

Examen II - Distribuciones de Pérdidas

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1. Considere los siguientes datos:

27	82	115	126	155	161	243	294	340	384
457	680	855	877	974	1.193	1.340	1.884	2.558	3.476

1. Calcule las funciones de densidad y probabilidad empíricas, y grafique en comparación con la respectiva distribución exponencial.

```
library(fitdistrplus)
```

```
datos <- c(27, 82, 115, 126, 155, 161, 243, 294, 340, 384, 457, 680, 855, 877, 974, 1193, 1340, 1884, 2558, 3476)
```

```
f.exp<-fitdist(datos, "exp",method = "mme")
f.exp
```

Fitting of the distribution ' exp ' by matching moments

Parameters:

```
estimate
rate 0.00123297
```

```
f.gamma<-fitdist(datos, "gamma", method = "mme")
f.gamma
```

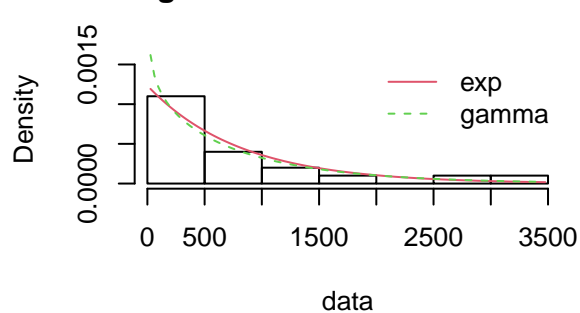
Fitting of the distribution ' gamma ' by matching moments

Parameters:

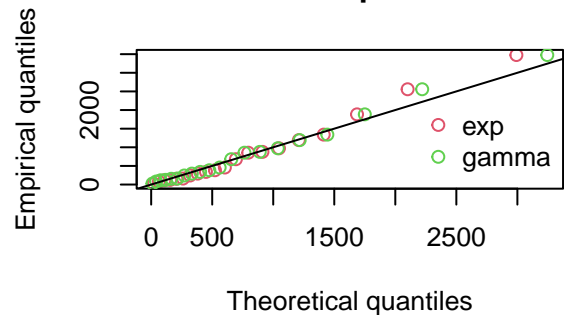
```
estimate
shape 0.829860219
rate 0.001023192
```

```
par(mfrow=c(2,2))
plot.legend<-c("exp","gamma")
denscomp(list(f.exp,f.gamma), legendtext=plot.legend)
qqcomp(list(f.exp, f.gamma), legendtext=plot.legend)
cdfcomp(list(f.exp, f.gamma), legendtext=plot.legend)
ppcomp(list(f.exp, f.gamma), legendtext=plot.legend)
```

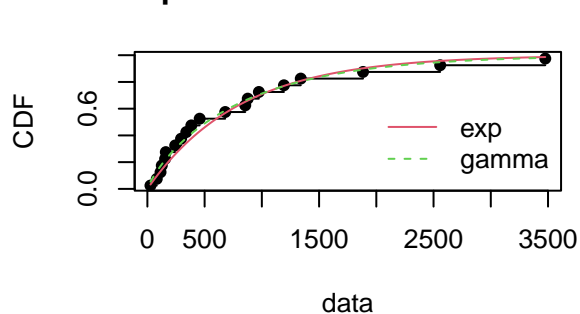
Histogram and theoretical densities



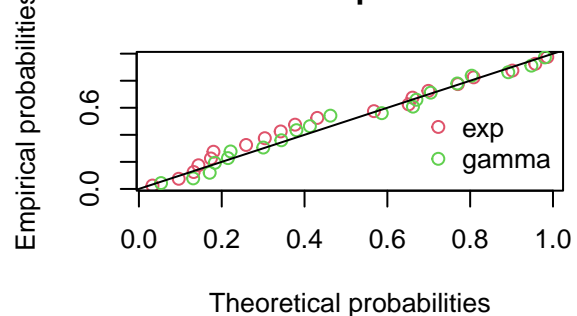
Q-Q plot



Empirical and theoretical CDFs



P-P plot



2. Realice los test Kolmogorov-Smirnov y Anderson-Darling y analice los resultados.

```
comparacion <- gofstat(f = list(f.exp, f.gamma))
comparacion
```

Goodness-of-fit statistics

	1-mme-exp	2-mme-gamma
Kolmogorov-Smirnov statistic	0.12284329	0.08751566
Cramer-von Mises statistic	0.05581739	0.02785829
Anderson-Darling statistic	0.32587814	0.20105473

Goodness-of-fit criteria

	1-mme-exp	2-mme-gamma
Akaike's Information Criterion	309.9332	311.9601
Bayesian Information Criterion	310.9289	313.9516

3. Determine si un modelo gamma es más apropiado que el modelo exponencial.

El más apropiado es gamma debido al resultado de las pruebas y el hecho de que los valores extremos se acercan más al ajuste de la gamma.

