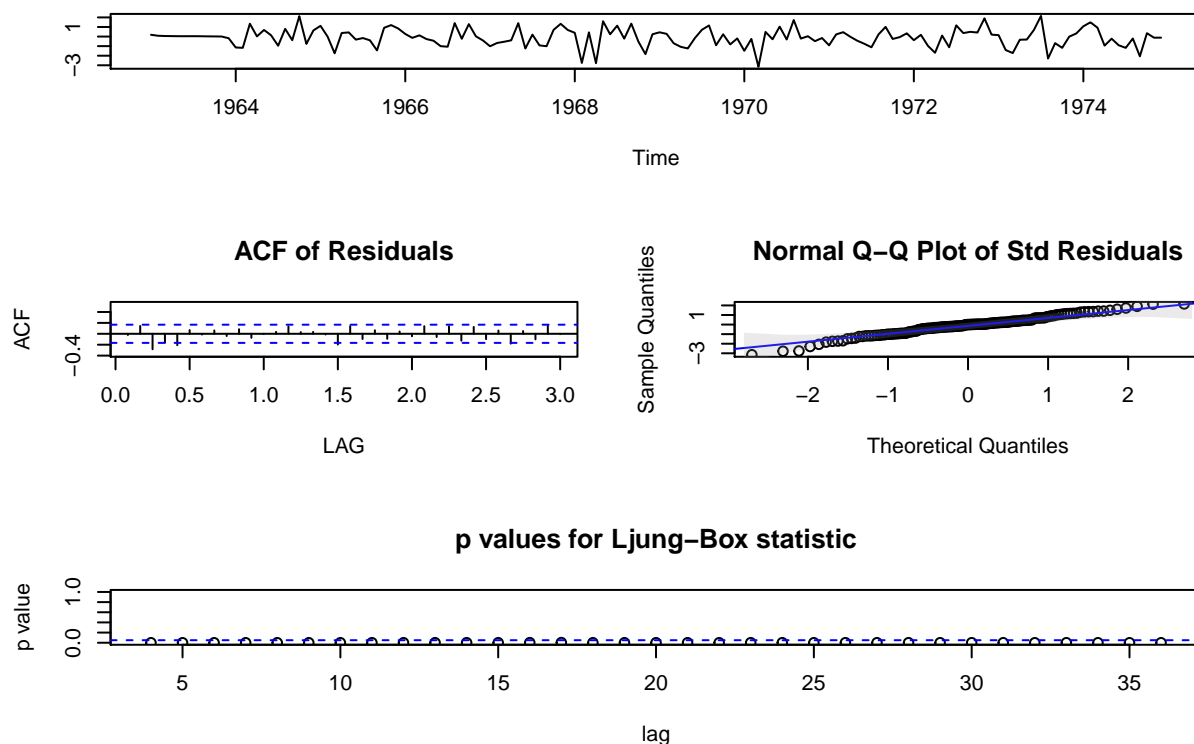
```
## $fit
##
## Call:
## stats::arima(x = xdata, order = c(p, d, q), seasonal = list(order = c(P, D,
##     Q), period = S), include.mean = !no.constant, optim.control = list(trace = trc,
##     REPORT = 1, reltol = tol))
##
## Coefficients:
##          ma1      ma2      ma3      ma4      sma1
##      -0.6473  0.0231 -0.3321  0.0101 -0.5684
## s.e.   0.0959  0.1262  0.0844  0.1265  0.0889
##
## sigma^2 estimated as 0.0003435:  log likelihood = 332.7,  aic = -653.39
##
## $degrees_of_freedom
## [1] 126
##
## $ttable
##      Estimate      SE t.value p.value
## ma1   -0.6473  0.0959 -6.7527  0.0000
## ma2    0.0231  0.1262  0.1828  0.8553
## ma3   -0.3321  0.0844 -3.9338  0.0001
## ma4    0.0101  0.1265  0.0798  0.9365
## sma1  -0.5684  0.0889 -6.3910  0.0000
##
## $AIC
## [1] -6.906753
##
```

```
## $AICc
## [1] -6.888606
##
## $BIC
## [1] -7.803634
```

```
sarima(l.hotel.train, 1,1,1, 0,1,1, 12) #AIC -6.8
```

```
## initial value -3.619580
## iter 2 value -3.761664
## iter 3 value -3.818141
## iter 4 value -3.821599
## iter 5 value -3.823133
## iter 6 value -3.823140
## iter 7 value -3.823149
## iter 8 value -3.823158
## iter 9 value -3.823187
## iter 10 value -3.823210
## iter 11 value -3.823250
## iter 12 value -3.823287
## iter 13 value -3.823411
## iter 14 value -3.823514
## iter 15 value -3.823721
## iter 16 value -3.823919
## iter 17 value -3.824582
## iter 18 value -3.825201
## iter 19 value -3.826905
## iter 20 value -3.828765
## iter 21 value -3.835236
## iter 22 value -3.842605
## iter 23 value -3.848161
## iter 24 value -3.851174
## iter 25 value -3.853932
## iter 26 value -3.854899
## iter 27 value -3.855000
## iter 28 value -3.855039
## iter 29 value -3.855039
## iter 29 value -3.855039
## iter 29 value -3.855039
## final value -3.855039
## converged
## initial value -3.880827
## iter 2 value -3.918116
## iter 3 value -3.919192
## iter 4 value -3.921234
## iter 5 value -3.921778
## iter 6 value -3.921779
## iter 6 value -3.921779
## iter 6 value -3.921779
## final value -3.921779
## converged
```

