Obligatorio Series Temporales

Ventas semanales del agua / temperatura media semanal en Uruguay

Fuentes de datos

La temperatura se descargó de la web https://en.tutiempo.net/ (https://en.tutiempo.net/) y los datos son de la estación meteorológica cercana al aeropuerto de Carrasco. La bajada fue por día desde el 01/01/2017 y se pasó a semanal haciendo el promedio de los valores de la semana.

La venta de agua está en litros, también es semanal y del mismo período pero en este caso es la suma de los valores de la semana. Los datos se obtuvieron de una empresa que hace venta minorista, por lo que el factor stock no tiene incidencia en el dataset. Se excluyó aguas saborizadas del análisis y solo se tomó en cuenta agua mineral tanto con como sin gas y en todos sus calibres.

In [1]:
```
#install.packages("xlsx")
#install.packages("astsa")

library(xlsx)
library(astsa)
library(lubridate)

options(repr.plot.width=10, repr.plot.height=5) #ajusta tamaño de graficas
```

```
Attaching package: ‘lubridate’

The following object is masked from ‘package:base’:

    date
```

Adicionalmente a los criterios dados en clase para identificar la mejor predicción de la serie (AIC, BIC, ruido blanco Gaussiano, varianza) utilizaremos la función mape definida a continuación.

In [2]:
```
mape <- function(actual,pred){
  mape <- mean(abs((actual - pred)/actual))*100
  return (mape)
}
```

In [3]:
```
base <- read.xlsx("Base time series.xlsx", sheetIndex = 1)

base_train <- base[base$Class == 'Train',]
base_test <- base[base$Class == 'Test',]

Litros=round(base_train[4] / 10000, 2)
# Normalizamos los datos de venta para pasarlos a la misma escala que la tempe
ratura

Temp = round(base_train[5], 2)
#Temp
```

In [4]:
```r
head(base)

head(Litros)

head(Temp)
```

A data.frame: 6 x 6

Year	Weeknum	Yearweek	Sales_Liters	Temp_Avg	Class
<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<fct>
2017	1	1	263778.2	22.88571	Train
2017	2	2	249777.5	23.24286	Train
2017	3	3	266308.4	23.52857	Train
2017	4	4	261133.6	21.95714	Train
2017	5	5	292004.5	24.58571	Train
2017	6	6	236130.0	21.11429	Train

A data.frame: 6 x 1

Sales_Liters
<dbl>
26.38
24.98
26.63
26.11
29.20
23.61

A data.frame: 6 x 1

Temp_Avg
<dbl>
22.89
23.24
23.53
21.96
24.59
21.11

Metodología

Según lo visto en el curso utilizaremos la receta de Box-Jenkins para trabajar con nuestra serie temporal, es decir vamos a:

Graficar los datos

Trasnformar los datos (por ejemplo, transformación logarítmica, o detrend o ambos, diferenciación).

Identificar los órdenes de dependencia (acf, pacf).

Estimación de parámetros (fit, básicamente mínimos cuadrados o máxima verosimilitud).

Diagnóstico (análisis de residuos por ejemplo).

Elección del modelo (criterios de información tipo AIC, evitar overfitting, etc.)

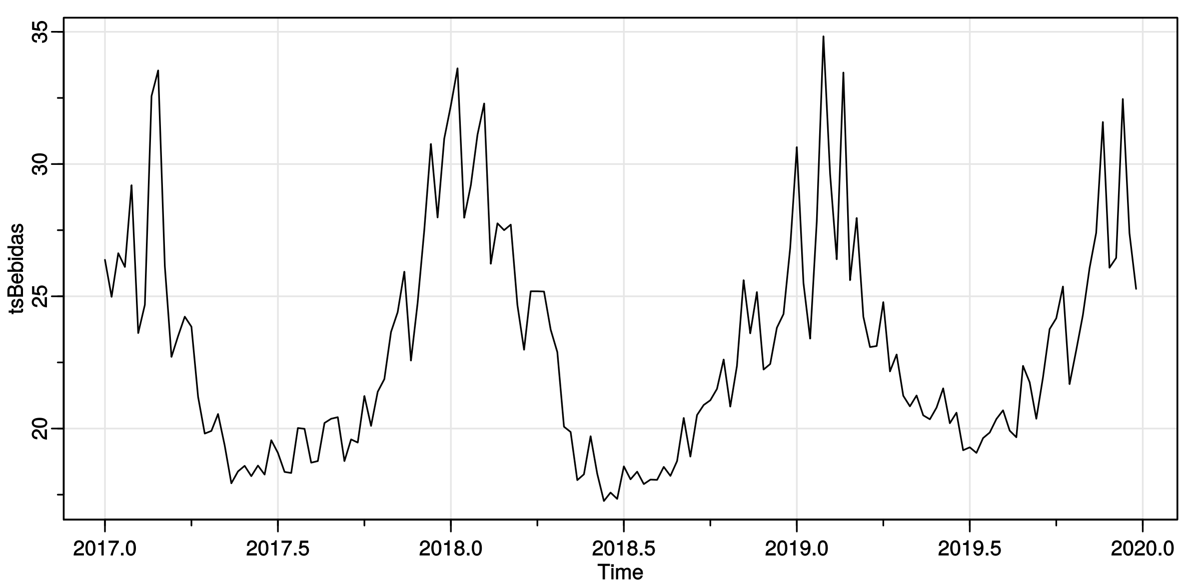
Predicción en base a estimadores lineales calculados recursivamente e intervalos de confianza.

Graficamos los datos

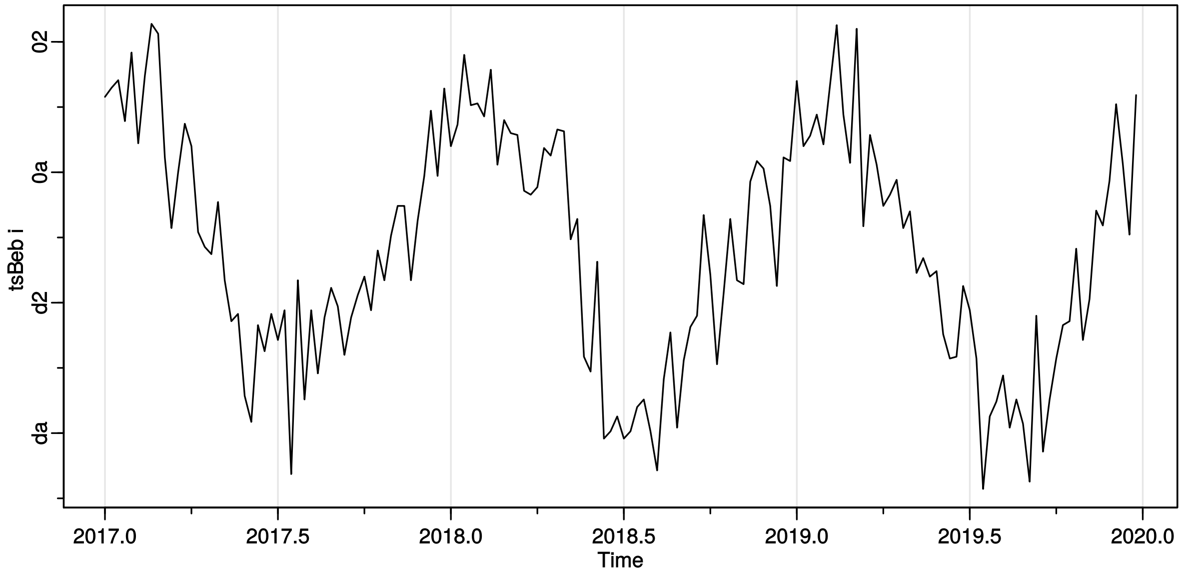
In [5]:
```
tsBebidas = ts(Litros,  start=c(2017,1,1), freq = 52)
```

In [6]:
```
tsTemp = ts(Temp,  start=c(2017,1,1), freq = 52)
```

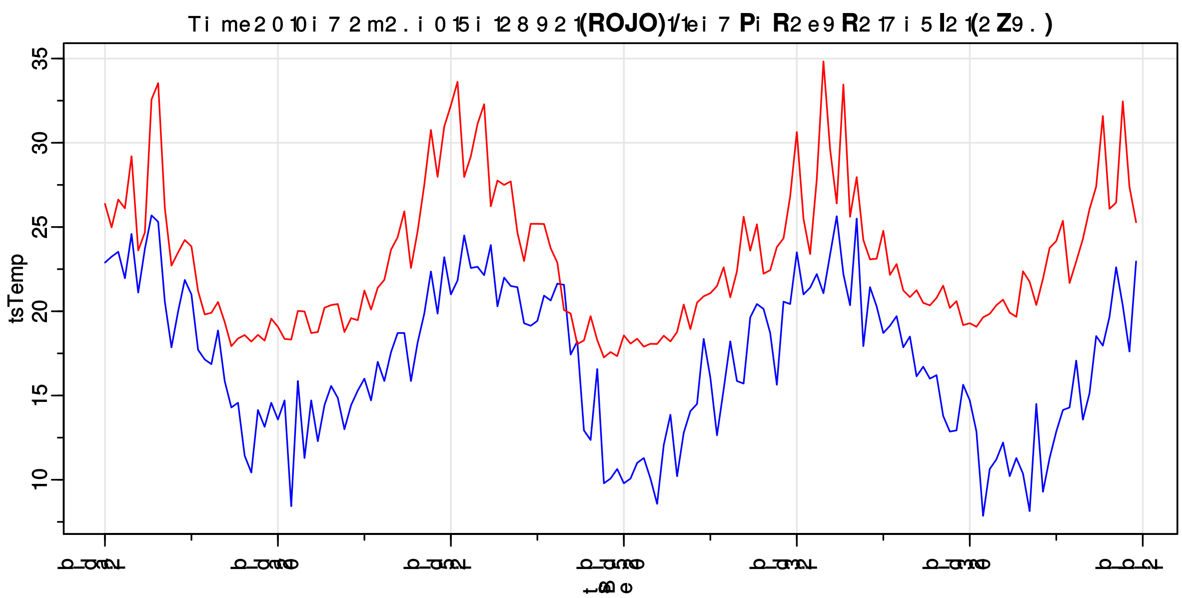
In [7]:
```
tsplot(tsBebidas)
```



In [8]:
```
tsplot(tsTemp)
```



In [9]:
```
tsplot(tsTemp, ylim=c(min(tsTemp),max(tsBebidas)), col = "blue", main = "VENTAS SEMANALES DE AGUA (ROJO) / TEMPERATURA MEDIA (AZUL)")
lines(tsBebidas, col = "red")
```



Prueba de algunos modelos

Se procede a ajustar algunos modelos que representen la serie de Venta de Agua *a partir de la temperatura y de sus valores historicos*:

1. $A_t = \beta_0 + \beta_1 t + w_t$.
2. $A_t = \beta_0 + \beta_1 t + \beta_2 (T_t - \bar{T}) + w_t$.
3. $A_t = \beta_0 + \beta_1 t + \beta_2 (T_t - \bar{T}) + \beta_3 (T_t - \bar{T})^2 + w_t$.

Modelo 1 : regresión lineal ventas vs trend

In [10]:
```
A=tsBebidas
T=tsTemp
```

In [11]:
```
#   Modelo 1
trend = time(A)        # time

fit = lm(A ~ trend, na.action=NULL)

summary(fit)       # regression results

num = length(A)                                           # sample size
AIC(fit)/num - log(2*pi)                                  # AIC
BIC(fit)/num - log(2*pi)                                  # BIC
```

```
Call:
lm(formula = A ~ trend, na.action = NULL)

Residuals:
    Min      1Q  Median      3Q     Max 
-5.7745 -3.2703 -0.9166  2.3601 11.6573 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -416.3563   774.8193  -0.537    0.592
trend          0.2177     0.3839   0.567    0.571

Residual standard error: 4.152 on 154 degrees of freedom
Multiple R-squared:  0.002084,  Adjusted R-squared:  -0.004396 
F-statistic: 0.3216 on 1 and 154 DF,  p-value: 0.5715
```

3.87274004614084

3.93139112320333

Modelo 2 : regresión lineal ventas vs trend + centered temp

In [12]:
```
#  Modelo 2
temp  = T-mean(T)  # center temperature
trend = time(A)        # time

fit = lm(A ~ trend + temp , na.action=NULL)

summary(fit)       # regression results

num = length(A)                                          # sample size
AIC(fit)/num - log(2*pi)                                 # AIC
BIC(fit)/num - log(2*pi)                                 # BIC
```

```
Call:
lm(formula = A ~ trend + temp, na.action = NULL)

Residuals:
    Min      1Q  Median      3Q     Max 
-6.1859 -1.7303 -0.3024  1.2555  8.2124 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept) -1955.1057   495.7802  -3.943 0.000122 ***
trend           0.9800     0.2456   3.990 0.000102 ***
temp            0.7466     0.0483  15.458  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.603 on 153 degrees of freedom
Multiple R-squared:  0.6104,	Adjusted R-squared:  0.6054 
F-statistic: 119.9 on 2 and 153 DF,  p-value: < 2.2e-16
```

2.9449006406558

3.02310207673912

Modelo 3 : regresión lineal ventas vs trend + centered temp + temp^2

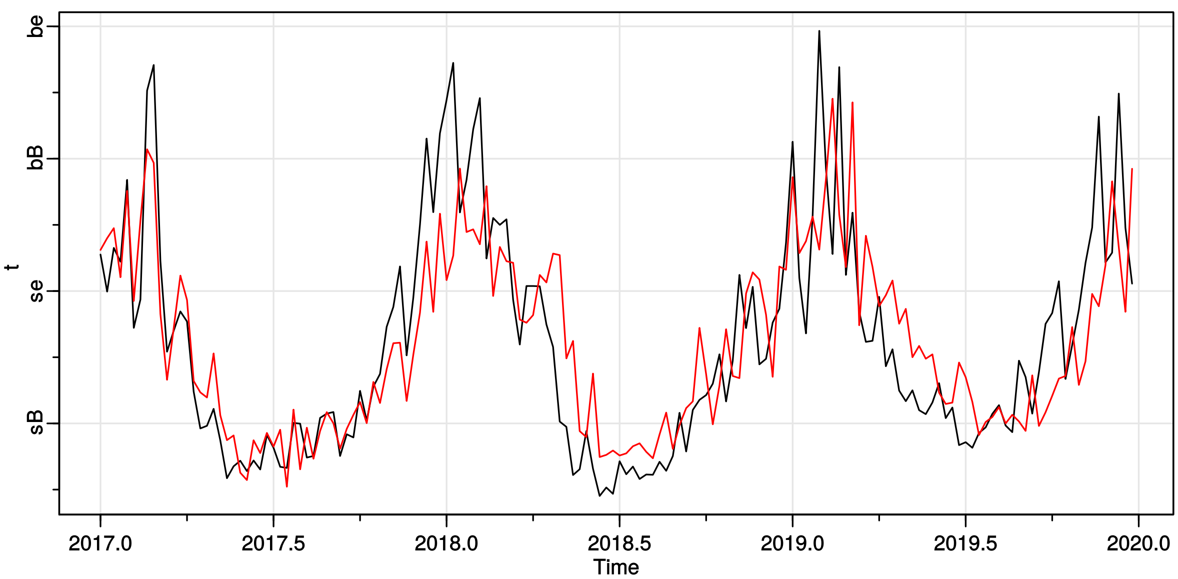
In [13]:
```r
#  Modelo 3
Tmed=mean(T)
temp  = T-Tmed  # center temperature
temp2 = temp^2             # square it
trend = time(A)        # time

fit = lm(A ~ trend + temp + temp2, na.action=NULL)

summary(fit)       # regression results

num = length(A)                                             # sample size
AIC(fit)/num - log(2*pi)                                    # AIC
BIC(fit)/num - log(2*pi)                                    # BIC
```

```
Call:
lm(formula = A ~ trend + temp + temp2, na.action = NULL)

Residuals:
    Min      1Q  Median      3Q     Max 
-6.2873 -1.4381 -0.2104  1.2219  8.2644 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept) -1.998e+03  4.756e+02  -4.201 4.51e-05 ***
trend        1.001e+00  2.356e-01   4.248 3.74e-05 ***
temp         7.615e-01  4.648e-02  16.381  < 2e-16 ***
temp2        3.790e-02  9.996e-03   3.791 0.000216 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.496 on 152 degrees of freedom
Multiple R-squared:  0.6441,    Adjusted R-squared:  0.6371 
F-statistic: 91.69 on 3 and 152 DF,  p-value: < 2.2e-16
```

2.86737058328647

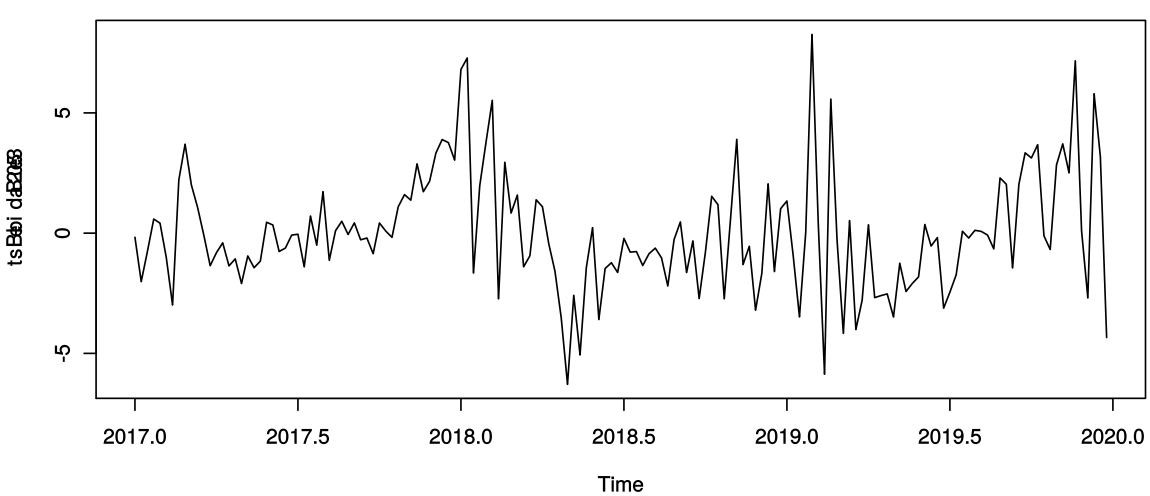
2.96512237839062

In [14]:
```
# El modelo 3 es por ahora la mejor aproximacion de acuerdo a los indices de A
IC y BIC

predictions = ts(fitted(fit), start = 2017,frequency=52) #Creo una serie tempo
ral con los valores ajustados.
tsplot(A)
lines(predictions,col=2)
```

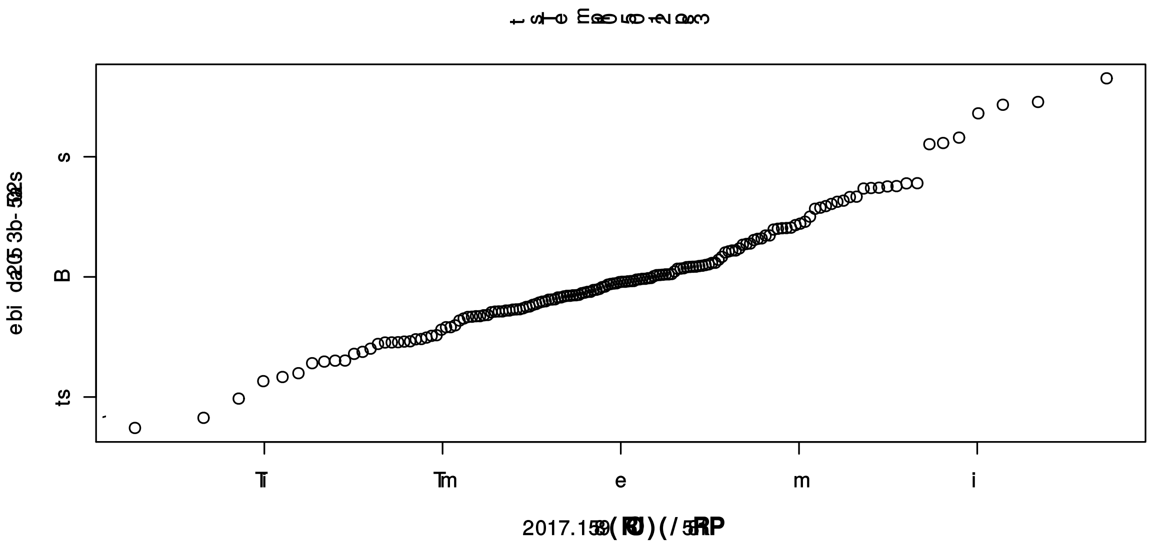


Residuos modelo 3

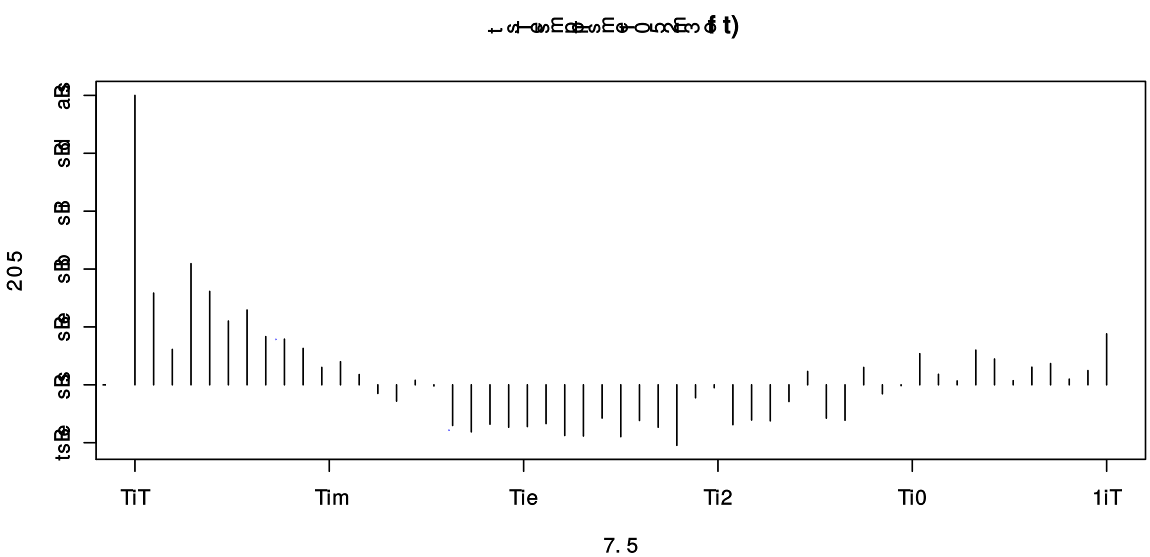
In [15]:
```
plot(residuals(fit))
```



In [16]:
```r
qqnorm(residuals(fit))
qqline(residuals(fit))

# No es Gaussiano
```