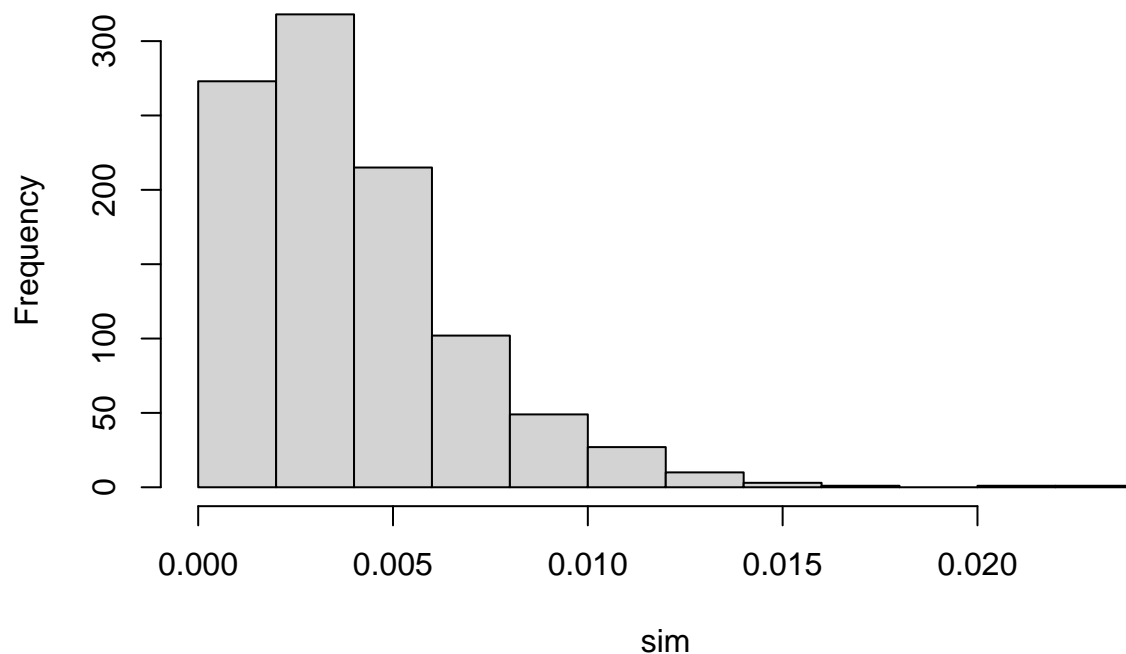
2. Simule 1,000 observaciones de una distribución gamma con $\alpha = 2$ y $\theta = 500$. Realice las pruebas de bondad de ajuste de chi-cuadrado y Kolmogorov-Smirnov para ver si los valores indicados eran en realidad de esa distribución

```
library(EnvStats)

set.seed(3)

sim <- rgamma(1000,2,500)
hist(sim)
```

Histogram of sim



```
f<-fitdist(sim,"gamma",method = "mle")
f
```

Fitting of the distribution ' gamma ' by maximum likelihood
Parameters:

	estimate	Std. Error
shape	2.004136	0.08324291
rate	503.042024	23.72342133

```
test.chi <- gofTest(sim, test = "chisq", distribution = "gamma",
  param.list = list(shape = 2, scale = 1/500))
```

```
test.chi$p.value
```

```
[1] 0.6425503
```

```
test.KS <- gofTest(sim, test = "ks", distribution = "gamma",
  param.list = list(shape = 2, scale = 1/500))
```

```
test.KS$p.value
```

```
[1] 0.6376003
```

```
ks.test(sim,"pgamma",2,500)
```

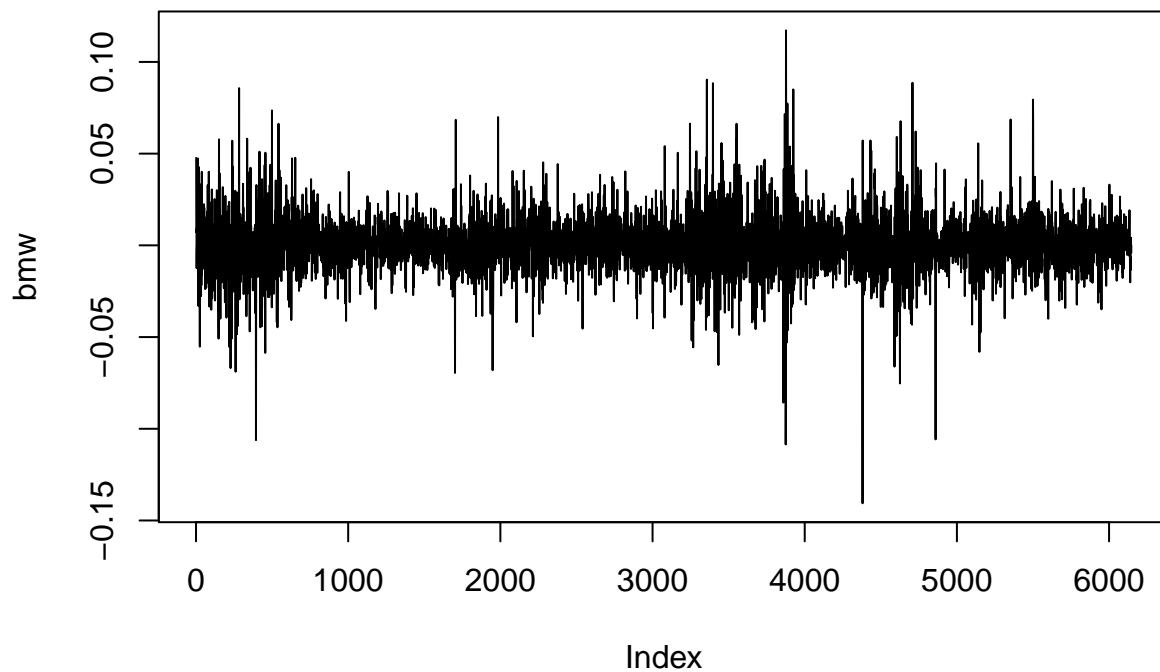
One-sample Kolmogorov-Smirnov test

```
data: sim  
D = 0.023521, p-value = 0.6376  
alternative hypothesis: two-sided
```

Tenemos un valor p de 0.63, por lo tanto no rechazamos la hipótesis nula y por lo tanto los datos simulados siguen una distribución Gamma.

