meeting report 6.10

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2019.6.10

Well, I did not send Aaron meeting report this time, cause I did not read much things recently, all content we talked was the things I have done before. And the meeting result compared with the former was better. I guess Aaron and I are getting used with each other? LOL.
I hope to plot something to clearfy the point I want to express, but unfortunatly I can't. I will add some photos in this folder.

I

Note the curve of *trend + season* in **report 6.6** is pretty close to our data, which is totally opposite to the situation from StatCan… although I am not sure how they get the plot, at least I believe what I got is reasonable.
Here is the thing, $Y_t - T_t - S_t$ is ϵ_t, and differences between our data and trend+season actually reflect the deviation of the noise ϵ. By controling the deviation of the noise, we can control the smoothness of the trend+season curve(since t.s Y_t is fixed).

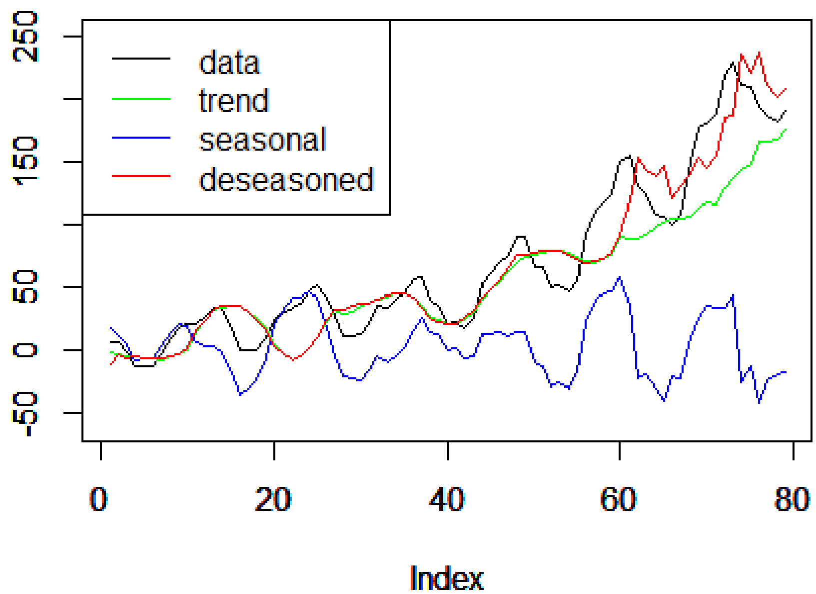
——————————————————UPDATE 6.12——————————————————
昨天试着理清为什么 Aaron 说可以 change $\omega_t = \phi(Y_t - T_t - S_t)$ into $\omega_t = \phi(\frac{Y_t - T_t - S_t}{c})(c > 1)$. But I still do not understand the theory behind it clearly… I give up temporarily :) Let's see whether this could work in our s.s model before(*report 6.6*) ## change sd in expression of w from 1 to 5

```r
library(seasonal)
library(forecast)

## Registered S3 methods overwritten by 'ggplot2':
##   method         from
##   [.quosures     rlang
##   c.quosures     rlang
##   print.quosures rlang

## Registered S3 method overwritten by 'xts':
##   method     from
##   as.zoo.xts zoo

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

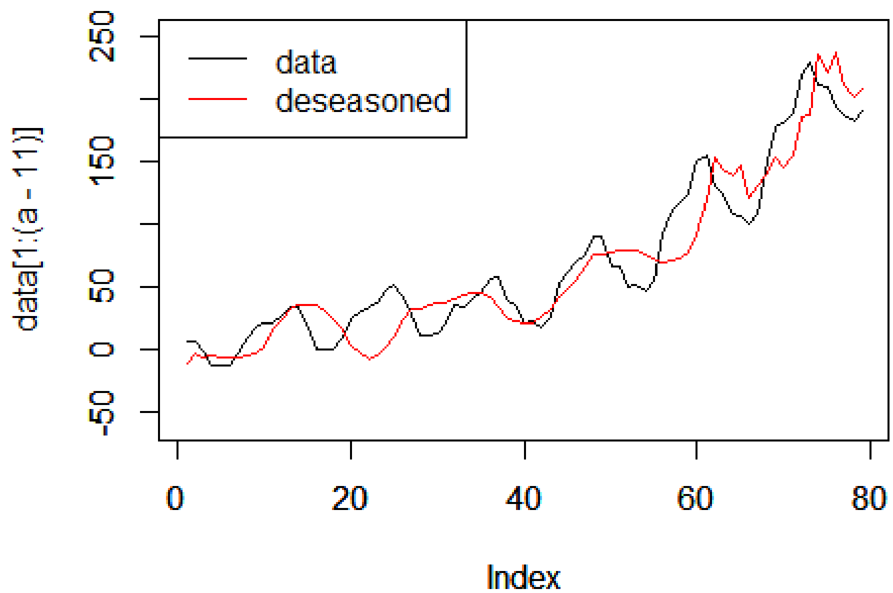
```
## Registered S3 methods overwritten by 'forecast':
##   method              from
##   fitted.fracdiff     fracdiff
##   residuals.fracdiff fracdiff
```