In [17]:
```r
acf(residuals(fit),52)

# No es ruido blanco
```

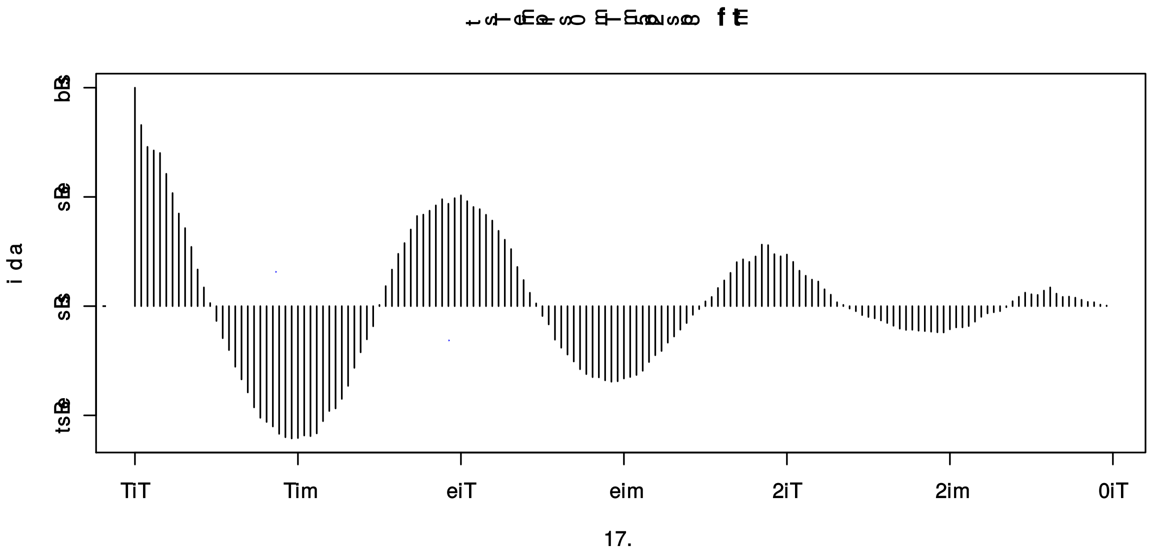


Como se puede observar todavia quedan componentes de autocorrelacion

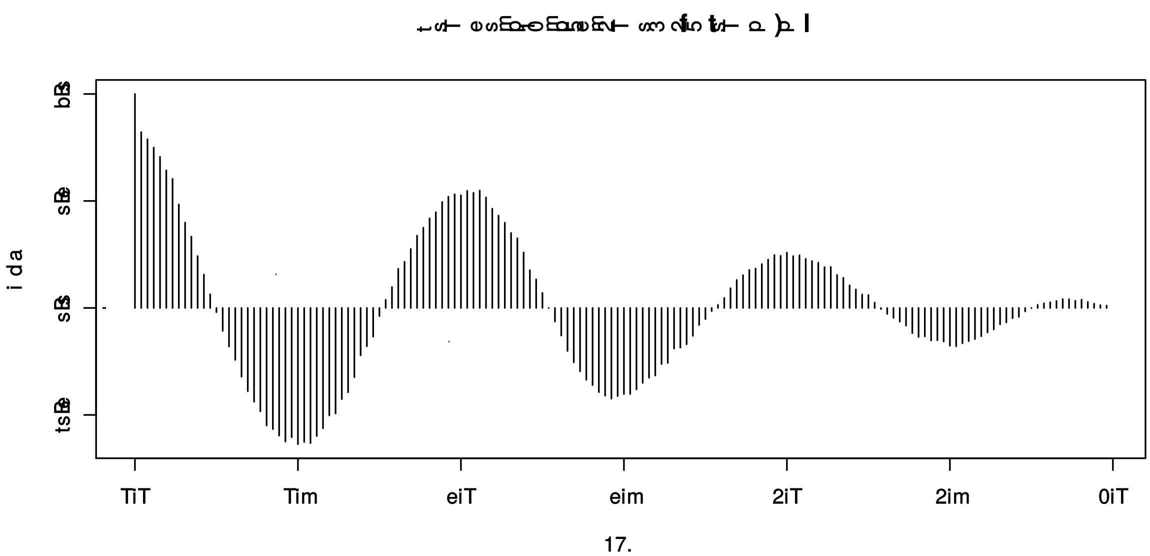
Procederemos con análisis de componentes estacionarias tanto en la serie de Agua como en la de Temperaturas

Análisis de componentes estacionarias

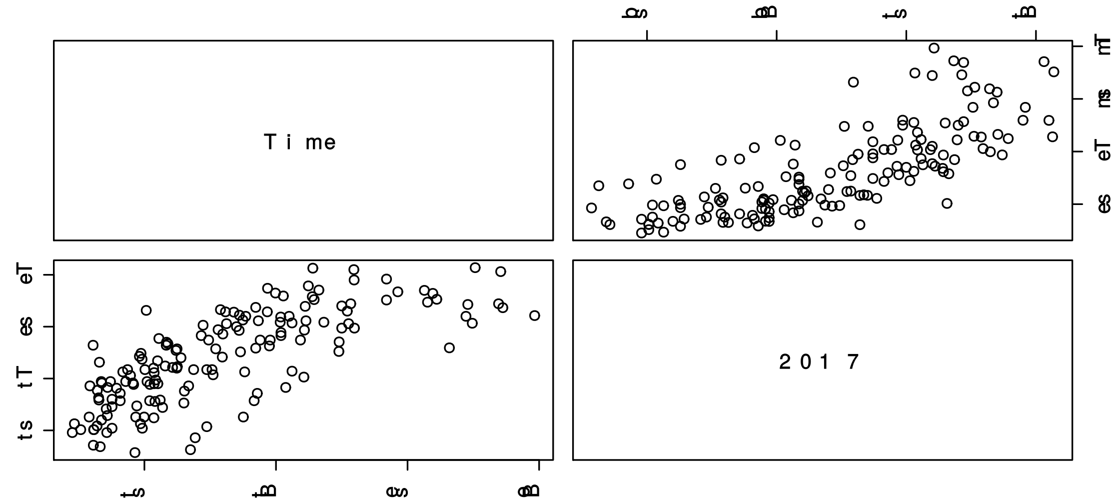
In [18]:
```
acf(tsBebidas,181,main="Venta Semanal de Agua")
```



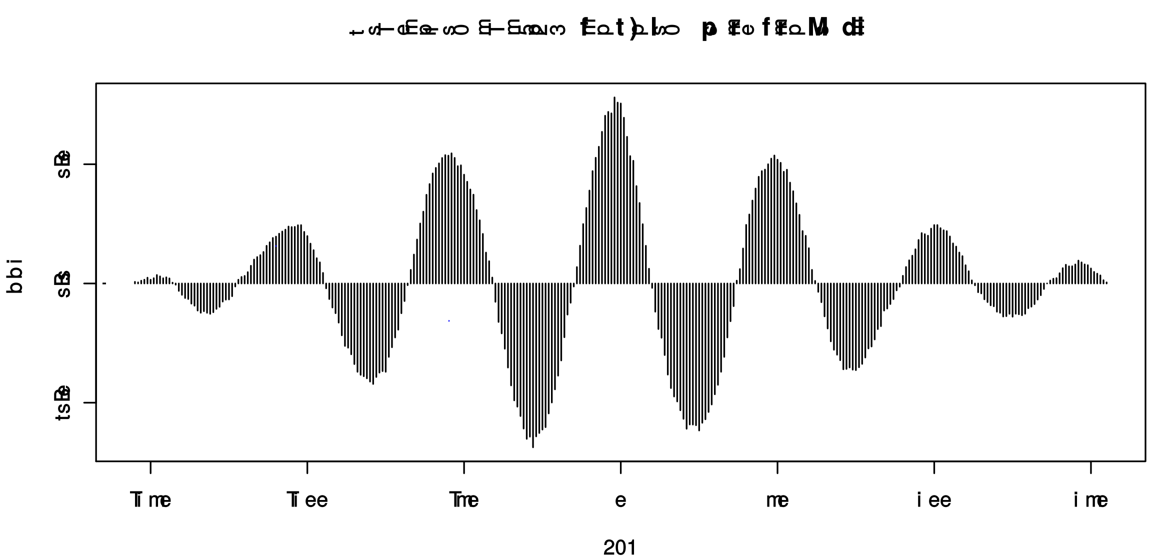
In [19]:
```
acf(tsTemp,181,main="Temperatura promedio Semanal")
```



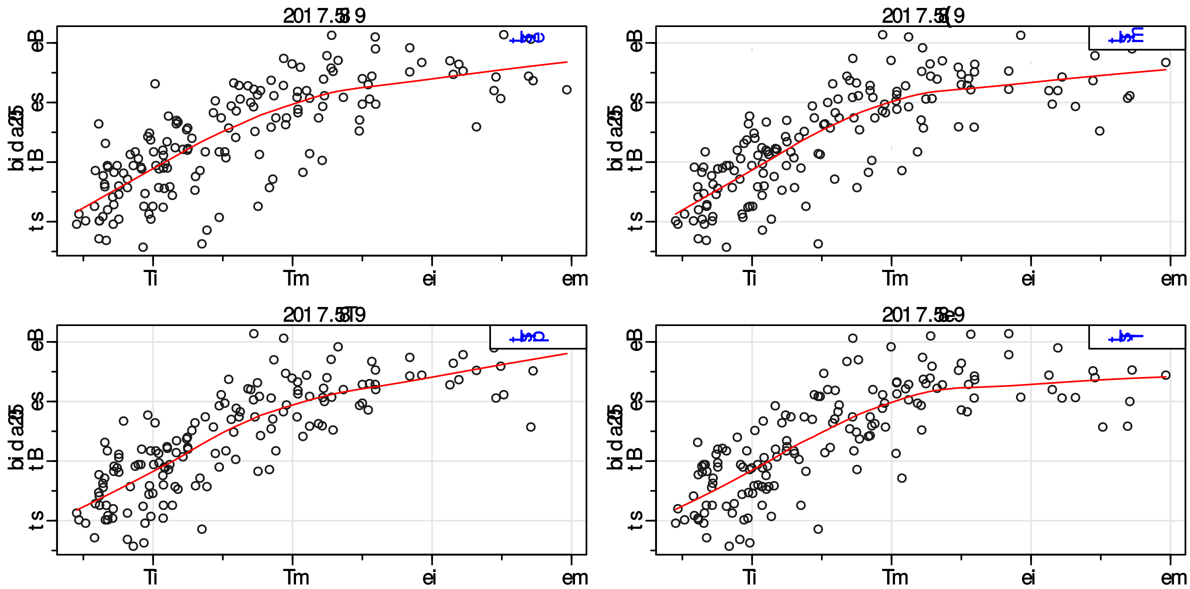
In [20]:
```
pairs(cbind(Agua=tsBebidas, Temp=tsTemp))

# Observamos una alta correlación
```



In [21]:
```
numA=as.numeric(A)
numT=as.numeric(T)
ccf(numA,numT, 157, main="Venta Semanal Agua vs Temperatura Media", ylab="CCF"
)

#Vemos una muy fuerte correlación cruzada en el mismo lag, además se notan cor
relaciones negativas muy altas a los 6 meses y positivas al año, tanto para ad
elante como para atrás
```

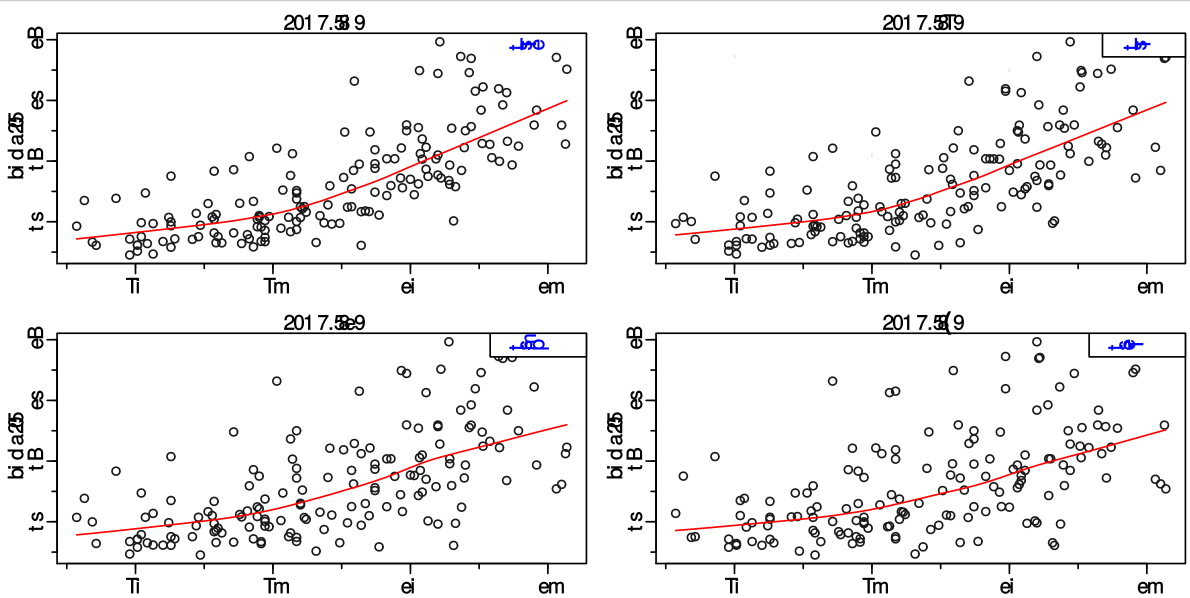


In [22]:
```
lag2.plot(numA,numT,3)
```



La serie de Ventas esta correlacionada fuertemente con la temperatura de la semana actual pero tambien se observa correlacion con las siguientes

In [23]:
```
lag2.plot(numT,numA,3)
```



En sentido inverso tambien se observa que el pronostico de temperatura para una semana dos y hasta tres tienen gran correlacion con la venta actual de Agua

Observaciones:

- La serie de Venta de Bebidas al igual que la Temperatura muestra correlaciones fuertes cada 6 y cada 12 meses.
- Cada 6 meses se obtiene el pico de correlacion negativa debido a estar en la estación opuesta.
- Cada 12 meses se da el pico de correlacion positivo porque tiene una fuerte estacionalidad anual.
- Se observa cierta correlacion en las ventas de acuerdo a las temperaturas experimentadas en las semanas anteriores y tambien pronosticos.

Se propone un modelo:

$$A_t = \beta_0 + \beta_1 T_t + \beta_2 T_{t-1} + \beta_3 T_{t+1} + w_t.$$

Es decir, estimar la venta de agua actual por una media más algo que depende de la temperatura actual, la previa y el pronostico de la semana siguiente.

Problema: como alineamos las series A y T_t, T_{t-1} ,T_{t+1}.

In [24]:
```
temp_ant=lag(tsTemp,-1)
temp_post=lag(tsTemp,1)
```

In [25]:
```
agua = ts.intersect(A,tsTemp,temp_ant,temp_post, dframe=TRUE)
agua
```

A data.frame: 154 x 4

Sales_Liters	Temp_Avg	Temp_Avg.1	Temp_Avg.2
<dbl>	<dbl>	<dbl>	<dbl>
24.98	23.24	22.89	23.53
26.63	23.53	23.24	21.96
26.11	21.96	23.53	24.59
29.20	24.59	21.96	21.11
23.61	21.11	24.59	23.70
24.68	23.70	21.11	25.69
32.57	25.69	23.70	25.31
33.54	25.31	25.69	20.57
26.14	20.57	25.31	17.86
22.71	17.86	20.57	20.00
23.50	20.00	17.86	21.86
24.23	21.86	20.00	21.00
23.85	21.00	21.86	17.71
21.20	17.71	21.00	17.14
19.81	17.14	17.71	16.86
19.91	16.86	17.14	18.86
20.55	18.86	16.86	15.86
19.36	15.86	18.86	14.29
17.93	14.29	15.86	14.57
18.38	14.57	14.29	11.43
18.59	11.43	14.57	10.43
18.20	10.43	11.43	14.14
18.60	14.14	10.43	13.14
18.26	13.14	14.14	14.57
19.56	14.57	13.14	13.57
19.08	13.57	14.57	14.71
18.36	14.71	13.57	8.43
18.32	8.43	14.71	15.86
20.02	15.86	8.43	11.29
19.99	11.29	15.86	14.71
...	...	...	...
20.79	16.21	16.00	13.79
21.52	13.79	16.21	12.86
20.20	12.86	13.79	12.93

Sales_Liters	Temp_Avg	Temp_Avg.1	Temp_Avg.2
<dbl>	<dbl>	<dbl>	<dbl>
20.60	12.93	12.86	15.64
19.18	15.64	12.93	14.71
19.29	14.71	15.64	12.86
19.08	12.86	14.71	7.86
19.64	7.86	12.86	10.64
19.85	10.64	7.86	11.21
20.36	11.21	10.64	12.21
20.69	12.21	11.21	10.21
19.92	10.21	12.21	11.29
19.67	11.29	10.21	10.36
22.37	10.36	11.29	8.14
21.75	8.14	10.36	14.50
20.37	14.50	8.14	9.29
21.93	9.29	14.50	11.29
23.76	11.29	9.29	12.86
24.17	12.86	11.29	14.14
25.37	14.14	12.86	14.29
21.68	14.29	14.14	17.07
22.96	17.07	14.29	13.57
24.29	13.57	17.07	15.14
26.06	15.14	13.57	18.53
27.40	18.53	15.14	17.96
31.59	17.96	18.53	19.67
26.08	19.67	17.96	22.61
26.45	22.61	19.67	20.33
32.46	20.33	22.61	17.61
27.39	17.61	20.33	22.96

Modelo 4: Regresión ventas t vs temperatura t + temperatura t+1 + temperatura t-1

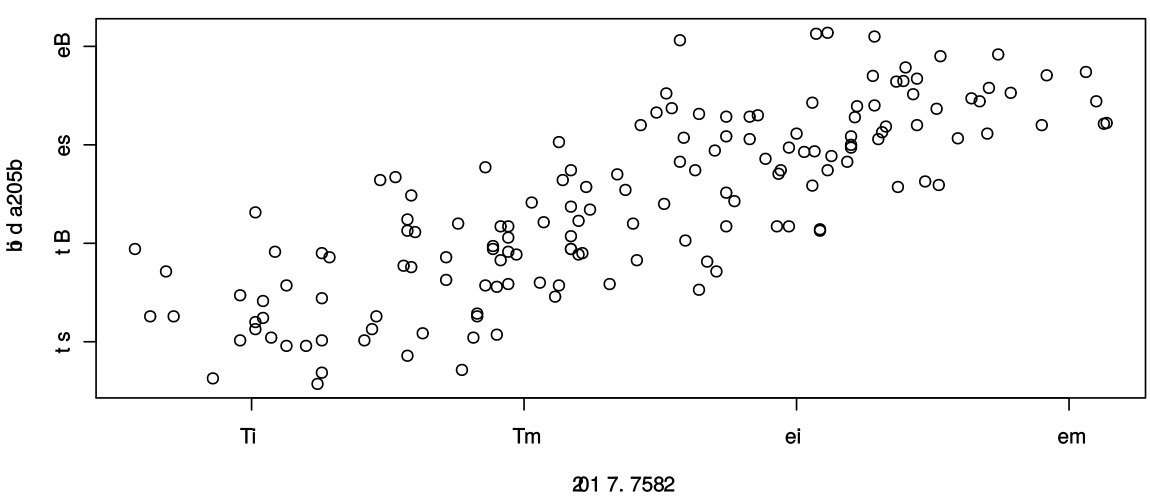
In [26]:
```r
summary(fit1 <- lm(A ~ tsTemp + +temp_ant + temp_post , data=agua, na.action=NULL))
```

```
Call:
lm(formula = A ~ tsTemp + +temp_ant + temp_post, data = agua,
    na.action = NULL)

Residuals:
    Min      1Q  Median      3Q     Max
-6.1714 -1.9582 -0.4968  1.2242  8.9426

Coefficients: (2 not defined because of singularities)
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 10.97180    0.87288   12.57   <2e-16 ***
tsTemp       0.70791    0.04956   14.29   <2e-16 ***
temp_ant          NA         NA      NA       NA
temp_post         NA         NA      NA       NA
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.726 on 154 degrees of freedom
Multiple R-squared:  0.5699,    Adjusted R-squared:  0.5671
F-statistic: 204.1 on 1 and 154 DF,  p-value: < 2.2e-16
```

In [27]:
```r
plot(temp_post,temp_ant)
cor(temp_post,temp_ant)
```

A matrix: 1 x 1 of type dbl

	Temp_Avg
Temp_Avg	1

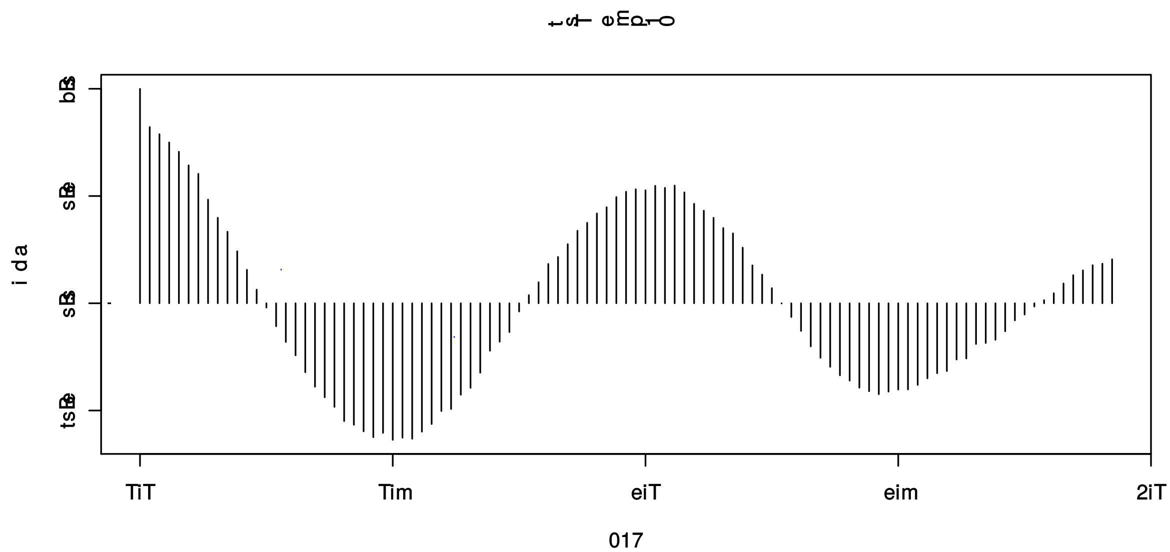


Los Coeficientes correspondientes a la temperatura actual se obtienen, pero para la anterior y para el pronostico futuro no ya que existe una fuerte correlacion entre ambos ; *Nota error: Error "not defined because of singularities" will occur due to strong correlation between your independent variables*