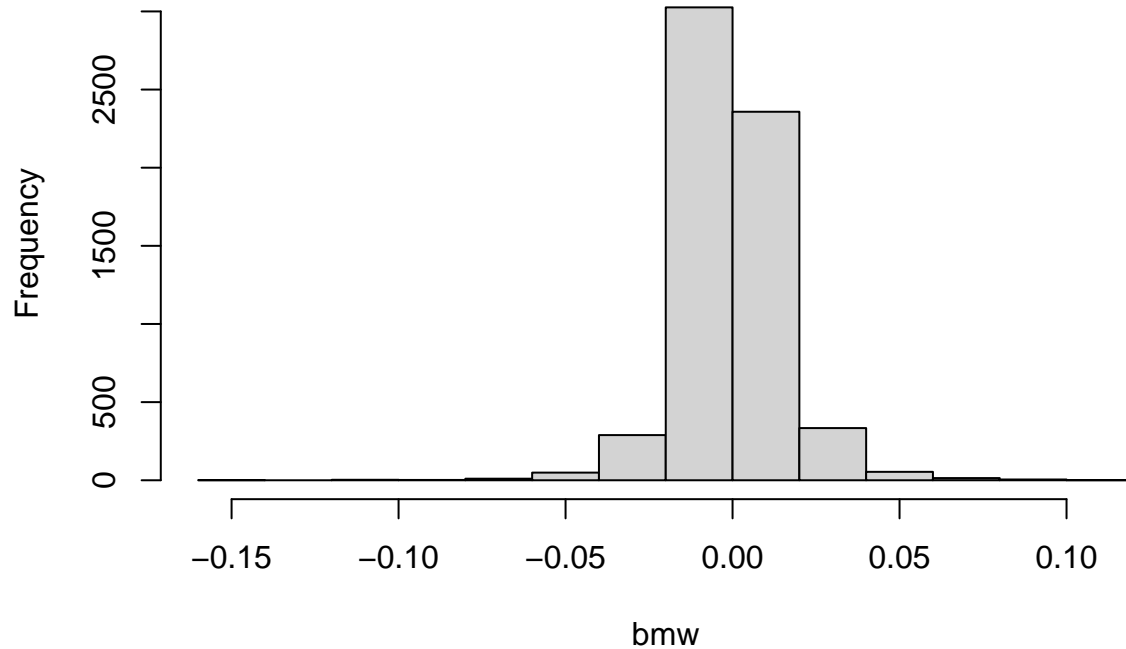
3. Utilice los datos BMW, del paquete evir y ajuste un modelo para los valores extremos.

```
library(evir)  
data(bmw)  
plot(bmw,type="l") # reclamos
```



```
hist(bmw)
```

Histogram of bmw

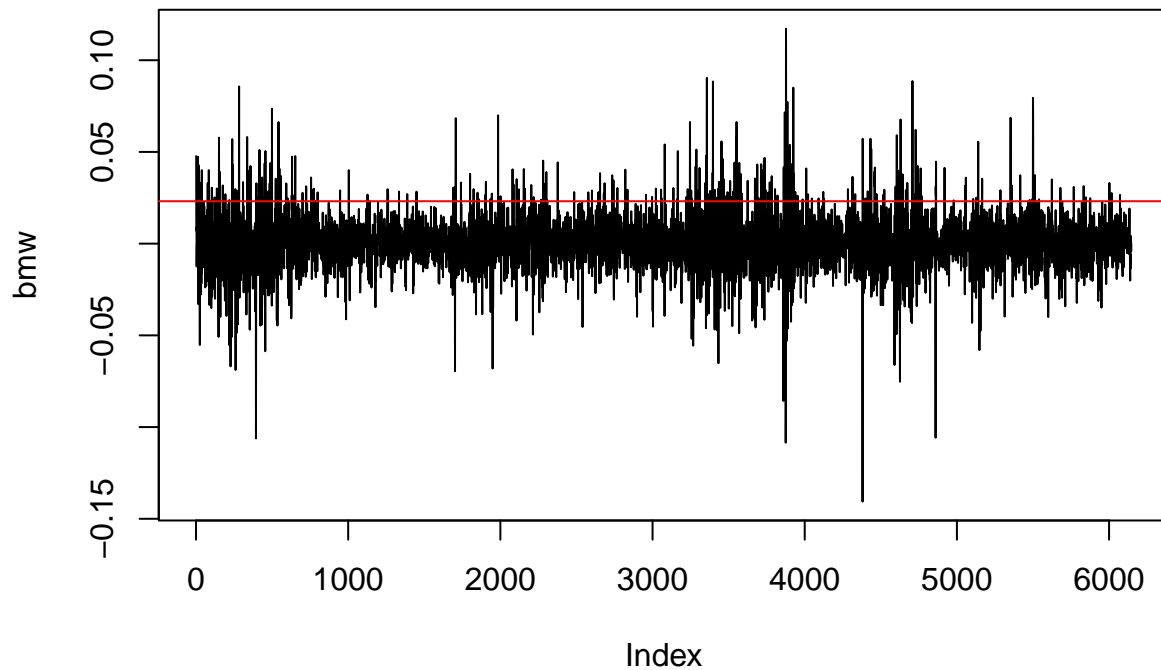


```
#findthresh(danish, 100)
umbral=quantile(bmw,0.95)[[1]]
umbral
```

```
[1] 0.02313954
```

Aunque observamos que hay valores extremos muy grandes y muy pequeños, para efectos de examen solo ajustaremos para la cola derecha.

```
plot(bmw,type="l")
abline(umbral,0,col="red")
```



