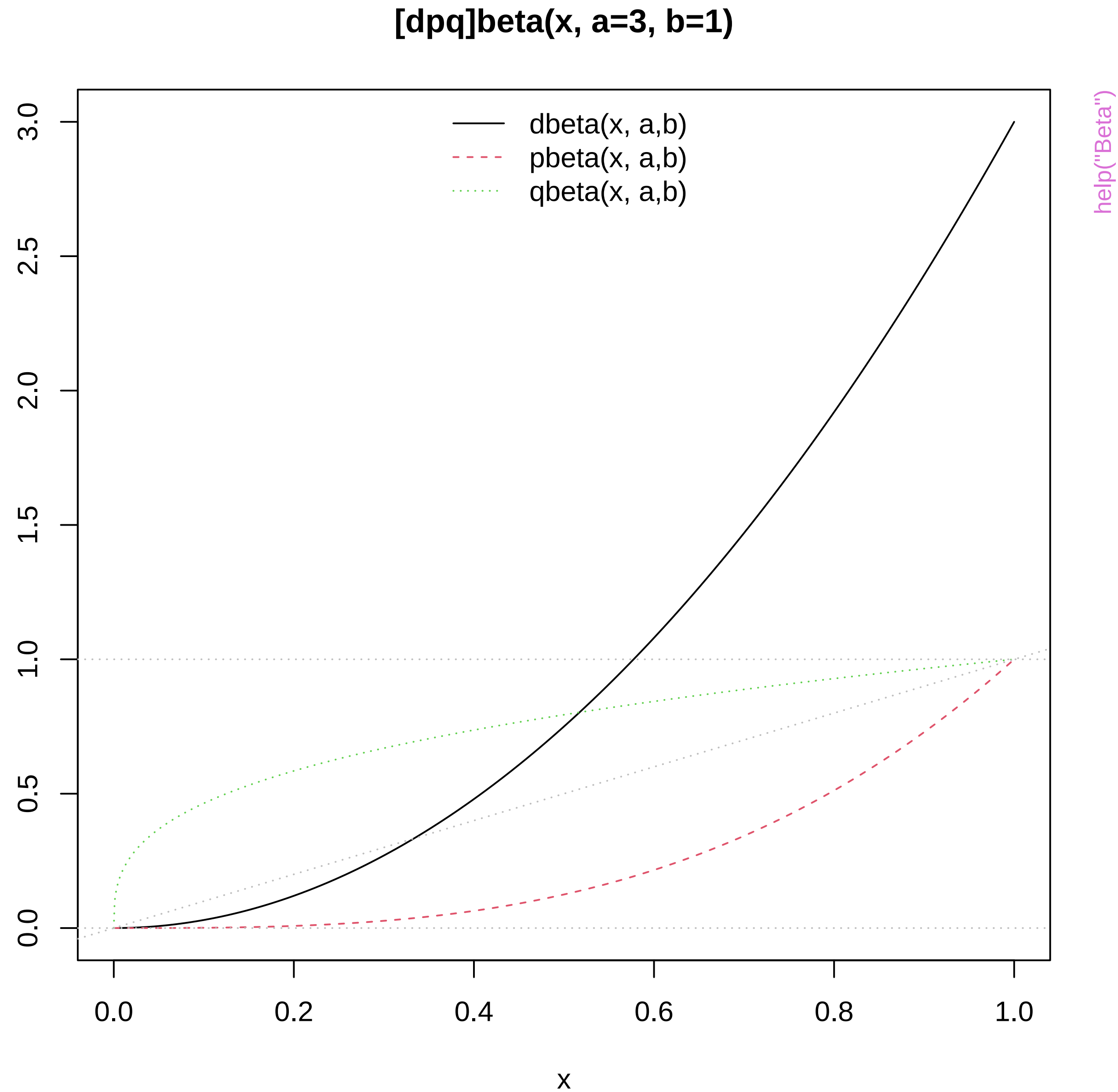
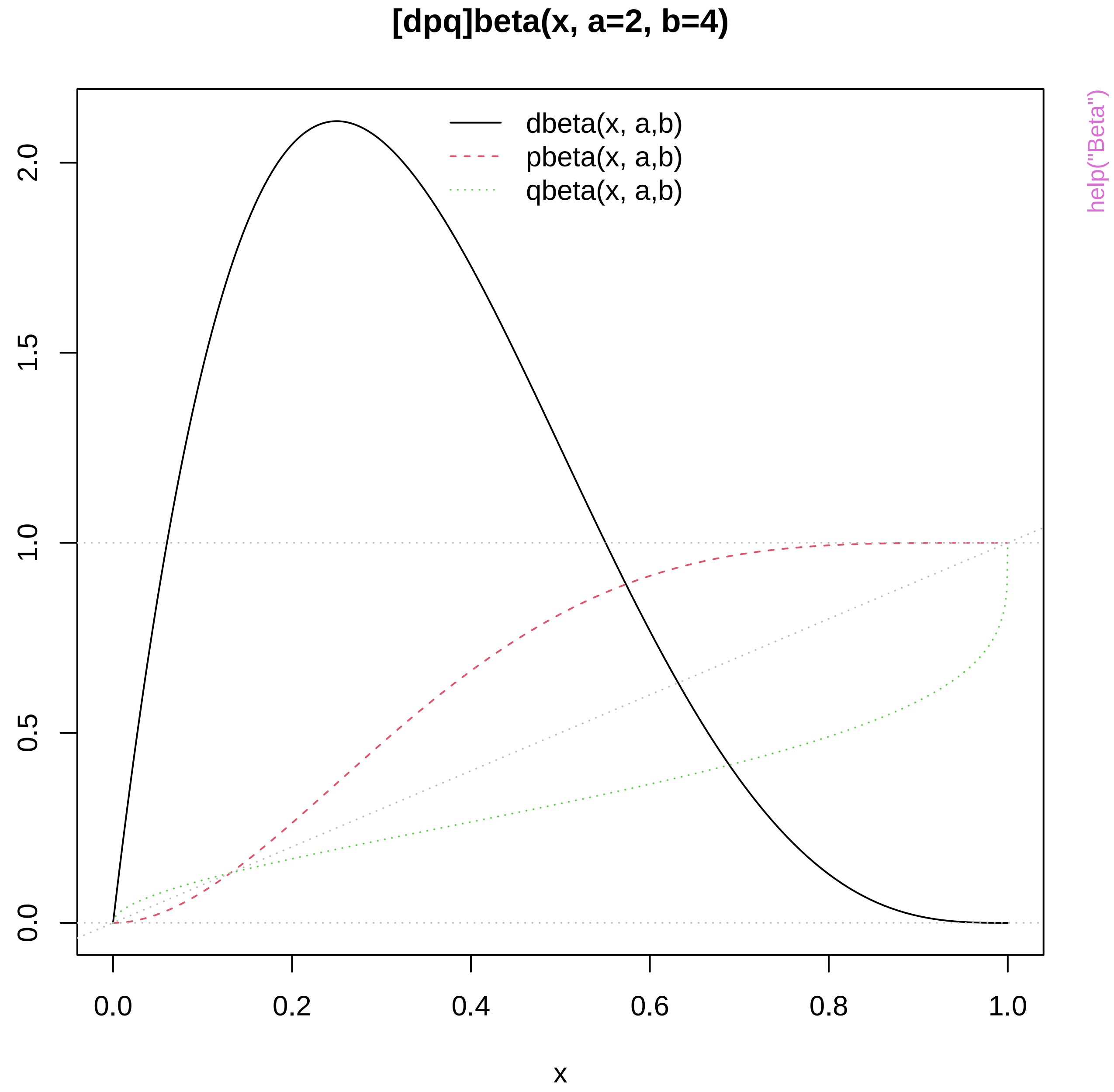
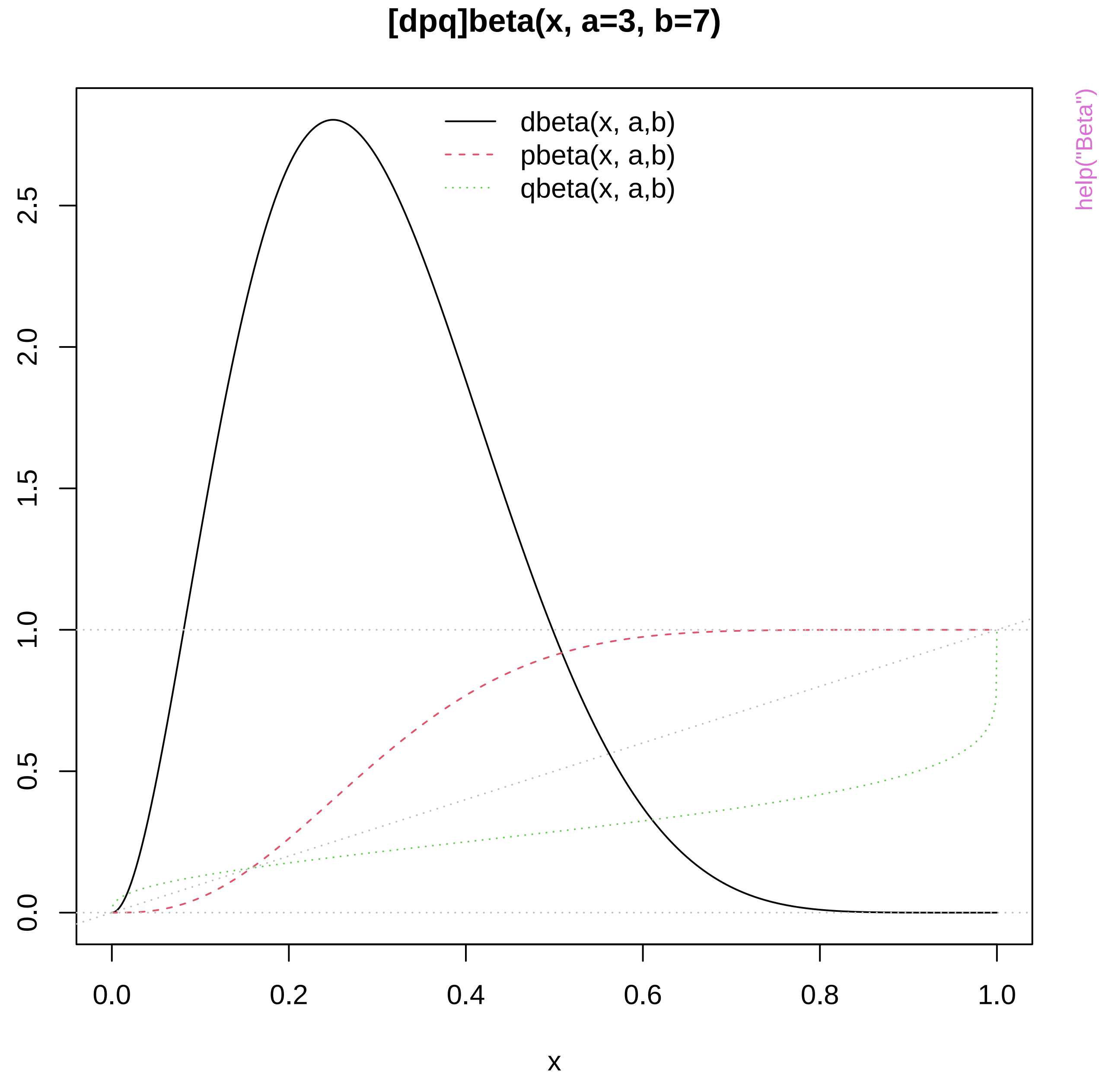
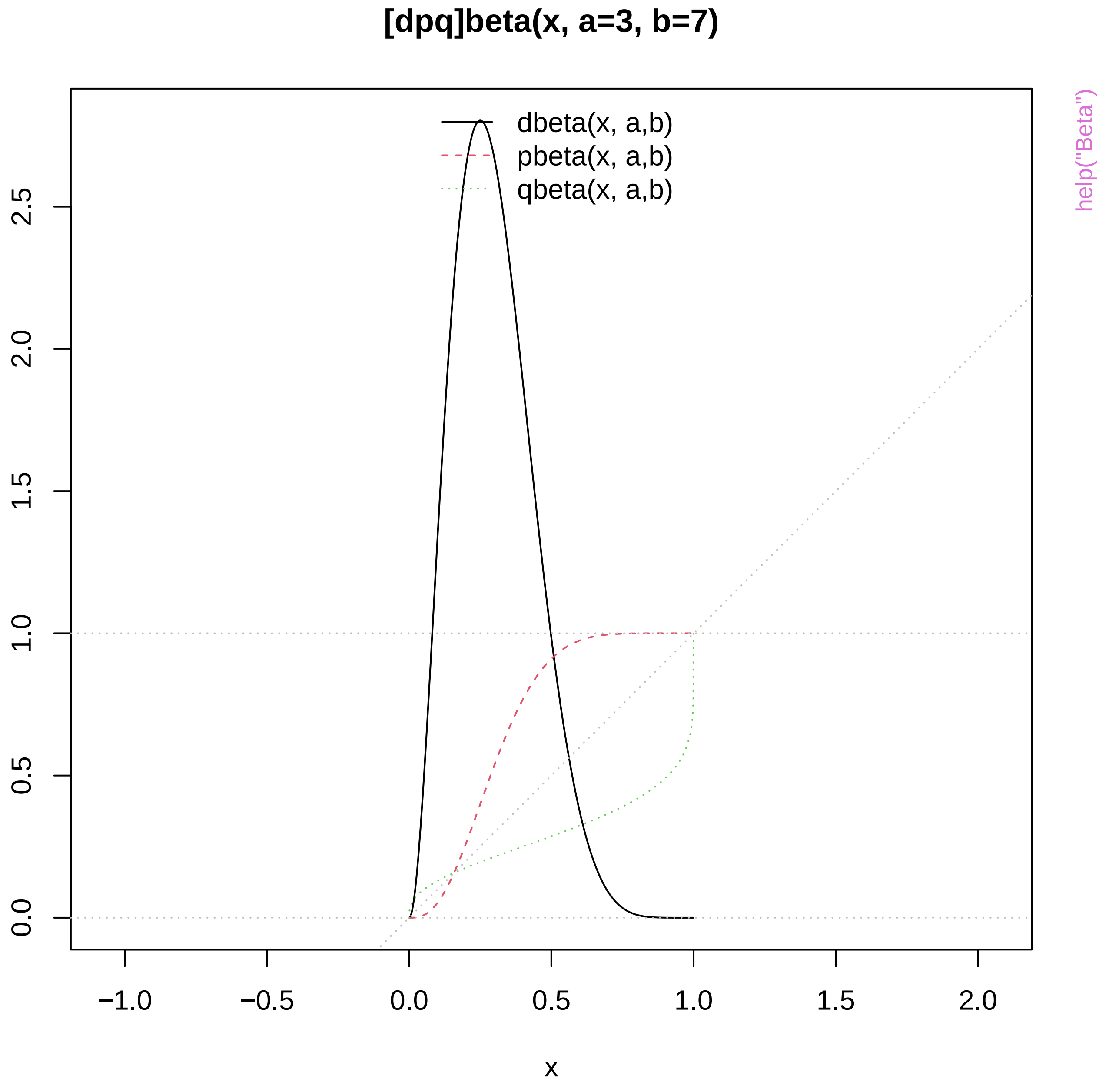


[dpq]beta(x, a=3, b=1)
dbeta(x, a,b)
pbeta(x, a,b)
qbeta(x, a,b)
help("Beta")
0.0
0.5
1.0
1.5
2.0
2.5
3.0
0.0
0.2
0.4
0.6
0.8
1.0
x

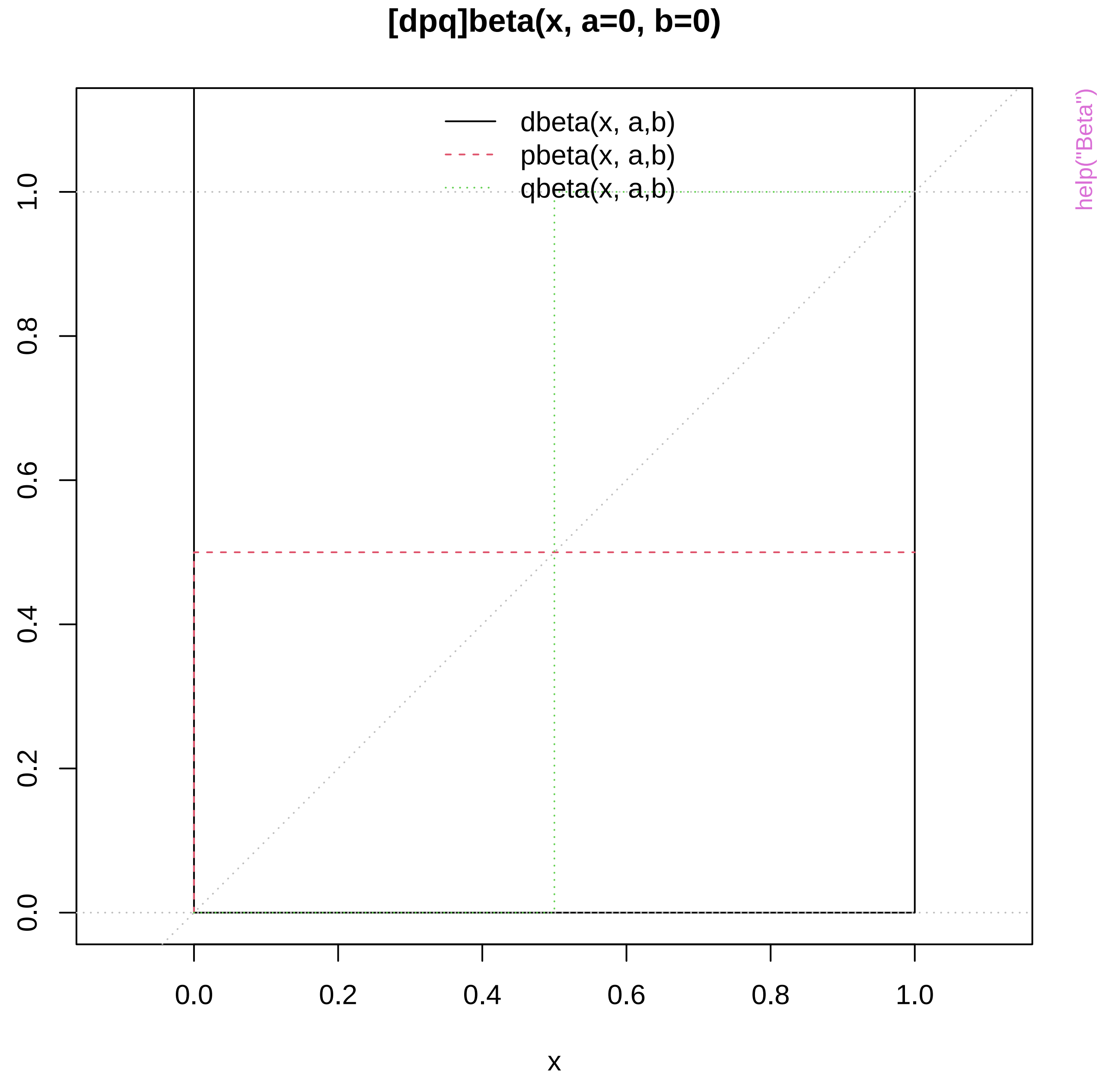

[dpq]beta(x, a=2, b=4)
dbeta(x, a,b)
pbeta(x, a,b)
qbeta(x, a,b)
help("Beta")
0.0
0.5
1.0
1.5
2.0
0.0
0.2
0.4
0.6
0.8
1.0
x

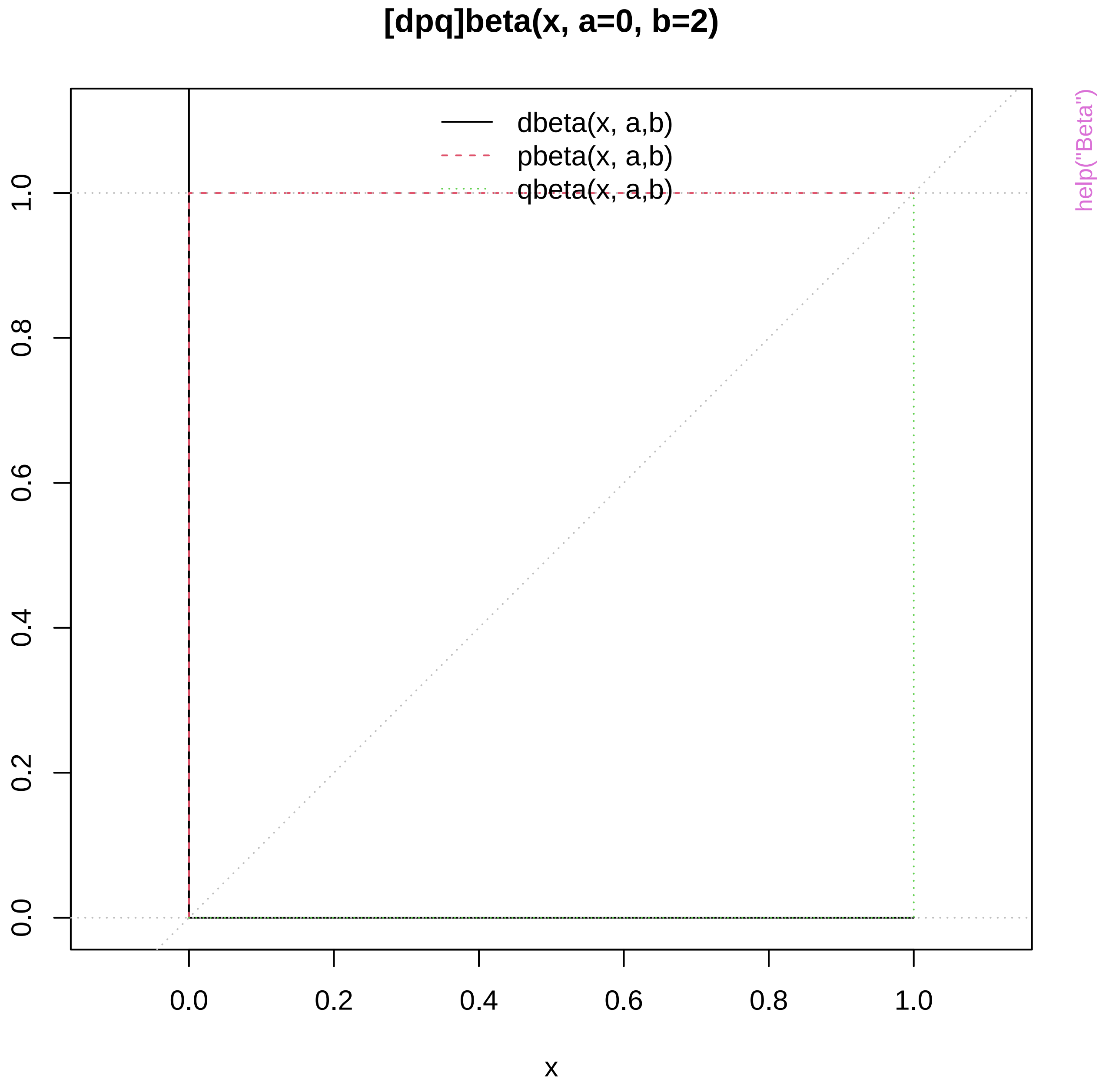


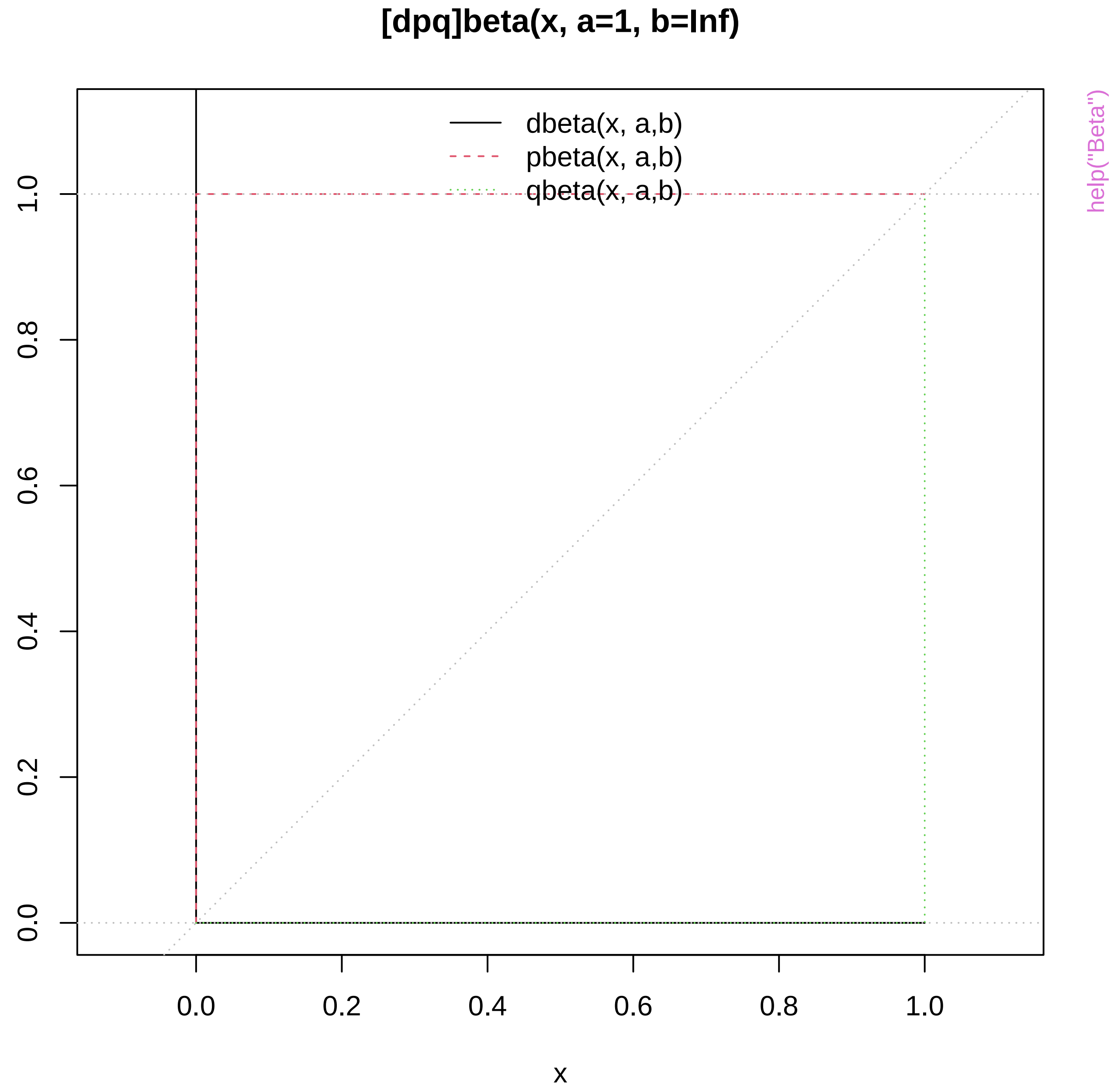
[dpq]beta(x, a=3, b=7)
dbeta(x, a,b)
pbeta(x, a,b)
qbeta(x, a,b)
help("Beta")
0.0
0.5
1.0
1.5
2.0
2.5
0.0
0.2
0.4
0.6
0.8
1.0
x



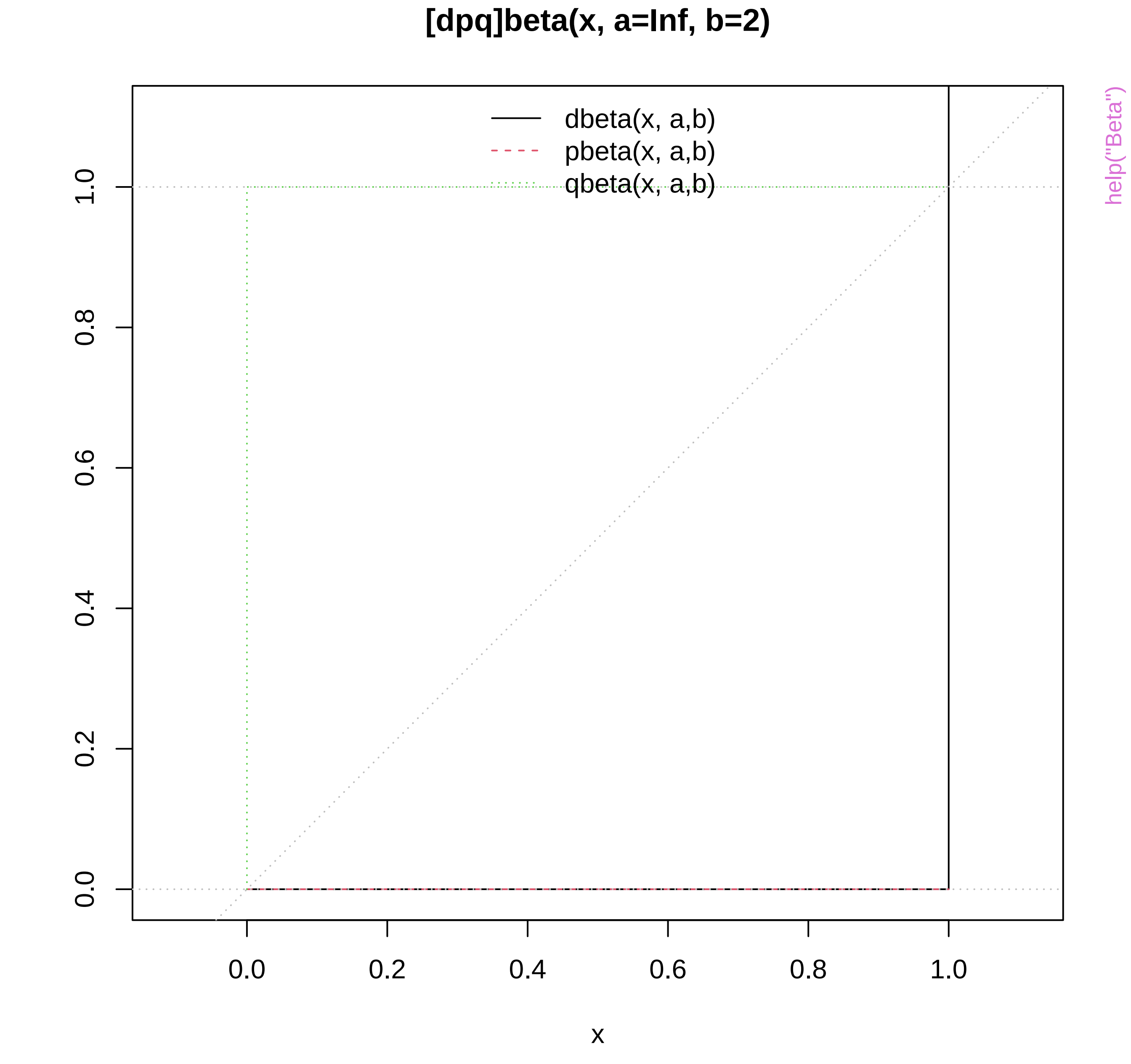
[dpq]beta(x, a=3, b=7)
dbeta(x, a,b)
pbeta(x, a,b)
qbeta(x, a,b)
0.0
0.5
1.0
1.5
2.0
2.5
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
x
help("Beta")

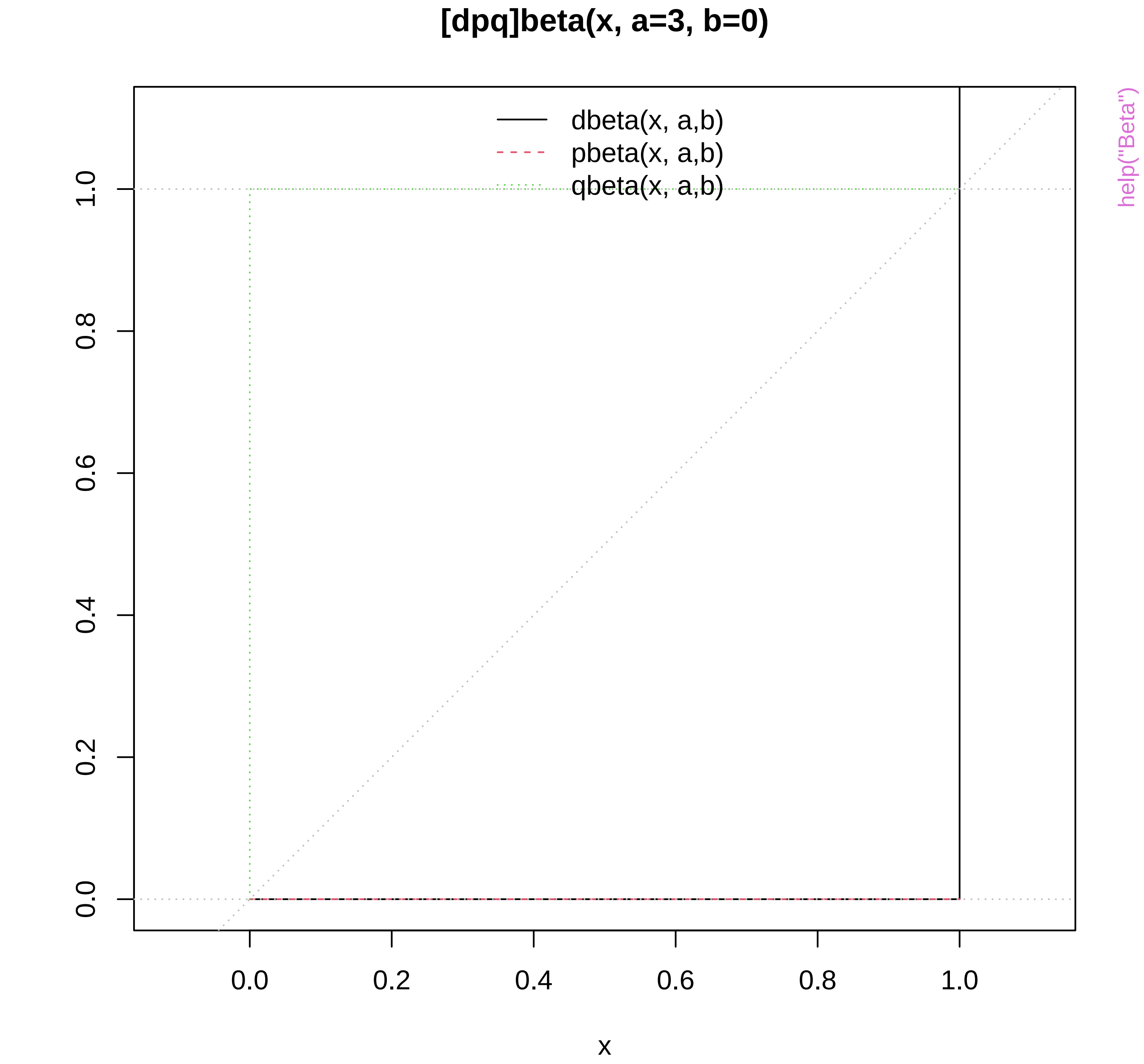

[dpq]beta(x, a=0, b=0)
dbeta(x, a,b)
pbeta(x, a,b)
qbeta(x, a,b)
help("Beta")
0.0
0.2
0.4
0.6
0.8
1.0
x

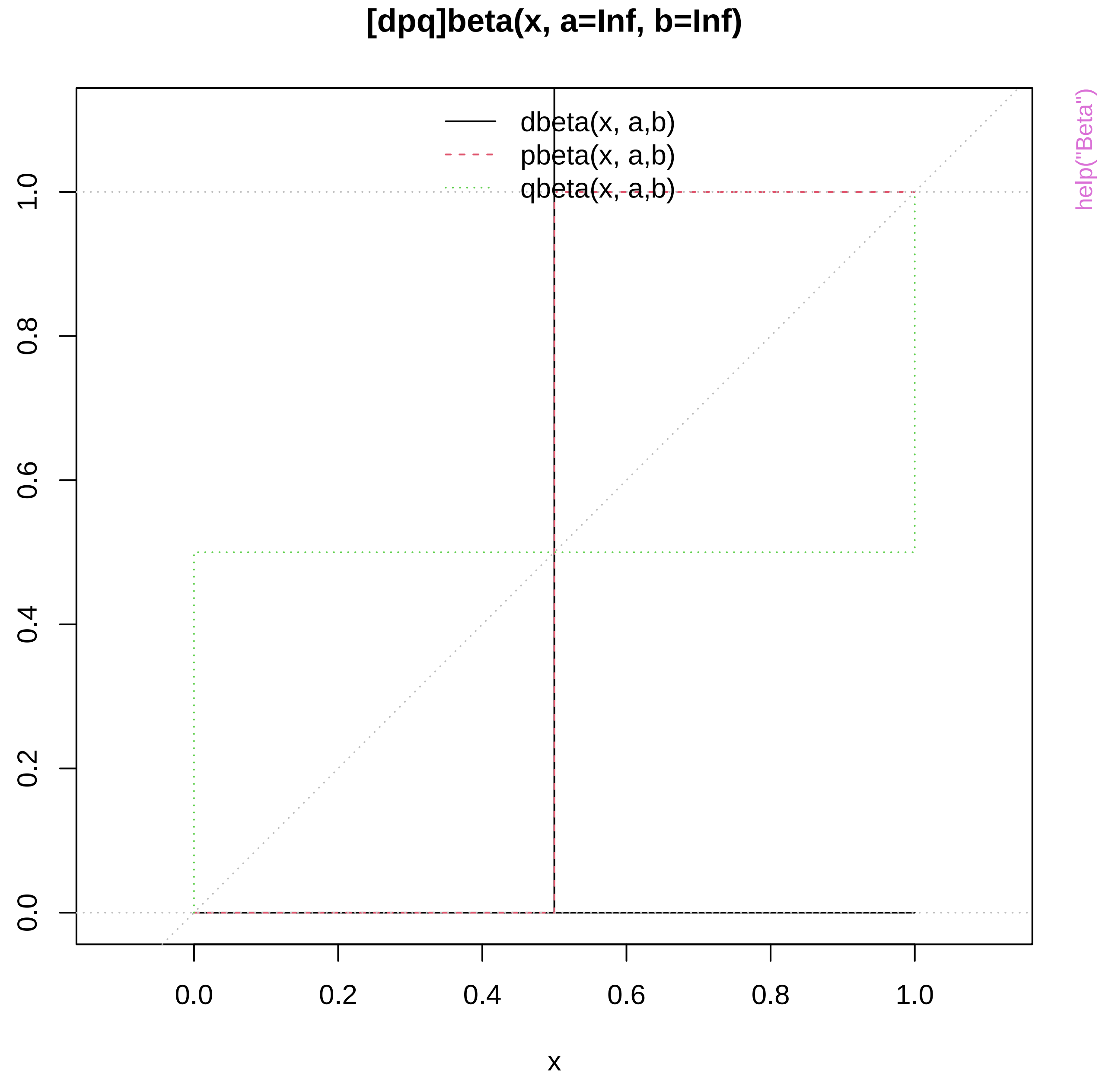

[dpq]beta(x, a=0, b=2)
dbeta(x, a,b)
pbeta(x, a,b)
qbeta(x, a,b)
help("Beta")
0.0
0.2
0.4
0.6
0.8
1.0
x

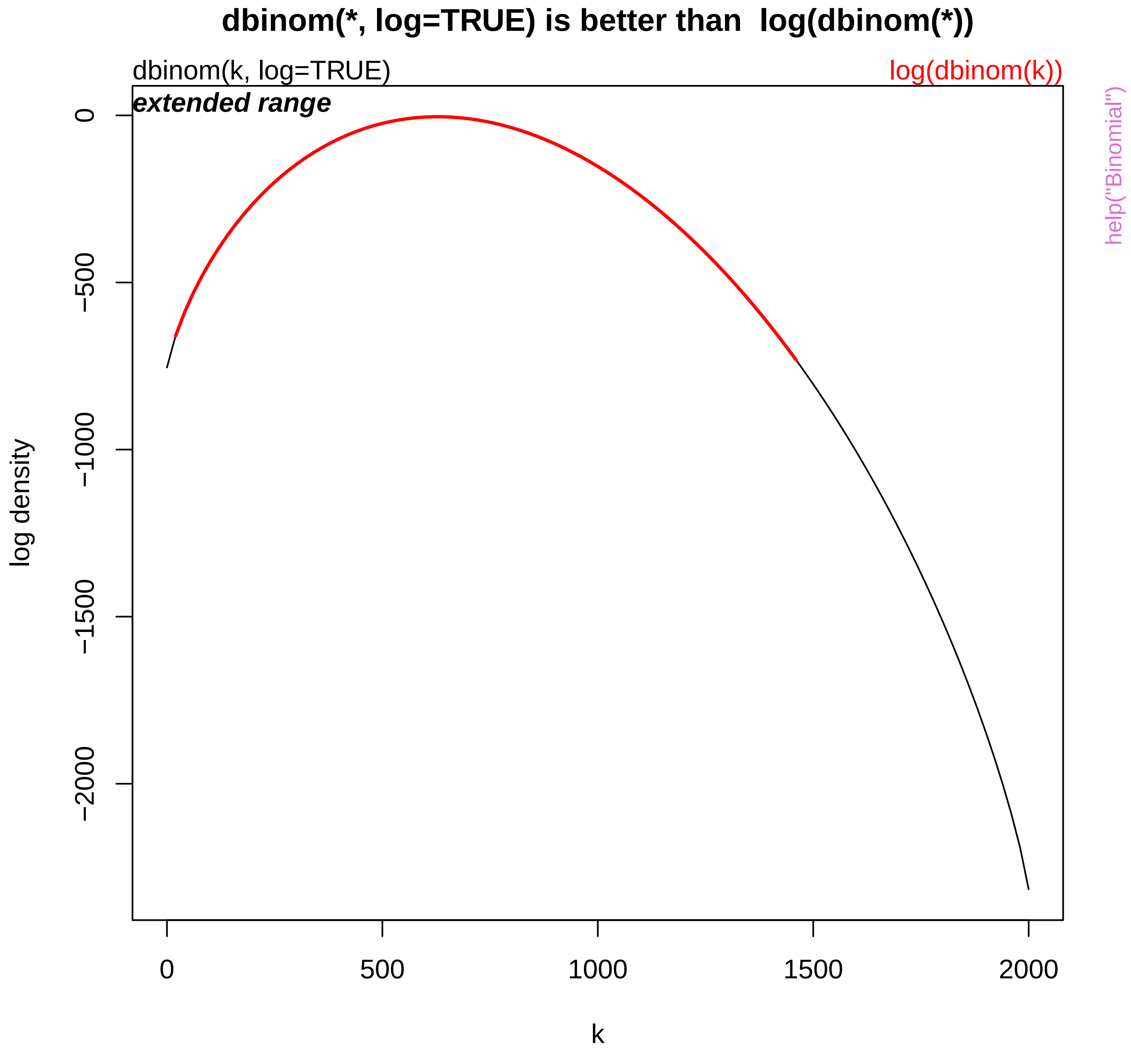


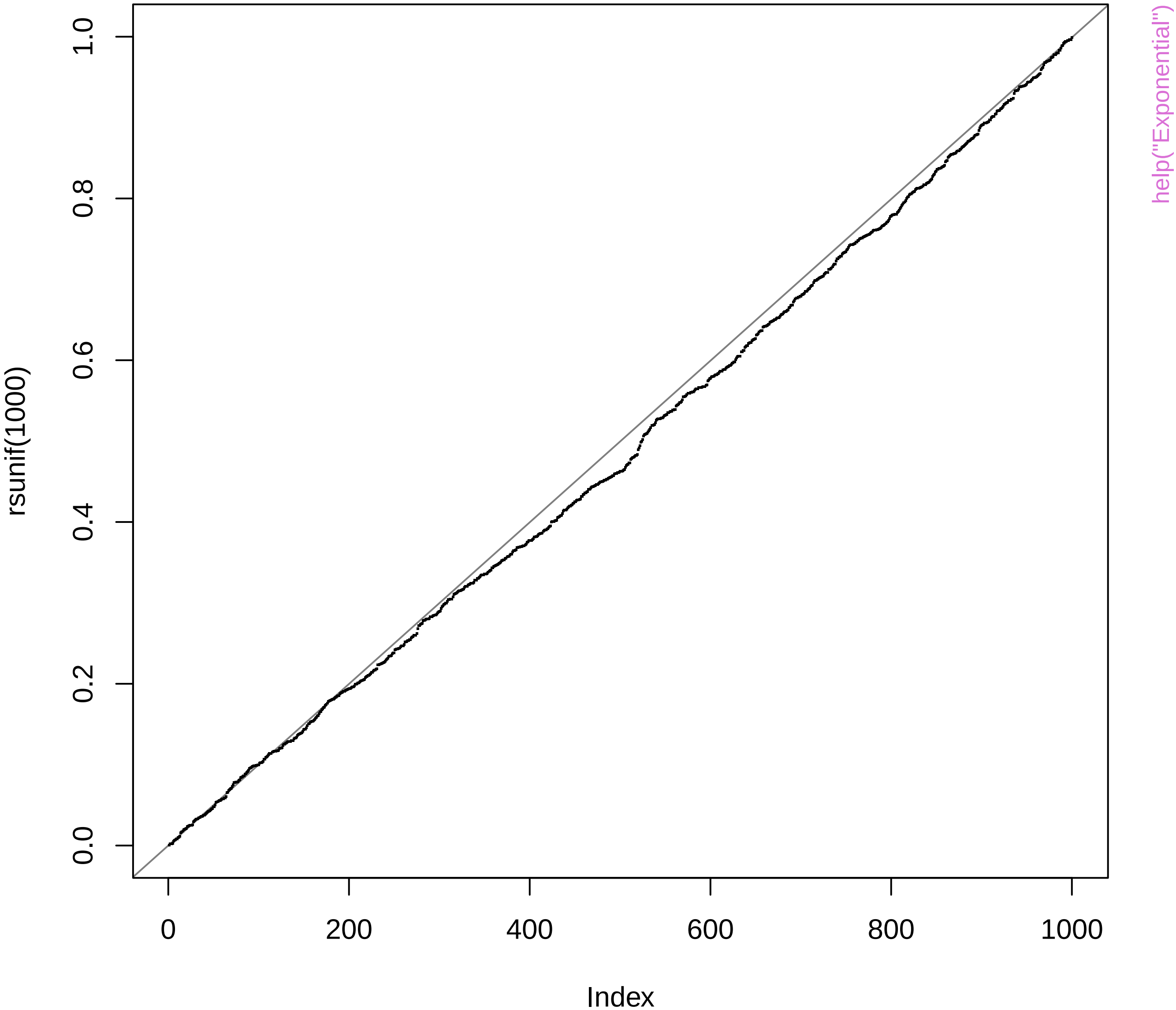
[dpq]beta(x, a=1, b=Inf)
dbeta(x, a,b)
pbeta(x, a,b)
qbeta(x, a,b)
help("Beta")
0.0
0.2
0.4
0.6
0.8
1.0
x


[dpq]beta(x, a=Inf, b=2)
dbeta(x, a,b)
pbeta(x, a,b)
qbeta(x, a,b)
help("Beta")
0.0
0.2
0.4
0.6
0.8
1.0
x

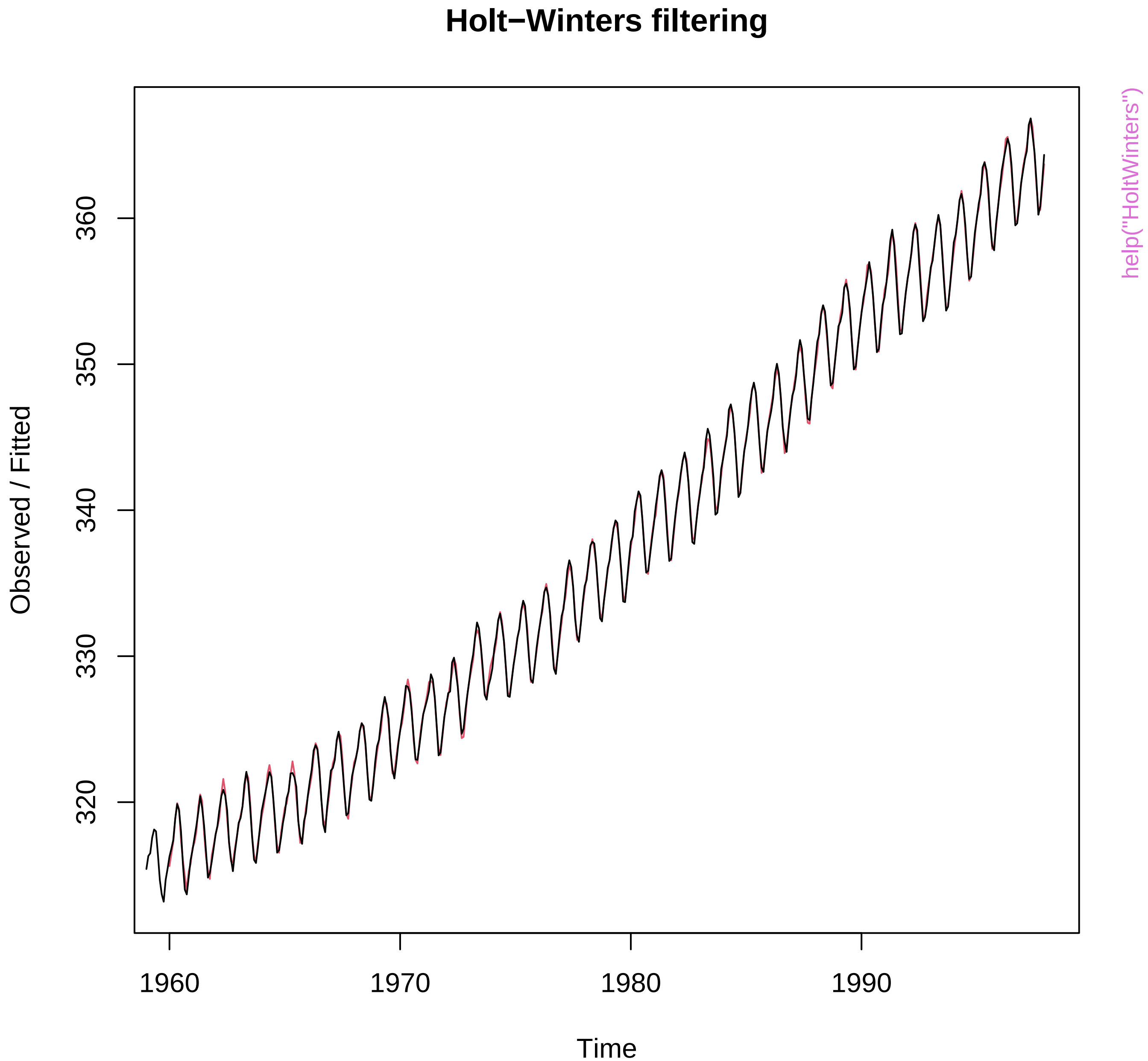

[dpq]beta(x, a=3, b=0)
dbeta(x, a,b)
pbeta(x, a,b)
qbeta(x, a,b)
help("Beta")
x
0.0
0.2
0.4
0.6
0.8
1.0


[dpq]beta(x, a=Inf, b=Inf)
dbeta(x, a,b)
pbeta(x, a,b)
qbeta(x, a,b)
0.0
0.2
0.4
0.6
0.8
1.0
0.0
0.2
0.4
0.6
0.8
1.0
x
help("Beta")

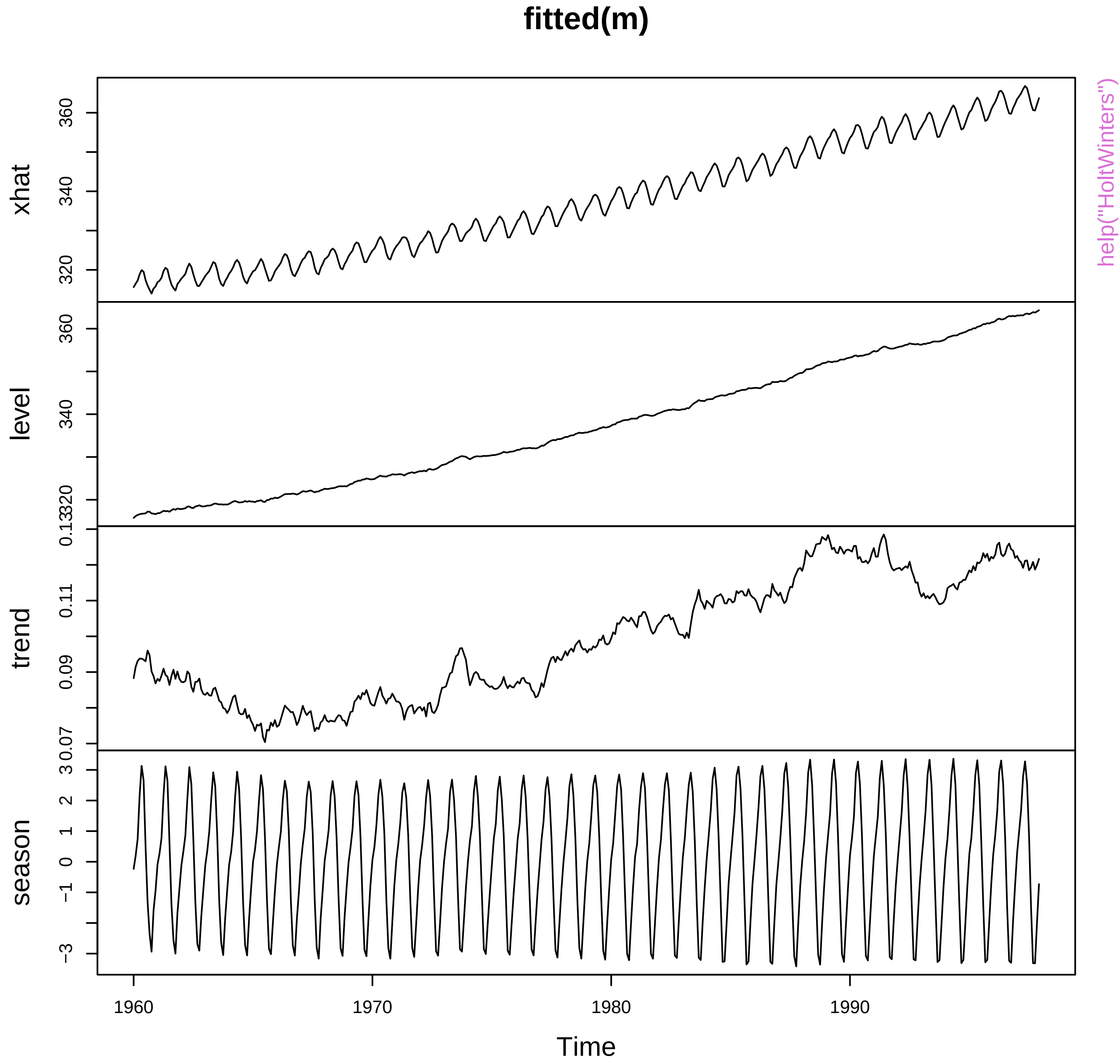

dbinom(*, log=TRUE) is better than log(dbinom(*))
dbinom(k, log=TRUE)
log(dbinom(k))
extended range
log density
0
−500
−1000
−1500
−2000
0
500
1000
1500
2000
k
help("Binomial")

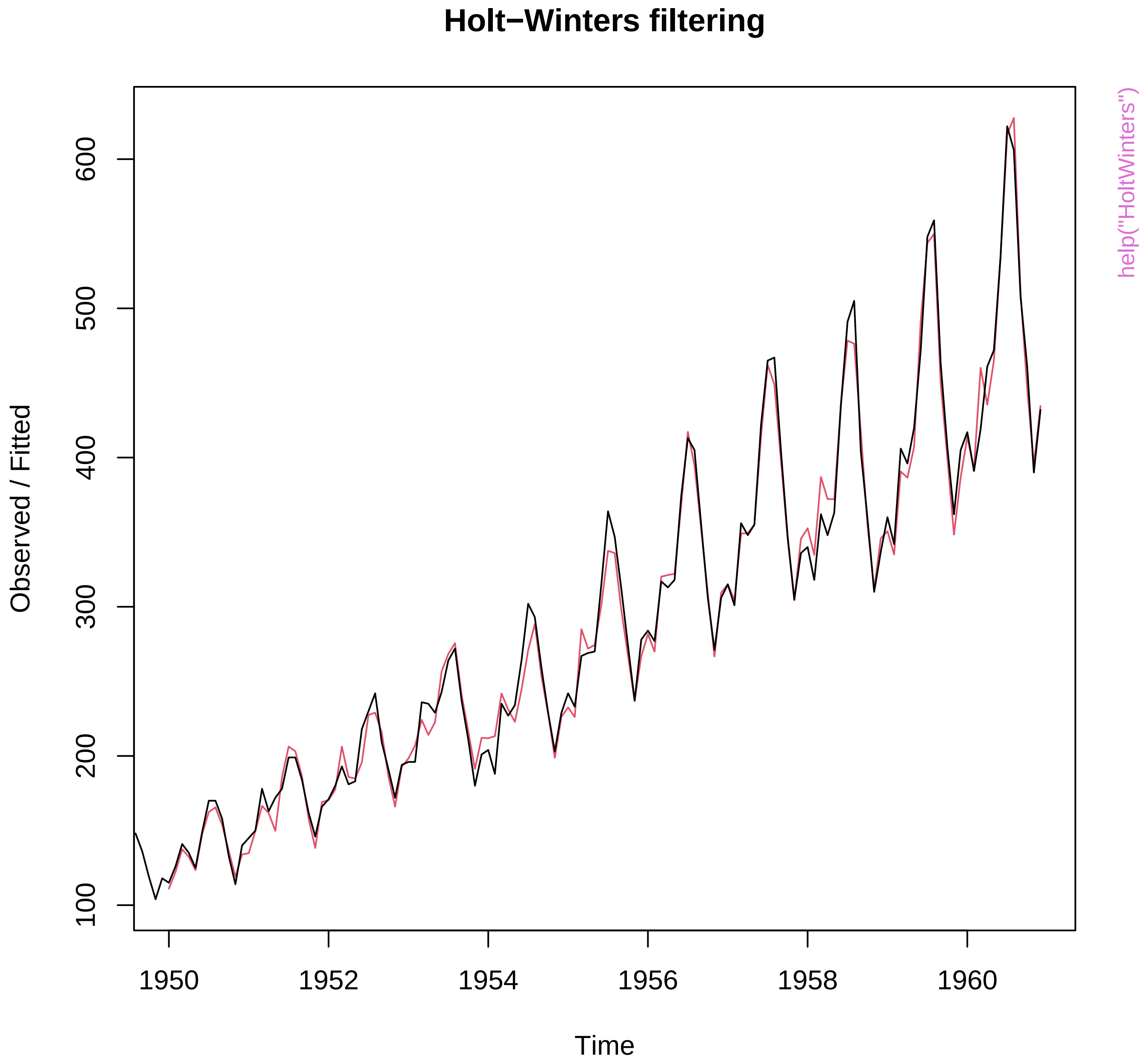


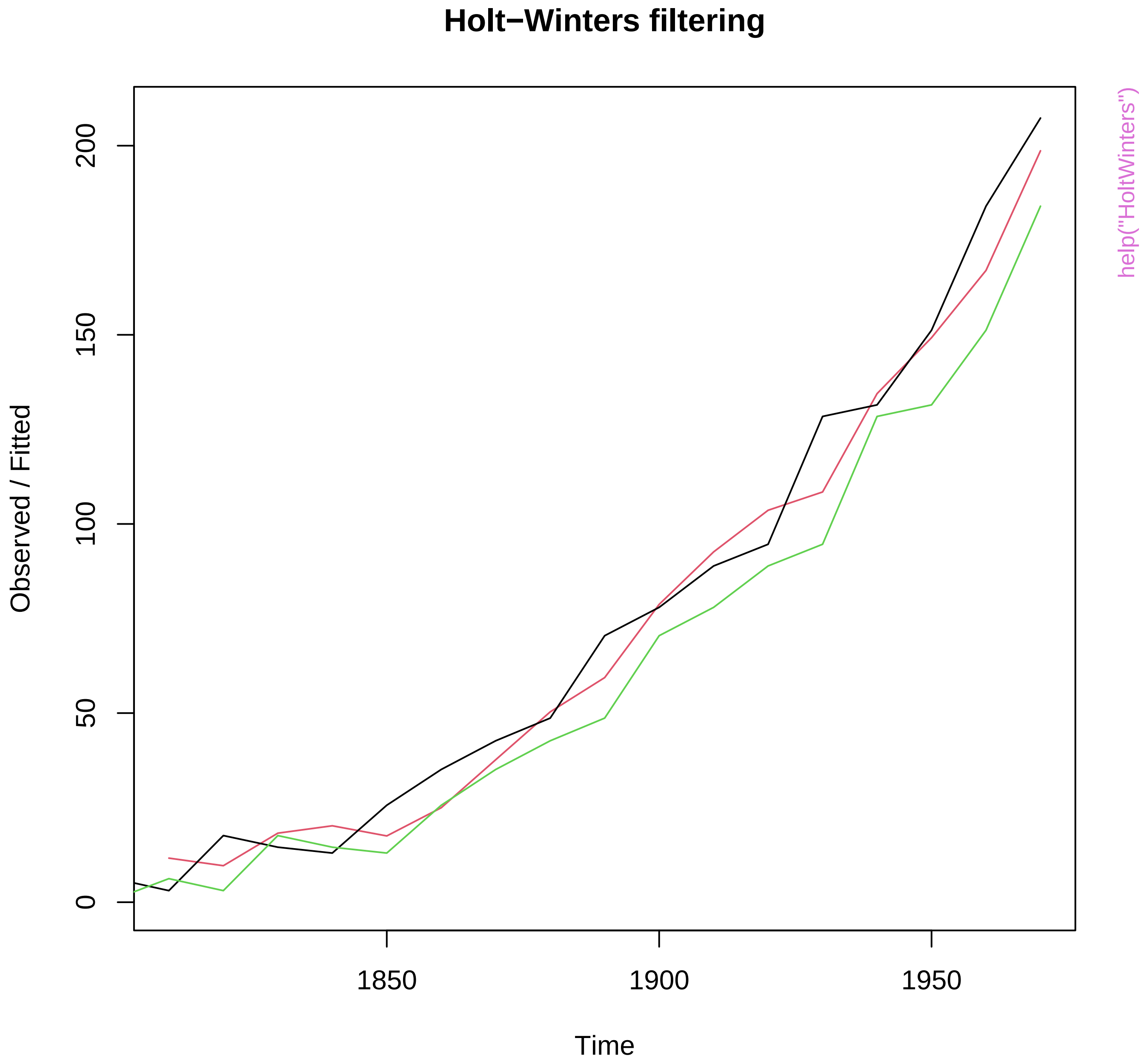
rsunif(1000)
0.0
0.2
0.4
0.6
0.8
1.0
0
200
400
600
800
1000
Index
help("Exponential")



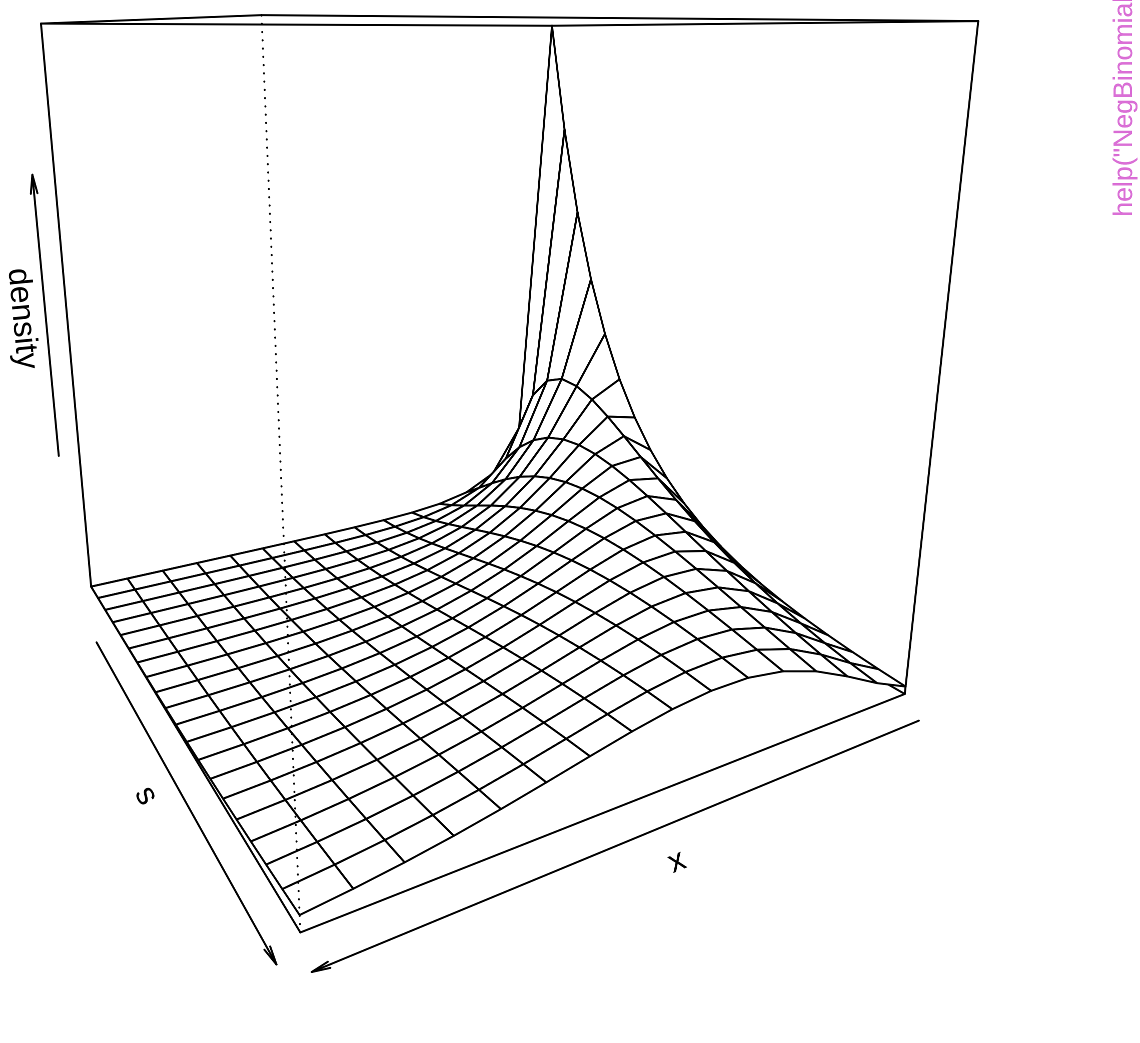
Holt−Winters filtering
Observed / Fitted
Time
320
330
340
350
360
1960
1970
1980
1990
help("HoltWinters")

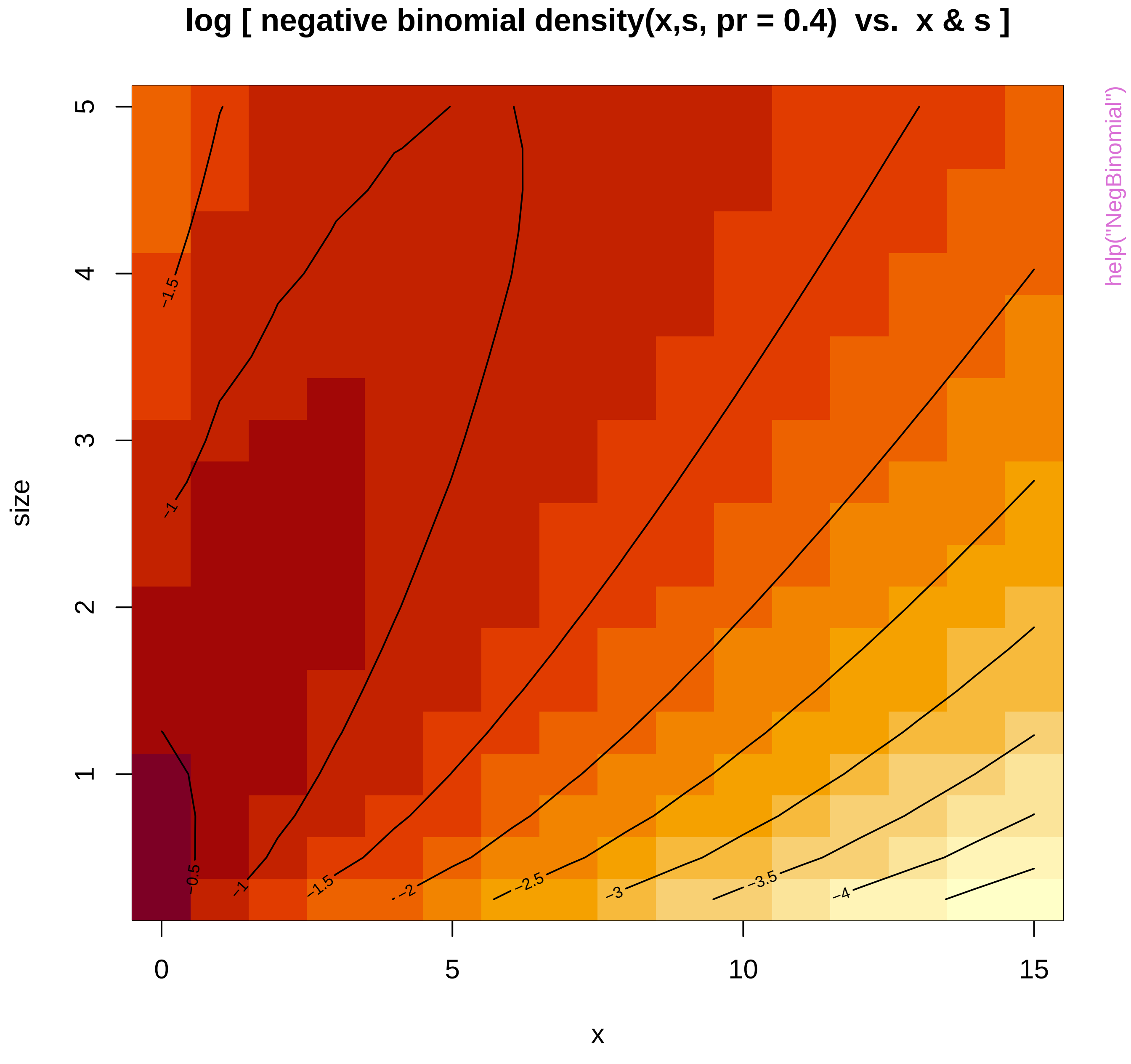

fitted(m)
xhat
320
340
360
level
320
340
360
trend
0.07
0.09
0.11
0.13
season
−3
−1
0
1
2
3
1960
1970
1980
1990
Time
help("HoltWinters")


Holt−Winters filtering
Observed / Fitted
Time
100
200
300
400
500
600
1950
1952
1954
1956
1958
1960
help("HoltWinters")

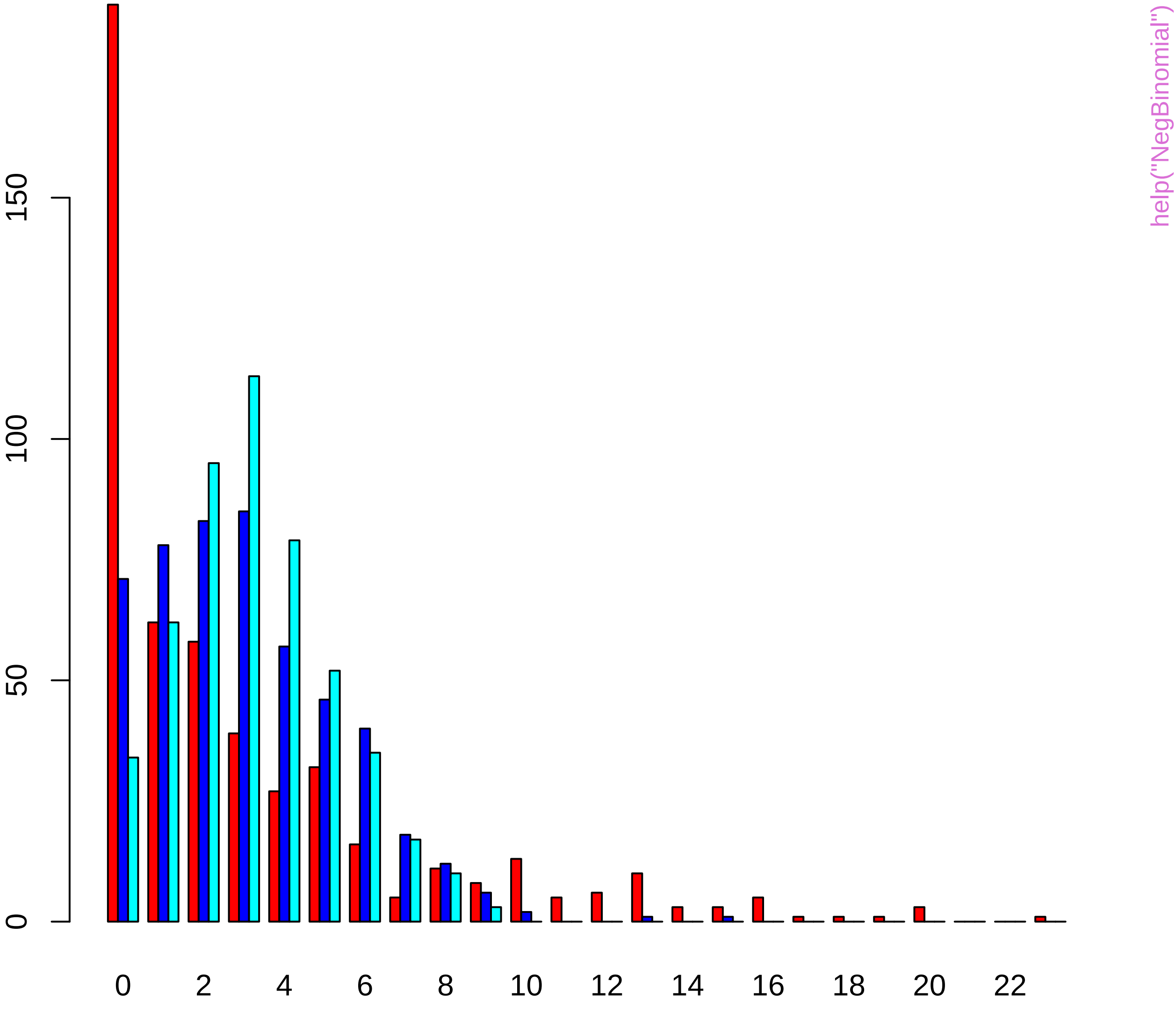

Holt−Winters filtering
Observed / Fitted
0
50
100
150
200
1850
1900
1950
Time
help("HoltWinters")

