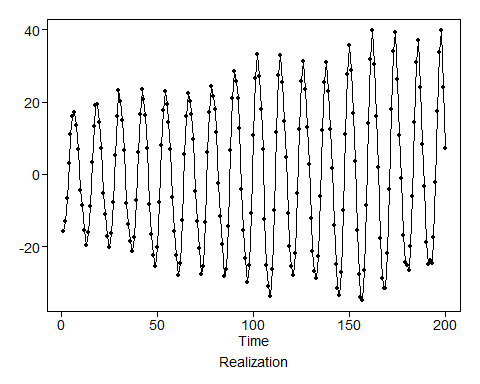
10.9 Seasonal Models - More General Model

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March 8, 2020

## Model

x=gen.aruma.wge(n=200, s=12,phi = c(1.5,-0.8), sn=87)

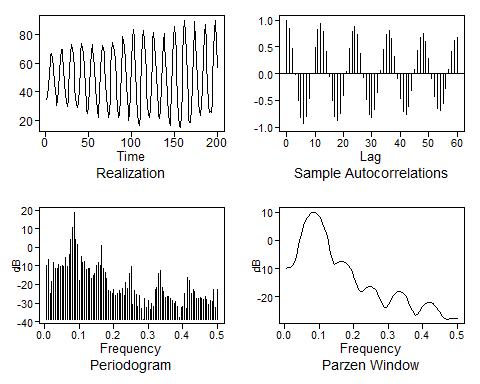


# add in the mean  
x=x+50

## Visualize The Data

See what we are dealing with:

plot=plotts.sample.wge(x,lag.max = 60)



## Overfit Factor Table

Use a number over what you think the seasonality looks to be.

d15=est.ar.wge(x,p=17, type = 'burg')

##   
## Coefficients of Original polynomial:   
## 1.3330 -0.5138 -0.1128 -0.1721 0.1693 -0.0499 -0.0030 -0.0388 0.0590 -0.1264 0.0688 0.8973 -1.2428 0.4347 0.0738 0.1762 -0.1623   
##   
## Factor Roots Abs Recip System Freq   
## 1-1.7276B+0.9985B^2 0.8651+-0.5031i 0.9992 0.0838  
## 1-1.0028B+0.9955B^2 0.5036+-0.8665i 0.9977 0.1662  
## 1+1.0010B+0.9936B^2 -0.5037+-0.8676i 0.9968 0.3337  
## 1-0.0157B+0.9930B^2 0.0079+-1.0035i 0.9965 0.2487  
## 1+1.7329B+0.9899B^2 -0.8753+-0.4941i 0.9949 0.4182  
## 1+0.9836B -1.0166 0.9836 0.5000  
## 1-0.9136B 1.0945 0.9136 0.0000  
## 1-1.4286B+0.7747B^2 0.9220+-0.6638i 0.8802 0.0993  
## 1-0.7137B 1.4011 0.7137 0.0000  
## 1+0.7516B+0.3366B^2 -1.1166+-1.3132i 0.5801 0.3621  
##   
##

Look in the factor table for patterens matching know seasonal tables.

Here is a factor table of .

#(1-B^12)  
factor.wge(c(rep(0,11),1))

##   
## Coefficients of Original polynomial:   
## 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 1.0000   
##   
## Factor Roots Abs Recip System Freq   
## 1-1.0000B+1.0000B^2 0.5000+-0.8660i 1.0000 0.1667  
## 1-1.0000B 1.0000 1.0000 0.0000  
## 1-1.7321B+1.0000B^2 0.8660+-0.5000i 1.0000 0.0833  
## 1+1.0000B+1.0000B^2 -0.5000+-0.8660i 1.0000 0.3333  
## 1-0.0000B+1.0000B^2 0.0000+-1.0000i 1.0000 0.2500  
## 1+1.7321B+1.0000B^2 -0.8660+-0.5000i 1.0000 0.4167  
## 1+1.0000B -1.0000 1.0000 0.5000  
##   
##