Model: (1,1,1) (0,1,1) [12] Standardized Residuals



```
## $fit
##
## Call:
## stats::arima(x = xdata, order = c(p, d, q), seasonal = list(order = c(P, D,
##     Q), period = S), include.mean = !no.constant, optim.control = list(trace = trc,
##     REPORT = 1, reltol = tol))
##
## Coefficients:
##          ar1      ma1      sma1
##         0.3075 -0.9640 -0.5431
## s.e.  0.0875  0.0252  0.0909
##
## sigma^2 estimated as 0.0003716:  log likelihood = 327.87,  aic = -647.74
##
## $degrees_of_freedom
## [1] 128
##
## $ttable
##      Estimate      SE  t.value p.value
## ar1    0.3075 0.0875   3.5119  6e-04
## ma1   -0.9640 0.0252  -38.2915  0e+00
## sma1  -0.5431 0.0909  -5.9734  0e+00
##
## $AIC
## [1] -6.856096
##
## $AICc
## [1] -6.840209
```

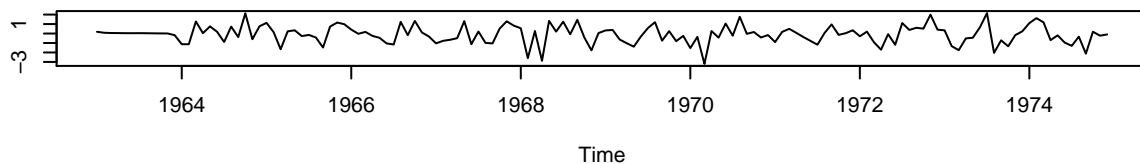
```
##
## $BIC
## [1] -7.794225
```

```
sarima(l.hotel.train, 0,1,2, 0,1,1, 12) # AIC -6.8
```

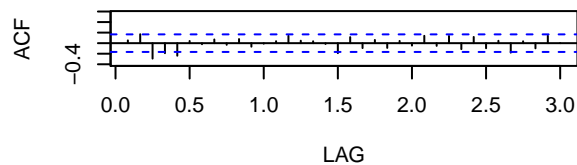
```
## initial value -3.618183
## iter 2 value -3.775789
## iter 3 value -3.784697
## iter 4 value -3.868252
## iter 5 value -3.903339
## iter 6 value -3.913558
## iter 7 value -3.916894
## iter 8 value -3.916901
## iter 9 value -3.916986
## iter 9 value -3.916987
## iter 9 value -3.916987
## final value -3.916987
## converged
## initial value -3.907874
## iter 2 value -3.908885
## iter 3 value -3.909396
## iter 4 value -3.909413
## iter 5 value -3.909413
## iter 5 value -3.909413
## iter 5 value -3.909413
## final value -3.909413
## converged
```

Model: (0,1,2) (0,1,1) [12]

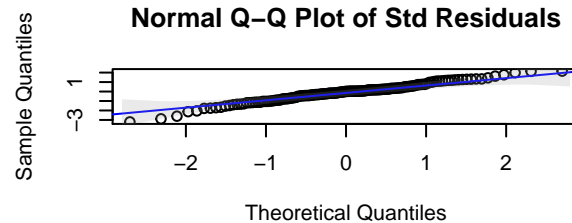
Standardized Residuals



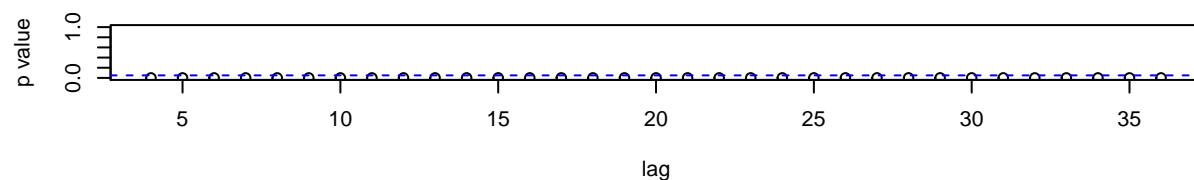
ACF of Residuals



Normal Q-Q Plot of Std Residuals



p values for Ljung-Box statistic



```

## $fit
##
## Call:
## stats::arima(x = xdata, order = c(p, d, q), seasonal = list(order = c(P, D,
##      Q), period = S), include.mean = !no.constant, optim.control = list(trace = trc,
##      REPORT = 1, reltol = tol))
##
## Coefficients:
##          ma1          ma2          sma1
##      -0.7387  -0.2083  -0.5236
## s.e.    0.0706    0.0666    0.0906
##
## sigma^2 estimated as 0.000382:  log likelihood = 326.25,  aic = -644.5
##
## $degrees_of_freedom
## [1] 128
##
## $ttable
##      Estimate      SE  t.value p.value
## ma1   -0.7387 0.0706 -10.4643  0.0000
## ma2   -0.2083 0.0666  -3.1273  0.0022
## sma1  -0.5236 0.0906  -5.7790  0.0000
##
## $AIC
## [1] -6.8284
##
## $AICc
## [1] -6.812513
##
## $BIC
## [1] -7.766529