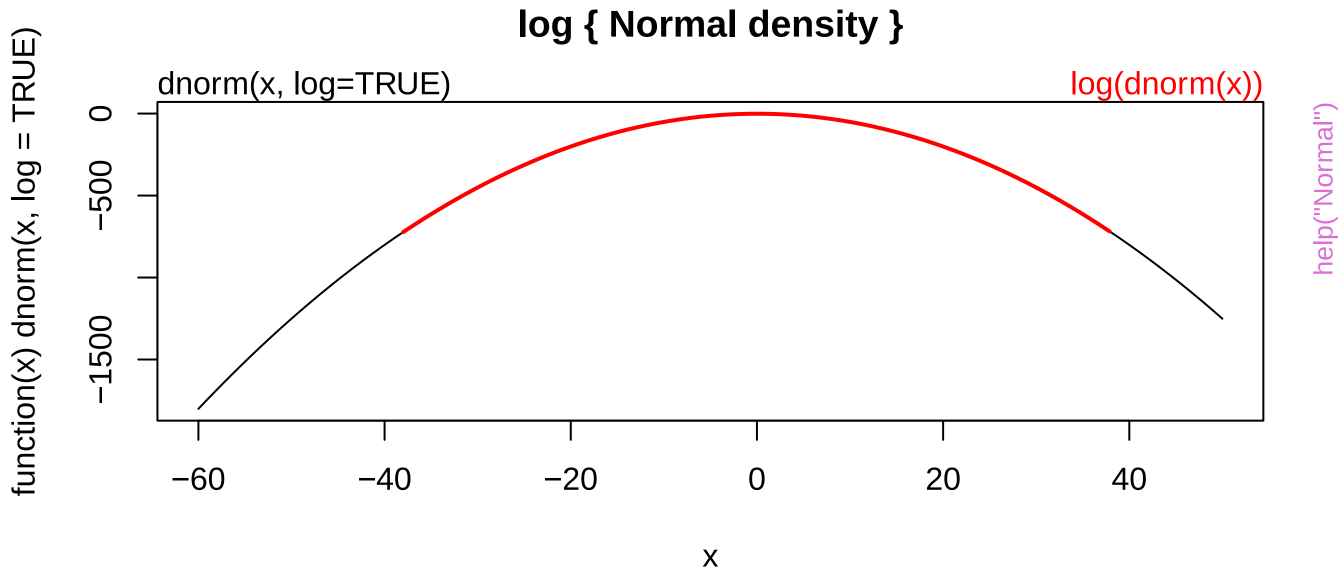
negative binomial density(x,s, pr = 0.4) vs. x & s

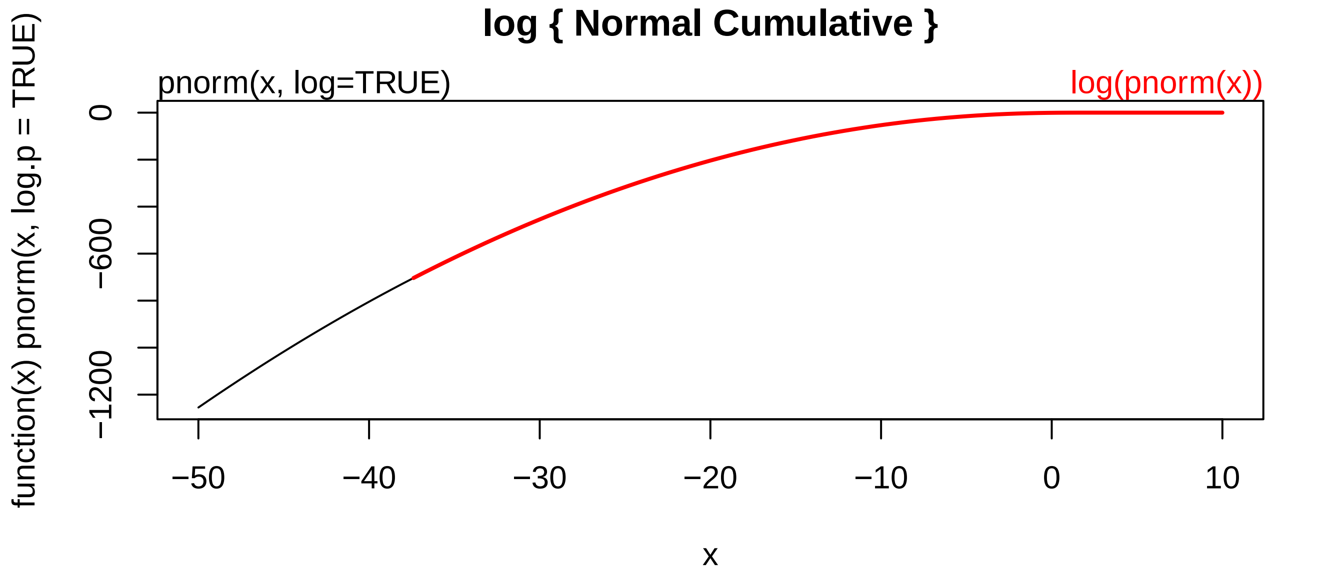


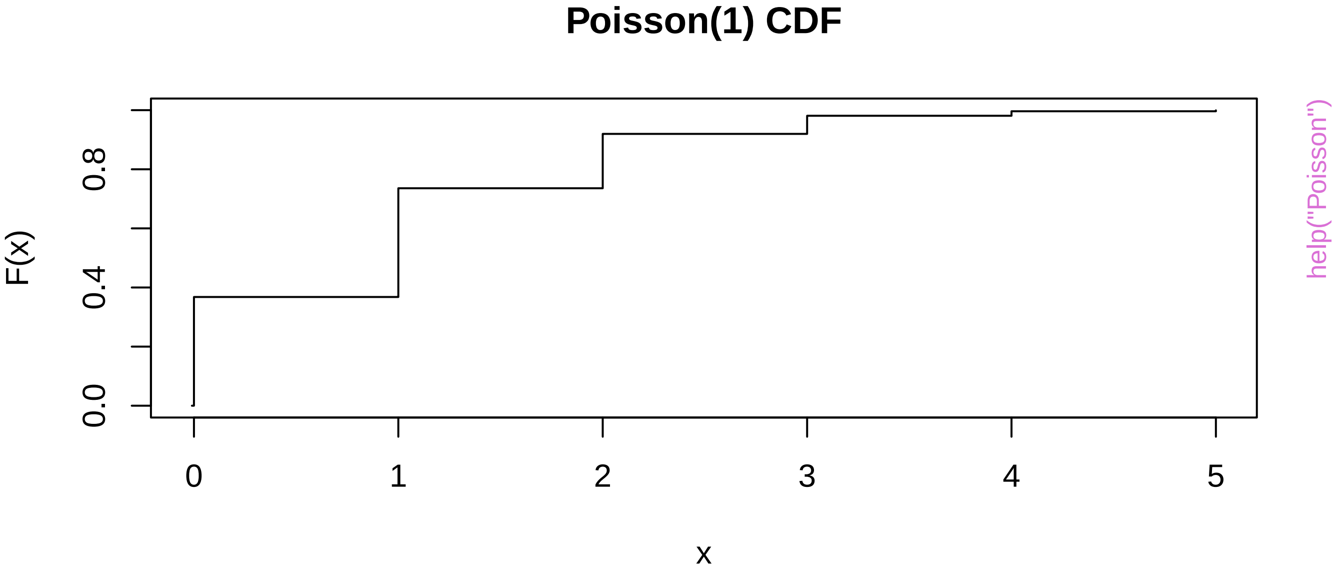


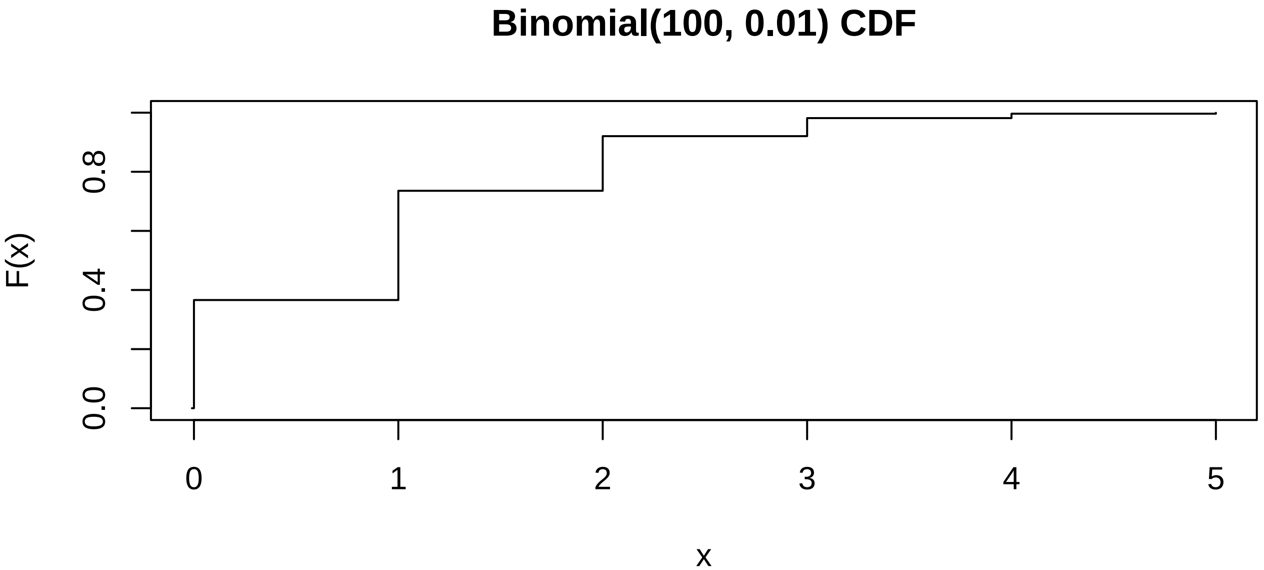
log [negative binomial density(x,s, pr = 0.4) vs. x & s]
help("NegBinomial")
size
x
0
5
10
15
1
2
3
4
5
−0.5
−1
−1.5
−2
−2.5
−3
−3.5
−4

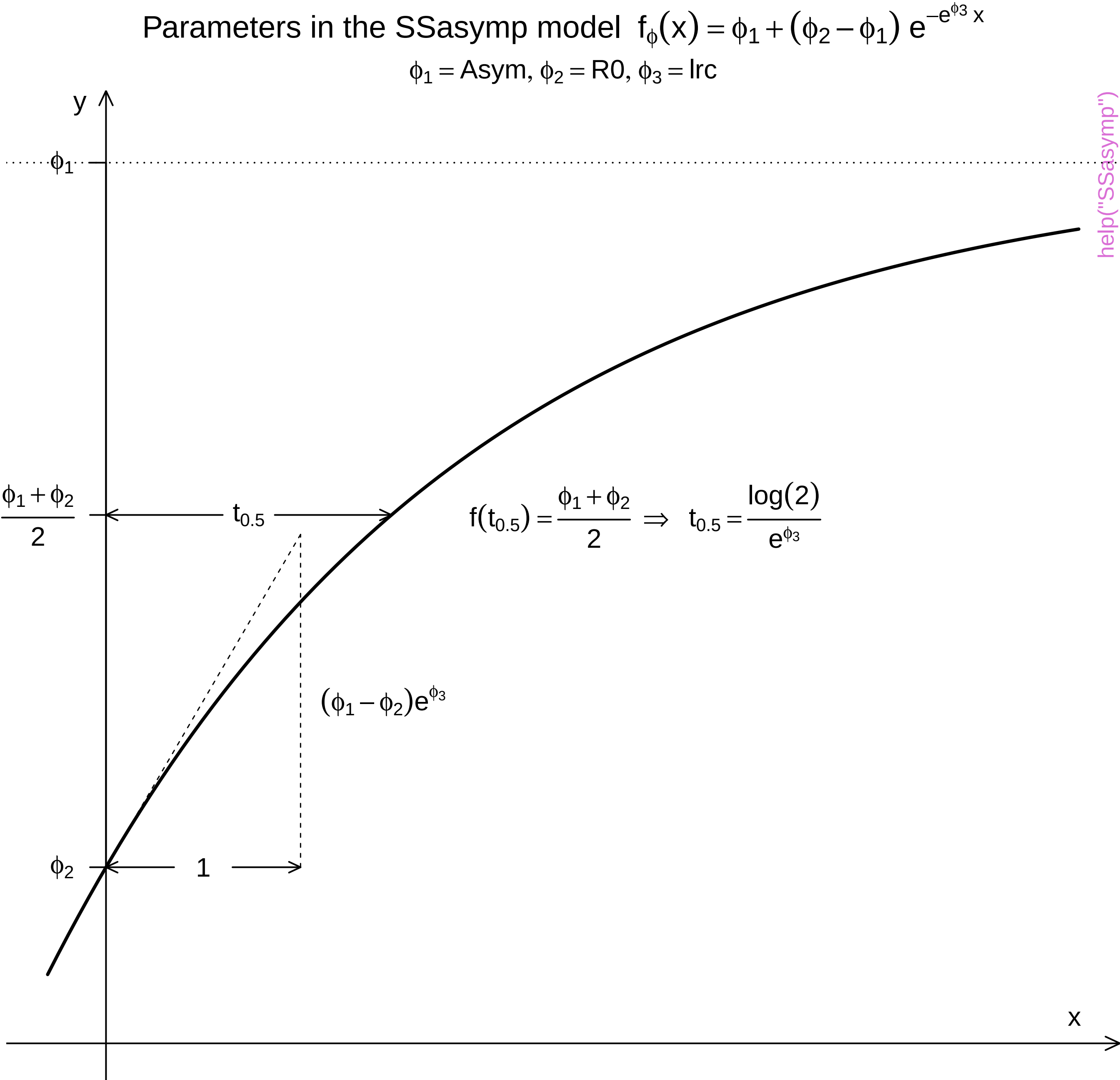

0
50
100
150
0
2
4
6
8
10
12
14
16
18
20
22
help("NegBinomial")

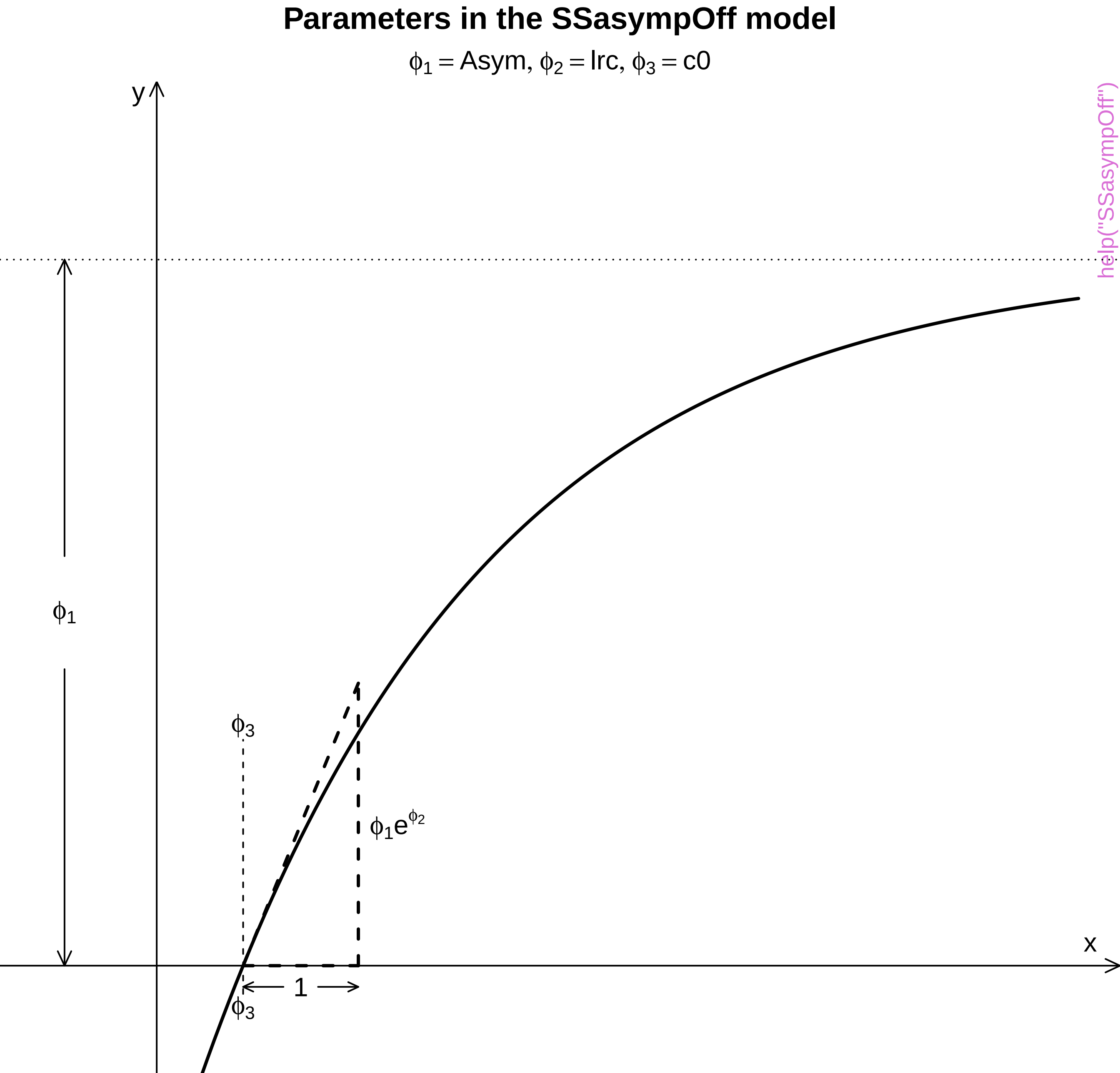

log { Normal density }
dnorm(x, log=TRUE)
log(dnorm(x))
function(x) dnorm(x, log = TRUE)
0
−500
−1500
−60
−40
−20
0
20
40
x
help("Normal")

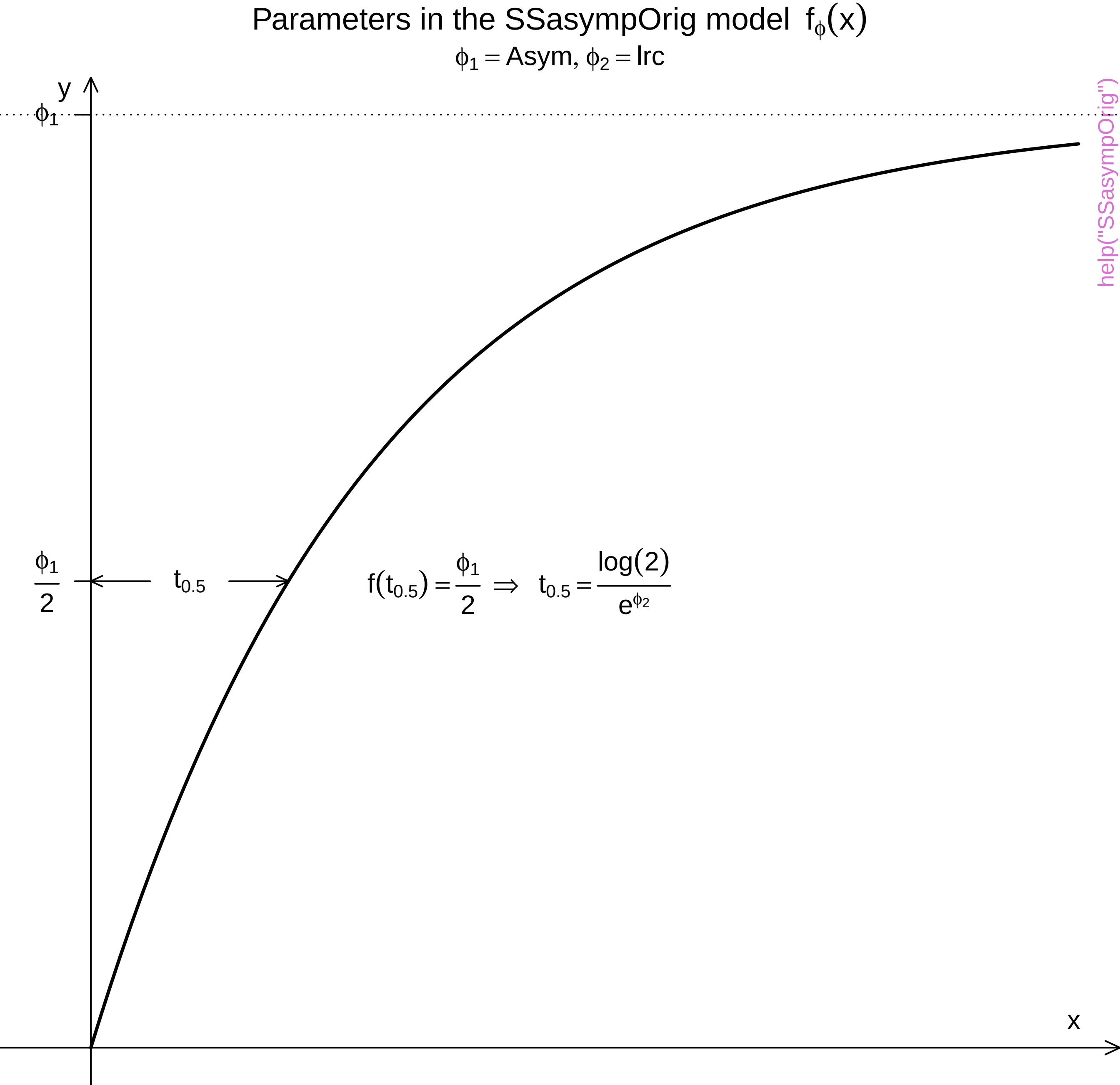

log { Normal Cumulative }
pnorm(x, log=TRUE)
log(pnorm(x))
function(x) pnorm(x, log.p = TRUE)
0
−600
−1200
−50
−40
−30
−20
−10
0
10
x

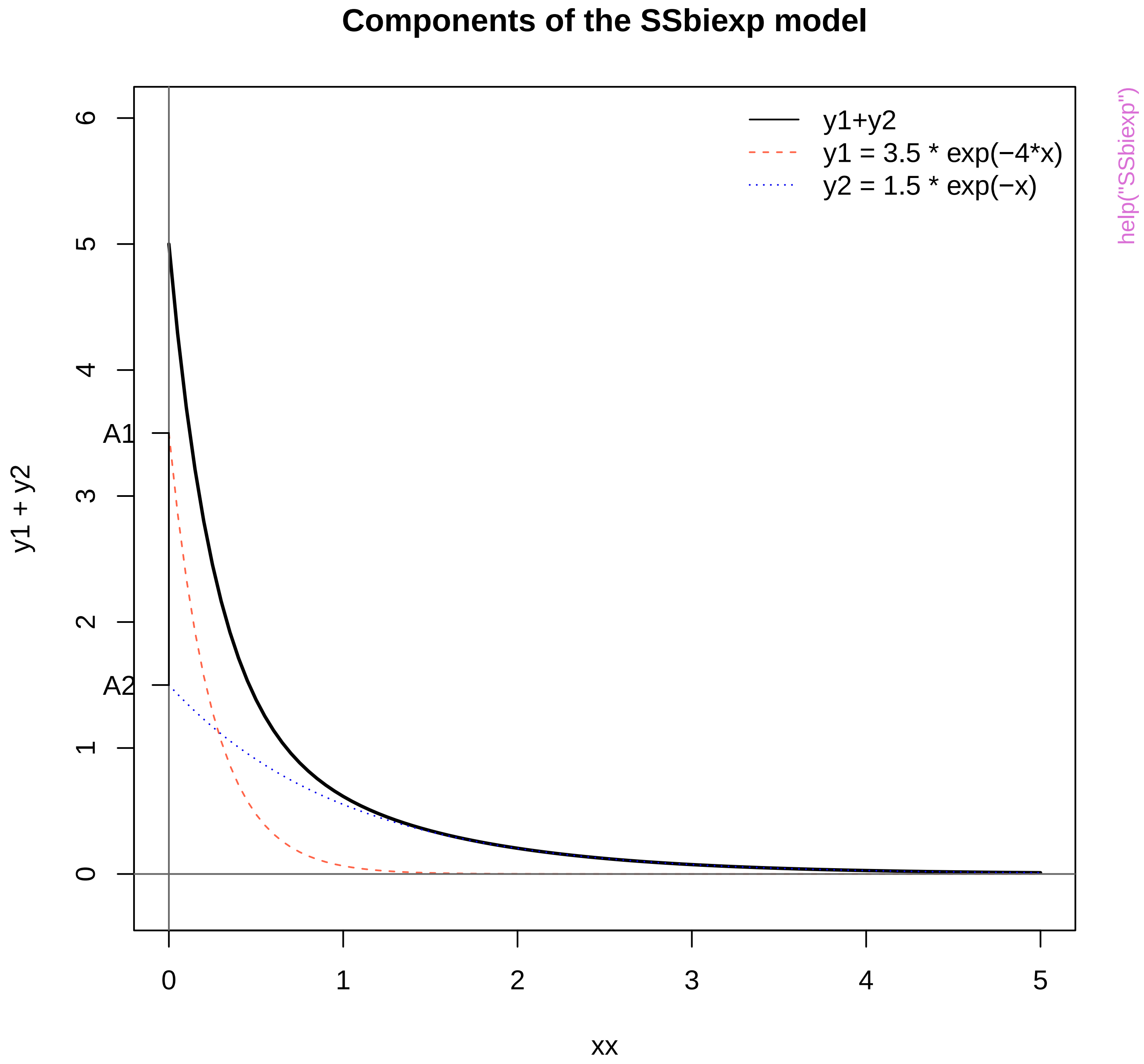

Poisson(1) CDF
F(x)
0.0
0.4
0.8
0
1
2
3
4
5
x
help("Poisson")


Binomial(100, 0.01) CDF
F(x)
0.0
0.4
0.8
0
1
2
3
4
5
x

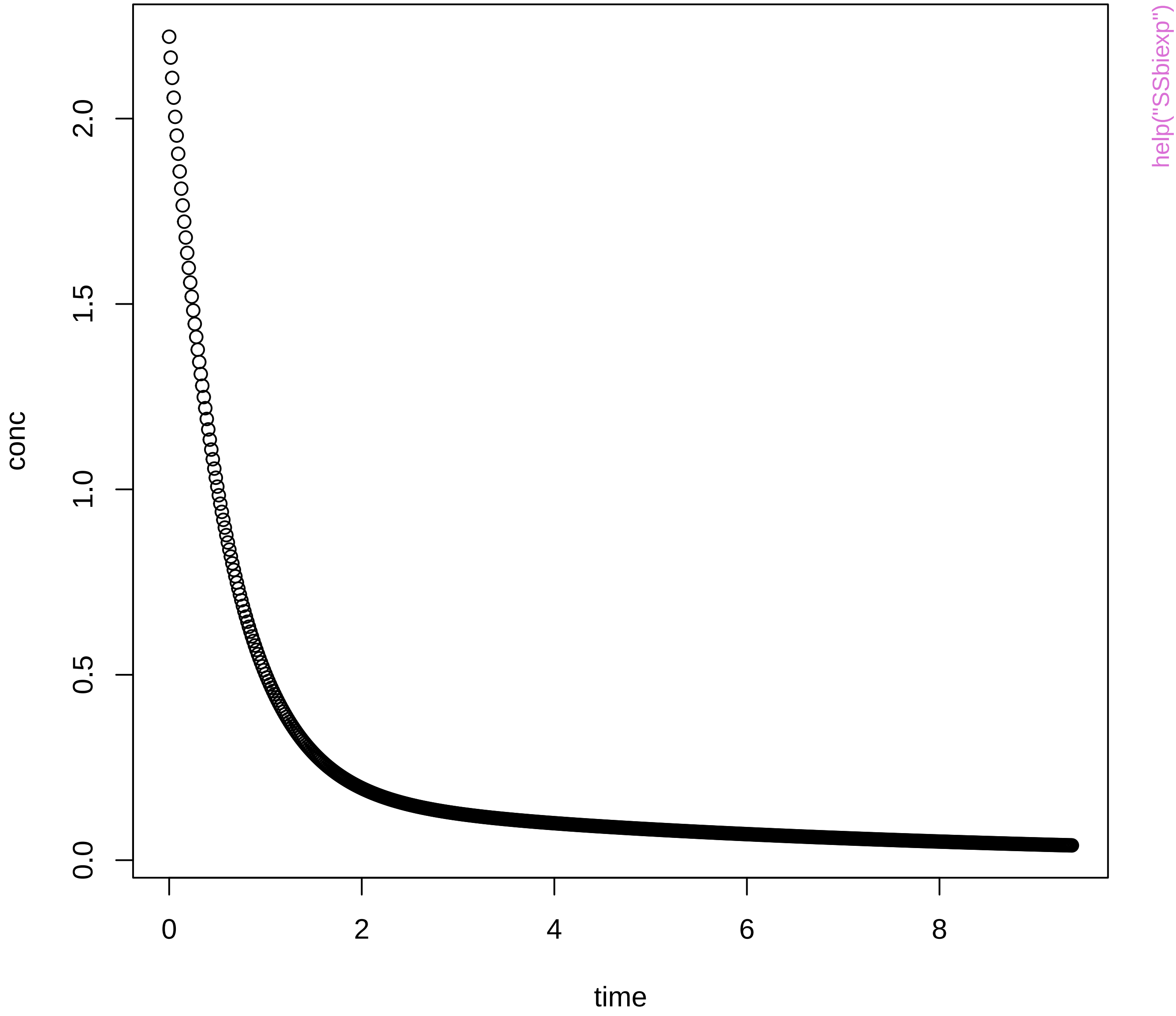

Parameters in the SSasymp model $f_\phi(x) = \phi_1 + (\phi_2 - \phi_1)\, e^{-e^{\phi_3}\, x}$
$\phi_1 = \text{Asym},\ \phi_2 = \text{R0},\ \phi_3 = \text{lrc}$
y
ϕ_1
$\frac{\phi_1 + \phi_2}{2}$
$t_{0.5}$
$f(t_{0.5}) = \frac{\phi_1 + \phi_2}{2} \Rightarrow t_{0.5} = \frac{\log(2)}{e^{\phi_3}}$
$(\phi_1 - \phi_2)e^{\phi_3}$
ϕ_2
1
x
help("SSasymp")


Parameters in the SSasympOff model
$\phi_1 = \text{Asym}, \phi_2 = \text{lrc}, \phi_3 = \text{c0}$
y
x
ϕ_1
ϕ_3
$\phi_1 e^{\phi_2}$
1
ϕ_3
help("SSasympOff")

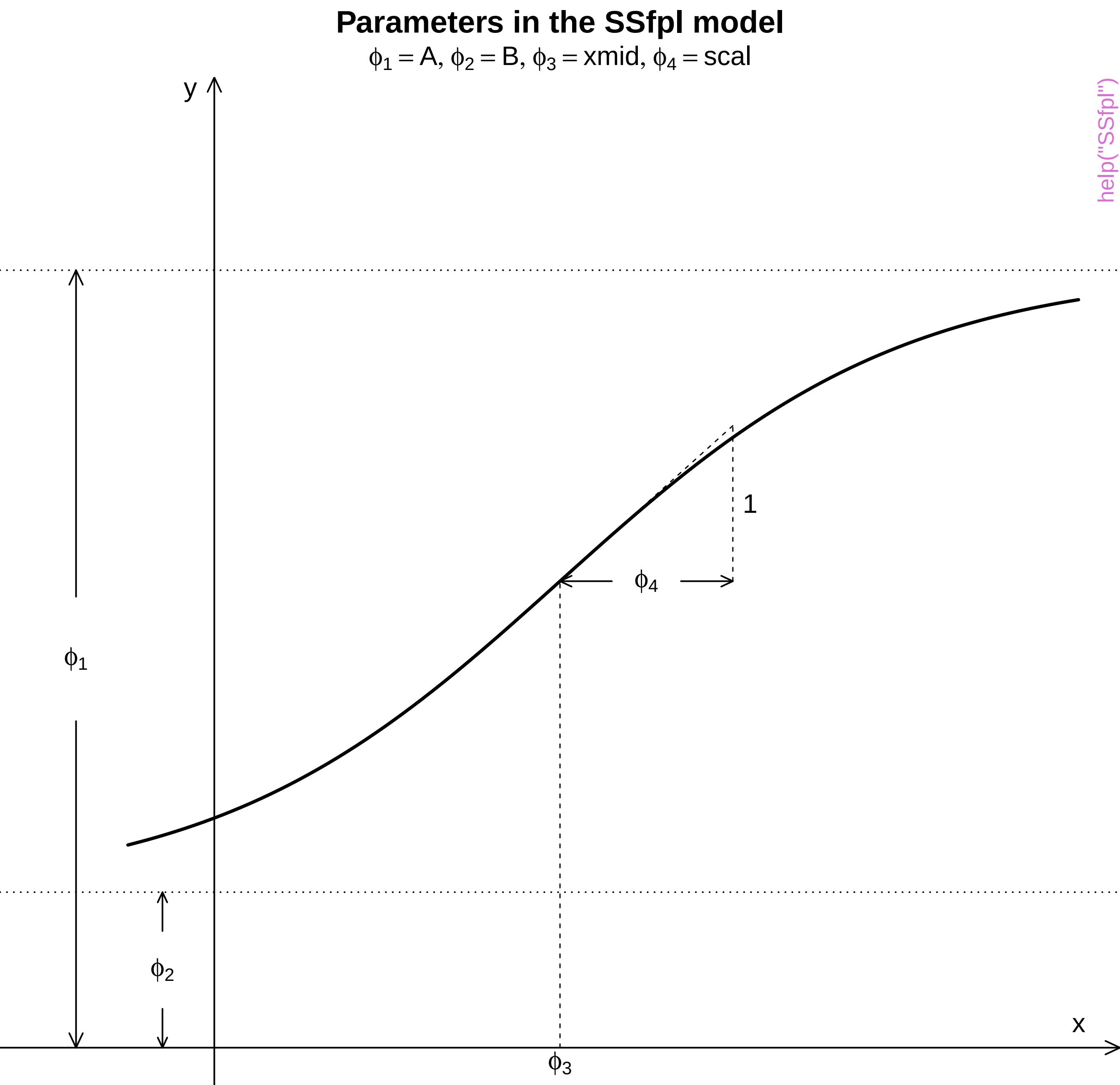

Parameters in the SSasympOrig model $f_\phi(x)$
$\phi_1 = \mathrm{Asym}, \phi_2 = \mathrm{lrc}$
y
ϕ_1
$\frac{\phi_1}{2}$
$t_{0.5}$
$f(t_{0.5}) = \frac{\phi_1}{2} \Rightarrow t_{0.5} = \frac{\log(2)}{e^{\phi_2}}$
x
help("SSasympOrig")

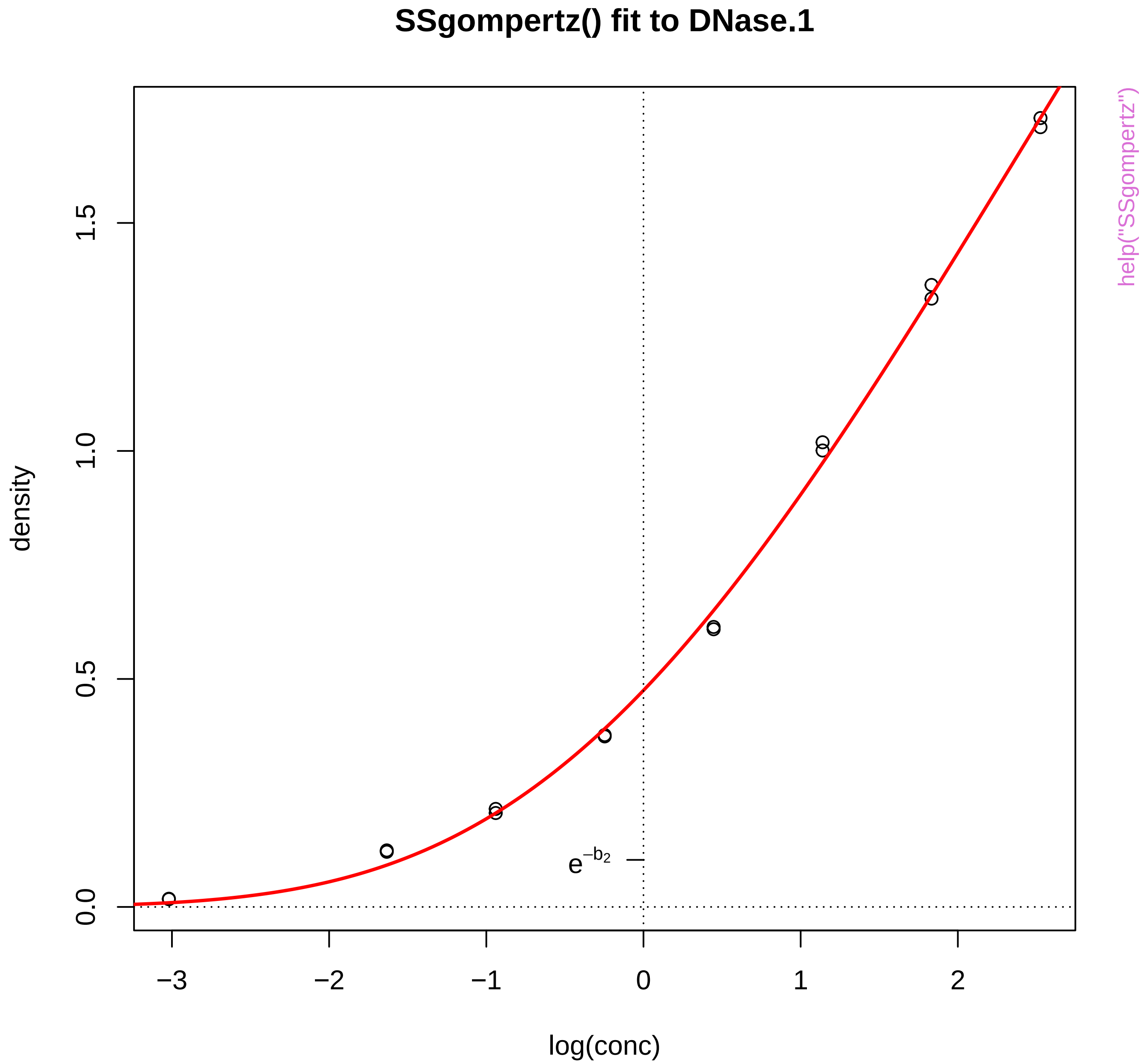


Components of the SSbiexp model
y1+y2
y1 = 3.5 * exp(−4*x)
y2 = 1.5 * exp(−x)
help("SSbiexp")
A1
A2
0
1
2
3
4
5
6
y1 + y2
xx

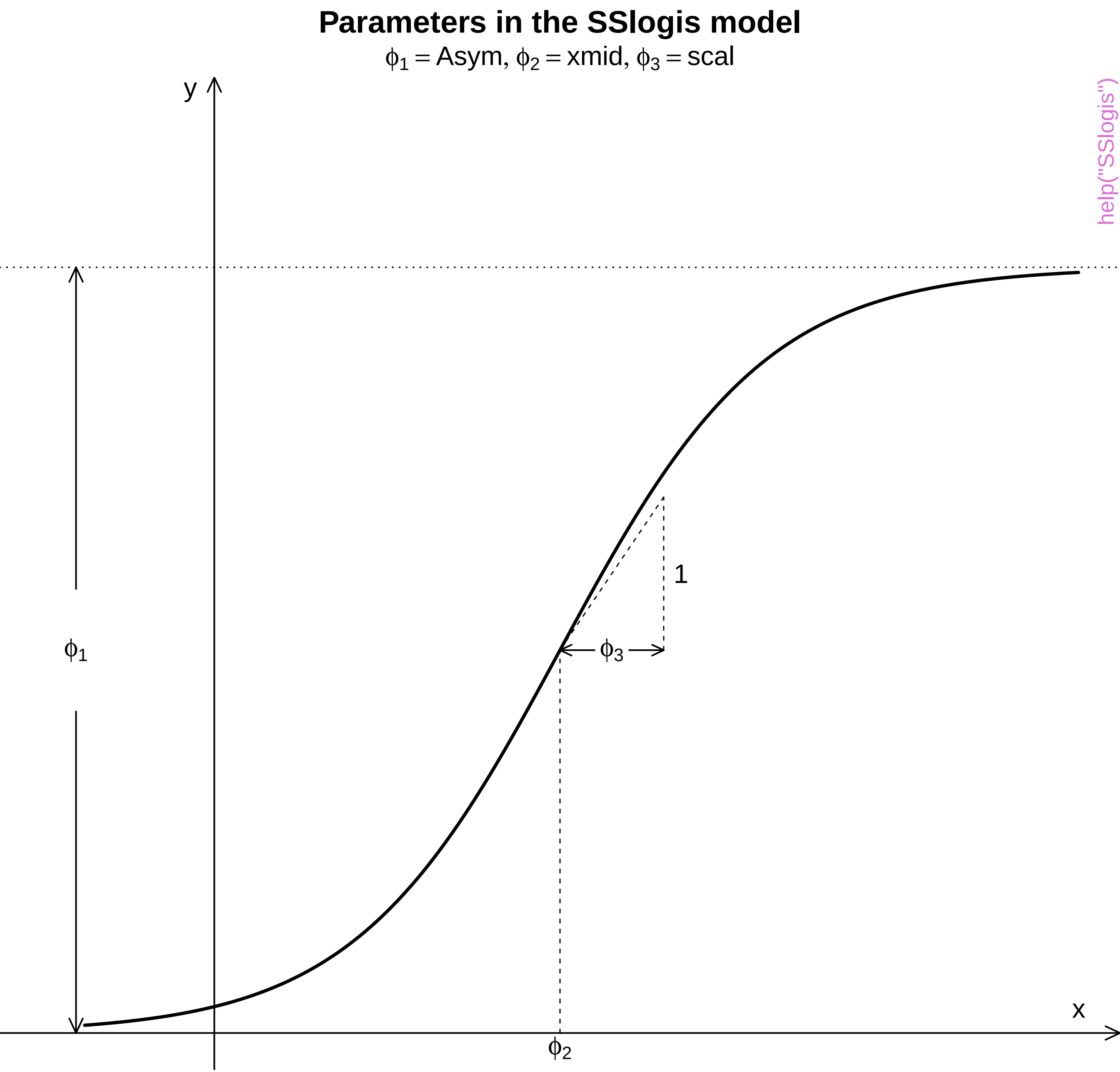


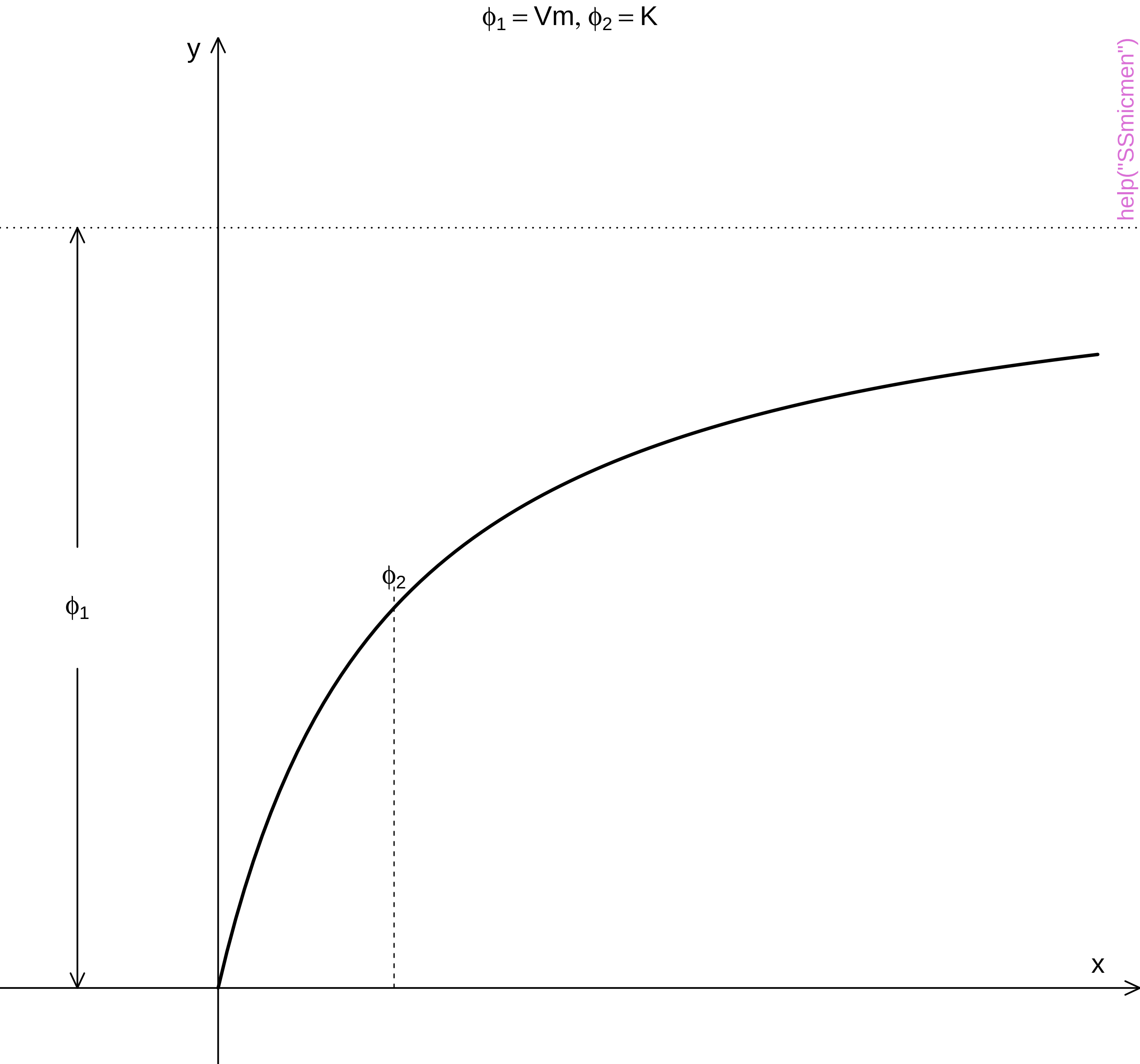
2.0
1.5
1.0
0.5
0.0
conc
0
2
4
6
8
time
help("SSbiexp")


Parameters in the SSfpl model
$\phi_1 = A, \phi_2 = B, \phi_3 = xmid, \phi_4 = scal$
y
x
ϕ_1
ϕ_2
ϕ_3
ϕ_4
1
help("SSfpl")

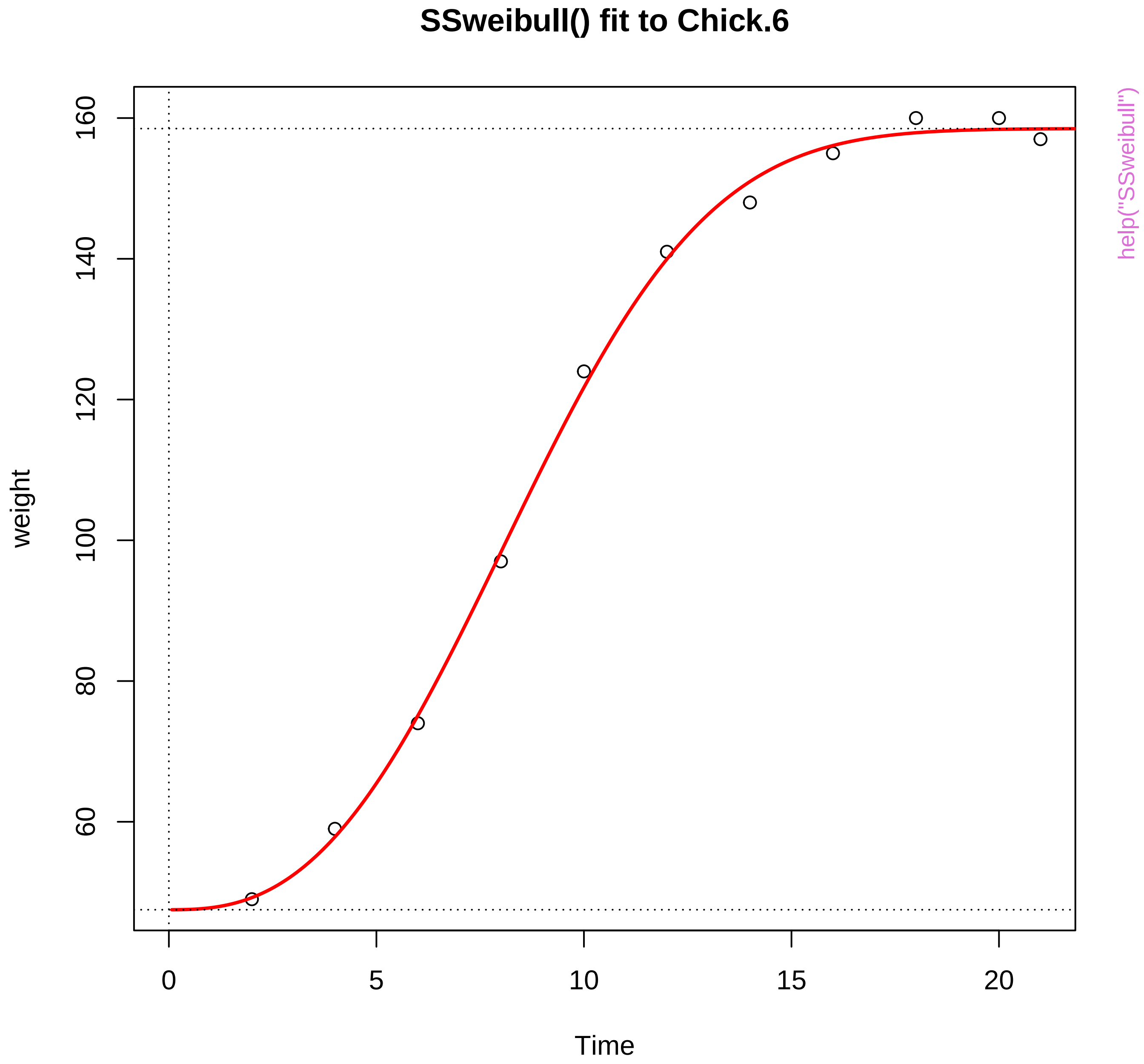


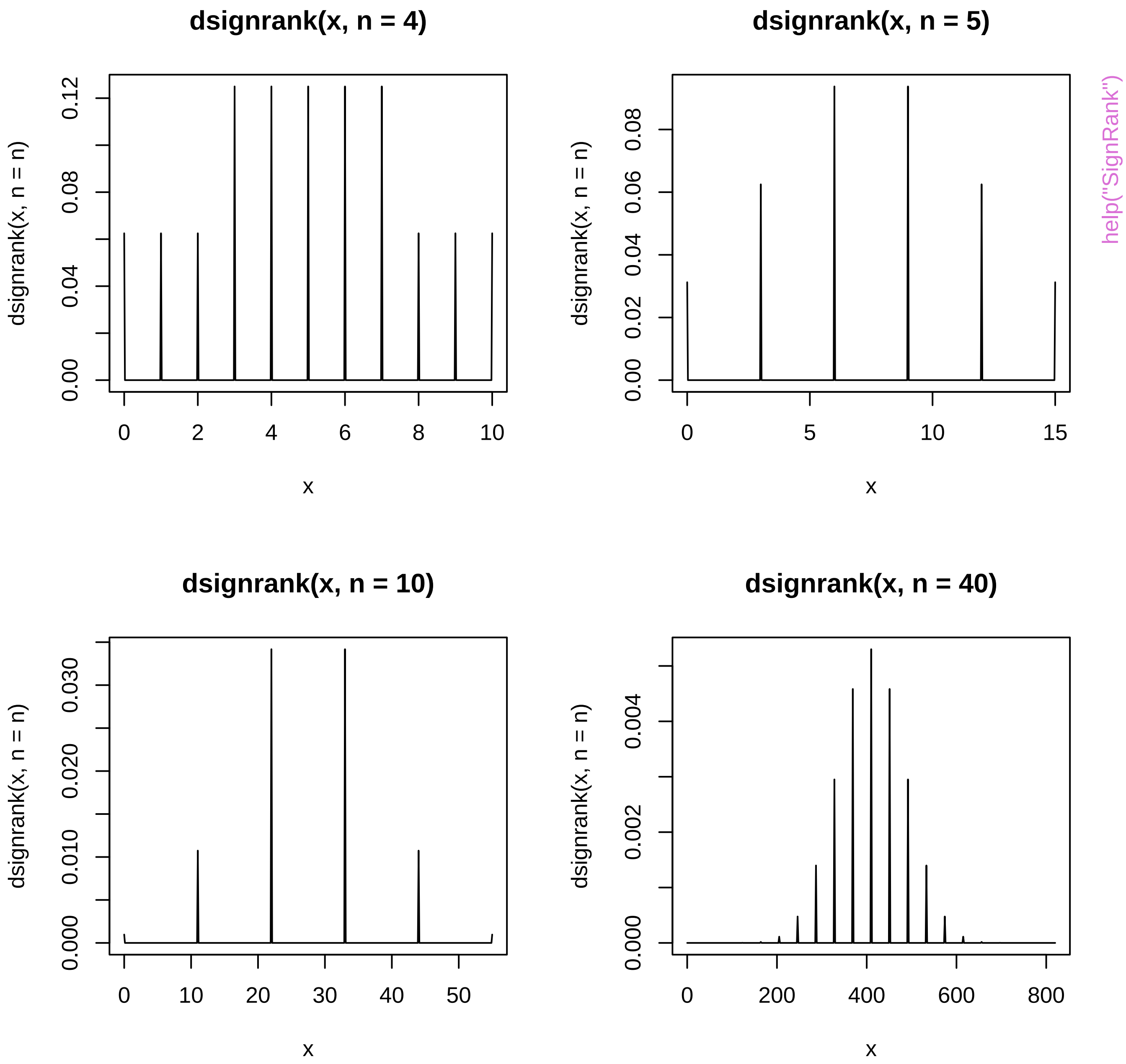
SSgompertz() fit to DNase.1
density
log(conc)
0.0
0.5
1.0
1.5
−3
−2
−1
0
1
2
e^{-b_2}
help("SSgompertz")

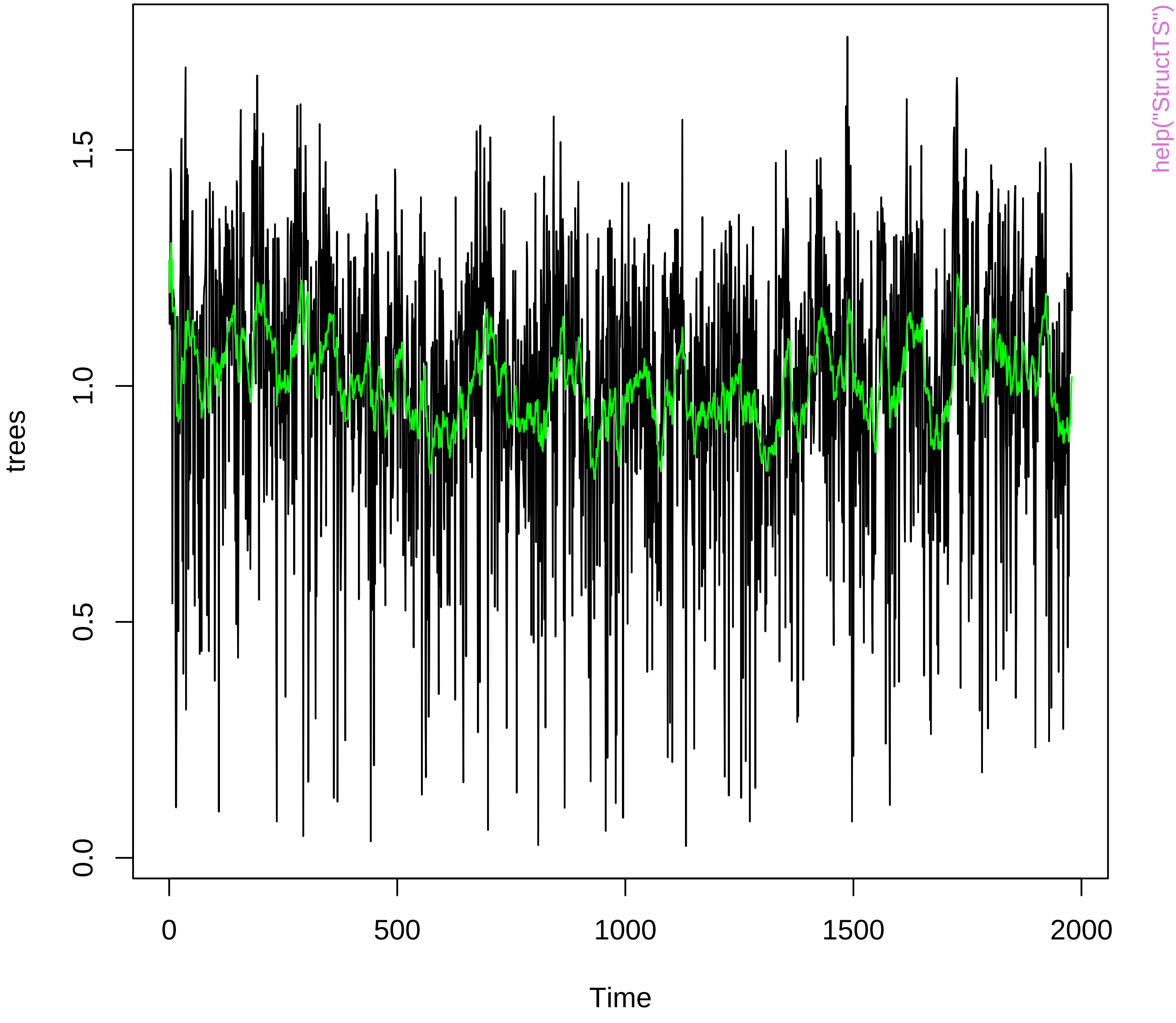

Parameters in the SSlogis model
$\phi_1 = \text{Asym}, \phi_2 = \text{xmid}, \phi_3 = \text{scal}$
y
x
ϕ_1
ϕ_2
ϕ_3
1
help("SSlogis")



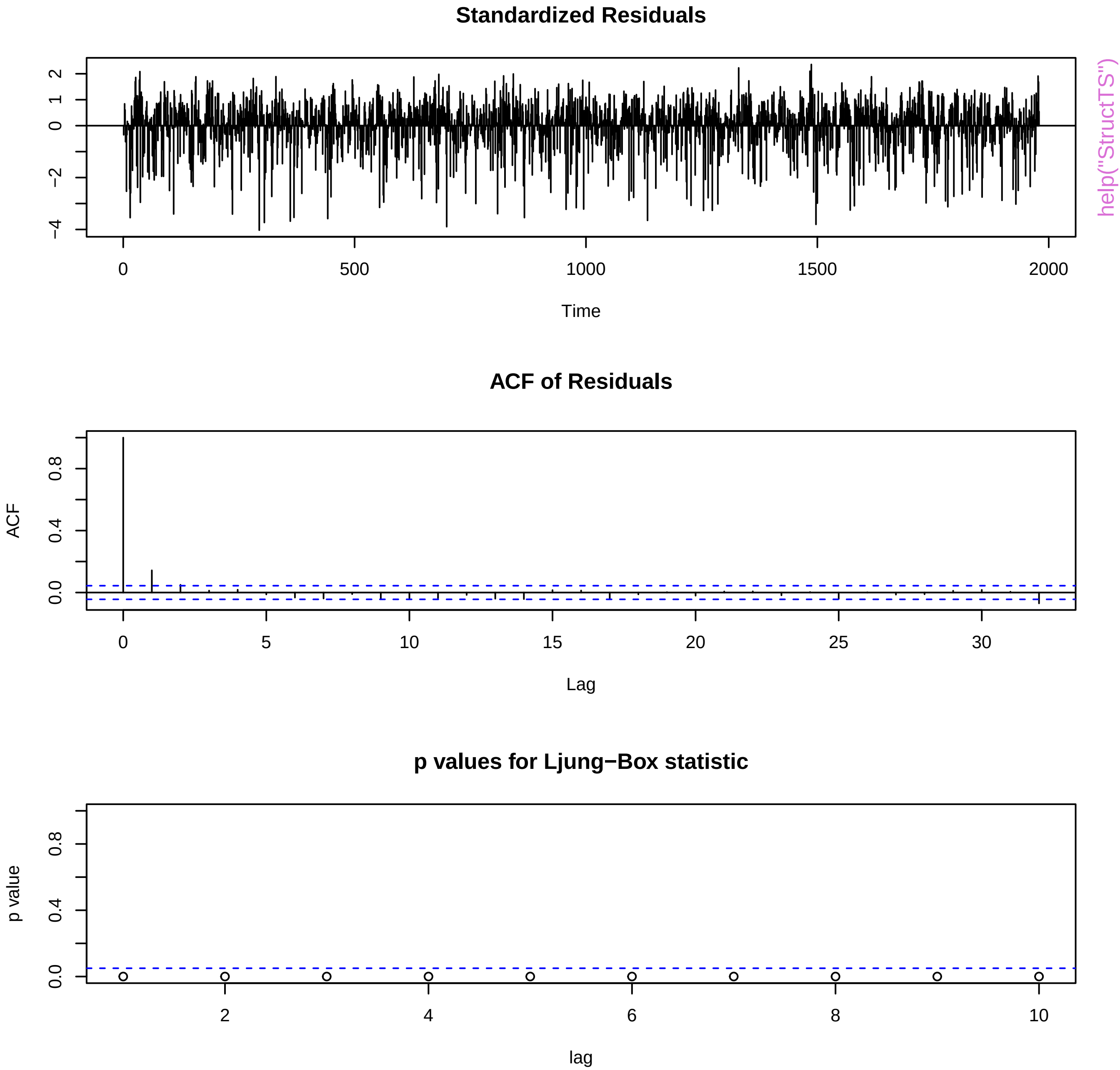
$\phi_1 = \mathrm{Vm}, \phi_2 = \mathrm{K}$
y
help("SSmicmen")
ϕ_2
ϕ_1
x

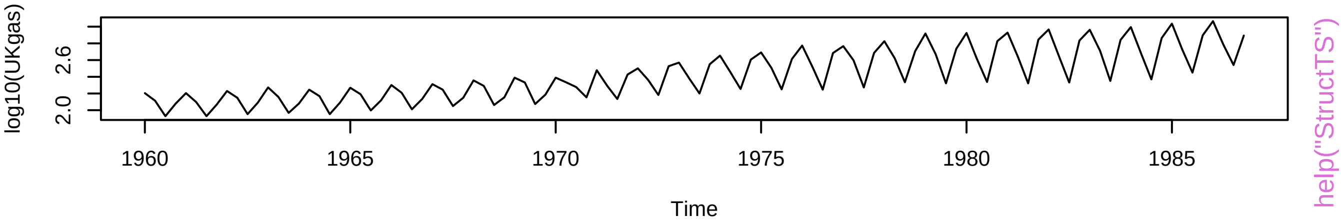

SSweibull() fit to Chick.6
weight
Time
0
5
10
15
20
60
80
100
120
140
160
help("SSweibull")

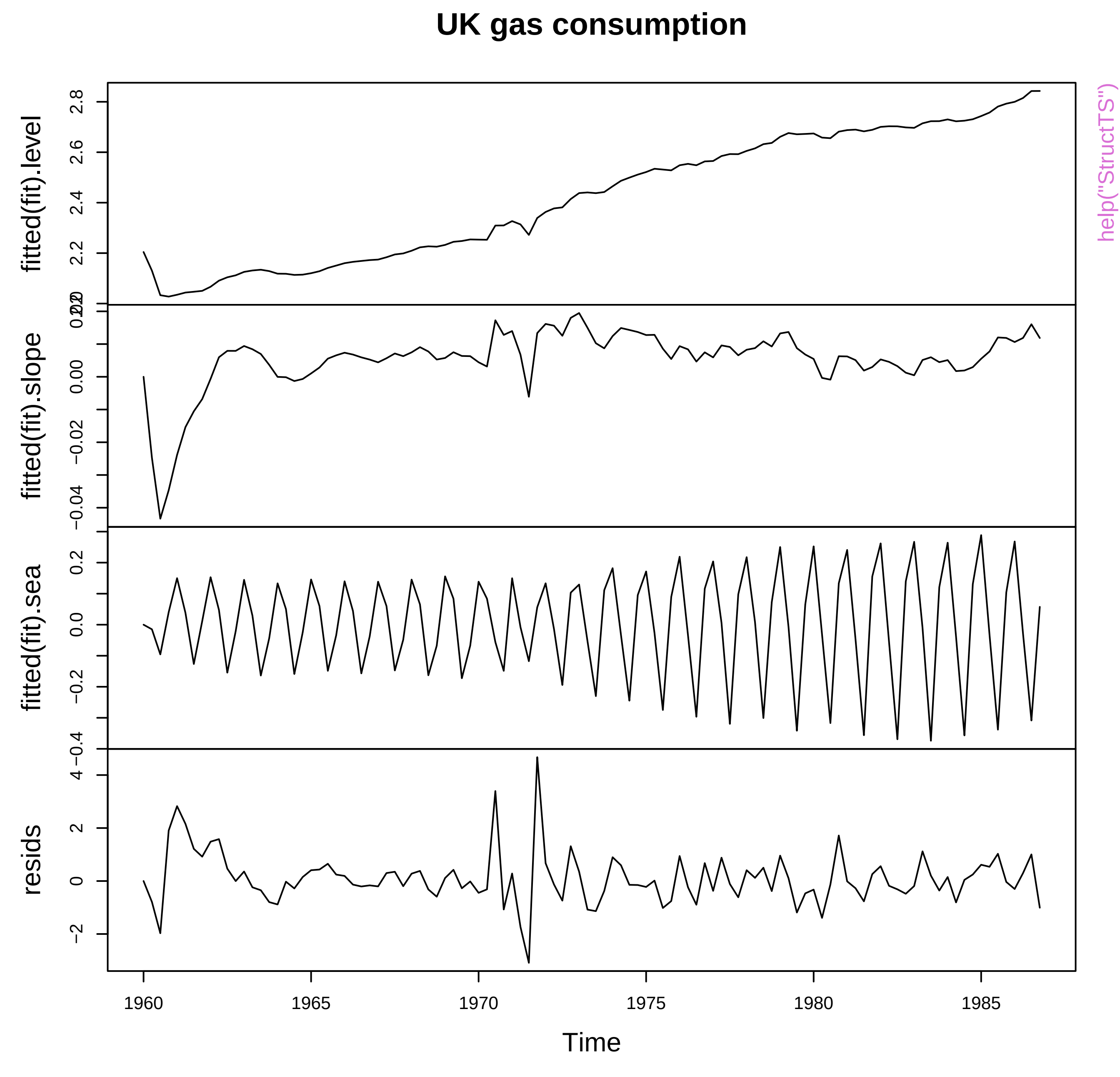

dsignrank(x, n = 4)
dsignrank(x, n = 5)
dsignrank(x, n = 10)
dsignrank(x, n = 40)
dsignrank(x, n = n)
x
help("SignRank")



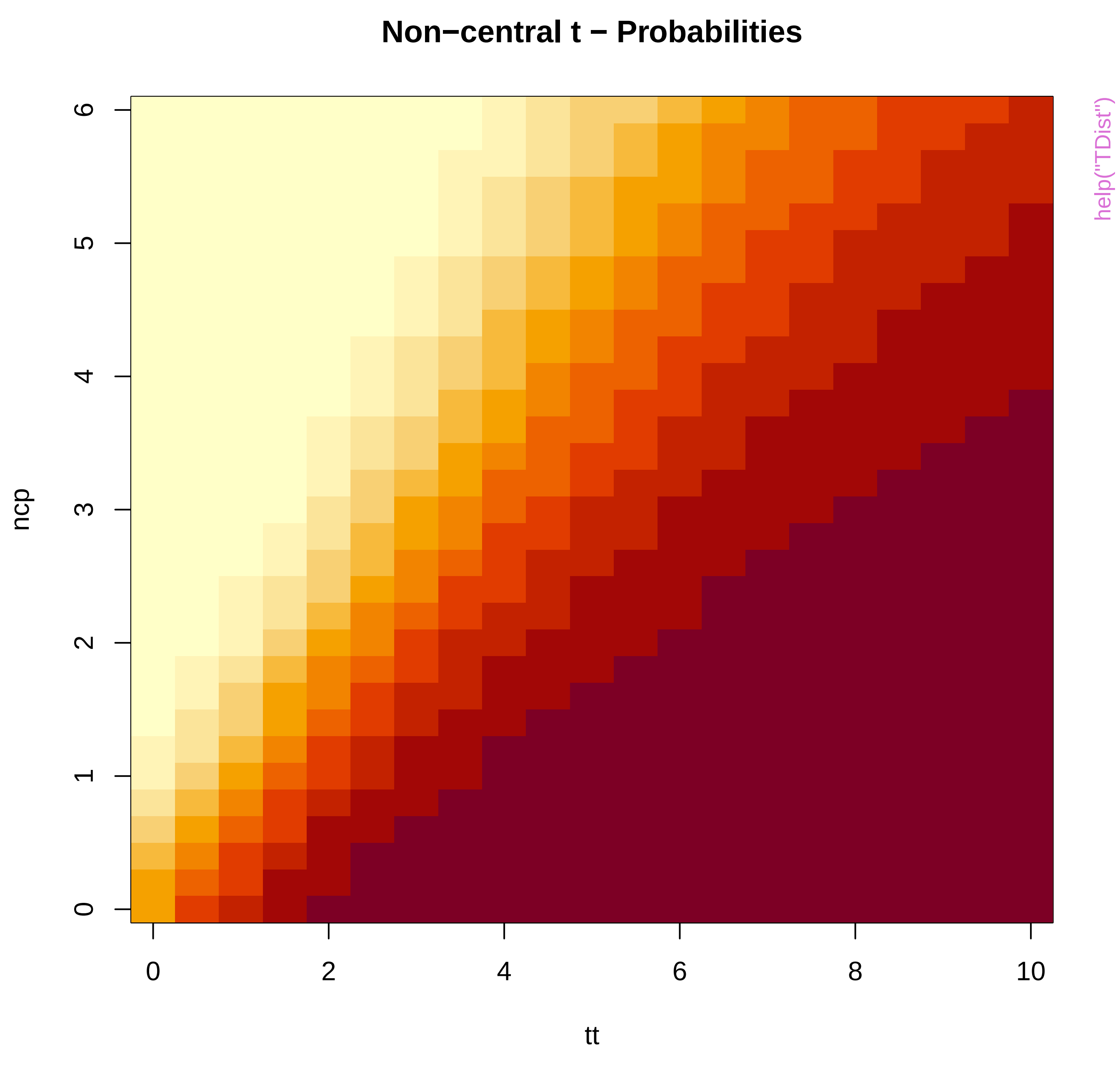
trees
0.0
0.5
1.0
1.5
0
500
1000
1500
2000
Time
help("StructTS")


Standardized Residuals
−4
−2
0
1
2
0
500
1000
1500
2000
Time
help("StructTS")
ACF of Residuals
ACF
0.0
0.4
0.8
0
5
10
15
20
25
30
Lag
p values for Ljung−Box statistic
p value
0.0
0.4
0.8
2
4
6
8
10
lag

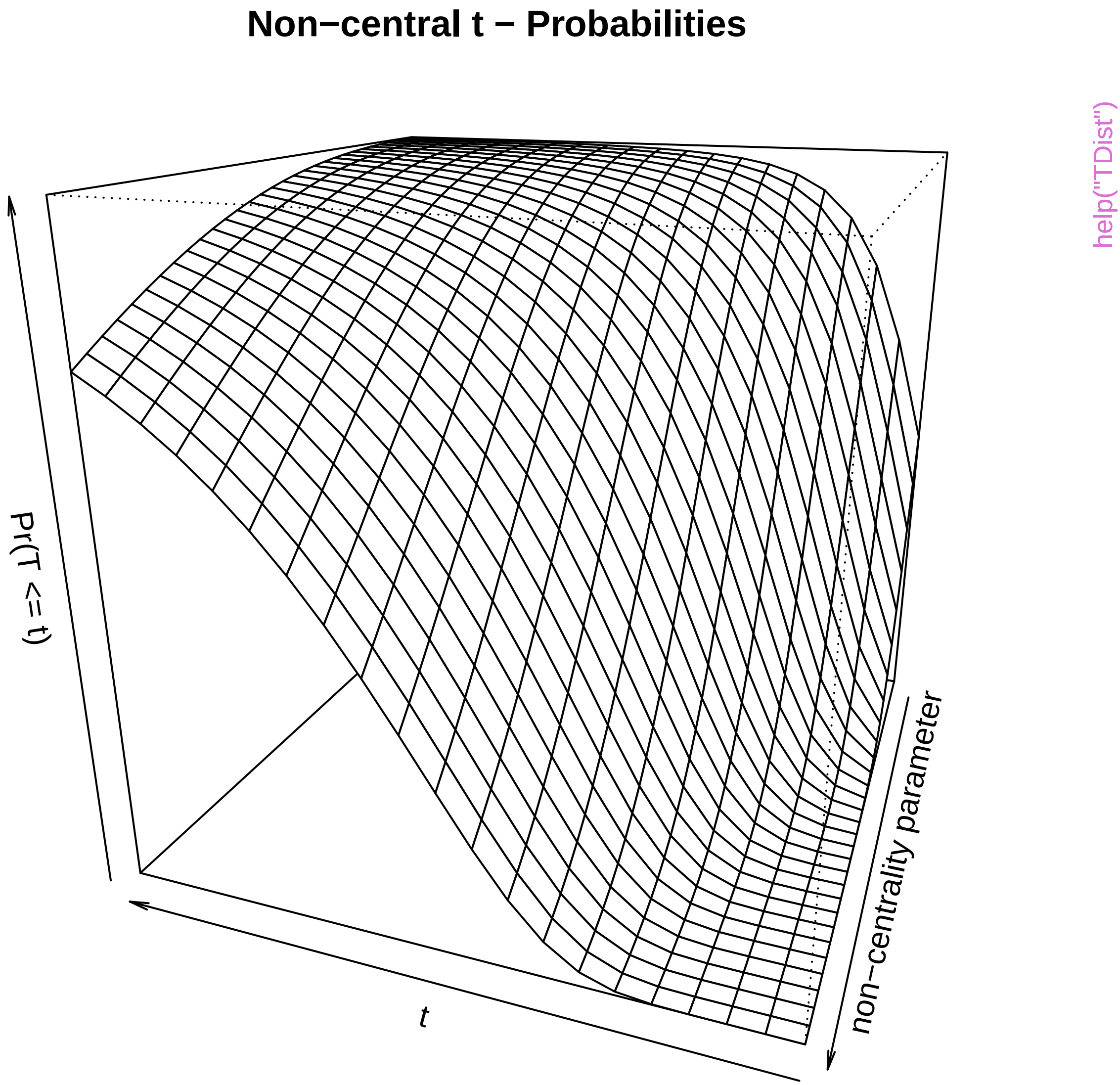

log10(UKgas)
2.0
2.6
1960
1965
1970
1975
1980
1985
Time
help("StructTS")