```r
set.seed(1)

# generate data
model <- Arima(ts(rnorm(24000),freq=12), order=c(0,1,1), seasonal=c(0,1,
1),fixed=c(theta=0.5, Theta=0.5))
data <- simulate(model,nsim=240)

# define m_x11
m_x11 <- seas(data, x11 = "", regression.aictest =  NULL)

# Initialization
S <- matrix(0,1000,251) # Cause Seasonal component's state space model,
 we have additional 11 zero-values.
Tr <- matrix(0,1000,251)
Tr[,11] <- data[1]
S[,1:11] <- rep(as.numeric(data-final(m_x11))[1:11],1000)
component <- c()
a = 90 # a-11 is the length of our t.s.

for (i in 12:a) {

  # update particles
  Tr[,i] <- Tr[,i-1] + rnorm(1000,sd=5)
  for (j in 1:11) S[,i] <- S[,i]-S[,i-j]
  S[,i] <- S[,i] + rnorm(1000,sd=5)

  # update weights
  w <- dnorm(data[i-11]-Tr[,i]-S[,i],sd=5)
  w <- w/sum(w)

  # evaluate state value
  t <- sum(w * Tr[,i])
  s <- sum(w * S[,i])

  # add to our component path
  component <- rbind(component, c(t,s))

  # resample
  Tr[,i] <- sample(Tr[,i], size =1000, replace = TRUE, prob = w)
  S[,i] <- sample(S[,i], size = 1000, replace = TRUE, prob = w)
}