```

```

sarima(1.hotel.train, 0,1,1, 1,1,1, 12)# AIC -6.75

```

```

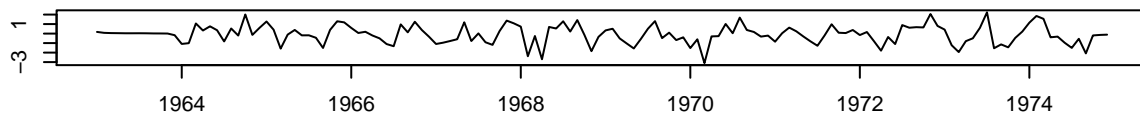
## initial  value -3.628213
## iter    2 value -3.794209
## iter    3 value -3.815477
## iter    4 value -3.823057
## iter    5 value -3.825543
## iter    6 value -3.826248
## iter    7 value -3.826633
## iter    8 value -3.826934
## iter    9 value -3.827712
## iter   10 value -3.829404
## iter   11 value -3.829525
## iter   12 value -3.829645
## iter   13 value -3.829654
## iter   14 value -3.829655
## iter   14 value -3.829655
## iter   14 value -3.829655
## final   value -3.829655
## converged
## initial  value -3.851850
## iter    2 value -3.865842
## iter    3 value -3.872573

```



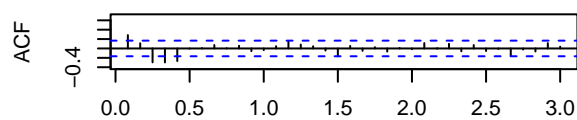
```
## iter 4 value -3.873454
## iter 5 value -3.874285
## iter 6 value -3.875736
## iter 7 value -3.875854
## iter 8 value -3.875924
## iter 9 value -3.875927
## iter 10 value -3.875931
## iter 11 value -3.875932
## iter 12 value -3.875933
## iter 13 value -3.875934
## iter 14 value -3.875934
## iter 14 value -3.875934
## iter 14 value -3.875934
## final value -3.875934
## converged
```

Model: (0,1,1) (1,1,1) [12] Standardized Residuals



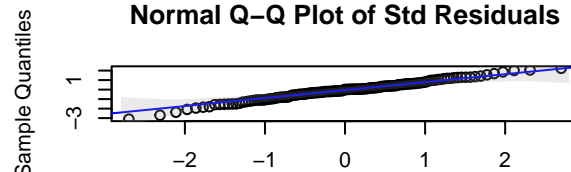
Time

ACF of Residuals



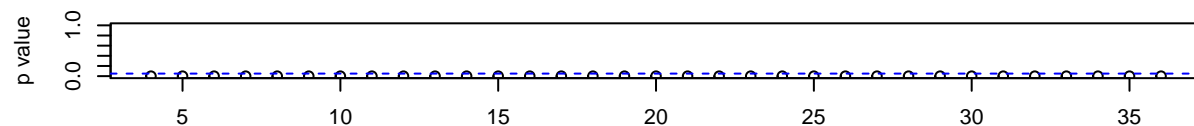
LAG

Normal Q-Q Plot of Std Residuals



Theoretical Quantiles

p values for Ljung-Box statistic



lag

```
## $fit
##
## Call:
## stats::arima(x = xdata, order = c(p, d, q), seasonal = list(order = c(P, D,
##     Q), period = S), include.mean = !no.constant, optim.control = list(trace = trc,
##     REPORT = 1, reltol = tol))
##
## Coefficients:
##          ma1      sar1      sma1
##       -0.9465  0.0012 -0.5021
## s.e.   0.0294  0.1905  0.1737
##
## sigma^2 estimated as 0.0004096:  log likelihood = 321.87,  aic = -635.73
```

```
##
## $degrees_of_freedom
## [1] 128
##
## $ttable
##      Estimate      SE  t.value p.value
## ma1    -0.9465 0.0294 -32.1514 0.0000
## sar1     0.0012 0.1905   0.0060 0.9952
## sma1    -0.5021 0.1737  -2.8900 0.0045
##
## $AIC
## [1] -6.75855
##
## $AICc
## [1] -6.742662
##
## $BIC
## [1] -7.696678
```

```
sarima(1,hotel.train, 0,1,6, 2,1,1, 12) # AIC -7.00
```

```
## initial value -3.621738
## iter 2 value -3.941921
## iter 3 value -3.973425
## iter 4 value -3.992559
## iter 5 value -4.003881
## iter 6 value -4.032396
## iter 7 value -4.045952
## iter 8 value -4.048727
## iter 9 value -4.053736
## iter 10 value -4.057005
## iter 11 value -4.061510
## iter 12 value -4.064213
## iter 13 value -4.067672
## iter 14 value -4.068399
## iter 15 value -4.069049
## iter 16 value -4.071590
## iter 17 value -4.075770
## iter 18 value -4.076852
## iter 19 value -4.082695
## iter 20 value -4.083603
## iter 21 value -4.084407
## iter 22 value -4.086668
## iter 23 value -4.089393
## iter 24 value -4.090503
## iter 25 value -4.092870
## iter 26 value -4.094454
## iter 27 value -4.094492
## iter 28 value -4.094503
## iter 29 value -4.095508
## iter 29 value -4.095508
## iter 30 value -4.095513
## iter 31 value -4.097573
## iter 31 value -4.097573
## iter 32 value -4.097841
```