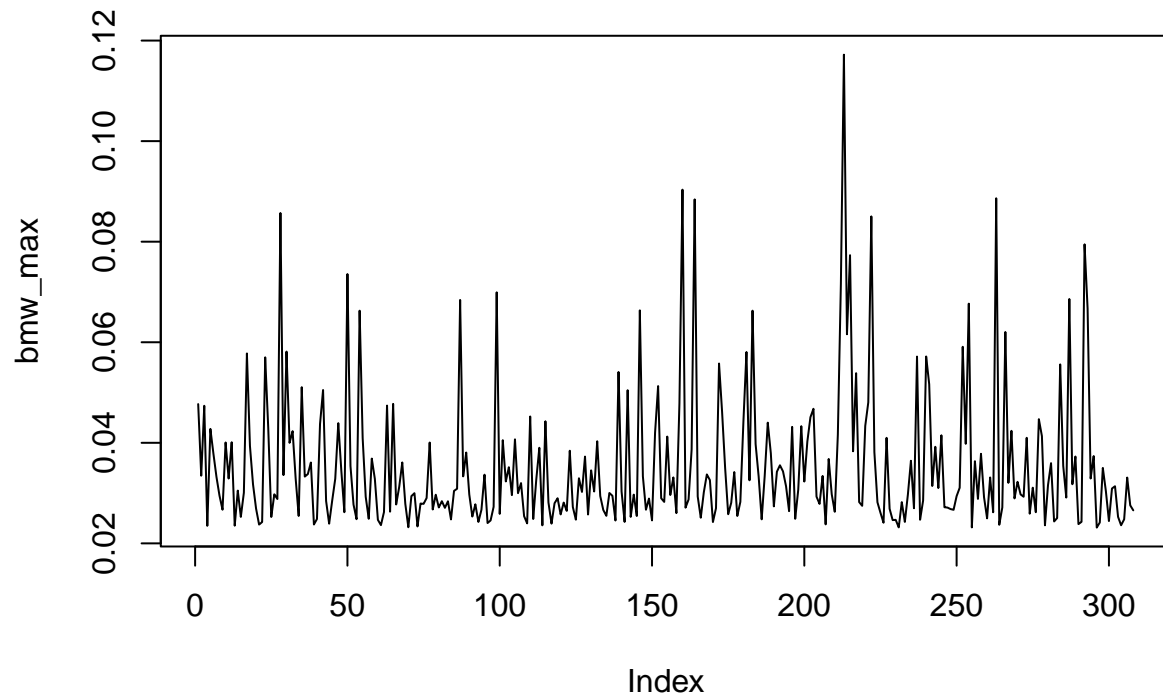
Seleccionamos los valores extremos muy grandes.

```
bmw_max = bmw [bmw > umbral]
bmw_max
```

```
[1] 0.04770410 0.03345517 0.04737021 0.02348919 0.04277424 0.03785610
[7] 0.03323864 0.02949422 0.02669554 0.04007255 0.03289267 0.04012086
[13] 0.02351833 0.03049844 0.02526246 0.03007232 0.05777954 0.03938238
[19] 0.03174870 0.02694025 0.02373553 0.02424703 0.05700682 0.04296787
[25] 0.02524532 0.02975924 0.02882430 0.08570879 0.03358474 0.05814339
[31] 0.03999634 0.04232692 0.03290903 0.02545048 0.05106974 0.03328449
[37] 0.03378306 0.03608405 0.02375827 0.02484257 0.04373824 0.05050920
[43] 0.02842941 0.02391716 0.02854240 0.03285567 0.04391641 0.03443060
[49] 0.02619513 0.07356377 0.03538940 0.02771967 0.02480504 0.06627812
[55] 0.04093036 0.02926907 0.02488772 0.03686648 0.03282389 0.02468098
[61] 0.02363220 0.02621992 0.04740888 0.02630146 0.04774362 0.02773400
[67] 0.03121549 0.03609579 0.02786285 0.02320689 0.02939476 0.02998439
[73] 0.02337254 0.02792824 0.02785748
[ reached getOption("max.print") -- omitted 233 entries ]
```

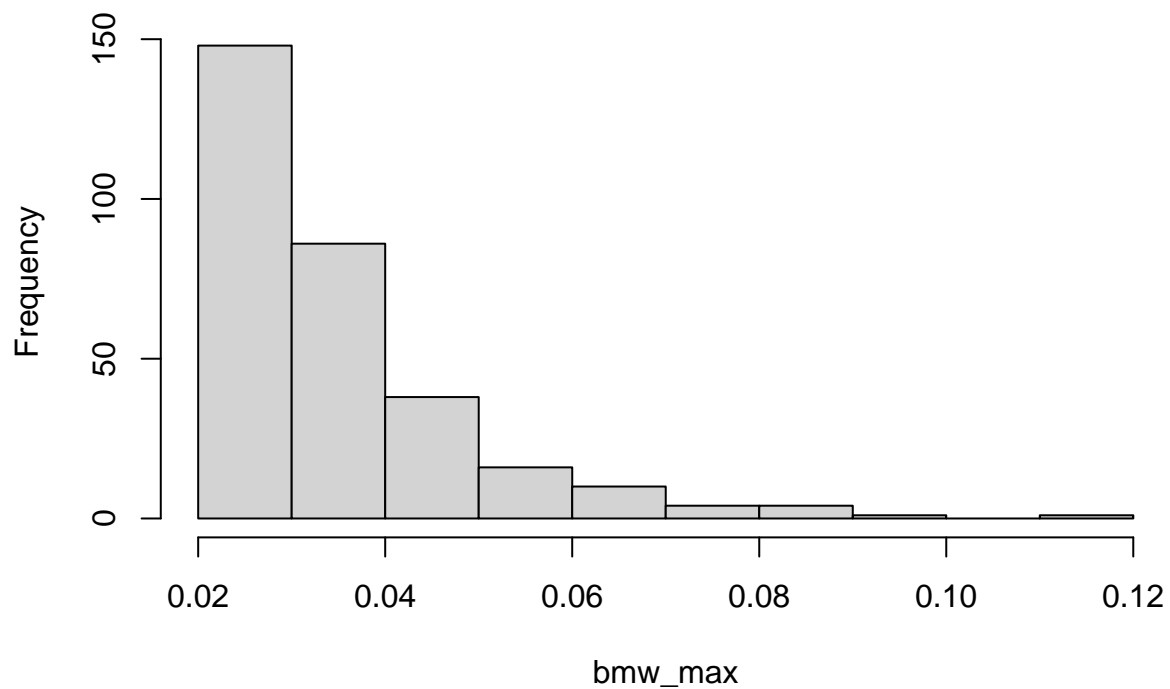
Valores fuera del umbral

```
plot(bmw_max,type="l")
```



```
hist(bmw_max)
```