# plot four curves together
plot(data[1:(a-11)],type = "l",ylim = c(-60,250),ylab='')
```

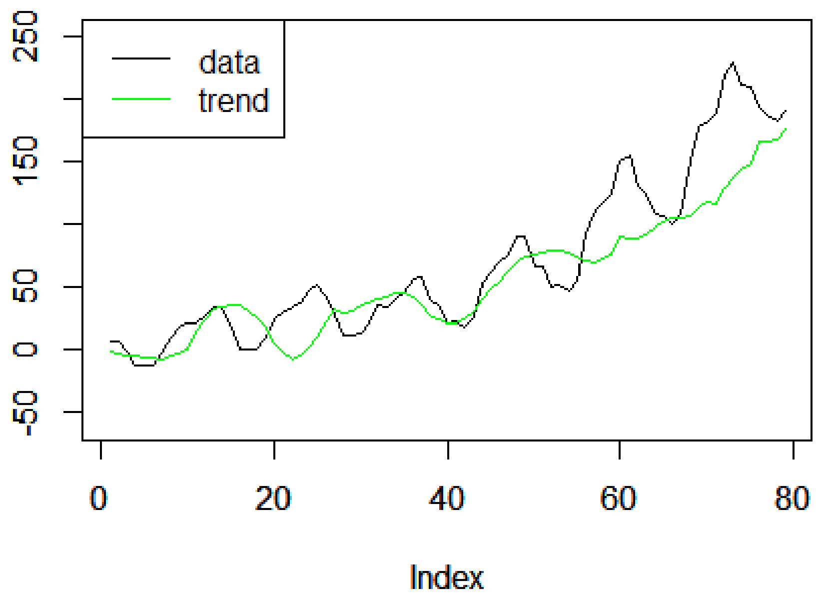
```
par(new=TRUE)
plot(component[,1],type="l",col="green",ylim = c(-60,250),ylab='')
par(new=TRUE)
plot(component[,2],type="l",col="blue",ylim = c(-60,250),ylab='')
par(new=TRUE)
plot(data[1:(a-11)]-component[,2],type="l",col="red",ylim=c(-60,250),yl
ab='')
legend("topleft",c("data","trend","seasonal","deseasoned"),col=c("black
","green","blue","red"),lty=c(1,1,1,1))
```



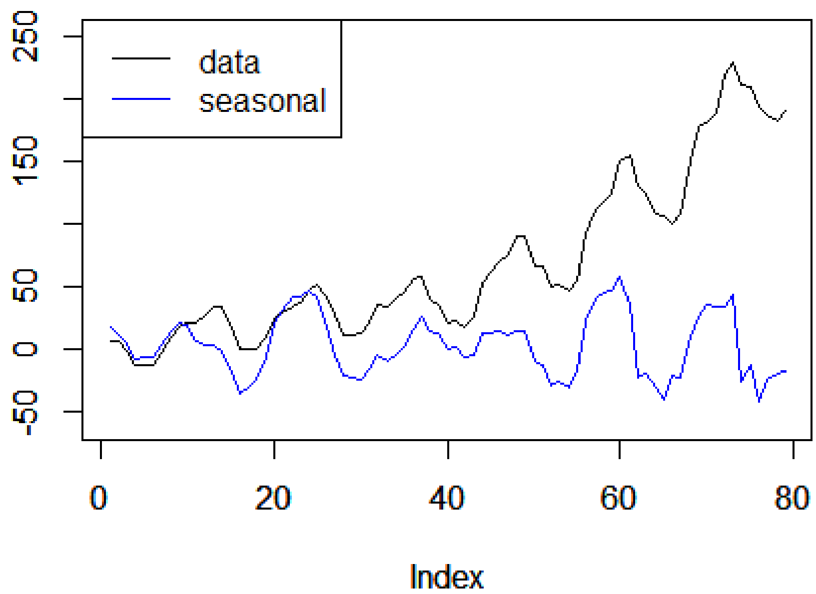

```
# data vs deseasoned
plot(data[1:(a-11)],type = "l",ylim = c(-60,250))
par(new=TRUE)
plot(data[1:(a-11)]-component[,2],type="l",col="red",ylim=c(-60,250),yl
ab='')
legend("topleft", c("data","deseasoned"),col=c("black","red"),lty=c(1,
1))
```



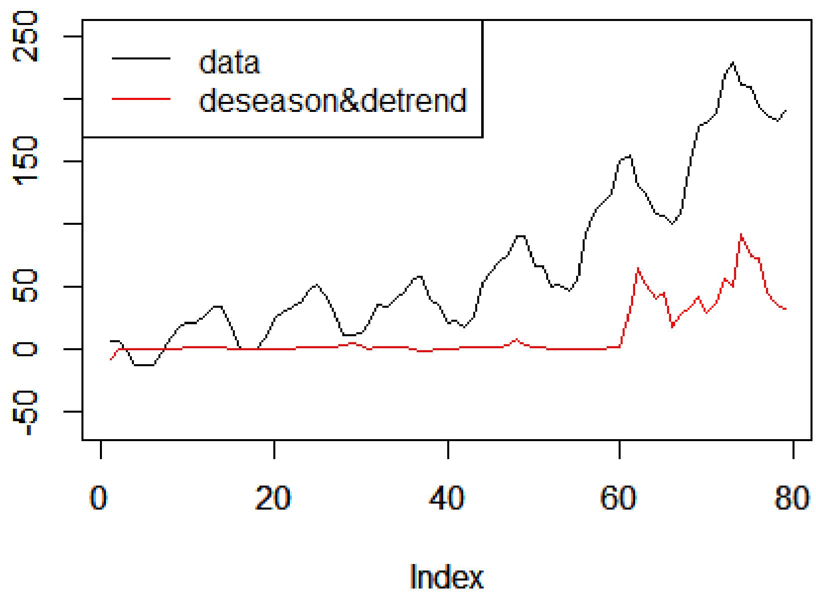