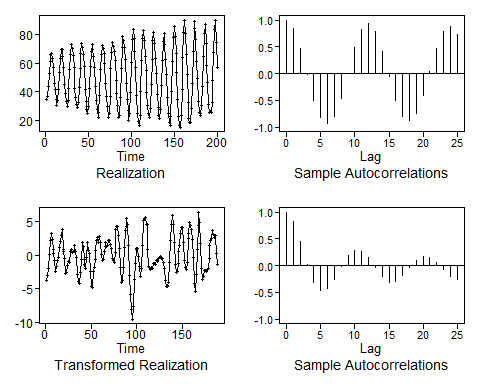
**Note:** The factor 1-0.9136B is not very close to the unit circle, but since all other factors are consistent with we conclude that this overfit table suggests also.

## Transform

Base on the overfit table we can now transform the data to remove the seasonality.

Transform data to create

#rep will repeat the 11 zeros then we can add a one at the end  
y=artrans.wge(x,phi.tr = (c(rep(0,11),1)))



The transformed data appear stationary, so we use AIC to identify a model.

We use **aic5.wge** to model the transformed data (y) When using AIC to model data that has been stationarized using the seasonal transform , it is good practice to allow a range of p values to include s to uncover any seasonal stationary information that might be in the data. In R code to follow, we consider the range p=0:13 and q=0:3

# y is the transformed data  
aic5.wge(y,p=0:13,q=0:3)

## ---------WORKING... PLEASE WAIT...   
##   
##   
## Five Smallest Values of aic

## p q aic  
## 19 4 2 0.06290065  
## 9 2 0 0.06764617  
## 20 4 3 0.06910374  
## 13 3 0 0.07338218  
## 10 2 1 0.07361012

AIC selects an ARMA(4,2) model. Factoring the ARMA(4,2) model we obtain:

est = est.arma.wge(y,p=4, q=2, factor = TRUE)

##   
## Coefficients of Original polynomial:   
## 1.8831 -2.1943 1.5169 -0.6321   
##   
## Factor Roots Abs Recip System Freq   
## 1-0.4098B+0.8135B^2 0.2519+-1.0798i 0.9019 0.2135  
## 1-1.4733B+0.7771B^2 0.9480+-0.6231i 0.8815 0.0925  
##   
##

est$phi

## [1] 1.8831035 -2.1942981 1.5169278 -0.6321408

est$theta

## [1] 0.4957013 -0.9262404

**Note:** The dominant behavior of the transformed data is a pseudo cyclic behavior of length about 10 . The factors associated with frequency about essentially cancel.

We can look for a simpler model using BIC. Use the y data.

aic5.wge(y,p=0:13,q=0:3,type='bic')

## ---------WORKING... PLEASE WAIT...   
##   
##   
## Five Smallest Values of bic

## p q bic  
## 9 2 0 0.1192915  
## 13 3 0 0.1422426  
## 10 2 1 0.1424706  
## 11 2 2 0.1692218  
## 17 4 0 0.1700640

BIC picks a simpler AR(2) model. This is consistent with:

* The pseudo cyclic data
* Damping cyclical sample autocorrelations

**Decision:** We choose to model the transformed data as an AR(2).

est2=est.ar.wge(y,p=2)

##   
## Coefficients of Original polynomial:   
## 1.4653 -0.7597   
##   
## Factor Roots Abs Recip System Freq   
## 1-1.4653B+0.7597B^2 0.9644+-0.6215i 0.8716 0.0911  
##   
##   
##   
## Coefficients of Original polynomial:   
## 1.4653 -0.7597   
##   
## Factor Roots Abs Recip System Freq   
## 1-1.4653B+0.7597B^2 0.9644+-0.6215i 0.8716 0.0911  
##   
##

We can now write our model using data collected from **est.ar.wge**.