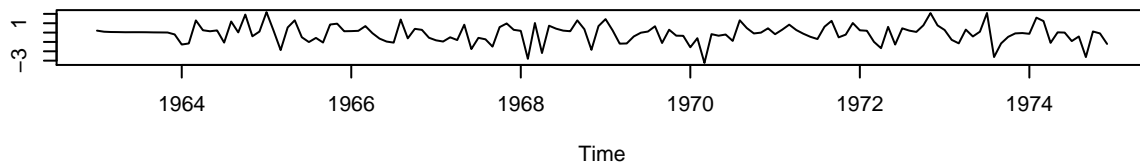
```

## iter 32 value -4.097841
## iter 33 value -4.097865
## iter 33 value -4.097865
## iter 33 value -4.097865
## final value -4.097865
## converged
## initial value -3.998589
## iter 2 value -4.022125
## iter 3 value -4.026332
## iter 4 value -4.026408
## iter 5 value -4.029059
## iter 6 value -4.029449
## iter 7 value -4.029593
## iter 8 value -4.029684
## iter 9 value -4.030067
## iter 10 value -4.030201
## iter 11 value -4.030385
## iter 12 value -4.030411
## iter 13 value -4.030415
## iter 14 value -4.030416
## iter 15 value -4.030416
## iter 15 value -4.030416
## iter 15 value -4.030416
## final value -4.030416
## converged

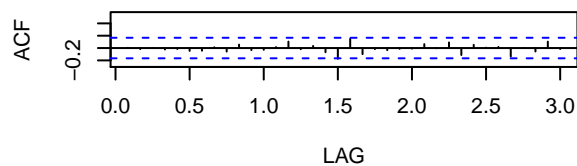
```

Model: (0,1,6) (2,1,1) [12]

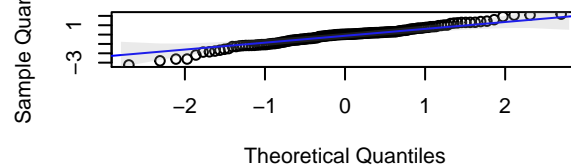
Standardized Residuals



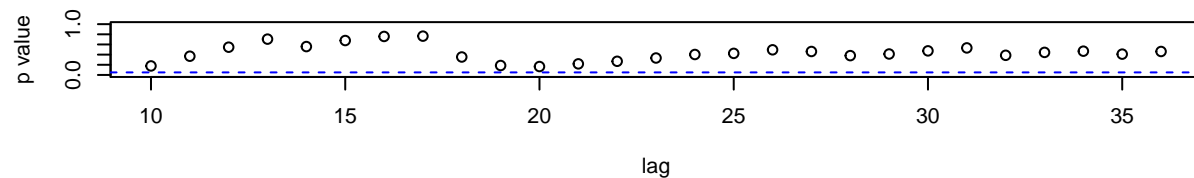
ACF of Residuals



Normal Q-Q Plot of Std Residuals



p values for Ljung-Box statistic



```

## $fit
##
## Call:

```

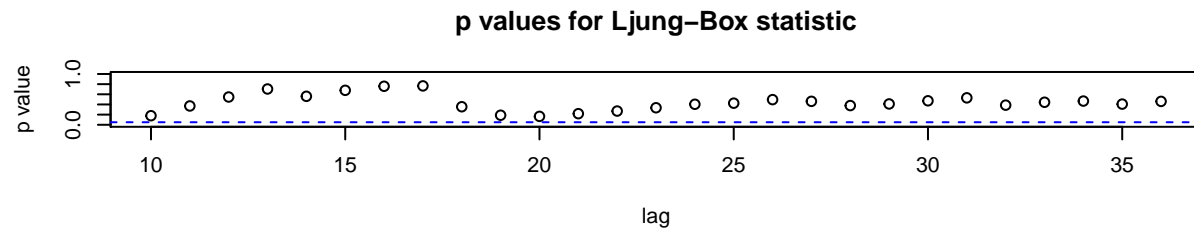
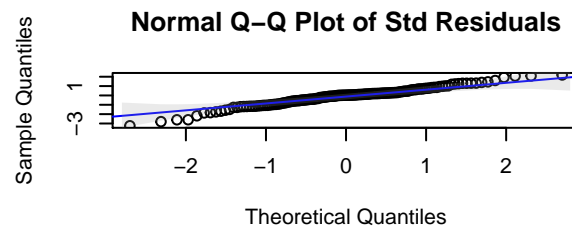
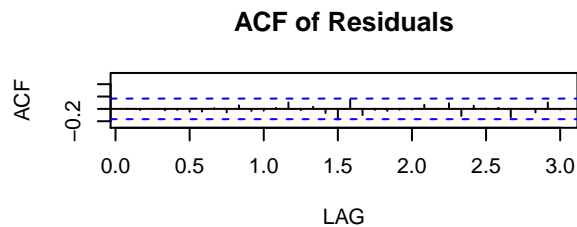
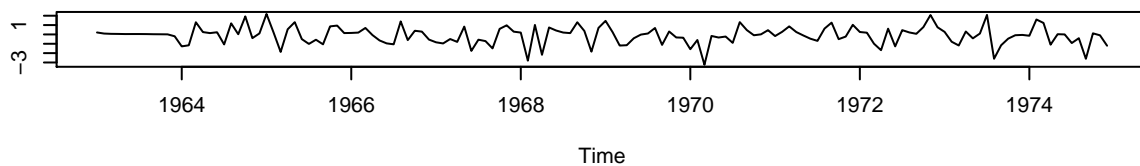
```
## stats::arima(x = xdata, order = c(p, d, q), seasonal = list(order = c(P, D,
##      Q), period = S), include.mean = !no.constant, optim.control = list(trace = trc,
##      REPORT = 1, reltol = tol))
##
## Coefficients:
##      ma1      ma2      ma3      ma4      ma5      ma6      sar1      sar2
##      -0.7351  0.0005 -0.4504 -0.0730 -0.0264  0.3719  0.0607  0.0580
## s.e.    0.0847  0.1084  0.1033  0.1147  0.1096  0.0942  0.2986  0.1875
##      sma1
##      -0.6163
## s.e.    0.2848
##
## sigma^2 estimated as 0.000296:  log likelihood = 342.1,  aic = -664.21
##
## $degrees_of_freedom
## [1] 122
##
## $ttable
##      Estimate      SE t.value p.value
## ma1    -0.7351  0.0847 -8.6808  0.0000
## ma2     0.0005  0.1084  0.0050  0.9960
## ma3    -0.4504  0.1033 -4.3584  0.0000
## ma4    -0.0730  0.1147 -0.6363  0.5258
## ma5    -0.0264  0.1096 -0.2414  0.8097
## ma6     0.3719  0.0942  3.9482  0.0001
## sar1     0.0607  0.2986  0.2034  0.8391
## sar2     0.0580  0.1875  0.3093  0.7576
## sma1    -0.6163  0.2848 -2.1639  0.0324
##
## $AIC
## [1] -7.000033
##
## $AICc
## [1] -6.974657
##
## $BIC
## [1] -7.81442
```

```
sarima(l.hotel.train, 0,1,6, 0,1,3, 12) #AIC -7.00
```

```
## initial value -3.618183
## iter 2 value -3.877024
## iter 3 value -3.953588
## iter 4 value -3.977262
## iter 5 value -3.996886
## iter 6 value -4.017744
## iter 7 value -4.020510
## iter 8 value -4.020695
## iter 9 value -4.022566
## iter 10 value -4.022699
## iter 11 value -4.022723
## iter 12 value -4.022724
## iter 13 value -4.022725
## iter 14 value -4.022725
## iter 15 value -4.022725
```

```
## iter 15 value -4.022725
## iter 15 value -4.022725
## final value -4.022725
## converged
## initial value -4.026609
## iter 2 value -4.026976
## iter 3 value -4.029252
## iter 4 value -4.030194
## iter 5 value -4.030455
## iter 6 value -4.030500
## iter 7 value -4.030509
## iter 8 value -4.030513
## iter 9 value -4.030513
## iter 10 value -4.030513
## iter 10 value -4.030513
## iter 10 value -4.030513
## final value -4.030513
## converged
```