```r
# data vs trend
plot(data[1:(a-11)],type = "l",ylim = c(-60,250),ylab='')
par(new=TRUE)
plot(component[,1],type="l",col="green",ylim = c(-60,250),ylab='')
legend("topleft",c("data","trend"),col=c("black","green"),lty=c(1,1))
```



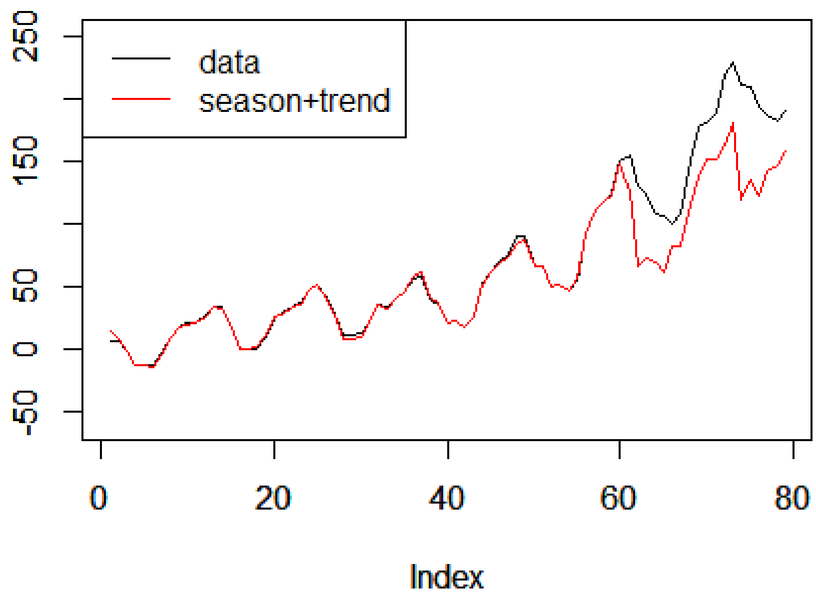

```r
# data vs season
plot(data[1:(a-11)],type = "l",ylim = c(-60,250),ylab='')
par(new=TRUE)
plot(component[,2],type="l",col="blue",ylim = c(-60,250),ylab='')
legend("topleft",c("data","seasonal"),col=c("black","blue"),lty=c(1,1))
```




```
# data vs deseason&detrend
plot(data[1:(a-11)],type = "l",ylim = c(-60,250),ylab='')
par(new=TRUE)
plot(data[1:(a-11)]-component[,1]-component[,2], type="l",col="red",yli
m = c(-60,250),ylab='')
legend("topleft",c("data","deseason&detrend"),col=c("black","red"),lty=
c(1,1))
```