Histogram of bmw_max



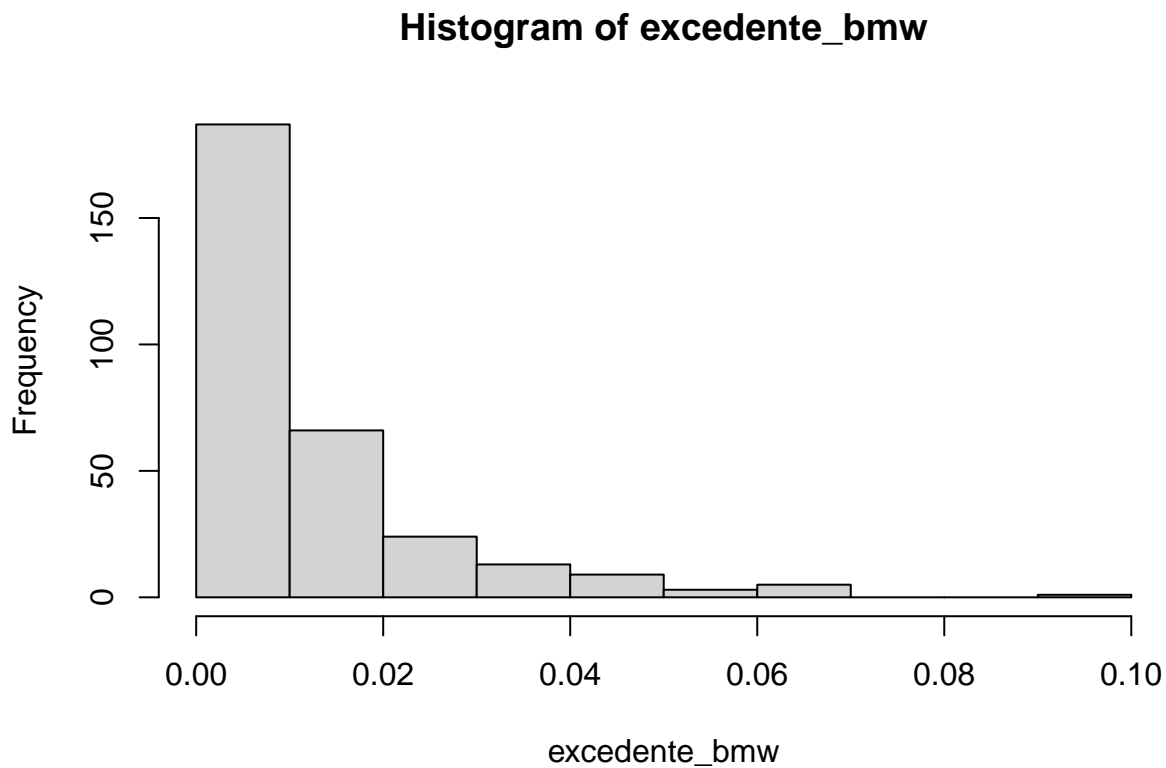
```
## calculariamos los excedentes
excedente_bmw = bmw_max - umbral
excedente_bmw
```

```
[1] 2.456456e-02 1.031564e-02 2.423068e-02 3.496522e-04 1.963470e-02
```