Model: (0,1,6) (0,1,3) [12] Standardized Residuals



```
## $fit
##
## Call:
## stats::arima(x = xdata, order = c(p, d, q), seasonal = list(order = c(P, D,
##     Q), period = S), include.mean = !no.constant, optim.control = list(trace = trc,
##     REPORT = 1, reltol = tol))
##
## Coefficients:
##      ma1      ma2      ma3      ma4      ma5      ma6      sma1      sma2
## -0.7342  0.0006 -0.4509 -0.0737 -0.0262  0.372  -0.5543  0.0259
```

```

## s.e.    0.0850  0.1084   0.1033   0.1151   0.1098  0.094   0.1027  0.1172
##          sma3
##        -0.0403
## s.e.    0.1150
##
## sigma^2 estimated as 0.0002959:  log likelihood = 342.12,  aic = -664.23
##
## $degrees_of_freedom
## [1] 122
##
## $ttable
##      Estimate      SE t.value p.value
## ma1   -0.7342  0.0850  -8.6387  0.0000
## ma2    0.0006  0.1084   0.0053  0.9958
## ma3   -0.4509  0.1033  -4.3646  0.0000
## ma4   -0.0737  0.1151  -0.6409  0.5228
## ma5   -0.0262  0.1098  -0.2389  0.8116
## ma6    0.3720  0.0940   3.9557  0.0001
## sma1  -0.5543  0.1027  -5.3982  0.0000
## sma2   0.0259  0.1172   0.2208  0.8256
## sma3  -0.0403  0.1150  -0.3506  0.7265
##
## $AIC
## [1] -7.000506
##
## $AICc
## [1] -6.97513
##
## $BIC
## [1] -7.814892

```

Get the best model

```
sarima(l.hotel.train, 0,1,6, 0,1,1, 12)
```

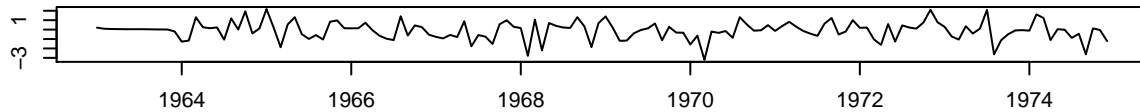
```

## initial  value -3.618183
## iter    2 value -3.879886
## iter    3 value -3.966292
## iter    4 value -3.982463
## iter    5 value -4.000071
## iter    6 value -4.017342
## iter    7 value -4.021022
## iter    8 value -4.022382
## iter    9 value -4.022683
## iter   10 value -4.022703
## iter   11 value -4.022716
## iter   12 value -4.022716
## iter   13 value -4.022716
## iter   13 value -4.022716
## iter   13 value -4.022716
## final    value -4.022716
## converged
## initial  value -4.026552
## iter    2 value -4.026884
## iter    3 value -4.028991

```

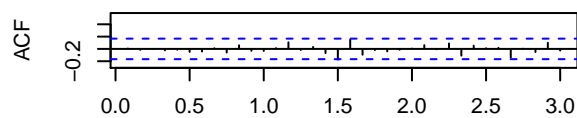
```
## iter 4 value -4.029885
## iter 5 value -4.030013
## iter 6 value -4.030027
## iter 7 value -4.030027
## iter 8 value -4.030028
## iter 8 value -4.030028
## iter 8 value -4.030028
## final value -4.030028
## converged
```