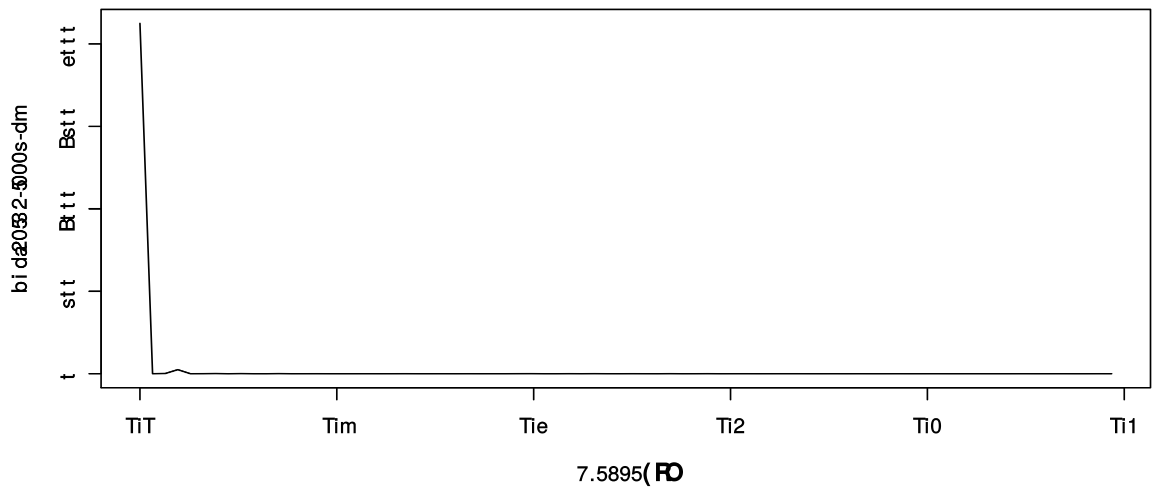
En conclusión: obligatoriamente tenemos que sacar la periodicidad de la serie

Componentes Estacionales y Periodograma de las ventas

In [28]:
```
plot(acf(T,lag.max=100))
```



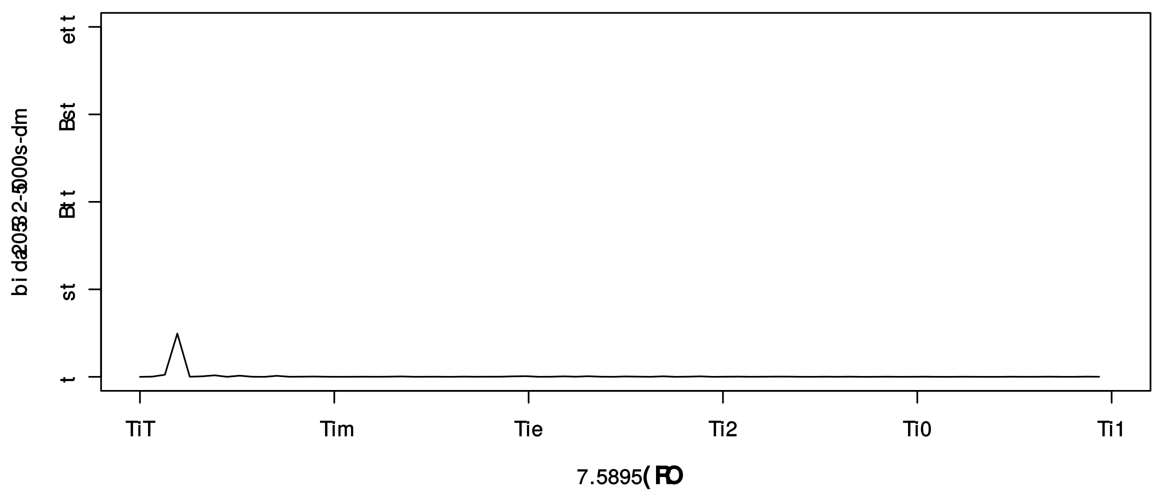
```
In [29]: # Periodograma

n=length(A)
I = abs(fft(A))^2/n # the periodogram
P = (4/n)*I[1:(n/2)]
# the scaled periodogram
f = (0:(n/2-1))/n
# frequencies
plot(f, P, type="l", xlab="Frequency", ylab="Scaled Periodogram")
```



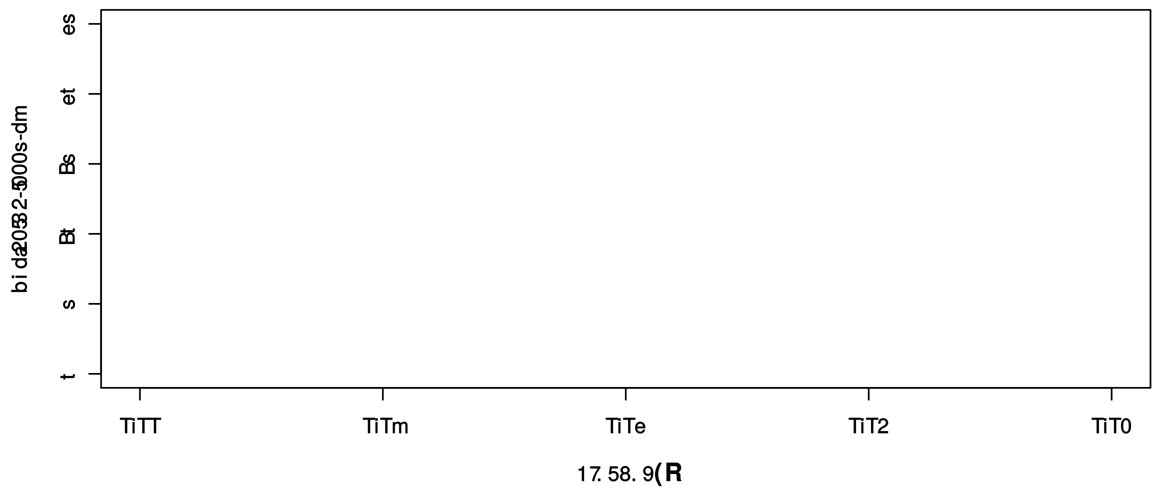
El pico se debe a la componente de continua que tiene la serie, es decir que la transformada de fourier grafica todas las componentes , y la continua es una delta (salto infinito) en el origen

```
In [30]: # Para sacar la componente de continua se resta la media nada mas
Amed=mean(A)
A=A-Amed
```

In [31]:
```
# Periodograma
n=length(A)
I = abs(fft(A))^2/n # the periodogram
P = (4/n)*I[1:(n/2)]
# the scaled periodogram
f = (0:(n/2-1))/n
# frequencies
plot(f, P, type="l", xlab="Frequency", ylab="Scaled Periodogram",xlim=c(0,0.5
),ylim=c(0,200))

## Ahi  si graficando en todo el rango se visualiza mejor
```



In [32]:
```
# Periodograma
n=length(A)
I = abs(fft(A))^2/n # the periodogram
P = (4/n)*I[1:(n/2)]
# the scaled periodogram
f = (0:(n/2-1))/n
# frequencies
plot(f, P, type="l", xlab="Frequency", ylab="Scaled Periodogram",xlim=c(0,0.08
),ylim=c(0,25))

## Ahi  si graficando en todo el rango se visualiza mejor
```



In [33]:
```
which.max(P)
# hay otra compnente en frecuencia 0.04 (periodo de 25 semanas)  y posiblement
e en 0.05 (periodo  20 semanas) ,mas chiquitas y otra en  0.7, 14 semanas
```

4

In [34]:
```
f
```

0 0.00641025641025641 0.0128205128205128 0.0192307692307692
0.0256410256410256 0.032051282051282 0.0384615384615385 0.0448717948717949
0.0512820512820513 0.0576923076923077 0.0641025641025641 0.0705128205128205
0.0769230769230769 0.0833333333333333 0.0897435897435897 0.0961538461538462
0.102564102564103 0.108974358974359 0.115384615384615 0.121794871794872
0.128205128205128 0.134615384615385 0.141025641025641 0.147435897435897
0.153846153846154 0.16025641025641 0.166666666666667 0.173076923076923
0.179487179487179 0.185897435897436 0.192307692307692 0.198717948717949
0.205128205128205 0.211538461538462 0.217948717948718 0.224358974358974
0.230769230769231 0.237179487179487 0.243589743589744 0.25
0.256410256410256 0.262820512820513 0.269230769230769 0.275641025641026
0.282051282051282 0.288461538461538 0.294871794871795 0.301282051282051
0.307692307692308 0.314102564102564 0.320512820512821 0.326923076923077
0.333333333333333 0.33974358974359 0.346153846153846 0.352564102564103
0.358974358974359 0.365384615384615 0.371794871794872 0.378205128205128
0.384615384615385 0.391025641025641 0.397435897435897 0.403846153846154
0.41025641025641 0.416666666666667 0.423076923076923 0.429487179487179
0.435897435897436 0.442307692307692 0.448717948717949 0.455128205128205
0.461538461538462 0.467948717948718 0.474358974358974 0.480769230769231
0.487179487179487 0.493589743589744

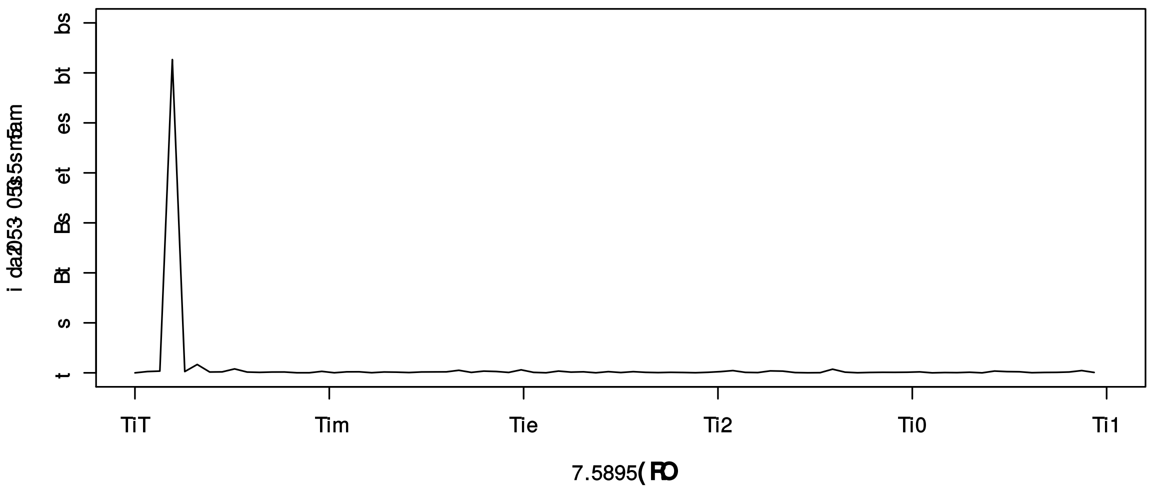
In [35]:
```
Tmed
mean(T)
T=T-Tmed
```

17.0547435897436

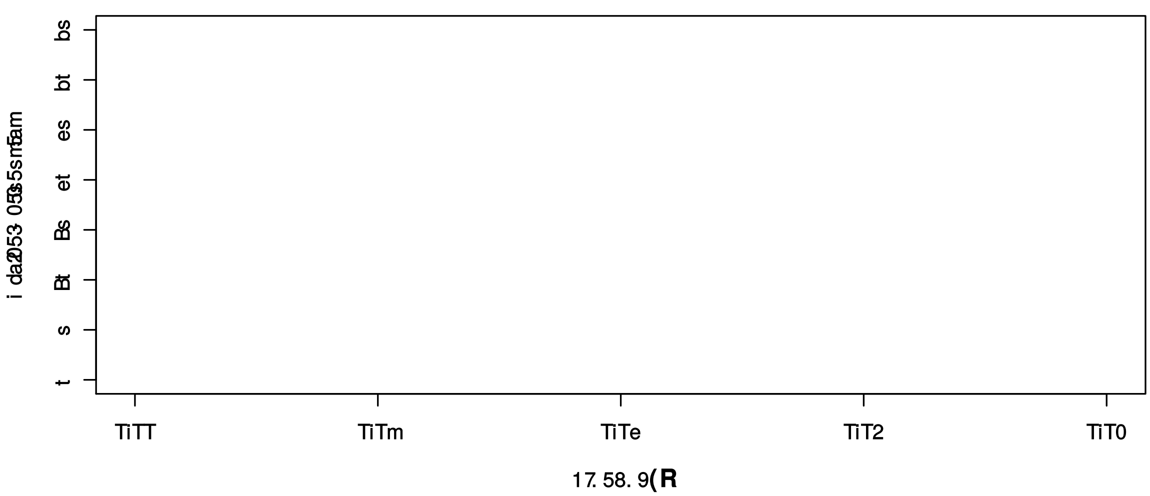
17.0547435897436

Periodograma de la temperatura

In [36]:
```
n=length(T)
I = abs(fft(T))^2/n # the periodogram
P = (4/n)*I[1:(n/2)]
# the scaled periodogram
f = (0:(n/2-1))/n
# frequencies
plot(f, P, type="l", xlab="Frequency", ylab="Scaled Periodogram",xlim=c(0,0.5
),ylim=c(0,35))
```



In [37]:
```
plot(f, P, type="l", xlab="Frequency", ylab="Scaled Periodogram",xlim=c(0,0.08
),ylim=c(0,35))
```



In [38]:
```
max(P)
```

31.3344135457411

In [39]:
```
(which.max(P))
```

4

In [40]:
```
f1=f[4]
f2=f[8]
f3=f[9]
f4=f[12]
```

In [41]:
```
f1
1/f1
f2
1/f2
f3
1/f3
f4
1/f4
```

0.0192307692307692

52

0.0448717948717949

22.2857142857143

0.0512820512820513

19.5

0.0705128205128205

14.1818181818182

La componente f1 (1/0.19 ~ 52 semanas) y f3 (1/0.050 ~ 20 semanas) se encuentras en ambas series

In [42]:
```
periodo_ppal= 1/f1
periodo_ppal
periodo_secundario = 1/f3
periodo_secundario
```

52

19.5

In [43]:
```
# Normalizamos la ts Ventas

trend=time(A)
amp_max = max(c( max(A), max(-A)))
A_norm=A/amp_max
```

Modelo 5 : ajuste de las ventas normalizadas vs sin + cos

In [44]:
```
fit_estacional = lm(A_norm ~ sin(2*pi*trend*f1*52) + cos(2*pi*trend*f1*52) ,n
a.action=NULL)
```

In [45]:
```
summary(fit_estacional)
```

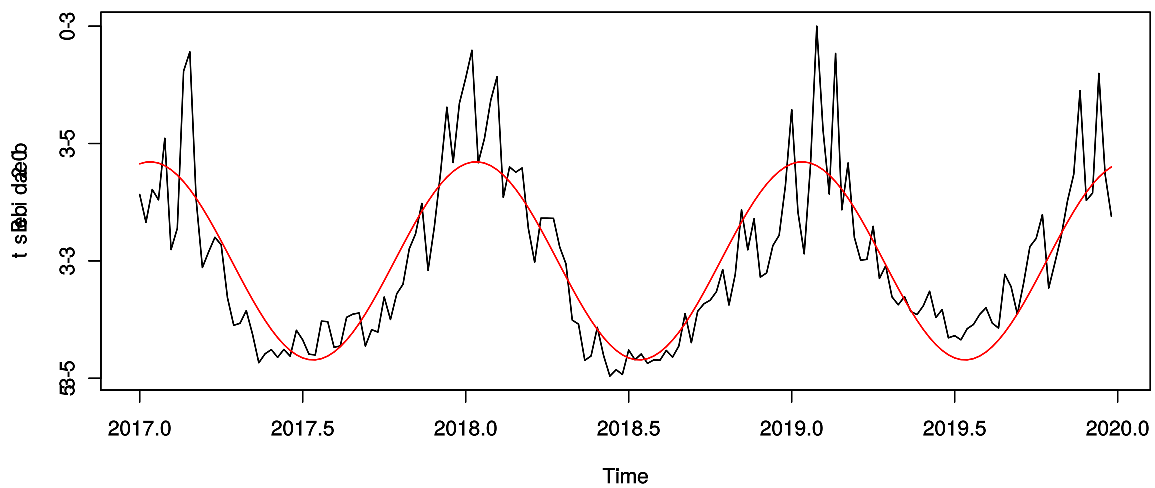
```
Call:
lm(formula = A_norm ~ sin(2 * pi * trend * f1 * 52) + cos(2 *
    pi * trend * f1 * 52), na.action = NULL)

Residuals:
     Min       1Q   Median       3Q      Max
-0.39164 -0.12326 -0.01602  0.09543  0.59454

Coefficients:
                                Estimate Std. Error t value Pr(>|t|)
(Intercept)                   -2.883e-14  1.484e-02   0.000        1
sin(2 * pi * trend * f1 * 52)  8.453e-02  2.099e-02   4.027 8.87e-05 ***
cos(2 * pi * trend * f1 * 52)  4.135e-01  2.099e-02  19.702  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1854 on 153 degrees of freedom
Multiple R-squared:  0.7255,    Adjusted R-squared:  0.7219
F-statistic: 202.2 on 2 and 153 DF,  p-value: < 2.2e-16
```

In [46]:
```
num = length(A)                                          # sample size
AIC(fit_estacional)/num - log(2*pi)                                 # AIC
BIC(fit_estacional)/num - log(2*pi)                                 # BIC
```

-2.33880399516711

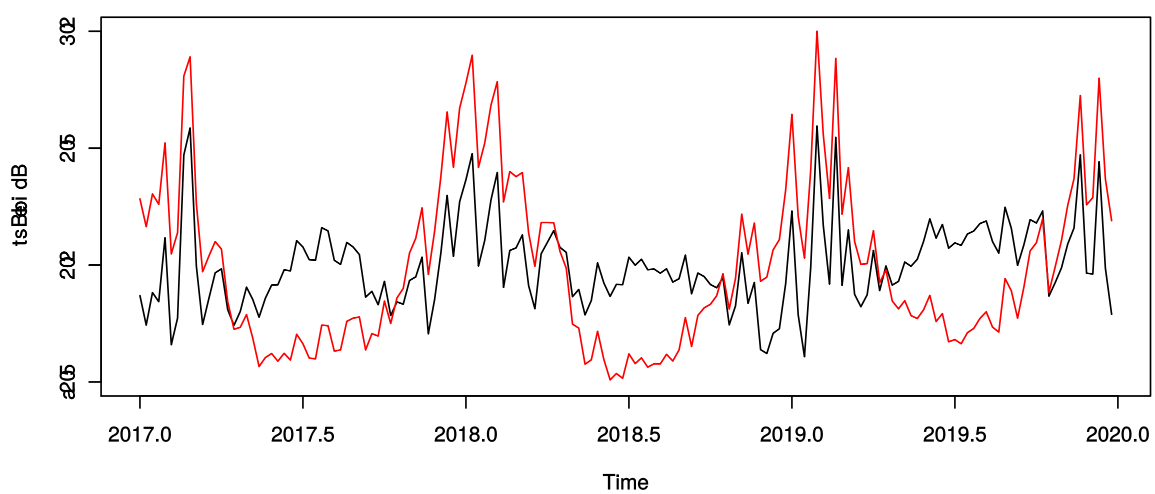
-2.26060255908379

In [47]:
```
#transformo el resultado en una serie
predictions = ts(fitted(fit_estacional),start=2017, frequency=52)

plot(A_norm )
lines(predictions,col=2)
```

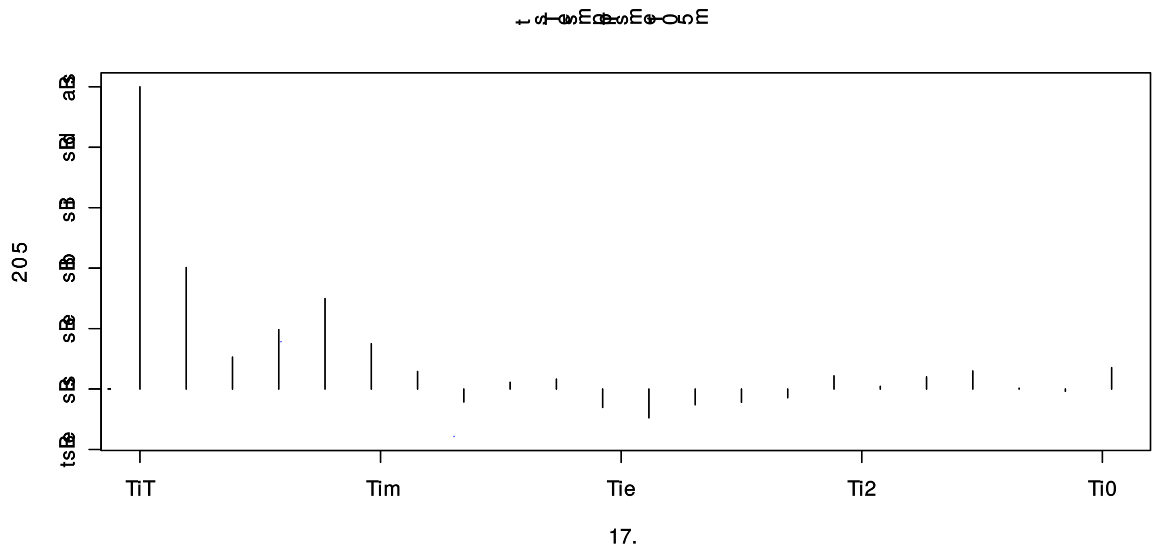


In [48]:
```
residuos=residuals(fit_estacional)
```

In [49]:
```
plot(residuos, ylim=c(-0.5,1) )
lines(A_norm,col=2)
```



```
In [50]: acf(residuos)
```