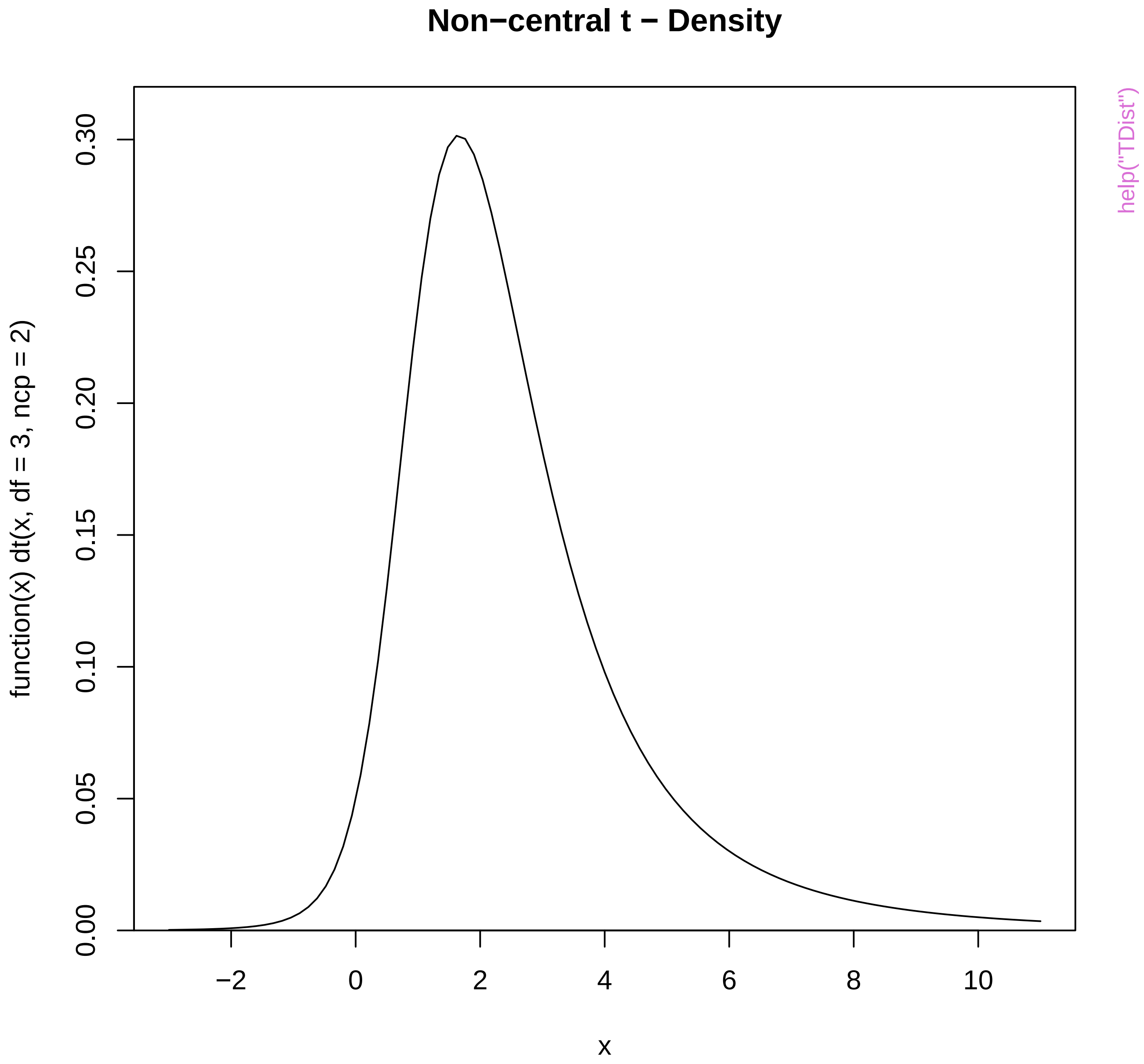


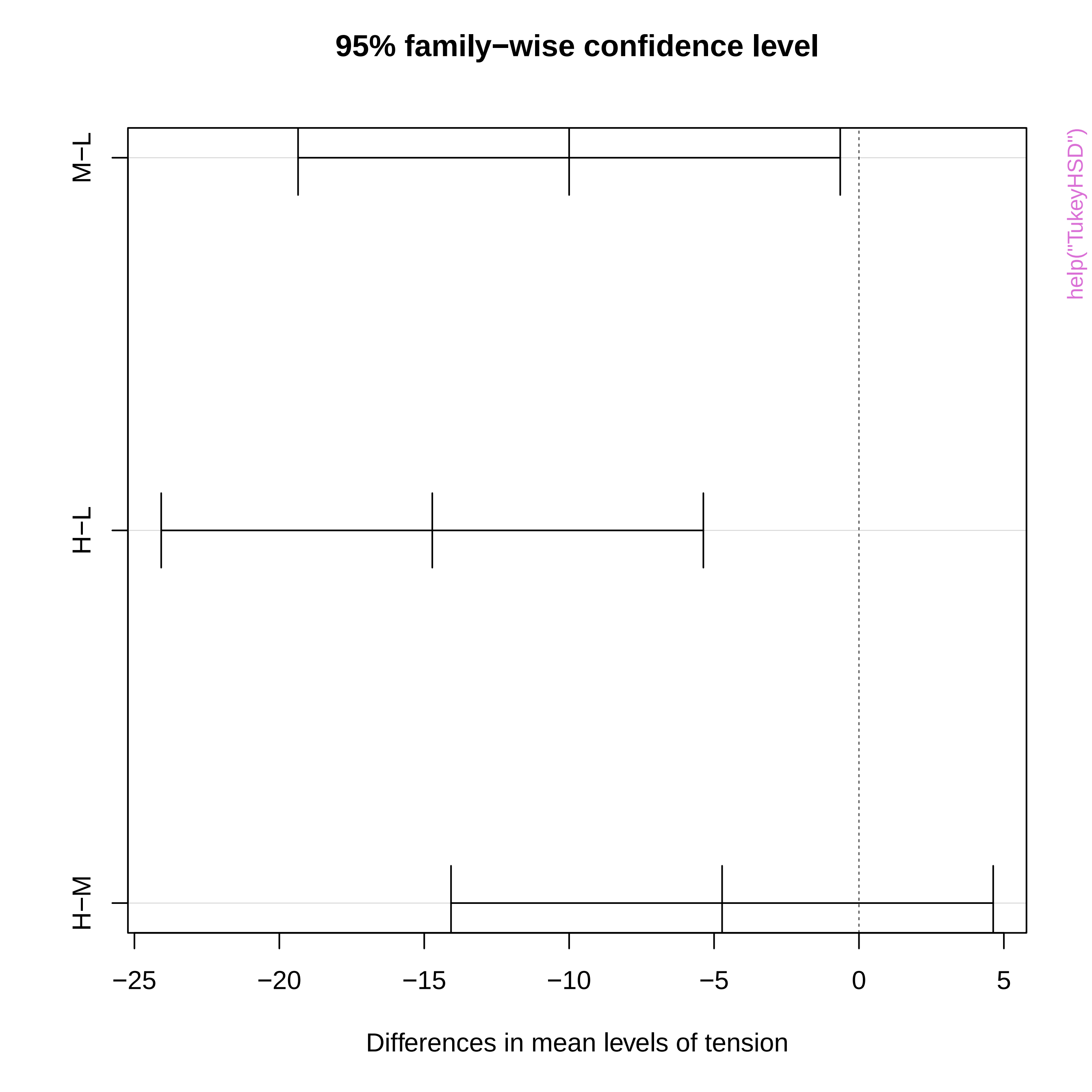
UK gas consumption
fitted(fit).level
fitted(fit).slope
fitted(fit).sea
resids
2.8
2.6
2.4
2.2
2.0
0.02
0.00
−0.02
−0.04
0.2
0.0
−0.2
−0.4
4
2
0
−2
1960
1965
1970
1975
1980
1985
Time
help("StructTS")

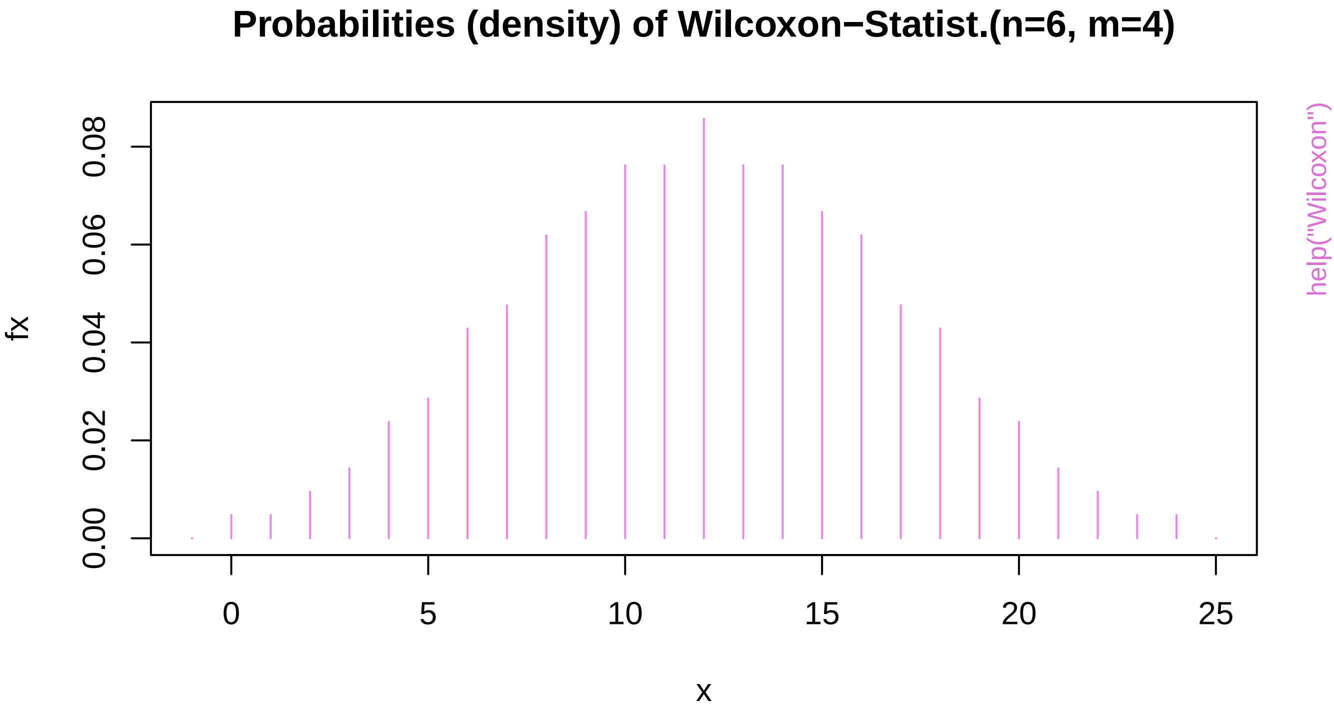


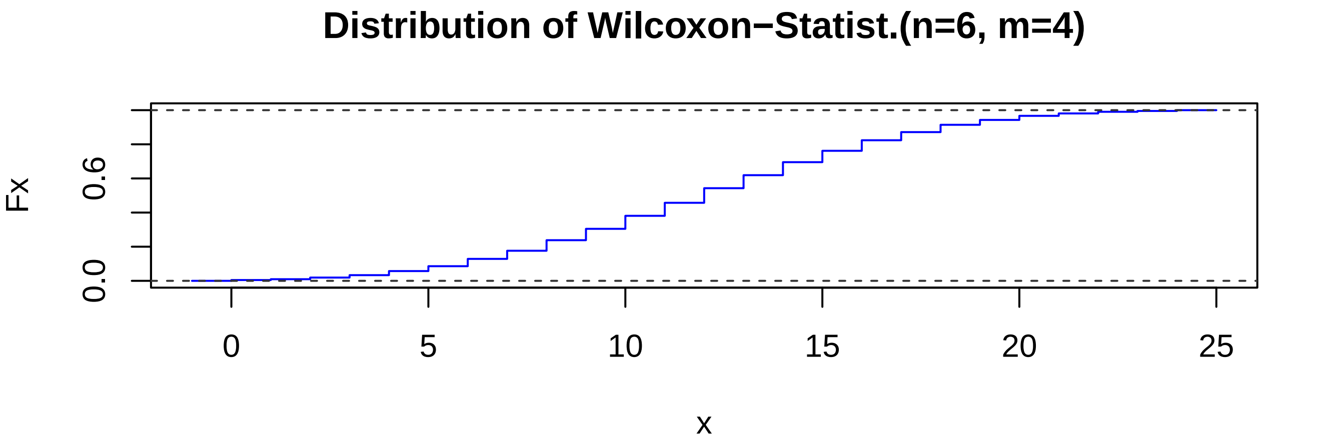
Non−central t − Probabilities
ncp
tt
0
1
2
3
4
5
6
0
2
4
6
8
10
help("TDist")

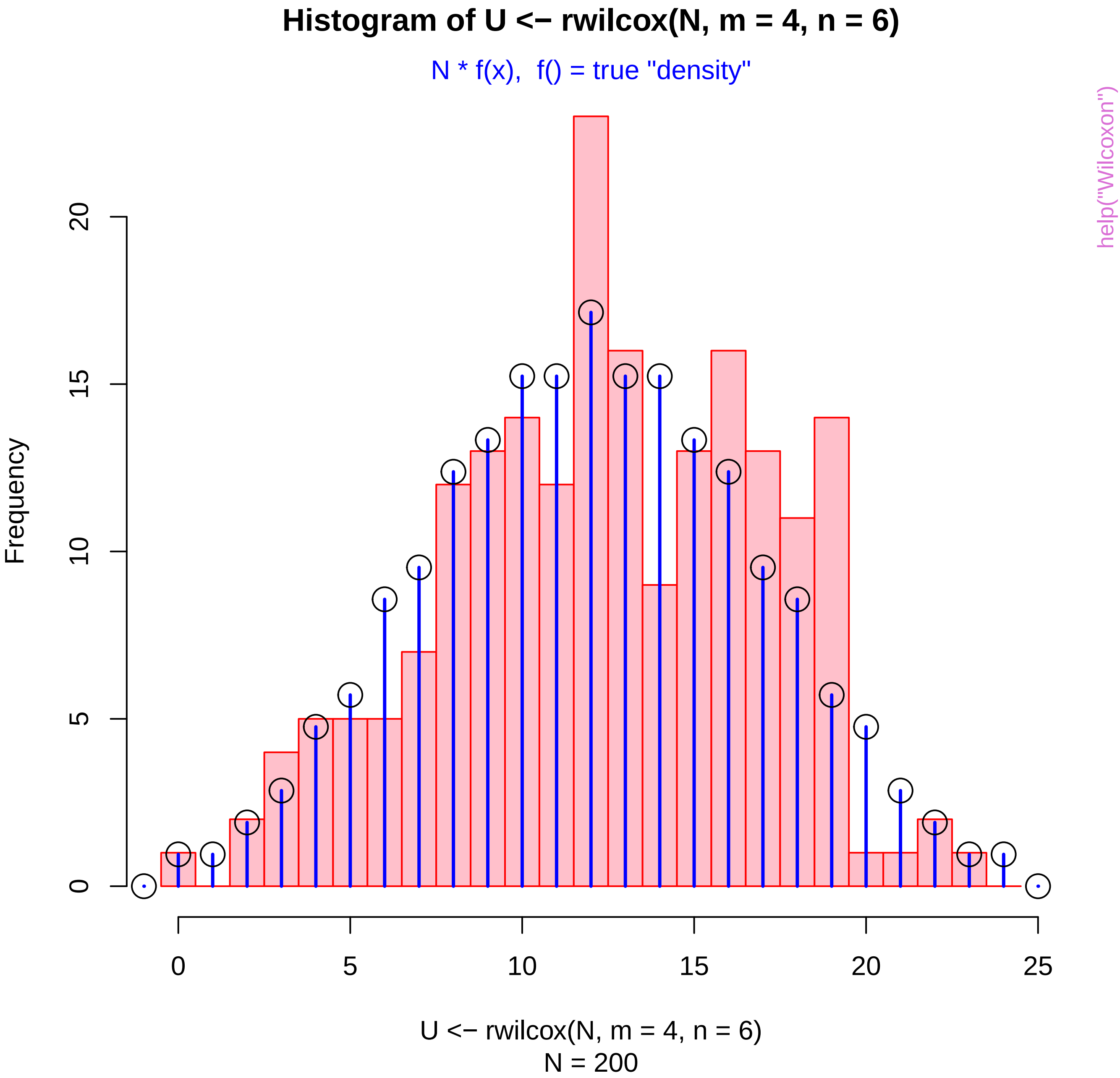

Non−central t − Probabilities
Pr(T <= t)
t
non−centrality parameter
help("TDist")


Non−central t − Density
function(x) dt(x, df = 3, ncp = 2)
0.00
0.05
0.10
0.15
0.20
0.25
0.30
−2
0
2
4
6
8
10
x
help("TDist")

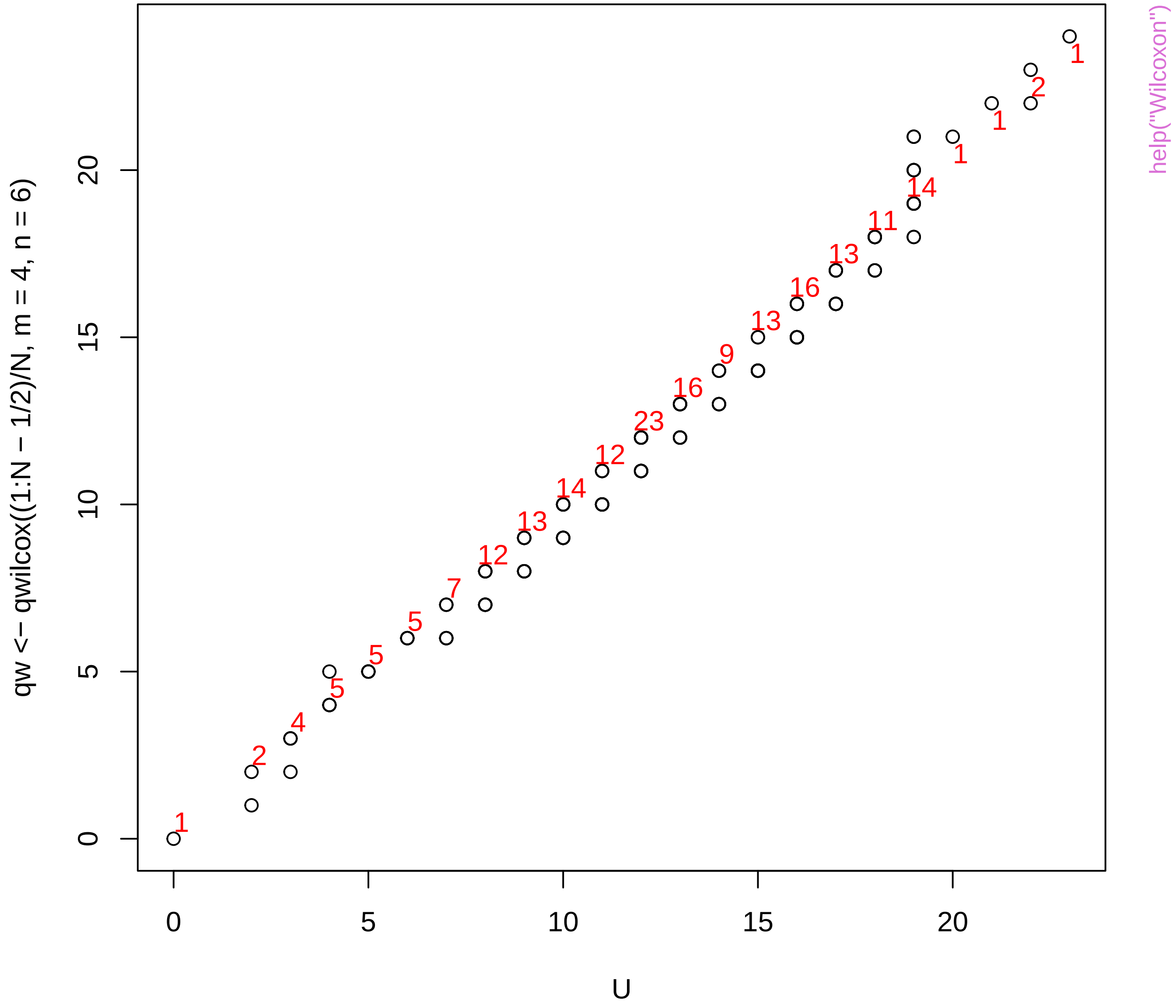

95% family−wise confidence level
M−L
H−L
H−M
−25
−20
−15
−10
−5
0
5
Differences in mean levels of tension
help("TukeyHSD")

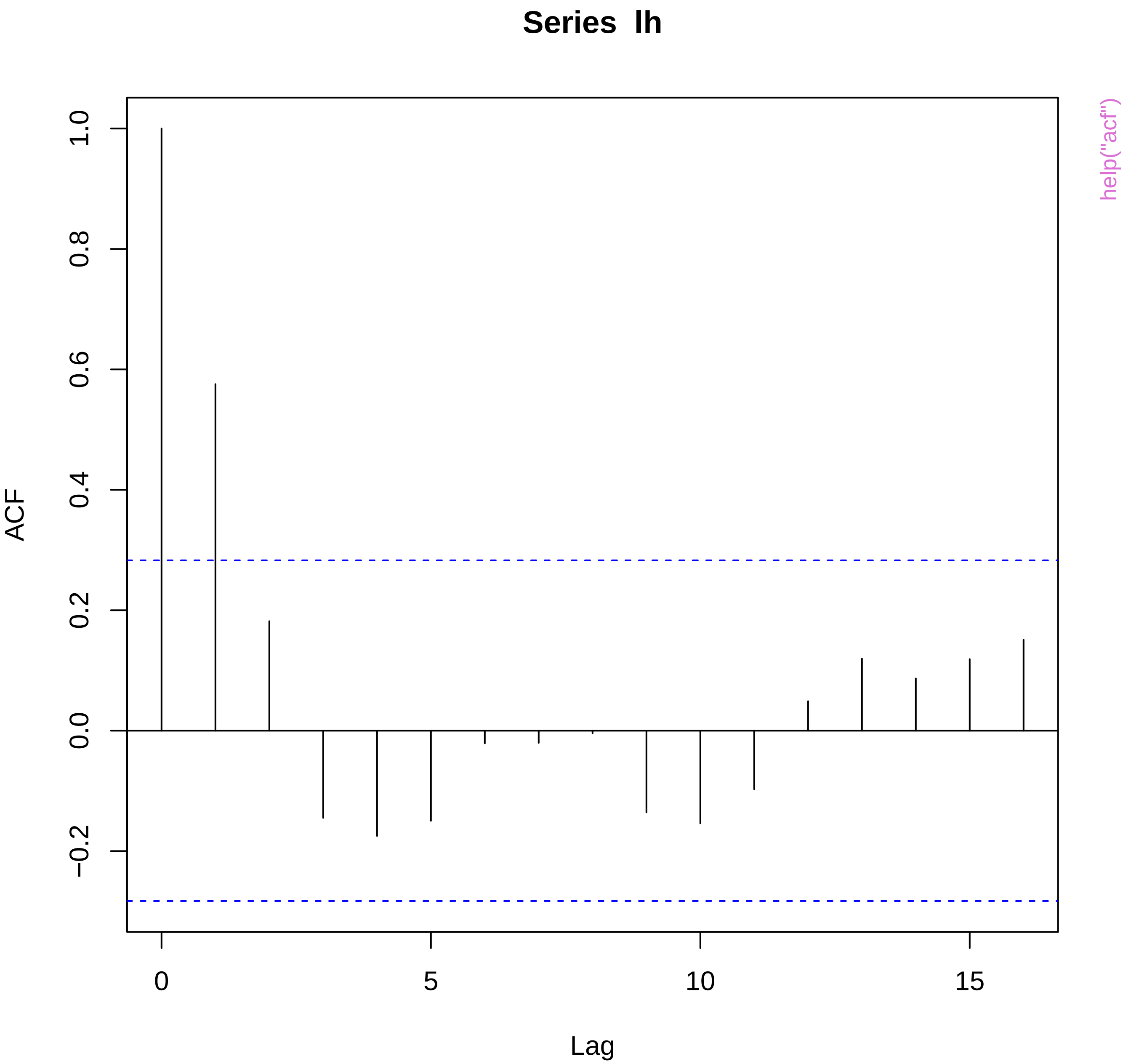

Probabilities (density) of Wilcoxon−Statist.(n=6, m=4)
fx
0.00
0.02
0.04
0.06
0.08
0
5
10
15
20
25
x
help("Wilcoxon")

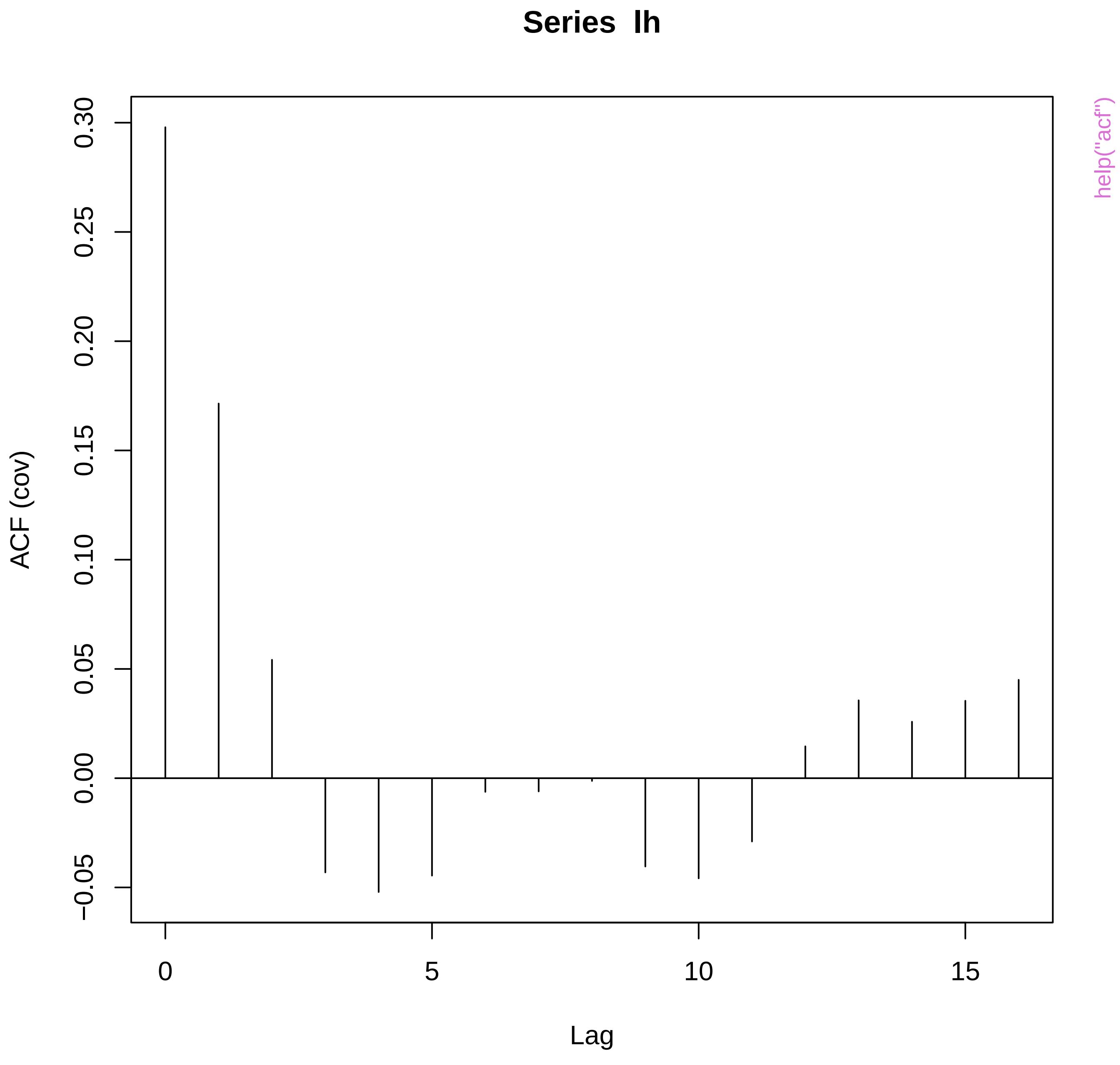

Distribution of Wilcoxon−Statist.(n=6, m=4)
Fx
0.0
0.6
0
5
10
15
20
25
x

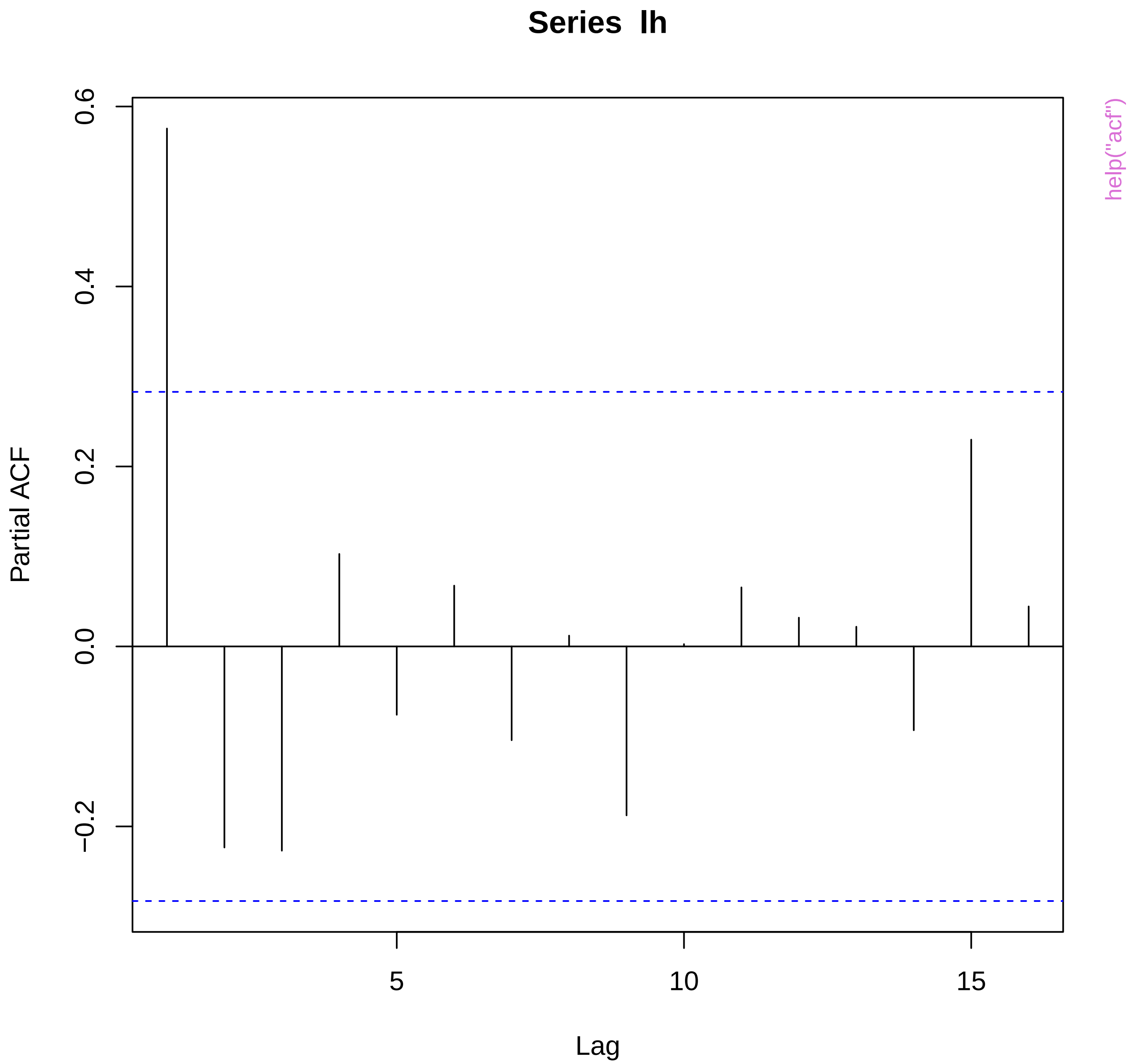

Histogram of U <− rwilcox(N, m = 4, n = 6)
N * f(x), f() = true "density"
help("Wilcoxon")
Frequency
0
5
10
15
20
0
5
10
15
20
25
U <− rwilcox(N, m = 4, n = 6)
N = 200

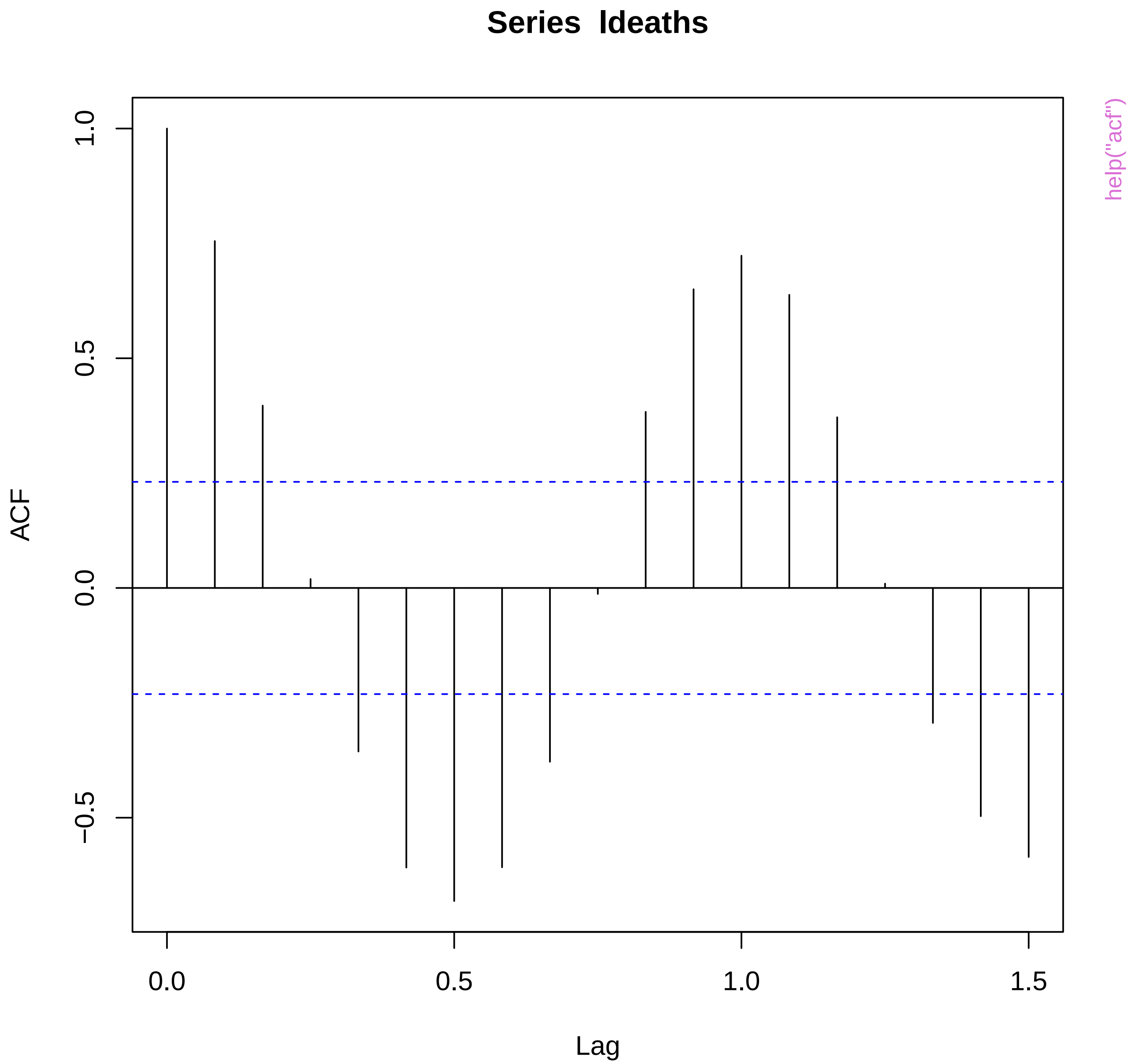
Q−Q−Plot of empirical and theoretical quantiles
Wilcoxon Statistic, (m=4, n=6)



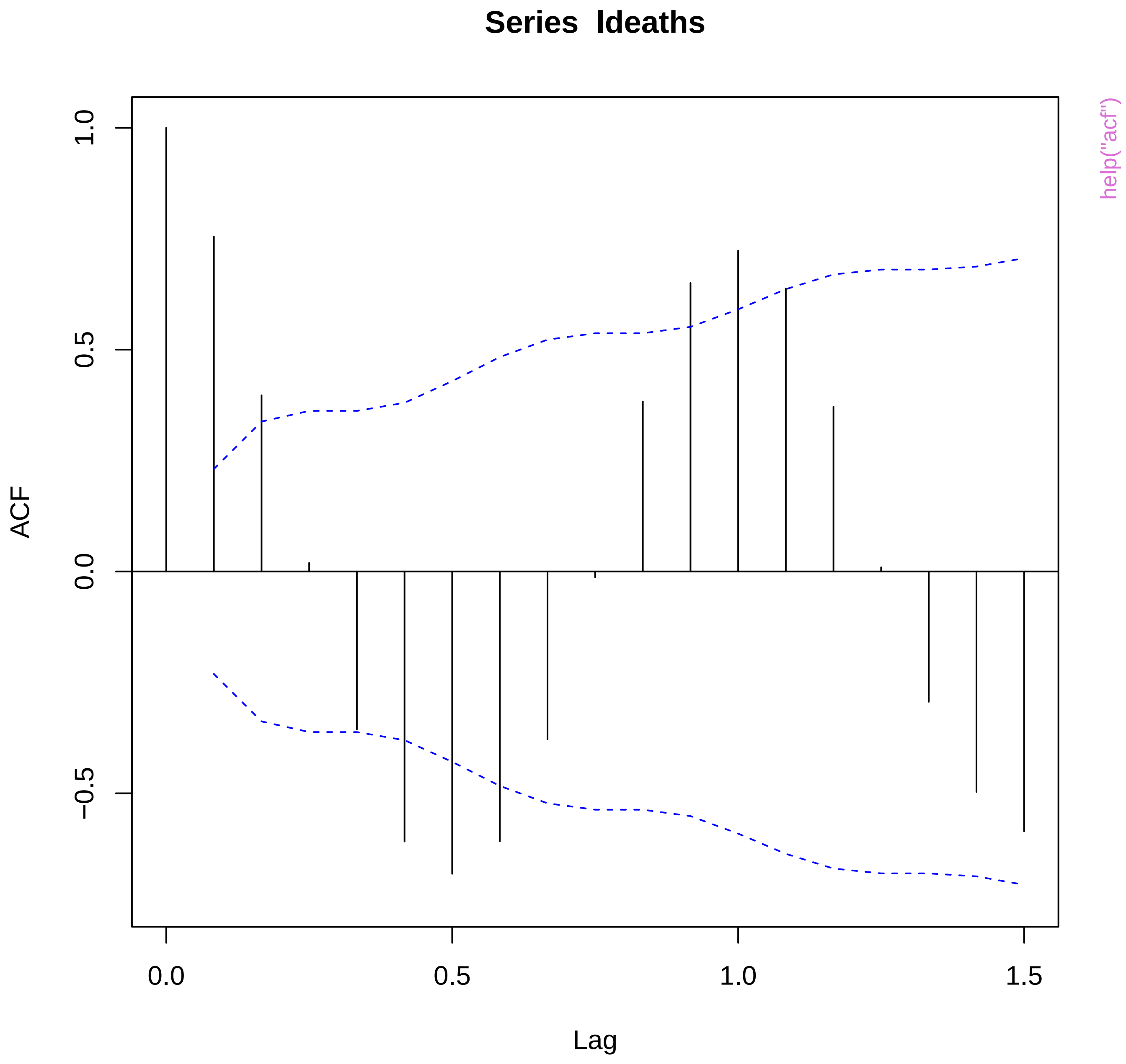

Series lh
ACF
Lag
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
0
5
10
15
help("acf")


Series lh
ACF (cov)
Lag
0
5
10
15
−0.05
0.00
0.05
0.10
0.15
0.20
0.25
0.30
help("acf")

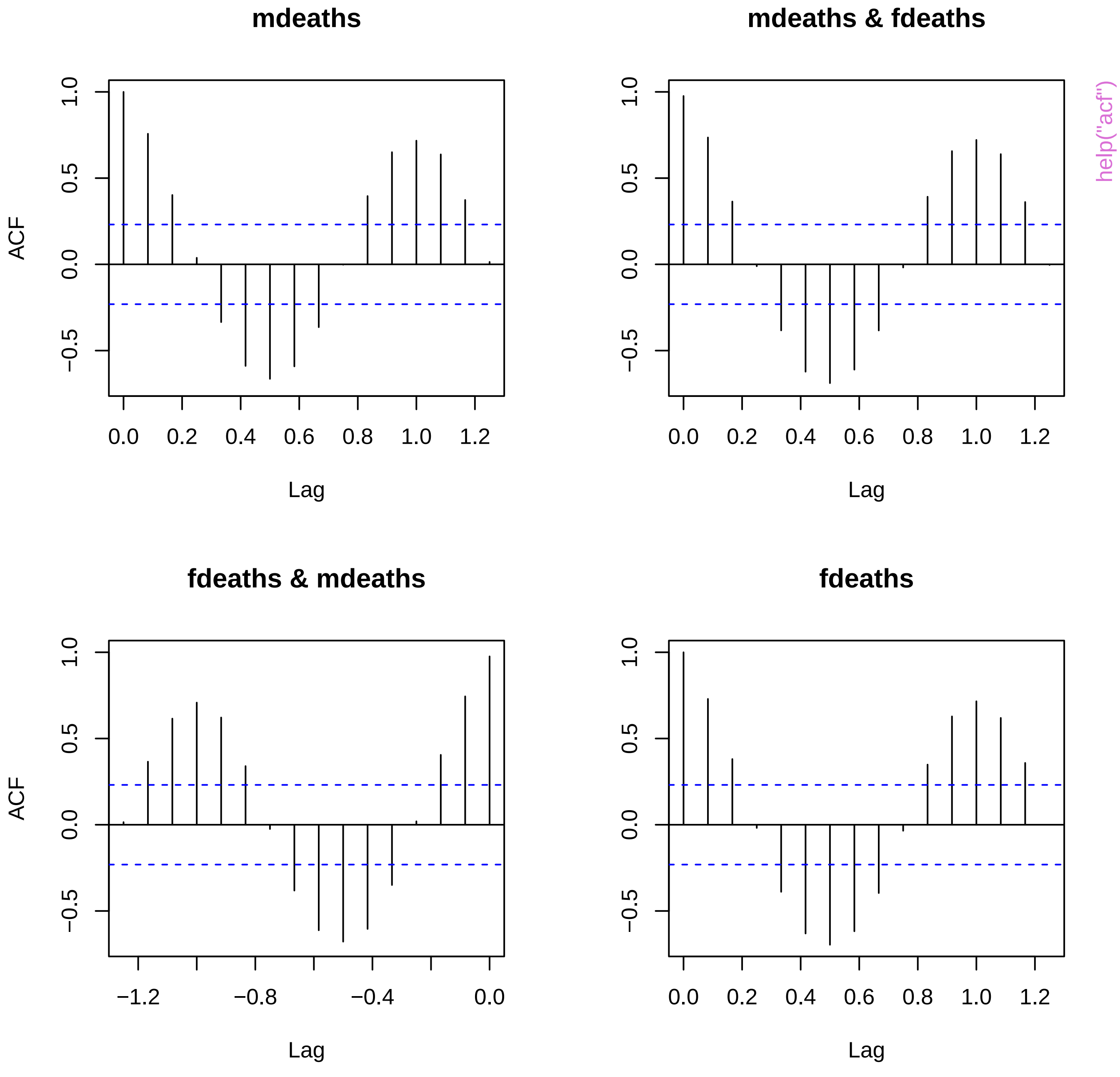

Series lh
Partial ACF
Lag
0.6
0.4
0.2
0.0
−0.2
5
10
15
help("acf")

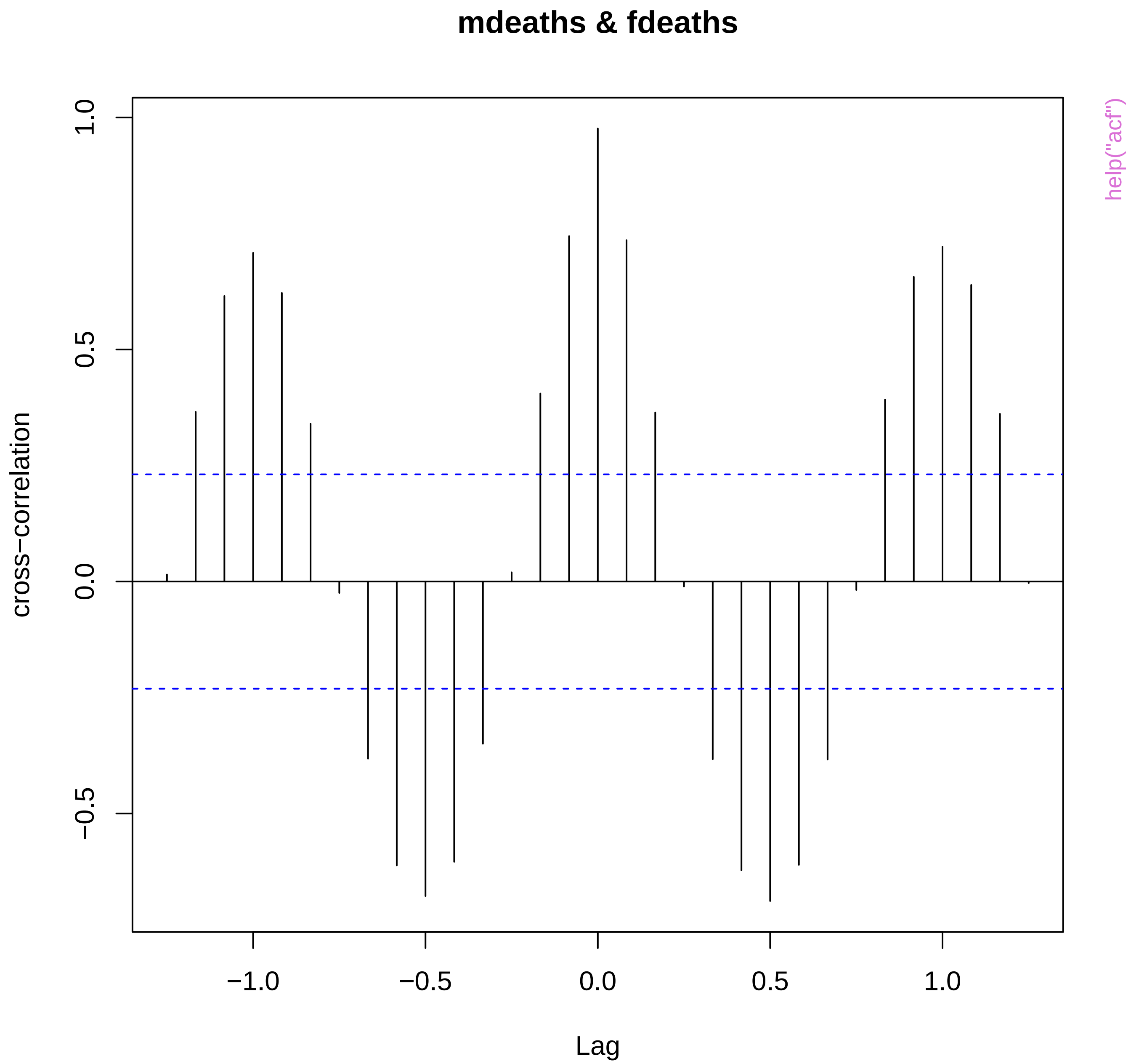


Series ldeaths
ACF
Lag
1.0
0.5
0.0
−0.5
0.0
0.5
1.0
1.5
help("acf")

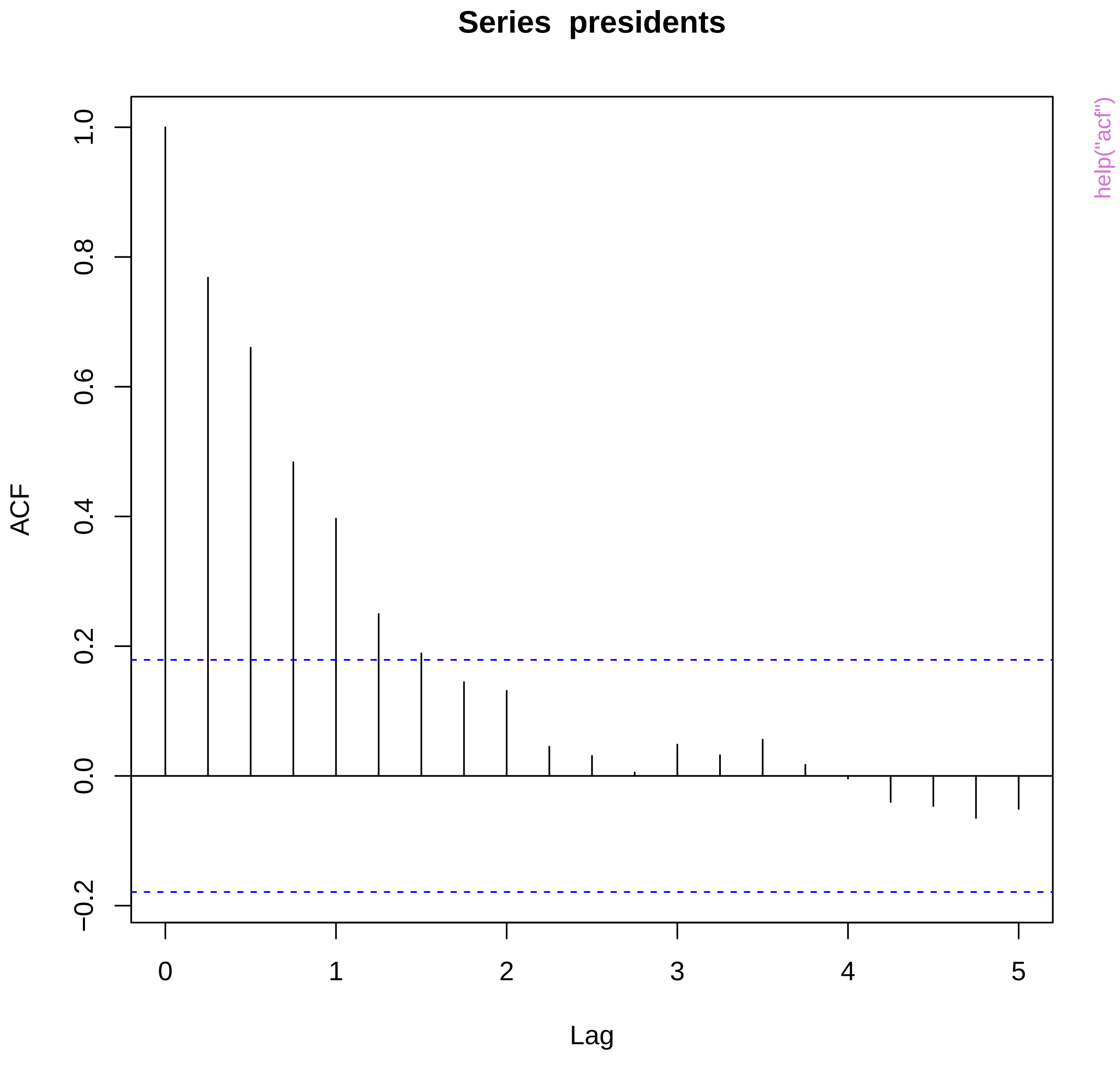


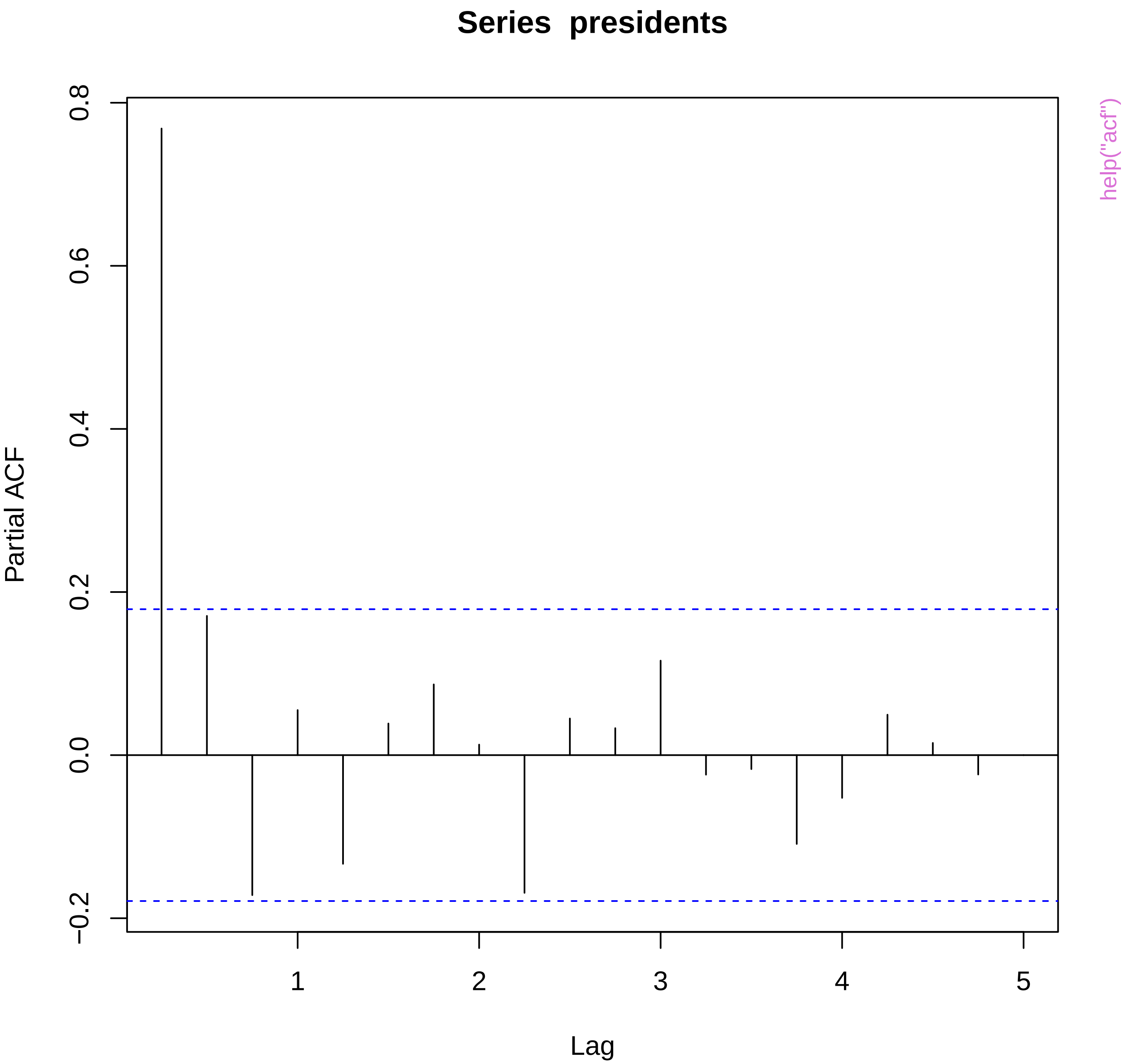
Series ldeaths
ACF
1.0
0.5
0.0
−0.5
0.0
0.5
1.0
1.5
Lag
help("acf")

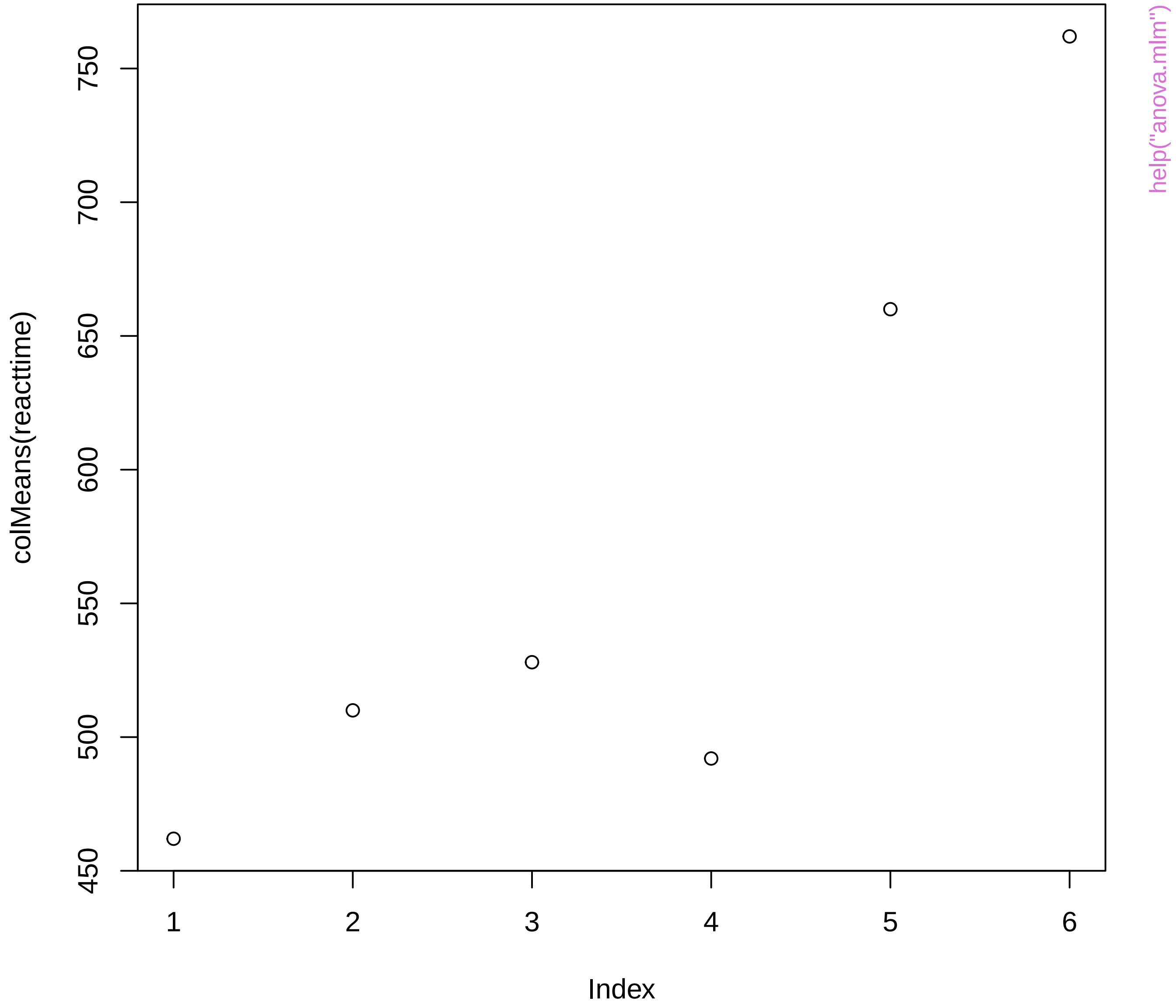

mdeaths
mdeaths & fdeaths
fdeaths & mdeaths
fdeaths
ACF
Lag
1.0
0.5
0.0
−0.5
0.0 0.2 0.4 0.6 0.8 1.0 1.2
−1.2 −0.8 −0.4 0.0
help("acf")

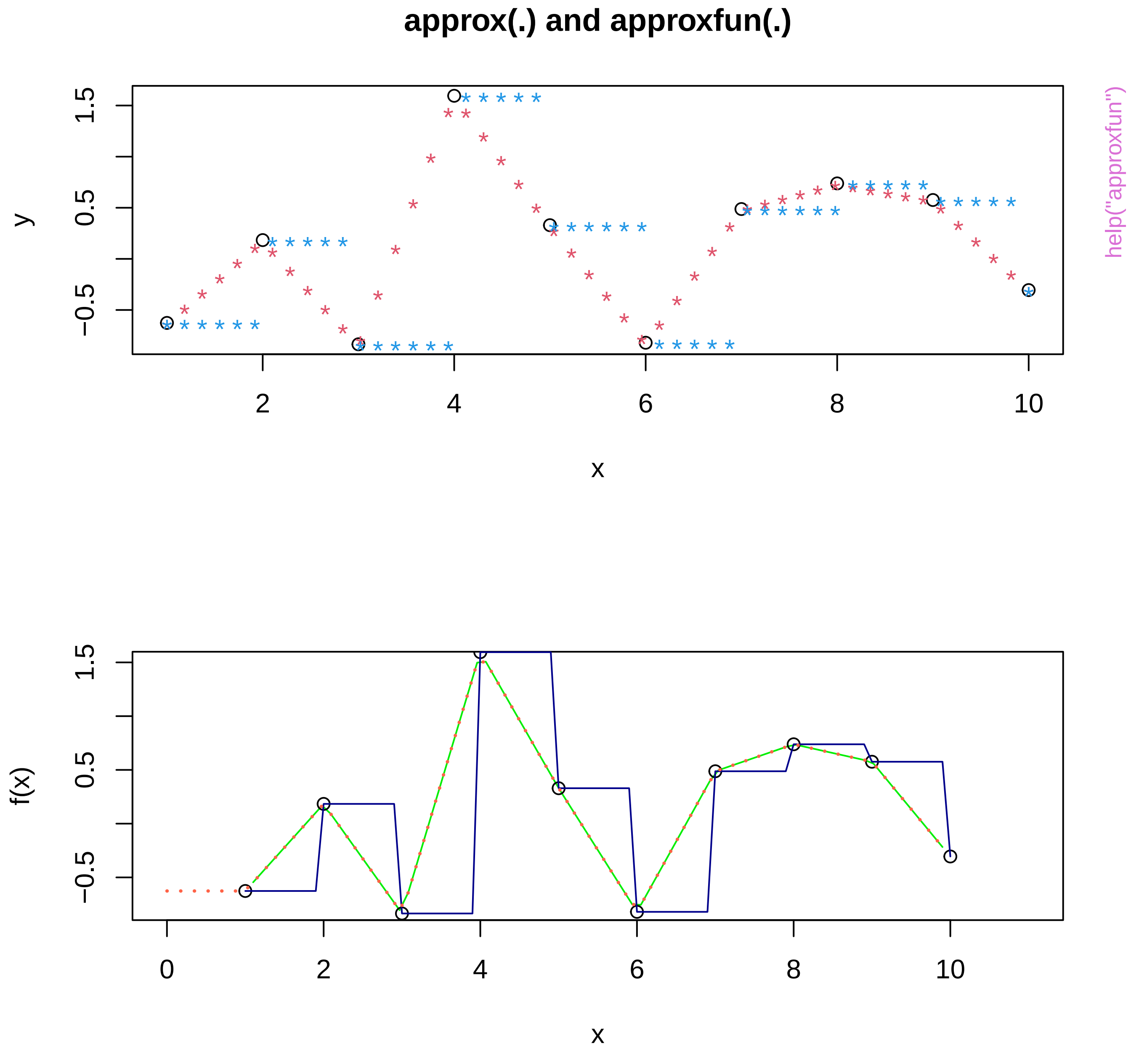


mdeaths & fdeaths
cross−correlation
1.0
0.5
0.0
−0.5
−1.0
−0.5
0.0
0.5
1.0
Lag
help("acf")

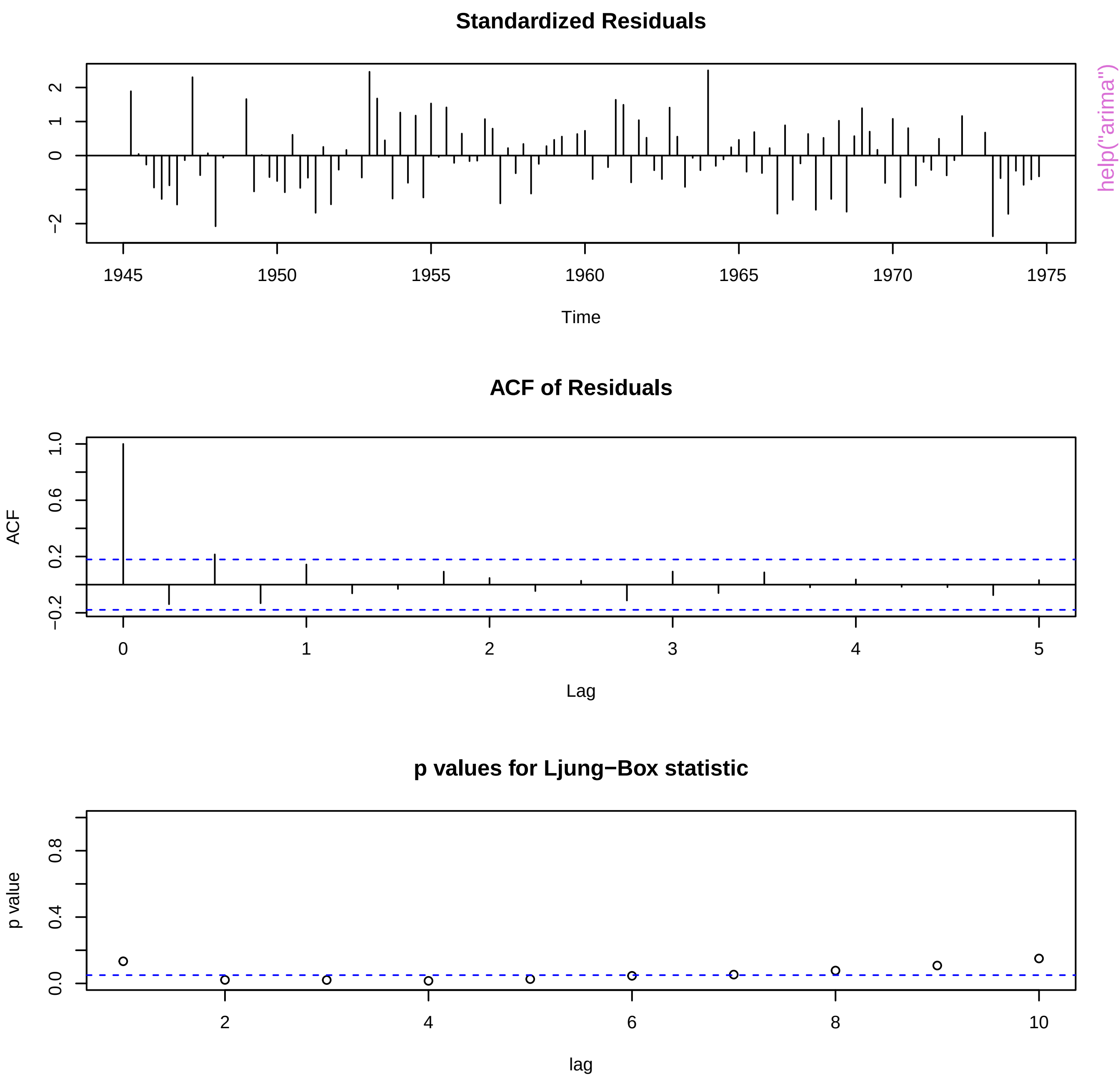

Series presidents
ACF
Lag
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
0
1
2
3
4
5
help("acf")

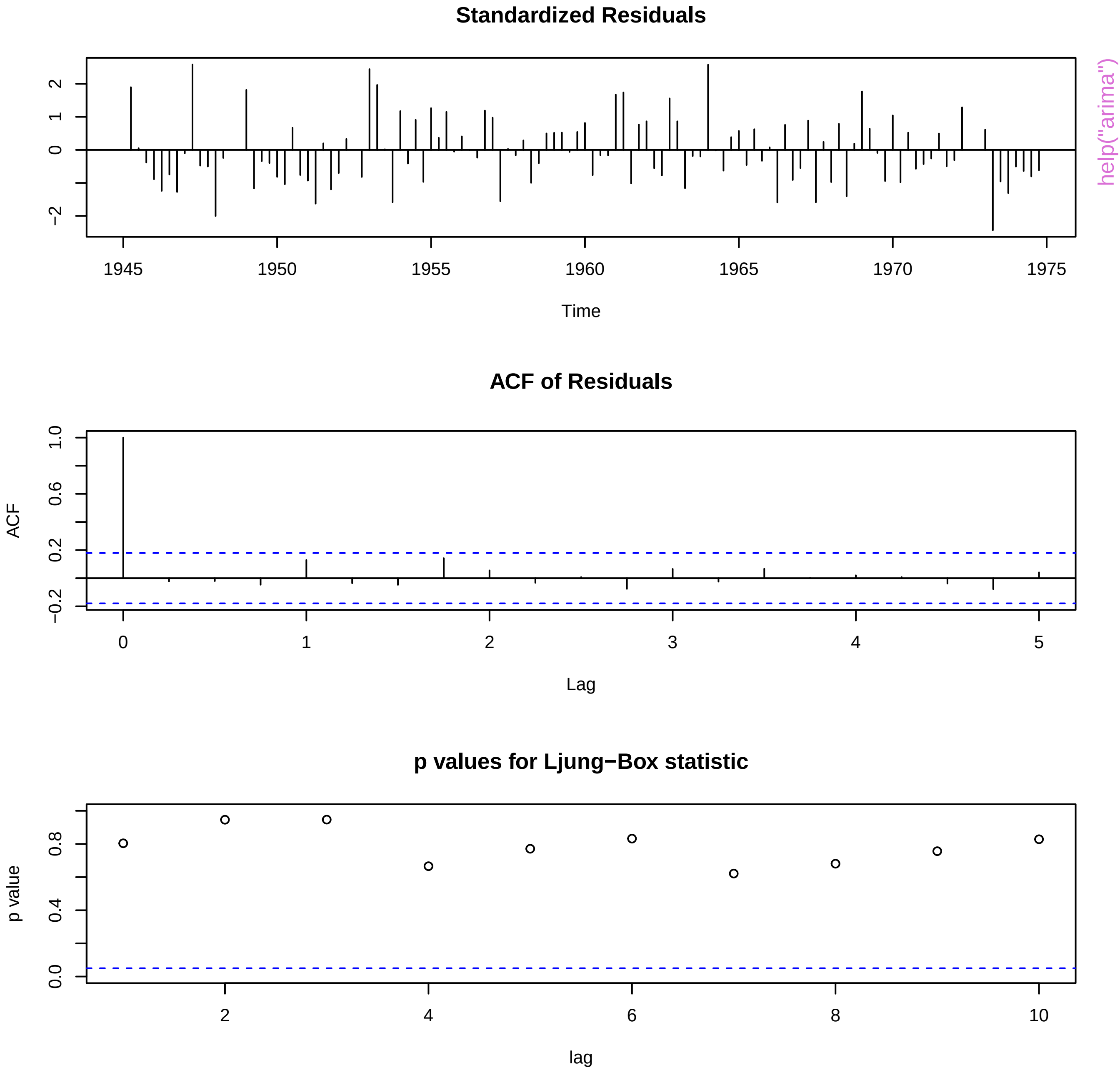

Series presidents
Partial ACF
Lag
0.8
0.6
0.4
0.2
0.0
−0.2
1
2
3
4
5
help("acf")


colMeans(reacttime)
450
500
550
600
650
700
750
1
2
3
4
5
6
Index
help("anova.mlm")

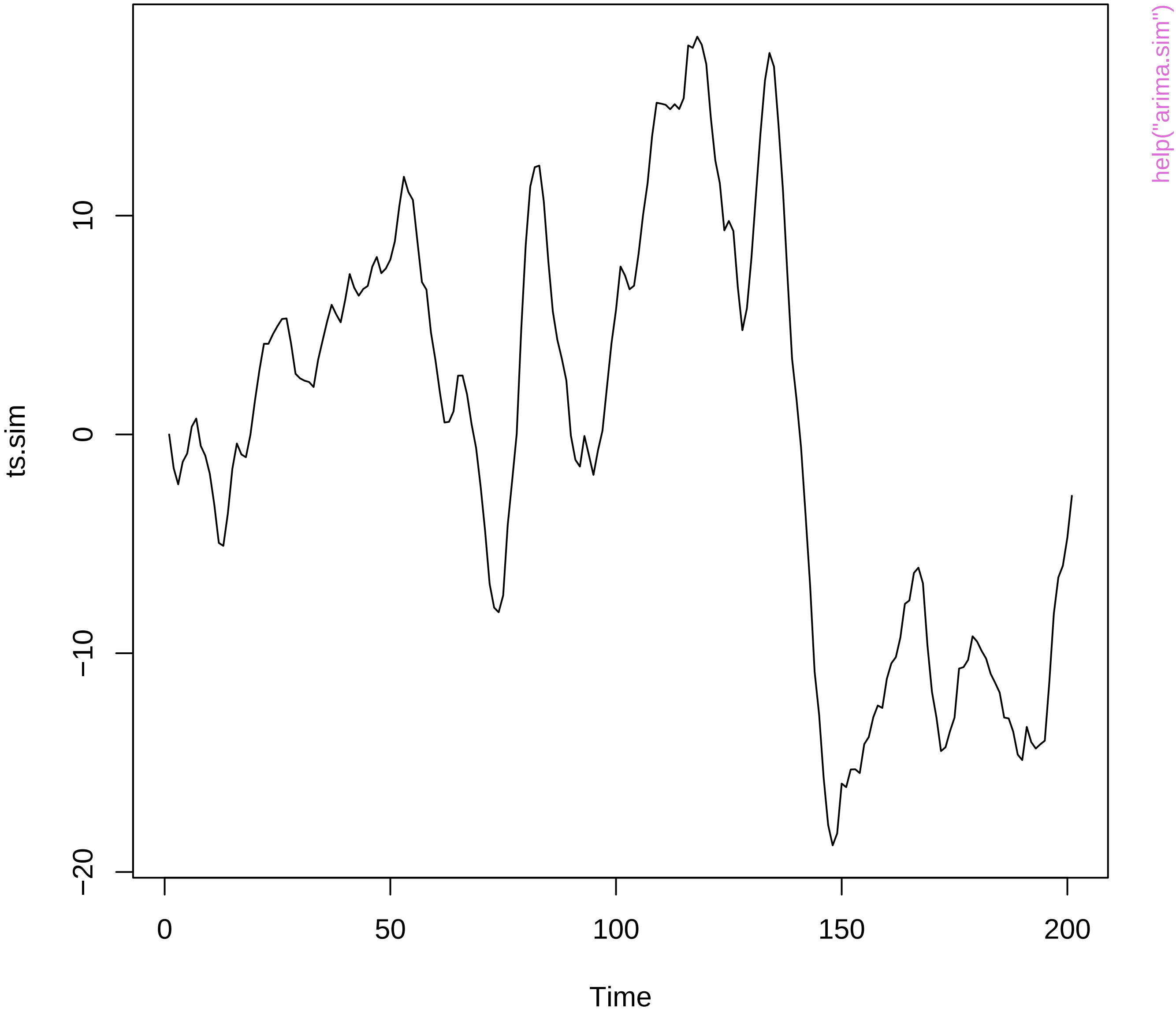


approx(.) and approxfun(.)
y
1.5
0.5
−0.5
2
4
6
8
10
x
help("approxfun")
f(x)
1.5
0.5
−0.5
0
2
4
6
8
10
x