```r
# data vs seanson+trend
plot(data[1:(a-11)],type = "l",ylim = c(-60,250),ylab='')
par(new=TRUE)
plot(component[,1]+component[,2], type="l",col="red",ylim = c(-60,250),
ylab='')
legend("topleft",c("data","season+trend"),col=c("black","red"),lty=c(1,
1))
```

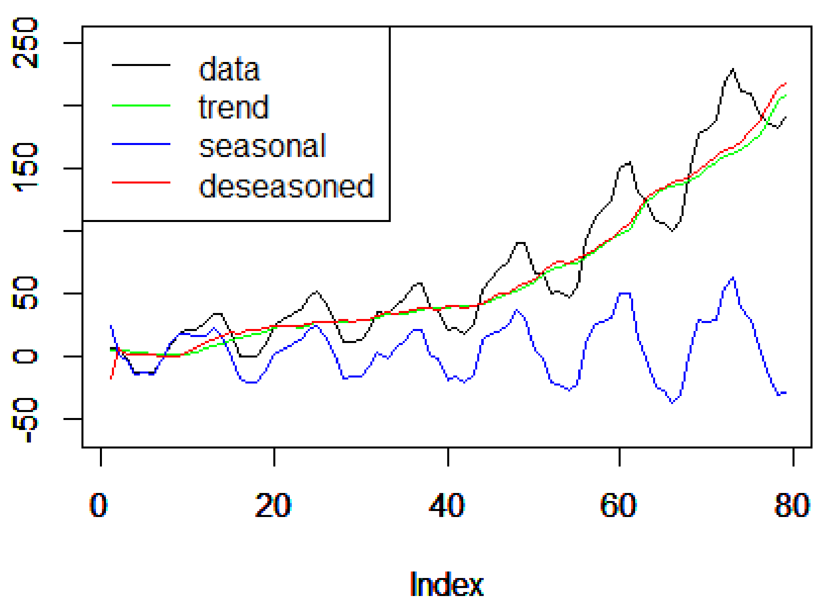


——————————————————UPDATE 6.16——————————————————

I am busy with my resume and the self-recommendation letter recently… I need to meet aaron tmr, but for now I don't have any things to show him, which is very very awkward… ## sd=20 in weights expression

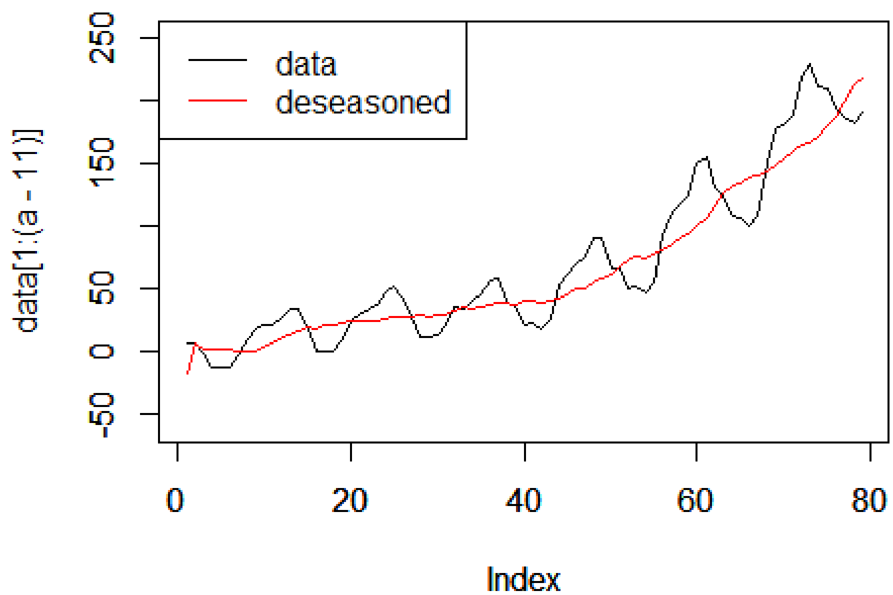
```
# Initialization
S <- matrix(0,1000,251) # Cause Seasonal component's state space model,
 we have additional 11 zero-values.
Tr <- matrix(0,1000,251)
Tr[,11] <- data[1]
S[,1:11] <- rep(as.numeric(data-final(m_x11))[1:11],1000)
component <- c()
a = 90 # a-11 is the length of our t.s.

for (i in 12:a) {

  # update particles
  Tr[,i] <- Tr[,i-1] + rnorm(1000,sd=5)
  for (j in 1:11) S[,i] <- S[,i]-S[,i-j]
  S[,i] <- S[,i] + rnorm(1000,sd=5)

  # update weights
  w <- dnorm(data[i-11]-Tr[,i]-S[,i],sd=20)
  w <- w/sum(w)
```

```
  # evaluate state value
  t <- sum(w * Tr[,i])
  s <- sum(w * S[,i])

  # add to our component path
  component <- rbind(component, c(t,s))

  # resample
  Tr[,i] <- sample(Tr[,i], size =1000, replace = TRUE, prob = w)
  S[,i] <- sample(S[,i], size = 1000, replace = TRUE, prob = w)
}