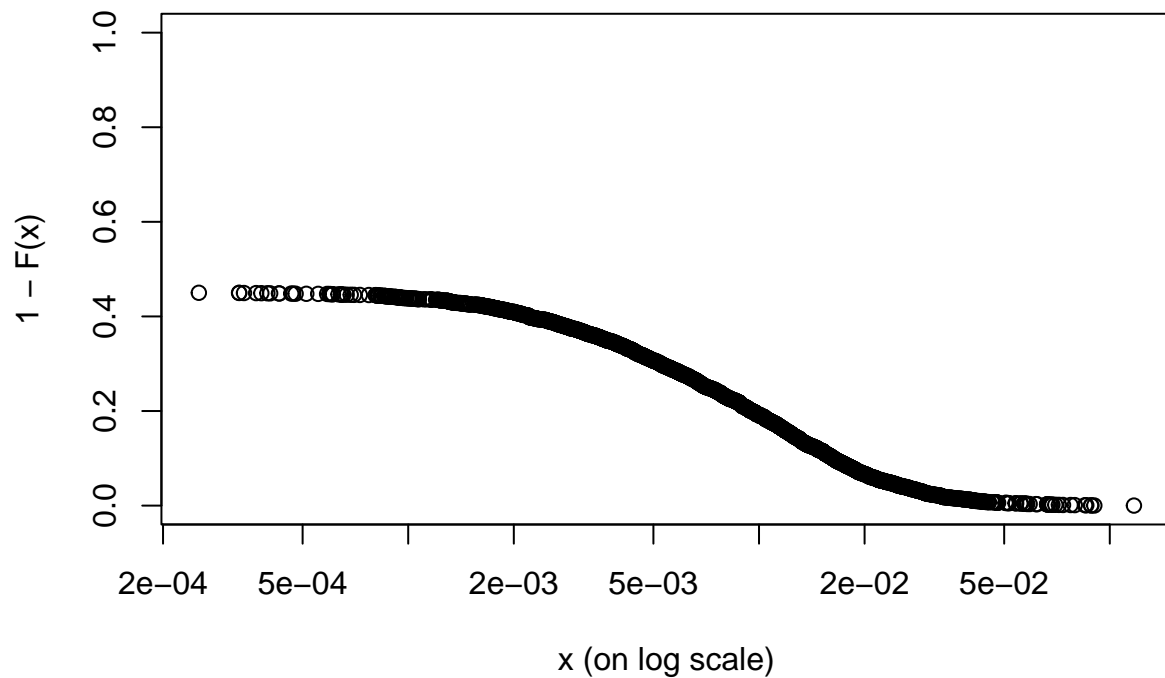


```
[6] 1.471656e-02 1.009910e-02 6.354681e-03 3.556006e-03 1.693301e-02
[11] 9.753133e-03 1.698133e-02 3.787969e-04 7.358901e-03 2.122919e-03
[16] 6.932778e-03 3.464000e-02 1.624284e-02 8.609161e-03 3.800710e-03
[21] 5.959918e-04 1.107492e-03 3.386728e-02 1.982833e-02 2.105785e-03
[26] 6.619706e-03 5.684765e-03 6.256925e-02 1.044520e-02 3.500386e-02
[31] 1.685681e-02 1.918739e-02 9.769497e-03 2.310938e-03 2.793020e-02
[36] 1.014495e-02 1.064352e-02 1.294452e-02 6.187292e-04 1.703032e-03
[41] 2.059870e-02 2.736966e-02 5.289869e-03 7.776228e-04 5.402863e-03
[46] 9.716128e-03 2.077687e-02 1.129107e-02 3.055594e-03 5.042423e-02
[51] 1.224986e-02 4.580131e-03 1.665502e-03 4.313858e-02 1.779082e-02
[56] 6.129529e-03 1.748178e-03 1.372694e-02 9.684348e-03 1.541444e-03
[61] 4.926598e-04 3.080381e-03 2.426934e-02 3.161918e-03 2.460408e-02
[66] 4.594460e-03 8.075956e-03 1.295625e-02 4.723313e-03 6.734853e-05
[71] 6.255218e-03 6.844853e-03 2.330036e-04 4.788699e-03 4.717947e-03
[ reached getOption("max.print") -- omitted 233 entries ]
```

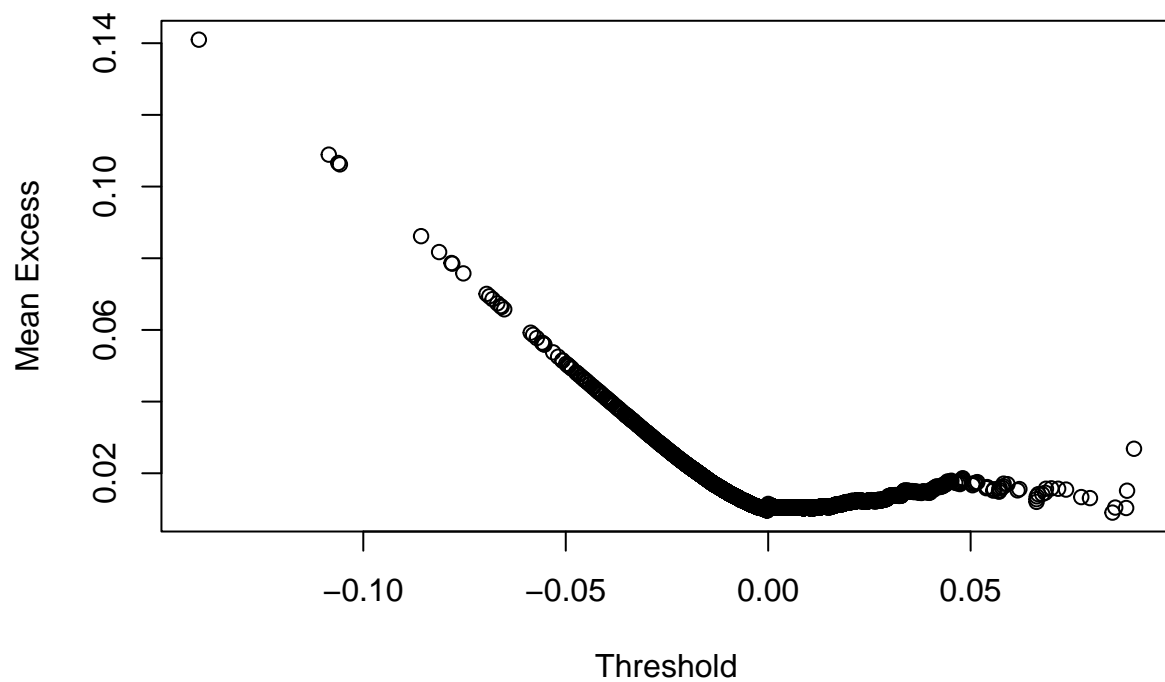
```
hist(excedente_bmw)
```



```
emplot(bmw) # distribución empírica
```



```
meplot(bmw, omit = 0) # gráfico los excesos medios de la muestra sobre los umbrales crecientes
```



```
fit<- gpd(bmw,threshold=umbral, nextremes=NA) # umbral y cantidad
fit
```

```
$n
[1] 6146
```

```
$data
```

```

[1] 0.04770410 0.03345517 0.04737021 0.02348919 0.04277424 0.03785610
[7] 0.03323864 0.02949422 0.02669554 0.04007255 0.03289267 0.04012086
[13] 0.02351833 0.03049844 0.02526246 0.03007232 0.05777954 0.03938238
[19] 0.03174870 0.02694025 0.02373553 0.02424703 0.05700682 0.04296787
[25] 0.02524532 0.02975924 0.02882430 0.08570879 0.03358474 0.05814339
[31] 0.03999634 0.04232692 0.03290903 0.02545048 0.05106974 0.03328449
[37] 0.03378306 0.03608405 0.02375827 0.02484257 0.04373824 0.05050920
[43] 0.02842941 0.02391716 0.02854240 0.03285567 0.04391641 0.03443060
[49] 0.02619513 0.07356377 0.03538940 0.02771967 0.02480504 0.06627812
[55] 0.04093036 0.02926907 0.02488772 0.03686648 0.03282389 0.02468098
[61] 0.02363220 0.02621992 0.04740888 0.02630146 0.04774362 0.02773400
[67] 0.03121549 0.03609579 0.02786285 0.02320689 0.02939476 0.02998439
[73] 0.02337254 0.02792824 0.02785748