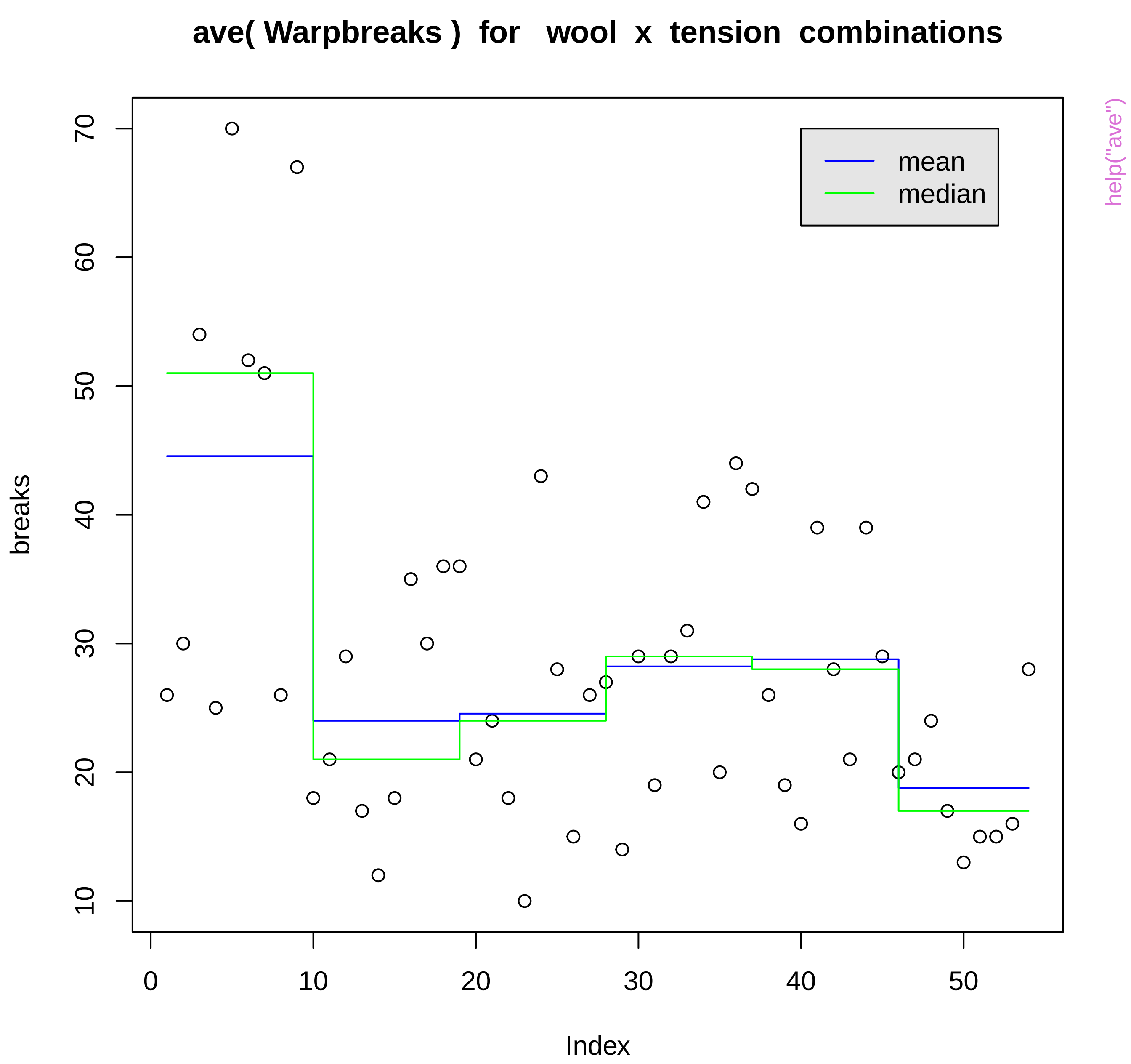

Standardized Residuals
Time
ACF of Residuals
ACF
Lag
p values for Ljung−Box statistic
p value
lag
help("arima")



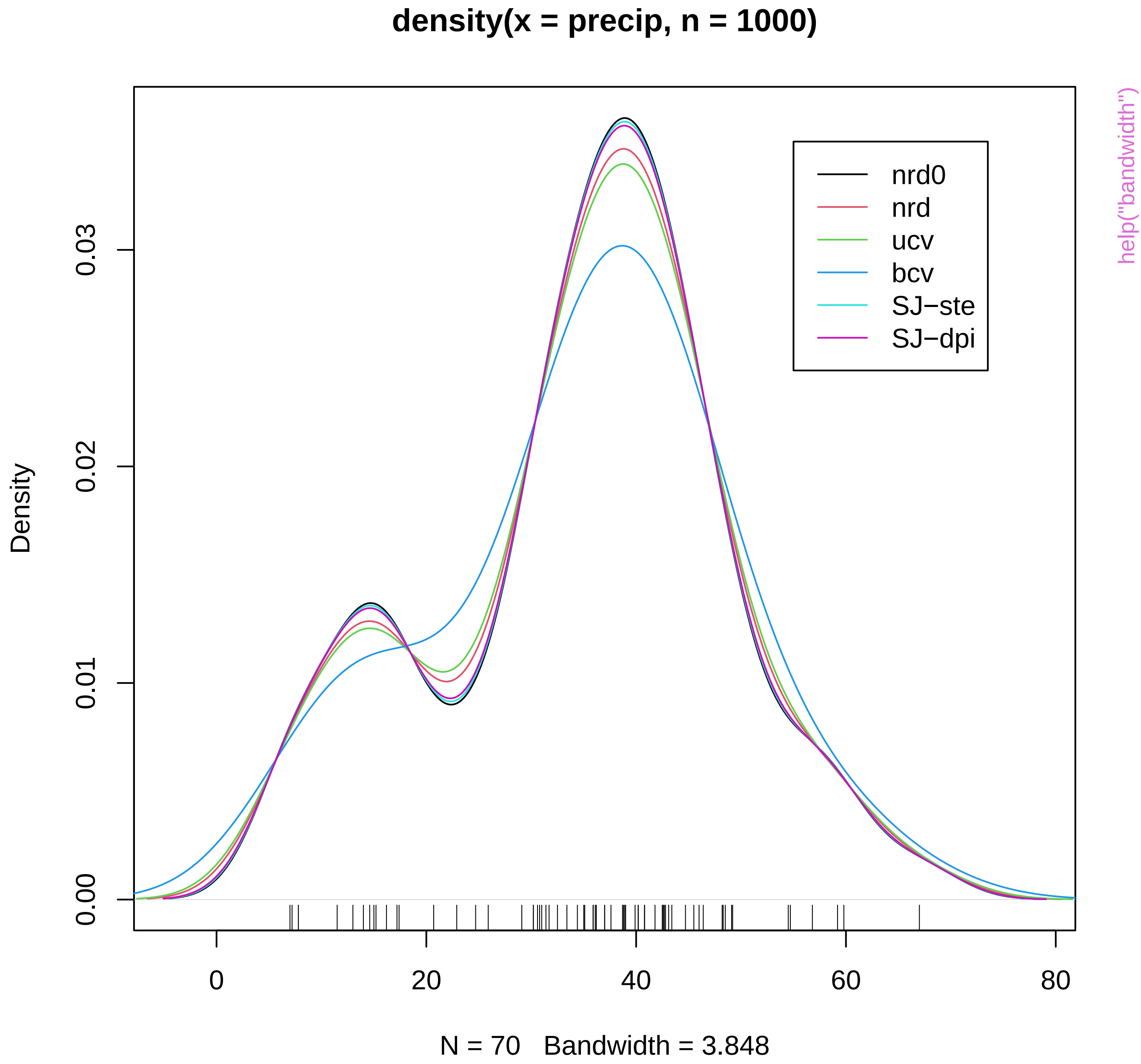
Standardized Residuals
2
1
0
−2
1945
1950
1955
1960
1965
1970
1975
Time
help("arima")
ACF of Residuals
ACF
1.0
0.6
0.2
−0.2
0
1
2
3
4
5
Lag
p values for Ljung−Box statistic
p value
0.8
0.4
0.0
2
4
6
8
10
lag



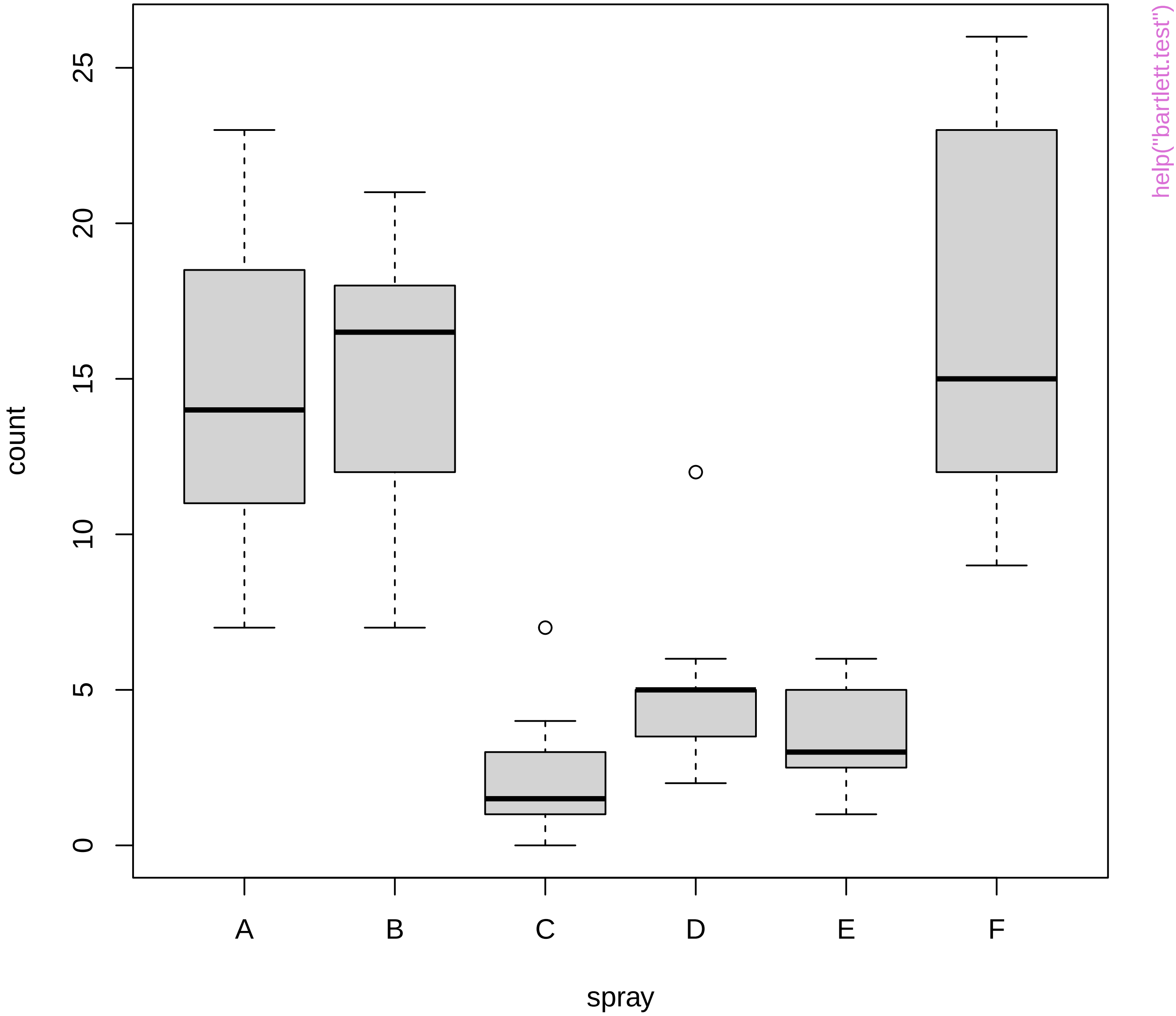
ts.sim
10
0
−10
−20
0
50
100
150
200
Time
help("arima.sim")



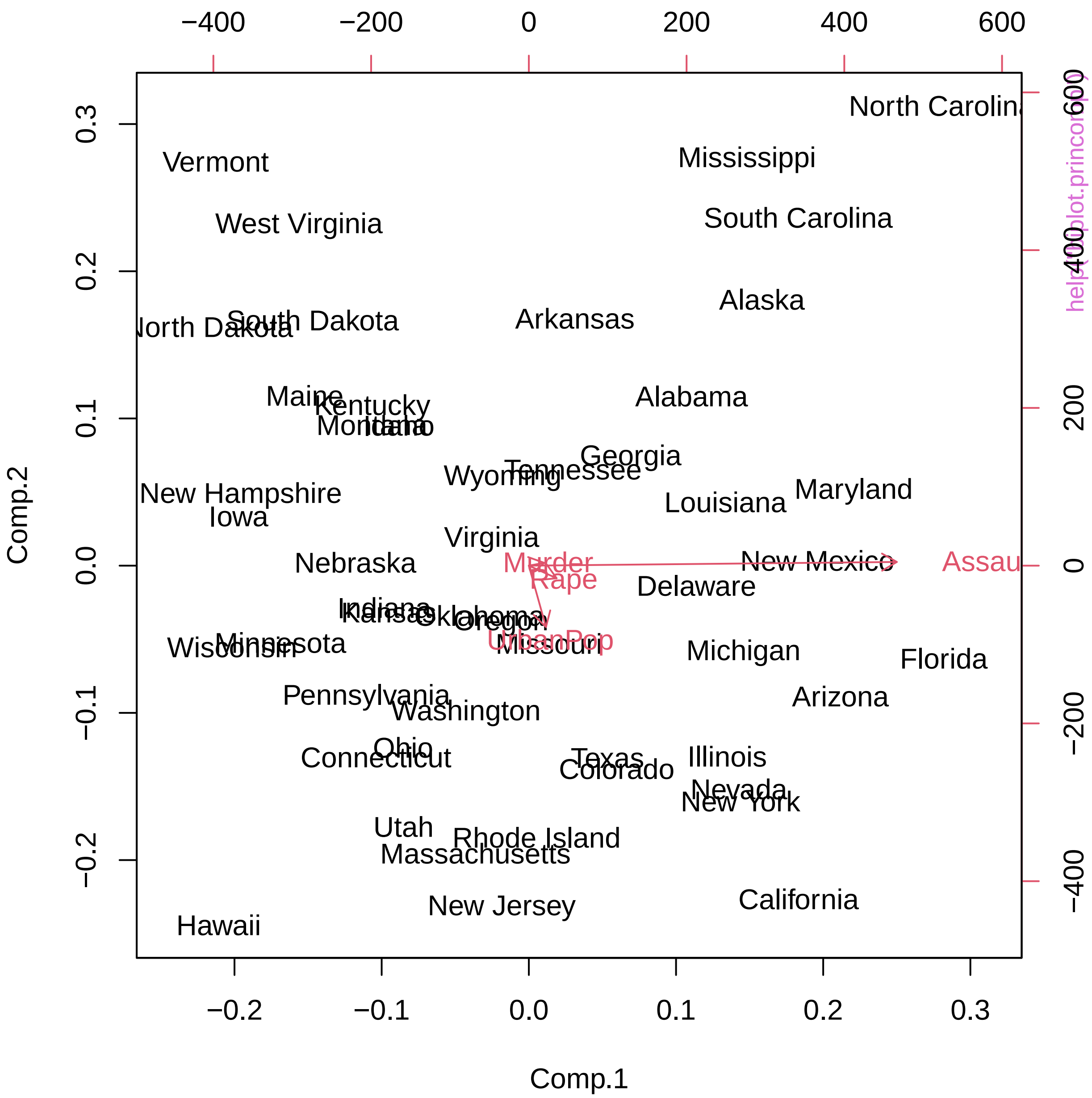
ave(Warpbreaks) for wool x tension combinations
mean
median
breaks
Index
0
10
20
30
40
50
70
60
50
40
30
20
10
help("ave")



density(x = precip, n = 1000)
Density
0.00
0.01
0.02
0.03
0
20
40
60
80
N = 70   Bandwidth = 3.848
nrd0
nrd
ucv
bcv
SJ−ste
SJ−dpi
help("bandwidth")

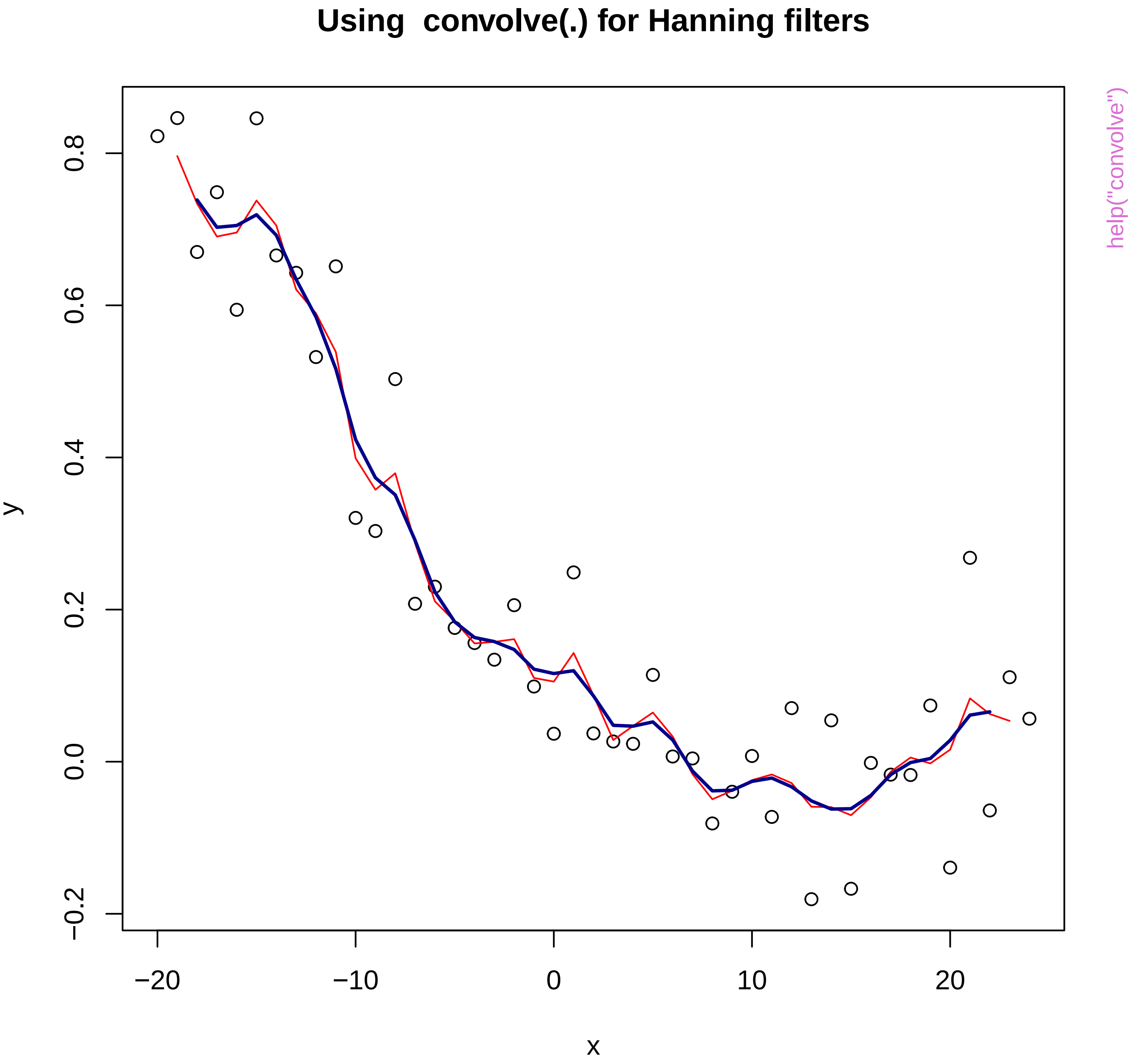


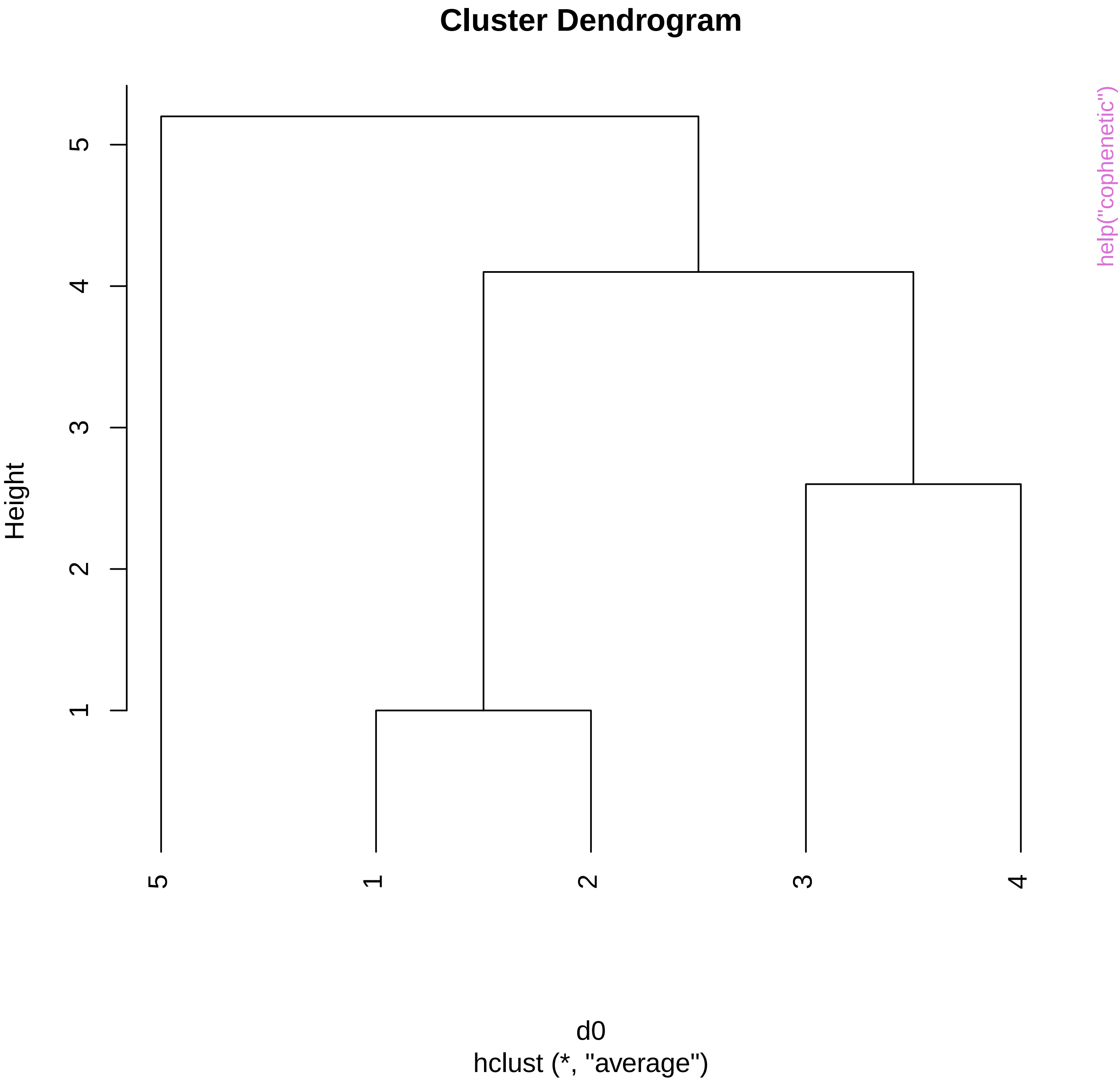
count
0
5
10
15
20
25
A
B
C
D
E
F
spray
help("bartlett.test")

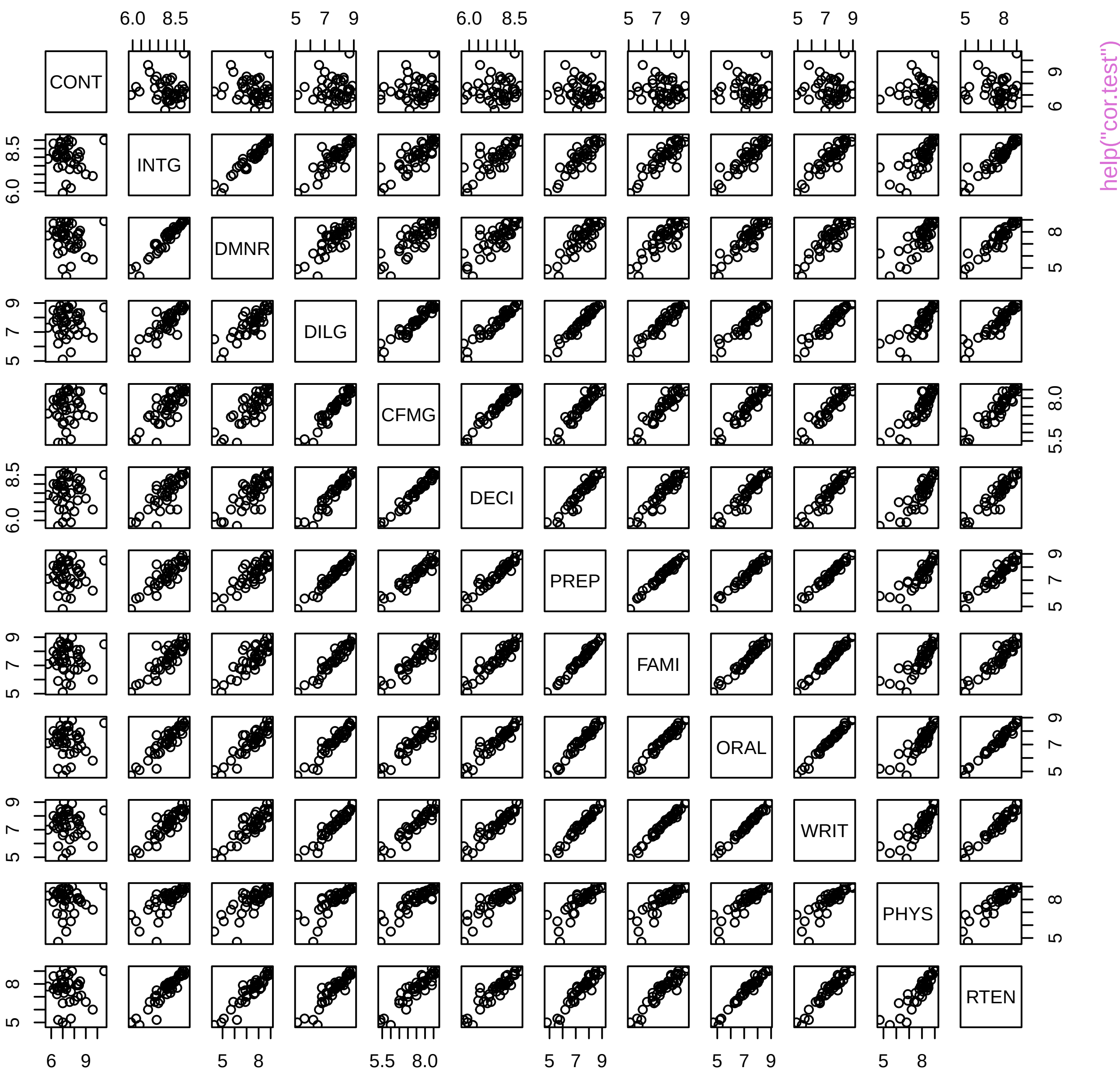


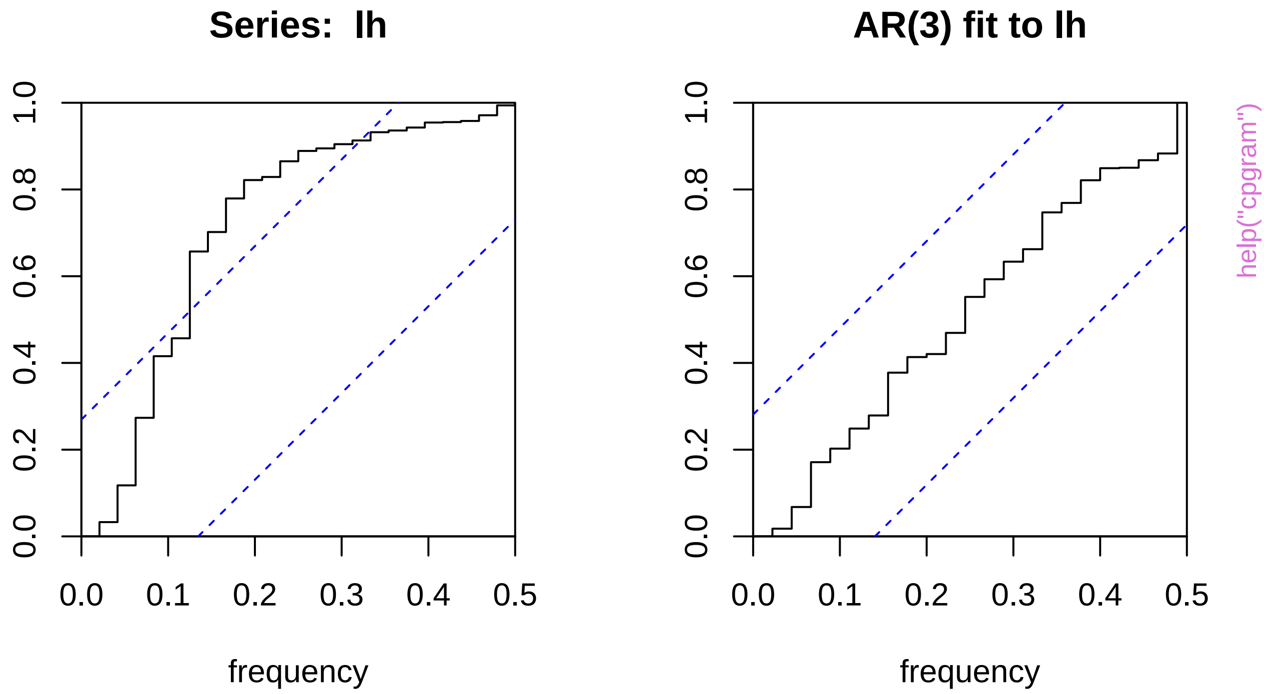
Comp.1
Comp.2
−0.2
−0.1
0.0
0.1
0.2
0.3
−400
−200
0
200
400
600
North Carolina
Mississippi
Vermont
South Carolina
West Virginia
Alaska
South Dakota
North Dakota
Arkansas
Alabama
Maine
Kentucky
Montana
Idaho
Georgia
Tennessee
Wyoming
Maryland
New Hampshire
Louisiana
Iowa
Virginia
Nebraska
Murder
New Mexico
Assault
Rape
Delaware
Indiana
Kansas
Oklahoma
Oregon
UrbanPop
Missouri
Wisconsin
Minnesota
Michigan
Florida
Pennsylvania
Washington
Arizona
Ohio
Connecticut
Texas
Colorado
Illinois
Nevada
New York
Utah
Rhode Island
Massachusetts
California
New Jersey
Hawaii
help(biplot.princomp)

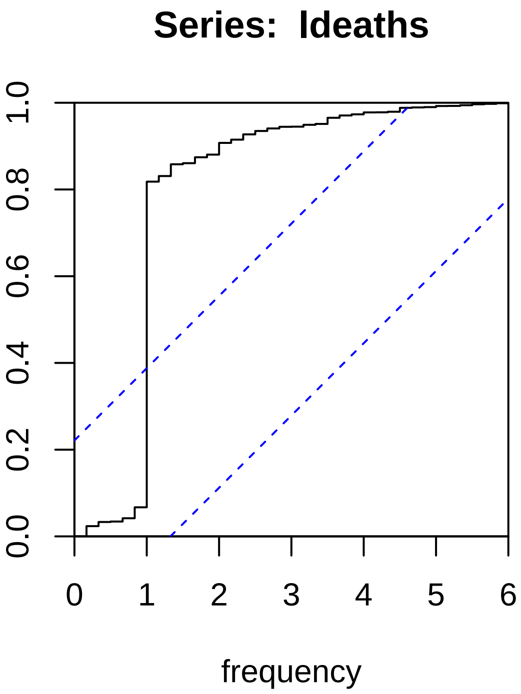
cmdscale(eurodist)

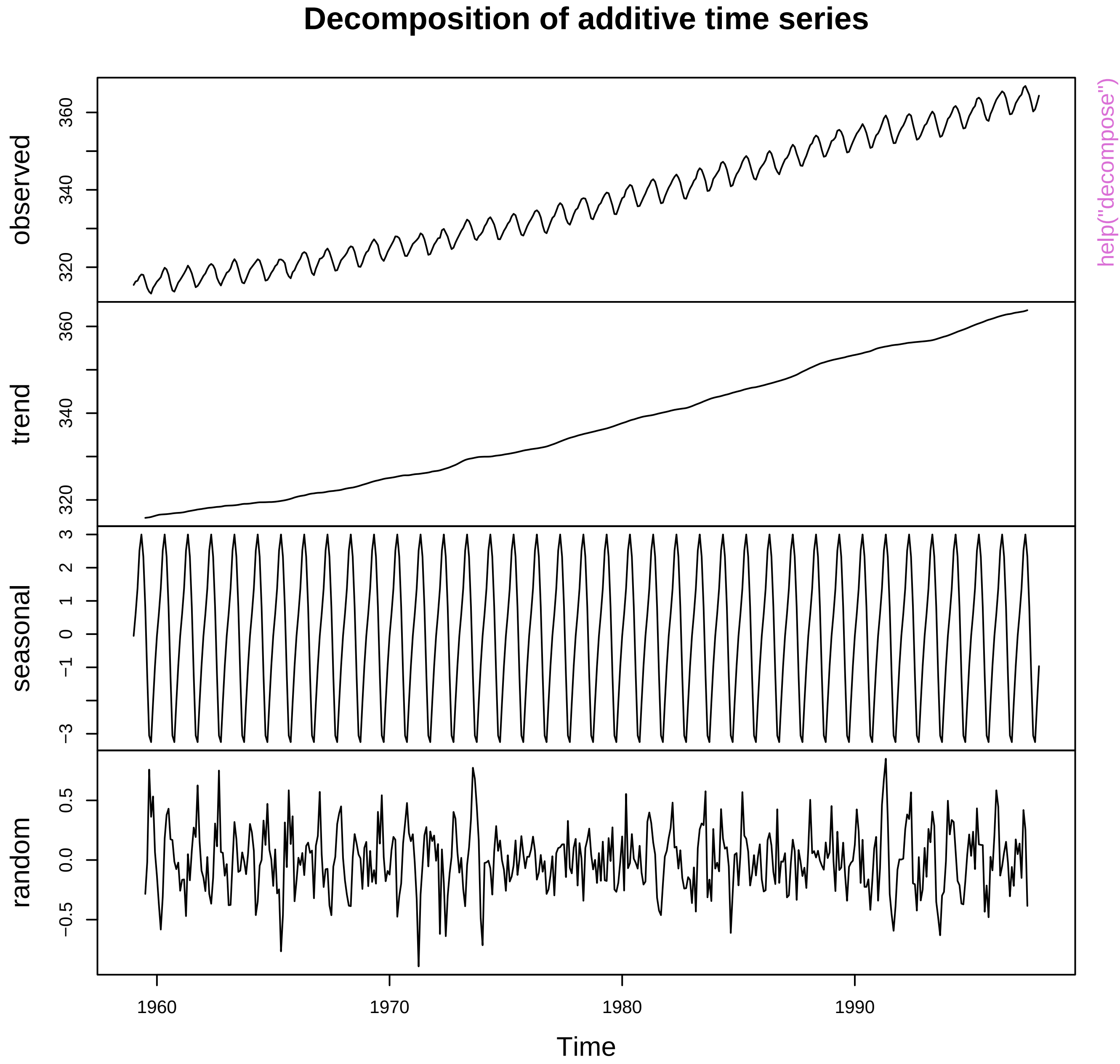

Using convolve(.) for Hanning filters
help("convolve")
y
x
0.8
0.6
0.4
0.2
0.0
−0.2
−20
−10
0
10
20


Cluster Dendrogram
Height
1
2
3
4
5
5
1
2
3
4
d0
hclust (*, "average")
help("cophenetic")

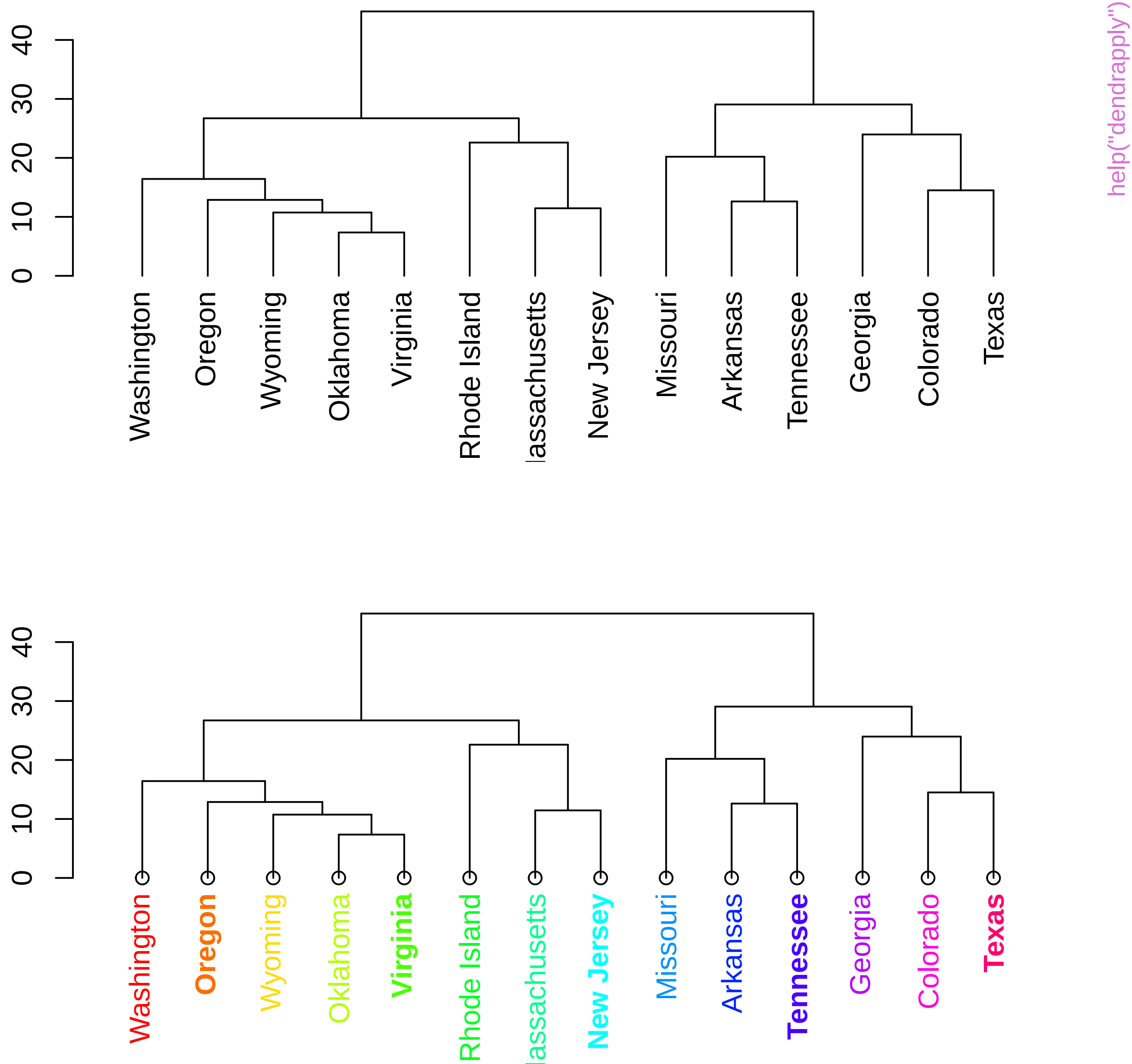

CONT
INTG
DMNR
DILG
CFMG
DECI
PREP
FAMI
ORAL
WRIT
PHYS
RTEN
help("cor.test")


Series: lh
AR(3) fit to lh
0.0
0.2
0.4
0.6
0.8
1.0
0.0
0.1
0.2
0.3
0.4
0.5
frequency
frequency
help("cpgram")

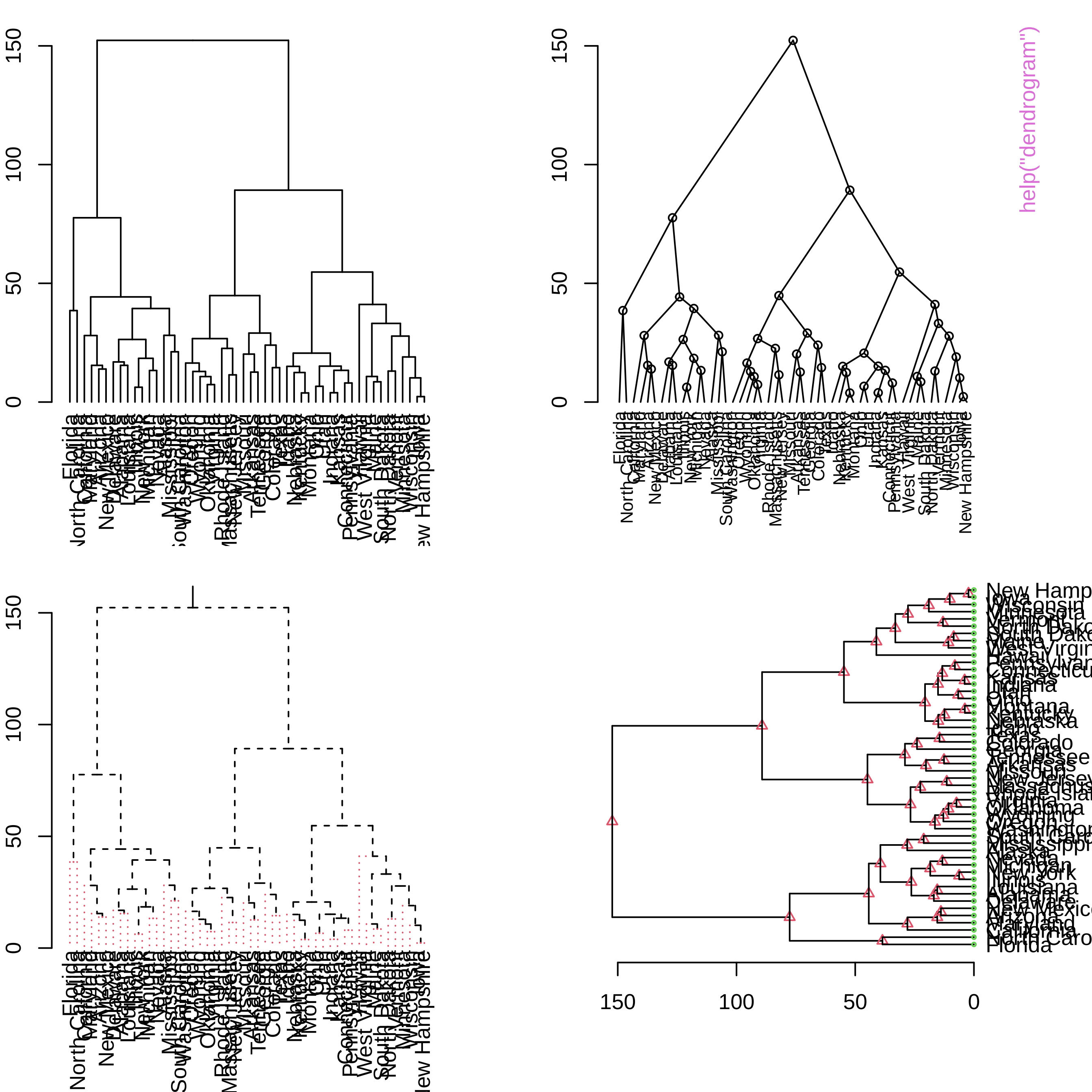

Series: ldeaths
0.0
0.2
0.4
0.6
0.8
1.0
0
1
2
3
4
5
6
frequency

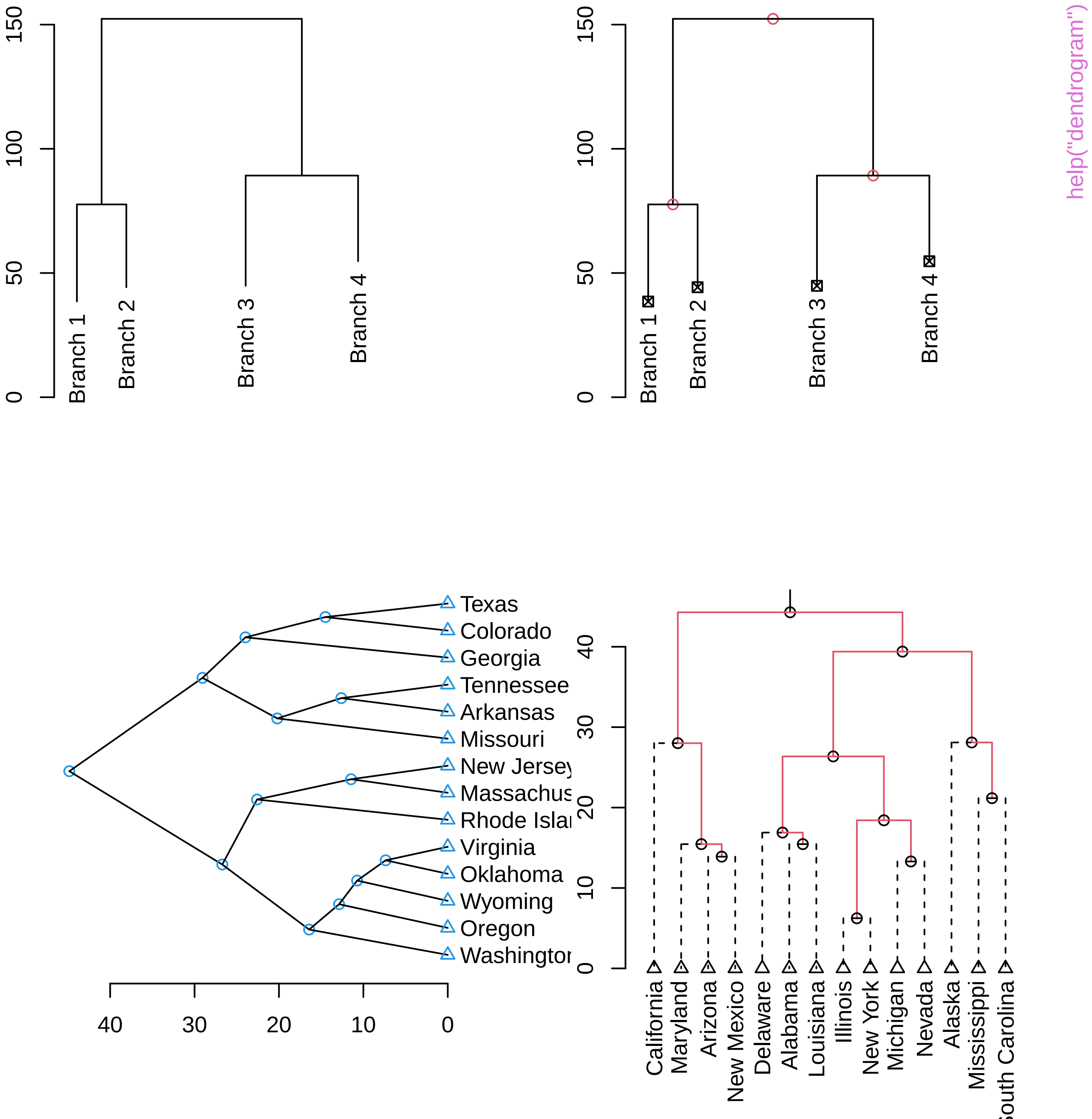


Decomposition of additive time series
observed
trend
seasonal
random
Time
1960
1970
1980
1990
320
340
360
320
340
360
3
2
1
0
−1
−3
0.5
0.0
−0.5
help("decompose")

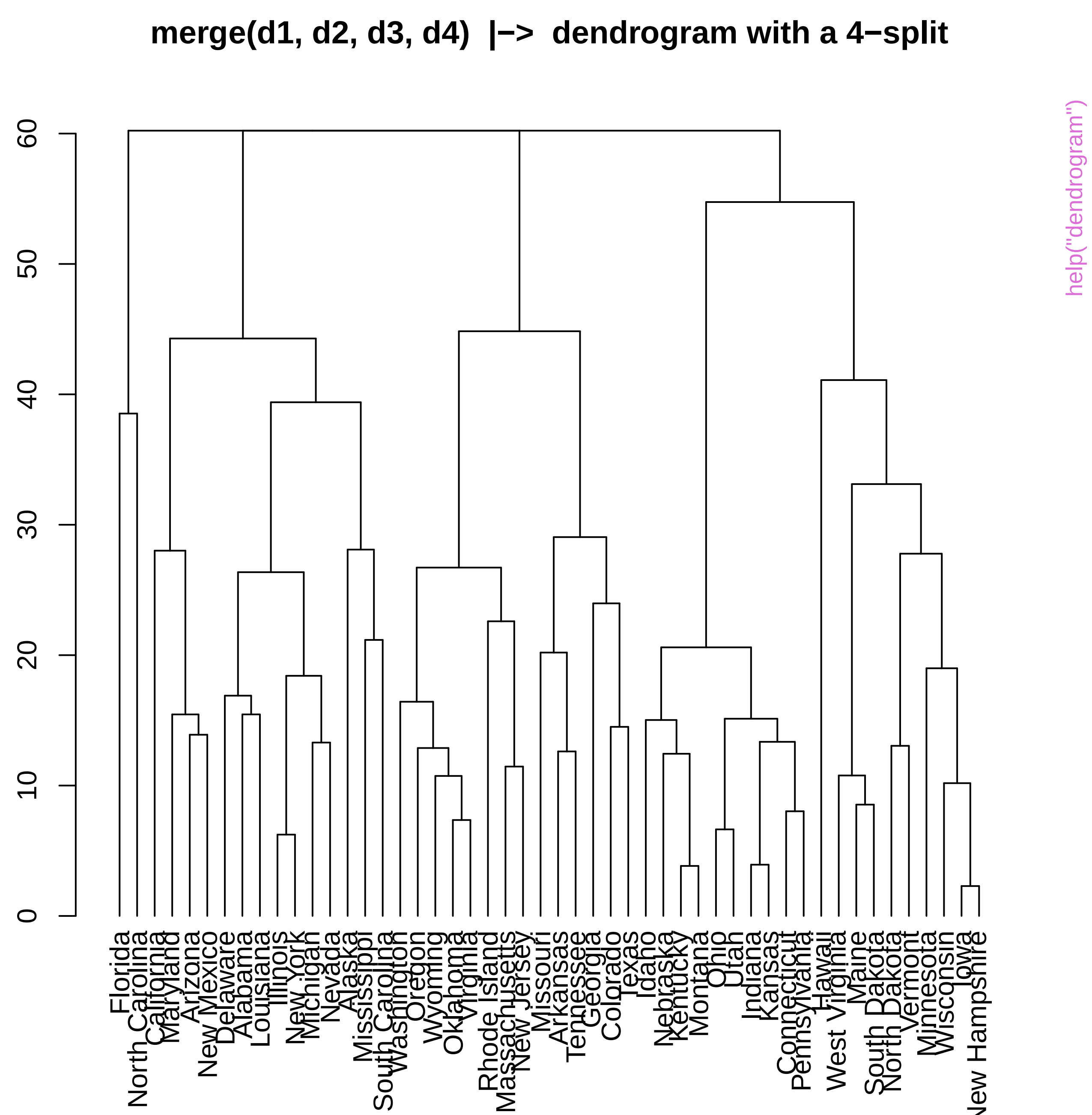


0
10
20
30
40
Washington
Oregon
Wyoming
Oklahoma
Virginia
Rhode Island
assachusetts
New Jersey
Missouri
Arkansas
Tennessee
Georgia
Colorado
Texas
help("dendrapply")

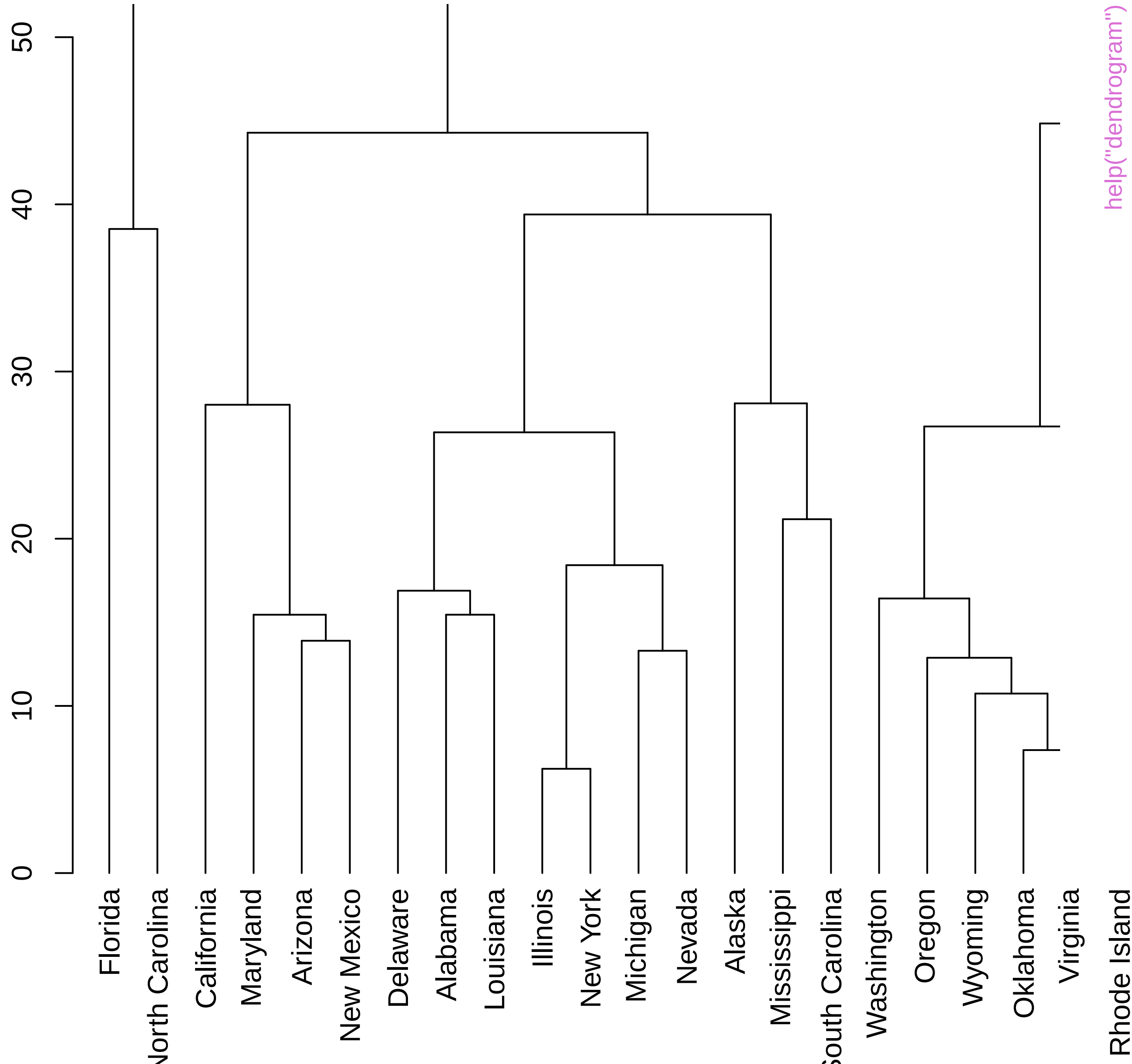

150
100
50
0
help("dendrogram")
Florida
North Carolina
New Hampshire

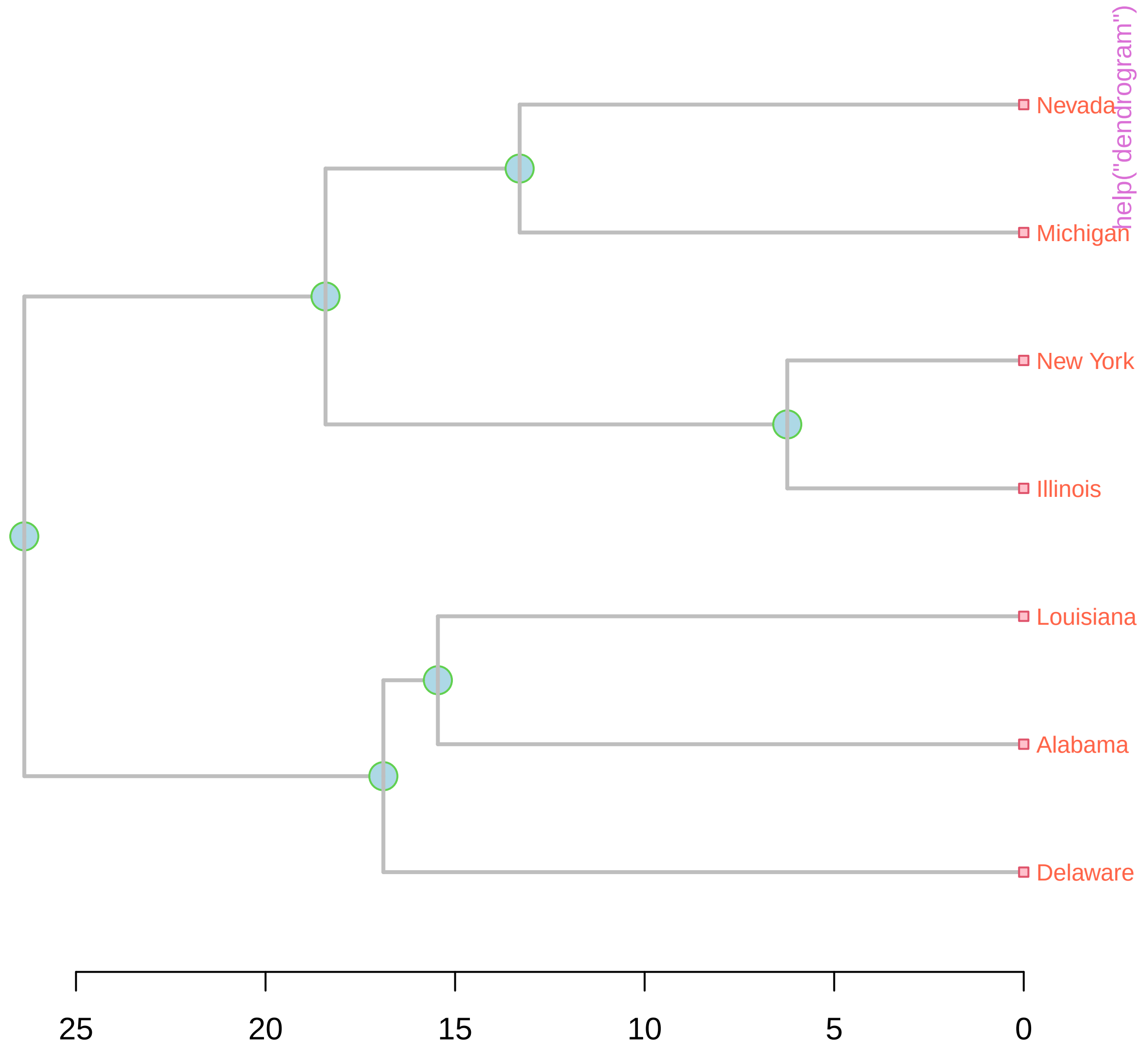


Branch 1
Branch 2
Branch 3
Branch 4
Branch 1
Branch 2
Branch 3
Branch 4
help("dendrogram")
Texas
Colorado
Georgia
Tennessee
Arkansas
Missouri
New Jersey
Massachus
Rhode Islai
Virginia
Oklahoma
Wyoming
Oregon
Washingtor
California
Maryland
Arizona
New Mexico
Delaware
Alabama
Louisiana
Illinois
New York
Michigan
Nevada
Alaska
Mississippi
South Carolina

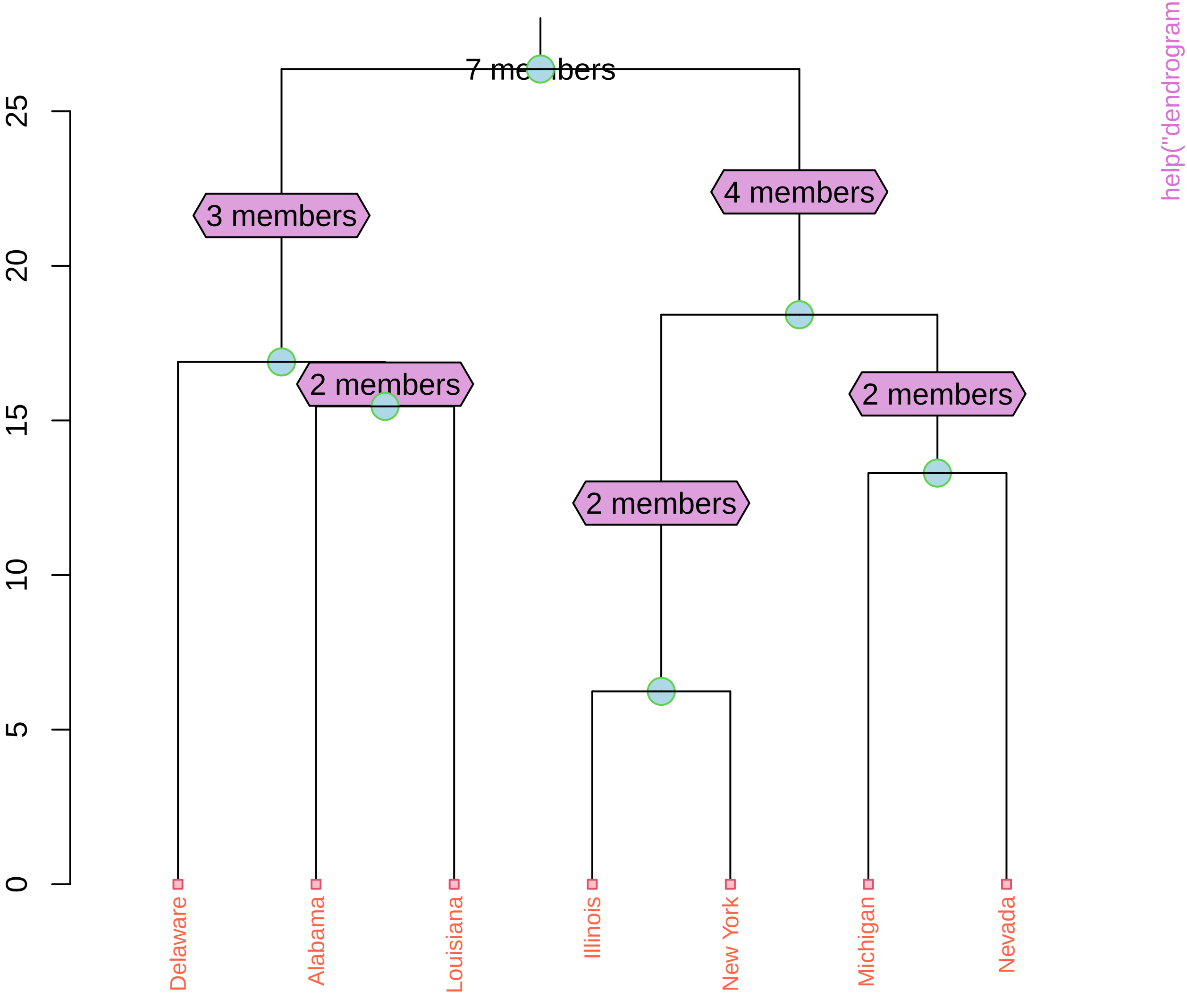


merge(d1, d2, d3, d4) |−> dendrogram with a 4−split
help("dendrogram")
0
10
20
30
40
50
60
Florida
North Carolina
California
Maryland
Arizona
New Mexico
Delaware
Alabama
Louisiana
Illinois
New York
Michigan
Nevada
Alaska
Mississippi
South Carolina
Washington
Oregon
Wyoming
Oklahoma
Virginia
Rhode Island
Massachusetts
New Jersey
Missouri
Arkansas
Tennessee
Georgia
Colorado
Texas
Idaho
Nebraska
Kentucky
Montana
Ohio
Utah
Indiana
Kansas
Connecticut
Pennsylvania
Hawaii
West Virginia
Maine
South Dakota
North Dakota
Vermont
Minnesota
Wisconsin
Iowa
New Hampshire

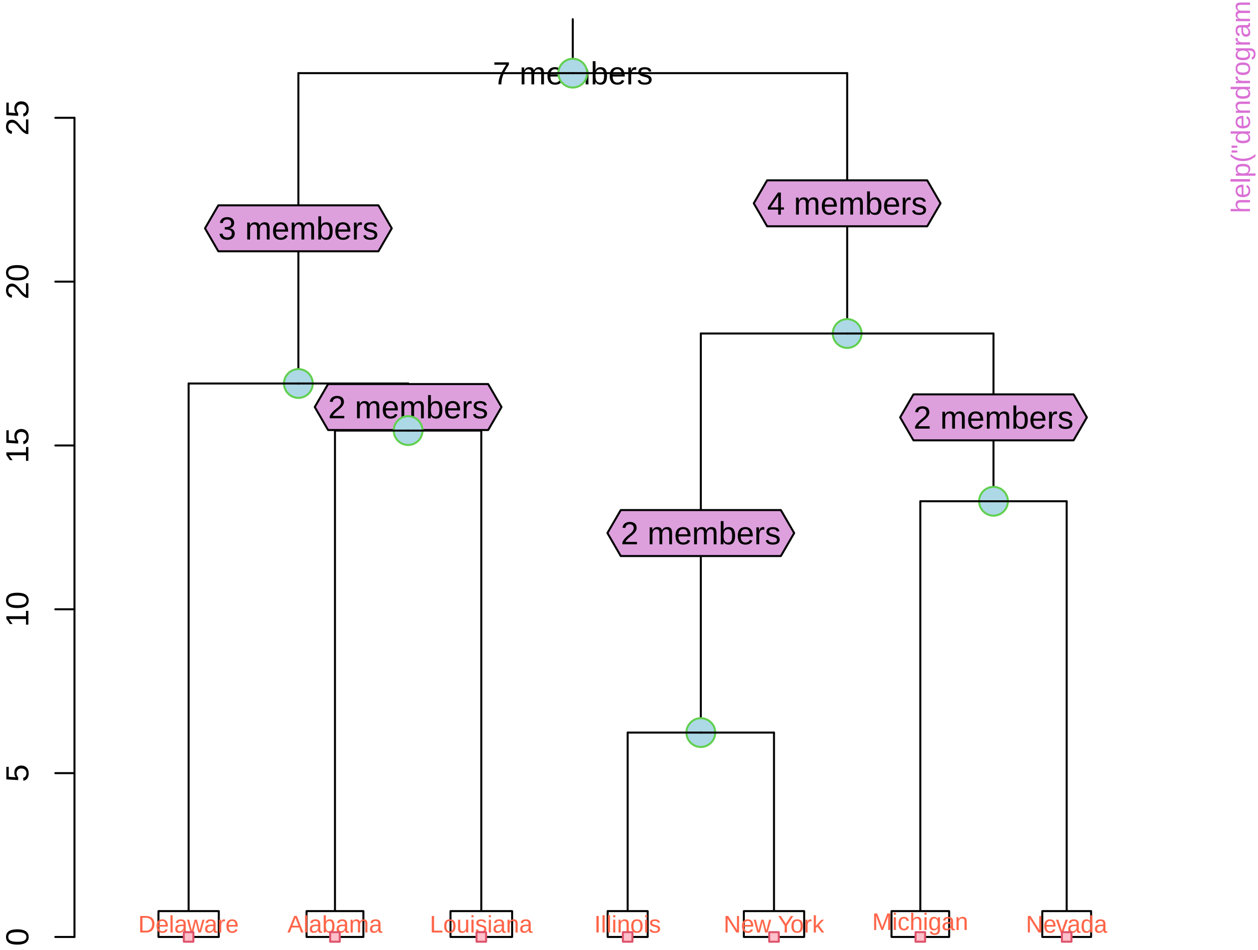

0
10
20
30
40
50
Florida
North Carolina
California
Maryland
Arizona
New Mexico
Delaware
Alabama
Louisiana
Illinois
New York
Michigan
Nevada
Alaska
Mississippi
South Carolina
Washington
Oregon
Wyoming
Oklahoma
Virginia
Rhode Island
help("dendrogram")



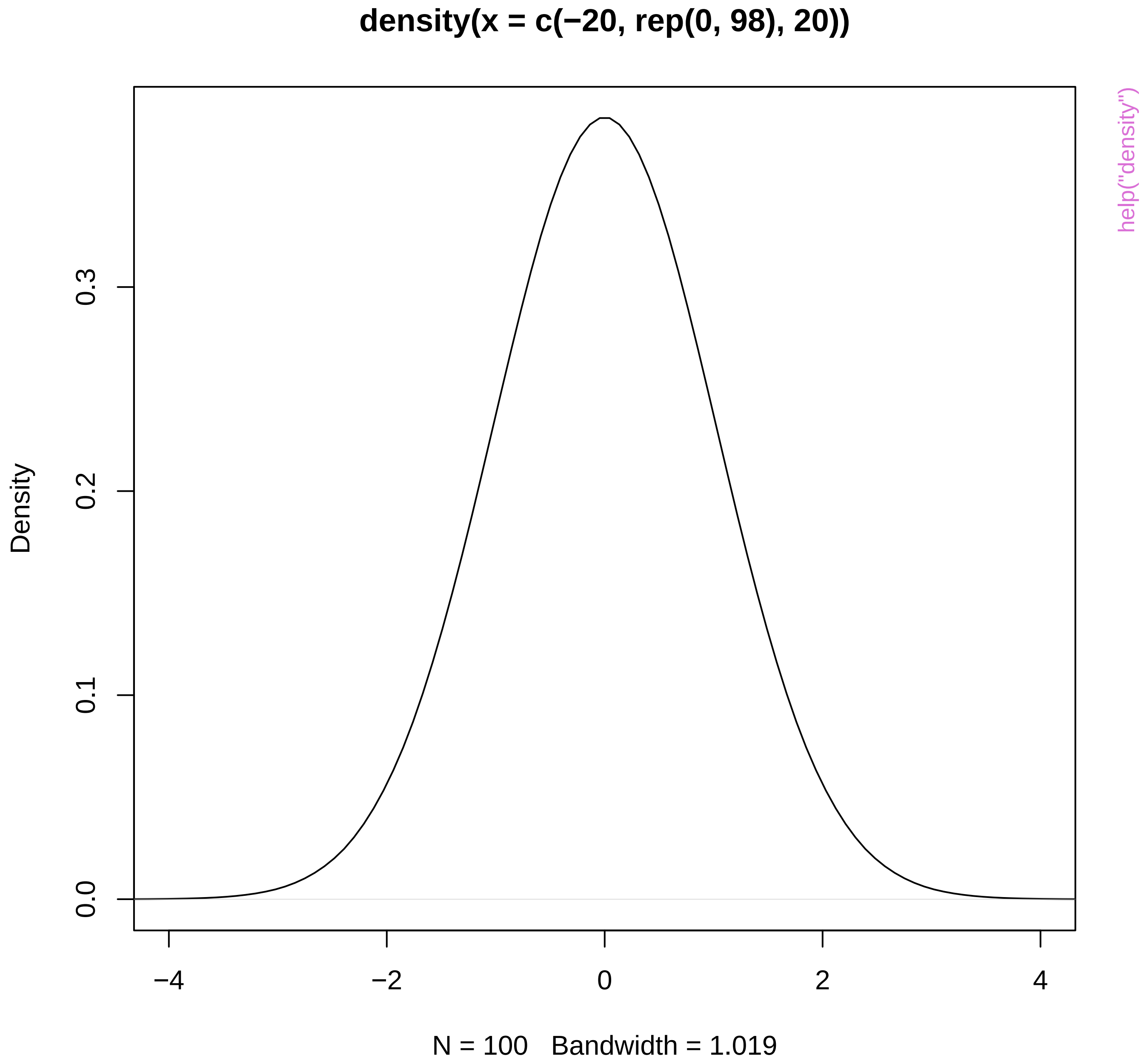
Nevada
Michigan
New York
Illinois
Louisiana
Alabama
Delaware
25
20
15
10
5
0
help("dendrogram")



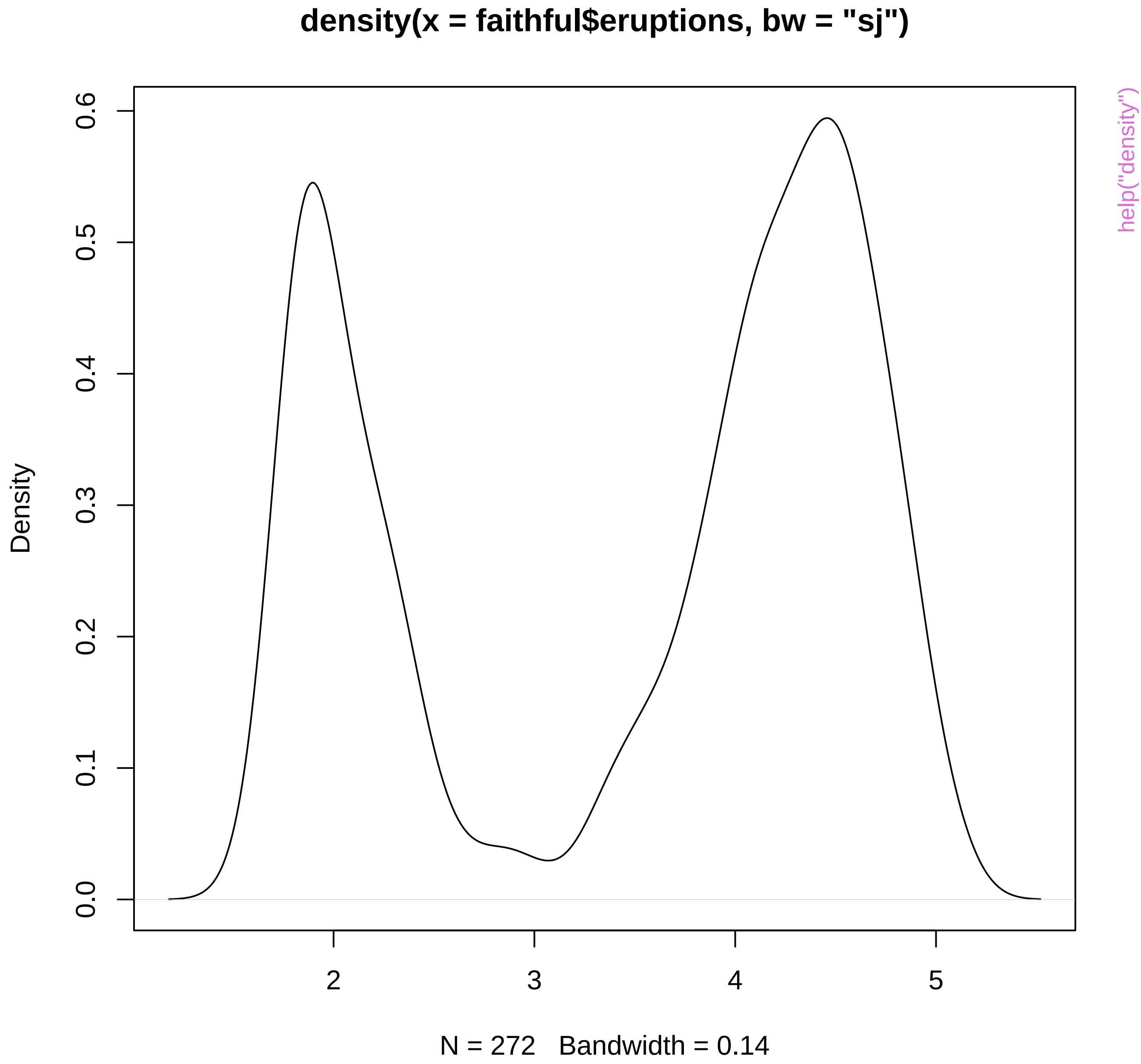
7 members
3 members
4 members
2 members
2 members
2 members
25
20
15
10
5
0
Delaware
Alabama
Louisiana
Illinois
New York
Michigan
Nevada
help("dendrogram")