# plot four curves together
plot(data[1:(a-11)],type = "l",ylim = c(-60,250),ylab='')
par(new=TRUE)
plot(component[,1],type="l",col="green",ylim = c(-60,250),ylab='')
par(new=TRUE)
plot(component[,2],type="l",col="blue",ylim = c(-60,250),ylab='')
par(new=TRUE)
plot(data[1:(a-11)]-component[,2],type="l",col="red",ylim=c(-60,250),yl
ab='')
legend("topleft",c("data","trend","seasonal","deseasoned"),col=c("black
","green","blue","red"),lty=c(1,1,1,1))
```

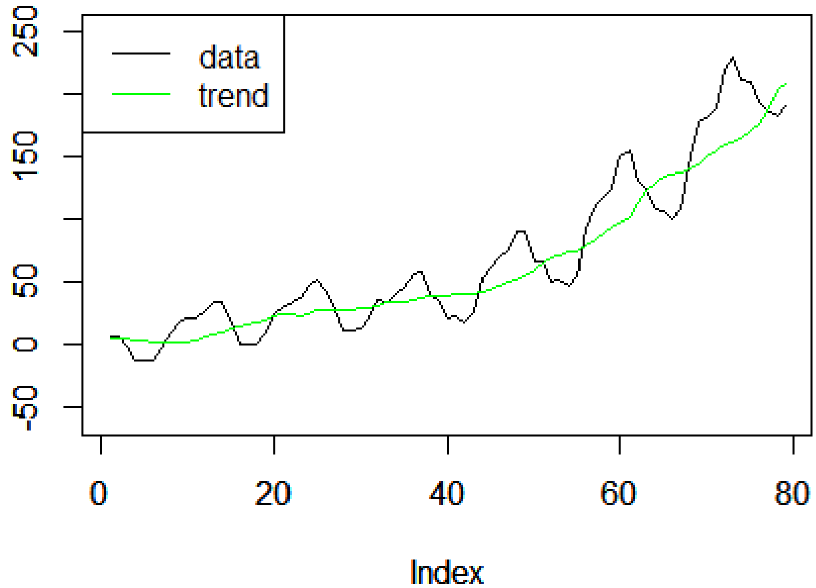



```
# data vs deseasoned
plot(data[1:(a-11)],type = "l",ylim = c(-60,250))
```

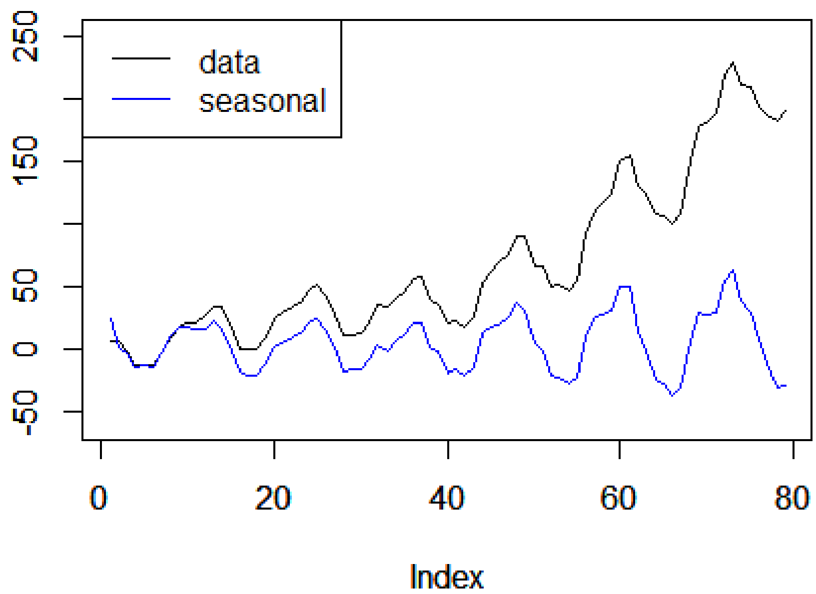
```
par(new=TRUE)
plot(data[1:(a-11)]-component[,2],type="l",col="red",ylim=c(-60,250),yl
ab='')
legend("topleft", c("data","deseasoned"),col=c("black","red"),lty=c(1,
1))
```



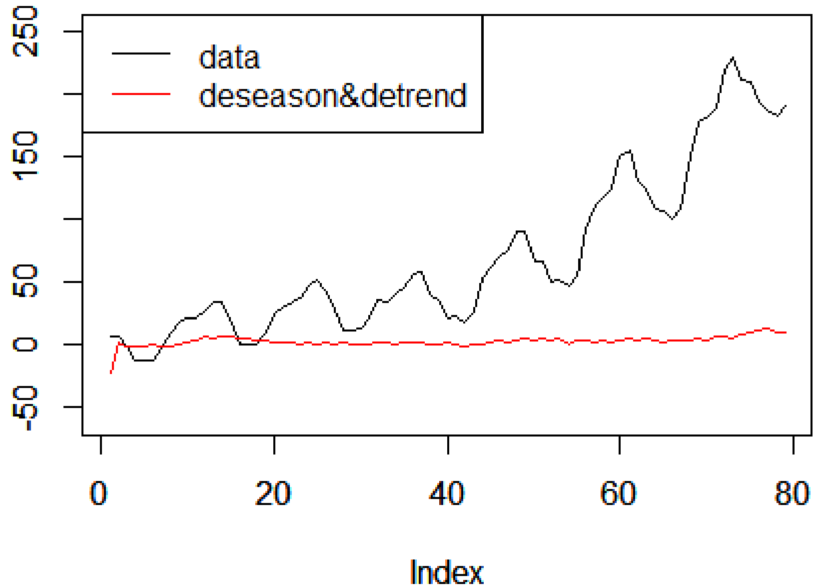

