# Cycles and Forecasting of Hawaiin Hotel Occupancy Presentation

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# Background and Key Question

Understanding the dynamics and forecasting the Hawaiin hotel room occupancy is essential to better control a budget for a trip.

Key Questions:

- Is there a predominant cycle present in the Hawaiian hotel occupancy rate change?
- What are the forecast, and forecast error bounds for the Hawaiin hotel occupany rate change for the next 3 years?

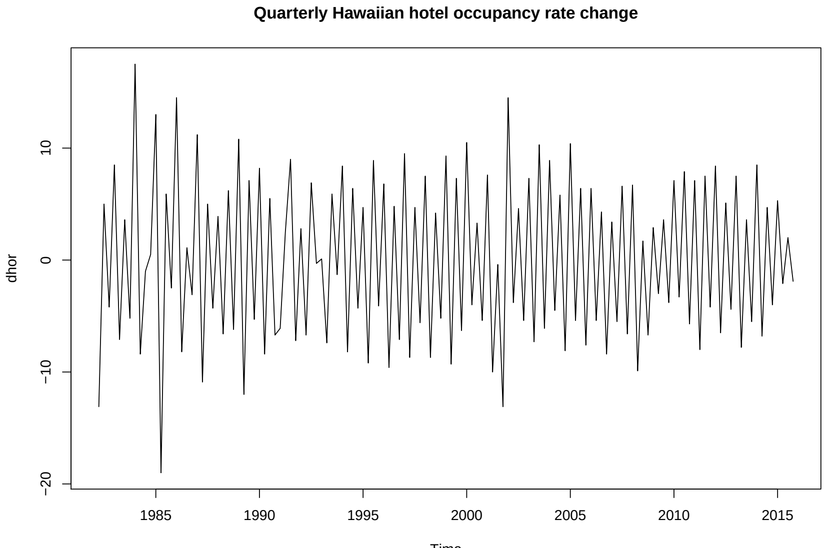
To better address these questions, a time series model will be developed. In addition, since it is a quarterly data, I will also develop a model based spectral density estimate, which will address possible cycles in the data.

# Data: Definition, Aquisition and Exploration

I am using the Quarterly Hawaiian hotel occupancy rate change from 1982-I to 2015-IV from the *astsa* package. It is defined as a ts object.

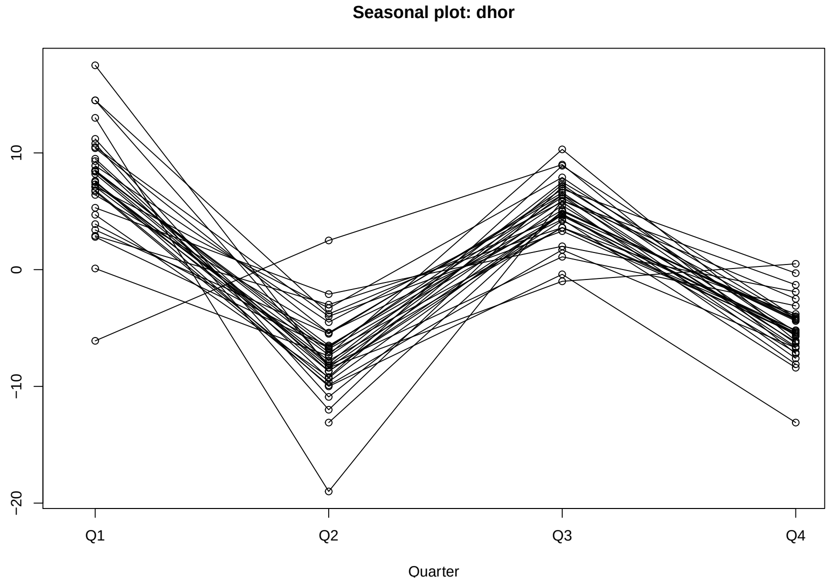
# Plot1

```
dhor<-diff(hor)
ts.plot(dhor, main="Quarterly Hawaiian hotel occupancy rate
```