#Get the phi's for the model  
est2$phi

## [1] 1.4652837 -0.7596714

#Get the White Noise Var  
est2$avar

## [1] 1.036377

#Figure the mean with the original x data  
mean(x)

## [1] 49.77867

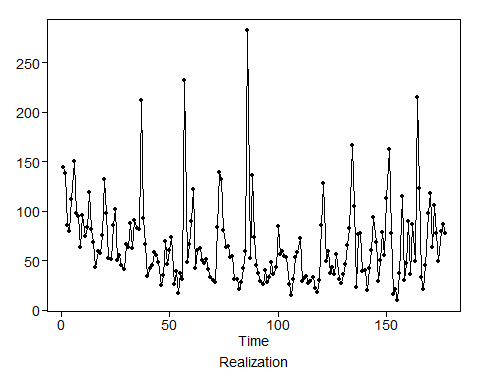
#### Our final model:

#### The Original Model:

### 10.9.4 Concept Check

Consider the attached Southwest Airlines flight delay data (SWADelay.csv). Use **est.ar.wge()** to overfit an **AR(15)** model with the Burg estimates. We are trying to gauge if there is sufficient evidence to suggest a factor is in the model. Look at the factor table, and answer the following questions.

#read in the data  
SWA = read.csv("swadelay.csv",header = TRUE)  
plotts.wge(SWA$arr\_cancelled)



#Get and an estimate using the arr\_delay information  
#Overfitting with and AR(15)  
d15SW=est.ar.wge(SWA$arr\_delay,p=15, type = 'burg')

##   
## Coefficients of Original polynomial:   
## 0.4443 0.0482 -0.0541 0.0820 0.0090 0.0304 0.0410 -0.0837 0.0588 0.0568 0.0252 0.3759 -0.0127 -0.0074 -0.1486   
##   
## Factor Roots Abs Recip System Freq   
## 1-0.9700B 1.0310 0.9700 0.0000  
## 1-0.9946B+0.9342B^2 0.5323+-0.8872i 0.9666 0.1640  
## 1-1.6636B+0.9322B^2 0.8923+-0.5259i 0.9655 0.0848  
## 1+0.9229B -1.0836 0.9229 0.5000  
## 1+1.6328B+0.8443B^2 -0.9669+-0.4994i 0.9189 0.4241  
## 1-0.1460B+0.8319B^2 0.0877+-1.0928i 0.9121 0.2372  
## 1+0.7038B+0.7209B^2 -0.4882+-1.0719i 0.8490 0.3180  
## 1+0.7885B+0.5243B^2 -0.7520+-1.1584i 0.7241 0.3416  
## 1-0.7182B 1.3924 0.7182 0.0000  
##   
##

*10.9.4* What is the root associated with the factor (from the factor table you generated) that would be matched with the term from the $(1-B^{12}) factor table?

Express your response rounded to four decimal places. *1.0310*

*10.9.5* Look at the system frequencies from the factor table you generated. What is the system frequency associated with the the factor that would be matched with the factor from the factor table?

factor.wge(phi = c(rep(0,11),1))

##   
## Coefficients of Original polynomial:   
## 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 1.0000   
##   
## Factor Roots Abs Recip System Freq   
## 1-1.0000B+1.0000B^2 0.5000+-0.8660i 1.0000 0.1667  
## 1-1.0000B 1.0000 1.0000 0.0000  
## 1-1.7321B+1.0000B^2 0.8660+-0.5000i 1.0000 0.0833  
## 1+1.0000B+1.0000B^2 -0.5000+-0.8660i 1.0000 0.3333  
## 1-0.0000B+1.0000B^2 0.0000+-1.0000i 1.0000 0.2500  
## 1+1.7321B+1.0000B^2 -0.8660+-0.5000i 1.0000 0.4167  
## 1+1.0000B -1.0000 1.0000 0.5000  
##   
##

Express your response rounded to four decimal places. *0.0848*

*10.9.6* Do you feel that there is enough evidence to suggest a factor should be present in our final model?

*Yes*

This is subjective, but there is only one term that doesn’t match up almost exactly (the ) B. No. We will take this answer, but you would almost have some domain knowledge or other evidence to not include a in this case. Note: The spectral density shows a clear peak at 1/12 = .08, but this does not in and of itself mean that is appropriate. There are many other factors of smaller degree that will yield this frequency.

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