```

```
[ reached getOption("max.print") -- omitted 233 entries ]
```

```
$threshold
```

```
[1] 0.02313954
```

```
$p.less.thresh
```

```
[1] 0.9498861
```

```
$n.exceed
```

```
[1] 308
```

```
$method
```

```
[1] "ml"
```

```
$par.ests
```

```

          xi          beta
0.12437449 0.01073653

```

```
$par.ses
```

```

          xi          beta
0.0654954914 0.0009074181

```

```
$varcov
```

```

          [,1]      [,2]
[1,] 4.289659e-03 -4.013864e-05
[2,] -4.013864e-05 8.234076e-07

```

```
$information
```

```
[1] "observed"
```

```
$converged
```

```
[1] 0
```

```
$nllh.final
```

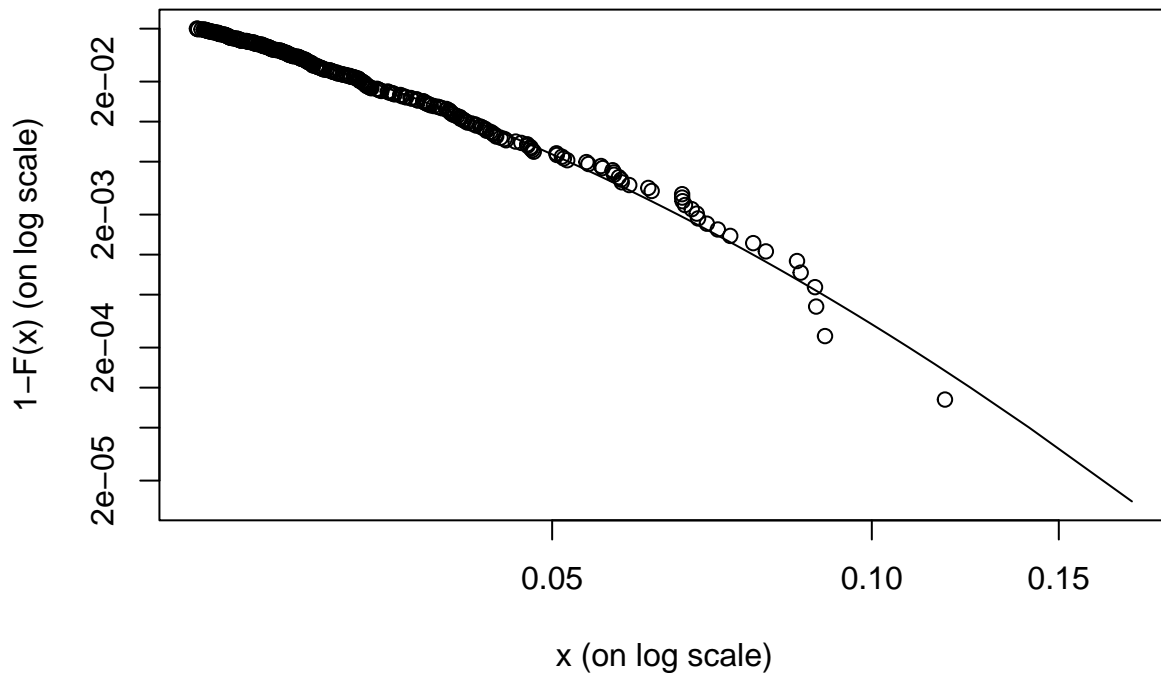
```
[1] -1050.31
```

```
attr(,"class")
```

```
[1] "gpd"
```

Observamos que el modelo si ajusta bien.

```
#gráfico de la cola de la distribución subyacente de los datos.
tp<-tailplot(fit)
```



```
tp
```

```
$lastfit
```

```
$n
```

```
[1] 6146
```

```
$data
```

```
[1] 0.04770410 0.03345517 0.04737021 0.02348919 0.04277424 0.03785610
[7] 0.03323864 0.02949422 0.02669554 0.04007255 0.03289267 0.04012086
[13] 0.02351833 0.03049844 0.02526246 0.03007232 0.05777954 0.03938238
[19] 0.03174870 0.02694025 0.02373553 0.02424703 0.05700682 0.04296787
[25] 0.02524532 0.02975924 0.02882430 0.08570879 0.03358474 0.05814339
[31] 0.03999634 0.04232692 0.03290903 0.02545048 0.05106974 0.03328449
[37] 0.03378306 0.03608405 0.02375827 0.02484257 0.04373824 0.05050920
[43] 0.02842941 0.02391716 0.02854240 0.03285567 0.04391641 0.03443060
[49] 0.02619513 0.07356377 0.03538940 0.02771967 0.02480504 0.06627812
[55] 0.04093036 0.02926907 0.02488772 0.03686648 0.03282389 0.02468098
[61] 0.02363220 0.02621992 0.04740888 0.02630146 0.04774362 0.02773400
[67] 0.03121549 0.03609579 0.02786285 0.02320689 0.02939476 0.02998439
[73] 0.02337254 0.02792824 0.02785748
[ reached getOption("max.print") -- omitted 233 entries ]
```

```
$threshold
```

```
[1] 0.02313954
```

```
$p.less.thresh
```

```
[1] 0.9498861
```

```

$n.exceed
[1] 308

$method
[1] "ml"

$par.ests
      xi      beta
0.12437449 0.01073653

$par.ses
      xi      beta
0.0654954914 0.0009074181

$varcov
      [,1]      [,2]
[1,] 4.289659e-03 -4.013864e-05
[2,] -4.013864e-05 8.234076e-07

$information
[1] "observed"

$converged
[1] 0

$nullh.final
[1] -1050.31

attr("class")
[1] "gpd"

$type
[1] "tail"

$dist
[1] "gpd"

$plotmin
[1] 0.02313954

$plotmax
[1] 0.1757877

$alog
[1] "xy"

$location
[1] -0.003695129

$shape
[1] 0.1243745

$scale
[1] 0.007398978