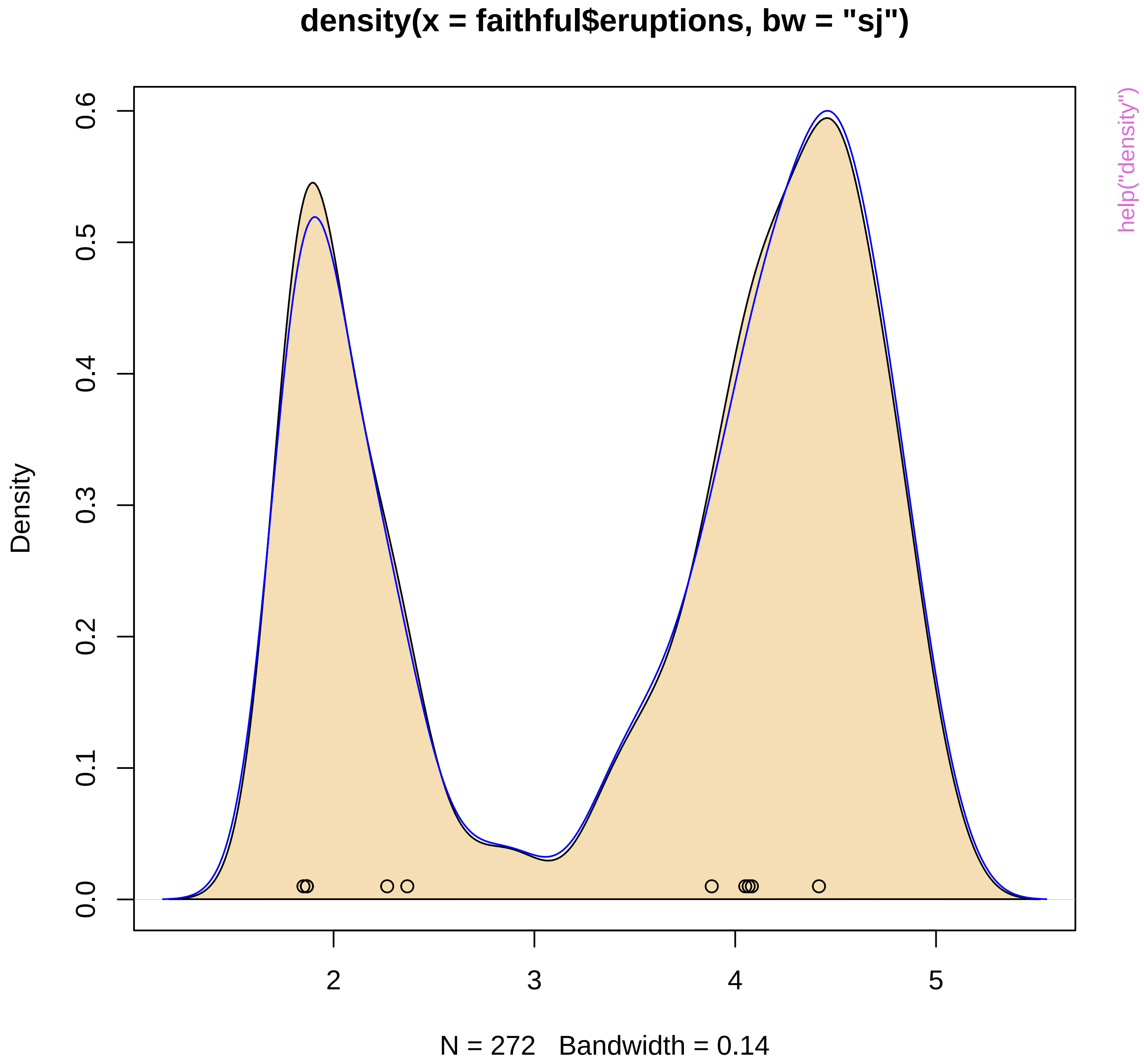


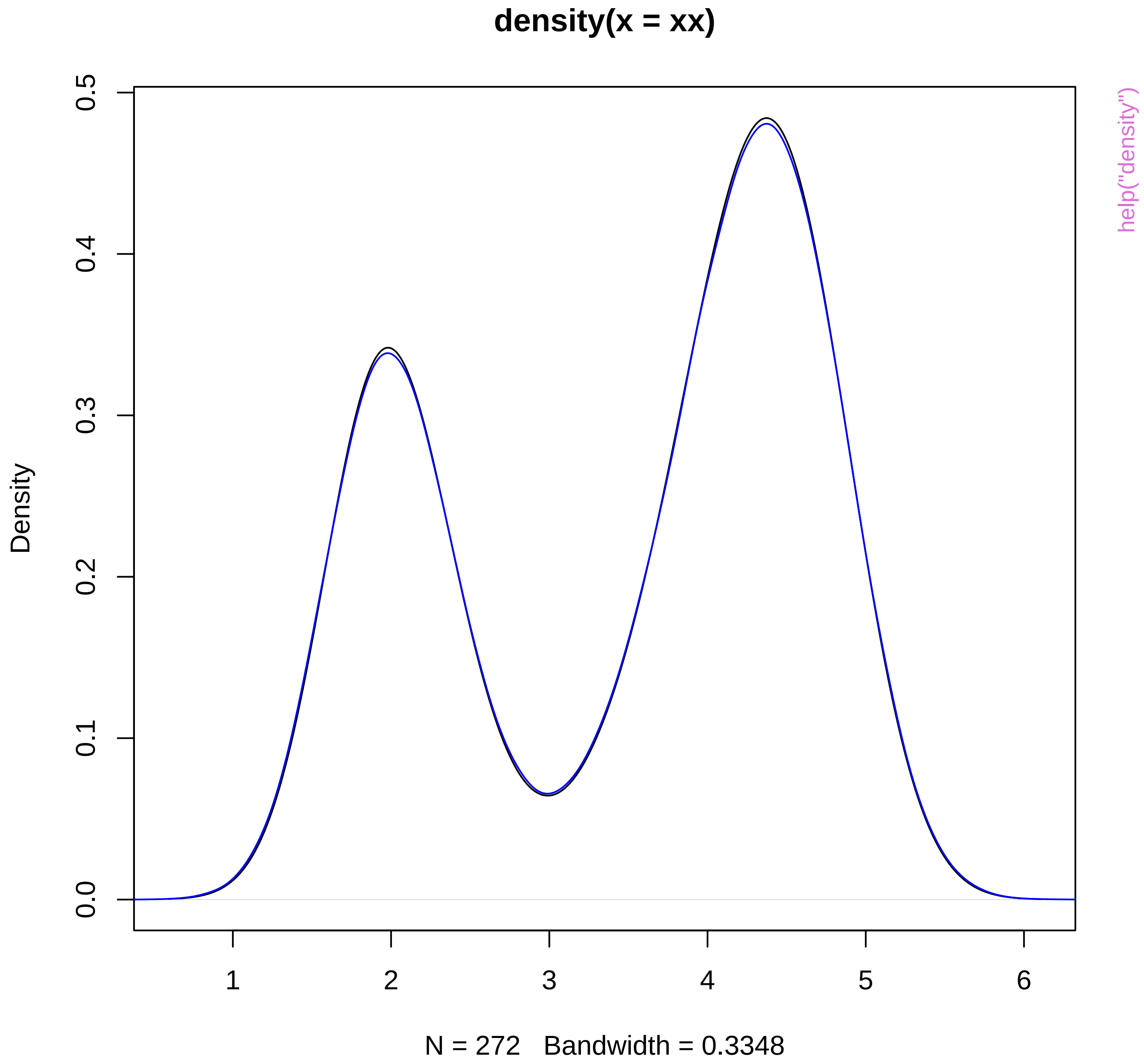
help("dendrogram")
7 members
3 members
4 members
2 members
2 members
2 members
0
5
10
15
20
25
Delaware
Alabama
Louisiana
Illinois
New York
Michigan
Nevada

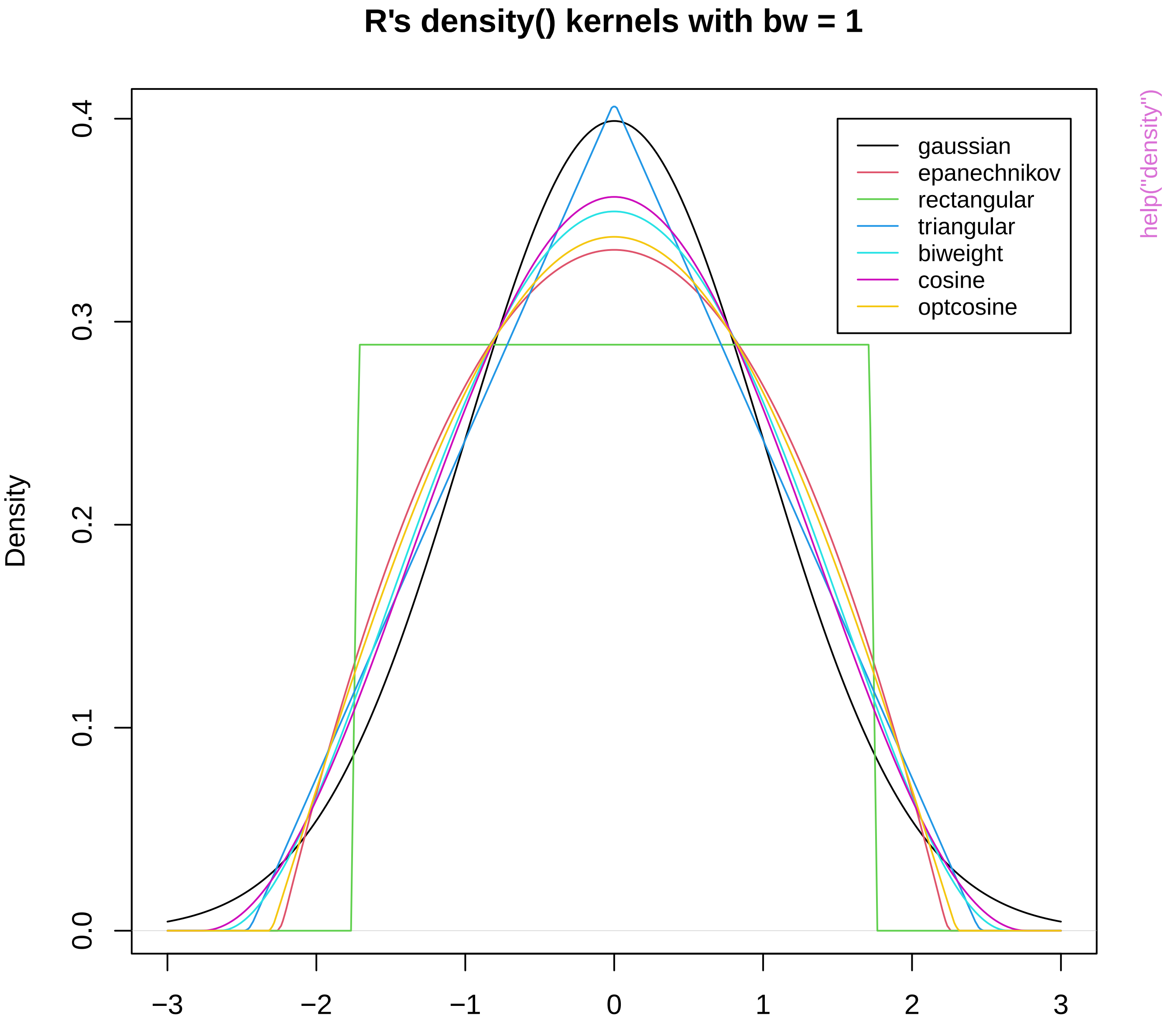


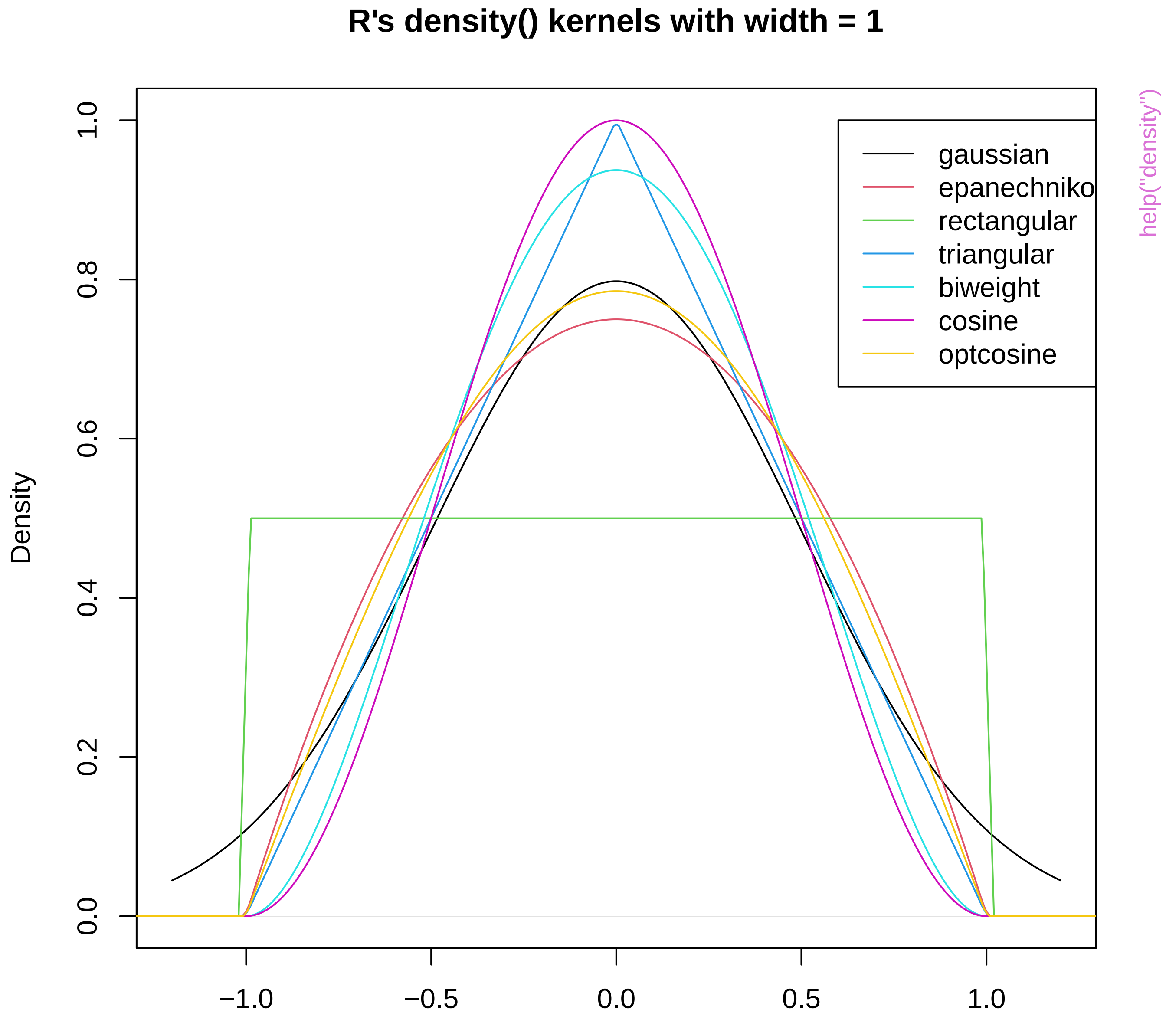
density(x = c(−20, rep(0, 98), 20))
Density
0.0
0.1
0.2
0.3
−4
−2
0
2
4
N = 100   Bandwidth = 1.019
help("density")

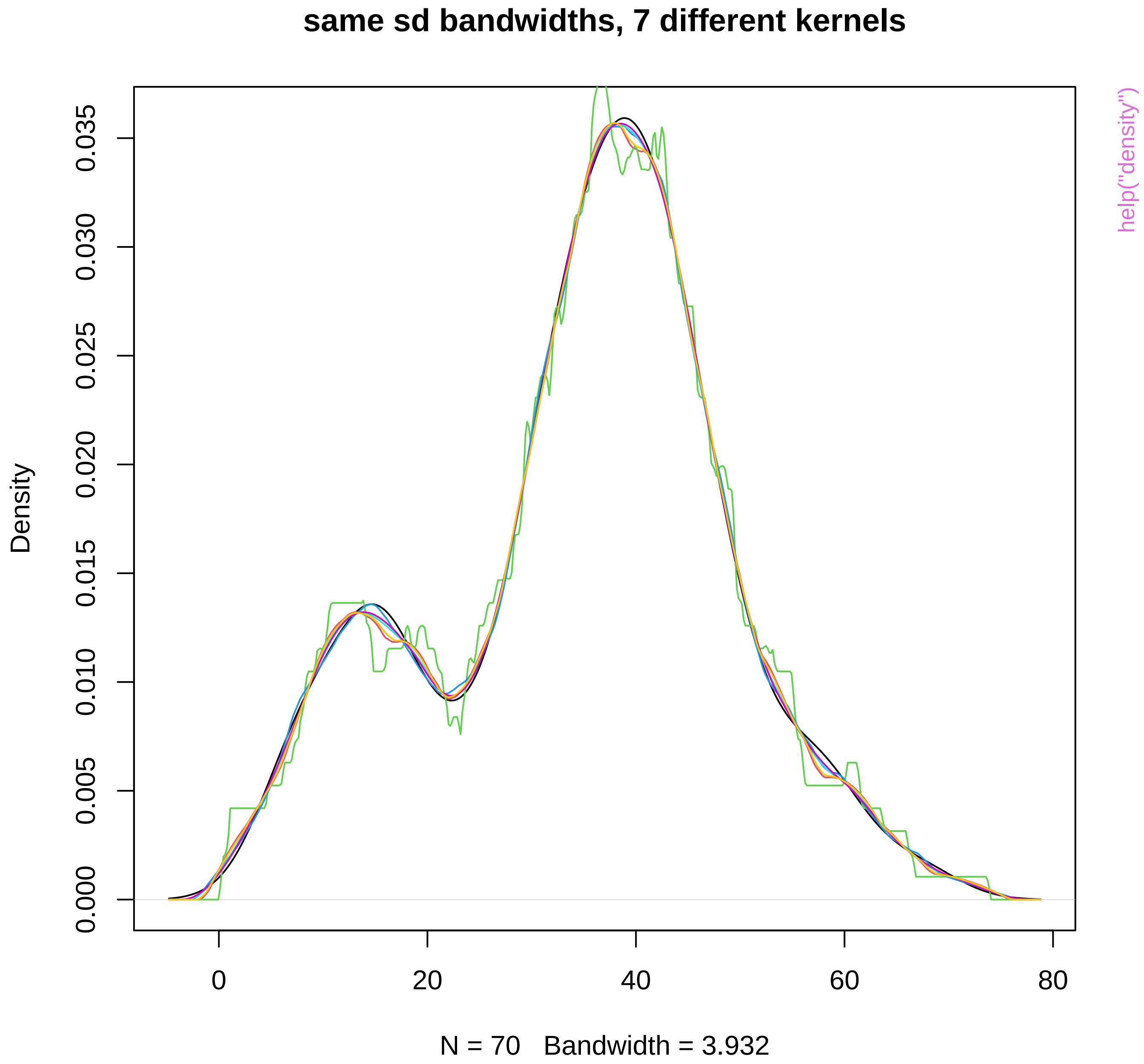

density(x = faithful$eruptions, bw = "sj")
Density
0.0
0.1
0.2
0.3
0.4
0.5
0.6
2
3
4
5
N = 272 Bandwidth = 0.14
help("density")


density(x = faithful$eruptions, bw = "sj")
Density
0.0
0.1
0.2
0.3
0.4
0.5
0.6
2
3
4
5
N = 272   Bandwidth = 0.14
help("density")

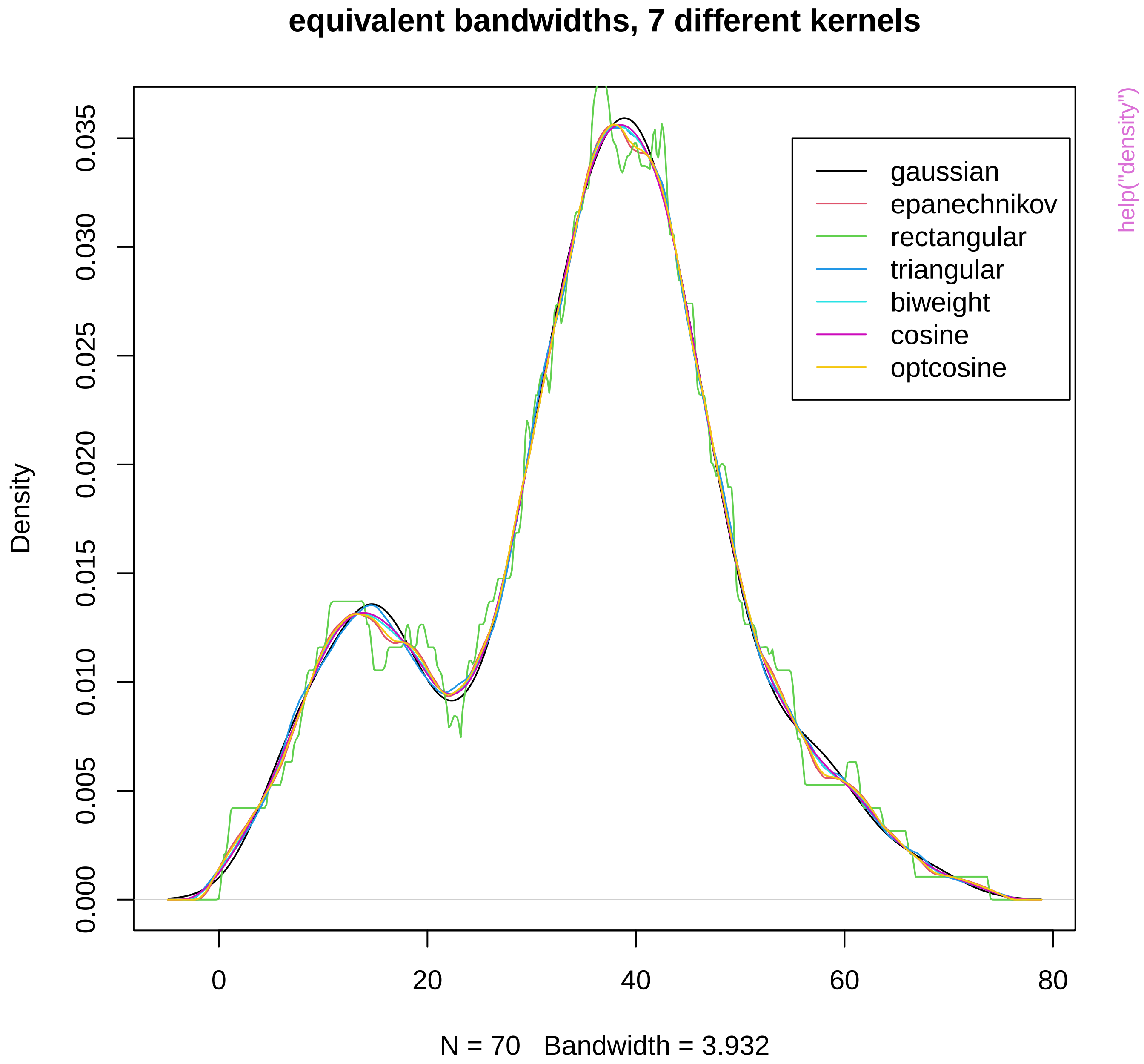

density(x = xx)
Density
0.0
0.1
0.2
0.3
0.4
0.5
1
2
3
4
5
6
N = 272   Bandwidth = 0.3348
help("density")

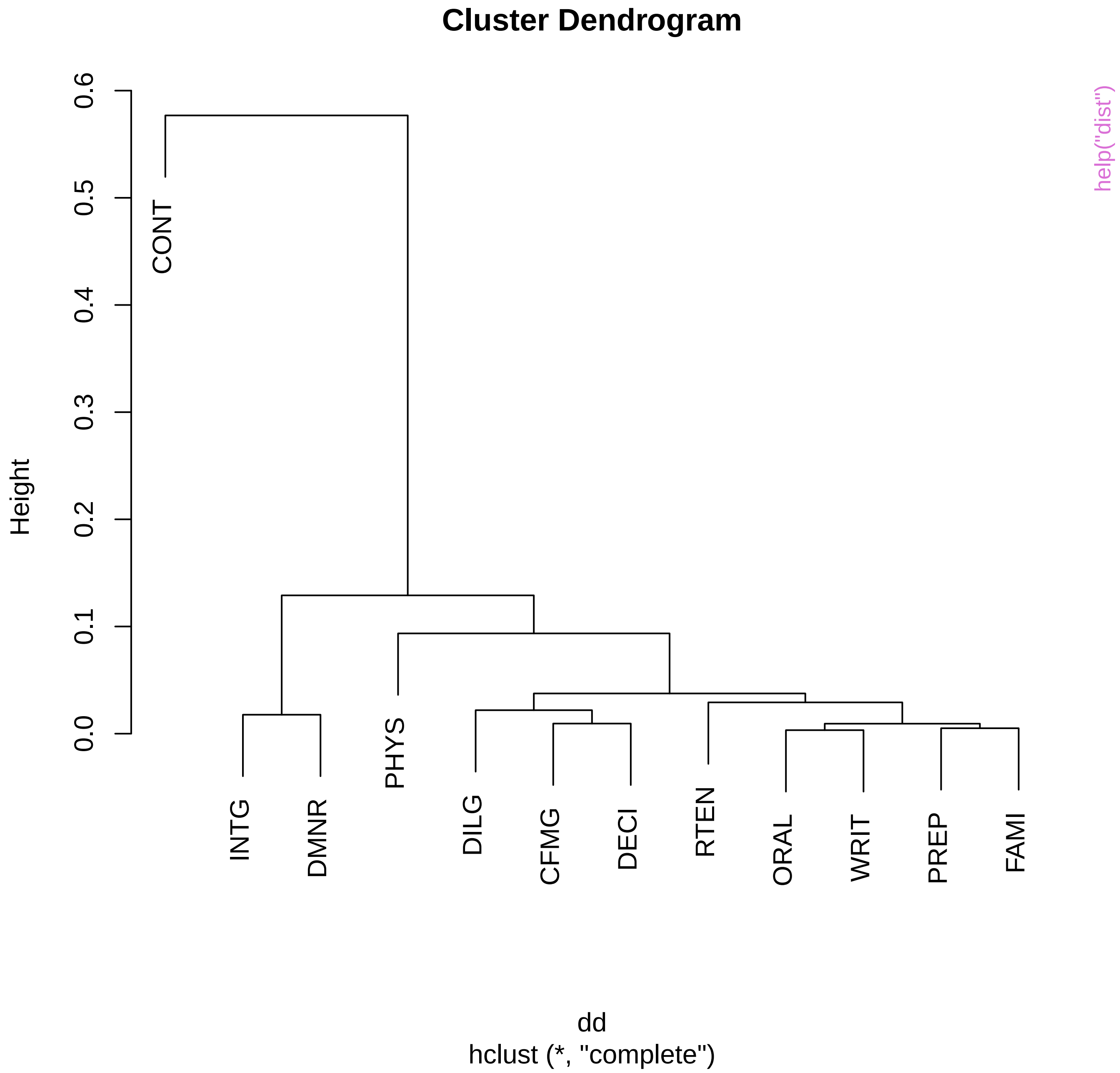

R's density() kernels with bw = 1
Density
0.0
0.1
0.2
0.3
0.4
−3
−2
−1
0
1
2
3
gaussian
epanechnikov
rectangular
triangular
biweight
cosine
optcosine
help("density")

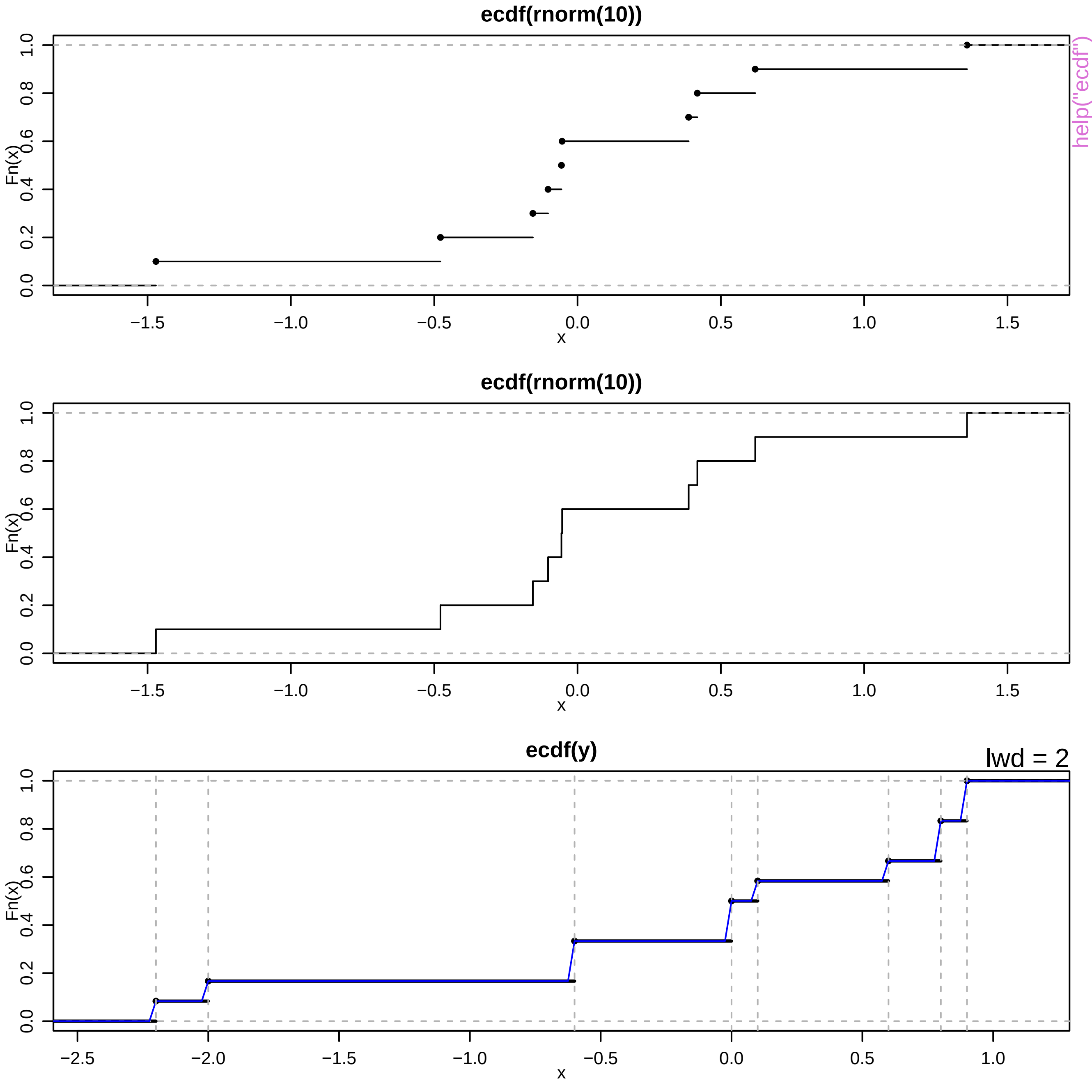

R's density() kernels with width = 1
Density
1.0
0.8
0.6
0.4
0.2
0.0
−1.0
−0.5
0.0
0.5
1.0
gaussian
epanechniko
rectangular
triangular
biweight
cosine
optcosine
help("density")

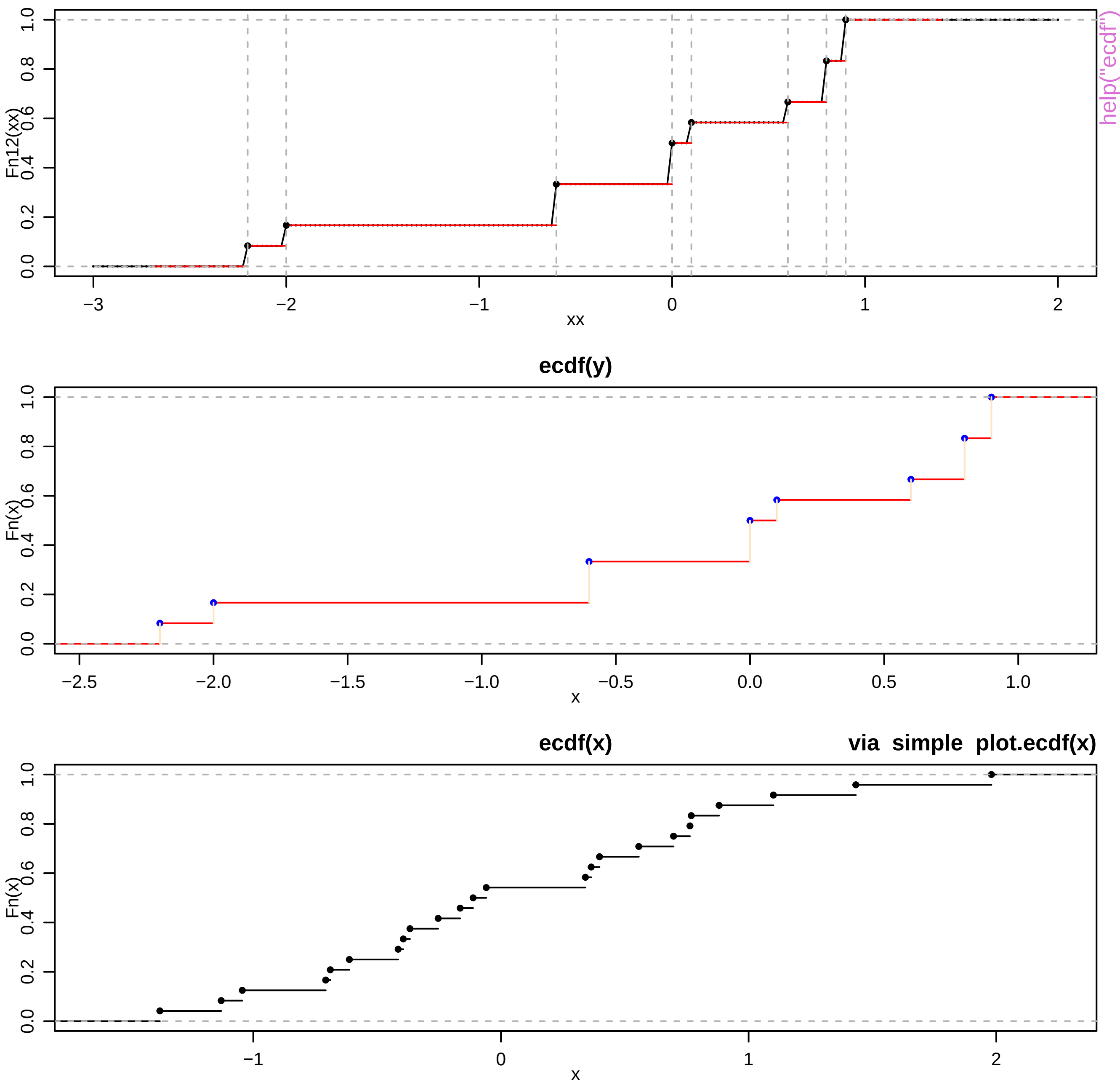


same sd bandwidths, 7 different kernels
Density
0.000
0.005
0.010
0.015
0.020
0.025
0.030
0.035
0
20
40
60
80
N = 70   Bandwidth = 3.932
help("density")

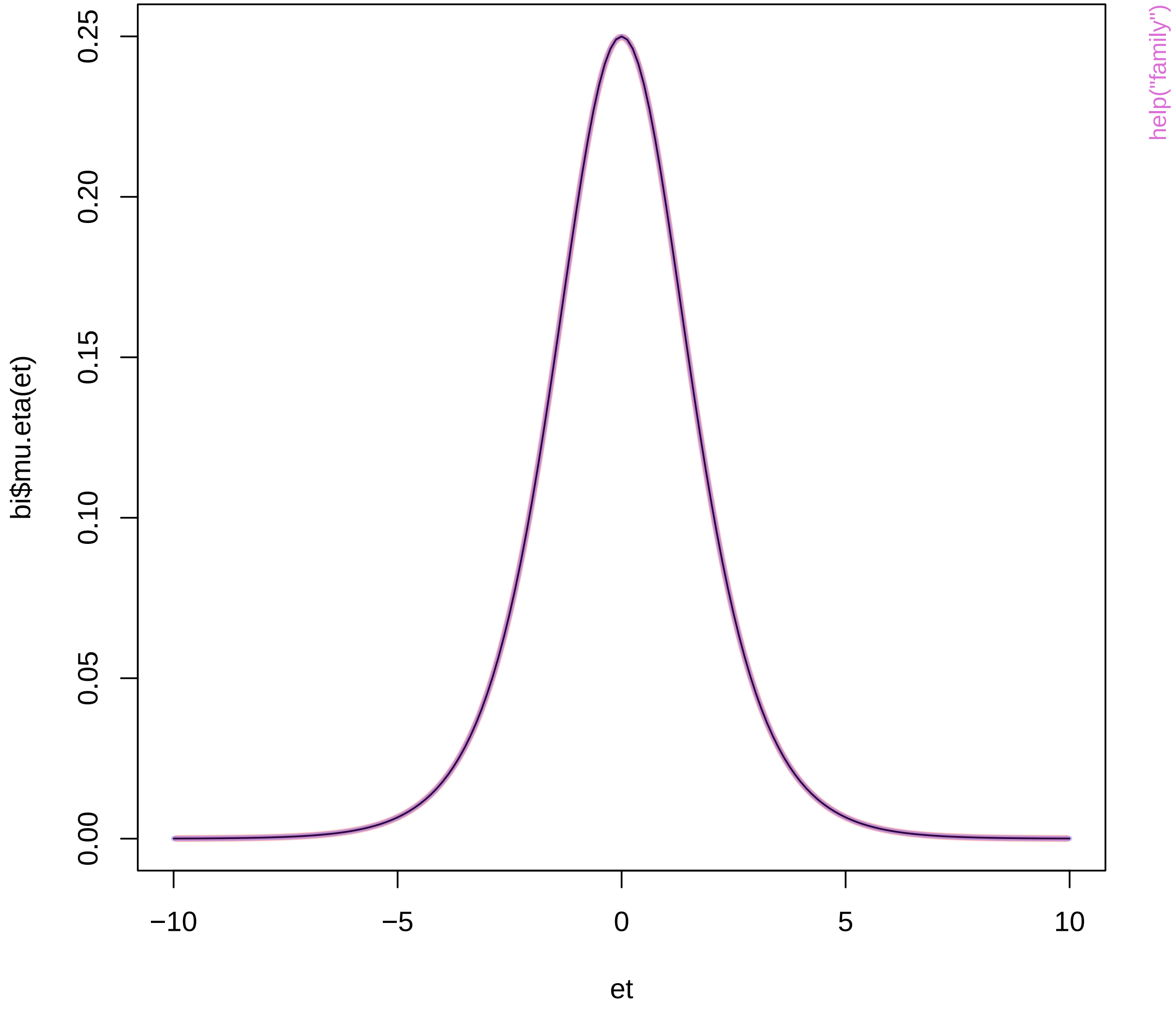

equivalent bandwidths, 7 different kernels
Density
0.000
0.005
0.010
0.015
0.020
0.025
0.030
0.035
0
20
40
60
80
N = 70   Bandwidth = 3.932
gaussian
epanechnikov
rectangular
triangular
biweight
cosine
optcosine
help("density")


Cluster Dendrogram
Height
0.0
0.1
0.2
0.3
0.4
0.5
0.6
CONT
INTG
DMNR
PHYS
DILG
CFMG
DECI
RTEN
ORAL
WRIT
PREP
FAMI
help("dist")
dd
hclust (*, "complete")

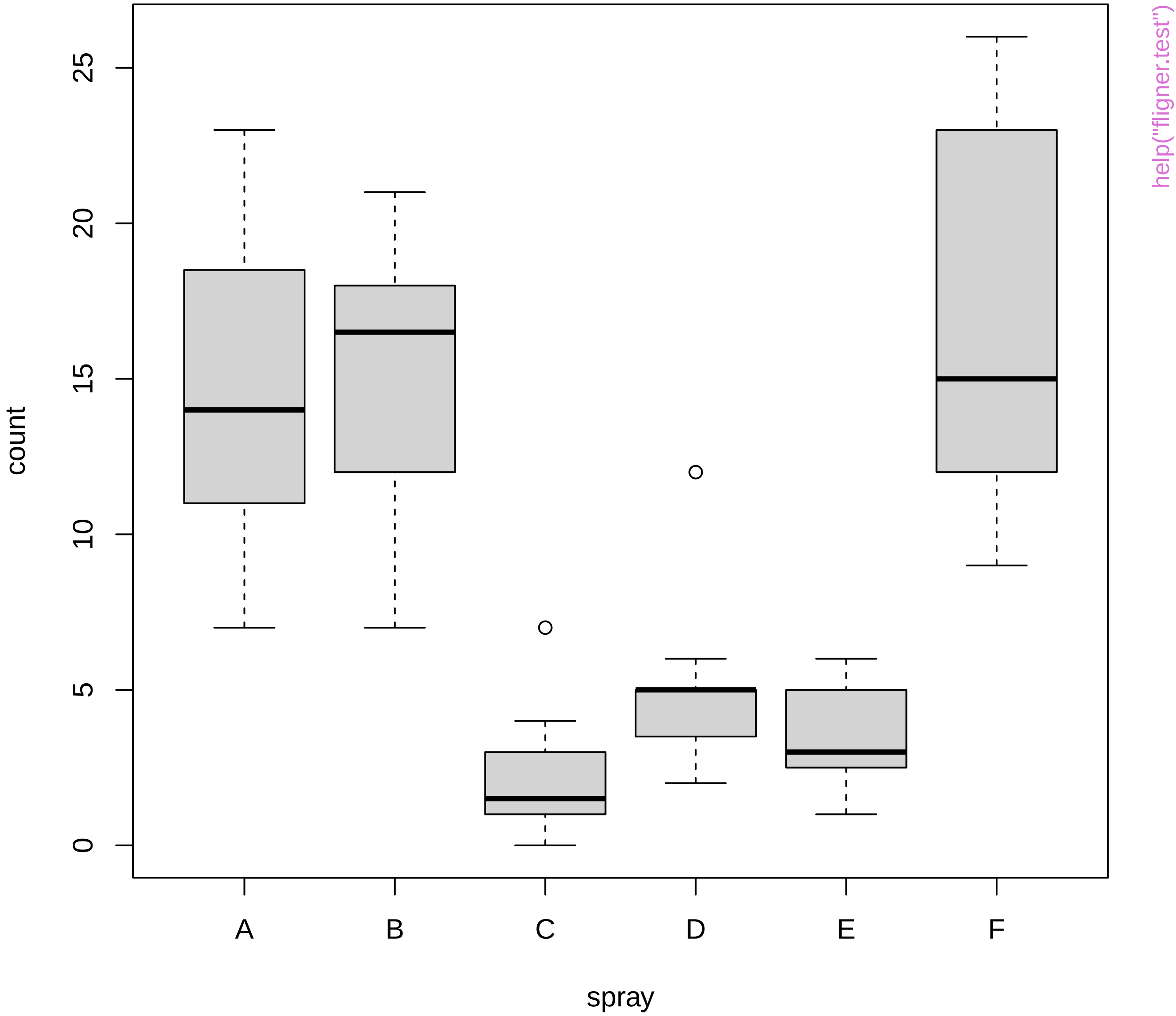

ecdf(rnorm(10))
Fn(x)
0.0
0.2
0.4
0.6
0.8
1.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
x
help("ecdf")
ecdf(rnorm(10))
Fn(x)
0.0
0.2
0.4
0.6
0.8
1.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
x
ecdf(y)
lwd = 2
Fn(x)
0.0
0.2
0.4
0.6
0.8
1.0
−2.5
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
x



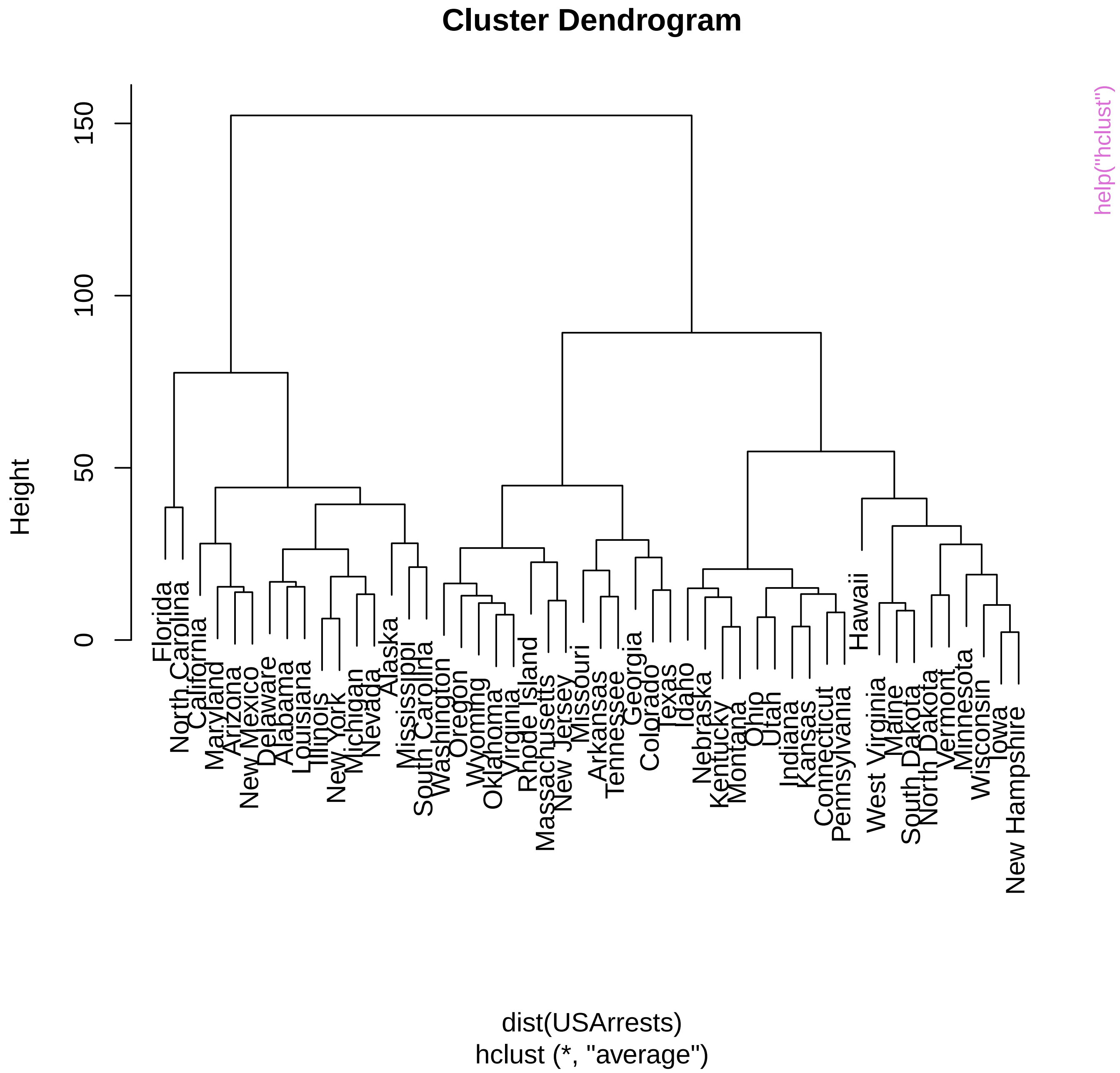
help("ecdf")
Fn12(xx)
xx
ecdf(y)
Fn(x)
x
ecdf(x)
via simple plot.ecdf(x)
Fn(x)
x

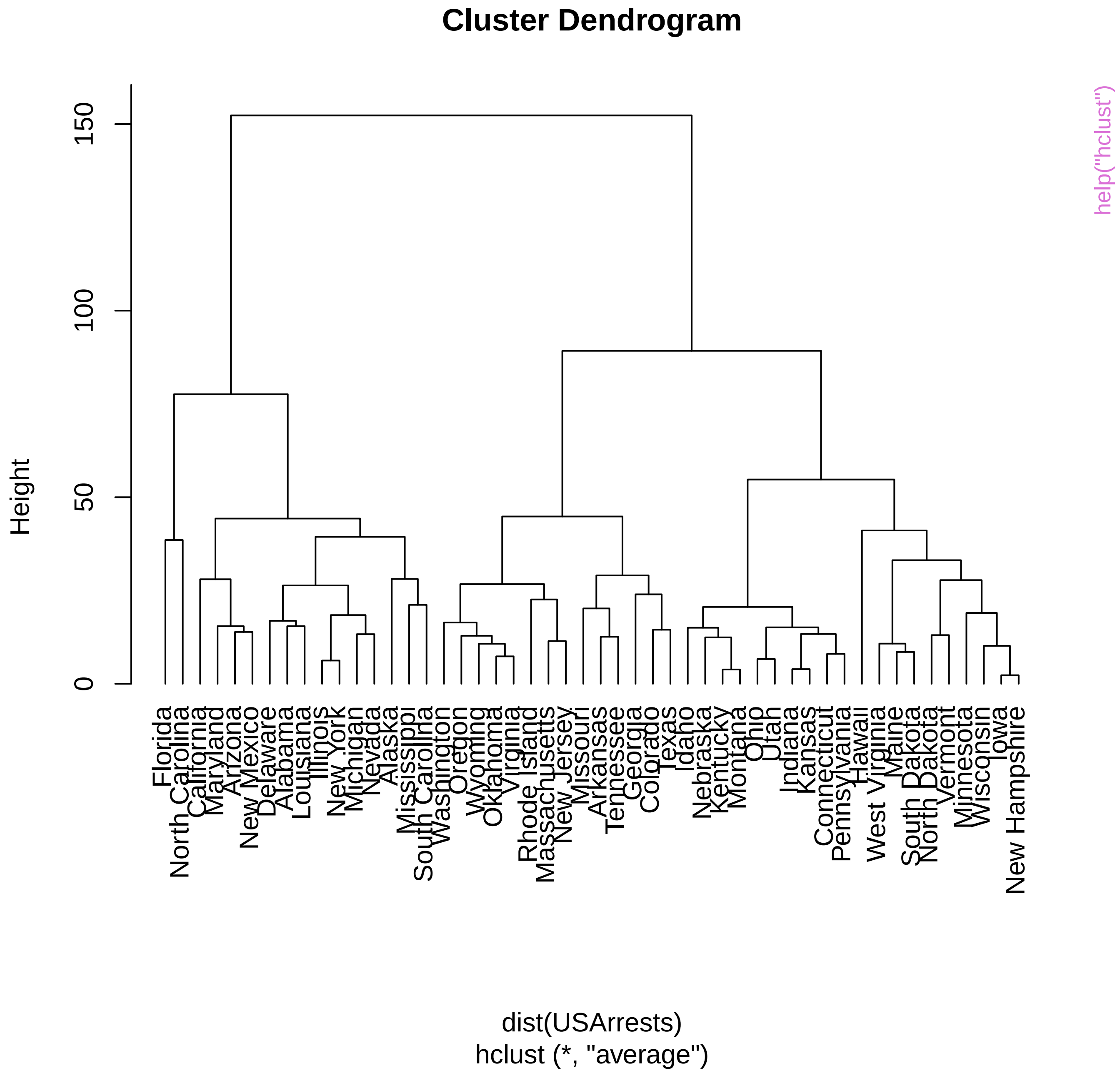


0.00
0.05
0.10
0.15
0.20
0.25
bi$mu.eta(et)
−10
−5
0
5
10
et
help("family")

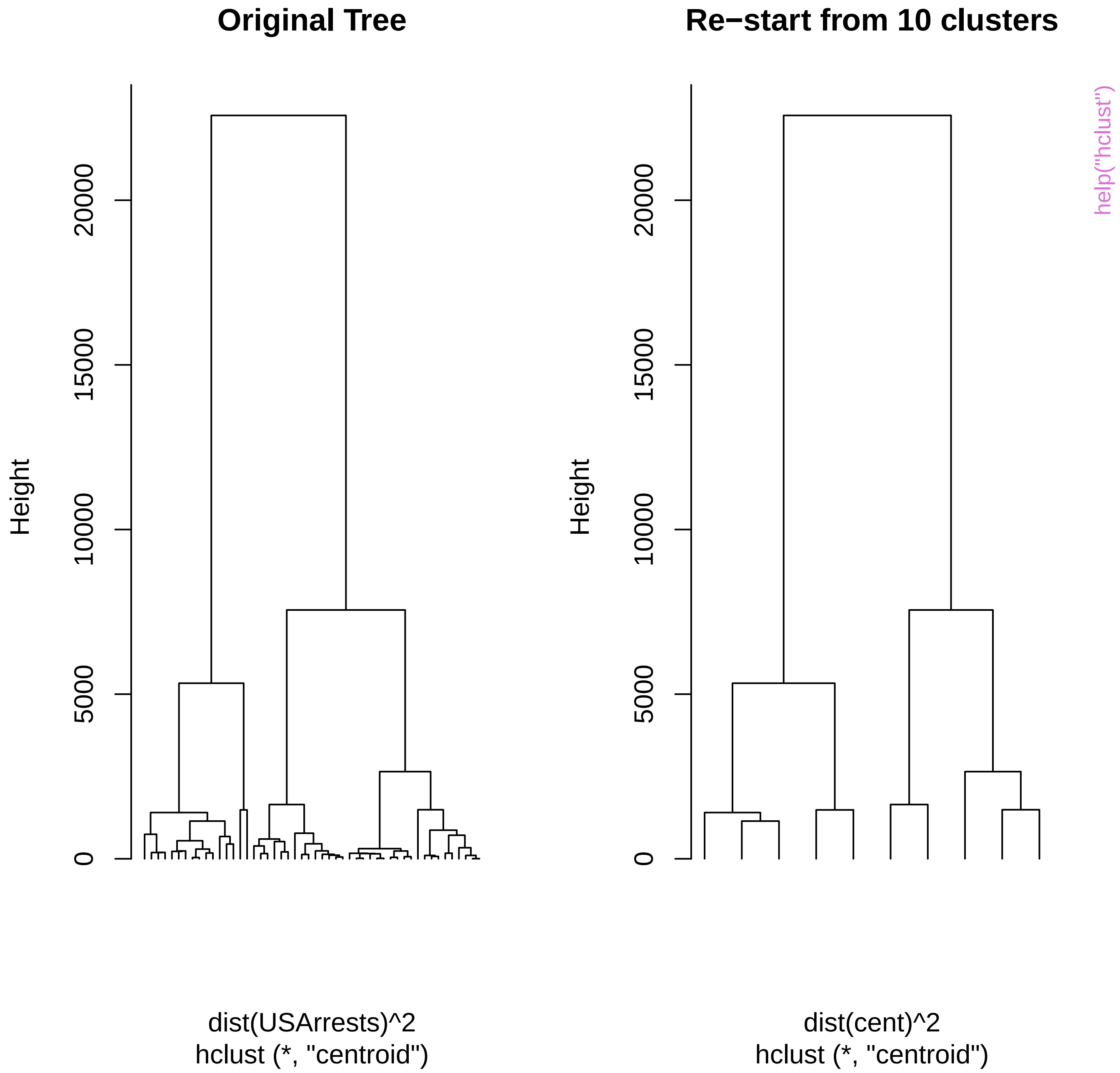


25
20
15
10
5
0
count
A
B
C
D
E
F
spray
help("fligner.test")

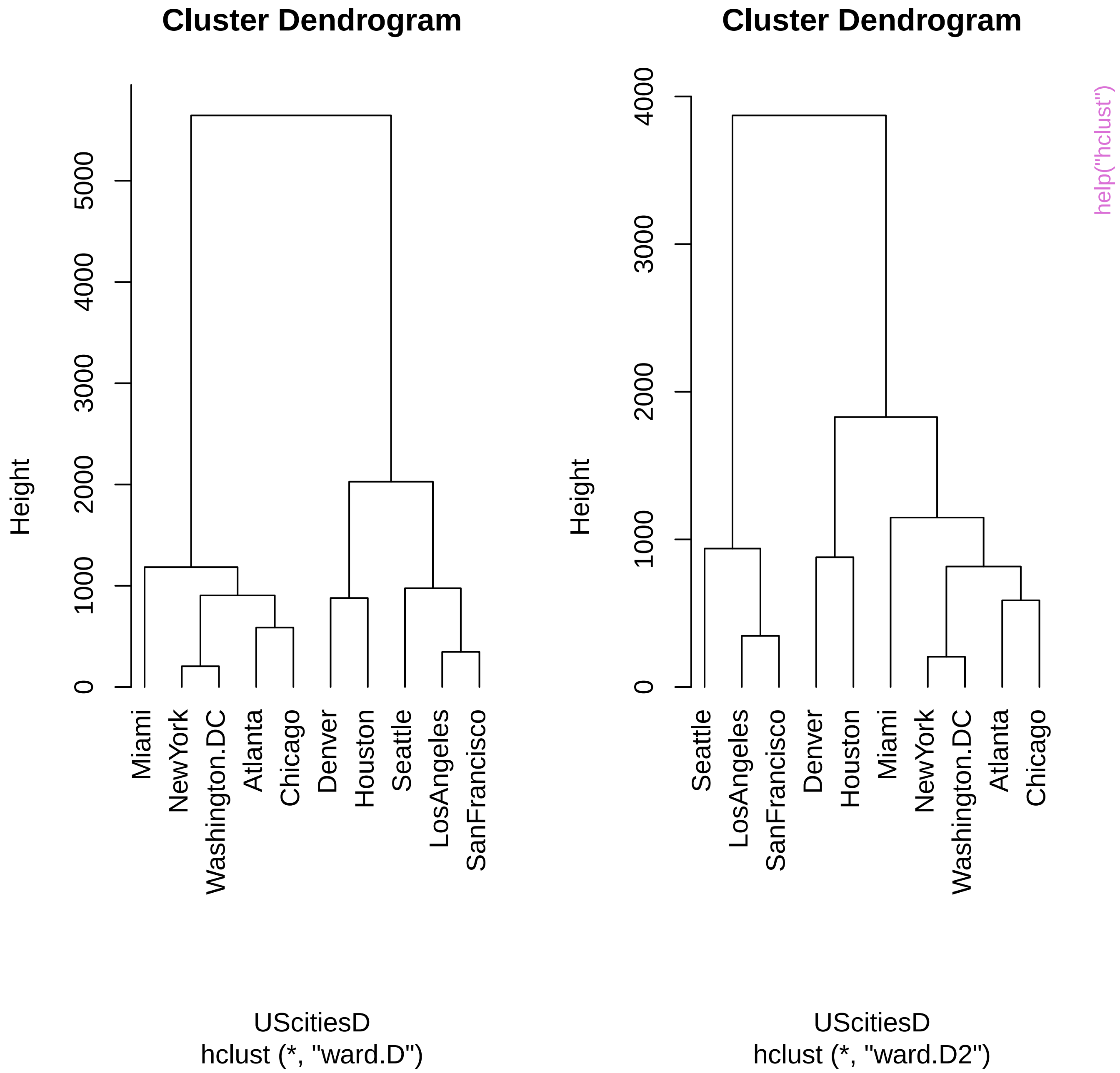

Cluster Dendrogram
Height
0
50
100
150
Florida
North Carolina
California
Maryland
Arizona
New Mexico
Delaware
Alabama
Louisiana
Illinois
New York
Michigan
Nevada
Alaska
Mississippi
South Carolina
Washington
Oregon
Wyoming
Oklahoma
Virginia
Rhode Island
Massachusetts
New Jersey
Missouri
Arkansas
Tennessee
Georgia
Colorado
Texas
Idaho
Nebraska
Kentucky
Montana
Ohio
Utah
Indiana
Kansas
Connecticut
Pennsylvania
Hawaii
West Virginia
Maine
South Dakota
North Dakota
Vermont
Minnesota
Wisconsin
Iowa
New Hampshire
dist(USArrests)
hclust (*, "average")
help("hclust")

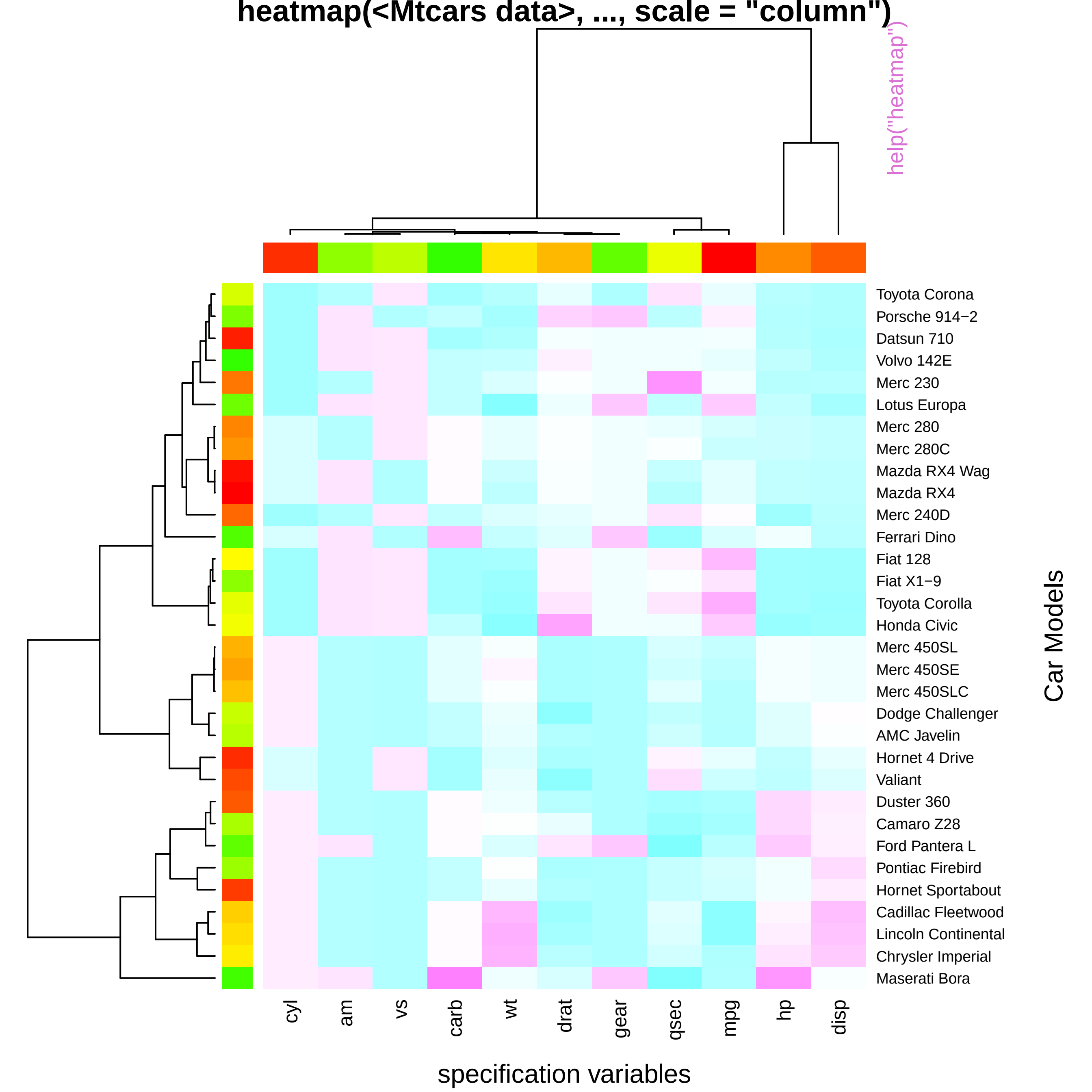


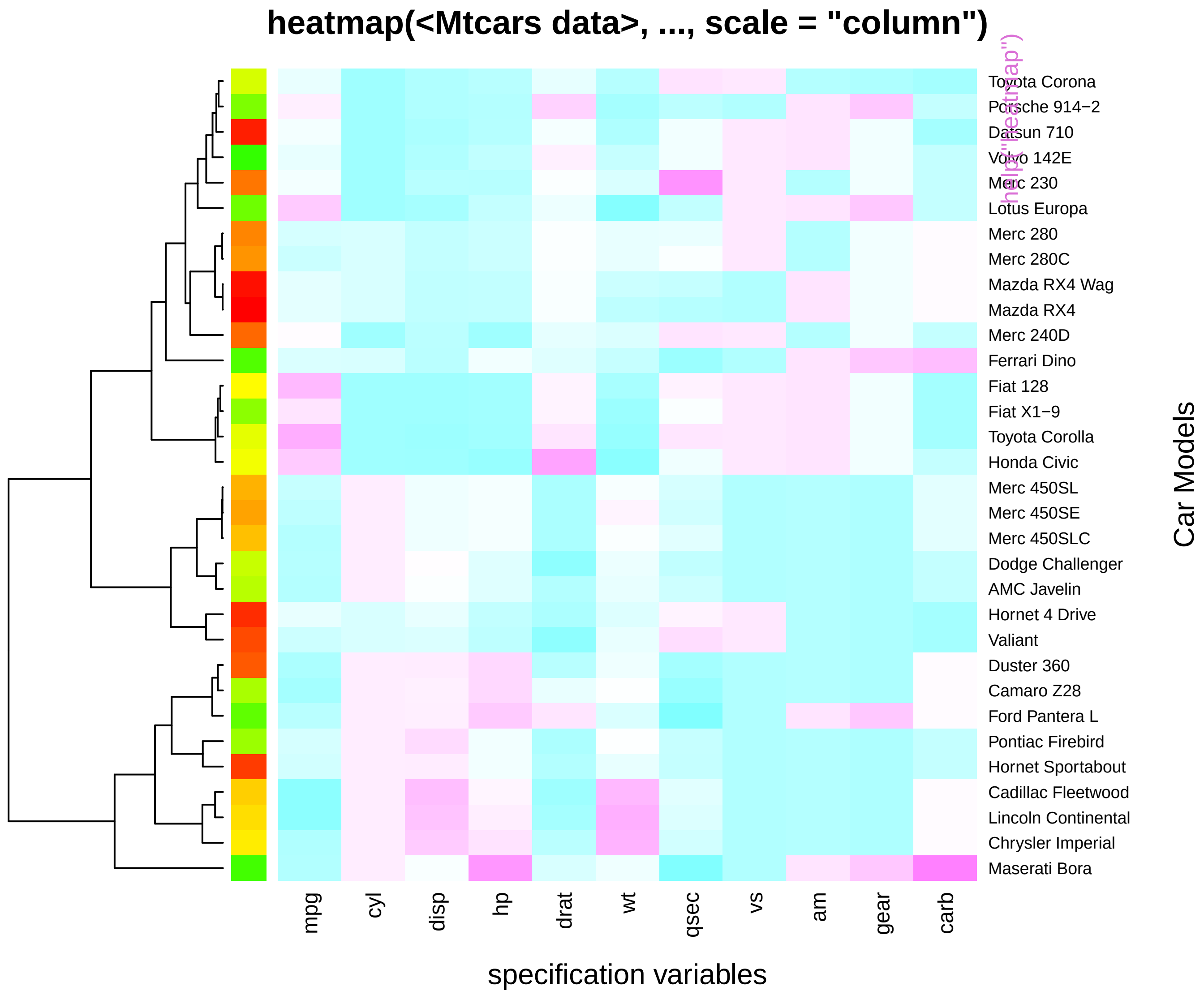
Cluster Dendrogram
Height
0
50
100
150
Florida
North Carolina
California
Maryland
Arizona
New Mexico
Delaware
Alabama
Louisiana
Illinois
New York
Michigan
Nevada
Alaska
Mississippi
South Carolina
Washington
Oregon
Wyoming
Oklahoma
Virginia
Rhode Island
Massachusetts
New Jersey
Missouri
Arkansas
Tennessee
Georgia
Colorado
Texas
Idaho
Nebraska
Kentucky
Montana
Ohio
Utah
Indiana
Kansas
Connecticut
Pennsylvania
Hawaii
West Virginia
Maine
South Dakota
North Dakota
Vermont
Minnesota
Wisconsin
Iowa
New Hampshire
dist(USArrests)
hclust (*, "average")
help("hclust")


Original Tree
Re−start from 10 clusters
Height
0
5000
10000
15000
20000
Height
0
5000
10000
15000
20000
dist(USArrests)^2
hclust (*, "centroid")
dist(cent)^2
hclust (*, "centroid")
help("hclust")

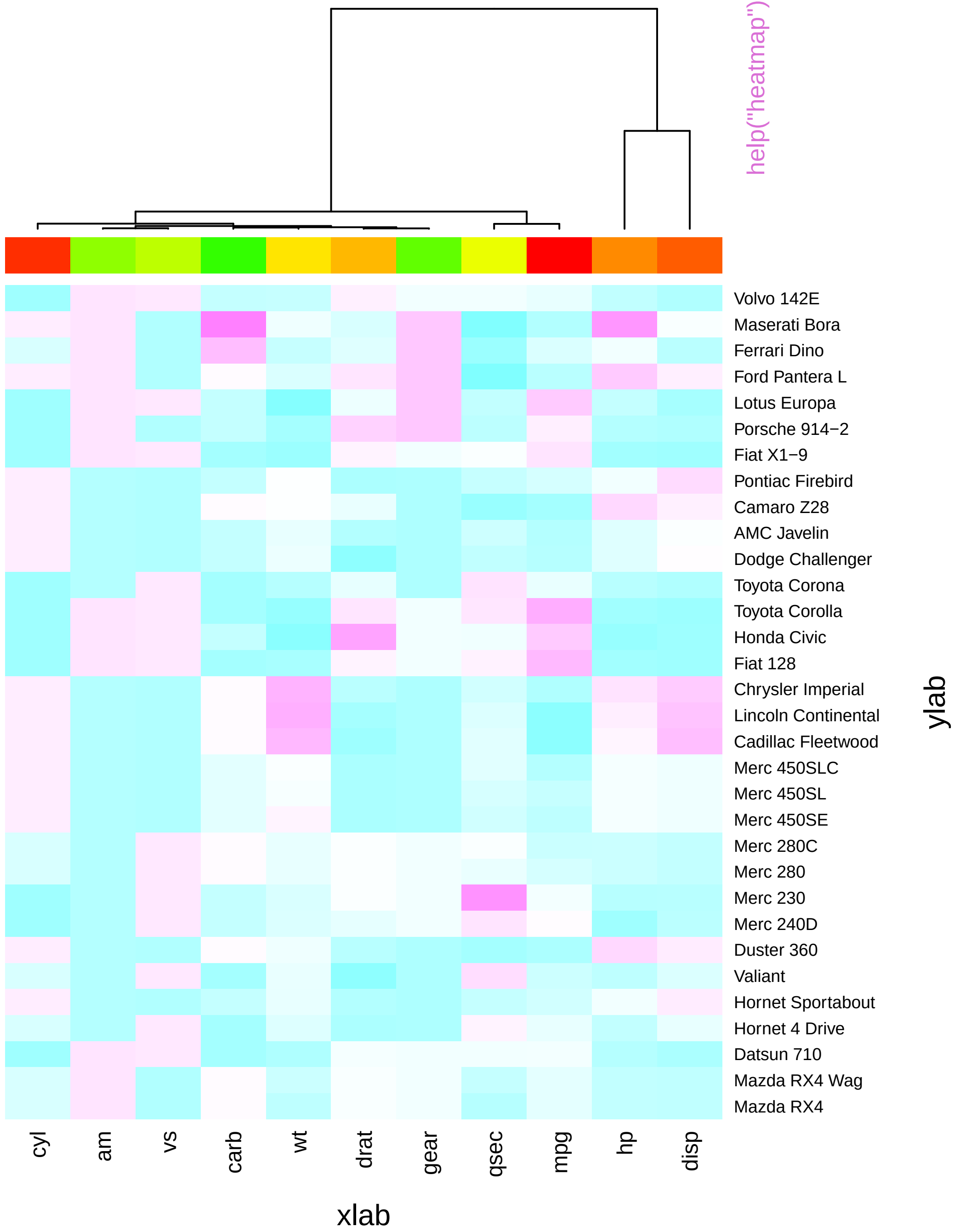

Seattle
NewYork
Chicago
Washington.DC
Denver
SanFrancisco
Atlanta
LosAngeles
Houston
Miami
help("hclust")


Cluster Dendrogram
Height
0
1000
2000
3000
4000
5000
Miami
NewYork
Washington.DC
Atlanta
Chicago
Denver
Houston
Seattle
LosAngeles
SanFrancisco
UScitiesD
hclust (*, "ward.D")
Cluster Dendrogram
Height
0
1000
2000
3000
4000
Seattle
LosAngeles
SanFrancisco
Denver
Houston
Miami
NewYork
Washington.DC
Atlanta
Chicago
UScitiesD
hclust (*, "ward.D2")
help("hclust")

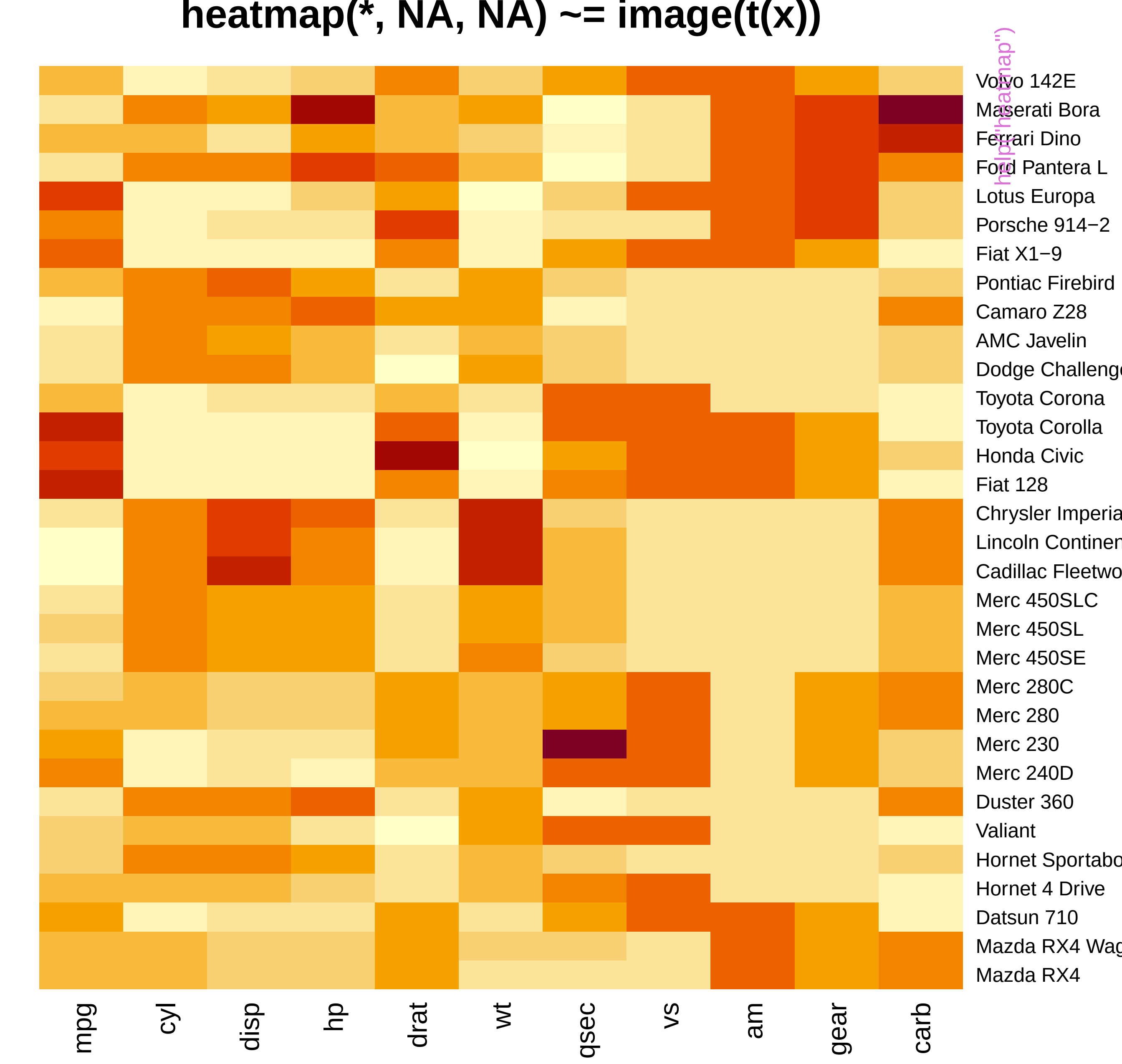

heatmap(<Mtcars data>, ..., scale = "column")
help("heatmap")
Toyota Corona
Porsche 914−2
Datsun 710
Volvo 142E
Merc 230
Lotus Europa
Merc 280
Merc 280C
Mazda RX4 Wag
Mazda RX4
Merc 240D
Ferrari Dino
Fiat 128
Fiat X1−9
Toyota Corolla
Honda Civic
Merc 450SL
Merc 450SE
Merc 450SLC
Dodge Challenger
AMC Javelin
Hornet 4 Drive
Valiant
Duster 360
Camaro Z28
Ford Pantera L
Pontiac Firebird
Hornet Sportabout
Cadillac Fleetwood
Lincoln Continental
Chrysler Imperial
Maserati Bora
Car Models
cyl
am
vs
carb
wt
drat
gear
qsec
mpg
hp
disp
specification variables