Mejora el modelo pero existen todavia algunas componentes de correlacion , vamos a probar ajustar un modelo con mas componentes estacionarias

Modelo 6 : modelo no lineal con tres componentes estacionarias

```
In [51]: ## haciendo un planteo de modelo no lineal
fit2_estacional <- nls( A_norm ~ a *(sin(2*pi*trend*f_1*52) + cos(2*pi*trend*f_1*52)) +b*(sin(2*pi*trend*f_2*52) + cos(2*pi*trend*f_2*52)) + c*(sin(2*pi*trend*f_3*52) + cos(2*pi*trend*f_3*52)),start=list(a=0.5,b=0.4,c=0.7,f_1=f1,f_2=f3,f_3=f4))
```

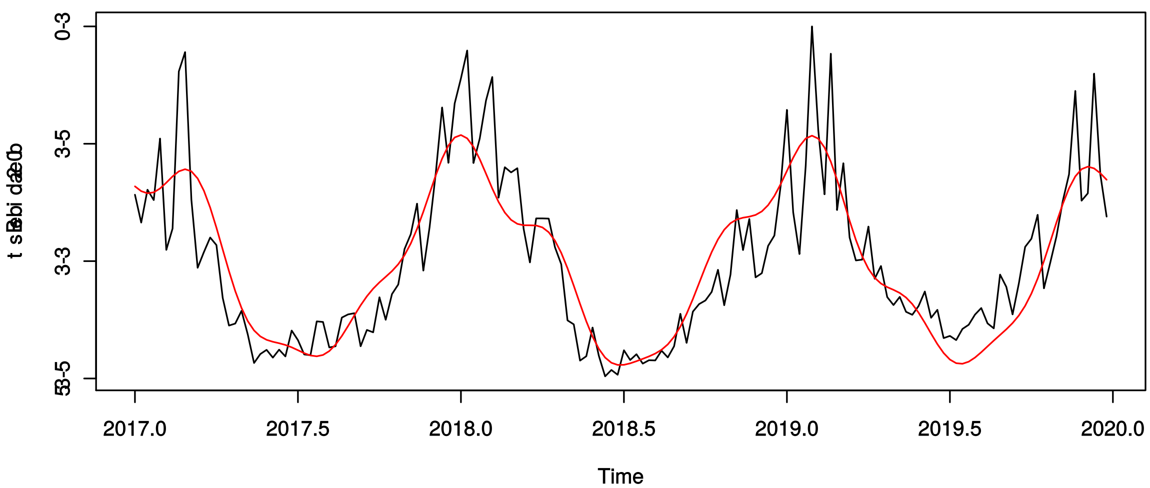
In [52]:
```
summary(fit2_estacional)
```

```
Formula: A_norm ~ a * (sin(2 * pi * trend * f_1 * 52) + cos(2 * pi * trend *
    f_1 * 52)) + b * (sin(2 * pi * trend * f_2 * 52) + cos(2 *
    pi * trend * f_2 * 52)) + c * (sin(2 * pi * trend * f_3 *
    52) + cos(2 * pi * trend * f_3 * 52))

Parameters:
     Estimate Std. Error   t value Pr(>|t|)
a   2.985e-01  1.395e-02 2.139e+01  < 2e-16 ***
b   4.916e-02  1.395e-02 3.524e+00 0.000563 ***
c   4.582e-02  1.395e-02 3.285e+00 0.001270 **
f_1 1.923e-02  7.087e-08 2.714e+05  < 2e-16 ***
f_2 5.128e-02  4.302e-07 1.192e+05  < 2e-16 ***
f_3 7.050e-02  4.617e-07 1.527e+05  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1742 on 150 degrees of freedom

Number of iterations to convergence: 9
Achieved convergence tolerance: 2.887e-07
```

In [53]:
```
coef(fit2_estacional)

# f_1, f_2 y f_3 dan muy cercano a lo que nos había dado el periodograma
```

a	0.298453735422649
b	0.049163126437584
c	0.0458202265832083
f_1	0.0192316544523848
f_2	0.0512809153936186
f_3	0.0705013288438199

```
In [54]: #transformo el resultado en una serie
predictions2 = ts(fitted(fit2_estacional),start=2017, frequency=52)

plot(A_norm )
lines(predictions2,col=2)
```



Estudiamos los residuos del modelo 6

```
In [55]: round(mape(A_norm, predictions2))
```

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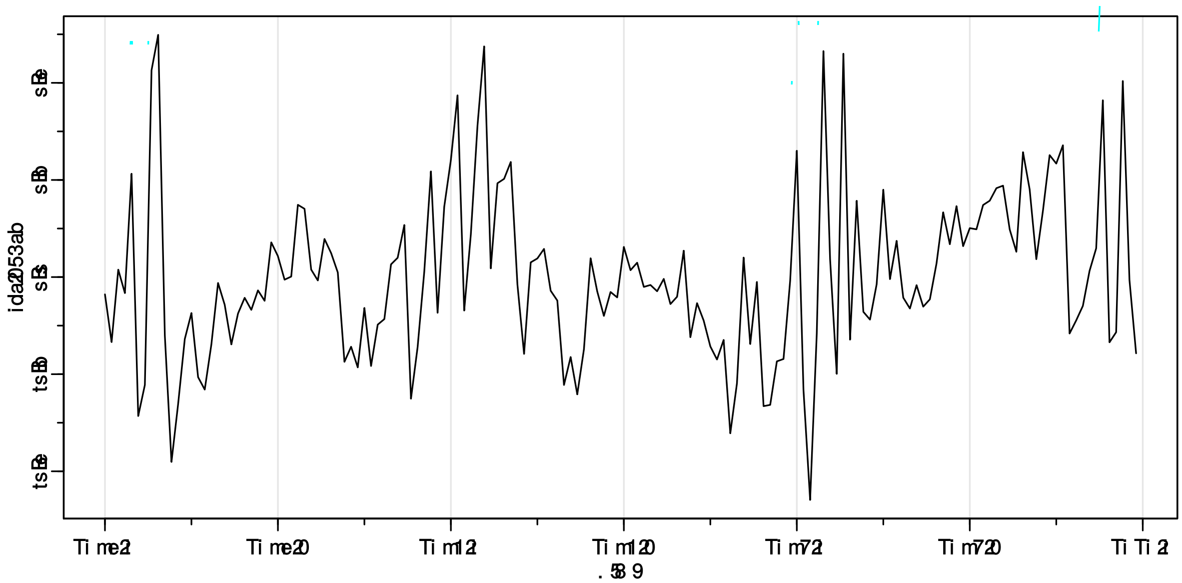
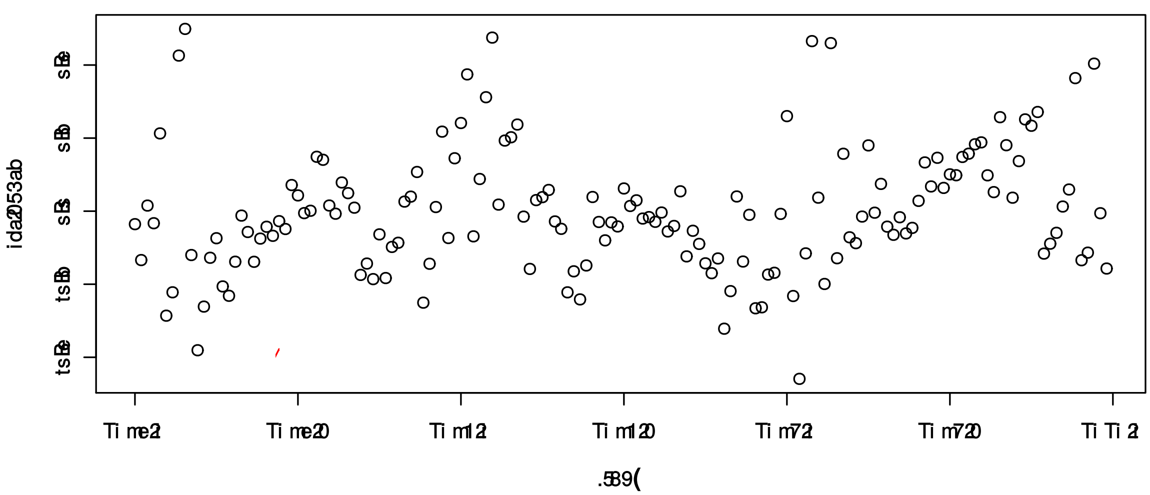
In [56]:
```r
residuos2=residuals(fit2_estacional)
tsplot(trend,residuos2)
lines(predictions2+residuos2,col=5,ylim=c(-10,10))
lines(predictions2,col=8,ylim=c(-10,10))

# Los residuos más altos se deben a que no captamos los picos altos de venta
```

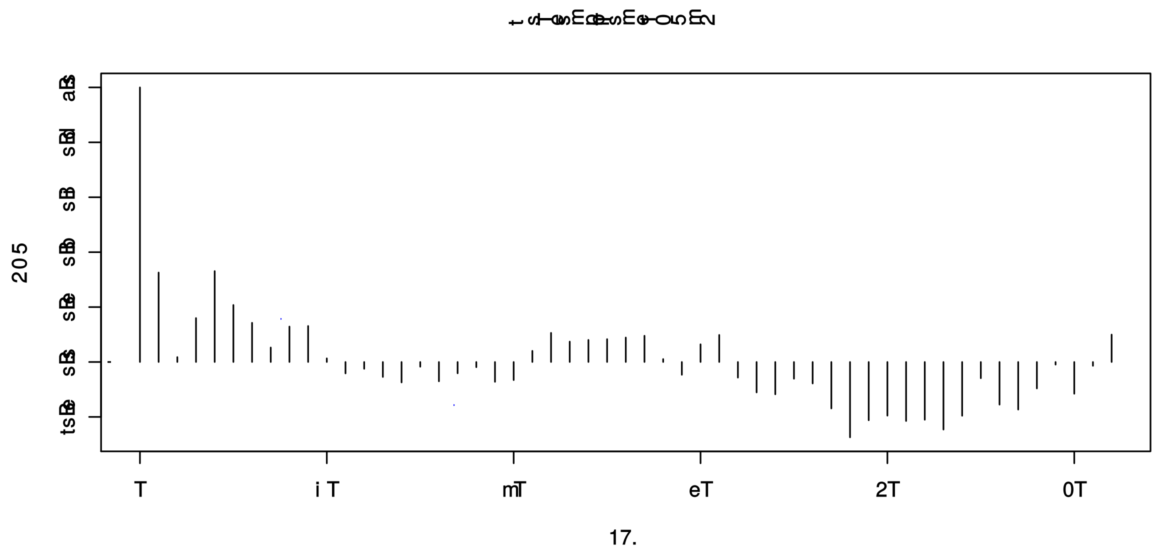


In [57]:
```r
plot(trend,residuos2)
lines(A_norm,col=2)
```



```
In [58]: acf(residuos2,52)

         # No es ruido blanco
```



Componentes Estacionales de la temperatura

```
In [59]: trend=time(T)
         temp_max = max(c( max(T), max(-T)))
         T_norm=T/temp_max
```

```
In [60]: fit_temp_estacional = lm(T_norm ~ sin(2*pi*trend*f1*52) + cos(2*pi*trend*f1*52
         ) ,na.action=NULL)
```

In [61]:
```
summary(fit_temp_estacional)
```

```
Call:
lm(formula = T_norm ~ sin(2 * pi * trend * f1 * 52) + cos(2 *
    pi * trend * f1 * 52), na.action = NULL)

Residuals:
     Min       1Q   Median       3Q      Max
-0.53721 -0.14075 -0.01347  0.15190  0.50941

Coefficients:
                                Estimate Std. Error t value Pr(>|t|)
(Intercept)                   -5.085e-14  1.697e-02    0.00        1
sin(2 * pi * trend * f1 * 52)  3.063e-01  2.400e-02   12.76   <2e-16 ***
cos(2 * pi * trend * f1 * 52)  5.261e-01  2.400e-02   21.92   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.212 on 153 degrees of freedom
Multiple R-squared:  0.8078,    Adjusted R-squared:  0.8053
F-statistic: 321.6 on 2 and 153 DF,  p-value: < 2.2e-16
```

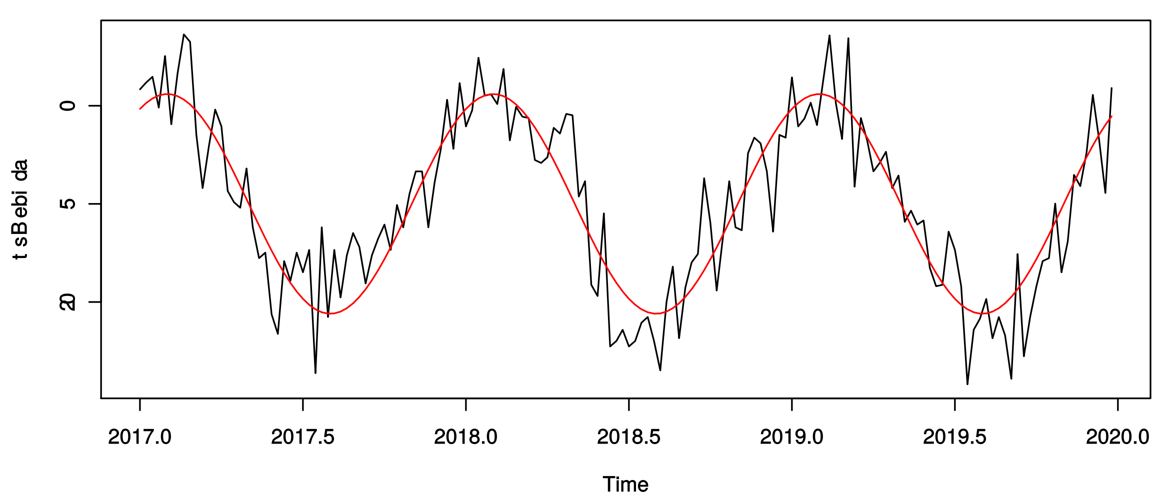
In [62]:
```
num = length(T)                                          # sample size
AIC(fit_temp_estacional)/num - log(2*pi)                                # AIC
BIC(fit_temp_estacional)/num - log(2*pi)                                # BIC
```

-2.07041399043761

-1.99221255435429

In [63]:
```
#transformo el resultado en una serie
predictions = ts(fitted(fit_temp_estacional),start=2017, frequency=52)

plot(T )
lines(predictions*temp_max,col=2)
```



In [64]:
```
round(mape(T_norm, predictions))
```

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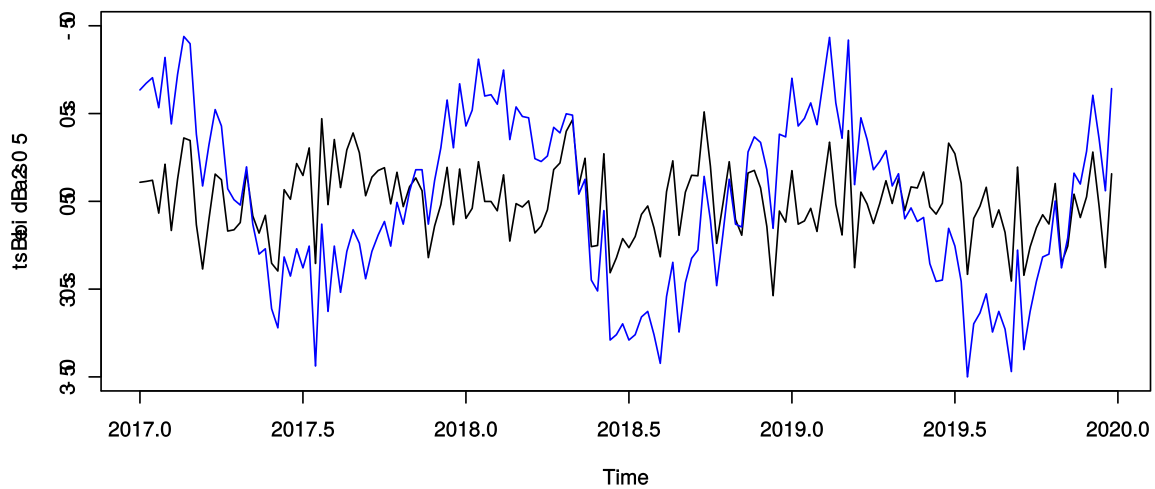
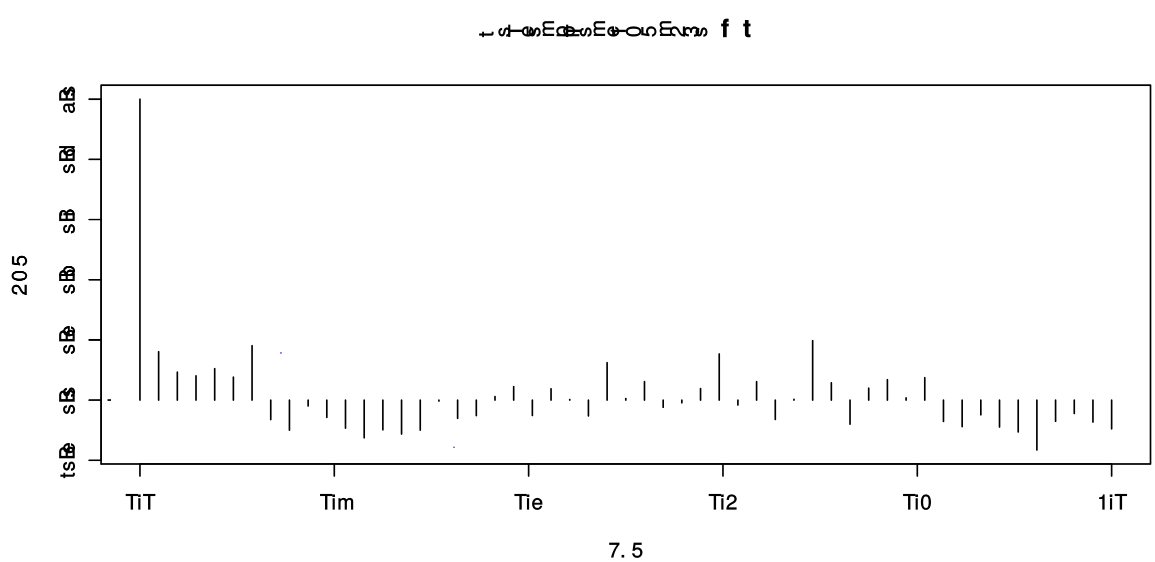
In [65]:
```
residuos_temp=residuals(fit_temp_estacional)
```

In [66]:
```
plot(residuos_temp,ylim=c(-1,1))
lines(predictions +residuos_temp,col=4) # la serie original (predicción ´+ res
iduos)
```



In [67]:
```
acf(residuos_temp, 52)
```



El residuo queda practicamente blanco por lo tanto podemos considerar que conseguimos extraer toda la componente estacionaria con frecuencia f1, periodo 52 Semanas

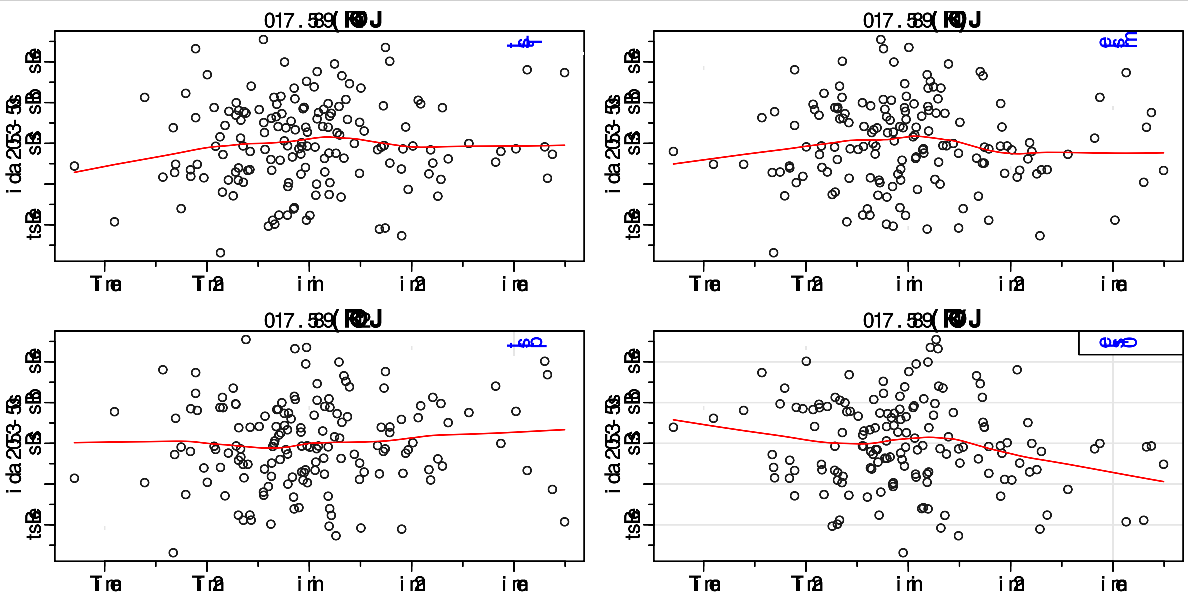
Buscamos mejorar nuestro Modelo 6 extrayendo las componentes estacionarias para explicar el comportamiento de la serie sin las tres componentes del modelo