Model: (0,1,6) (0,1,1) [12] Standardized Residuals



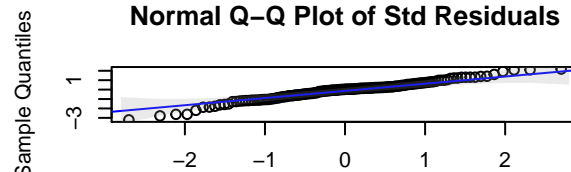
Time

ACF of Residuals



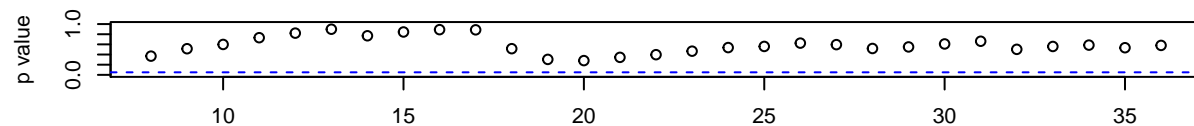
LAG

Normal Q-Q Plot of Std Residuals



Theoretical Quantiles

p values for Ljung-Box statistic



lag

```
## $fit
##
## Call:
## stats::arima(x = xdata, order = c(p, d, q), seasonal = list(order = c(P, D,
##     Q), period = S), include.mean = !no.constant, optim.control = list(trace = trc,
##     REPORT = 1, reltol = tol))
##
## Coefficients:
##      ma1      ma2      ma3      ma4      ma5      ma6      sma1
##    -0.7372 -0.0013 -0.4477 -0.0745 -0.0210  0.3685 -0.5510
## s.e.  0.0840  0.1083  0.1034  0.1111  0.1051  0.0940  0.0917
##
## sigma^2 estimated as 0.0002964:  log likelihood = 342.05,  aic = -668.11
##
## $degrees_of_freedom
## [1] 124
##
## $ttable
##      Estimate      SE t.value p.value
```

```
## ma1    -0.7372  0.0840 -8.7759  0.0000
## ma2    -0.0013  0.1083 -0.0120  0.9905
## ma3    -0.4477  0.1034 -4.3289  0.0000
## ma4    -0.0745  0.1111 -0.6706  0.5037
## ma5    -0.0210  0.1051 -0.1994  0.8422
## ma6     0.3685  0.0940  3.9200  0.0001
## sma1   -0.5510  0.0917 -6.0102  0.0000
##
## $AIC
## [1] -7.026553
##
## $AICc
## [1] -7.005257
##
## $BIC
## [1] -7.882187
```

by several trials of parameters, will write more choices of parameters for comparison purpose

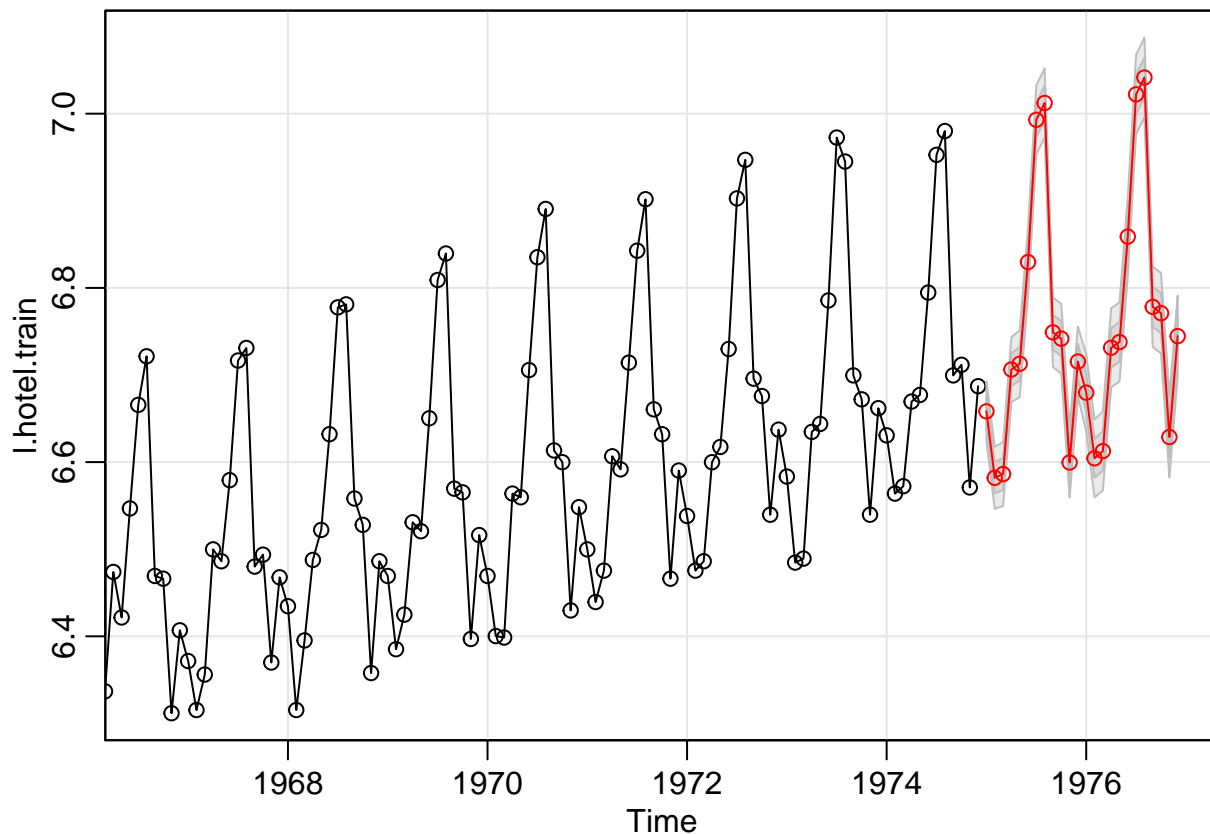
Verify the model:

Take the last two years as the test set

```
#hotel.train = ts(hotel.ts[1:144], start=c(1963, 1), end = c(1974,12), frequency = 12 ) # the train set
l.hotel.train = log(hotel.train)
#hotel.test = hotel[145:168,] # test set
```

predict the “unseen” test data for model verify purpose

```
test.arima = sarima.for(l.hotel.train, 24, 0,1,6, 0,1,1, 12)
```

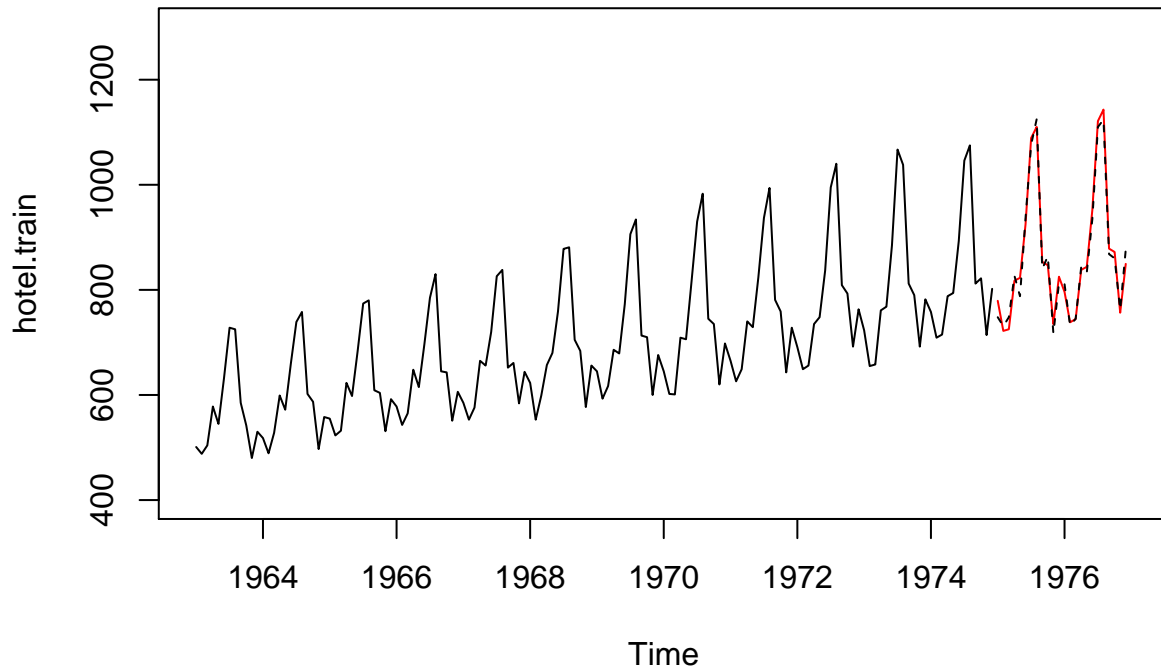


Plot the predicted value of the test data along with the test data

```
exp.test.arima = exp(test.arima$pred)

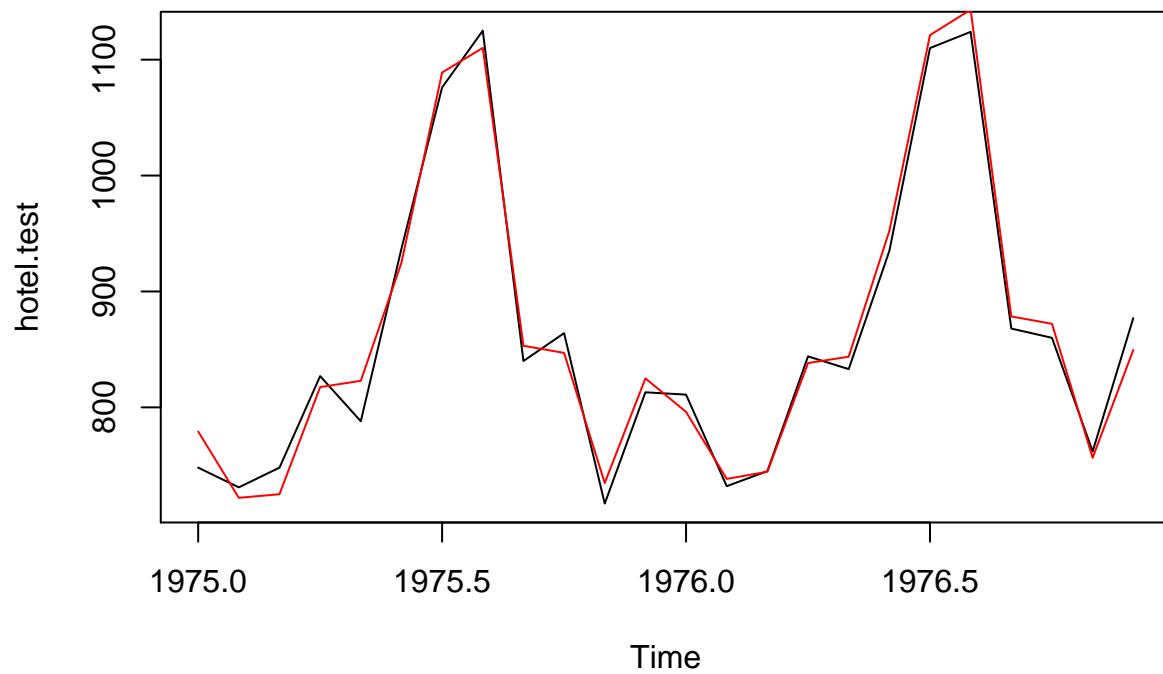
plot(hotel.train, xlim=c(1963, 1977), ylim=c(400,1300),
     main="Time Series predict vs. observed: Monthly data of hotel occupied room ")
lines(exp.test.arima, col="red") # red line denotes the predicted value
lines(hotel.test, lty = 2)
```