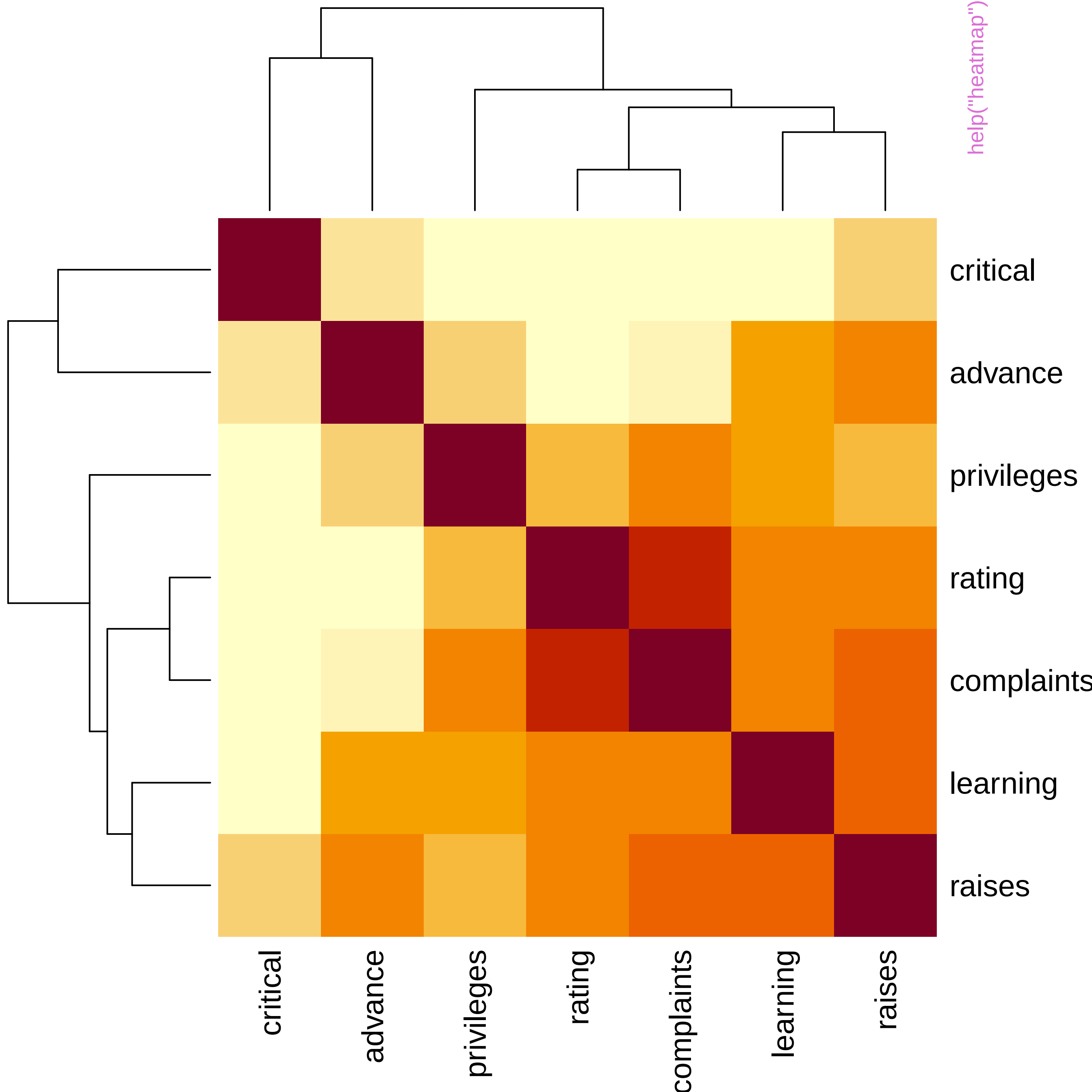


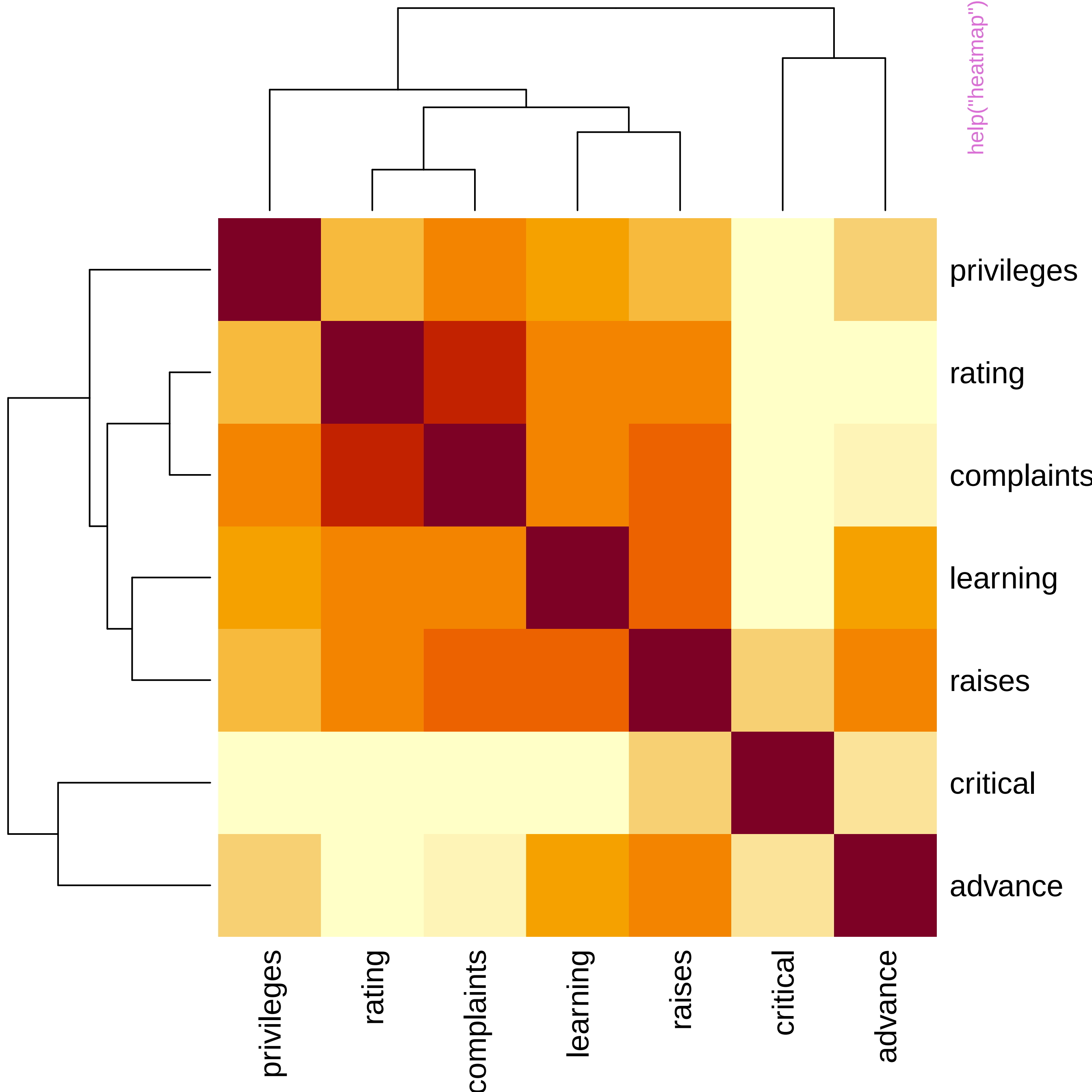
heatmap(<Mtcars data>, ..., scale = "column")
help("heatmap")
Toyota Corona
Porsche 914−2
Datsun 710
Volvo 142E
Merc 230
Lotus Europa
Merc 280
Merc 280C
Mazda RX4 Wag
Mazda RX4
Merc 240D
Ferrari Dino
Fiat 128
Fiat X1−9
Toyota Corolla
Honda Civic
Merc 450SL
Merc 450SE
Merc 450SLC
Dodge Challenger
AMC Javelin
Hornet 4 Drive
Valiant
Duster 360
Camaro Z28
Ford Pantera L
Pontiac Firebird
Hornet Sportabout
Cadillac Fleetwood
Lincoln Continental
Chrysler Imperial
Maserati Bora
mpg
cyl
disp
hp
drat
wt
qsec
vs
am
gear
carb
specification variables
Car Models

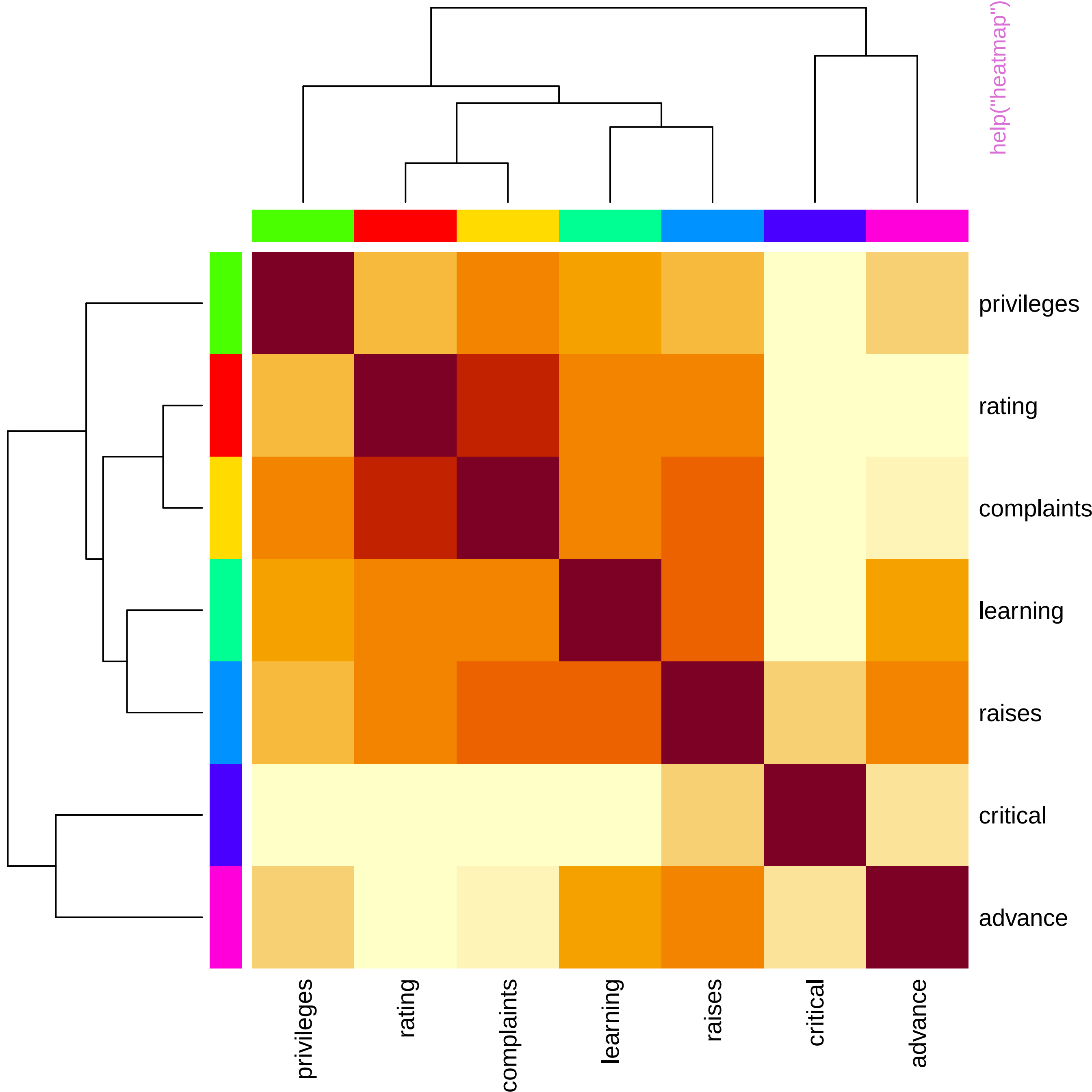


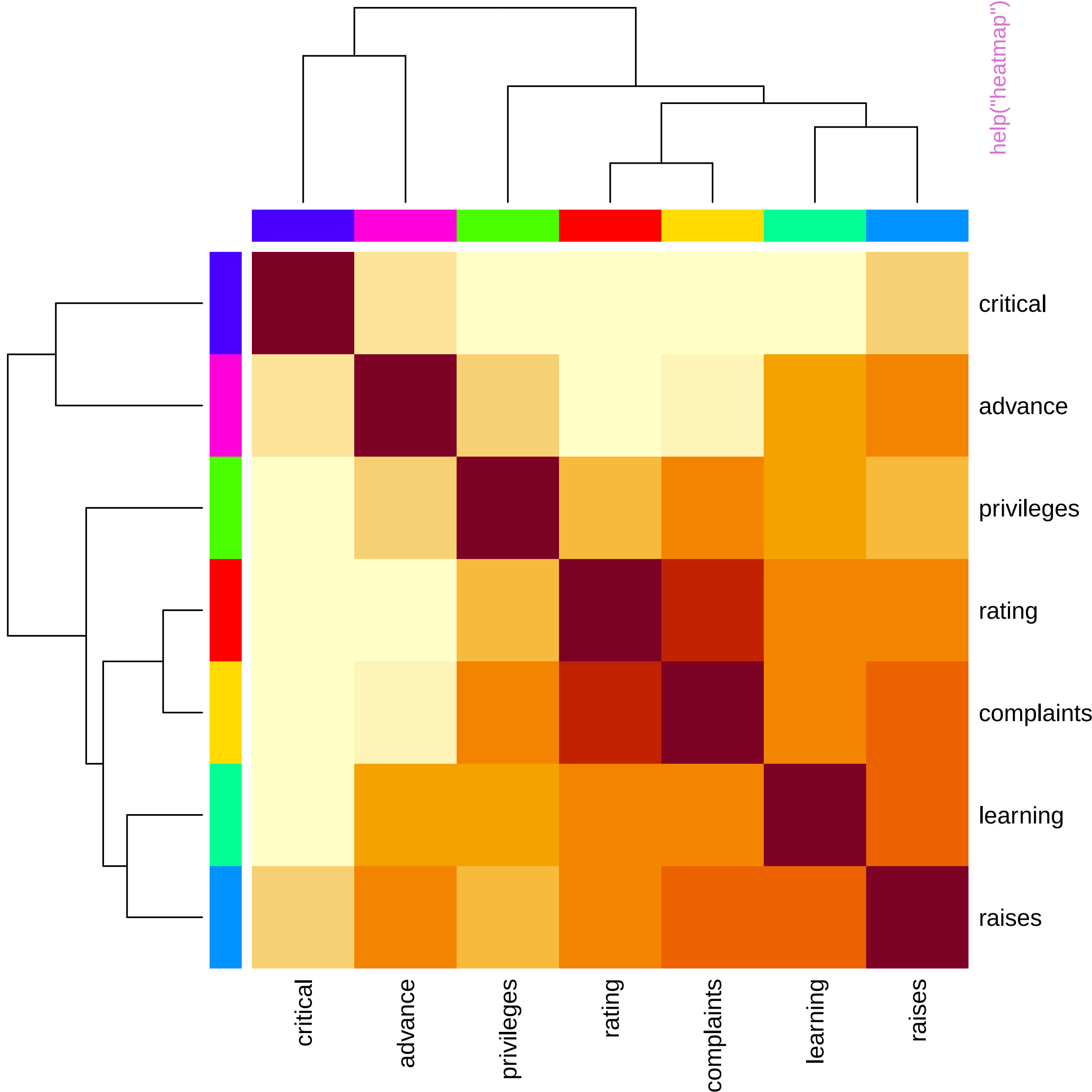
help("heatmap")
Volvo 142E
Maserati Bora
Ferrari Dino
Ford Pantera L
Lotus Europa
Porsche 914−2
Fiat X1−9
Pontiac Firebird
Camaro Z28
AMC Javelin
Dodge Challenger
Toyota Corona
Toyota Corolla
Honda Civic
Fiat 128
Chrysler Imperial
Lincoln Continental
Cadillac Fleetwood
Merc 450SLC
Merc 450SL
Merc 450SE
Merc 280C
Merc 280
Merc 230
Merc 240D
Duster 360
Valiant
Hornet Sportabout
Hornet 4 Drive
Datsun 710
Mazda RX4 Wag
Mazda RX4
ylab
cyl
am
vs
carb
wt
drat
gear
qsec
mpg
hp
disp
xlab


heatmap(*, NA, NA) ~= image(t(x))
help("heatmap")
Volvo 142E
Maserati Bora
Ferrari Dino
Ford Pantera L
Lotus Europa
Porsche 914−2
Fiat X1−9
Pontiac Firebird
Camaro Z28
AMC Javelin
Toyota Corona
Toyota Corolla
Honda Civic
Fiat 128
Merc 450SLC
Merc 450SL
Merc 450SE
Merc 280C
Merc 280
Merc 230
Merc 240D
Duster 360
Valiant
Hornet 4 Drive
Datsun 710
Mazda RX4
mpg
cyl
disp
hp
drat
wt
qsec
vs
am
gear
carb

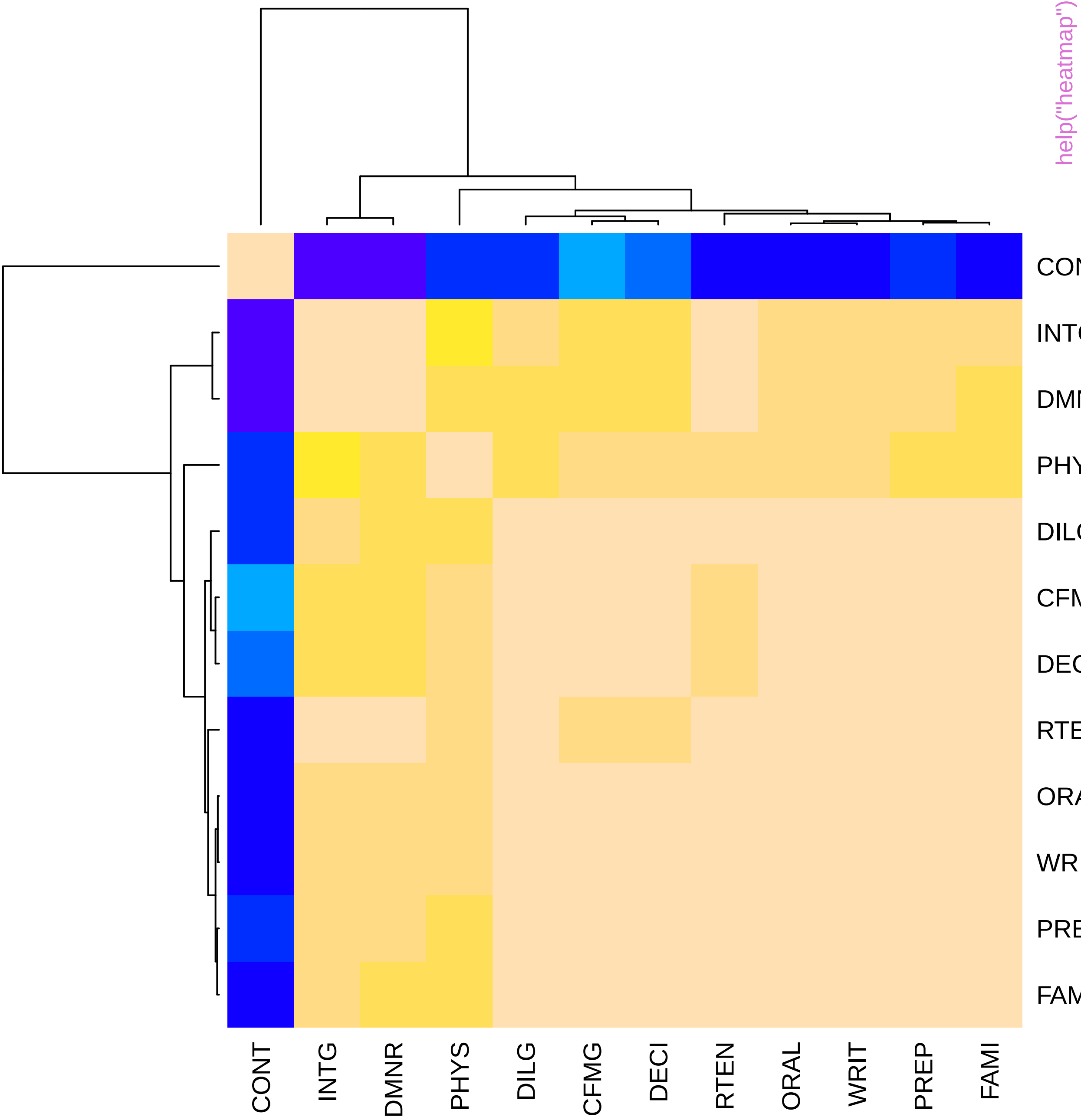

help("heatmap")
critical
advance
privileges
rating
complaints
learning
raises
critical
advance
privileges
rating
complaints
learning
raises


help("heatmap")
privileges
rating
complaints
learning
raises
critical
advance
privileges
rating
complaints
learning
raises
critical
advance

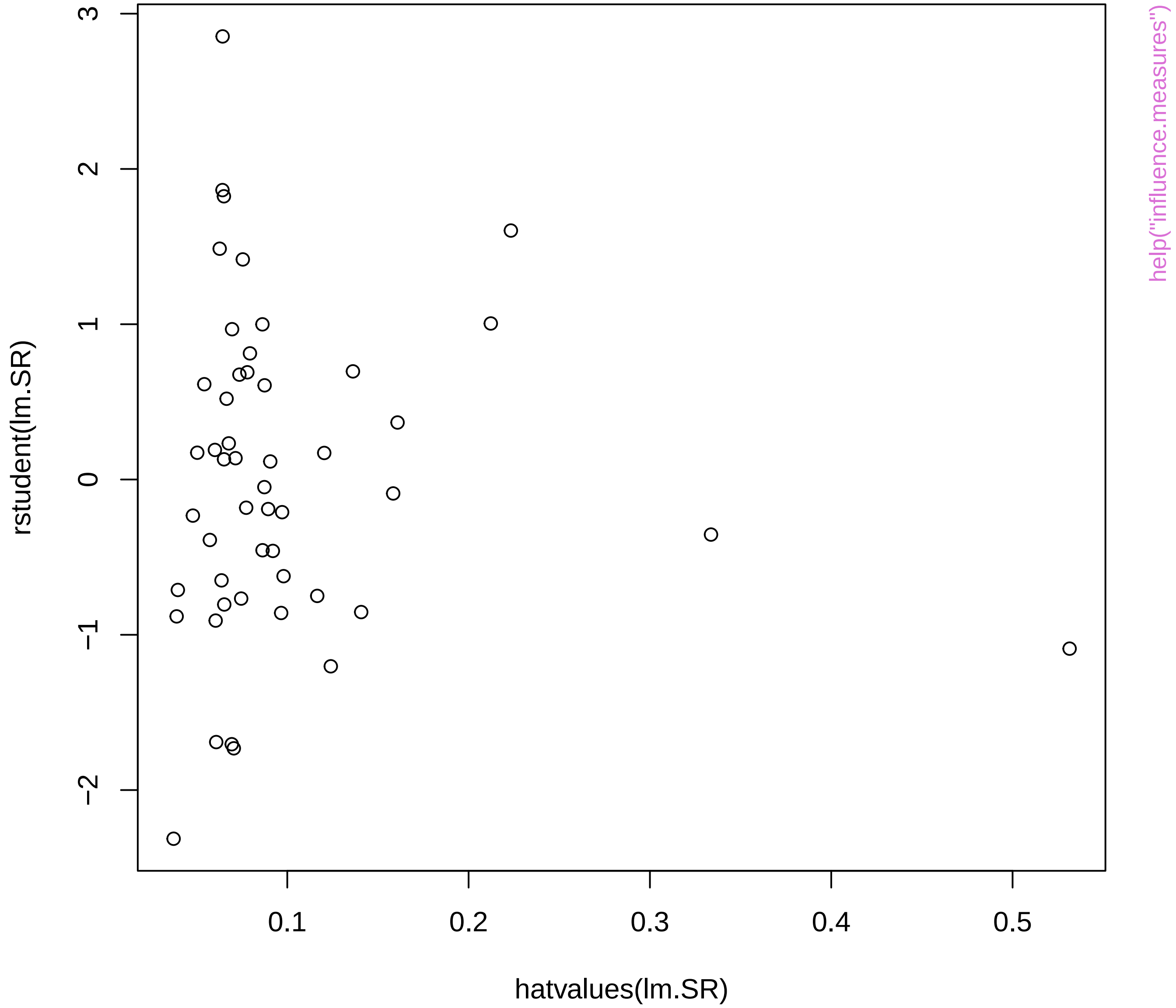

help("heatmap")
privileges
rating
complaints
learning
raises
critical
advance
privileges
rating
complaints
learning
raises
critical
advance



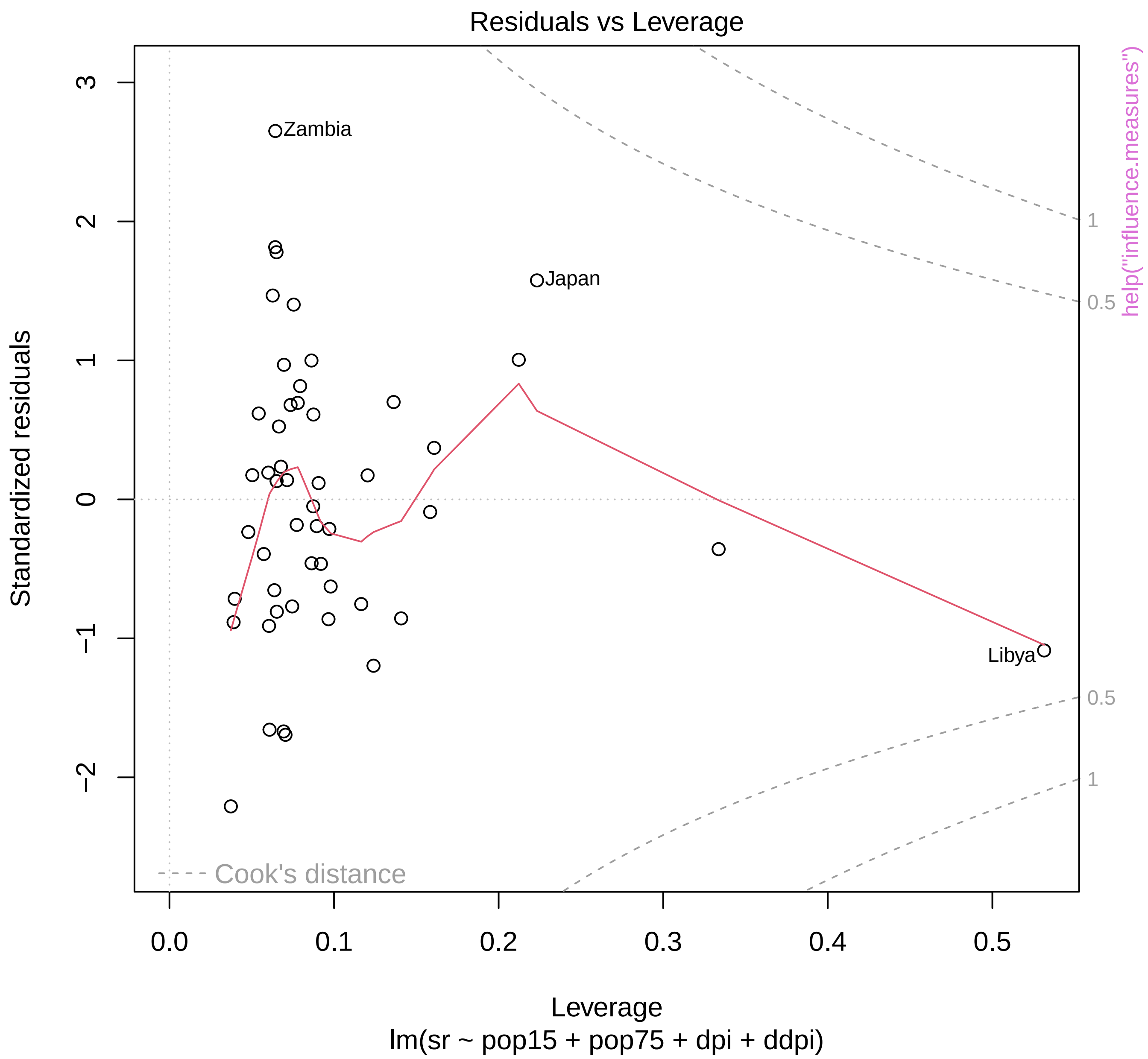
help("heatmap")
critical
advance
privileges
rating
complaints
learning
raises



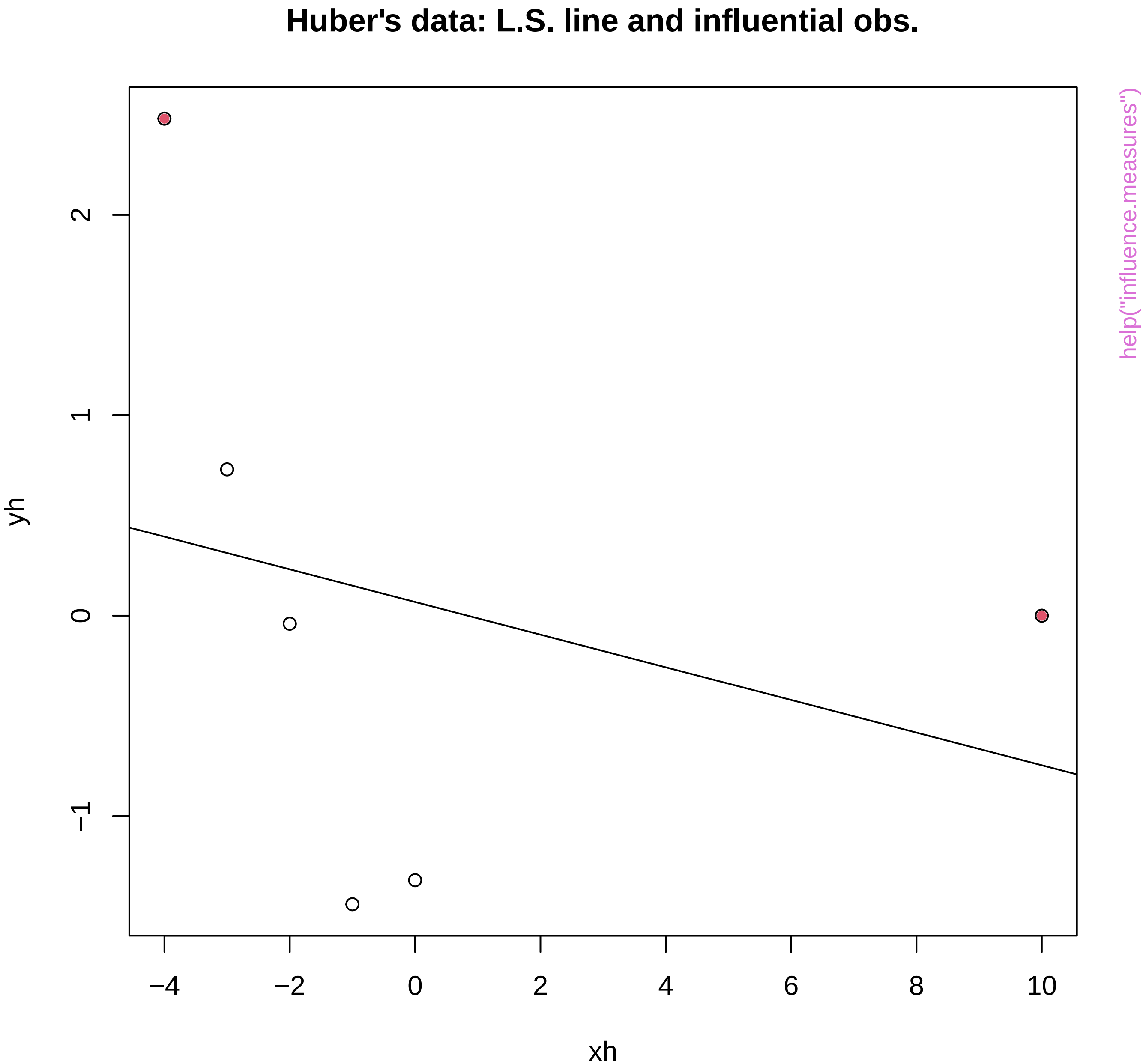
help("heatmap")
CONT
INTG
DMNR
PHYS
DILG
CFMG
DECI
RTEN
ORAL
WRIT
PREP
FAMI



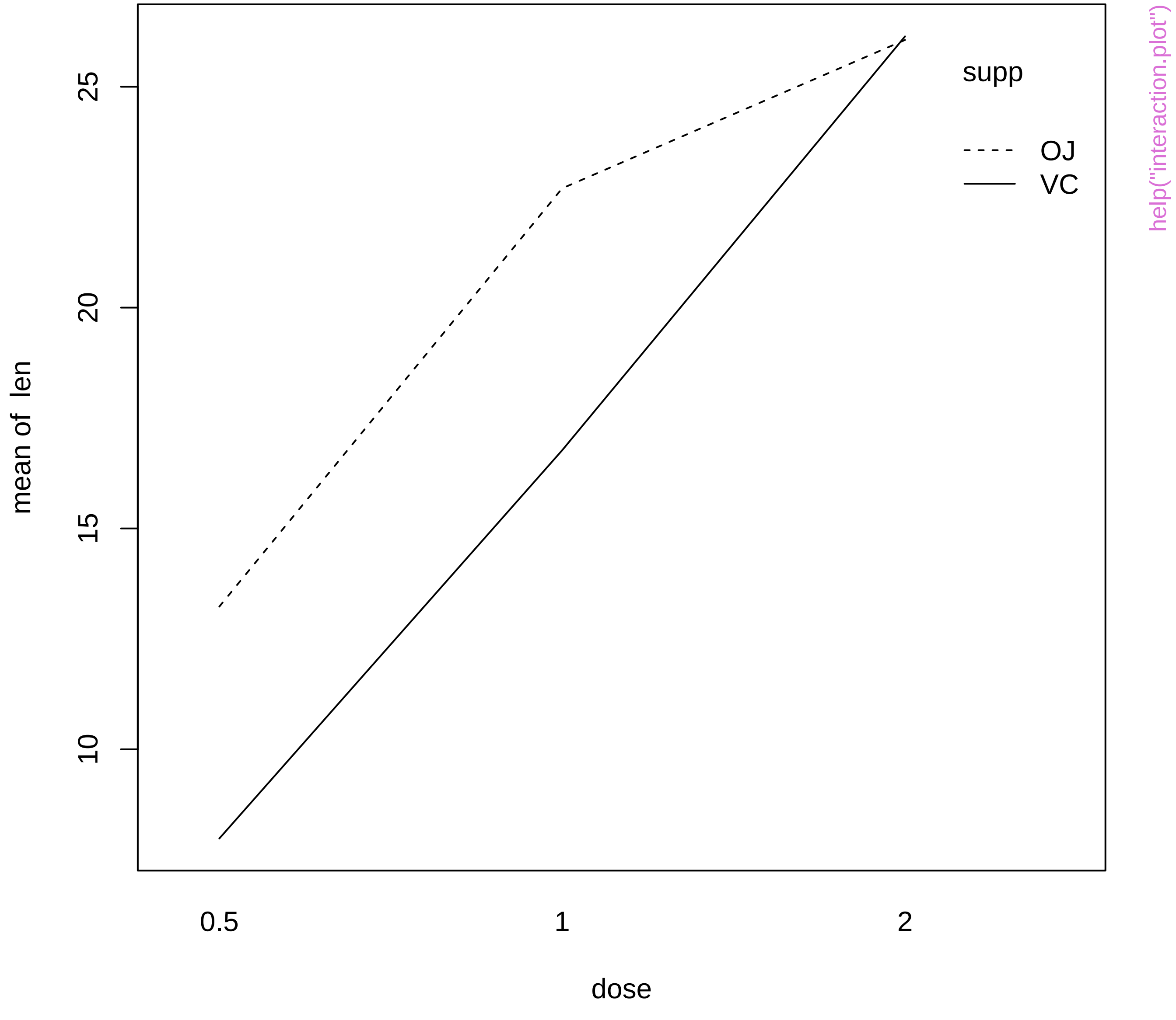
rstudent(lm.SR)
hatvalues(lm.SR)
3
2
1
0
−1
−2
0.1
0.2
0.3
0.4
0.5
help("influence.measures")



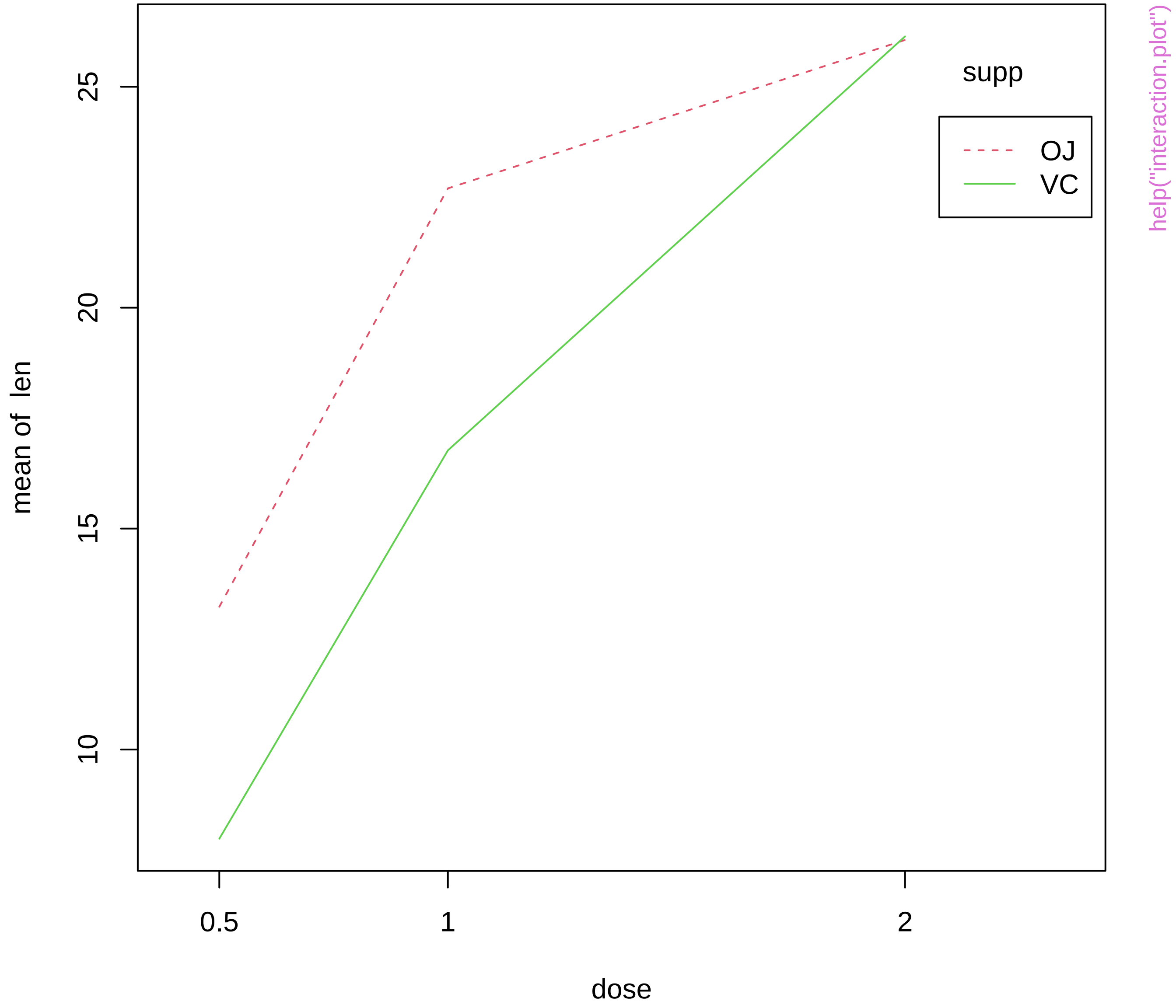
Residuals vs Leverage
Standardized residuals
Leverage
lm(sr ~ pop15 + pop75 + dpi + ddpi)
Zambia
Japan
Libya
Cook's distance
help("influence.measures")
3
2
1
0
−1
−2
0.0
0.1
0.2
0.3
0.4
0.5
1
0.5
0.5
1



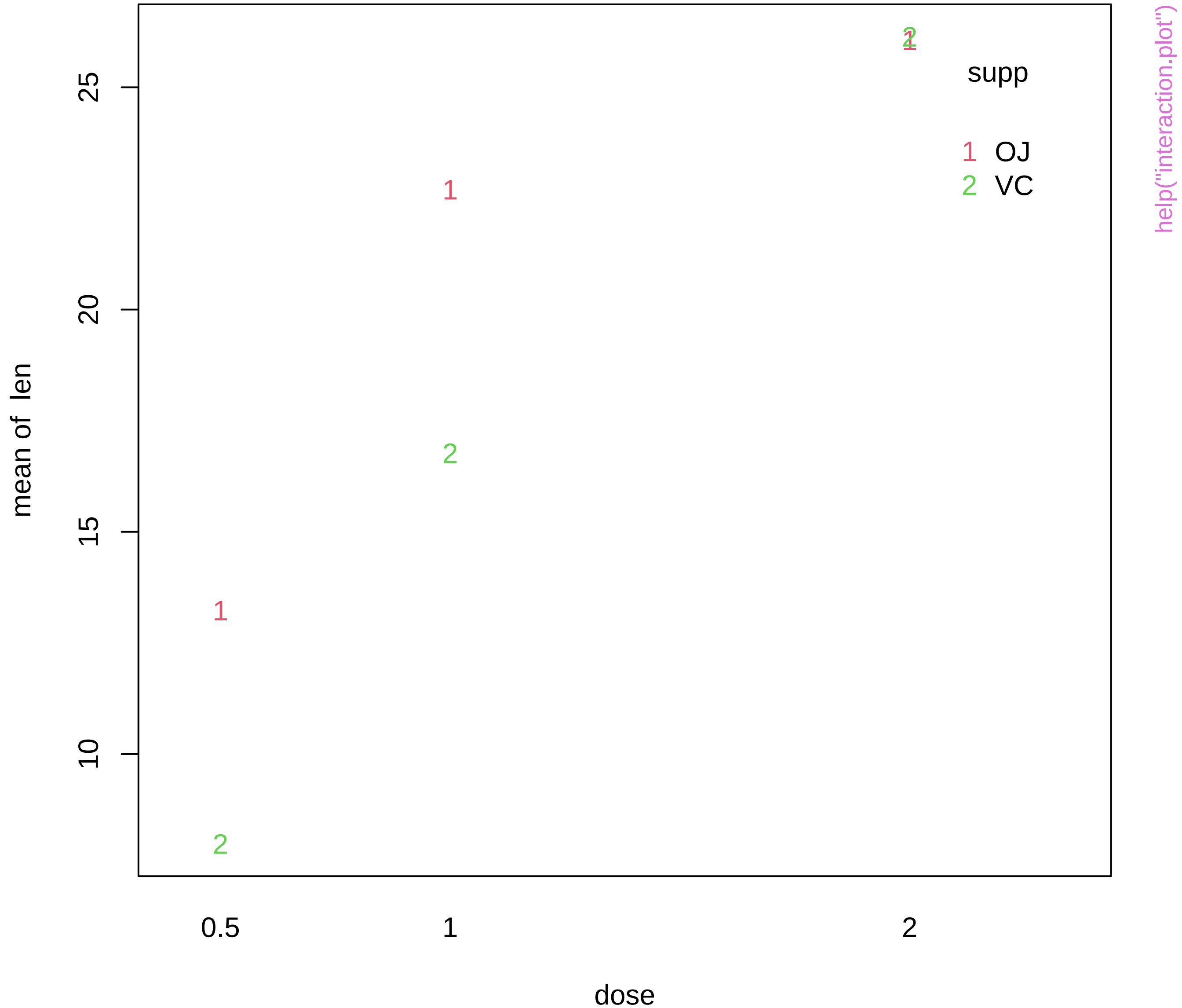
Huber's data: L.S. line and influential obs.
yh
xh
2
1
0
−1
−4
−2
0
2
4
6
8
10
help("influence.measures")



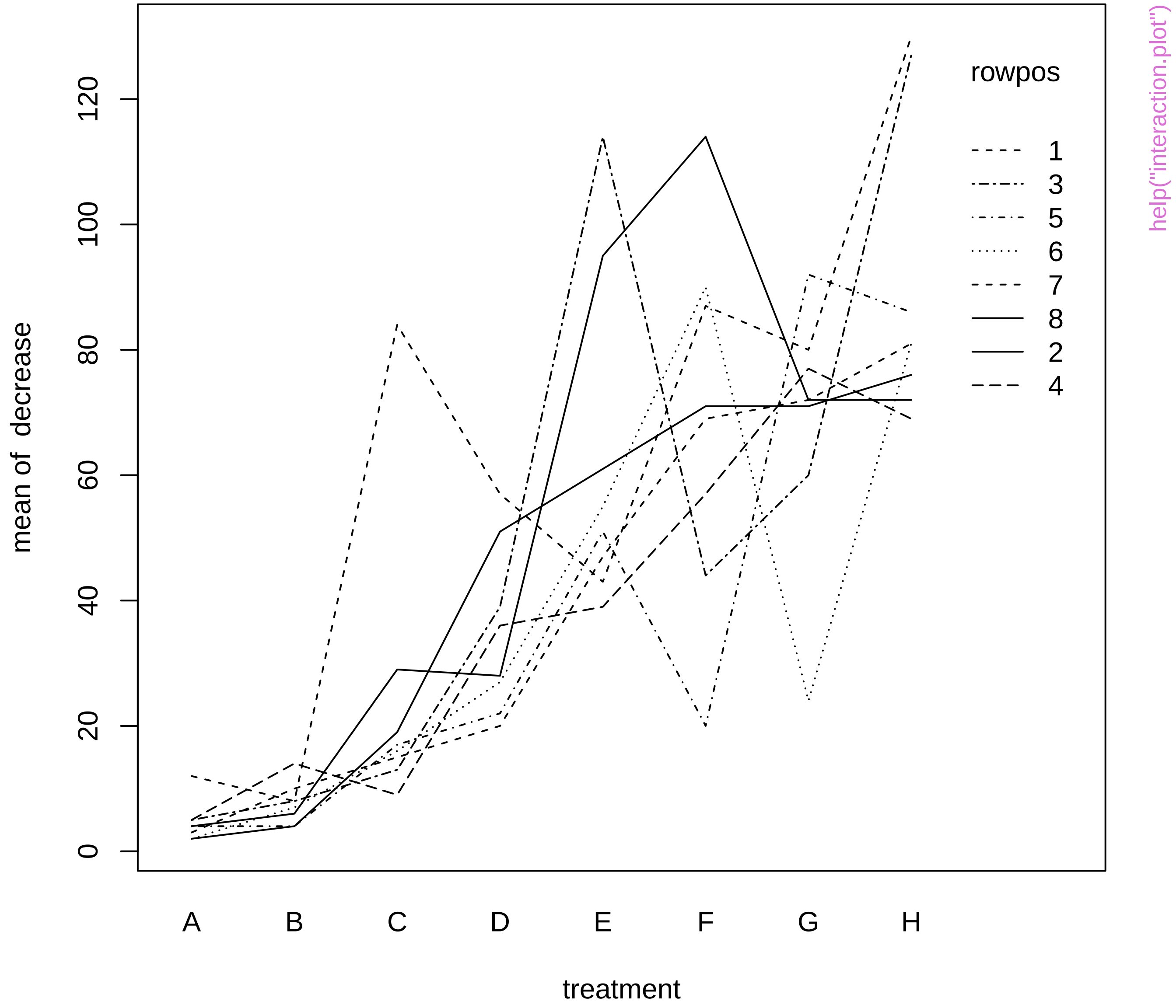
supp
OJ
VC
25
20
15
10
mean of len
0.5
1
2
dose
help("interaction.plot")



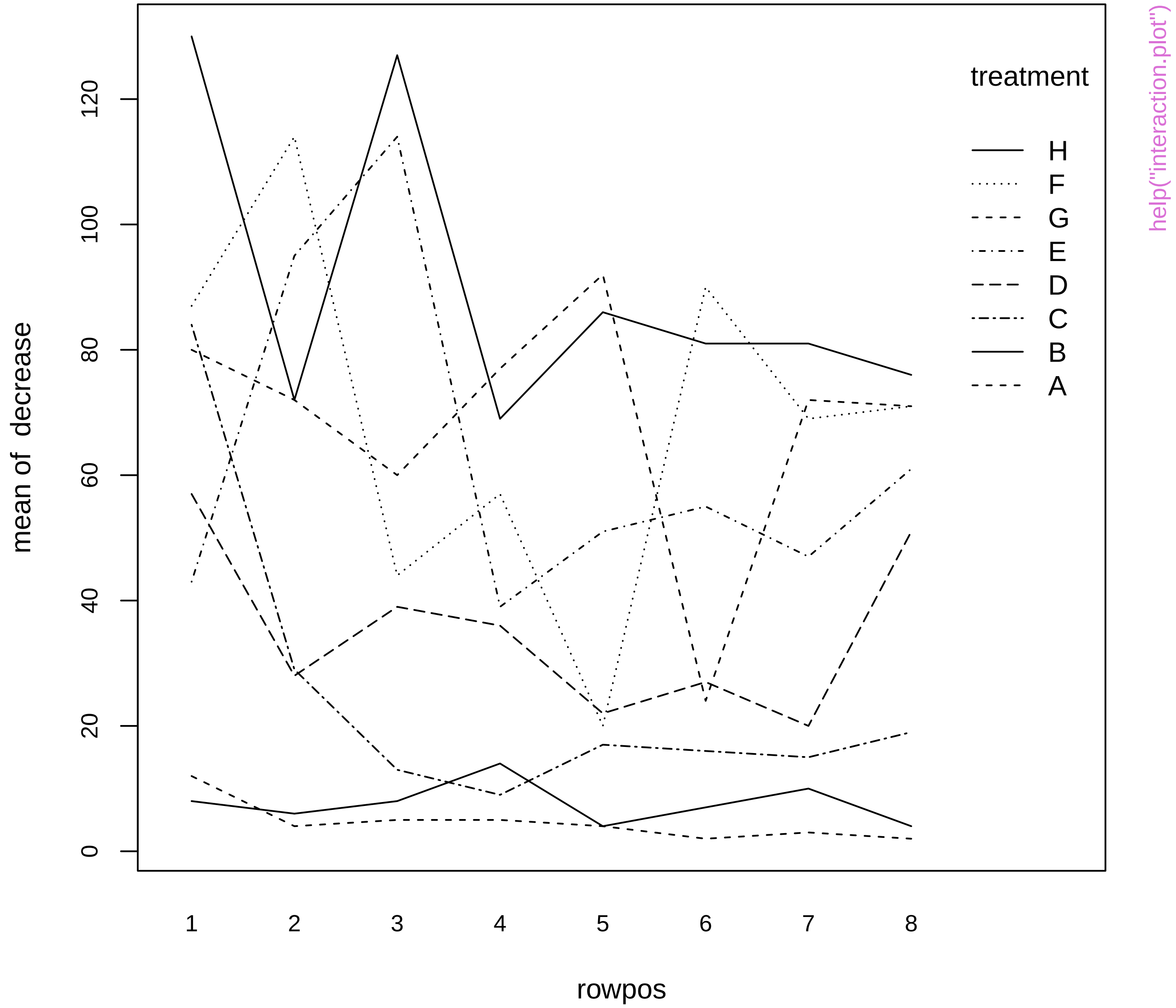
supp
OJ
VC
mean of len
dose
25
20
15
10
0.5
1
2
help("interaction.plot")



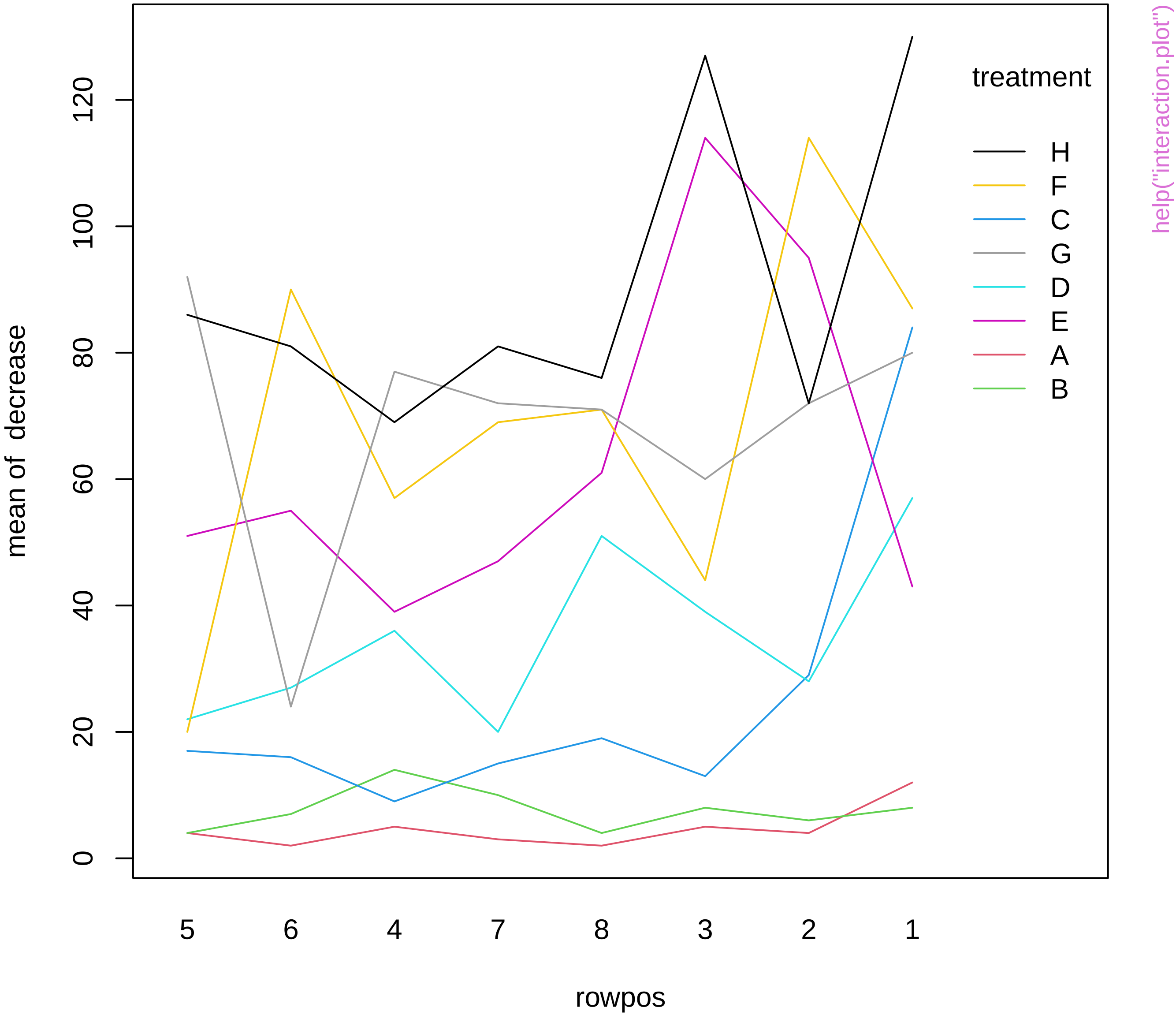
mean of len
dose
supp
1 OJ
2 VC
25
20
15
10
0.5
1
2
help("interaction.plot")

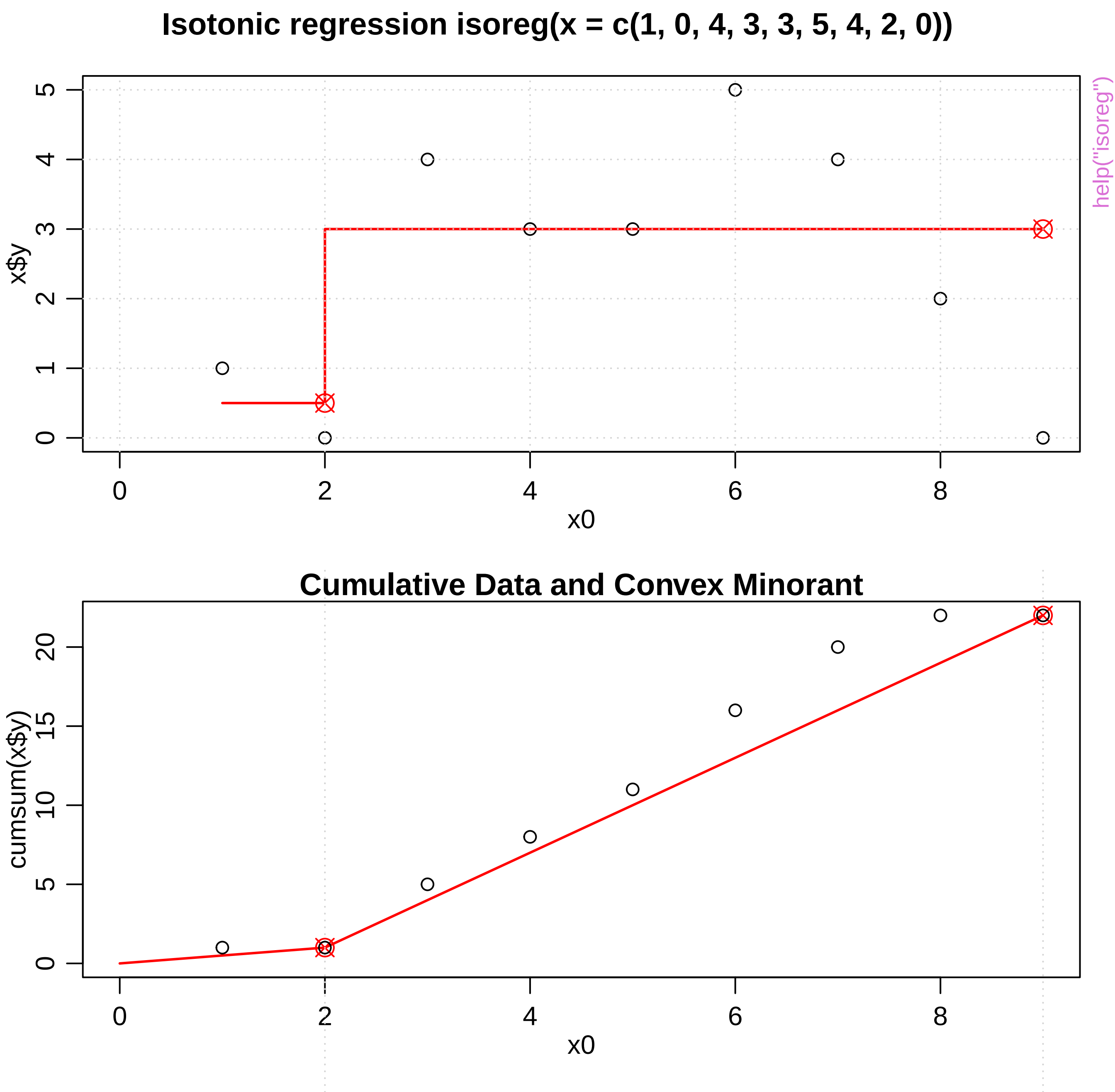


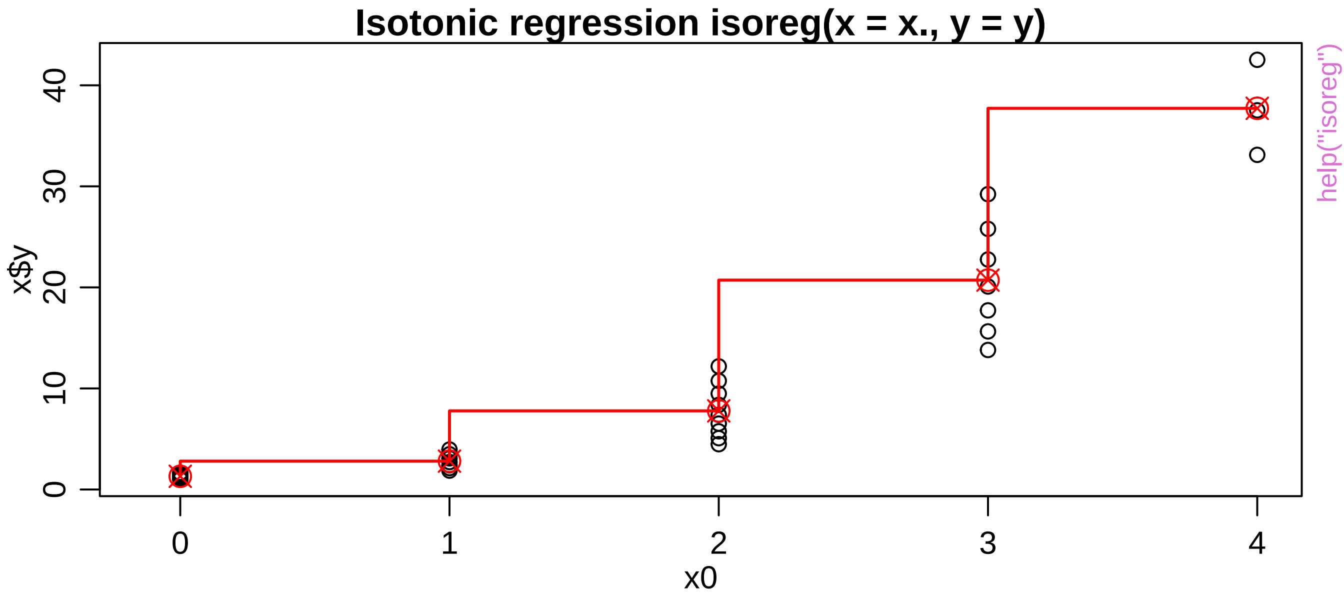
rowpos
1
3
5
6
7
8
2
4
mean of decrease
treatment
A
B
C
D
E
F
G
H
0
20
40
60
80
100
120
help("interaction.plot")



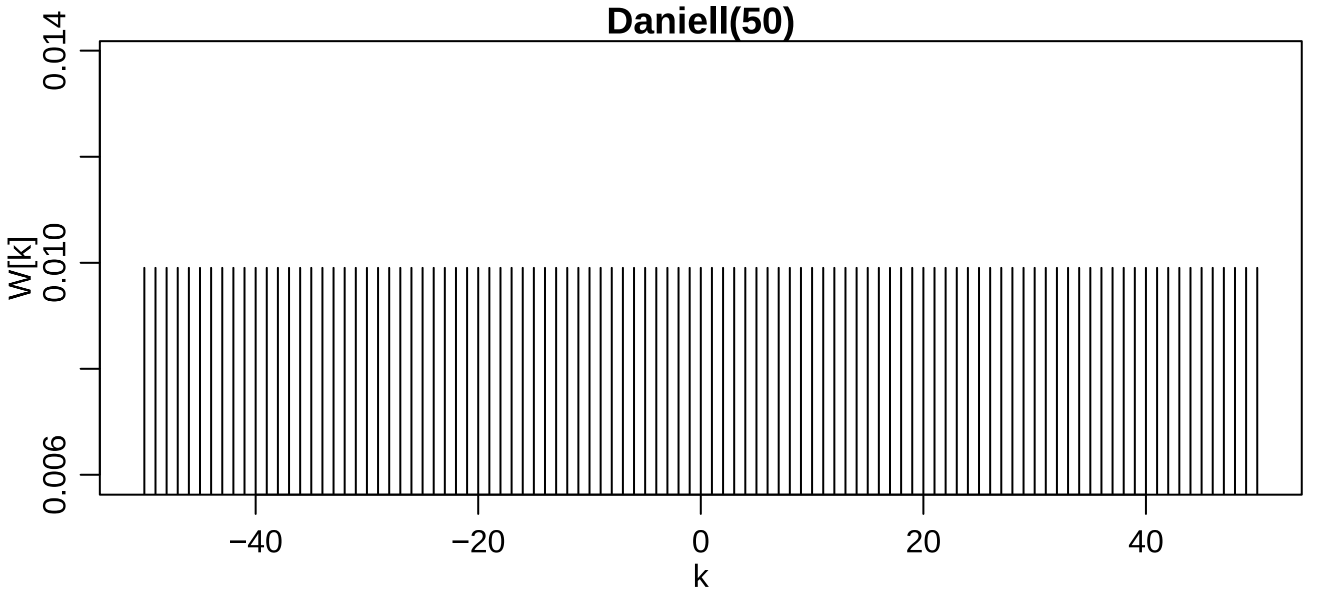
help("interaction.plot")
treatment
H
F
G
E
D
C
B
A
mean of decrease
rowpos
0
20
40
60
80
100
120
1
2
3
4
5
6
7
8


mean of decrease
rowpos
0
20
40
60
80
100
120
5
6
4
7
8
3
2
1
treatment
H
F
C
G
D
E
A
B
help("interaction.plot")

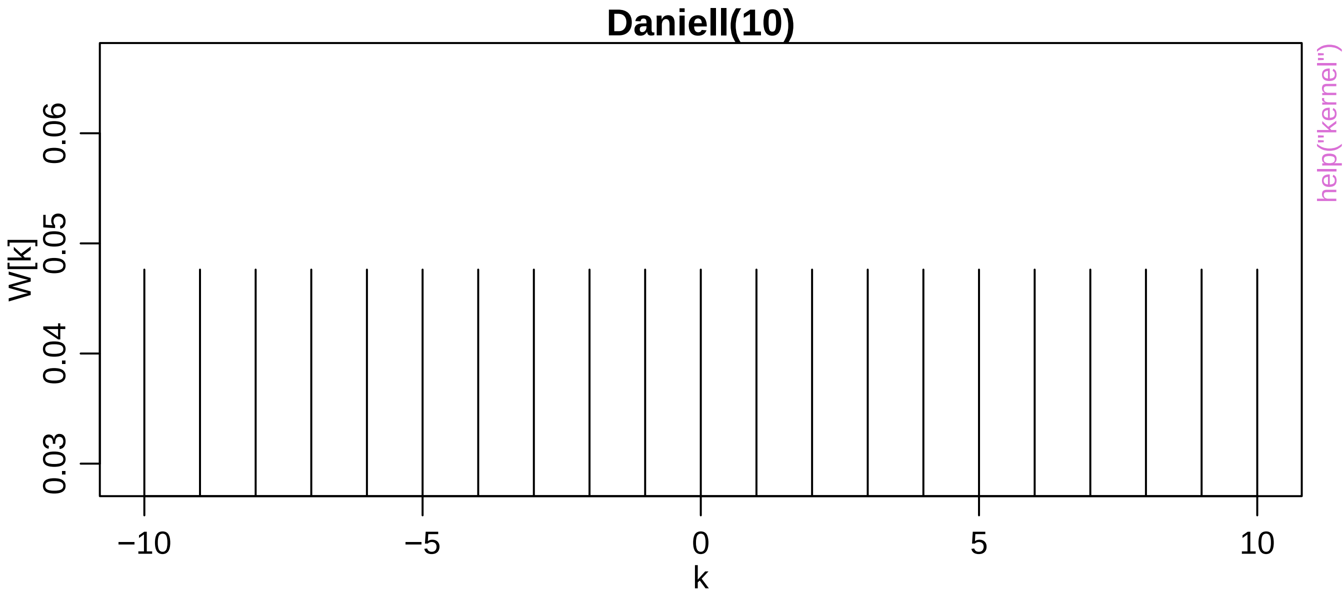

Isotonic regression isoreg(x = c(1, 0, 4, 3, 3, 5, 4, 2, 0))
x$y
x0
help("isoreg")
Cumulative Data and Convex Minorant
cumsum(x$y)
x0

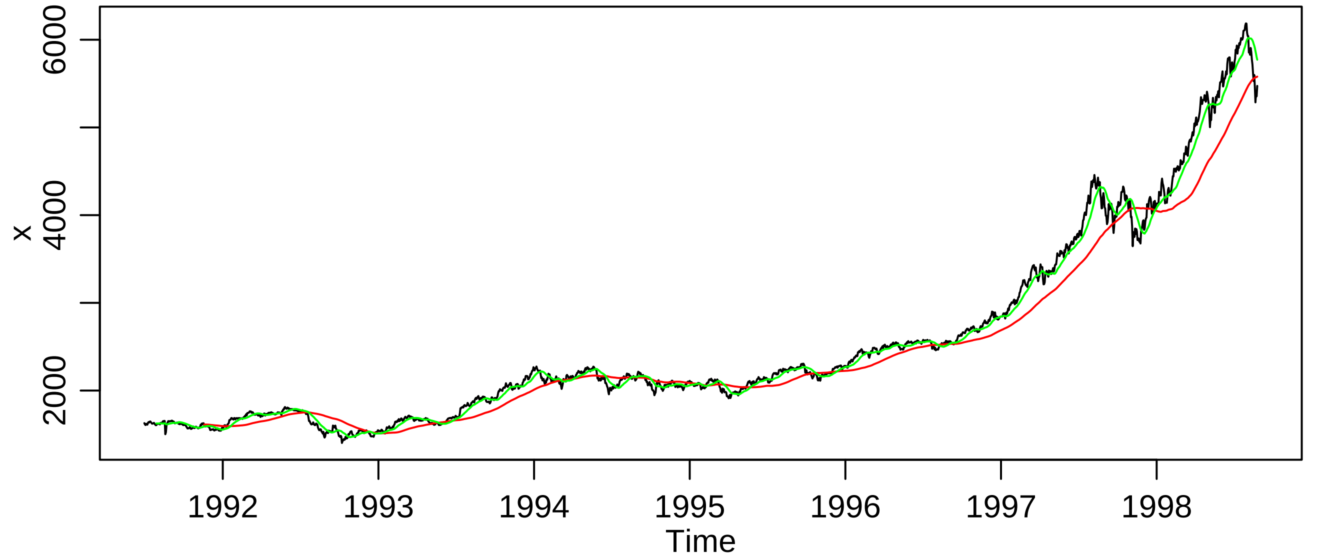


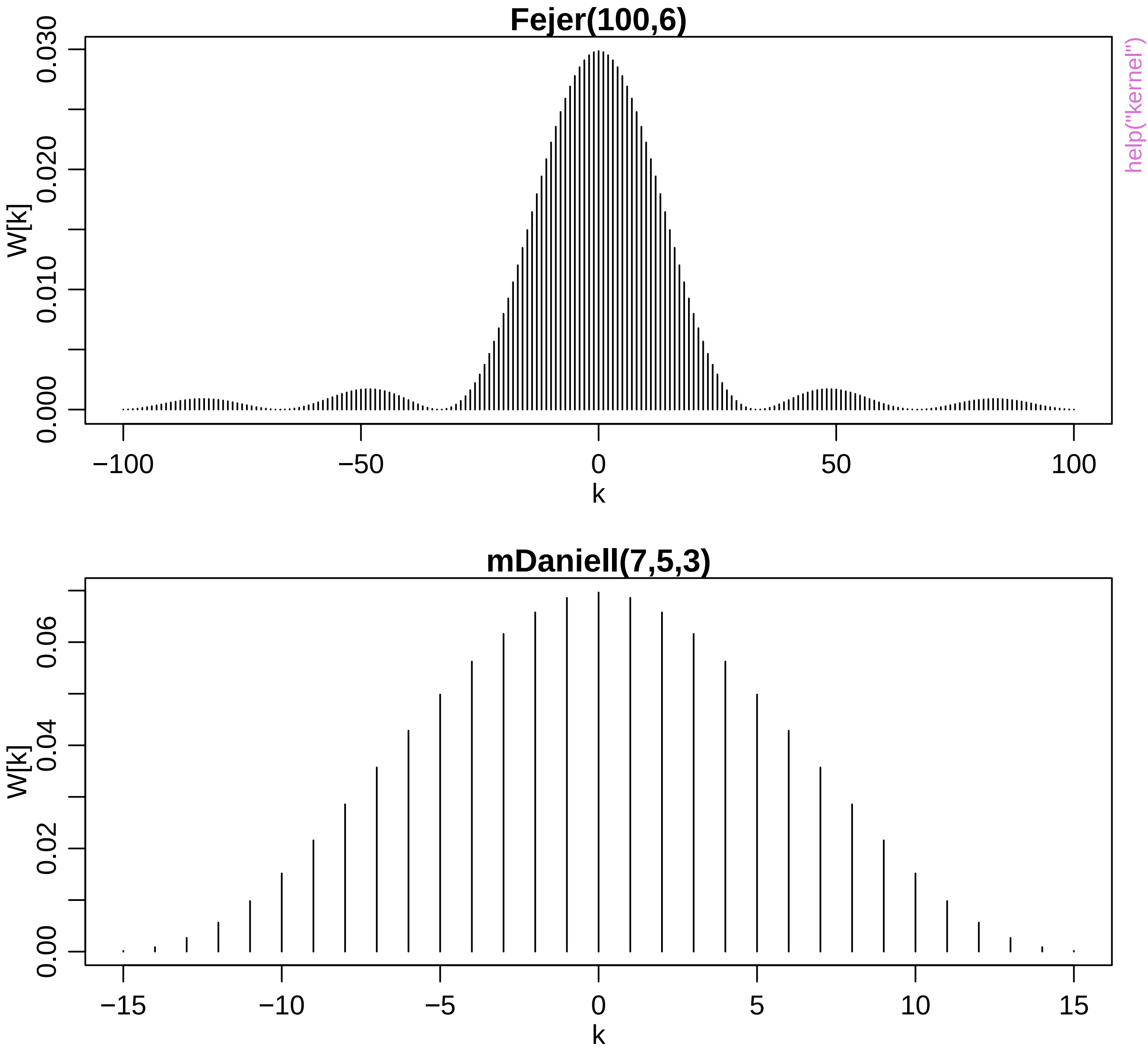
Isotonic regression isoreg(x = x., y = y)
x$y
0
10
20
30
40
0
1
2
3
4
x0
help("isoreg")