In [68]:

```
residuos_venta=ts(residuos2,start=c(2017,1,1),freq=52)
```

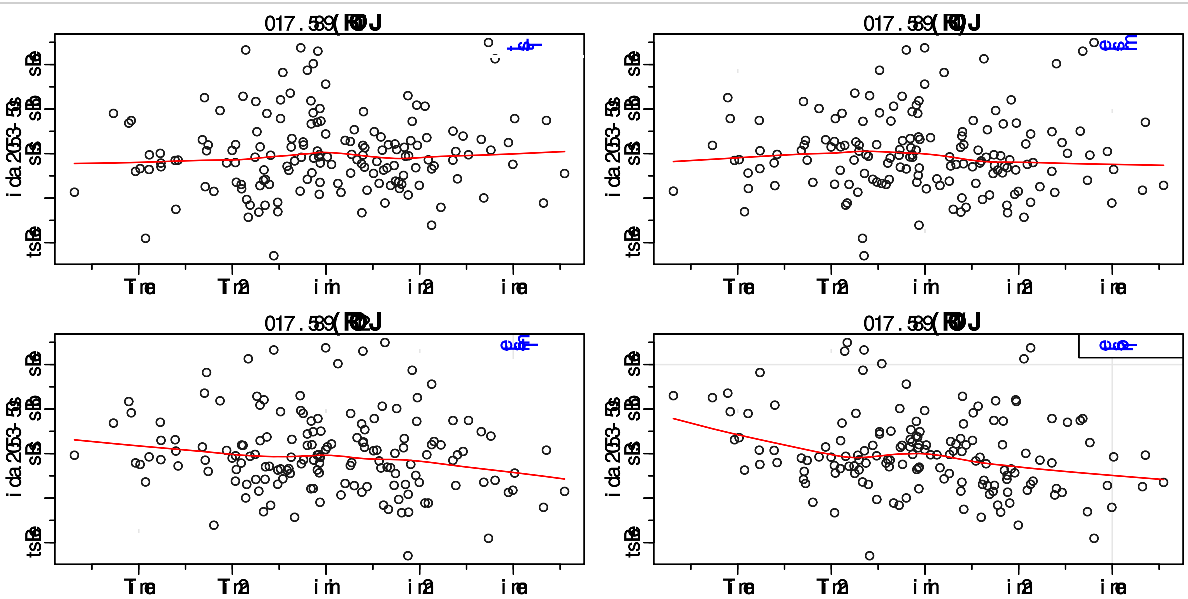
In [69]:

```
num_resA=as.numeric(residuos_venta)
num_resT=as.numeric(residuos_temp)
lag2.plot(num_resA,num_resT,3)
```

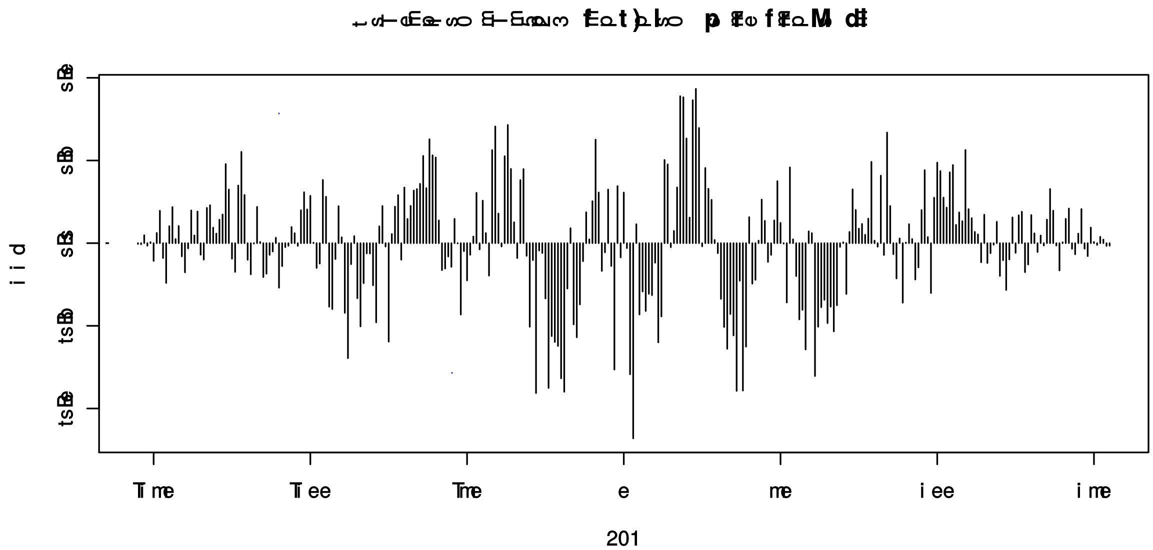


In [70]:

```
lag2.plot(num_resT,num_resA,3)
```



```
In [71]: ccf(num_resA,num_resT, 157, main="Venta Semanal Agua vs Temperatura Media", yl
ab="CCF")

# En los residuos vemos muy poca correlación
```



Modelo 7 : Función de Ventas vs temperatura t + residuos(temperatura t-1) + temperatura t+1

$$resA_t = \beta_0 + \beta_1(resT_t) + \beta_2(resT_{t-1}) + \beta_3(resT_{t+1}) + w_t.$$

Es decir, estimar la venta de agua actual por una media más algo que depende de la temperatura actual, el residuo en el cambio de la semana previa y el pronostico de la semana siguiente.

```
In [72]: restemp_ant=lag(residuos_temp,-1)  # past temp
restemp_post=lag(residuos_temp,1)  # forecast tem

trend = time(residuos_temp)          # time

residuos_temp2  = residuos_temp^2  # square it
restemp_ant2 = restemp_ant^2
restemp_post2 = restemp_post^2

# Aplicamos la función sign para tener valores positivos y negativos según si
 crece o decrere la temperatura

residuos_temp_exp  = sign(residuos_temp)*exp(residuos_temp)  # exponential it
restemp_ant_exp = sign(restemp_ant)*exp(restemp_ant )
restemp_post_exp = sign(restemp_post)*exp(restemp_post)
```

In [73]:

```
res_agua = ts.intersect(trend,residuos_venta,residuos_temp, residuos_temp2, re
siduos_temp_exp,  restemp_ant,restemp_ant2,restemp_post,restemp_post2,restemp_
ant_exp,restemp_post_exp, dframe=TRUE)
res_agua
```

A data.frame: 154 x 11

	trend	residuos_venta	residuos_temp	residuos_temp2	residuos_temp_exp	restemp_ant
	<ts>	<ts>	<ts>	<ts>	<ts>	<ts>
2	2017.019	-0.133886957	0.11346833	0.0128750619	1.1201564	0.10848384
3	2017.038	0.015265424	0.12008213	0.0144197188	1.1275895	0.11346833
4	2017.058	-0.033013742	-0.06707530	0.0044990953	-0.9351248	0.12008213
5	2017.077	0.212810317	0.21130752	0.0446508662	1.2352922	-0.06707530
6	2017.096	-0.286161760	-0.16595070	0.0275396344	-0.8470880	0.21130752
7	2017.115	-0.222120870	0.12580218	0.0158261883	1.1340578	-0.16595070
8	2017.135	0.425804115	0.36100484	0.1303244931	1.4347704	0.12580218
9	2017.154	0.498890182	0.34688221	0.1203272688	1.4146501	0.36100484
10	2017.173	-0.120112919	-0.13339042	0.0177930038	-0.8751234	0.34688221
11	2017.192	-0.380711640	-0.38536464	0.1485059046	-0.6802026	-0.13339042
12	2017.212	-0.261273537	-0.10296701	0.0106022042	-0.9021567	-0.38536464
13	2017.231	-0.127611140	0.15515092	0.0240718074	1.1678342	-0.10296701
14	2017.250	-0.074074320	0.12280602	0.0150813180	1.1306651	0.15515092
15	2017.269	-0.206086220	-0.16935419	0.0286808411	-0.8442098	0.12280602
16	2017.288	-0.231704479	-0.16218444	0.0263037942	-0.8502844	-0.16935419
17	2017.308	-0.138404346	-0.12097472	0.0146348821	-0.8860564	-0.16218444
18	2017.327	-0.012150767	0.16965801	0.0287838397	1.1848996	-0.12097472
19	2017.346	-0.057064281	-0.08310920	0.0069071392	-0.9202506	0.16965801
20	2017.365	-0.138660899	-0.18103563	0.0327739004	-0.8344056	-0.08310920
21	2017.385	-0.075128616	-0.07950494	0.0063210362	-0.9235735	-0.18103563
22	2017.404	-0.042718704	-0.35270718	0.1244023532	-0.7027830	-0.07950494
23	2017.423	-0.067533800	-0.39694494	0.1575652876	-0.6723710	-0.35270718
24	2017.442	-0.027369437	0.06634844	0.0044021149	1.0685990	-0.39694494
25	2017.462	-0.048859963	0.01180252	0.0001392995	1.0118724	0.06634844
26	2017.481	0.071473500	0.21515740	0.0462927089	1.2400571	0.01180252
27	2017.500	0.043084146	0.14715274	0.0216539293	1.1585309	0.21515740
28	2017.519	-0.005371428	0.30421736	0.0925482022	1.3555637	0.14715274
29	2017.538	0.001043961	-0.35385561	0.1252137931	-0.7019763	0.30421736
30	2017.558	0.148824836	0.47062247	0.2214855121	1.6009905	-0.35385561
31	2017.577	0.140599457	-0.01875045	0.0003515795	-0.9814242	0.47062247
...	...	...	...	...	...	...
126	2019.404	0.028146434	0.16715506	0.0279408149	1.1819375	0.07601870
127	2019.423	0.133388620	-0.03151877	0.0009934326	-0.9689728	0.16715506
128	2019.442	0.067627578	-0.07286154	0.0053088036	-0.9297296	-0.03151877

	trend	residuos_venta	residuos_temp	residuos_temp2	residuos_temp_exp	restemp_ant
	<ts>	<ts>	<ts>	<ts>	<ts>	<ts>
129	2019.462	0.146069067	-0.01103662	0.0001218069	-0.9890241	-0.07286154
130	2019.481	0.063639526	0.33152824	0.1099109747	1.3930955	-0.01103662
131	2019.500	0.100799654	0.27113662	0.0735150683	1.3114542	0.33152824
132	2019.519	0.098332119	0.10301545	0.0106121823	1.1085085	0.27113662
133	2019.538	0.148367550	-0.41584755	0.1729291859	-0.6597808	0.10301545
134	2019.558	0.157302675	-0.09709320	0.0094270885	-0.9074714	-0.41584755
135	2019.577	0.183059809	-0.02745108	0.0007535616	-0.9729223	-0.09709320
136	2019.596	0.188287946	0.08008782	0.0064140585	1.0833822	-0.02745108
137	2019.615	0.098083216	-0.14749796	0.0217556494	-0.8628642	0.08008782
138	2019.635	0.052099668	-0.04881421	0.0023828266	-0.9523581	-0.14749796
139	2019.654	0.257238969	-0.17716428	0.0313871838	-0.8376422	-0.04881421
140	2019.673	0.180532063	-0.45384588	0.2059760813	-0.6351806	-0.17716428
141	2019.692	0.036855974	0.19509428	0.0380617772	1.2154256	-0.45384588
142	2019.712	0.136992506	-0.42118977	0.1774008251	-0.6562655	0.19509428
143	2019.731	0.251193676	-0.25950262	0.0673416119	-0.7714352	-0.42118977
144	2019.750	0.233736197	-0.14993969	0.0224819113	-0.8607599	-0.25950262
145	2019.769	0.271451616	-0.07638265	0.0058343085	-0.9264616	-0.14993969
146	2019.788	-0.116230400	-0.12923066	0.0167005638	-0.8787712	-0.07638265
147	2019.808	-0.089097273	0.10145409	0.0102929319	1.1067791	-0.12923066
148	2019.827	-0.059289658	-0.35231532	0.1241260870	-0.7030584	0.10145409
149	2019.846	0.012647132	-0.25507176	0.0650616005	-0.7748609	-0.35231532
150	2019.865	0.059258076	0.04079386	0.0016641387	1.0416374	-0.25507176
151	2019.885	0.364149900	-0.09227659	0.0085149694	-0.9118529	0.04079386
152	2019.904	-0.134334896	0.02540200	0.0006452616	1.0257274	-0.09227659
153	2019.923	-0.113580138	0.28062988	0.0787531295	1.3239635	0.02540200
154	2019.942	0.403813280	-0.02713986	0.0007365719	-0.9732251	0.28062988
155	2019.962	-0.005647531	-0.37717292	0.1422594141	-0.6857975	-0.02713986

In [74]:
```
num = length(res_agua)                                          # sample size

summary(fit_res <- lm(residuos_venta ~  residuos_temp + residuos_temp2 +  resi
duos_temp_exp +  restemp_ant  + restemp_ant2 +restemp_ant_exp + restemp_post +
restemp_post2 + restemp_post_exp   , data=res_agua, na.action=NULL))

AIC(fit_res)/num - log(2*pi)                                 # AIC
BIC(fit_res)/num - log(2*pi)                                 # BIC
```

```
Call:
lm(formula = residuos_venta ~ residuos_temp + residuos_temp2 +
    residuos_temp_exp + restemp_ant + restemp_ant2 + restemp_ant_exp +
    restemp_post + restemp_post2 + restemp_post_exp, data = res_agua,
    na.action = NULL)

Residuals:
     Min       1Q   Median       3Q      Max
-0.50487 -0.10989 -0.01250  0.09026  0.45414

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)
(Intercept)       -0.0015059  0.0221173  -0.068   0.9458
residuos_temp      0.3081217  0.1161844   2.652   0.0089 **
residuos_temp2     0.1493599  0.2562121   0.583   0.5608
residuos_temp_exp -0.0615818  0.0236611  -2.603   0.0102 *
restemp_ant        0.1819881  0.1169788   1.556   0.1220
restemp_ant2       0.0937169  0.2559178   0.366   0.7148
restemp_ant_exp   -0.0515322  0.0235756  -2.186   0.0304 *
restemp_post      -0.0235971  0.1161218  -0.203   0.8393
restemp_post2      0.0467675  0.2578199   0.181   0.8563
restemp_post_exp  -0.0006471  0.0237585  -0.027   0.9783
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1698 on 144 degrees of freedom
Multiple R-squared:  0.08345,   Adjusted R-squared:  0.02617
F-statistic: 1.457 on 9 and 144 DF,  p-value: 0.1695
```

-10.7026413633411

-7.66568876092749

In [75]:
```
fit_nls <- nls(residuos_venta ~ g*residuos_temp + h*residuos_temp2 + i*restemp
_ant + j*restemp_post+ k*restemp_post_exp, start=list(g=0.5,h=0.5,i=1.1,j=0.9,
k=0.1), data=res_agua, na.action=NULL)
```

In [76]:
```
summary(fit_nls)
AIC(fit_res)/num - log(2*pi)                                  # AIC
BIC(fit_res)/num - log(2*pi)                                  # BIC
```

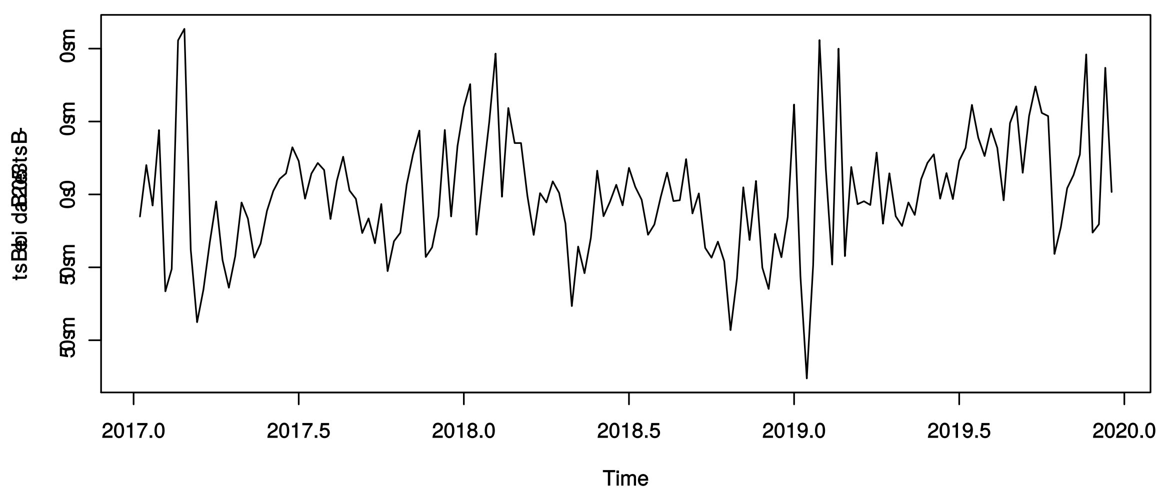
```
Formula: residuos_venta ~ g * residuos_temp + h * residuos_temp2 + i *
    restemp_ant + j * restemp_post + k * restemp_post_exp

Parameters:
    Estimate Std. Error t value Pr(>|t|)
g  0.0605975  0.0682539   0.888    0.376
h -0.0551075  0.1942592  -0.284    0.777
i -0.0210050  0.0687997  -0.305    0.761
j -0.0201838  0.1124583  -0.179    0.858
k -0.0003184  0.0227548  -0.014    0.989

Residual standard error: 0.1738 on 149 degrees of freedom

Number of iterations to convergence: 1
Achieved convergence tolerance: 1.034e-08
```

-10.7026413633411

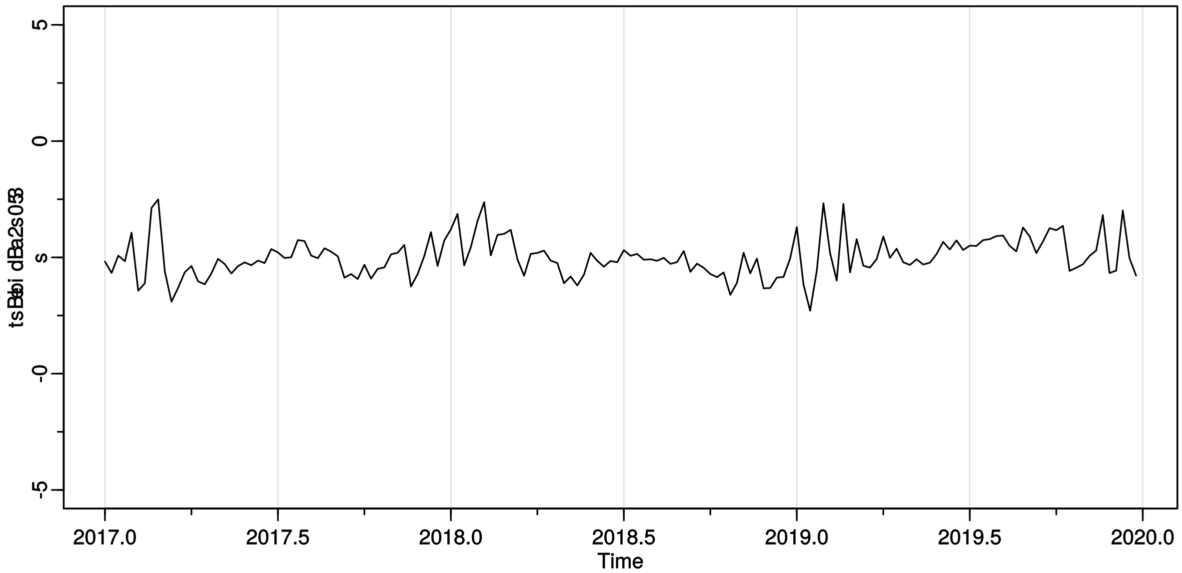
-7.66568876092749

Análisis de residuos Modelo 7

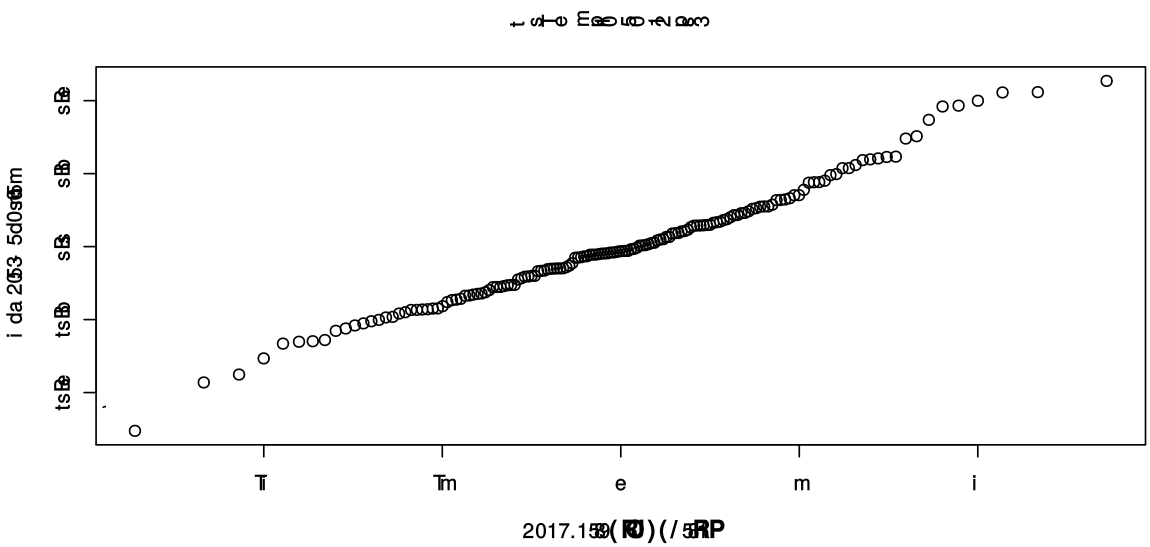
In [77]:
```
plot(residuals(fit_res))
```



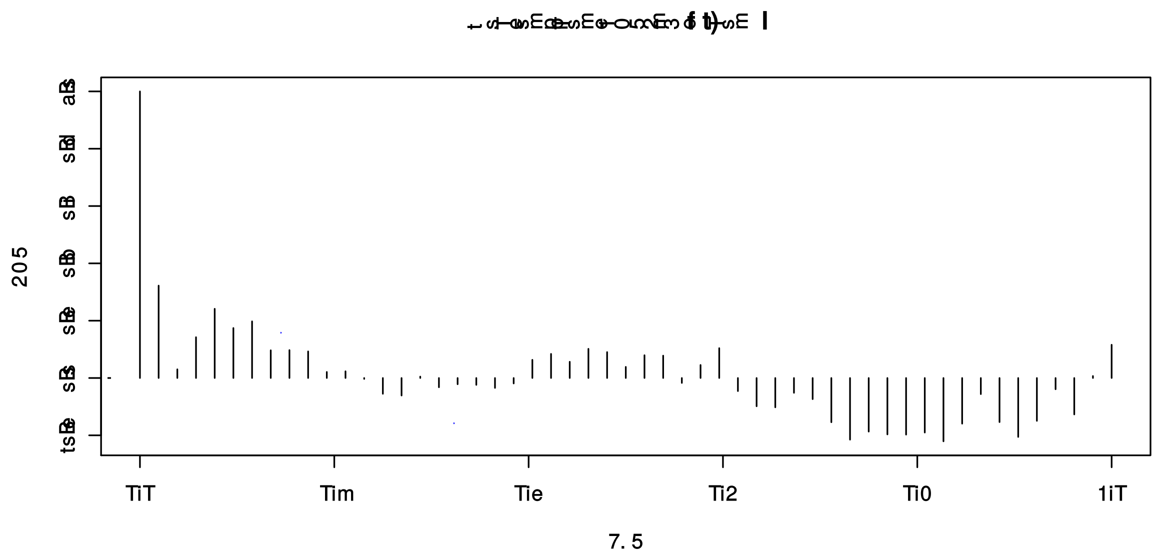
In [78]:
```
# hasta aqui se obtiene la mejor aproximacion de acuerdo a los indices de AIC
 y BIC
predict_nls = ts(fitted(fit_nls), start = 2017,frequency=52) #Creo una serie t
emporal con los valores ajustados.
tsplot(residuos_venta,ylim=c(-2,2))
```