Time Series predict vs. observed: Monthly data of hotel occupied roo



Comparison of test set and observed set

```
plot(hotel.test)
lines(exp.test.arima, col="red") # red line denotes the predicted value
```



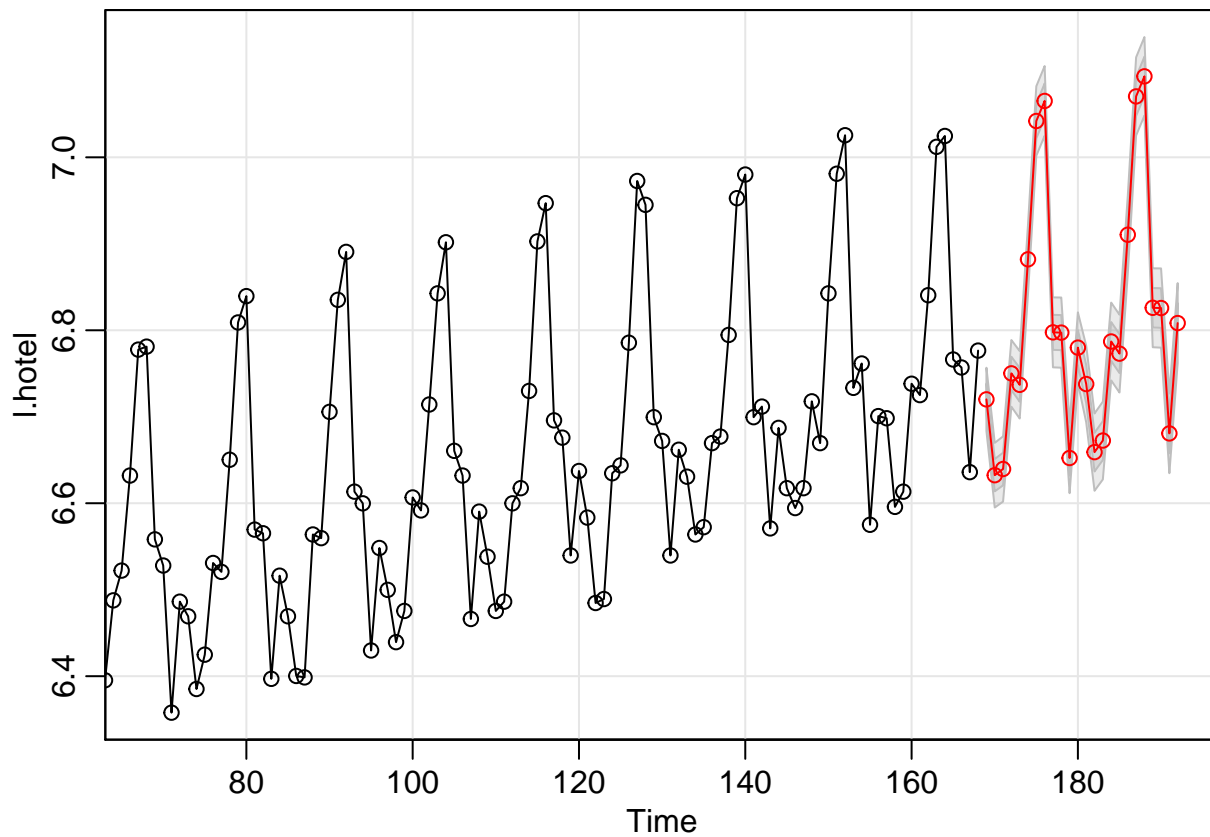
Mean square error

```
mean((exp.test.arima - hotel.test)^2) # 274.4558
```

```
## [1] 274.4558
```

Prediction

```
pred.hotel = sarima.for(l.hotel, 24, 0,1,6, 0,1,1, 12)
```



Plot back to the original scale

```
plot(hotel.ts, xlim=c(1963, 1979), ylim=c(400,1300),
     main="Time Series predict vs. observed: Monthly data of hotel occupied room ")
arimapre = ts(exp(pred.hotel$pred), start=c(1977, 1), end = c(1978,12), frequency = 12)
lines(arimapre, col = "red")
# add CI for predicted value
lines(ts(exp(pred.hotel$pred + pred.hotel$se), start=c(1977, 1), end = c(1978,12), frequency = 12),
      col="blue", lty = 3) # upper CI
lines(ts(exp(pred.hotel$pred - pred.hotel$se), start=c(1977, 1), end = c(1978,12), frequency = 12), col="blue", lty = 3) # lower CI
```

Time Series predict vs. observed: Monthly data of hotel occupied roo