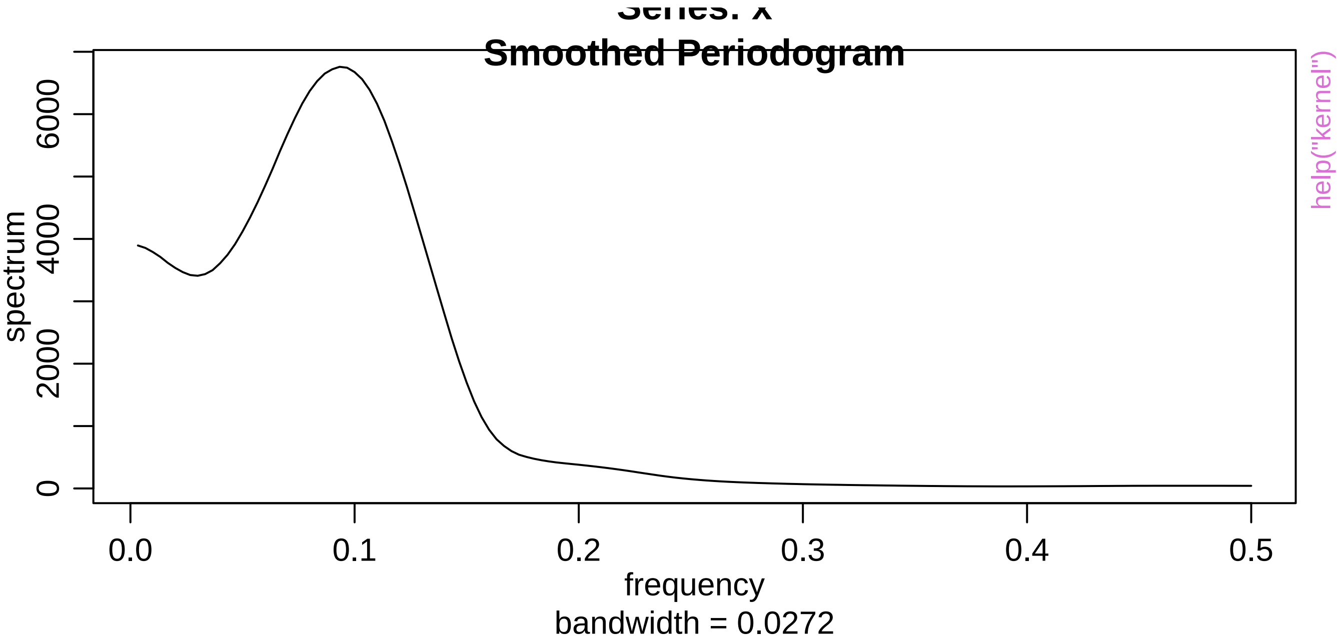


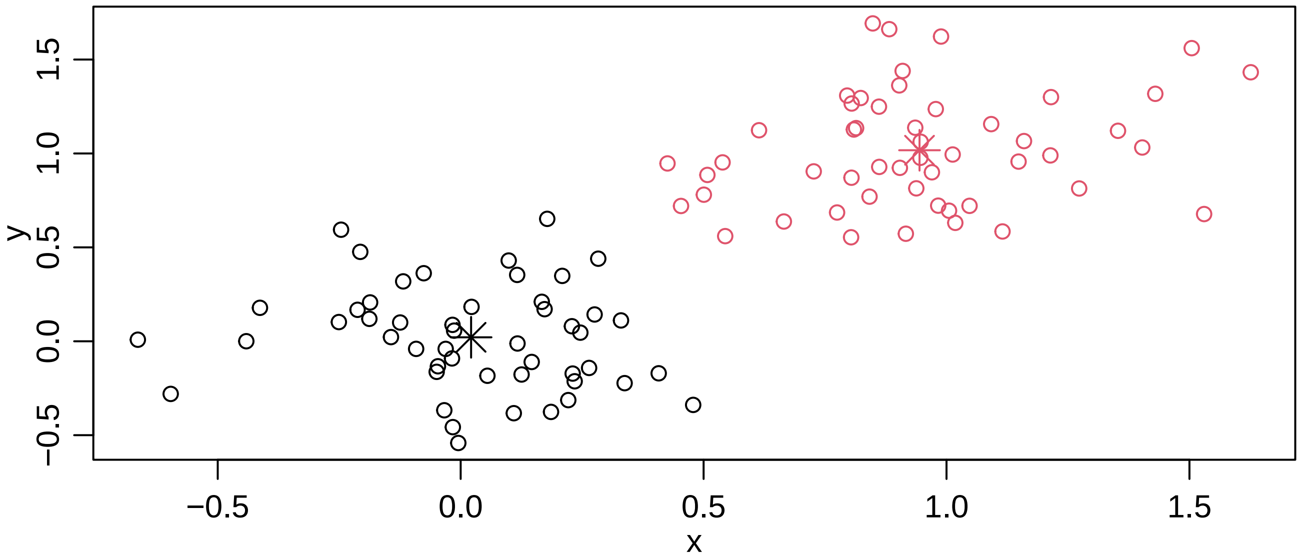
Daniell(50)
W[k]
0.006
0.010
0.014
−40
−20
0
20
40
k

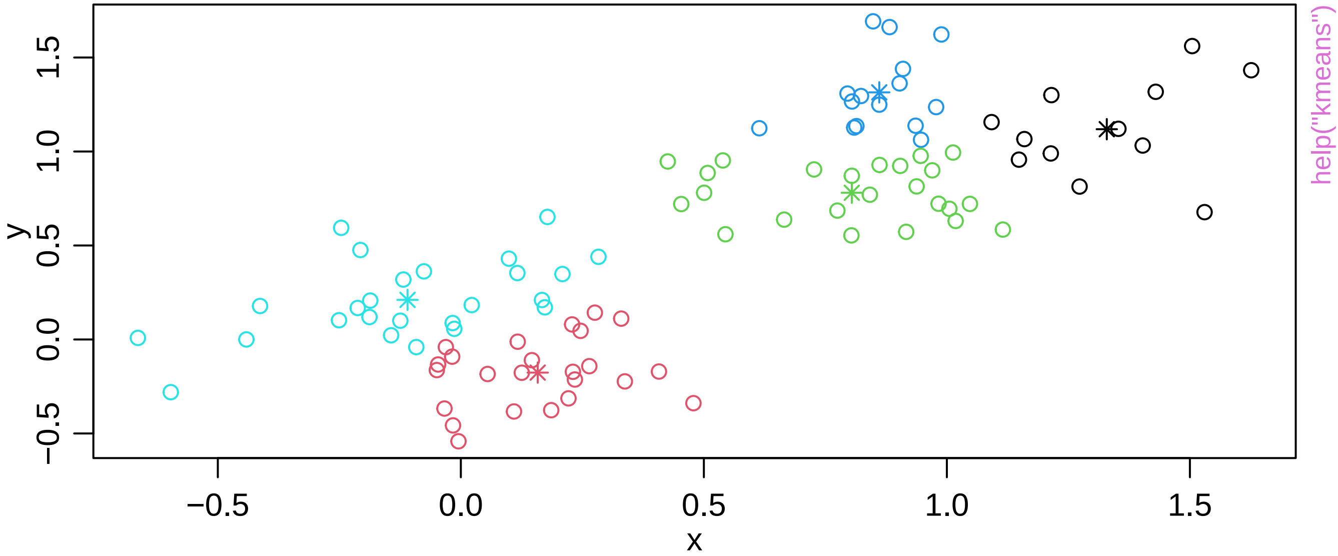

Daniell(10)
W[k]
0.06
0.05
0.04
0.03
−10
−5
0
5
10
k
help("kernel")


x
6000
4000
2000
1992
1993
1994
1995
1996
1997
1998
Time

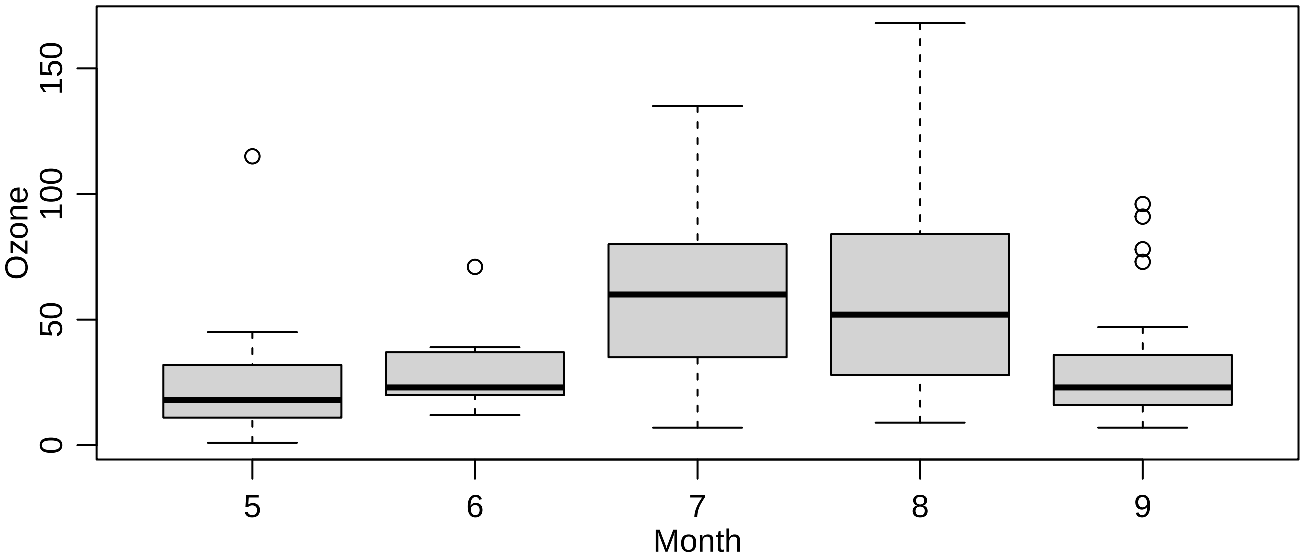

Fejer(100,6)
W[k]
0.000
0.010
0.020
0.030
−100
−50
0
50
100
k
help("kernel")
mDaniell(7,5,3)
W[k]
0.00
0.02
0.04
0.06
−15
−10
−5
0
5
10
15
k


Series: x
Smoothed Periodogram
spectrum
0
2000
4000
6000
0.0
0.1
0.2
0.3
0.4
0.5
frequency
bandwidth = 0.0272
help("kernel")

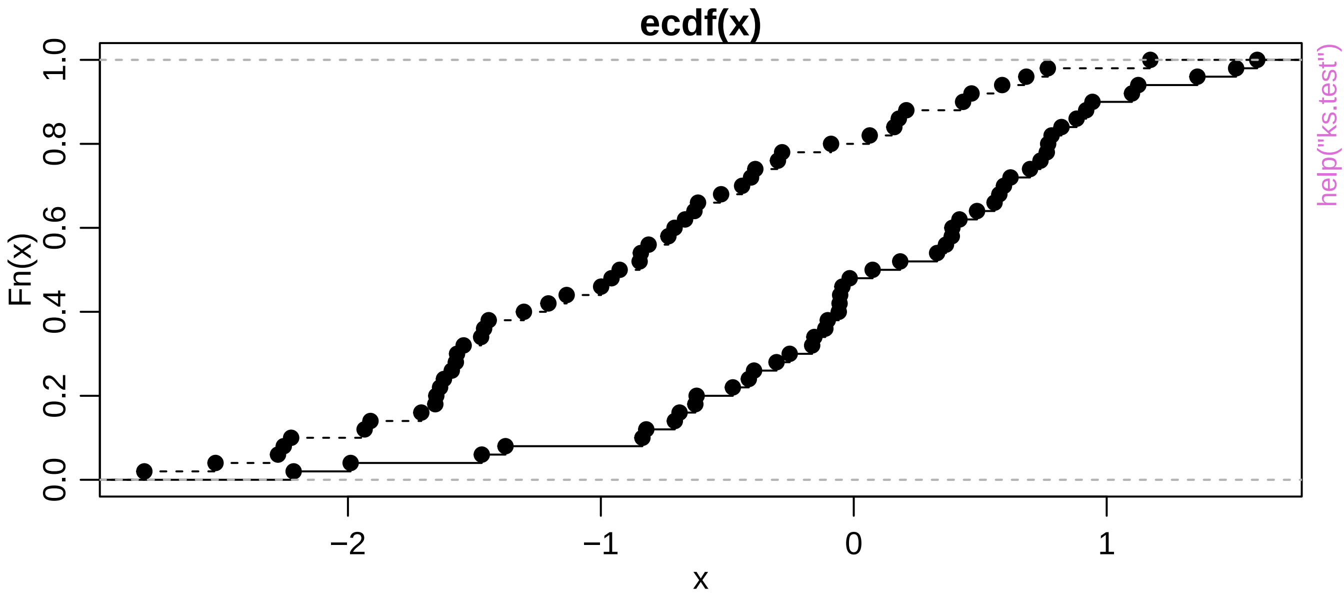

y
−0.5
0.0
0.5
1.0
1.5
−0.5
0.0
0.5
1.0
1.5
x

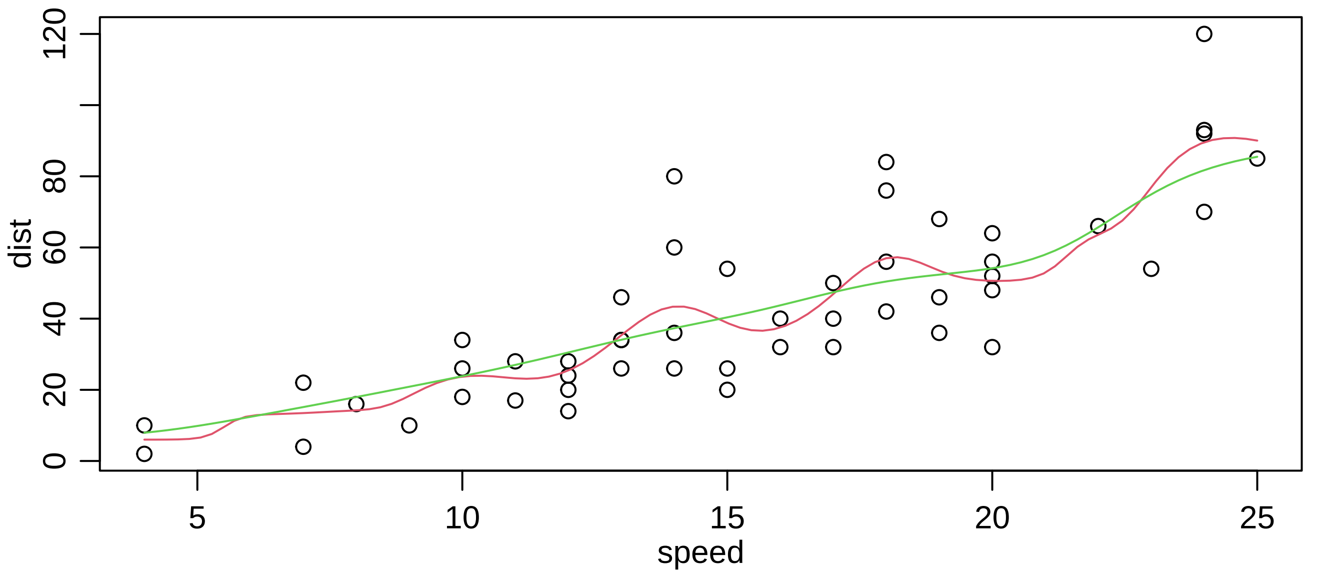


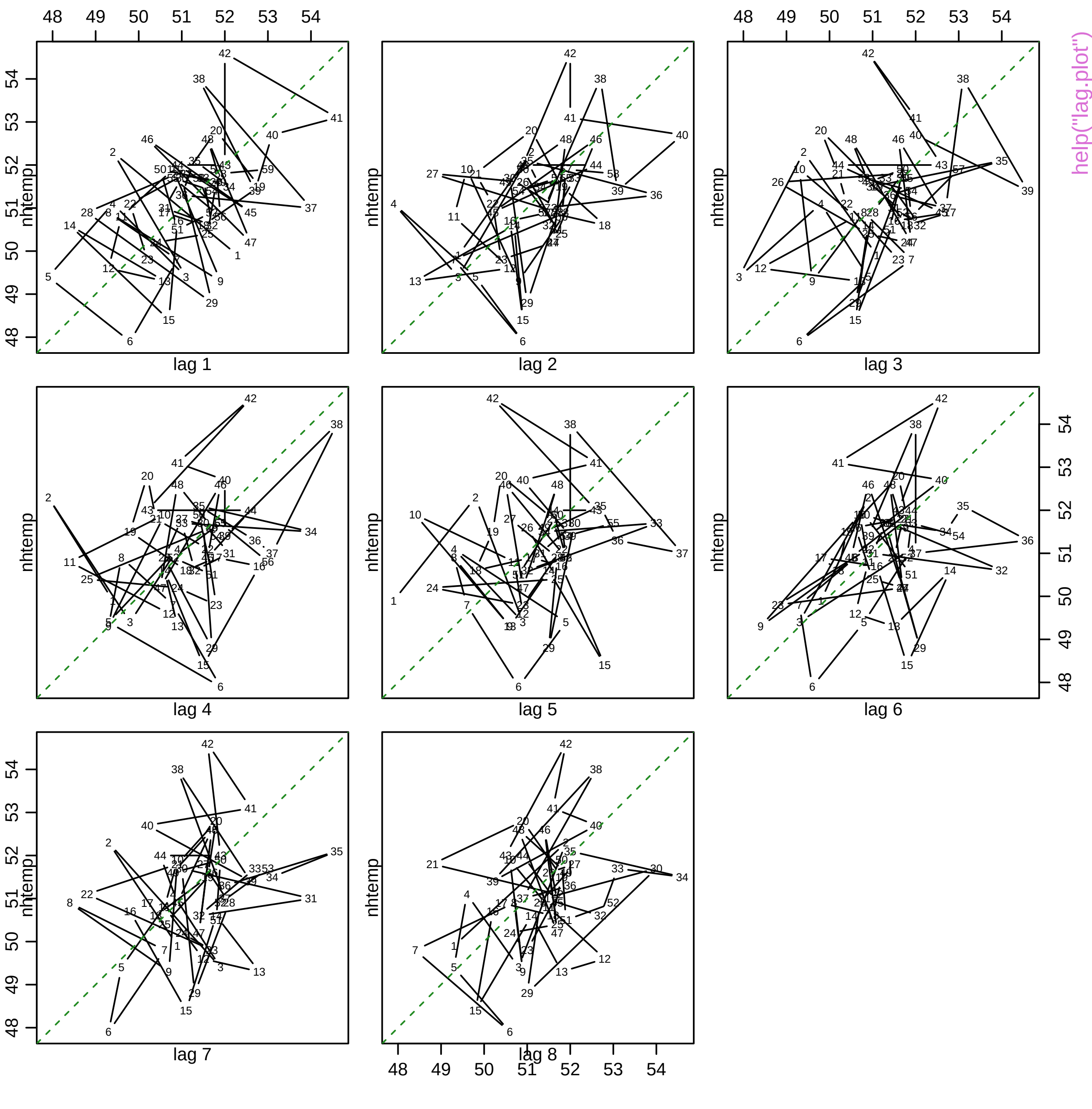
y
−0.5
0.0
0.5
1.0
1.5
x
help("kmeans")



Ozone
0
50
100
150
5
6
7
8
9
Month

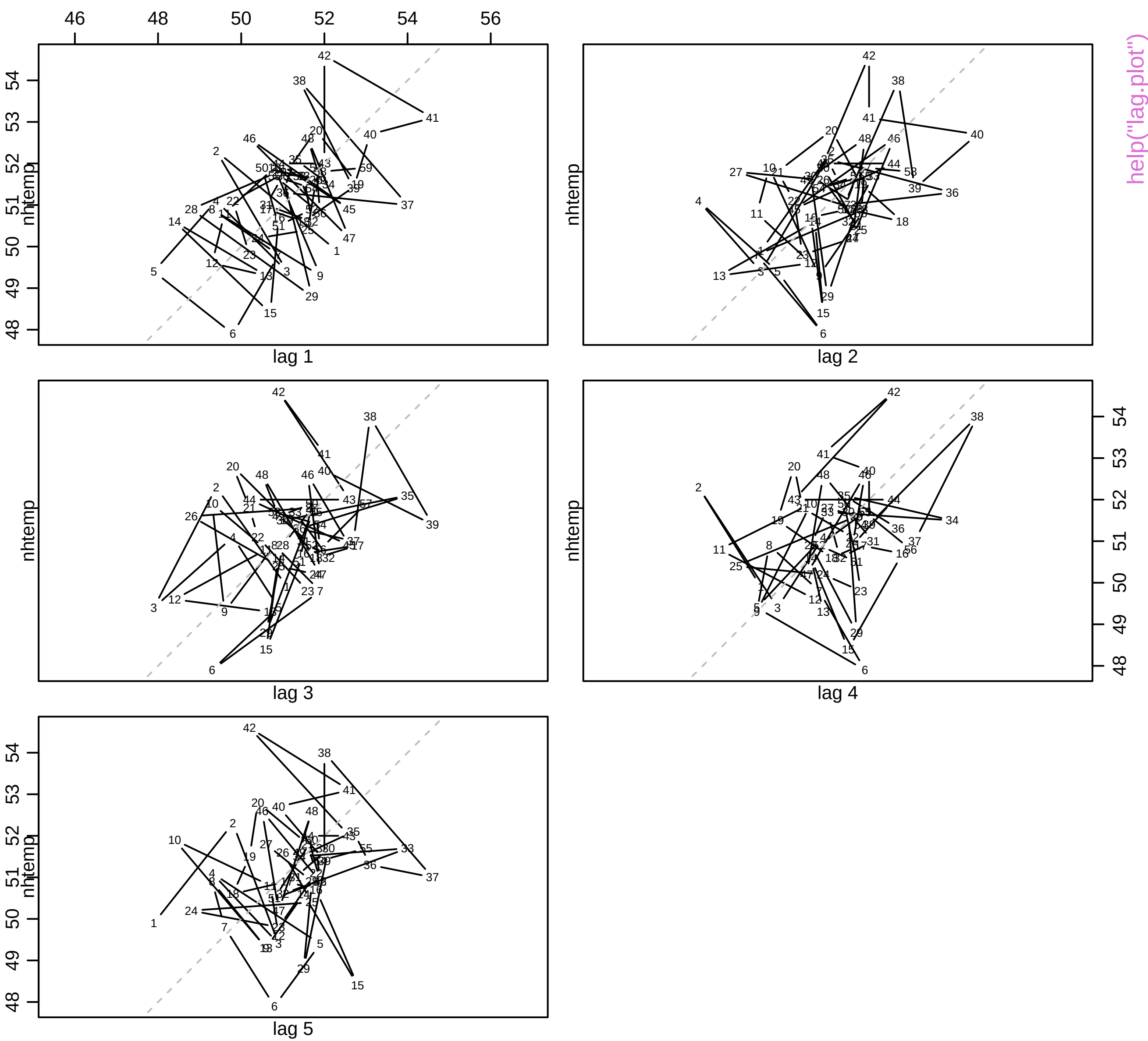

ecdf(x)
Fn(x)
0.0
0.2
0.4
0.6
0.8
1.0
−2
−1
0
1
x
help("ks.test")

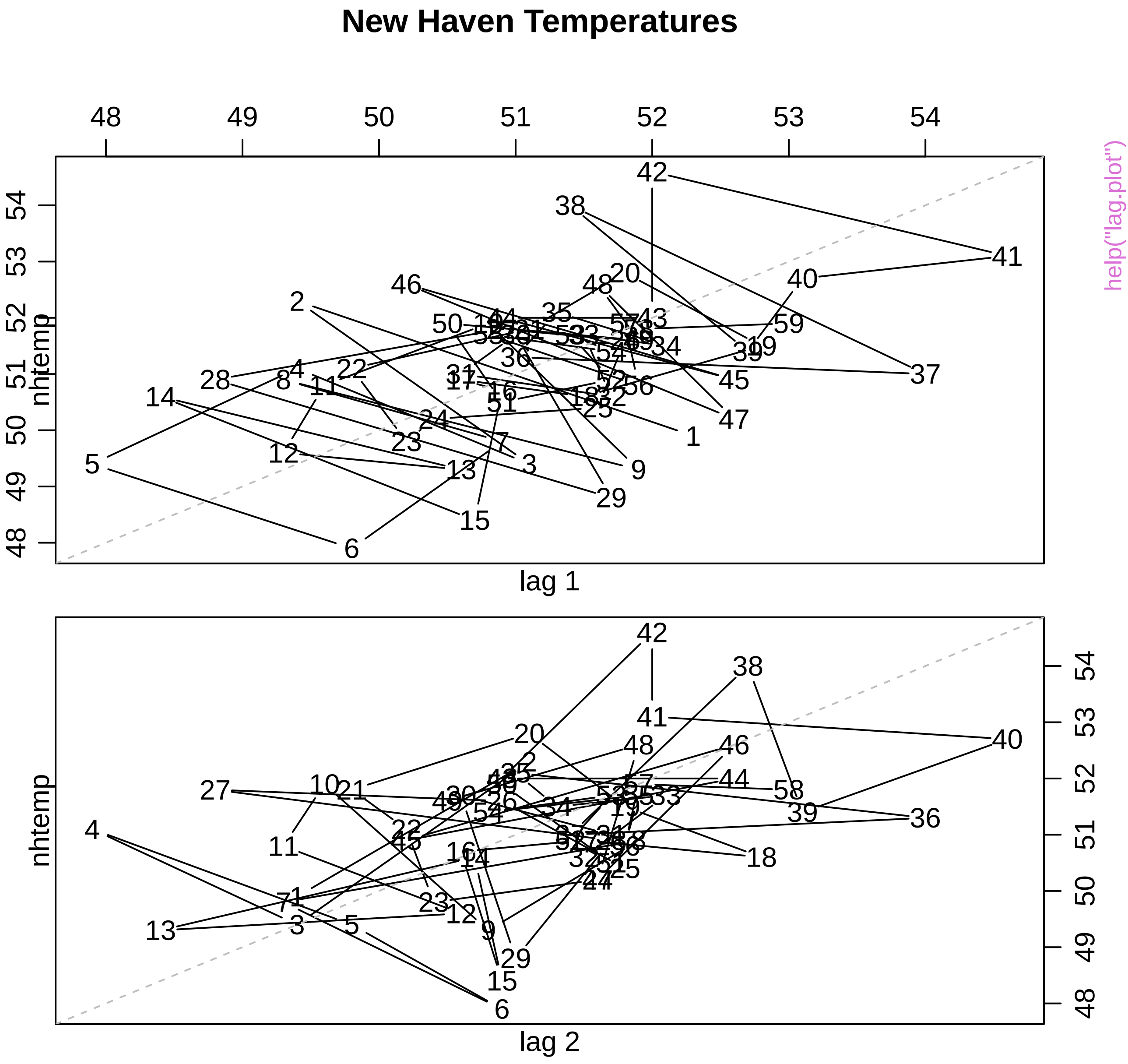

dist
0
20
40
60
80
120
5
10
15
20
25
speed

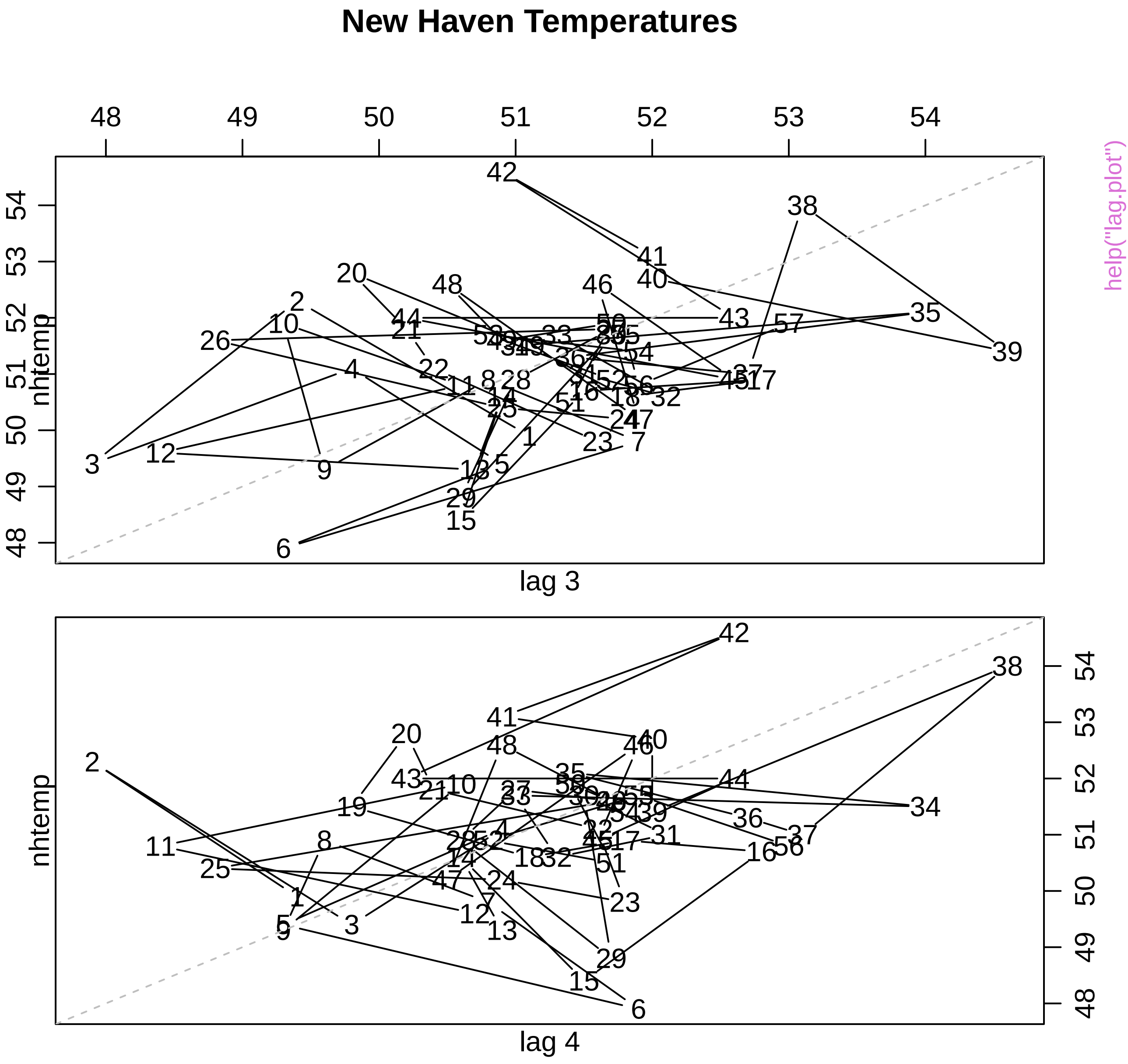


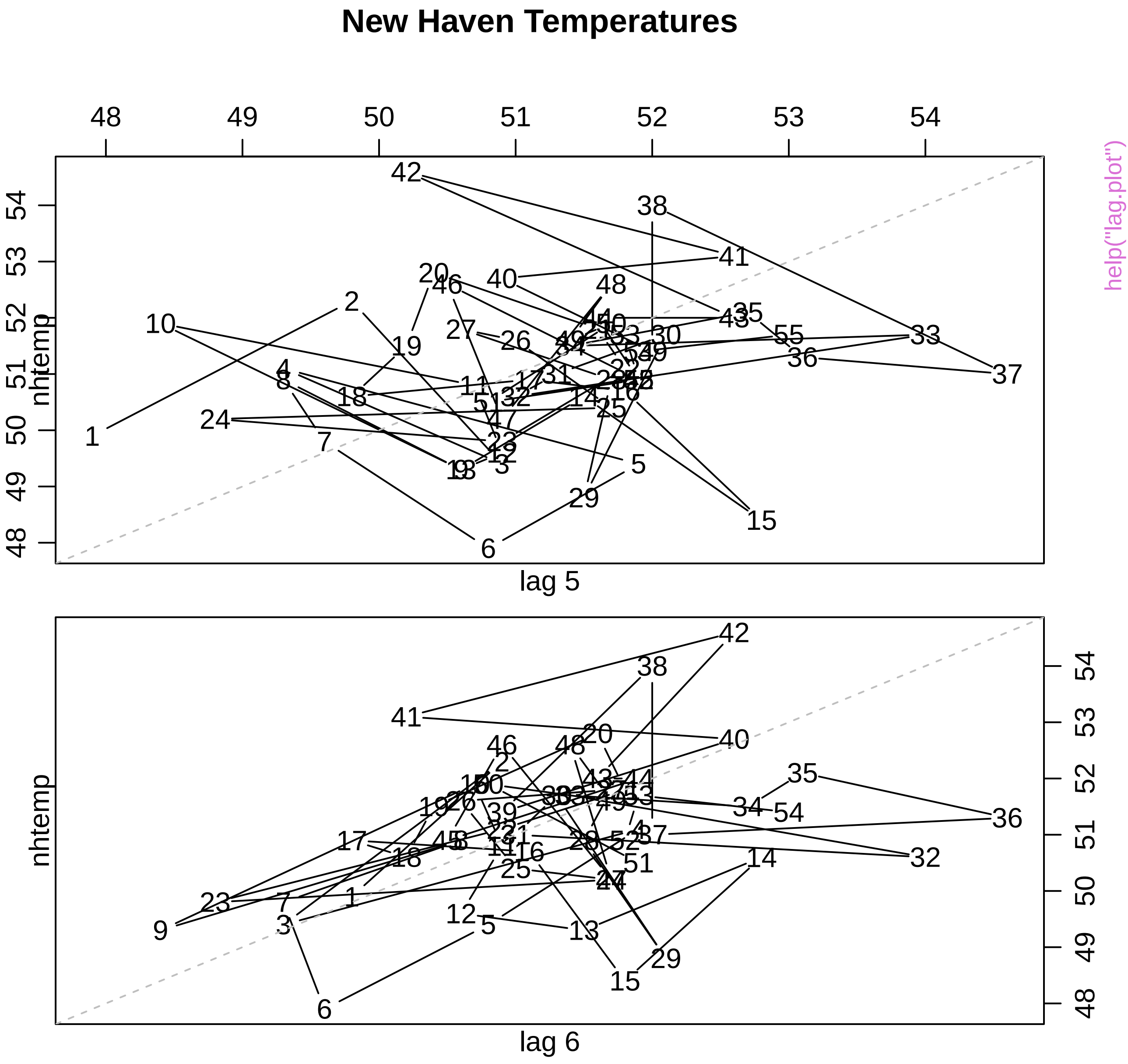
48 49 50 51 52 53 54
nhtemp
lag 1
lag 2
lag 3
lag 4
lag 5
lag 6
lag 7
lag 8
help("lag.plot")

Average Temperatures in New Haven

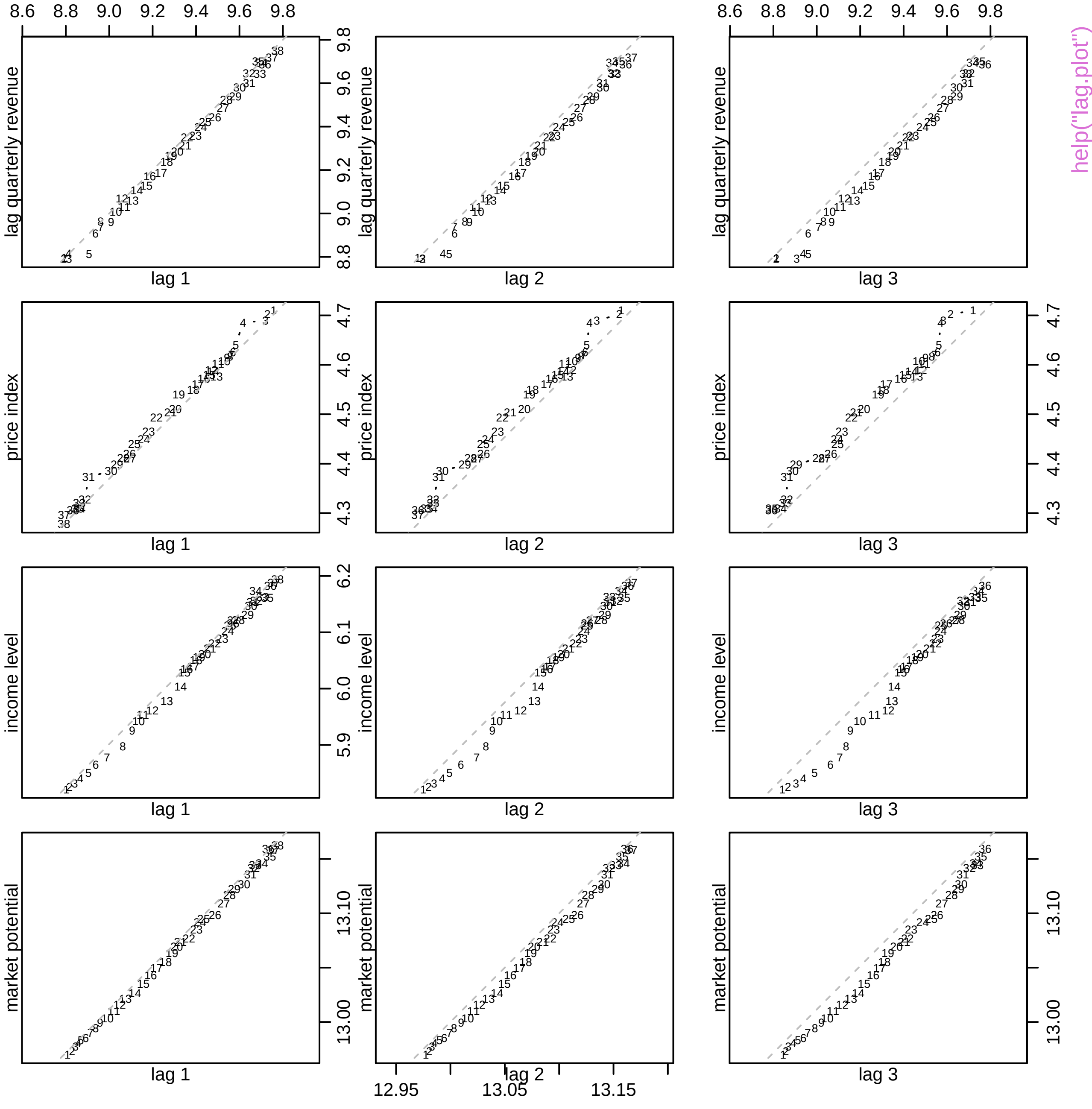



New Haven Temperatures
48
49
50
51
52
53
54
nhtemp
lag 1
lag 2
help("lag.plot")

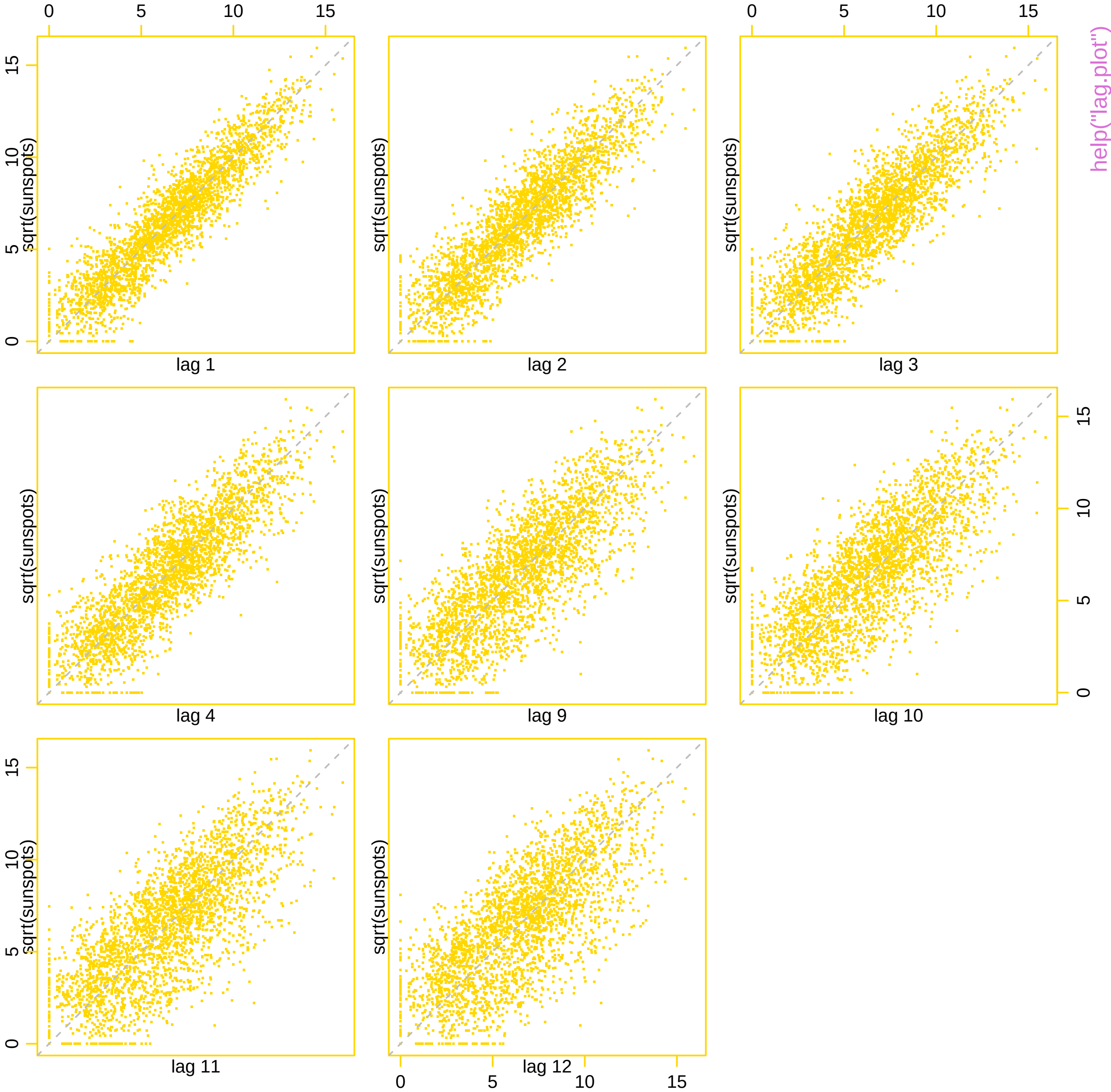

New Haven Temperatures
48
49
50
51
52
53
54
nhtemp
lag 3
lag 4
help("lag.plot")

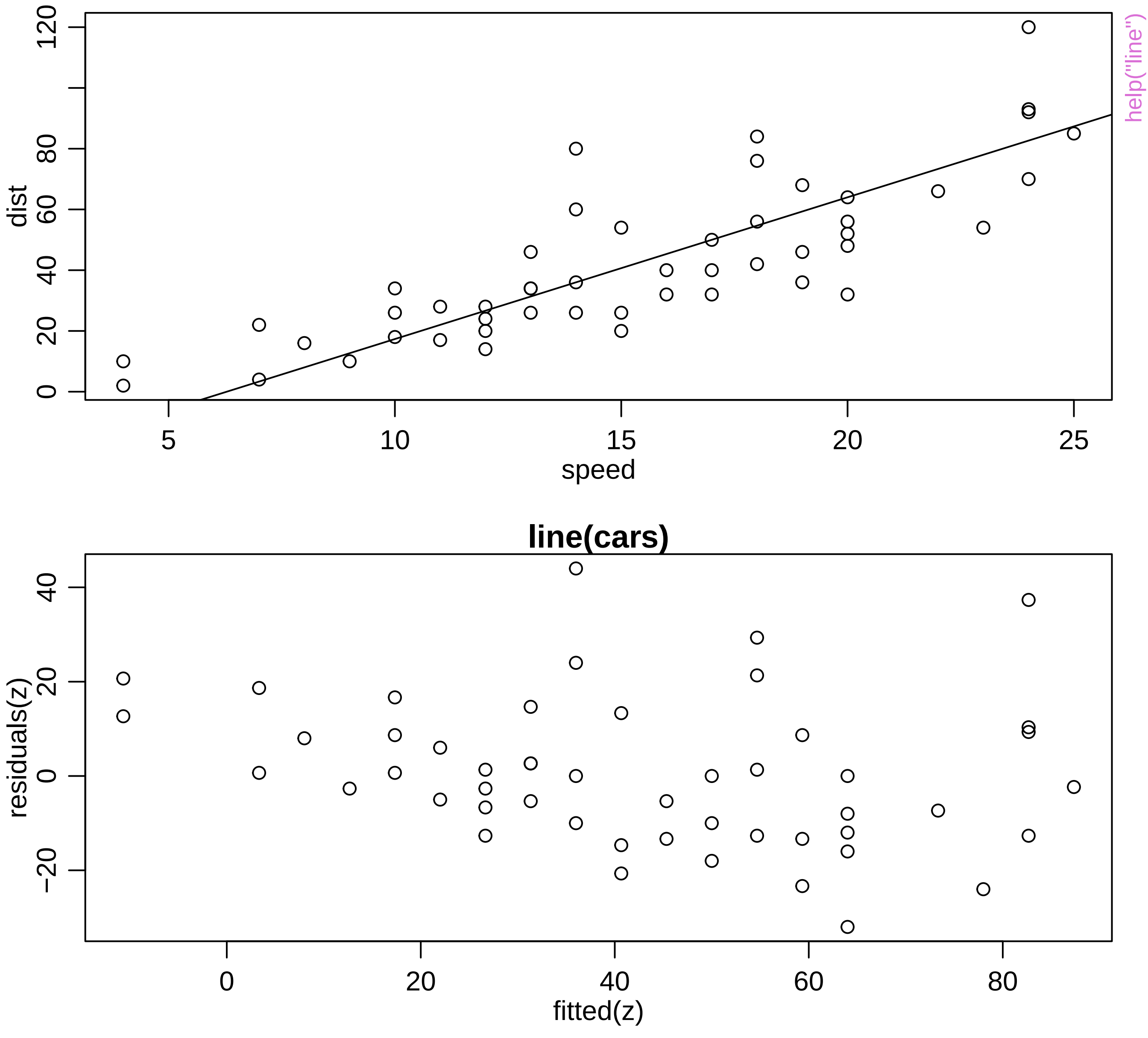


New Haven Temperatures
48
49
50
51
52
53
54
nhtemp
lag 5
lag 6
help("lag.plot")

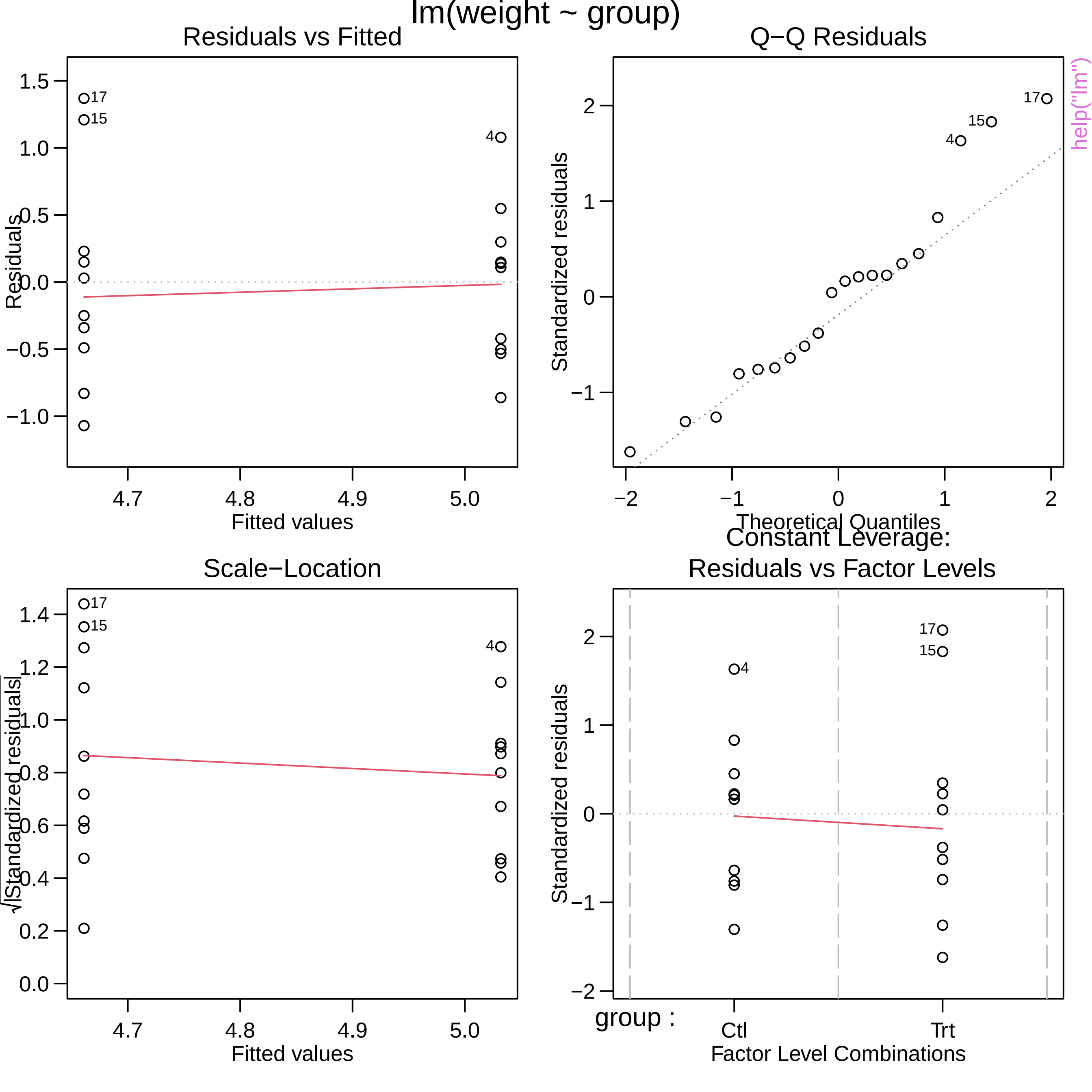


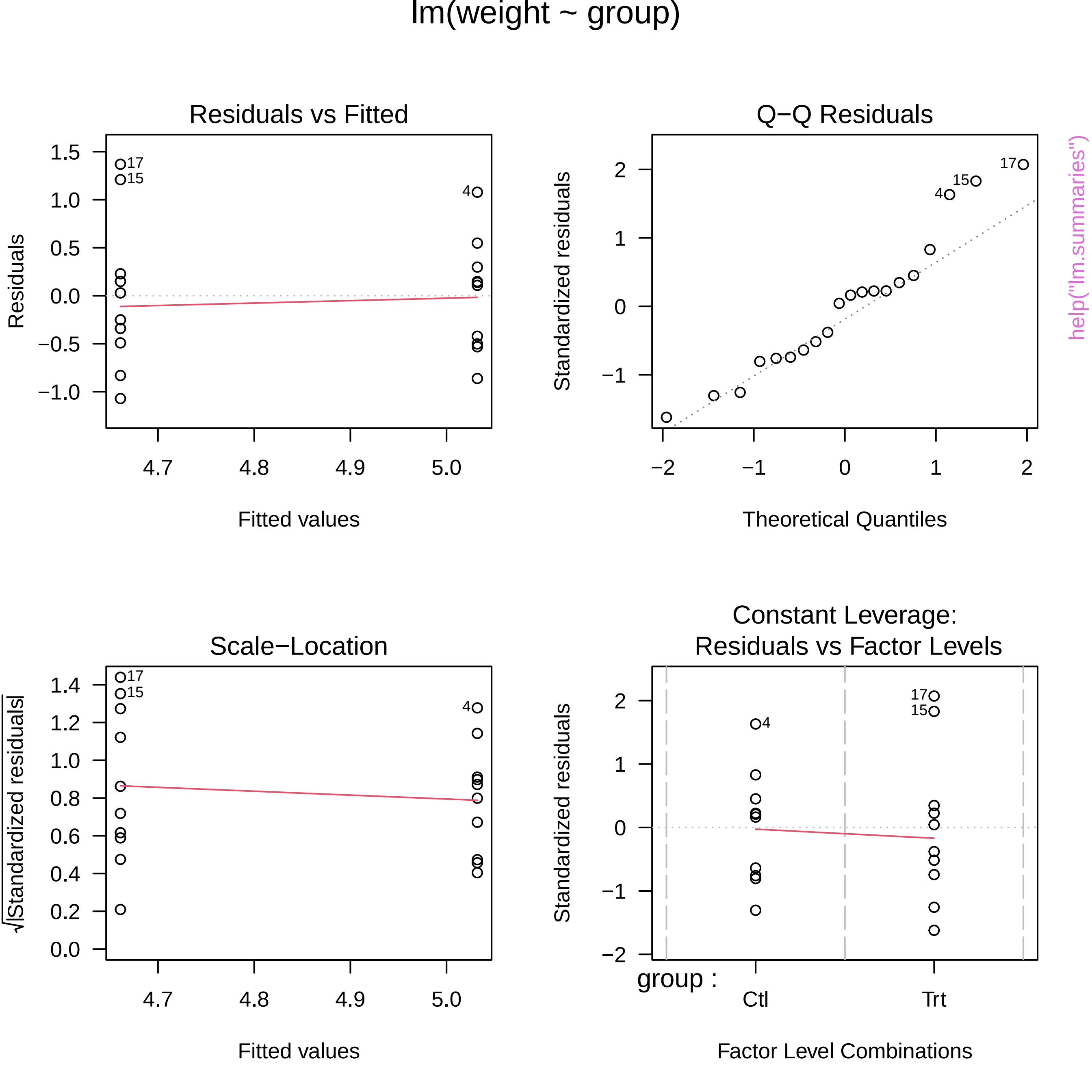
lag quarterly revenue
price index
income level
market potential
lag 1
lag 2
lag 3
help("lag.plot")

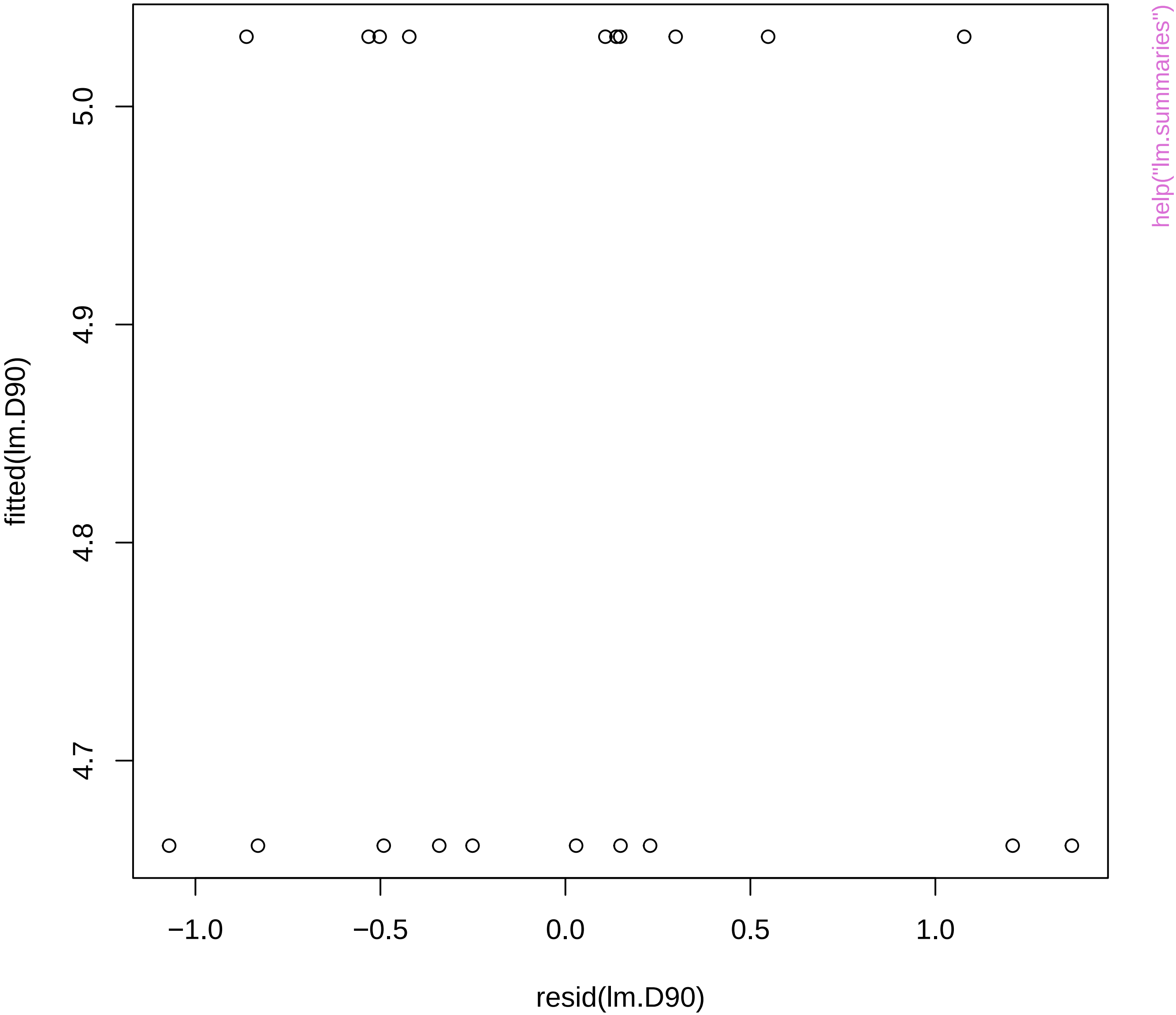

help("lag.plot")
sqrt(sunspots)
lag 1
lag 2
lag 3
lag 4
lag 9
lag 10
lag 11
lag 12
0
5
10
15



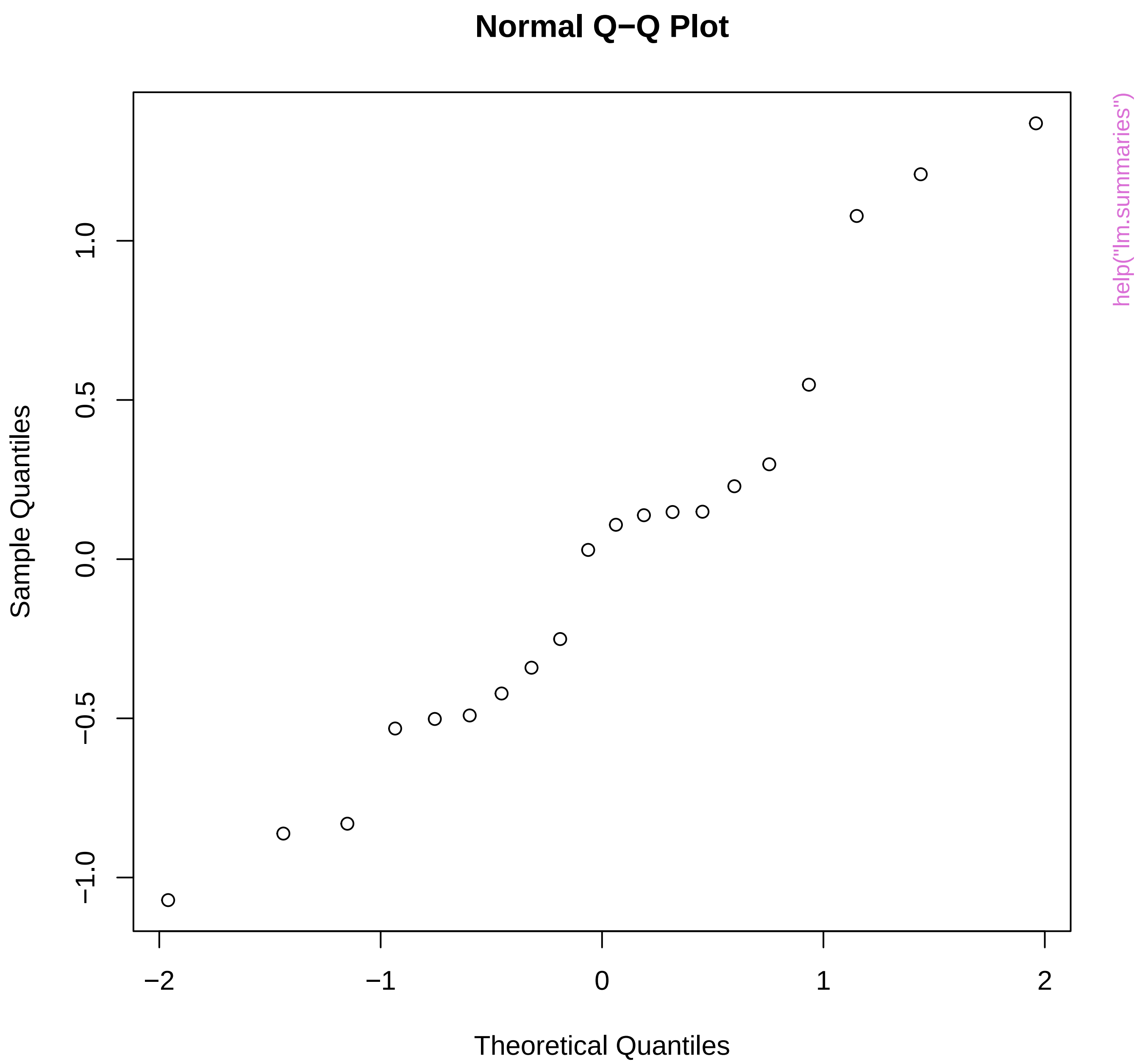
help("line")
dist
speed
line(cars)
residuals(z)
fitted(z)

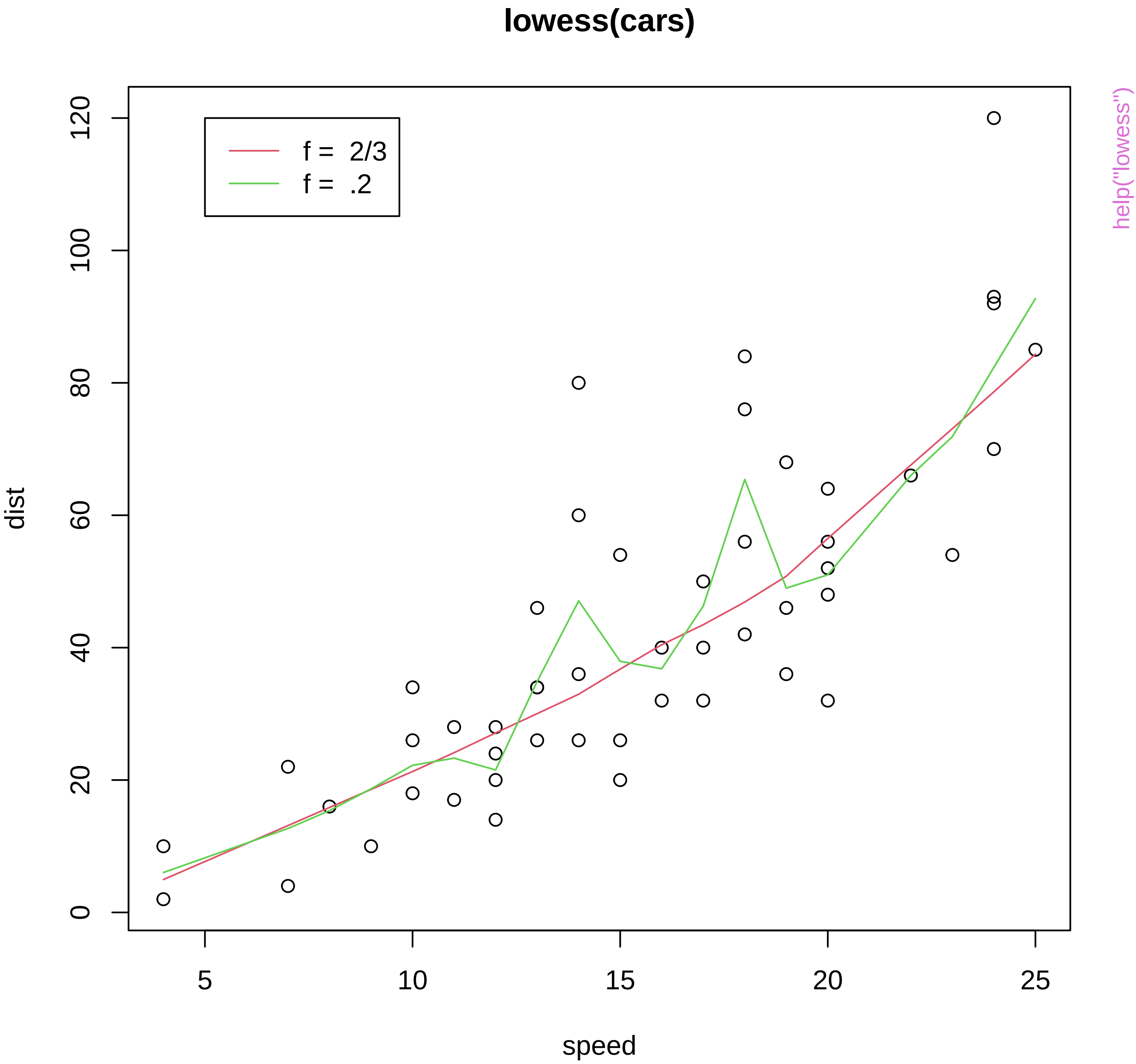

lm(weight ~ group)
Residuals vs Fitted
Residuals
Fitted values
Q−Q Residuals
Standardized residuals
Theoretical Quantiles
help("lm")
Scale−Location
√|Standardized residuals|
Fitted values
Constant Leverage:
Residuals vs Factor Levels
Standardized residuals
group :
Ctl
Trt
Factor Level Combinations

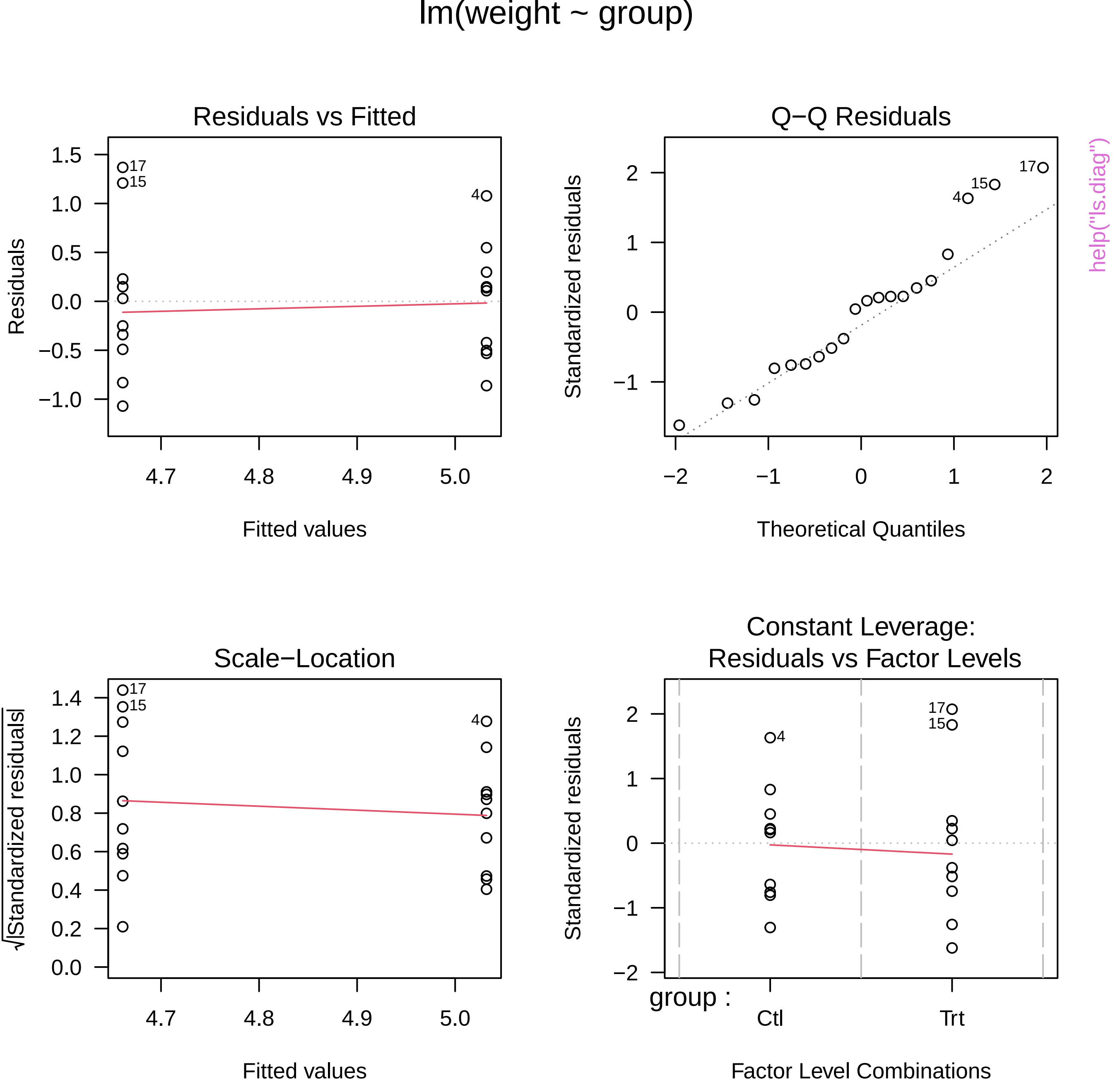

lm(weight ~ group)
Residuals vs Fitted
Residuals
Fitted values
1.5
1.0
0.5
0.0
−0.5
−1.0
4.7
4.8
4.9
5.0
17
15
4
Q−Q Residuals
Standardized residuals
Theoretical Quantiles
2
1
0
−1
−2
17
15
4
help("lm.summaries")
Scale−Location
√|Standardized residuals|
Fitted values
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
17
15
4
Constant Leverage:
Residuals vs Factor Levels
Standardized residuals
group :
Ctl
Trt
Factor Level Combinations
17
15
4

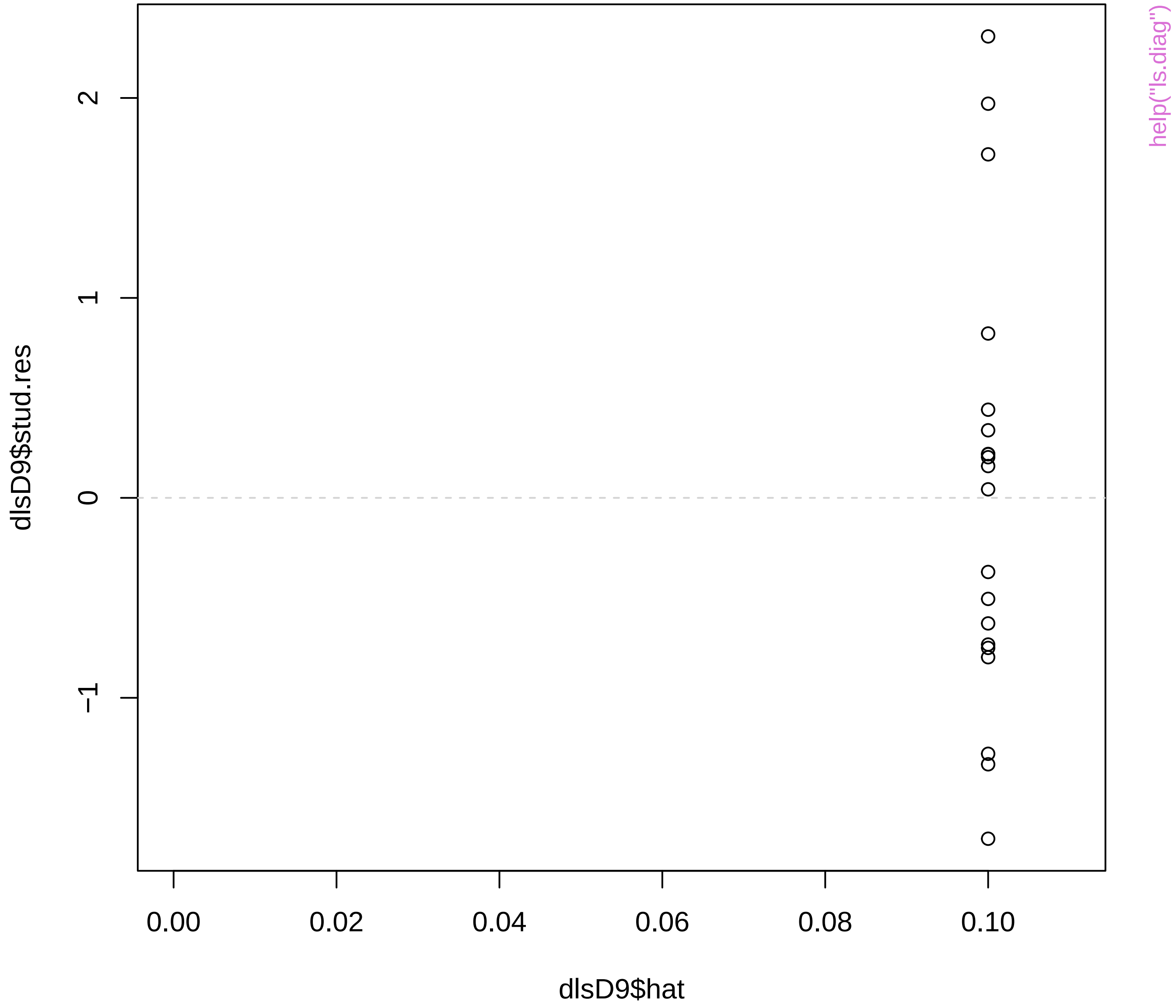


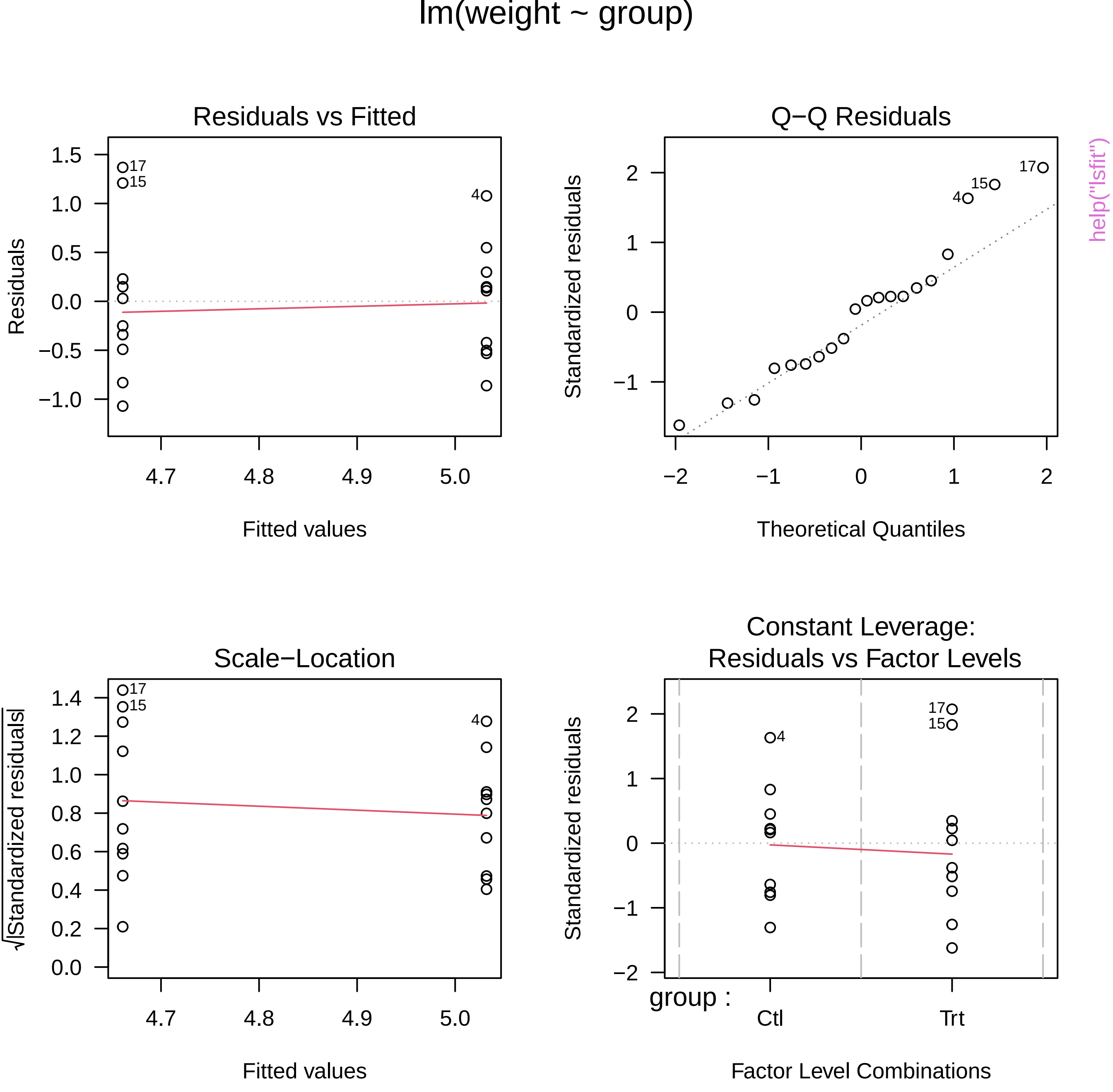
fitted(lm.D90)
5.0
4.9
4.8
4.7
−1.0
−0.5
0.0
0.5
1.0
resid(lm.D90)
help("lm.summaries")