In [79]:
```
qqnorm(residuals(fit_res))
qqline(residuals(fit_res))
```



```
In [80]: acf(residuals(fit_res),52)
```



Hacemos predicción combinando lo aprendido en el Modelo 6 y el Modelo 7 y comparamos con los datos de test, los cuáles nuestro modelo no ha visto cuando se entrenó

```
In [81]: head(base_test)
```

A data.frame: 6 x 6

	Year	Weeknum	Yearweek	Sales_Liters	Temp_Avg	Class
	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<fct>
157	2020	157	1	297444.3	21.44286	Test
158	2020	158	2	297221.2	21.98571	Test
159	2020	159	3	285992.0	23.73333	Test
160	2020	160	4	322162.2	21.37500	Test
161	2020	161	5	287530.2	23.61429	Test
162	2020	162	6	372673.3	21.38571	Test

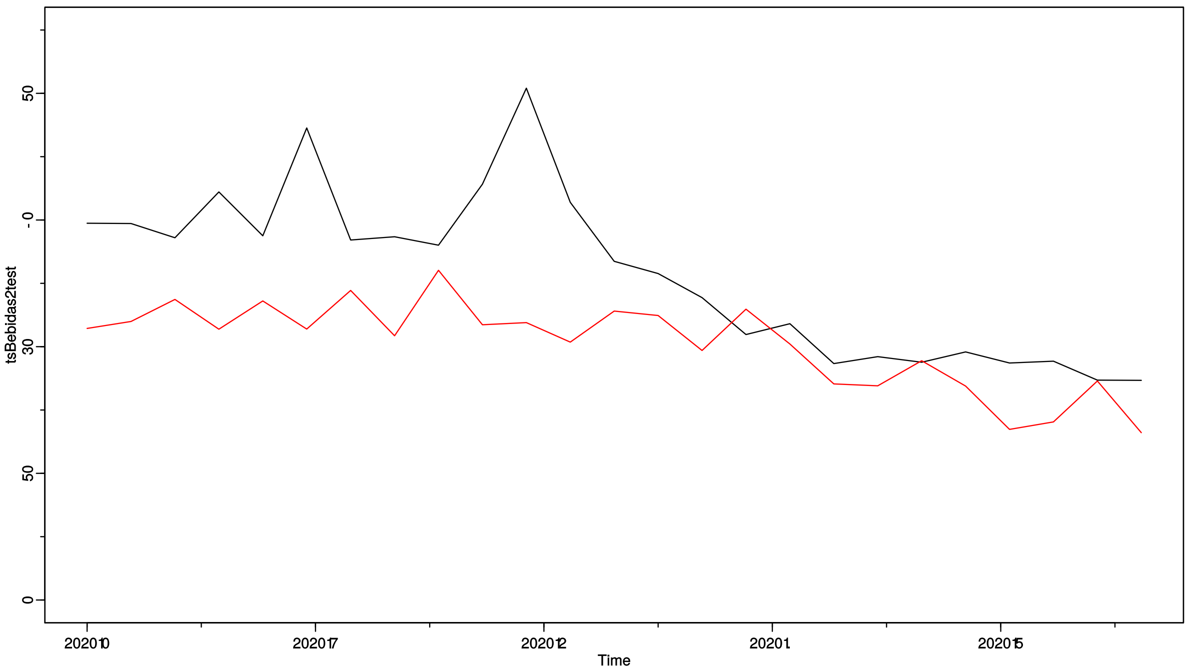
```
In [82]: Litros_test=base_test[4] / 10000
# Normalizamos los datos de venta para pasarlos a la misma escala que la tempe
ratura

Temp_test = round(base_test[5],2)
#Temp
```

In [83]:
```
tsBebidas_test = ts(Litros_test,  start=c(2020,1,1), freq = 52)

tsTemp_test = ts(Temp_test,  start=c(2020,1,1), freq = 52)
```

In [84]:
```
trend_test=time(tsBebidas_test)
```

In [85]:
```
options(repr.plot.width=14, repr.plot.height=8) #ajusta tamaño de graficas
```

In [86]:
```
tsplot(tsBebidas_test,ylim=c(0,45))
lines(tsTemp_test,col=2)

# Ventas vs temp
```



Reconstruyendo el Modelo 7 y agregamos las componentes estacionales del Modelo 6

In [87]:
```
# Componentes estacionales de las ventas

coef(fit2_estacional)
```

a	0.298453735422649
b	0.049163126437584
c	0.0458202265832083
f_1	0.0192316544523848
f_2	0.0512809153936186
f_3	0.0705013288438199

In [88]:
```
# Modelo 7 (nls de los residuos)

coef(fit_nls)
```

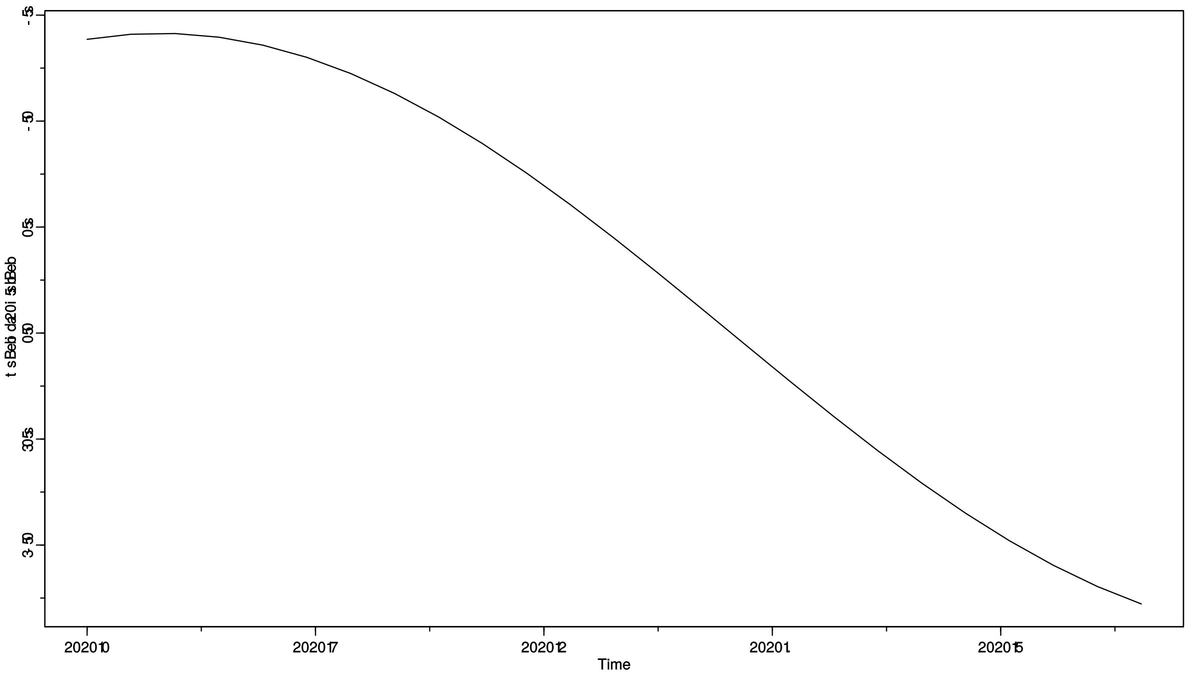
g	0.0605974974459932
h	-0.0551074739958787
i	-0.0210049526591887
j	-0.0201838025907531
k	-0.000318394006200873

In [89]:
```
coefs_estacional=as.numeric(coef(fit2_estacional))
a=coefs_estacional[1]
b=coefs_estacional[2]
c=coefs_estacional[3]
f1=coefs_estacional[4]
f2=coefs_estacional[5]
f3=coefs_estacional[6]
```

In [90]:
```
coefs_nls=as.numeric(coef(fit_nls))
g=coefs_nls[1]
h=coefs_nls[2]
i=coefs_nls[3]
j=coefs_nls[4]
k=coefs_nls[5]
print(trend_test)
```

```
Time Series:
Start = c(2020, 1)
End = c(2020, 25)
Frequency = 52
 [1] 2020.000 2020.019 2020.038 2020.058 2020.077 2020.096 2020.115 2020.135
 [9] 2020.154 2020.173 2020.192 2020.212 2020.231 2020.250 2020.269 2020.288
[17] 2020.308 2020.327 2020.346 2020.365 2020.385 2020.404 2020.423 2020.442
[25] 2020.462
```

In [91]:
```
T_estacional_test = (sin(2*pi*trend_test*f1*52) + cos(2*pi*trend_test*f1*52))
tsplot(T_estacional_test)
```



In [92]:
```
residuos_temp_test=as.numeric((tsTemp_test-Tmed)/temp_max) - (T_estacional_tes
t)
```

In [93]:
```
restemp_ant_test=lag(residuos_temp_test,-1)  # past temp
restemp_post_test=lag(residuos_temp_test,1)  # forecast tem

#trend_test= time(residuos_temp_test)        # time

residuos_temp_test2  = residuos_temp_test^2  # square it
restemp_ant_test2 = restemp_ant_test^2
restemp_post_test2 = restemp_post_test^2

residuos_temp_test_exp  = sign(residuos_temp_test)*exp(residuos_temp_test)  #
 exponential it
restemp_ant_test_exp = sign(restemp_ant_test)*exp(restemp_ant_test )
restemp_post_test_exp = sign(restemp_post_test)*exp(restemp_post_test)
```

In [94]:
```
res_agua_test = ts.intersect(trend_test,residuos_temp_test, residuos_temp_test
2, residuos_temp_test_exp,  restemp_ant_test,restemp_ant_test2,restemp_post_te
st,restemp_post_test2,restemp_ant_test_exp,restemp_post_test_exp, dframe=TRUE)
res_agua_test
```

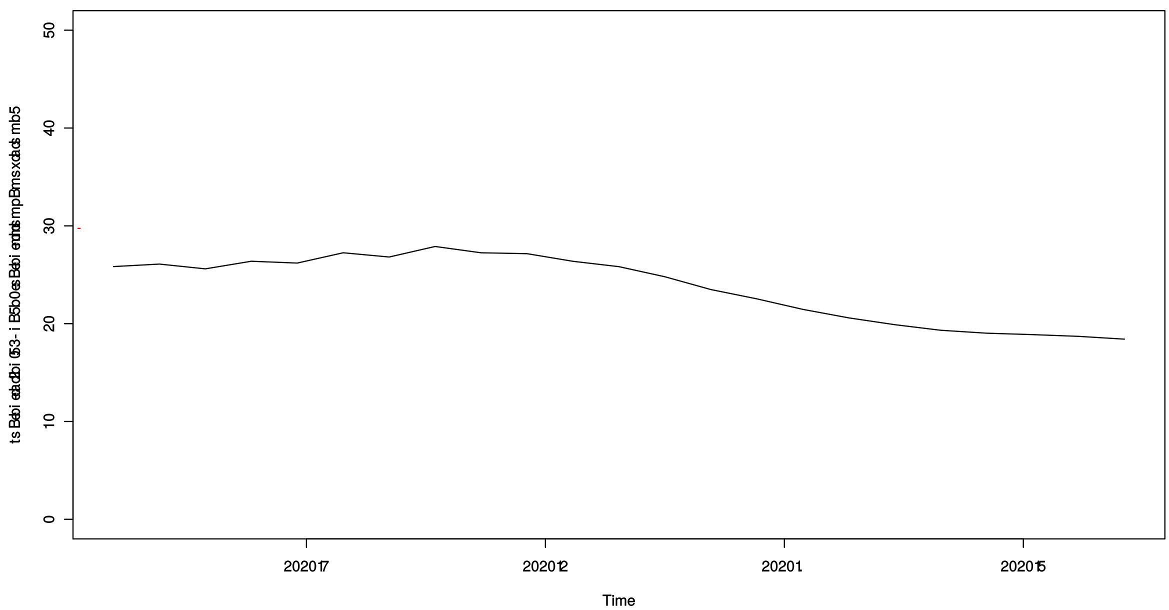
A data.frame: 23 x 10

trend_test	residuos_temp_test	residuos_temp_test2	residuos_temp_test_exp	restemp_ant_test
<ts>	<ts>	<ts>	<ts>	<ts>
2020.019	-0.8729057	0.761964385	-0.4177360	-0.9087645
2020.038	-0.6870673	0.472061492	-0.5030492	-0.8729057
2020.058	-0.9254409	0.856440822	-0.3963566	-0.6870673
2020.077	-0.6453473	0.416473154	-0.5244804	-0.9254409
2020.096	-0.8294173	0.687933018	-0.4363035	-0.6453473
2020.115	-0.4213617	0.177545713	-0.6561527	-0.8294173
2020.135	-0.7165118	0.513389132	-0.4884531	-0.4213617
2020.154	-0.0435464	0.001896289	-0.9573881	-0.7165118
2020.173	-0.3856468	0.148723430	-0.6800107	-0.0435464
2020.192	-0.2285604	0.052239841	-0.7956783	-0.3856468
2020.212	-0.2464316	0.060728532	-0.7815848	-0.2285604
2020.231	0.1784770	0.031854045	1.1953954	-0.2464316
2020.250	0.3053893	0.093262608	1.3571532	0.1784770
2020.269	0.1743147	0.030385630	1.1904302	0.3053893
2020.288	0.6996156	0.489461945	2.0129787	0.1743147
2020.308	0.5704454	0.325407917	1.7690548	0.6996156
2020.327	0.3944574	0.155596635	1.4835790	0.5704454
2020.346	0.5389985	0.290519408	1.7142892	0.3944574
2020.365	0.9071036	0.822837009	2.4771374	0.5389985
2020.385	0.8320348	0.692281869	2.2979899	0.9071036
2020.404	0.5901345	0.348258728	1.8042311	0.8320348
2020.423	0.7700610	0.592993937	2.1598980	0.5901345
2020.442	1.2211279	1.491153354	3.3910103	0.7700610

In [95]:
```
A_test = a *(sin(2*pi*trend_test*f1*52) + cos(2*pi*trend_test*f1*52)) +b*(sin(
2*pi*trend_test*f2*52) + cos(2*pi*trend_test*f2*52)) + c*(sin(2*pi*trend_test*
f3*52) + cos(2*pi*trend_test*f3*52))
```

In [96]:
```
residuos_venta_test = g*residuos_temp_test + h*residuos_temp_test2 + i*restemp
_ant_test + j*restemp_post_test+ k*restemp_post_test_exp
```

In [97]:
```
plot((A_test + residuos_venta_test)*amp_max+Amed,ylim=c(0,50))
lines(tsBebidas_test,col=2)
pred_test=(A_test + residuos_venta_test)*amp_max+Amed

# Predicción vs datos reales
```



La predicción da muy bien. No toma los picos de ventas que se deben a compras de pánico por el Covid 19. En nuestro dataset no habíamos tenido un comportamiento similar por lo que nos parece razonable y esperable que el modelo no captara estos picos.

In [98]:
```
length(pred_test)
length(tsBebidas_test)
```

23

25

In [99]:
```
pred_agua_test = ts.intersect(pred_test,tsBebidas_test, dframe=TRUE)
print(pred_agua_test$pred_test)
print(pred_agua_test$Sum.Litros)
```

```
Time Series:
Start = c(2020, 2)
End = c(2020, 24)
Frequency = 52
 [1] 25.83519 26.09151 25.60390 26.38106 26.19529 27.24741 26.81400 27.89104
 [9] 27.24611 27.15471 26.37487 25.82787 24.79523 23.48804 22.53880 21.46317
[17] 20.59290 19.89757 19.32672 19.02654 18.88048 18.70279 18.41705
NULL
```

In [100]:
```
head(pred_agua_test)
```

A data.frame: 6 x 2

pred_test	Sales_Liters
<dbl>	<dbl>
25.83519	29.72212
26.09151	28.59920
25.60390	32.21622
26.38106	28.75303
26.19529	37.26733
27.24741	28.42089

In [101]:
```
round(mape(pred_agua_test$pred_test,pred_agua_test$Sales_Liters),2)
```

10.68

Fue posible predecir la venta de de agua para el perido de 2020 con una exactitud del 89,3%

Modelo 8 : ARMAX - Multivariable AR

Finalmente realizaremos un analisis utilizando una libreria que permite aplicar modelos Autoregresivos (AR) y de media móvil (MA) para procesos que utilizan varias variables o sea ARIMA multivariable.

Este análisis se realizó basandose en el Capítulo 5.6 de Libro del Curso

In [102]:
```
install.packages("vars")
```

```
Installing package into ‘/home/nbuser/R’
(as ‘lib’ is unspecified)
```

In [103]:
```
library(vars)
```

```
Loading required package: MASS
Loading required package: strucchange
Loading required package: zoo

Attaching package: ‘zoo’

The following objects are masked from ‘package:base’:

    as.Date, as.Date.numeric

Loading required package: sandwich
Loading required package: urca
Loading required package: lmtest
```

In [104]:

```
tsBebidas2=tsBebidas^2
tsTemp2=tsTemp^2
x = cbind(tsBebidas, tsTemp,tsTemp2)
summary(VAR(x, p=1, type='both'))  # Primer aporxmacion para un corrimiento
#lag=1,orden de p=1 incluyendo const + trend
```

```
VAR Estimation Results:
=========================
Endogenous variables: tsBebidas, tsTemp, tsTemp2
Deterministic variables: both
Sample size: 155
Log Likelihood: -1347.9
Roots of the characteristic polynomial:
0.8876 0.4186 0.2243
Call:
VAR(y = x, p = 1, type = "both")


Estimation results for equation tsBebidas:
==========================================
tsBebidas = tsBebidas.l1 + tsTemp.l1 + tsTemp2.l1 + const + trend

              Estimate Std. Error t value Pr(>|t|)
tsBebidas.l1  0.639741   0.074095   8.634 8.05e-15 ***
tsTemp.l1    -0.177046   0.310845  -0.570   0.5698
tsTemp2.l1    0.011818   0.009517   1.242   0.2163
const         7.046036   2.896846   2.432   0.0162 *
trend         0.007677   0.004425   1.735   0.0848 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


Residual standard error: 2.256 on 150 degrees of freedom
Multiple R-Squared: 0.7118,     Adjusted R-squared: 0.7041
F-statistic: 92.63 on 4 and 150 DF,  p-value: < 2.2e-16


Estimation results for equation tsTemp:
=======================================
tsTemp = tsBebidas.l1 + tsTemp.l1 + tsTemp2.l1 + const + trend

              Estimate Std. Error t value Pr(>|t|)
tsBebidas.l1  0.407587   0.074357   5.482 1.74e-07 ***
tsTemp.l1     0.940211   0.311941   3.014  0.00303 **
tsTemp2.l1   -0.012433   0.009551  -1.302  0.19502
const        -3.814365   2.907064  -1.312  0.19149
trend        -0.009049   0.004441  -2.038  0.04334 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


Residual standard error: 2.264 on 150 degrees of freedom
Multiple R-Squared: 0.743,      Adjusted R-squared: 0.7361
F-statistic: 108.4 on 4 and 150 DF,  p-value: < 2.2e-16


Estimation results for equation tsTemp2:
========================================
tsTemp2 = tsBebidas.l1 + tsTemp.l1 + tsTemp2.l1 + const + trend

               Estimate Std. Error t value Pr(>|t|)
tsBebidas.l1   14.17696    2.52823   5.607  9.6e-08 ***
tsTemp.l1      19.02666   10.60644   1.794  0.07485 .
```

```
tsTemp2.l1      -0.04947    0.32475  -0.152  0.87913
const         -301.45909   98.84425  -3.050  0.00271 **
trend           -0.31209    0.15099  -2.067  0.04046 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


Residual standard error: 76.98 on 150 degrees of freedom
Multiple R-Squared: 0.7431,     Adjusted R-squared: 0.7363
F-statistic: 108.5 on 4 and 150 DF,  p-value: < 2.2e-16



Covariance matrix of residuals:
          tsBebidas  tsTemp tsTemp2
tsBebidas     5.089   1.578   59.58
tsTemp        1.578   5.125  169.07
tsTemp2      59.581 169.075 5925.37

Correlation matrix of residuals:
          tsBebidas tsTemp tsTemp2
tsBebidas    1.0000 0.3090  0.3431
tsTemp       0.3090 1.0000  0.9702
tsTemp2      0.3431 0.9702  1.0000
```

- Obtuvimos una aproximacion:

$$A_t = 7.046036 - 0.007677t + 0.639741A_{t-1} - 0.177046T_{t-1} + 0.011818T^2_{t-1}$$

In [105]:
```
# Para mayores orden de p utilizamos :
VARselect(x, lag.max=10, type="both")
```

$selection

AIC(n)	5
HQ(n)	3
SC(n)	2
FPE(n)	5

$criteria

A matrix: 4 x 10 of type dbl

	1	2	3	4	5	6	
AIC(n)	8.835624	8.573480	8.459981	8.423318	8.410002	8.432541	8.477
HQ(n)	8.960176	8.772764	8.733996	8.772064	8.833480	8.930750	9.050
SC(n)	9.142159	9.063936	9.134358	9.281615	9.452221	9.658681	9.887
FPE(n)	6875.393682	5291.249477	4726.024502	4560.058462	4506.092848	4618.111350	4842.589

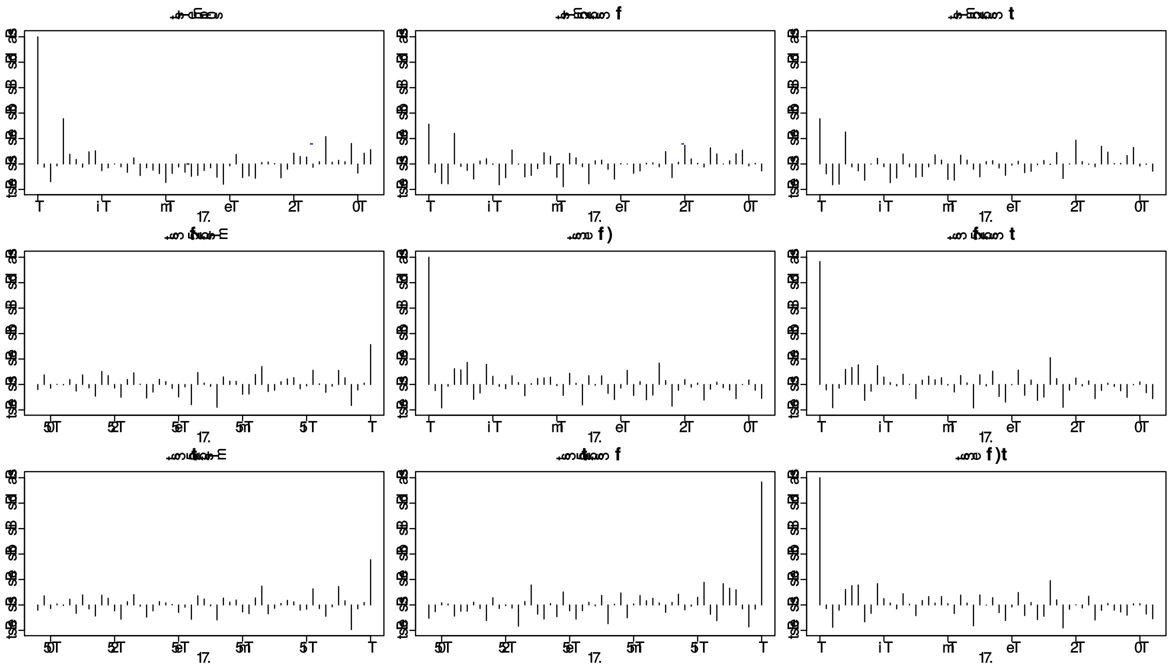
Para elegir el orden. Según el libro el criterio más confiable es BIC para multivariate time series. En este caso SC hace referencia a BIC, por lo que elegimos orden 2.