```

```
# Los 3 parámetros - localización, escala, forma
```

```
loc<-tp$location  
scal<-tp$scale  
shape<-tp$shape
```

```
loc;scal;shape
```

```
[1] -0.003695129
```

```
[1] 0.007398978
```

```
[1] 0.1243745
```

```
riskmeasures(fit, 0.99)
```

```
      p  quantile      sfall  
[1,] 0.99 0.04230004 0.05728316
```

4. Considere la spline de suavizado cúbico natural que suaviza los puntos (0, 0), (1, 2), (2, 1), (3, 3) usando $p = 0.9$ y desviaciones estándar de 0.5.

(a) Obtenga los valores de las intersecciones de los nodos.

```
p <- 0.9  
H <- matrix(c(4,1,1,4),nrow = 2, byrow = T)  
H
```

```
      [,1] [,2]  
[1,]     4     1  
[2,]     1     4
```

```
R <- matrix(c(1,-2,1,0,0,1,-2,1),nrow = 2, byrow = T)  
R
```

```
      [,1] [,2] [,3] [,4]  
[1,]     1    -2     1     0  
[2,]     0     1    -2     1
```

```
R1 <- 6*R  
R1
```

```
      [,1] [,2] [,3] [,4]  
[1,]     6   -12     6     0  
[2,]     0     6   -12     6
```

```
S <- diag(x = 0.25, nrow = 4, ncol = 4)
S
```

```
      [,1] [,2] [,3] [,4]
[1,] 0.25 0.00 0.00 0.00
[2,] 0.00 0.25 0.00 0.00
[3,] 0.00 0.00 0.25 0.00
[4,] 0.00 0.00 0.00 0.25
```

```
res <- R1%*%S%*%t(R1)
res
```

```
      [,1] [,2]
[1,]    54   -36
[2,]   -36    54
```

```
res2 <- H + ((1-p)/(6*p))*res
res2
```

```
      [,1] [,2]
[1,] 5.0000000 0.3333333
[2,] 0.3333333 5.0000000
```

```
inversa <- solve(res2)
inversa
```

```
      [,1] [,2]
[1,] 0.20089286 -0.01339286
[2,] -0.01339286 0.20089286
```

```
y <-c(0,2,1,3)
y
```

```
[1] 0 2 1 3
```

```
a <- y - (1-p)/(6*p) * S%*%t(R1) %*% inversa %*% R1%*%y
cat("Respuesta: a = ", a)
```

```
Respuesta: a = 0.1071429 1.678571 1.321429 2.892857
```

(b) Obtenga el spline de suavizado cúbico natural como el spline de interpolación natural.

```
H
```

```
      [,1] [,2]
[1,]    4    1
[2,]    1    4
```

```
u <- matrix(c(-11.571,11.571))
```

```
m <- solve(H)%*%u
```

```
m
```

```
      [,1]  
[1,] -3.857  
[2,]  3.857
```

```
m1 <-c(0,m,0)
```

```
m1
```

```
[1]  0.000 -3.857  3.857  0.000
```

```
y<- c(0,2,1,3)
```

```
x<- c(0,1,2,3)
```

```
h <- c(1,1,1)
```

```
g <- c(4,4)
```

```
u<- c(-18,18)
```

```
xj<-c()
```

```
aj<- c()
```

```
bj <- c()
```

```
cj <- c()
```

```
dj <- c()
```

```
for (i in 1:3){
```

```
  xj[i] <- x[i]
```

```
  aj[i] <- a[i]
```

```
  bj[i] <- ((a[i+1]-a[i])/h[i]) - ((h[i]*(2*m1[i] + m1[i+1]))/6)
```

```
  cj[i] <- m1[i]/2
```

```
  dj[i] <- (m1[i+1]-m1[i])/(6*h[i])
```

```
  print(i)
```

```
}
```

```
[1] 1
```

```
[1] 2
```

```
[1] 3
```

```
data.frame(xj,aj,bj,cj,dj)
```

```
      xj      aj      bj      cj      dj  
1  0 0.1071429 2.2142619  0.0000 -0.6428333  
2  1 1.6785714 0.2856905 -1.9285  1.2856667  
3  2 1.3214286 0.2857619  1.9285 -0.6428333
```


(c) Grafique el spline resultante de $x = 0.5$ a $x = 2.5$.

```
plot(x, y, main = "spline(.)")
lines(spline(x, y, n = 201), col = 2)
lines(spline(x, y, n = 201, method = "natural"), col = 3)
lines(spline(x, y, n = 201, method = "periodic"), col = 4)
legend(6,25, c("fmm", "natural", "periodic"), col=2:4, lty=1)
```