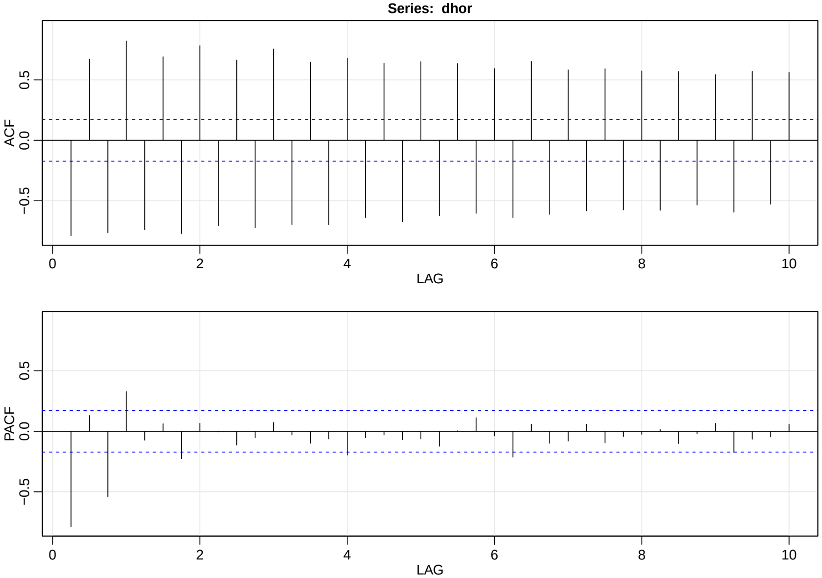
# Plot2

```
seasonplot(dhor)
```



# ACF and PACF

```r
invisible(astsa::acf2(dhor,40))
```



# Modeling Recruitment

```
recfit0<-invisible(astsa::sarima(dhor,p=4,d=0,q=0,
                                 no.constant=FALSE,
                                 details=F))
recfit1<-invisible(astsa::sarima(dhor,p=4,d=0,q=1,
                                 no.constant=FALSE,
                                 details=F))
recfit2<-invisible(astsa::sarima(dhor,p=4,d=0,q=2,
                                 no.constant=FALSE,
                                 details=F))
recfit3<-invisible(astsa::sarima(dhor,p=4,d=0,q=3,
                                 no.constant=FALSE,
                                 details=F))
recfit4<-invisible(astsa::sarima(dhor,p=4,d=0,q=4,
                                 no.constant=FALSE,
                                 details=F))
```

# Comparison

ARIMA(4,0,4) is the best model here.

```r
BIC<-c(recfit0$BIC,recfit1$BIC,recfit2$BIC,
       recfit3$BIC,recfit4$BIC)
AIC<-c(recfit0$AIC,recfit1$AIC,recfit2$AIC,
       recfit3$AIC,recfit4$AIC)
chart<-cbind(BIC,AIC)
rownames(chart) <- c('ARIMA(4,0,0)','ARIMA(4,0,1)',
                     'ARIMA(4,0,2)','ARIMA(4,0,3)',
                     'ARIMA(4,0,4)')
as.table(chart)
```

```
##                   BIC      AIC
## ARIMA(4,0,0) 2.595448 3.487845
## ARIMA(4,0,1) 2.522507 3.393384
## ARIMA(4,0,2) 2.517099 3.366455
## ARIMA(4,0,3) 2.552342 3.380178
## ARIMA(4,0,4) 2.512815 3.319130
```

# With seasonal Component

```
recfitar<-invisible(astsa::sarima(dhor,p=4,d=0,q=4,
                                  P=1,S=4,no.constant=F,
                                  details=F))
recfitma<-invisible(astsa::sarima(dhor,p=4,d=0,q=4,
                                  S=4,Q=1,no.constant=F,
                                  details=F))
recfit11<-invisible(astsa::sarima(dhor,p=4,d=0,q=4,
                                  P=1,S=4,Q=1,
                                  no.constant=FALSE,
                                  details=F))
```

# Comparison

ARIMA(4,0,4)xAR(1)[4] is the best fitted model here.

```
BIC<-c(recfitar$BIC,recfitma$BIC,recfit11$BIC)
AIC<-c(recfitar$AIC,recfitma$AIC,recfit11$AIC)
AICc<-c(recfitar$AICc,recfitma$AICc,recfit11$AICc)
chart<-cbind(BIC,AIC)
chart<-cbind(chart,AICc)
rownames(chart) <- c('ARIMA(4,0,4)xAR(1)[4]',
                     'ARIMA(4,0,4)xMA(1)[4]',
                     'ARIMA(4,0,2)xARMA(1,1)[4]')
as.table(chart)
```

```
##                                BIC      AIC     AICc
## ARIMA(4,0,4)xAR(1)[4]     2.505222 3.290016 3.320730
## ARIMA(4,0,4)xMA(1)[4]     2.511990 3.296784 3.327498
## ARIMA(4,0,2)xARMA(1,1)[4] 2.545871 3.309144 3.342903
```