In [106]:
```
summary(fit <- VAR(x, p=2, type="both"))
```

```
VAR Estimation Results:
=========================
Endogenous variables: tsBebidas, tsTemp, tsTemp2
Deterministic variables: both
Sample size: 154
Log Likelihood: -1315.41
Roots of the characteristic polynomial:
0.9144 0.6659 0.4576 0.4311 0.3714 0.3714
Call:
VAR(y = x, p = 2, type = "both")


Estimation results for equation tsBebidas:
==========================================
tsBebidas = tsBebidas.l1 + tsTemp.l1 + tsTemp2.l1 + tsBebidas.l2 + tsTemp.l2
+ tsTemp2.l2 + const + trend

              Estimate Std. Error t value Pr(>|t|)
tsBebidas.l1  0.619942   0.088101   7.037 7.09e-11 ***
tsTemp.l1    -0.366504   0.339318  -1.080   0.2819
tsTemp2.l1    0.017443   0.010165   1.716   0.0883 .
tsBebidas.l2  0.102528   0.092728   1.106   0.2707
tsTemp.l2     0.510119   0.343256   1.486   0.1394
tsTemp2.l2   -0.017253   0.010309  -1.673   0.0964 .
const         3.459272   3.551789   0.974   0.3317
trend         0.005516   0.004643   1.188   0.2367
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


Residual standard error: 2.258 on 146 degrees of freedom
Multiple R-Squared: 0.7187,     Adjusted R-squared: 0.7052
F-statistic: 53.28 on 7 and 146 DF,  p-value: < 2.2e-16


Estimation results for equation tsTemp:
=======================================
tsTemp = tsBebidas.l1 + tsTemp.l1 + tsTemp2.l1 + tsBebidas.l2 + tsTemp.l2 + t
sTemp2.l2 + const + trend

              Estimate Std. Error t value Pr(>|t|)
tsBebidas.l1  0.218250   0.080841   2.700 0.007759 **
tsTemp.l1     0.485003   0.311358   1.558 0.121469
tsTemp2.l1   -0.006142   0.009327  -0.659 0.511249
tsBebidas.l2  0.322386   0.085087   3.789 0.000221 ***
tsTemp.l2     0.938867   0.314972   2.981 0.003369 **
tsTemp2.l2   -0.022754   0.009460  -2.405 0.017408 *
const        -9.952794   3.259121  -3.054 0.002686 **
trend        -0.010050   0.004260  -2.359 0.019651 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


Residual standard error: 2.072 on 146 degrees of freedom
Multiple R-Squared: 0.7878,     Adjusted R-squared: 0.7776
F-statistic: 77.41 on 7 and 146 DF,  p-value: < 2.2e-16
```

```
Estimation results for equation tsTemp2:
========================================
tsTemp2 = tsBebidas.l1 + tsTemp.l1 + tsTemp2.l1 + tsBebidas.l2 + tsTemp.l2 +
tsTemp2.l2 + const + trend

               Estimate Std. Error t value Pr(>|t|)
tsBebidas.l1    7.01441    2.75062   2.550   0.0118 *
tsTemp.l1       6.59962   10.59395   0.623   0.5343
tsTemp2.l1      0.08114    0.31737   0.256   0.7986
tsBebidas.l2   12.18446    2.89509   4.209 4.47e-05 ***
tsTemp.l2      24.19451   10.71691   2.258   0.0255 *
tsTemp2.l2     -0.56831    0.32187  -1.766   0.0795 .
const        -479.23740  110.89154  -4.322 2.85e-05 ***
trend          -0.35398    0.14496  -2.442   0.0158 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


Residual standard error: 70.49 on 146 degrees of freedom
Multiple R-Squared: 0.7871,     Adjusted R-squared: 0.7768
F-statistic: 77.09 on 7 and 146 DF,  p-value: < 2.2e-16



Covariance matrix of residuals:
          tsBebidas  tsTemp tsTemp2
tsBebidas     5.097   1.466   56.61
tsTemp        1.466   4.292  141.11
tsTemp2      56.609 141.113 4968.62

Correlation matrix of residuals:
          tsBebidas tsTemp tsTemp2
tsBebidas    1.0000 0.3133  0.3557
tsTemp       0.3133 1.0000  0.9663
tsTemp2      0.3557 0.9663  1.0000
```

In [107]:
```
acf(resid(fit), 52)
```



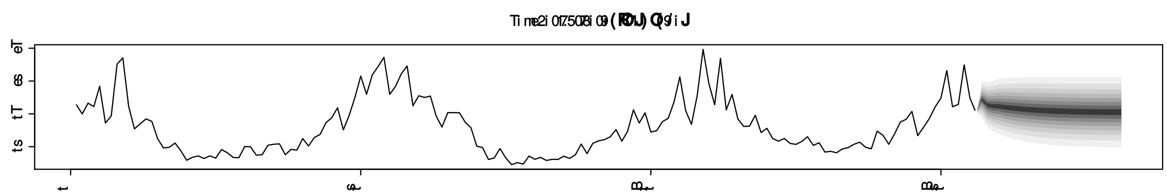
- Este grafico muestra la autocorrelacion ACF sobre la diagonal y la CCF sobre la diagonal inversa

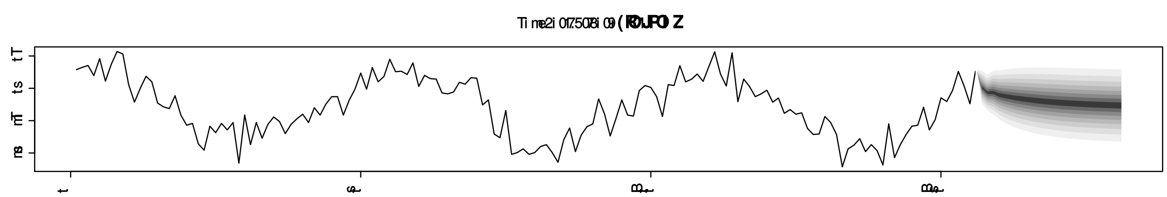
In [108]:

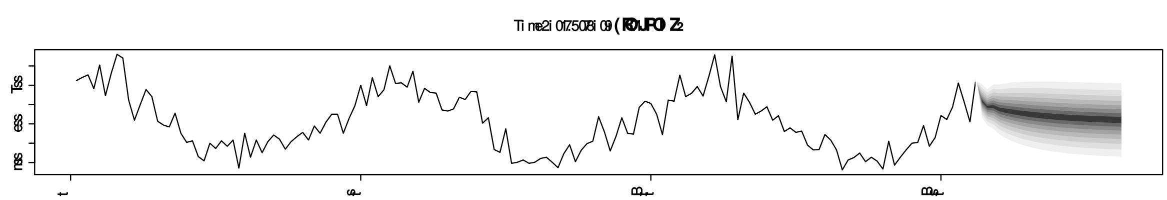
```
(fit.pr = predict(fit, n.ahead = 25, ci = 0.95)) # 25 weeks ahead
fanchart(fit.pr) # plot prediction + error
```

```
$tsBebidas
         fcst    lower    upper       CI
 [1,] 27.21901 22.79399 31.64402 4.425015
 [2,] 26.34663 20.83829 31.85497 5.508341
 [3,] 26.17810 20.11304 32.24315 6.065052
 [4,] 26.14887 19.59543 32.70230 6.553435
 [5,] 25.99588 19.09121 32.90054 6.904664
 [6,] 25.89958 18.72442 33.07474 7.175157
 [7,] 25.81573 18.42397 33.20748 7.391757
 [8,] 25.73522 18.17040 33.30004 7.564820
 [9,] 25.66600 17.96096 33.37104 7.705041
[10,] 25.60448 17.78493 33.42403 7.819554
[11,] 25.54982 17.63634 33.46330 7.913482
[12,] 25.50180 17.51094 33.49267 7.990865
[13,] 25.45969 17.40487 33.51451 8.054815
[14,] 25.42298 17.31519 33.53076 8.107788
[15,] 25.39121 17.23946 33.54296 8.151750
[16,] 25.36396 17.17567 33.55224 8.188287
[17,] 25.34083 17.12214 33.55952 8.218689
[18,] 25.32147 17.07746 33.56548 8.244008
[19,] 25.30556 17.04045 33.57067 8.265110
[20,] 25.29281 17.01010 33.57552 8.282708
[21,] 25.28294 16.98555 33.58033 8.297390
[22,] 25.27570 16.96606 33.58534 8.309644
[23,] 25.27087 16.95100 33.59075 8.319876
[24,] 25.26825 16.93983 33.59667 8.328420
[25,] 25.26764 16.93208 33.60320 8.335558

$tsTemp
         fcst     lower    upper       CI
 [1,] 20.19165 16.131255 24.25204 4.060393
 [2,] 19.32192 14.917727 23.72610 4.404189
 [3,] 19.36015 14.060786 24.65950 5.299359
 [4,] 18.97708 13.050859 24.90330 5.926220
 [5,] 18.78630 12.341232 25.23137 6.445069
 [6,] 18.63721 11.769555 25.50486 6.867651
 [7,] 18.48883 11.281150 25.69650 7.207677
 [8,] 18.36237 10.881547 25.84319 7.480822
 [9,] 18.24901 10.545743 25.95227 7.703264
[10,] 18.14496 10.260623 26.02930 7.884339
[11,] 18.05081 10.018115 26.08351 8.032700
[12,] 17.96496  9.810317 26.11960 8.154643
[13,] 17.88666  9.631463 26.14186 8.255198
[14,] 17.81527  9.476956 26.15359 8.338318
[15,] 17.75018  9.343004 26.15735 8.407173
[16,] 17.69082  9.226515 26.15512 8.464303
[17,] 17.63671  9.124939 26.14848 8.511771
[18,] 17.58740  9.036143 26.13865 8.551254
[19,] 17.54247  8.958344 26.12659 8.584125
[20,] 17.50155  8.890038 26.11306 8.611512
[21,] 17.46430  8.829954 26.09864 8.634344
[22,] 17.43040  8.777009 26.08378 8.653387
[23,] 17.39956  8.730282 26.06884 8.669278
[24,] 17.37153  8.688985 26.05407 8.682542
[25,] 17.34606  8.652439 26.03967 8.693617

$tsTemp2
```

	fcst	lower	upper	CI
[1,]	420.3725	282.21766	558.5273	138.1548
[2,]	387.0649	237.92307	536.2067	149.1418
[3,]	389.4851	210.02872	568.9414	179.4563
[4,]	375.6544	174.14552	577.1633	201.5089
[5,]	368.9411	149.74617	588.1360	219.1949
[6,]	363.9460	130.25896	597.6331	233.6871
[7,]	358.8626	113.61913	604.1061	245.2435
[8,]	354.5868	100.09287	609.0808	254.4939
[9,]	350.7639	88.76212	612.7657	262.0018
[10,]	347.2555	79.15605	615.3550	268.0995
[11,]	344.0852	70.99893	617.1714	273.0862
[12,]	341.1961	64.01594	618.3763	277.1802
[13,]	338.5622	58.00926	619.1151	280.5529
[14,]	336.1619	52.82276	619.5010	283.3391
[15,]	333.9739	48.32773	619.6200	285.6461
[16,]	331.9795	44.41978	619.5392	287.5597
[17,]	330.1622	41.01290	619.3114	289.1493
[18,]	328.5066	38.03536	618.9779	290.4713
[19,]	326.9989	35.42719	618.5707	291.5718
[20,]	325.6265	33.13788	618.1150	292.4886
[21,]	324.3776	31.12471	617.6305	293.2529
[22,]	323.2417	29.35139	617.1321	293.8903
[23,]	322.2092	27.78696	616.6315	294.4223
[24,]	321.2712	26.40494	616.1375	294.8663
[25,]	320.4196	25.18261	615.6566	295.2370







In [109]:
```
x_test = cbind(tsBebidas_test, tsTemp_test)
print(x_test)
```

```
Time Series:
Start = c(2020, 1)
End = c(2020, 25)
Frequency = 52
         tsBebidas_test tsTemp_test
2020.000       29.74443       21.44
2020.019       29.72212       21.99
2020.038       28.59920       23.73
2020.058       32.21622       21.38
2020.077       28.75303       23.61
2020.096       37.26733       21.39
2020.115       28.42089       24.44
2020.135       28.67805       20.86
2020.154       28.01215       26.03
2020.173       32.82848       21.73
2020.192       40.40622       21.90
2020.212       31.39477       20.36
2020.231       26.73832       22.81
2020.250       25.77284       22.46
2020.269       23.87235       19.70
2020.288       20.95774       22.96
2020.308       21.81312       20.21
2020.327       18.66503       17.06
2020.346       19.21226       16.91
2020.365       18.77107       18.89
2020.385       19.58575       16.89
2020.404       18.71079       13.47
2020.423       18.85455       14.06
2020.442       17.35902       17.29
2020.462       17.34106       13.21
```

In [110]:
```
print(x_test[1:25,1])
```

```
 [1] 29.74443 29.72212 28.59920 32.21622 28.75303 37.26733 28.42089 28.67805
 [9] 28.01215 32.82848 40.40622 31.39477 26.73832 25.77284 23.87235 20.95774
[17] 21.81312 18.66503 19.21226 18.77107 19.58575 18.71079 18.85455 17.35902
[25] 17.34106
```

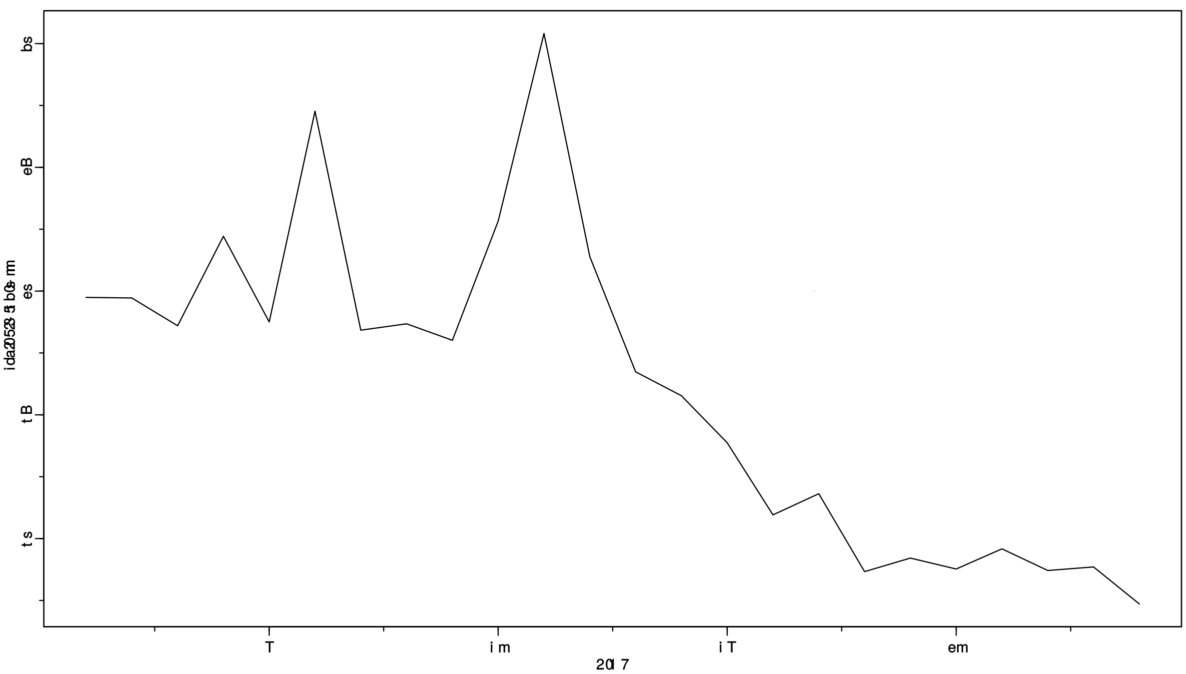
In [111]:
```
print(fit.pr$fcst$tsBebidas[,1])
```

```
 [1] 27.21901 26.34663 26.17810 26.14887 25.99588 25.89958 25.81573 25.73522
 [9] 25.66600 25.60448 25.54982 25.50180 25.45969 25.42298 25.39121 25.36396
[17] 25.34083 25.32147 25.30556 25.29281 25.28294 25.27570 25.27087 25.26825
[25] 25.26764
```

In [112]:
```
mape(x_test[,1],fit.pr$fcst$tsBebidas[,1])
```

21.3553427928945

```
In [113]: tsplot((x_test[1:24,1]))
          lines(fit.pr$fcst$tsBebidas[,1],col=4)
```



Como se puede observar el ajuste utilizando el paquete de **ARMAX**, *vars* no logra ajustar correctamente al final del semiciclo de los datos de test. Si bien este modelo es posible implementarlo rapidamente para tener una idea de valores de prediccion aproximados, lo mas recomendale es realizar antes todo el proceso de analisis de componentes estacionarias y luego aplicar un modelo predictivo.

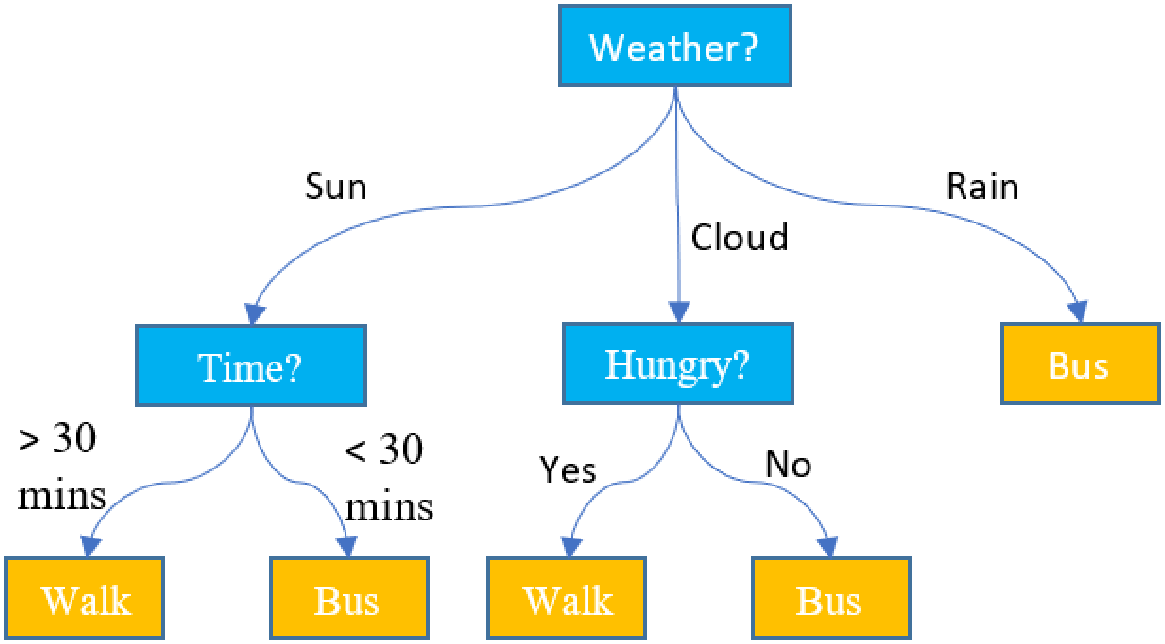
Modelo 9 : Random forest

El modelo Random Forest es un bagging aplicado en árboles de decisión. Bagging es crear diferentes modelos usando muestras aleatorias con reemplazo y luego combinar o ensamblar los resultados.