```
# data vs trend
plot(data[1:(a-11)],type = "l",ylim = c(-60,250),ylab='')
par(new=TRUE)
plot(component[,1],type="l",col="green",ylim = c(-60,250),ylab='')
legend("topleft",c("data","trend"),col=c("black","green"),lty=c(1,1))
```



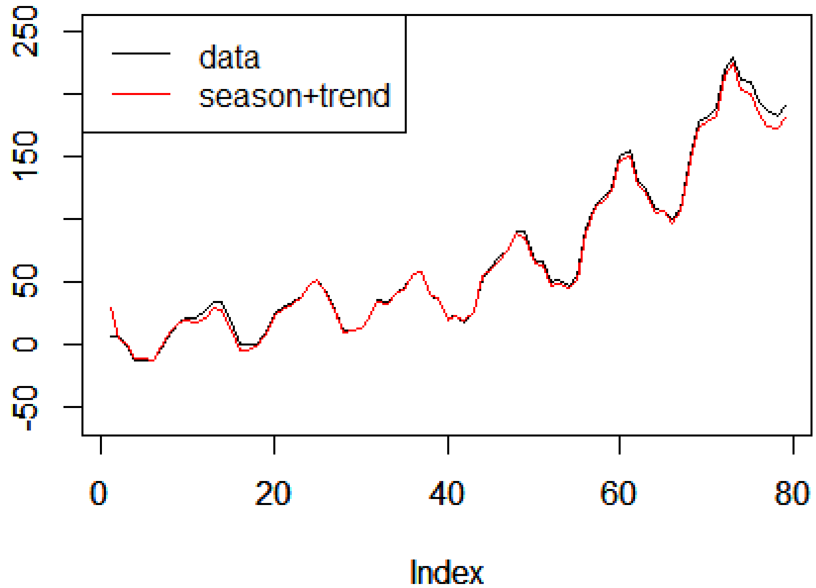

```r
# data vs season
plot(data[1:(a-11)],type = "l",ylim = c(-60,250),ylab='')
par(new=TRUE)
plot(component[,2],type="l",col="blue",ylim = c(-60,250),ylab='')
legend("topleft",c("data","seasonal"),col=c("black","blue"),lty=c(1,1))
```




```r
# data vs deseason&detrend
plot(data[1:(a-11)],type = "l",ylim = c(-60,250),ylab='')
par(new=TRUE)
plot(data[1:(a-11)]-component[,1]-component[,2], type="l",col="red",yli
m = c(-60,250),ylab='')
legend("topleft",c("data","deseason&detrend"),col=c("black","red"),lty=
c(1,1))
```




```
# data vs seanson+trend
plot(data[1:(a-11)],type = "l",ylim = c(-60,250),ylab='')
par(new=TRUE)
plot(component[,1]+component[,2], type="l",col="red",ylim = c(-60,250),
ylab='')
legend("topleft",c("data","season+trend"),col=c("black","red"),lty=c(1,
1))
```



Well, after enlarging the deviation of noise, the curves of trend and deseasonal become much more smooth, which should be something like that from StatCan.

I think I should understand a little bit about why aaron told me to add a demoninator in weights expression. Like we said before, we can control the smoothness of our curves by controling the deviation of our noise. Let's say we want

$$\epsilon \sim N(0,25)$$

which means

$$\frac{\epsilon}{5} \sim N(0,1)$$

or

$$\frac{Y_t - T_t - S_t}{5} \sim N(0,1)$$

and

$$\omega_t \propto p(Y_t|T_t, S_t)$$

that is

$$\omega_t \propto \phi(\frac{Y_t - T_t - S_t}{5})$$

And in R we can express $\phi(\frac{Y_t - T_t - S_t}{5})$ in two ways:
- dnorm((Y_t-T_t-S_t)\5)
- dnrom(Y_t-T_t-S_t, sd=5)
We choose the second one.