# Model Estimation

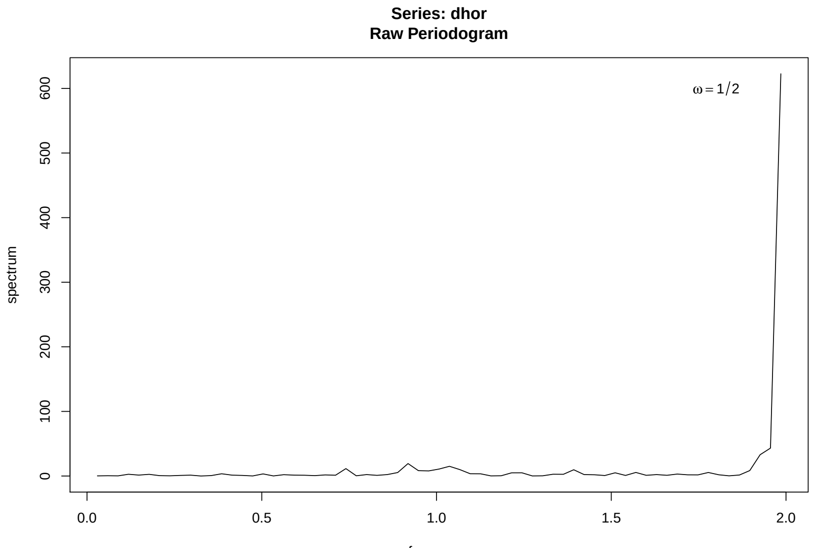
```
kable(recfitar$ttable, caption=
        "SARIMA(4,0,4)x(1,0,0)[4] Parameter Estimates")
```

Table 1: SARIMA(4,0,4)x(1,0,0)[4] Parameter Estimates

| | Estimate | SE | t.value | p.value |
|---|---|---|---|---|
| ar1 | -0.0234 | 0.0758 | -0.3086 | 0.7581 |
| ar2 | -0.1675 | 0.0575 | -2.9116 | 0.0043 |
| ar3 | -0.4188 | 0.0727 | -5.7590 | 0.0000 |
| ar4 | 0.7252 | 0.0726 | 9.9947 | 0.0000 |
| ma1 | -0.3325 | 0.0944 | -3.5218 | 0.0006 |
| ma2 | -0.0223 | 0.1078 | -0.2065 | 0.8367 |
| ma3 | 0.3133 | 0.1332 | 2.3521 | 0.0202 |
| ma4 | -0.9586 | 0.1141 | -8.4033 | 0.0000 |
| sar1 | 0.1899 | 0.1138 | 1.6689 | 0.0976 |
| xmean | -0.0010 | 0.0269 | -0.0368 | 0.9707 |

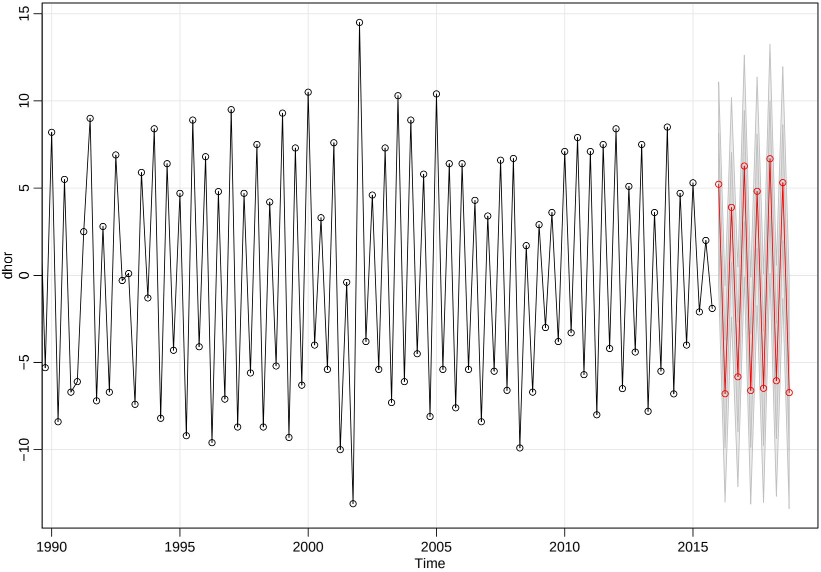
# What is the predominant period?

```
sa <- spec.pgram(dhor,log='no')
text(frequency(dhor)*0.45, 600, substitute(omega==1/2))
```



# Forecasting 2016-2018

```
sarima.for(dhor,n.ahead=12,p=4,d=0,q=4,P=1,S=4,Q=0)
```



# Summary Conclusions

-The temporal dynamics of the occupancy rate of Hawaiin hotels is well captured by a seasonal model ARIMA(4,0,4)xAR(1)[4].

-We also found the predominant cycle the occupancy rate change series, as indicated by the estimate of the spectral density.

-Forecasts predict the near term behavior of the series (3 years ahead). And we see that the longterm forecasts oscillates around the estimated mean of the process, as expected.