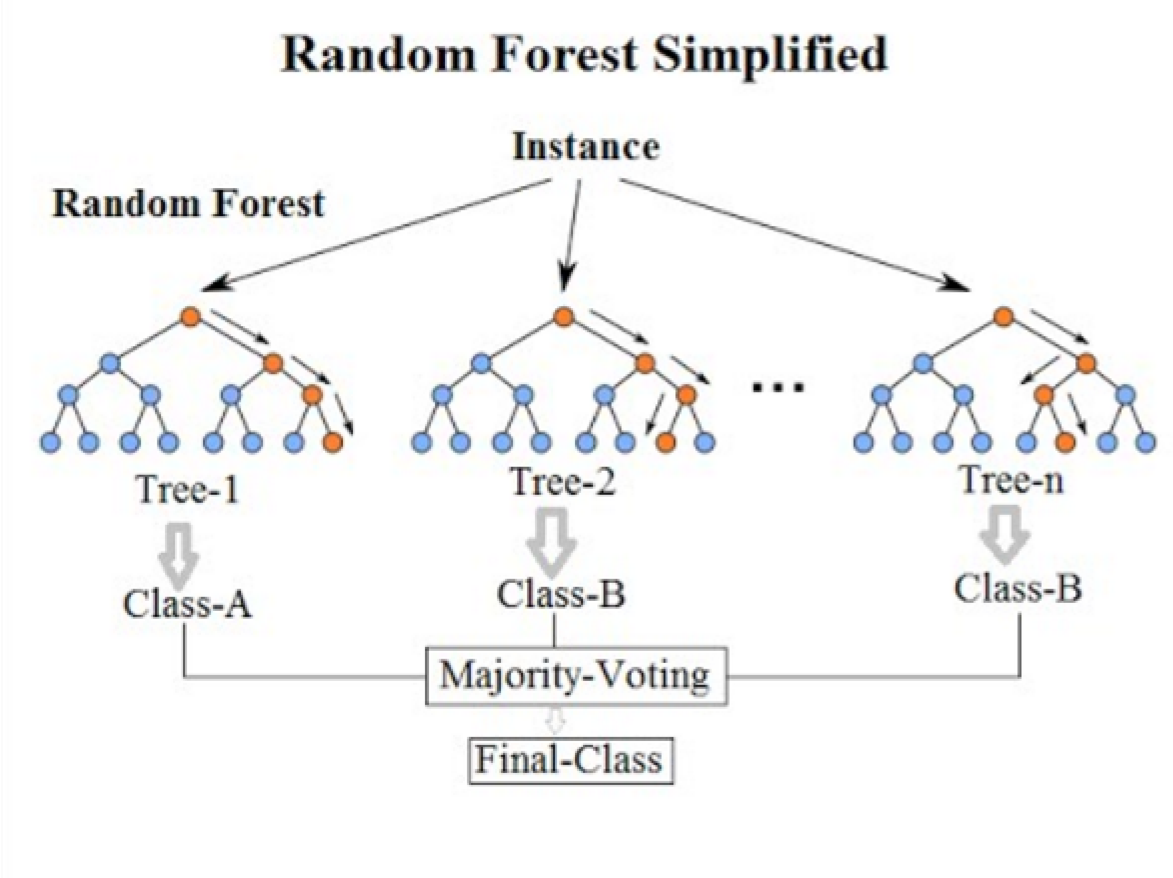
Random Forest consiste en la creación de varios Decision Tree independientes, cada uno de los Tree genera su propia predicción y las mismas son promediadas para llegar al resultado final. Esto permite reducir la varianza de dicho modelo.

Los árboles son los candidatos ideales para el bagging, dado que ellos pueden registrar estructuras de interacción compleja en los datos, y si crecen suficientemente profundo, tienen relativamente baja parcialidad.

DECISION TREE



RANDOM FOREST: conjunto de decision tree promediados


Random Forest Simplified
Instance
Random Forest
Tree-1
Tree-2
Tree-n
Class-A
Class-B
Class-B
Majority-Voting
Final-Class

In [114]:

```
library(dplyr)
library(randomForest)
library(tidyverse)
library(forecast)
```

```
Attaching package: ‘dplyr’

The following object is masked from ‘package:MASS’:

    select

The following objects are masked from ‘package:lubridate’:

    intersect, setdiff, union

The following objects are masked from ‘package:stats’:

    filter, lag

The following objects are masked from ‘package:base’:

    intersect, setdiff, setequal, union

randomForest 4.6-14
Type rfNews() to see new features/changes/bug fixes.

Attaching package: ‘randomForest’

The following object is masked from ‘package:dplyr’:

    combine

── Attaching packages ─────────────────────────────────────── tidyverse 1.2.1
──
✓ ggplot2 3.2.0     ✓ readr   1.3.1
✓ tibble  2.1.3     ✓ purrr   0.3.3
✓ tidyr   0.8.3     ✓ stringr 1.4.0
✓ ggplot2 3.2.0     ✓ forcats 0.4.0
── Conflicts ──────────────────────────────────────── tidyverse_conflicts()
──
✕ lubridate::as.difftime() masks base::as.difftime()
✕ stringr::boundary()      masks strucchange::boundary()
✕ randomForest::combine()  masks dplyr::combine()
✕ lubridate::date()        masks base::date()
✕ dplyr::filter()          masks stats::filter()
✕ lubridate::intersect()   masks base::intersect()
✕ dplyr::lag()             masks stats::lag()
✕ ggplot2::margin()        masks randomForest::margin()
✕ dplyr::select()          masks MASS::select()
✕ lubridate::setdiff()     masks base::setdiff()
✕ lubridate::union()       masks base::union()

Attaching package: ‘forecast’

The following object is masked from ‘package:astsa’:

    gas
```

In [115]:
```
head(base_train)
head(base_test)
```

A data.frame: 6 x 6

Year	Weeknum	Yearweek	Sales_Liters	Temp_Avg	Class
<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<fct>
2017	1	1	263778.2	22.88571	Train
2017	2	2	249777.5	23.24286	Train
2017	3	3	266308.4	23.52857	Train
2017	4	4	261133.6	21.95714	Train
2017	5	5	292004.5	24.58571	Train
2017	6	6	236130.0	21.11429	Train

A data.frame: 6 x 6

	Year	Weeknum	Yearweek	Sales_Liters	Temp_Avg	Class
	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<fct>
157	2020	157	1	297444.3	21.44286	Test
158	2020	158	2	297221.2	21.98571	Test
159	2020	159	3	285992.0	23.73333	Test
160	2020	160	4	322162.2	21.37500	Test
161	2020	161	5	287530.2	23.61429	Test
162	2020	162	6	372673.3	21.38571	Test

In [116]:
```
rf = randomForest(Sales_Liters ~ Year + Weeknum + Yearweek + Temp_Avg , data =
base_train)
```

In [117]:
```
print(rf)
```

```
Call:
 randomForest(formula = Sales_Liters ~ Year + Weeknum + Yearweek +      Temp_
Avg, data = base_train)
               Type of random forest: regression
                     Number of trees: 500
No. of variables tried at each split: 1

          Mean of squared residuals: 399772516
                    % Var explained: 76.56
```

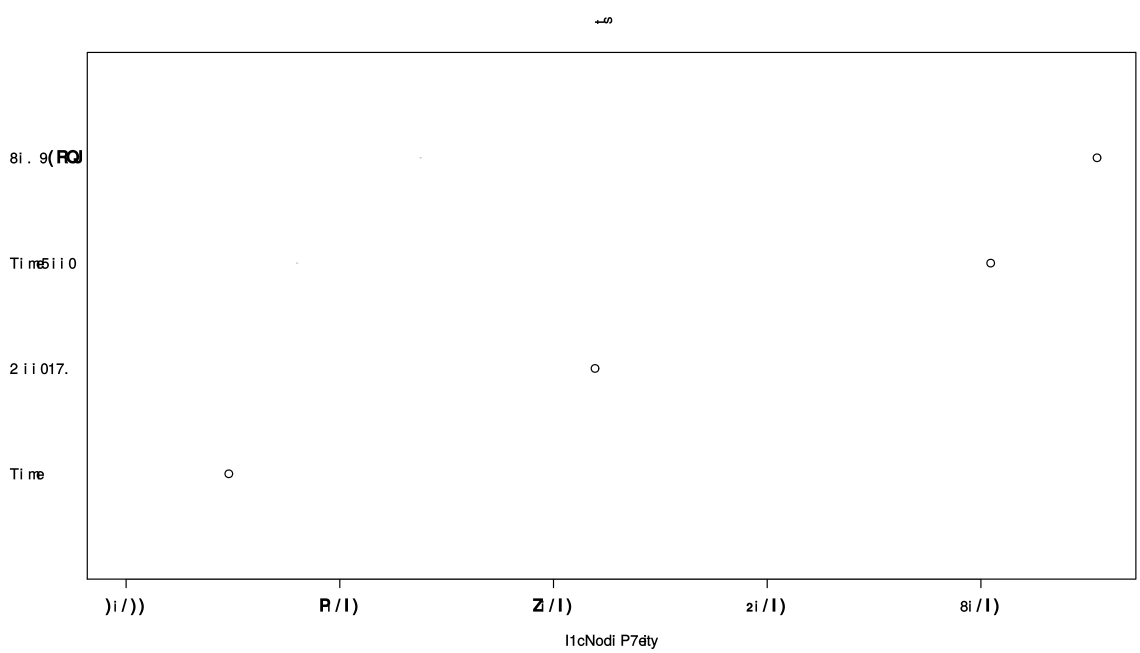
```
In [118]: predictions_train = predict(rf, newdata = base_train)
          round(mape(base_train$Sales_Liters, predictions_train),2)

          predictions_test = predict(rf, newdata = base_test)
          round(mape(base_test$Sales_Liters, predictions_test),2)
```

3.84

16.2

MAPE es 4% en train y 16% en test, es un claro caso de overfitting. Vamos a probar utilizando menos variables

```
In [119]: varImpPlot(rf)

          # Para ver que variables impactan más en el modelo
```



Yearweek y Temp_Avg son las variables que más influyen

```
In [120]: rf_revised = randomForest(Sales_Liters ~ Yearweek + Temp_Avg , data = base_tra
          in)
          print(rf_revised)
```

```
Call:
 randomForest(formula = Sales_Liters ~ Yearweek + Temp_Avg, data = base_trai
n)
               Type of random forest: regression
                     Number of trees: 500
No. of variables tried at each split: 1

          Mean of squared residuals: 558210144
                    % Var explained: 67.26
```

In [121]:
```
predictions_train = predict(rf_revised, newdata = base_train)
round(mape(base_train$Sales_Liters, predictions_train),2)

predictions_test = predict(rf_revised, newdata = base_test)
round(mape(base_test$Sales_Liters, predictions_test),2)
```

3.87

9.91

El modelo mejora desde 16% en test a 10%

Probamos utilizar solo la temperatura

In [122]:
```
rf_revised2 = randomForest(Sales_Liters ~ Temp_Avg , data = base_train)
print(rf_revised2)
```

```
Call:
 randomForest(formula = Sales_Liters ~ Temp_Avg, data = base_train)
               Type of random forest: regression
                     Number of trees: 500
No. of variables tried at each split: 1

          Mean of squared residuals: 944755305
                    % Var explained: 44.6
```

In [123]:
```
predictions_train2 = predict(rf_revised2, newdata = base_train)
round(mape(base_train$Sales_Liters, predictions_train2),2)

predictions_test2 = predict(rf_revised2, newdata = base_test)
round(mape(base_test$Sales_Liters, predictions_test2),2)
```

5.56

13.93

Sube el error en train y test, es razonable porque nos quedamos sin variable de tiempo

In [124]:
```
head(predictions_test)
```

157	283048.717626388
158	285721.409245238
159	271756.458183016
160	263674.583816666
161	288575.123252182
162	266826.652814166

In [125]:
```
RF_Pred <- data.frame(matrix(unlist(predictions_test), nrow=25, byrow=T))

colnames(RF_Pred)
```

'matrix.unlist.predictions_test...nrow...25..byrow...T.'

In [126]:
```
names(RF_Pred)[names(RF_Pred) == "matrix.unlist.predictions_test...nrow...25..byrow...T."] <- "Sales_Liters"
head(RF_Pred)
```

A data.frame: 6 x 1

Sales_Liters
<dbl>
283048.7
285721.4
271756.5
263674.6
288575.1
266826.7

In [127]:
```
RF_Pred$Weeknum <- c(157:181)
RF_Pred <- RF_Pred[, c(2,1)]
head(RF_Pred)
```

A data.frame: 6 x 2

Weeknum	Sales_Liters
<int>	<dbl>
157	283048.7
158	285721.4
159	271756.5
160	263674.6
161	288575.1
162	266826.7

In [128]:
```
train1 <- base_train %>% select(c(Weeknum, Sales_Liters))
head(train1)
```

A data.frame: 6 x 2

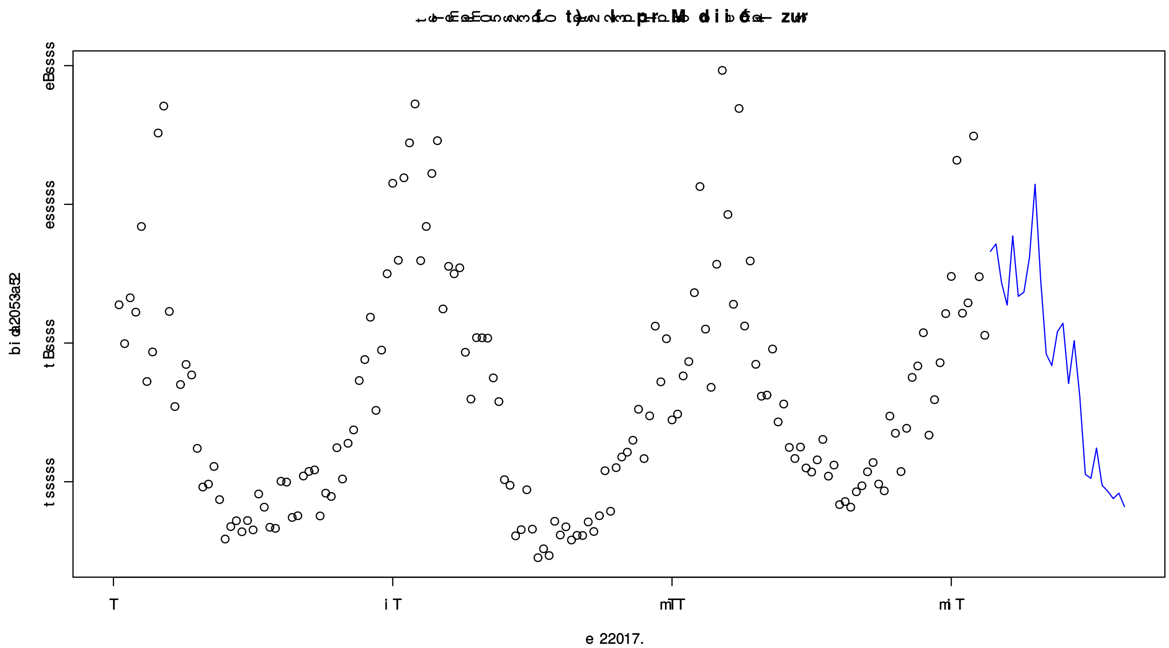
Weeknum	Sales_Liters
<dbl>	<dbl>
1	263778.2
2	249777.5
3	266308.4
4	261133.6
5	292004.5
6	236130.0

In [129]:
```
test <- base_test %>% select(c(Weeknum, Sales_Liters))
head(test)
```

A data.frame: 6 x 2

	Weeknum	Sales_Liters
	<dbl>	<dbl>
157	157	297444.3
158	158	297221.2
159	159	285992.0
160	160	322162.2
161	161	287530.2
162	162	372673.3

In [130]:
```
plot(train1, xlim = c(0,181), main = "Train (negro), Test (rojo) y la predicci
ón (azul)")
lines(RF_Pred, col='blue')
lines(test, col='red')
```



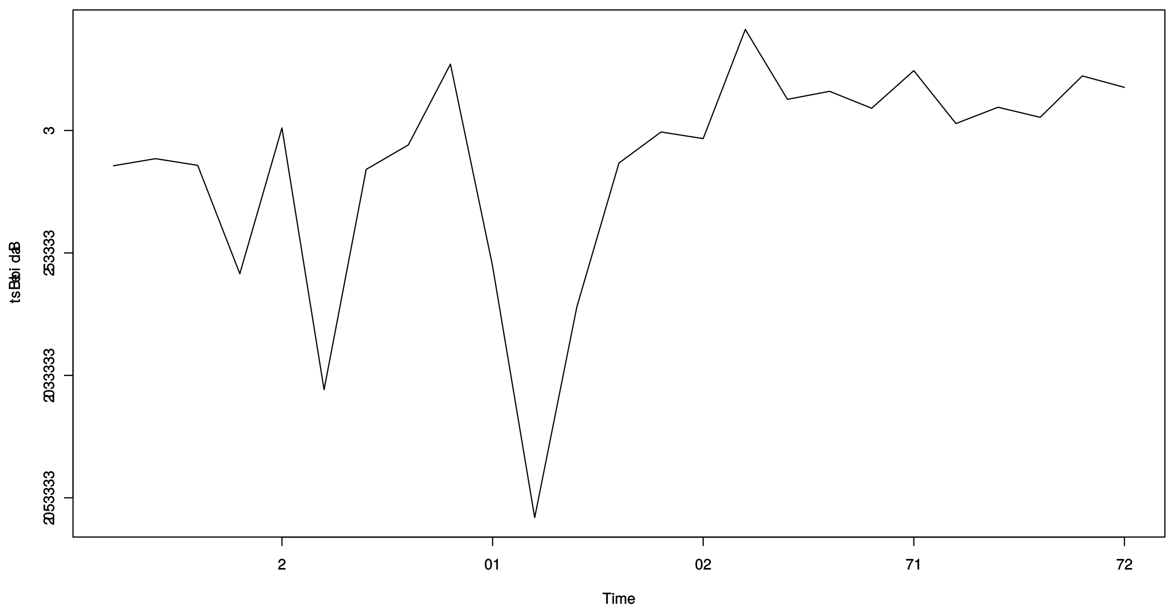
Vemos si los residuos del modelo son ruido blanco Gaussiano

In [134]:
```
residuals <- round(RF_Pred$Sales_Liters - test$Sales_Liters)
```

In [135]:
```
residuals_ts <- ts(residuals, start=157, end=181, frequency=1)
residuals_ts
ts.plot(residuals)
```

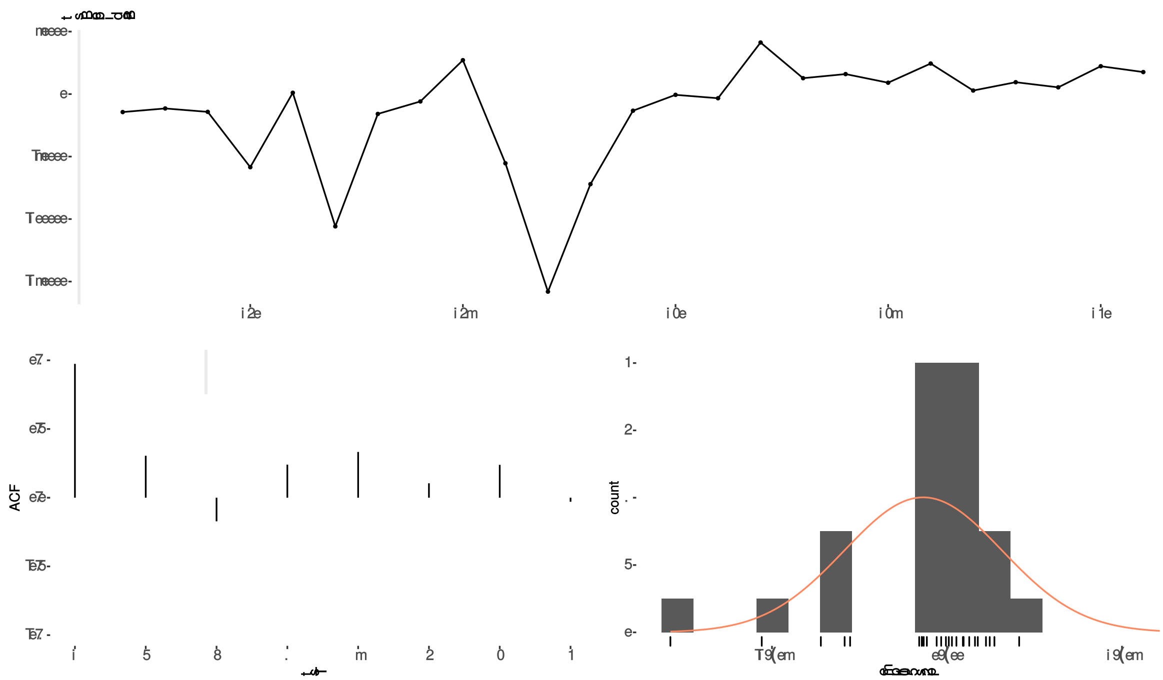
A Time Series:

-14396 -11500 -14236 -58488 1045 -105847 -15884 -5897 27106 -55359 -158054 -72069 -13305 -607 -3319 41252 12716 15997 9094 24431 2838 9494 5383 22283 17617



In [136]:
```
checkresiduals(residuals_ts)
```

```
Warning message in modeldf.default(object):
“Could not find appropriate degrees of freedom for this model.”
```



El ACF da muy bien en una serie que ha demostrado tener muy alta autocorrelación.

El ruido es blanco pero no llega a ser gaussiano. Entendemos que esto se da porque los grandes desaciertos son las compras de pánico en las que el modelo se queda corto, y no tiene grandes errores donde se pase. Como no tuvimos compras de pánico en los datos de entrenamiento es entendible que esto suceda y no lo vemos como una falla del modelo.

Para mejorar las predicciones de cara a futuro podemos crear una nueva variable dummy que sea situación de emergencia y llenar las semanas de marzo y abril donde esto sucedió así el modelo puede aprender de ello de cara a futuro y no nos altera a las demás variables.

CONCLUSIONES

Utilizamos datos reales de venta de agua y de la temperatura, para los cuáles no había un estudio previo adaptado a la realidad de nuestro país. Se trabajó mucho en la calidad de los datos previo a los análisis de la serie para poder llegar a un modelo que performe bien en la realidad y no sea sesgado por errores en los datos.

Realizamos 9 modelos en total (más varios que fueron a modo borrador) en los que incluimos diversas técnicas aprendidas en clase así como algunas otras que investigamos, ya sea con el libro o con papers que encontramos en la web.

Estas técnicas incluyeron:

- Análisis de componentes estacionarias
- Ajustes lineales y no lineales
- Análisis de residuos
- Correlaciones cruzadas
- Manejo de herramientas para series multivariables
- Técnicas de machine learning

Para validar los modelos utilizamos la metodología vista en clase de analizar el ruido y entender si es ruido blanco gaussiano con la menor varianza posible. Además dividimos nuestro dataset en train y test y comparamos nuestras predicciones con los datos de test que el modelo no utilizó para entrenar, como herramienta para evitar overfitting y tener otro indicador de la efectividad de predicción del modelo a efectos de la elección del modelo.

Nuestros modelos que realizaron mejores predicciones fueron el Random forest así como el Modelo 7 (basado en el análisis de residuos y agregando las componentes estacionarias). Para hacer la elección entendemos que en accuracy están muy parejos, por lo que elegiríamos el Modelo 7 por su mayor interpretabilidad ya que tiene una base estadística con una clara explicación y no es tan randómica como es un random forest. Igualmente nos quedamos con el random forest como modelo challenger para tener un respaldo y por si en los eventos futuros se adapta mejor a la dinámica de la realidad.