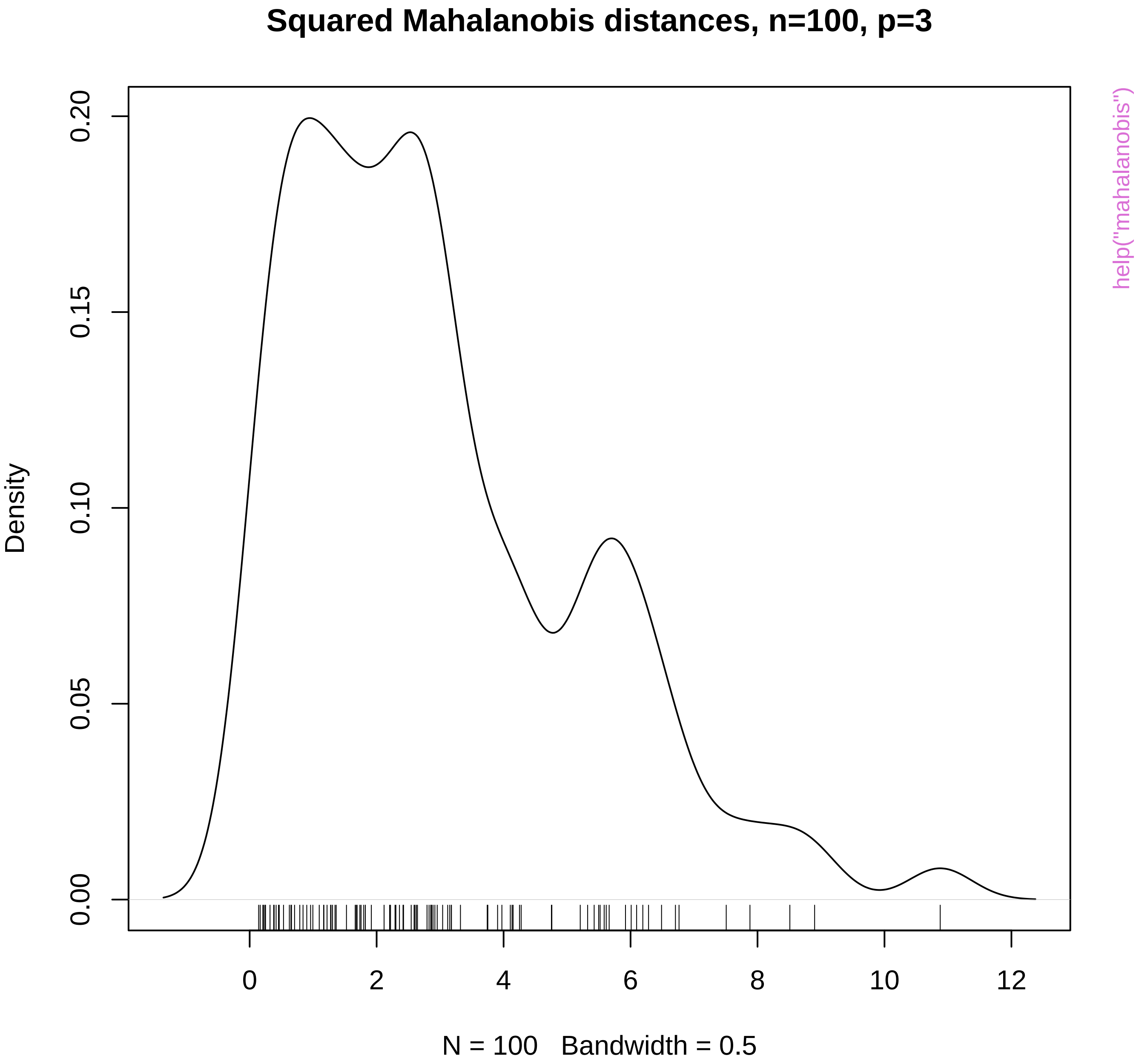

Normal Q−Q Plot
Sample Quantiles
Theoretical Quantiles
−1.0
−0.5
0.0
0.5
1.0
−2
−1
0
1
2
help("lm.summaries")


lowess(cars)
f = 2/3
f = .2
dist
speed
0
20
40
60
80
100
120
5
10
15
20
25
help("lowess")

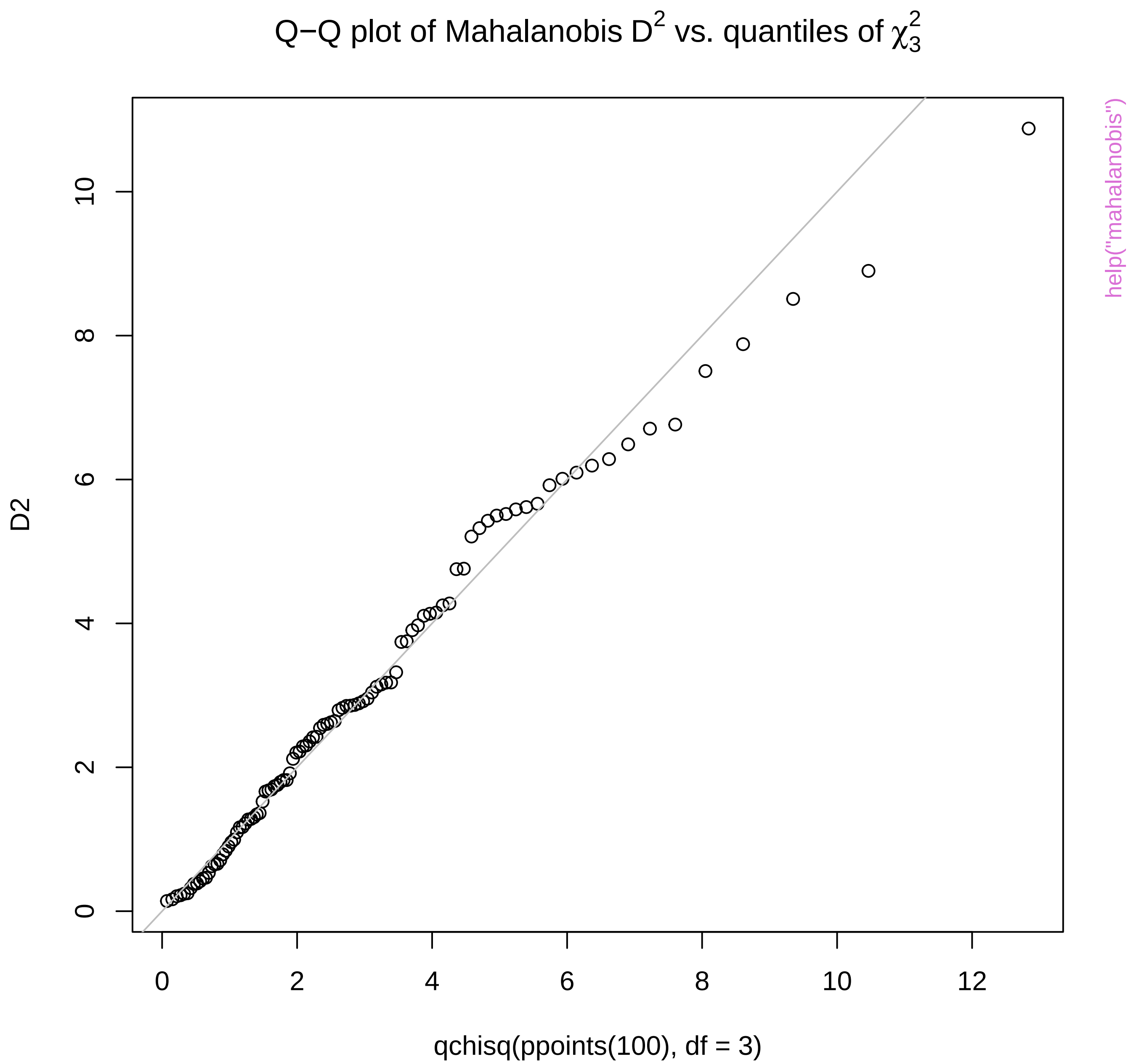

lm(weight ~ group)
Residuals vs Fitted
Residuals
1.5
1.0
0.5
0.0
−0.5
−1.0
17
15
4
4.7
4.8
4.9
5.0
Fitted values
Q−Q Residuals
Standardized residuals
2
1
0
−1
17
15
4
−2
−1
0
1
2
Theoretical Quantiles
help("ls.diag")
Scale−Location
√|Standardized residuals|
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
17
15
4
4.7
4.8
4.9
5.0
Fitted values
Constant Leverage:
Residuals vs Factor Levels
Standardized residuals
2
1
0
−1
−2
4
17
15
group :
Ctl
Trt
Factor Level Combinations


dlsD9$stud.res
dlsD9$hat
2
1
0
−1
0.00
0.02
0.04
0.06
0.08
0.10
help("ls.diag")

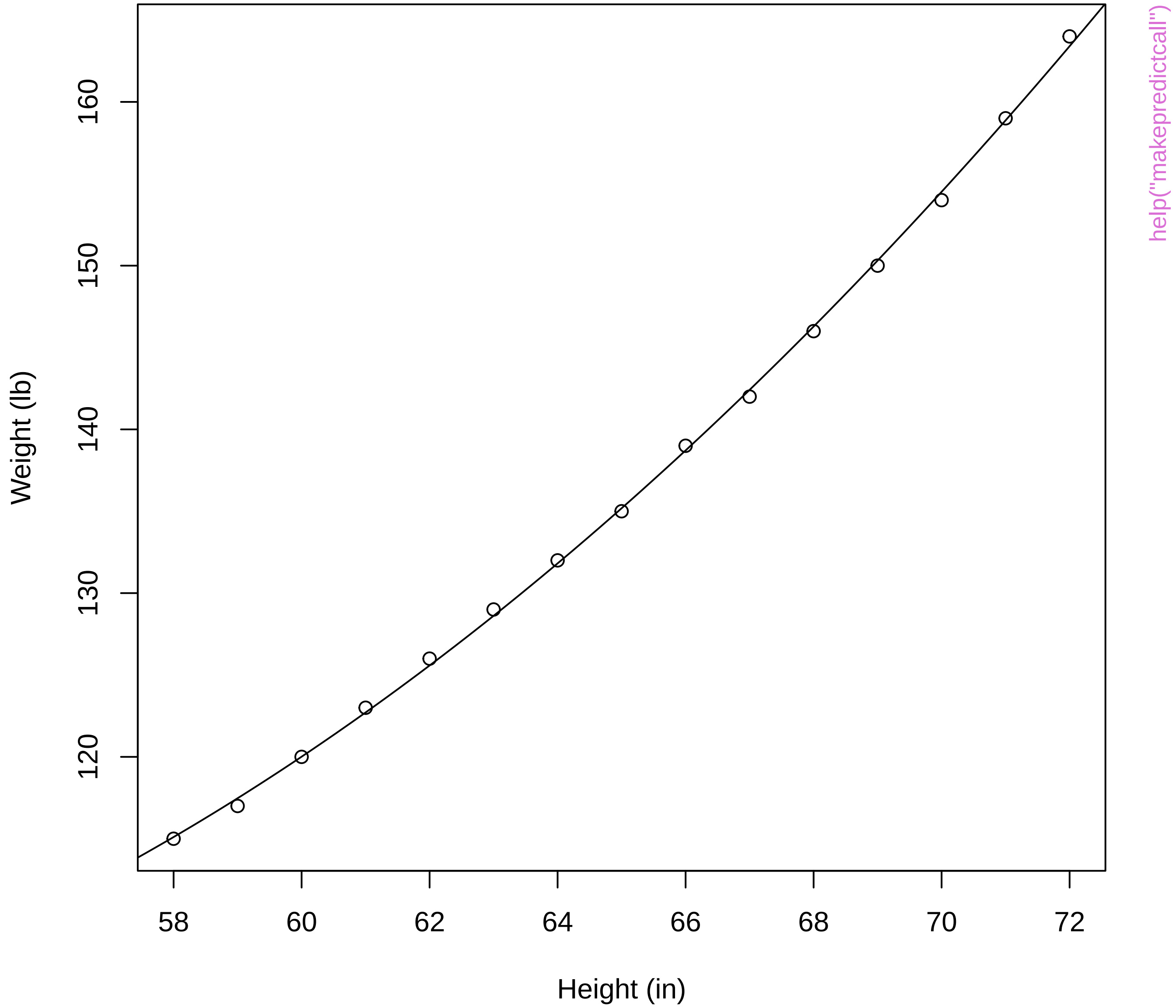

lm(weight ~ group)
Residuals vs Fitted
Residuals
Fitted values
1.5
1.0
0.5
0.0
−0.5
−1.0
4.7
4.8
4.9
5.0
17
15
4
Q−Q Residuals
Standardized residuals
Theoretical Quantiles
2
1
0
−1
−2
17
15
4
help("lsfit")
Scale−Location
√|Standardized residuals|
Fitted values
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
4.7
4.8
4.9
5.0
17
15
4
Constant Leverage:
Residuals vs Factor Levels
Standardized residuals
group :
Ctl
Trt
Factor Level Combinations
2
1
0
−1
−2
17
15
4



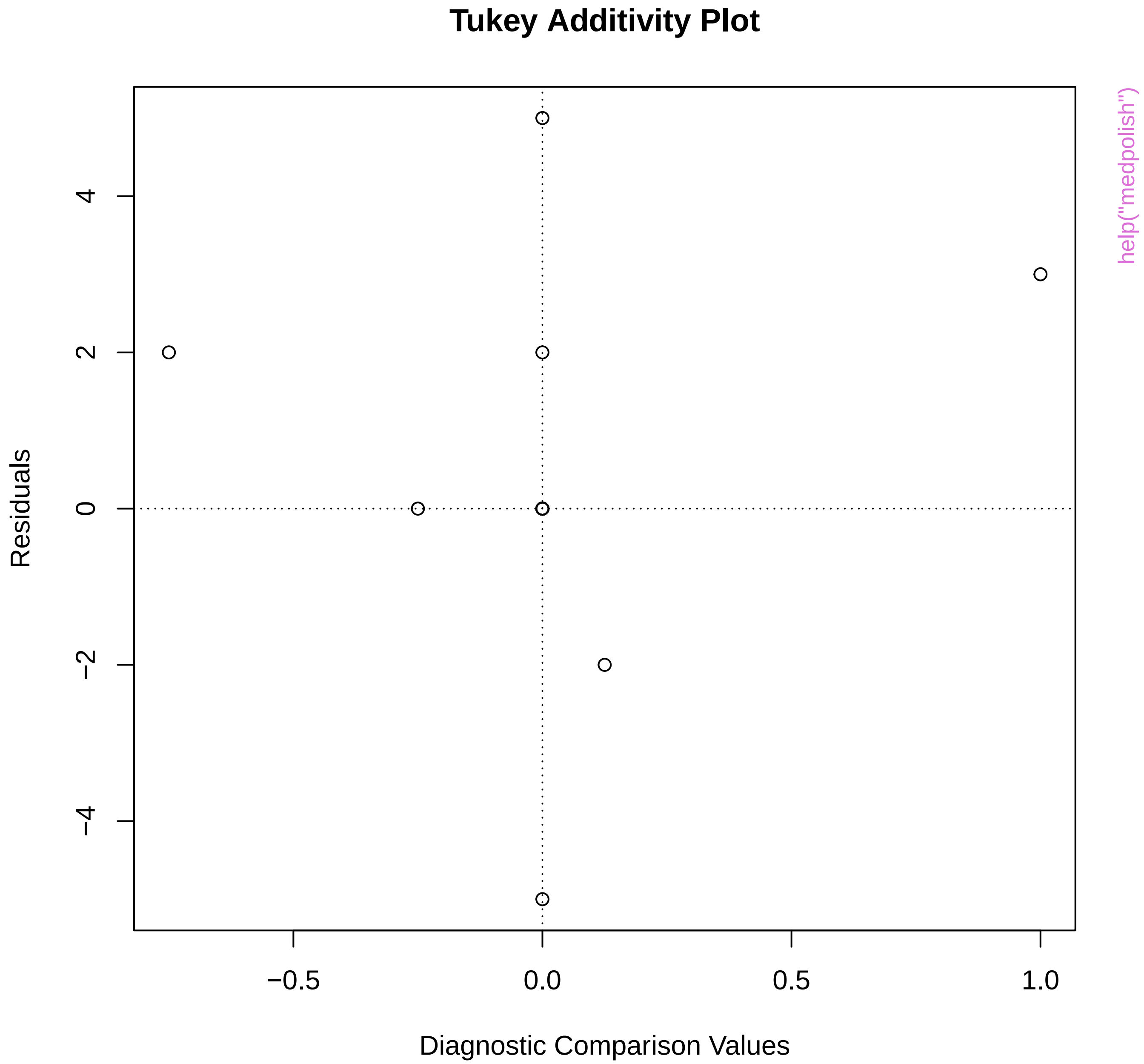
Squared Mahalanobis distances, n=100, p=3
Density
0.00
0.05
0.10
0.15
0.20
0
2
4
6
8
10
12
N = 100   Bandwidth = 0.5
help("mahalanobis")

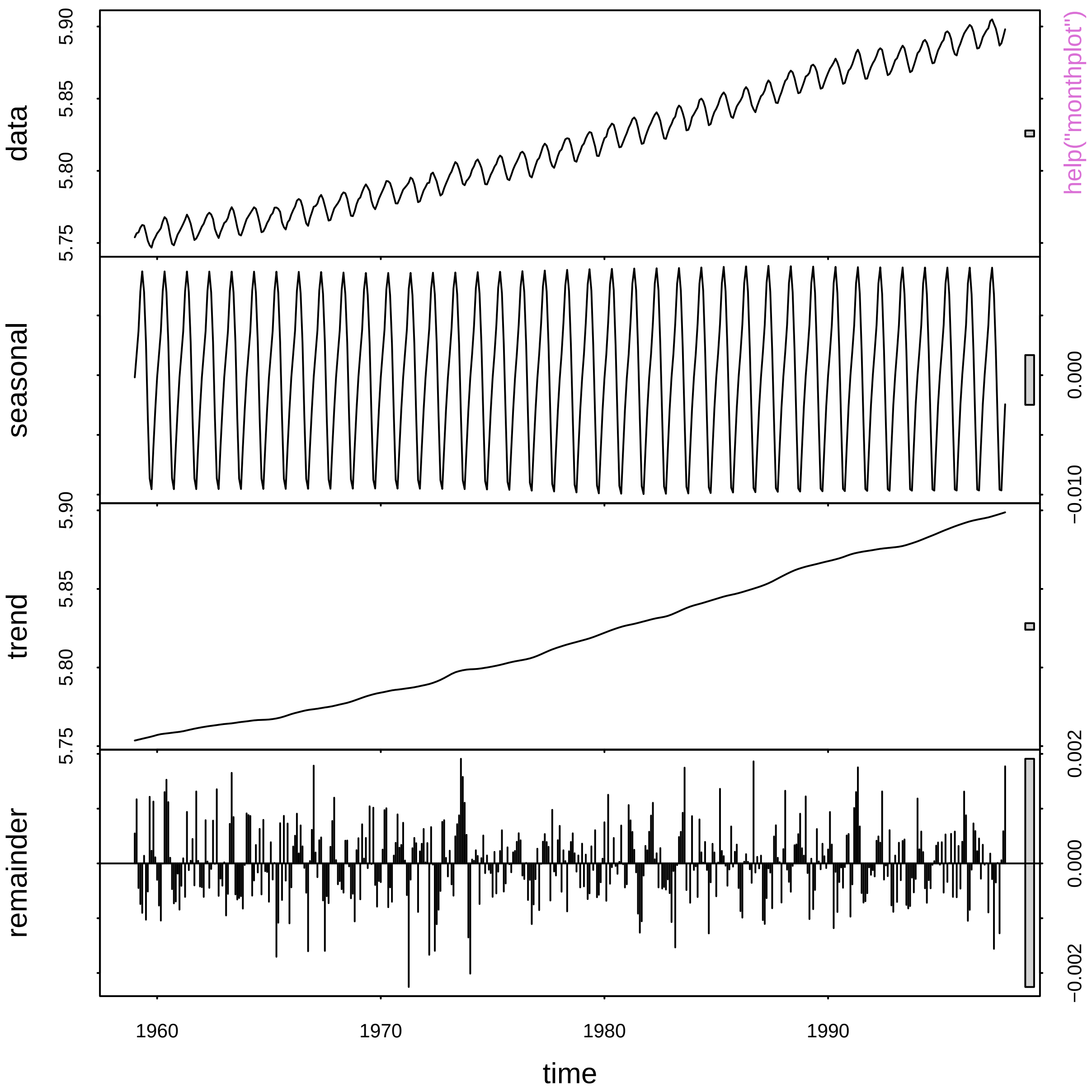


Q−Q plot of Mahalanobis D^2 vs. quantiles of χ^2_3
D2
qchisq(ppoints(100), df = 3)
0
2
4
6
8
10
12
help("mahalanobis")

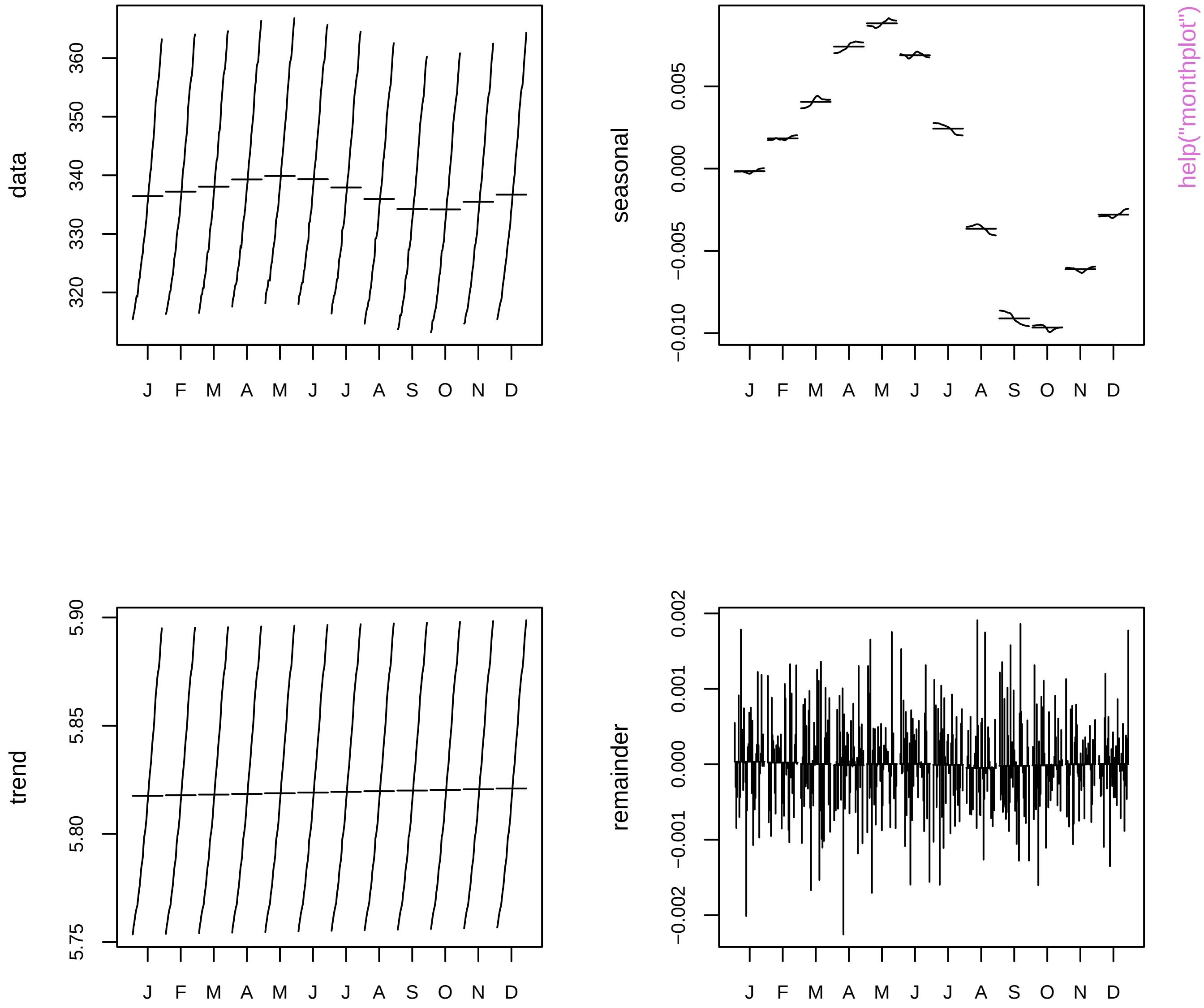


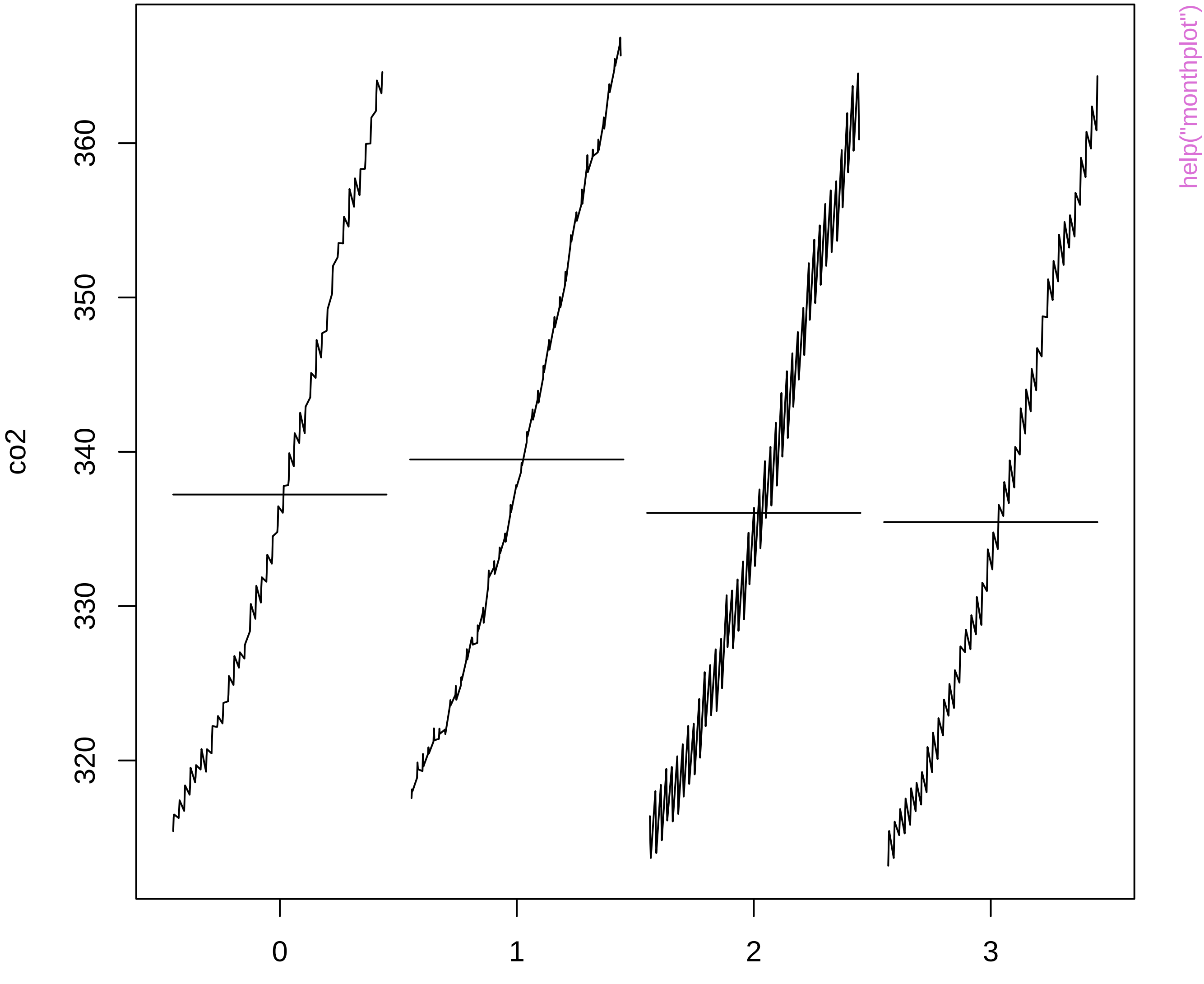
160
150
140
130
120
Weight (lb)
58
60
62
64
66
68
70
72
Height (in)
help("makepredictcall")


Tukey Additivity Plot
Residuals
Diagnostic Comparison Values
4
2
0
−2
−4
−0.5
0.0
0.5
1.0
help("medpolish")

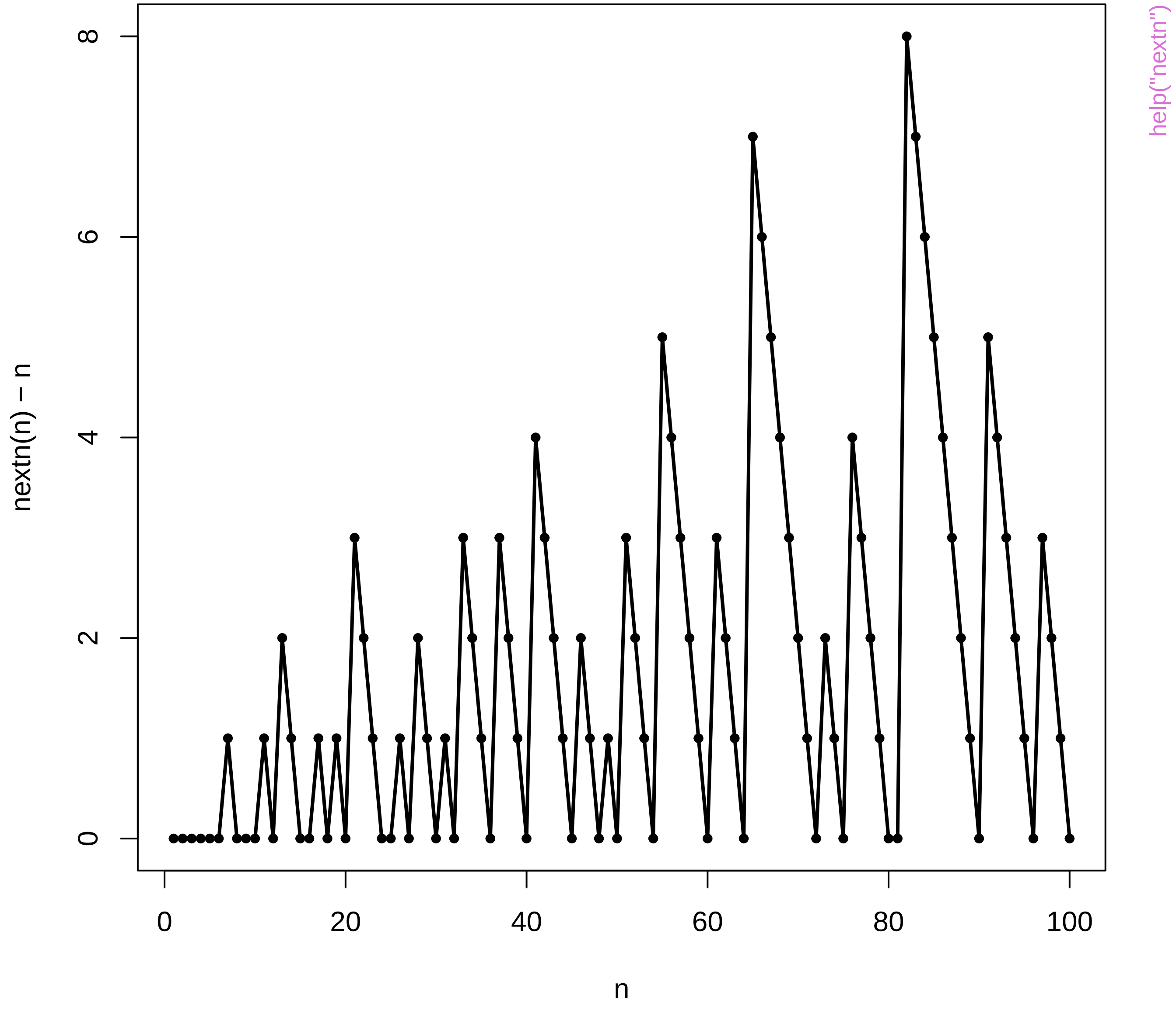


data
seasonal
trend
remainder
help("monthplot")
5.75
5.80
5.85
5.90
0.000
−0.010
0.002
−0.002
1960
1970
1980
1990
time

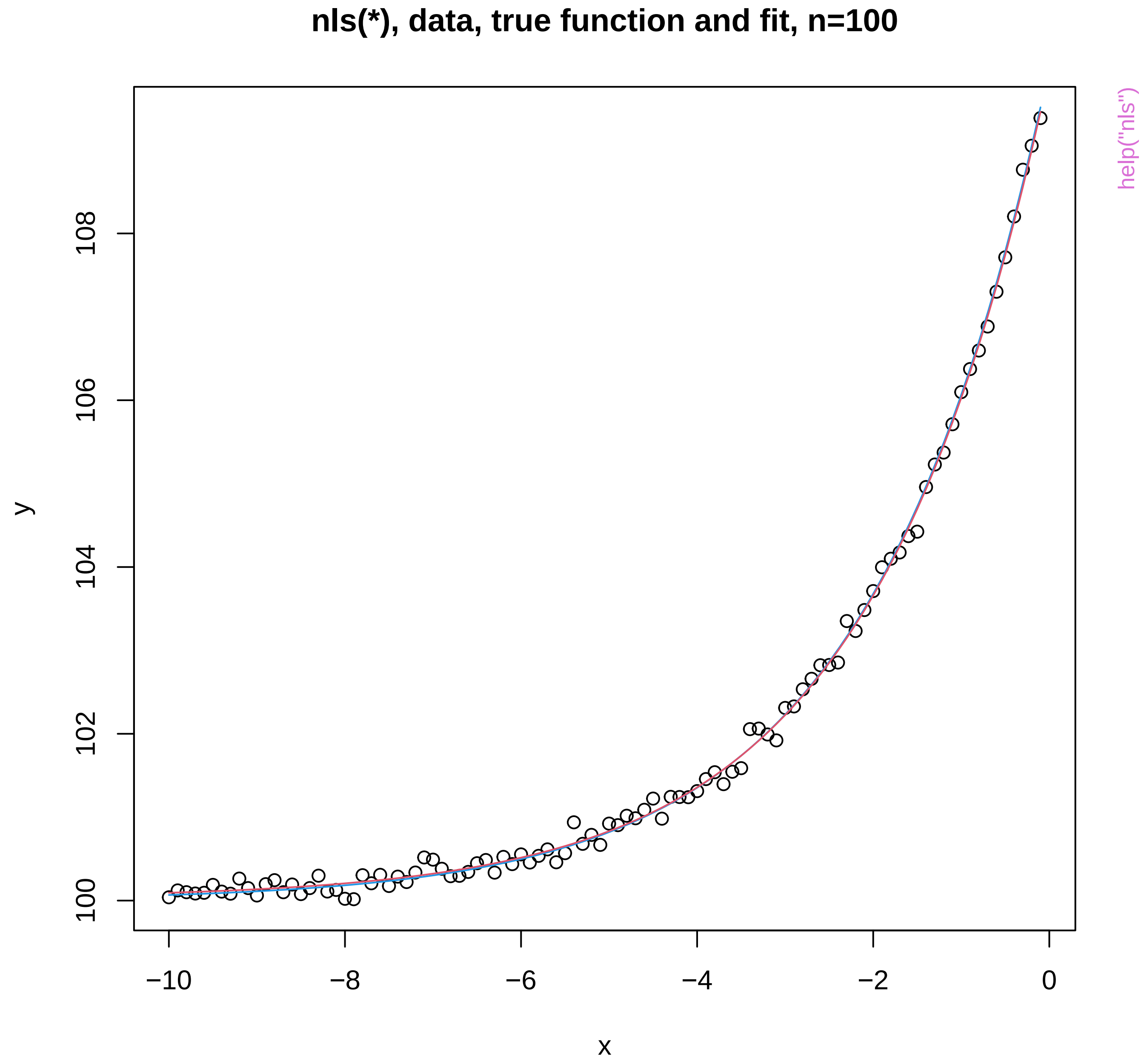

data
360
350
340
330
320
J F M A M J J A S O N D
seasonal
0.005
0.000
−0.005
−0.010
J F M A M J J A S O N D
help("monthplot")
trend
5.90
5.85
5.80
5.75
J F M A M J J A S O N D
remainder
0.002
0.001
0.000
−0.001
−0.002
J F M A M J J A S O N D

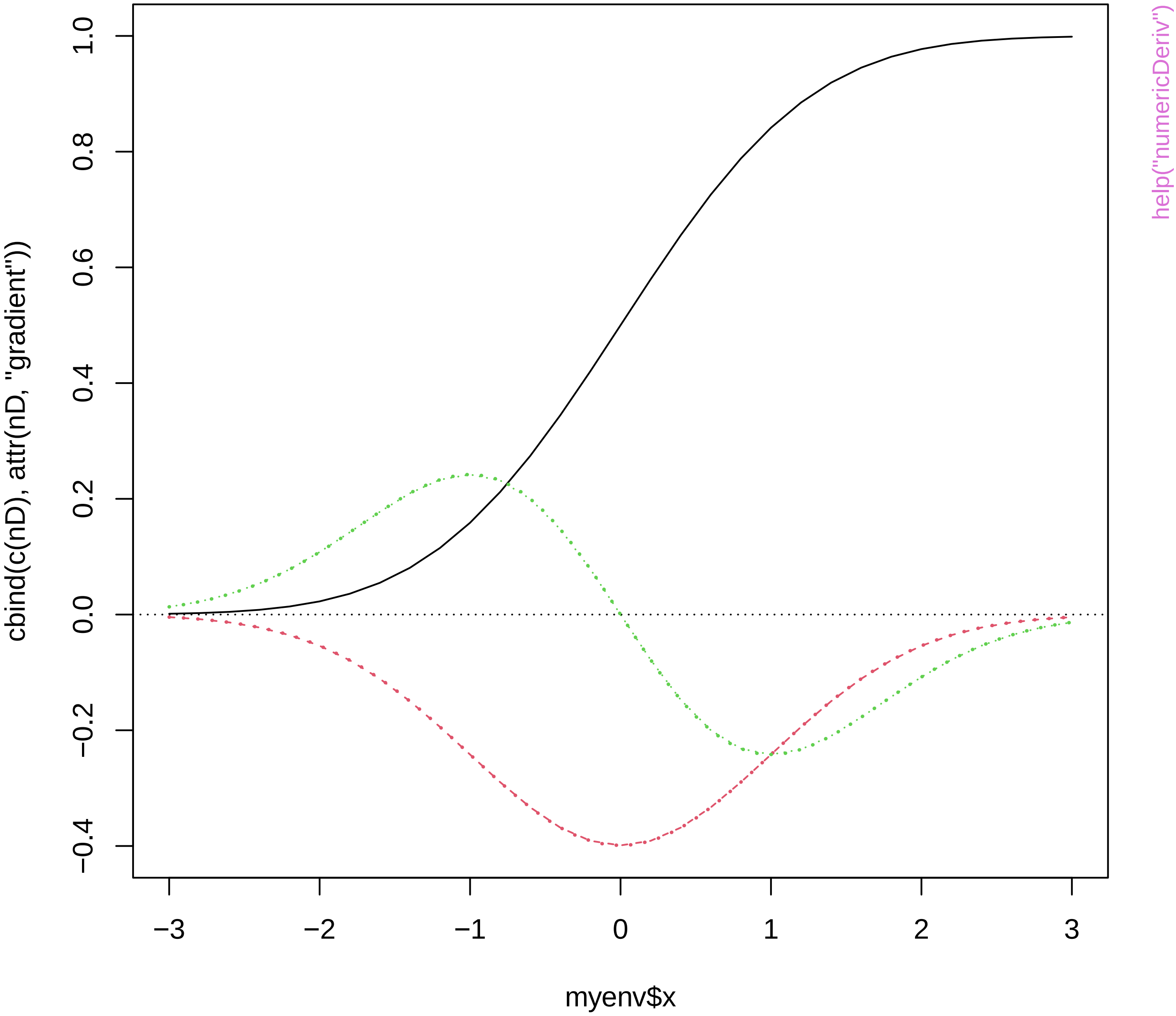


co2
320
330
340
350
360
0
1
2
3
help("monthplot")

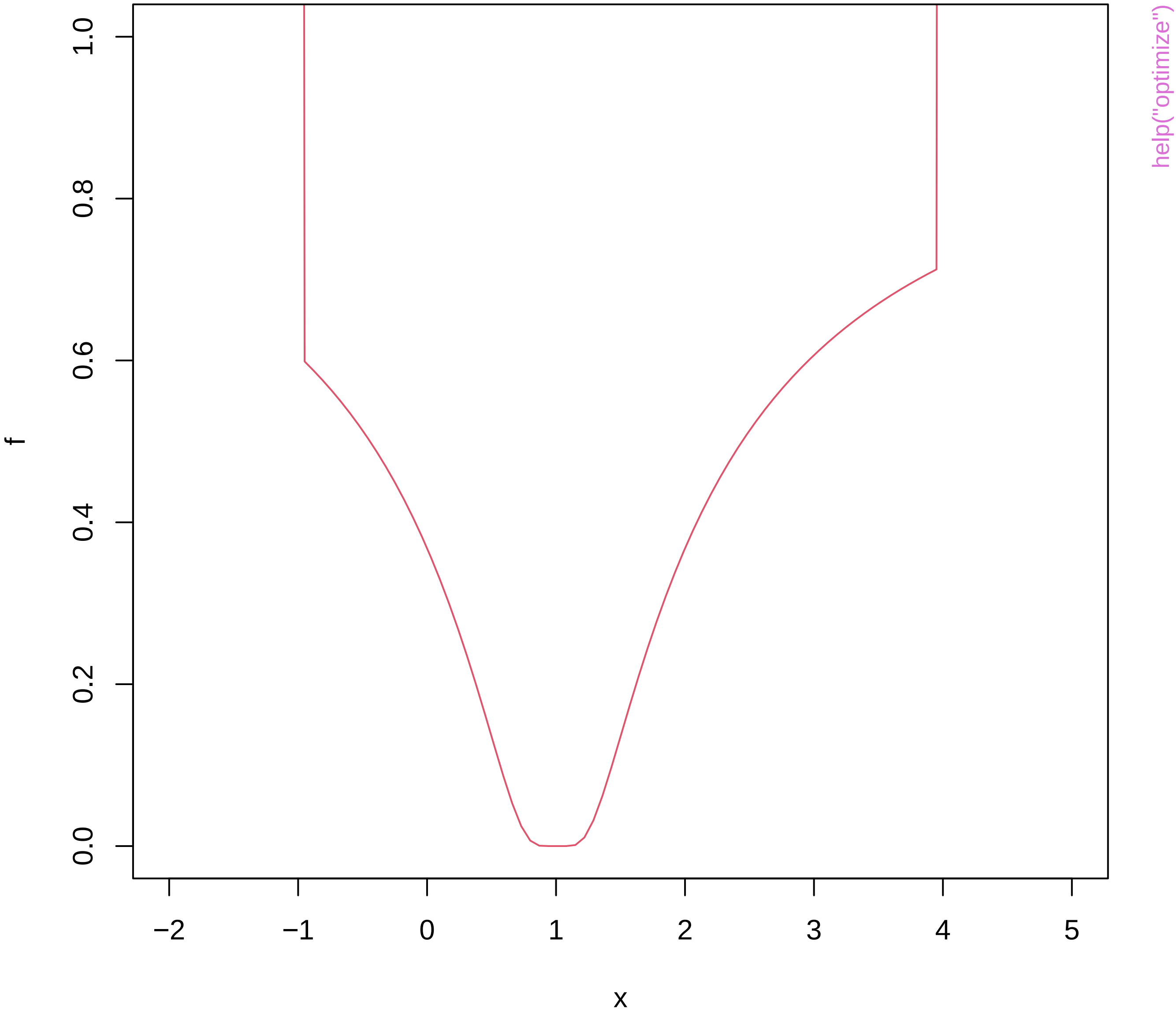


nextn(n) − n
n
0
2
4
6
8
0
20
40
60
80
100
help("nextn")

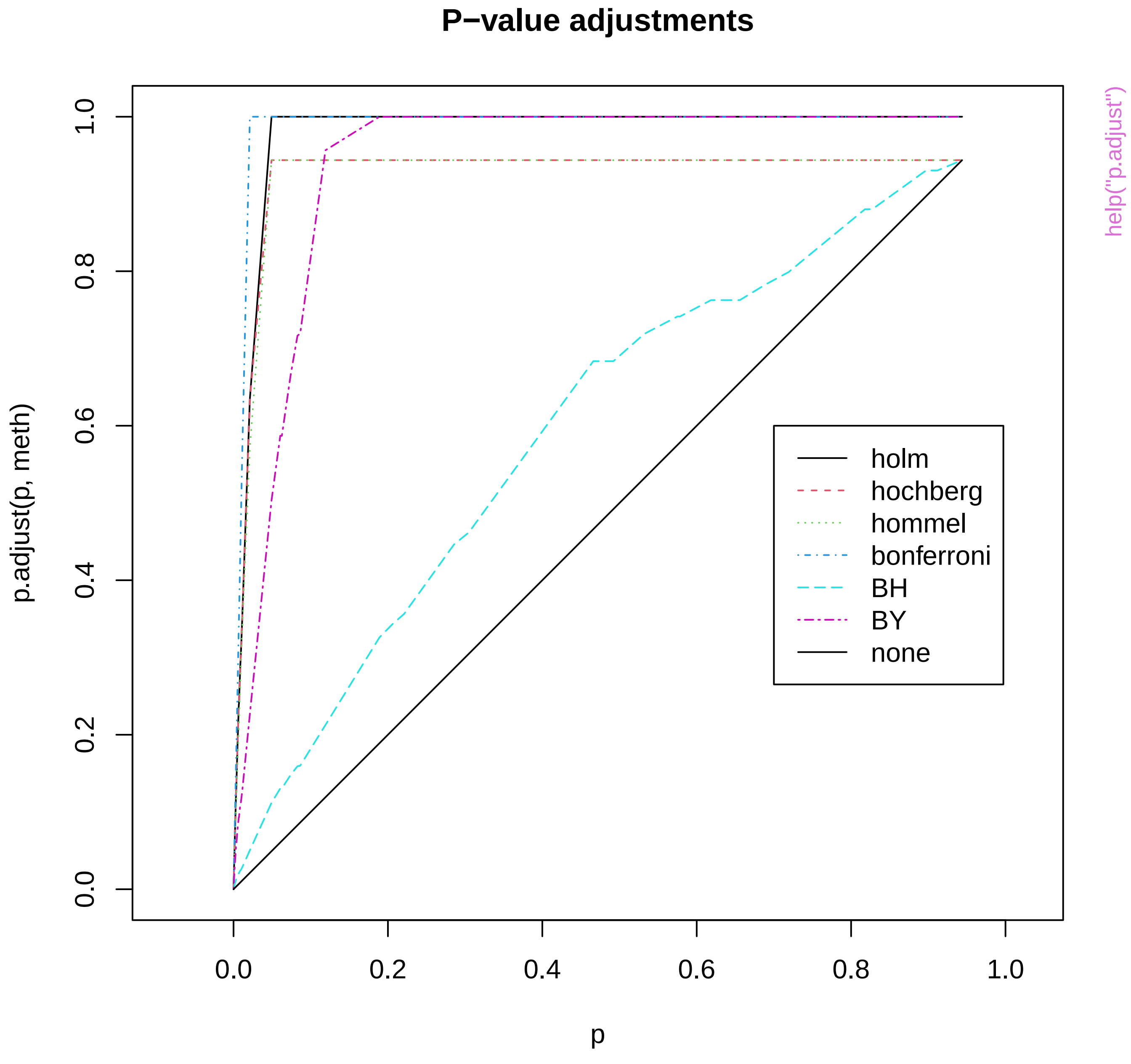

nls(*), data, true function and fit, n=100
help("nls")
y
x
100
102
104
106
108
−10
−8
−6
−4
−2
0



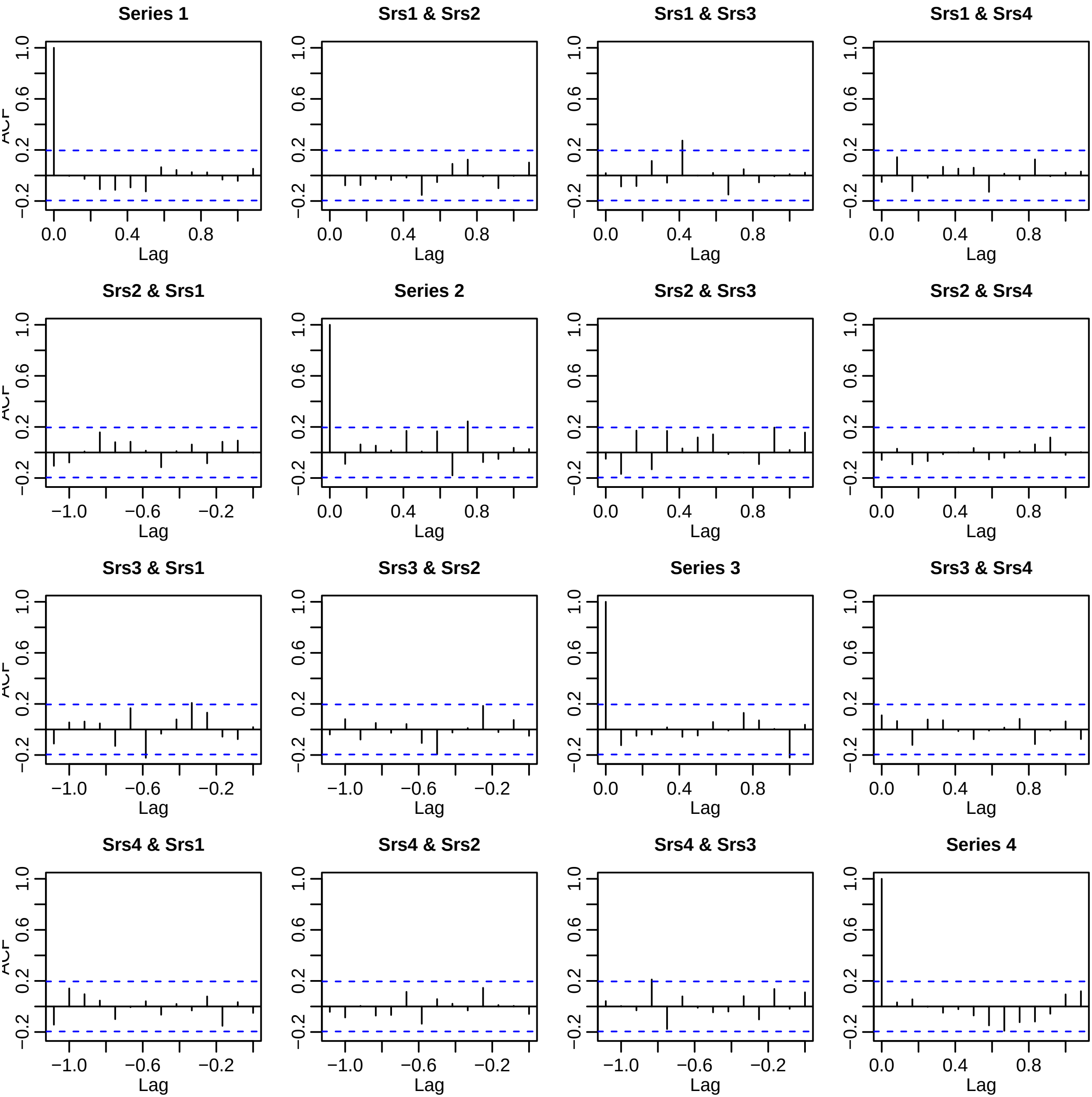
cbind(c(nD), attr(nD, "gradient"))
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
−3
−2
−1
0
1
2
3
myenv$x
help("numericDeriv")



f
x
0.0
0.2
0.4
0.6
0.8
1.0
−2
−1
0
1
2
3
4
5
help("optimize")

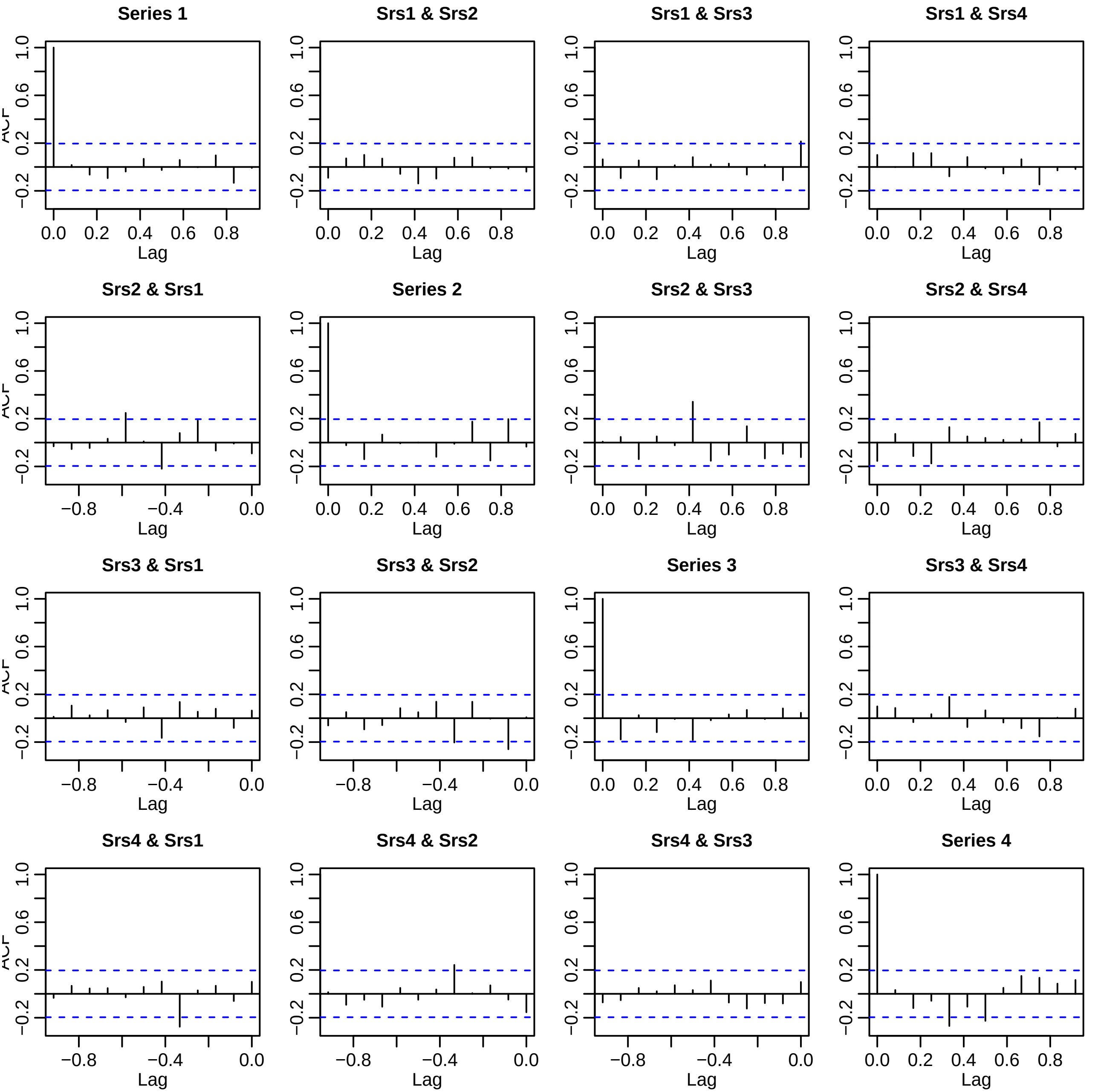


P−value adjustments
1.0
0.8
0.6
0.4
0.2
0.0
p.adjust(p, meth)
0.0
0.2
0.4
0.6
0.8
1.0
p
holm
hochberg
hommel
bonferroni
BH
BY
none
help("p.adjust")

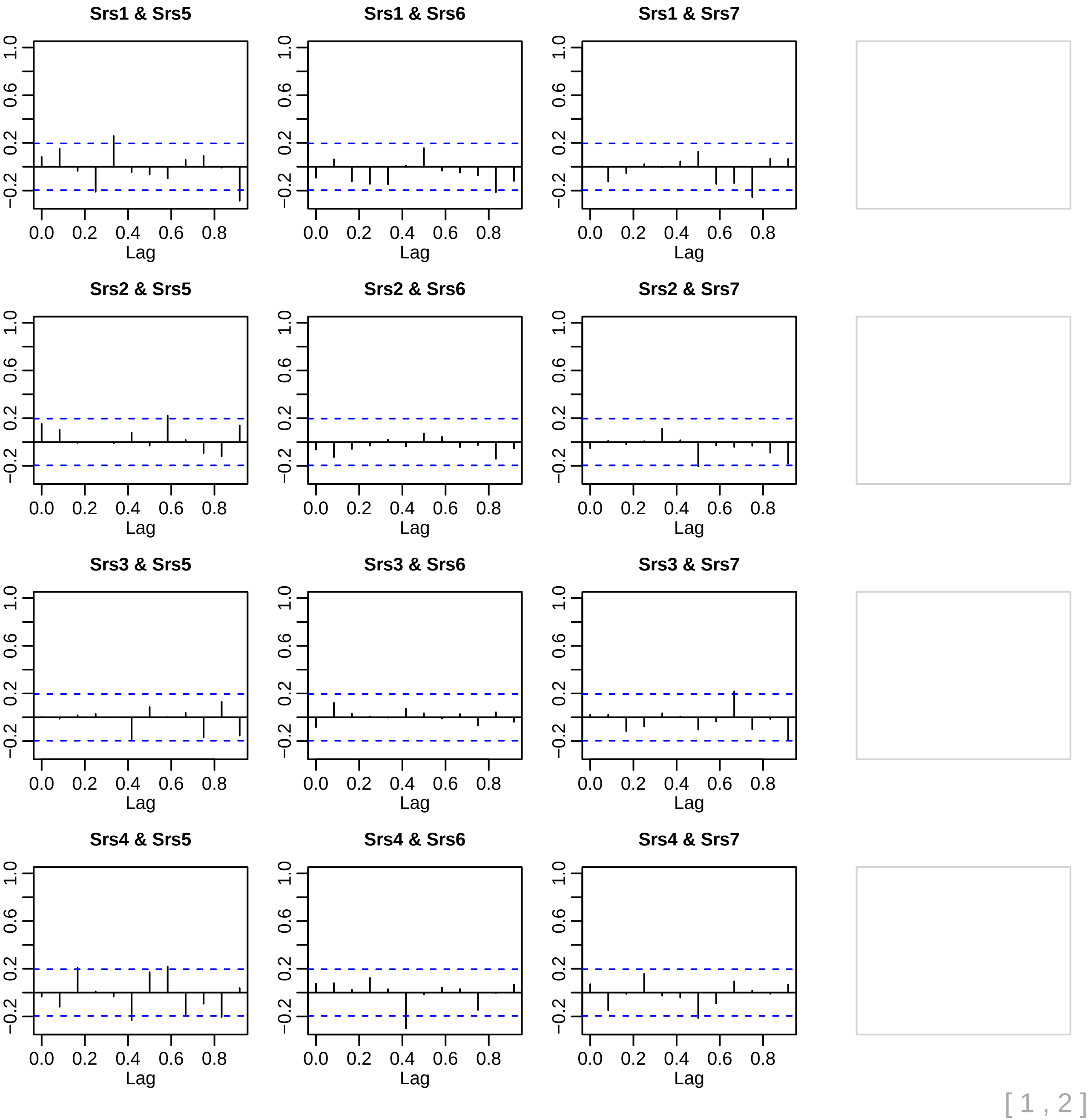


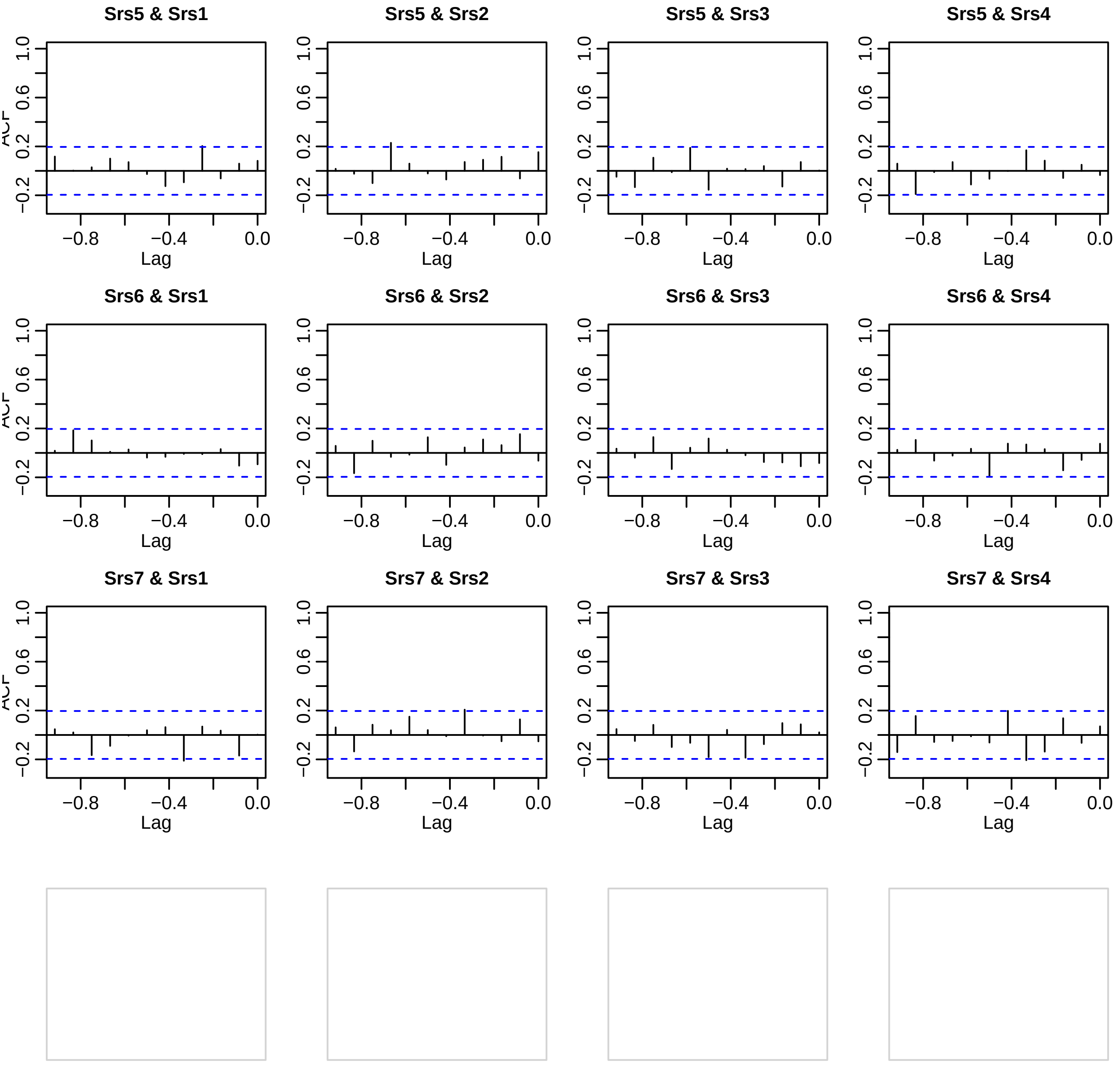
Series 1
Srs1 & Srs2
Srs1 & Srs3
Srs1 & Srs4
Srs2 & Srs1
Series 2
Srs2 & Srs3
Srs2 & Srs4
Srs3 & Srs1
Srs3 & Srs2
Series 3
Srs3 & Srs4
Srs4 & Srs1
Srs4 & Srs2
Srs4 & Srs3
Series 4
ACF
Lag


Series 1
Srs1 & Srs2
Srs1 & Srs3
Srs1 & Srs4
Srs1 & Srs5
Srs1 & Srs6
Srs1 & Srs7
Srs2 & Srs1
Series 2
Srs2 & Srs3
Srs2 & Srs4
Srs2 & Srs5
Srs2 & Srs6
Srs2 & Srs7
Srs3 & Srs1
Srs3 & Srs2
Series 3
Srs3 & Srs4
Srs3 & Srs5
Srs3 & Srs6
Srs3 & Srs7
Srs4 & Srs1
Srs4 & Srs2
Srs4 & Srs3
Series 4
Srs4 & Srs5
Srs4 & Srs6
Srs4 & Srs7
Srs5 & Srs1
Srs5 & Srs2
Srs5 & Srs3
Srs5 & Srs4
Series 5
Srs5 & Srs6
Srs5 & Srs7
Srs6 & Srs1
Srs6 & Srs2
Srs6 & Srs3
Srs6 & Srs4
Srs6 & Srs5
Series 6
Srs6 & Srs7
Srs7 & Srs1
Srs7 & Srs2
Srs7 & Srs3
Srs7 & Srs4
Srs7 & Srs5
Srs7 & Srs6
Series 7
Lag
−0.2
0.2
0.0
0.6
−0.8
−0.2

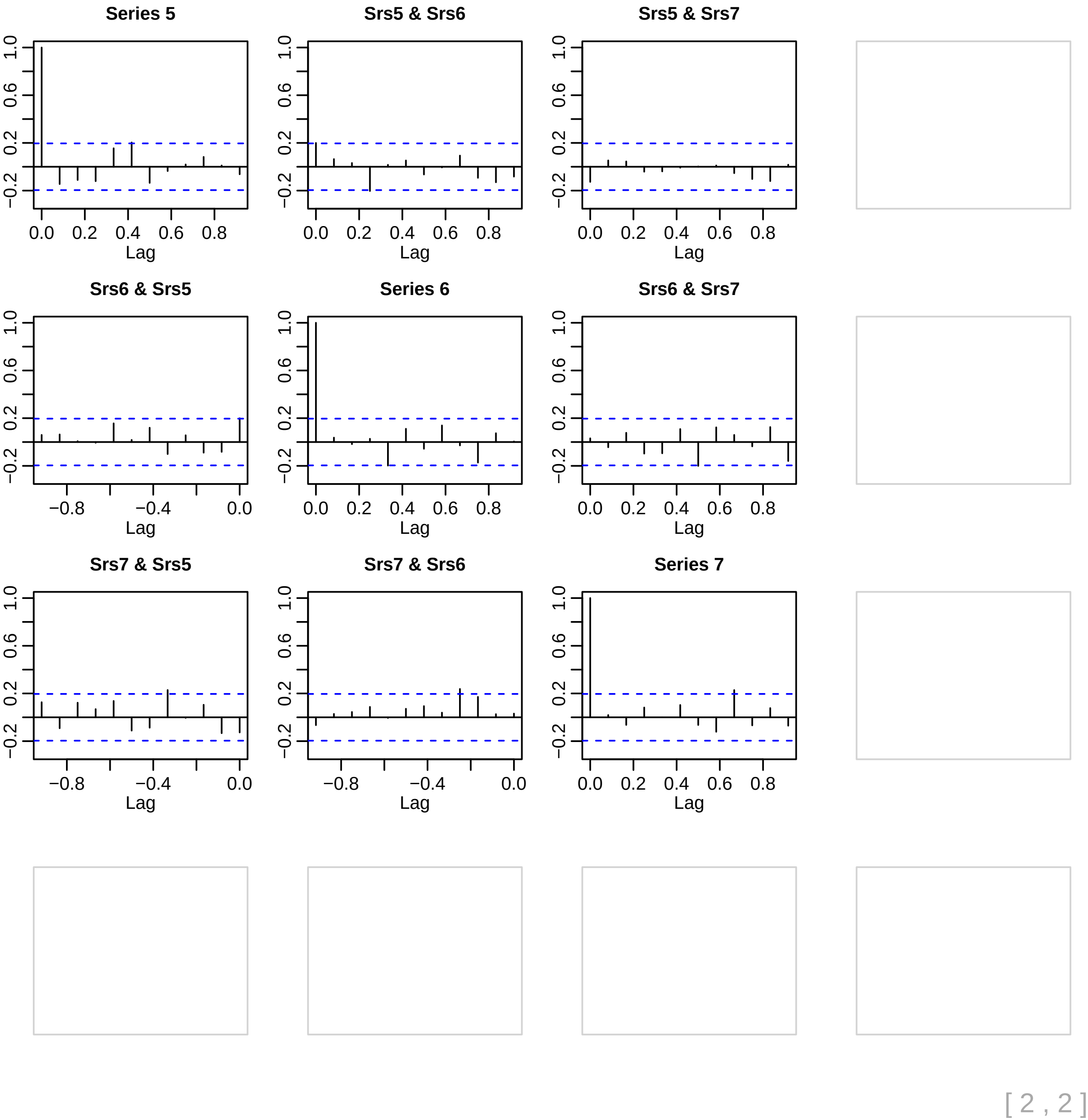

Series 1
Srs1 & Srs2
Srs1 & Srs3
Srs1 & Srs4
Srs2 & Srs1
Series 2
Srs2 & Srs3
Srs2 & Srs4
Srs3 & Srs1
Srs3 & Srs2
Series 3
Srs3 & Srs4
Srs4 & Srs1
Srs4 & Srs2
Srs4 & Srs3
Series 4
ACF
Lag
−0.2 0.2 0.6 1.0
0.0 0.2 0.4 0.6 0.8
−0.8 −0.4 0.0

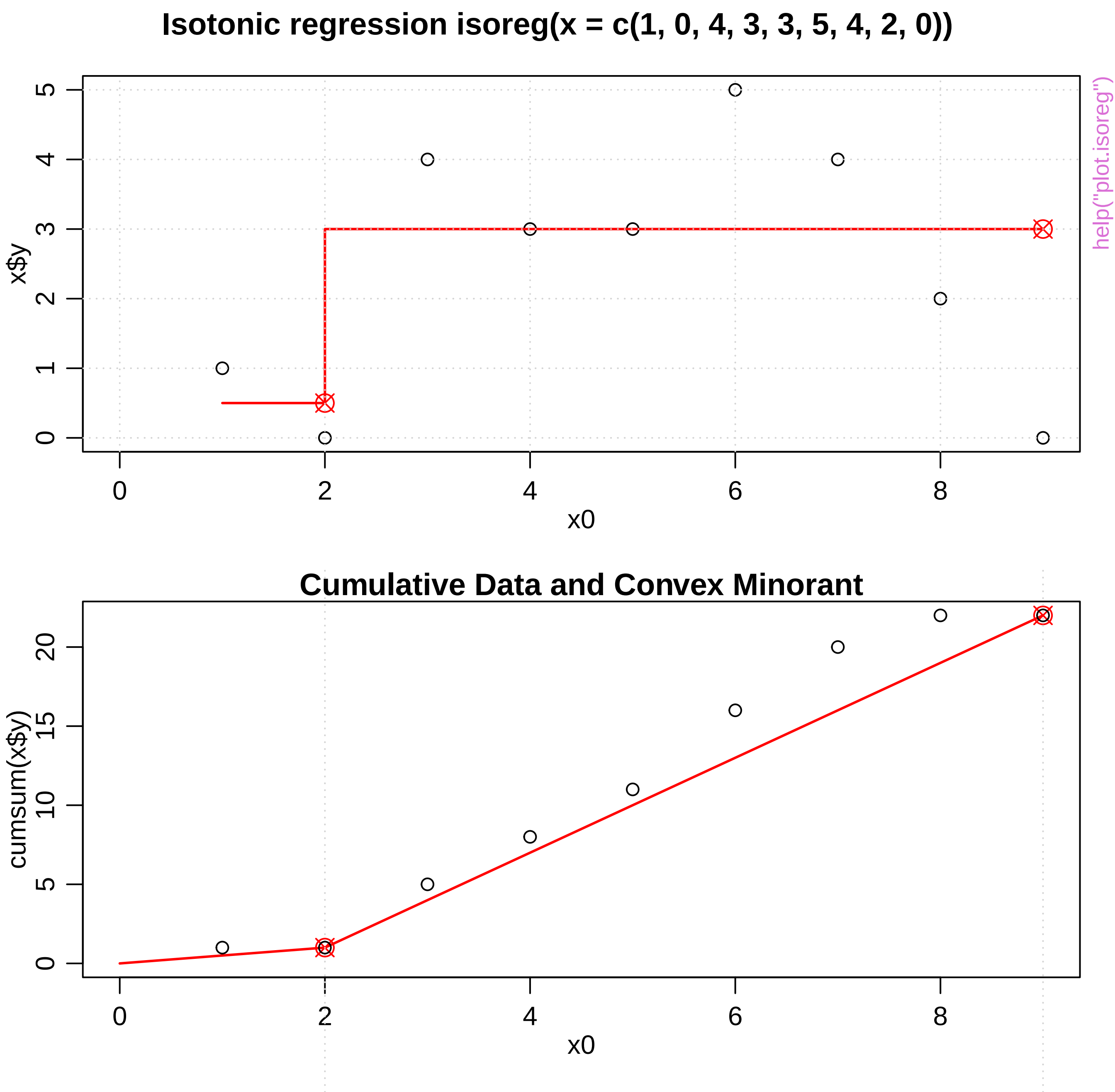
[1, 1]


Srs1 & Srs5
Srs1 & Srs6
Srs1 & Srs7
Srs2 & Srs5
Srs2 & Srs6
Srs2 & Srs7
Srs3 & Srs5
Srs3 & Srs6
Srs3 & Srs7
Srs4 & Srs5
Srs4 & Srs6
Srs4 & Srs7
Lag
[1 , 2]

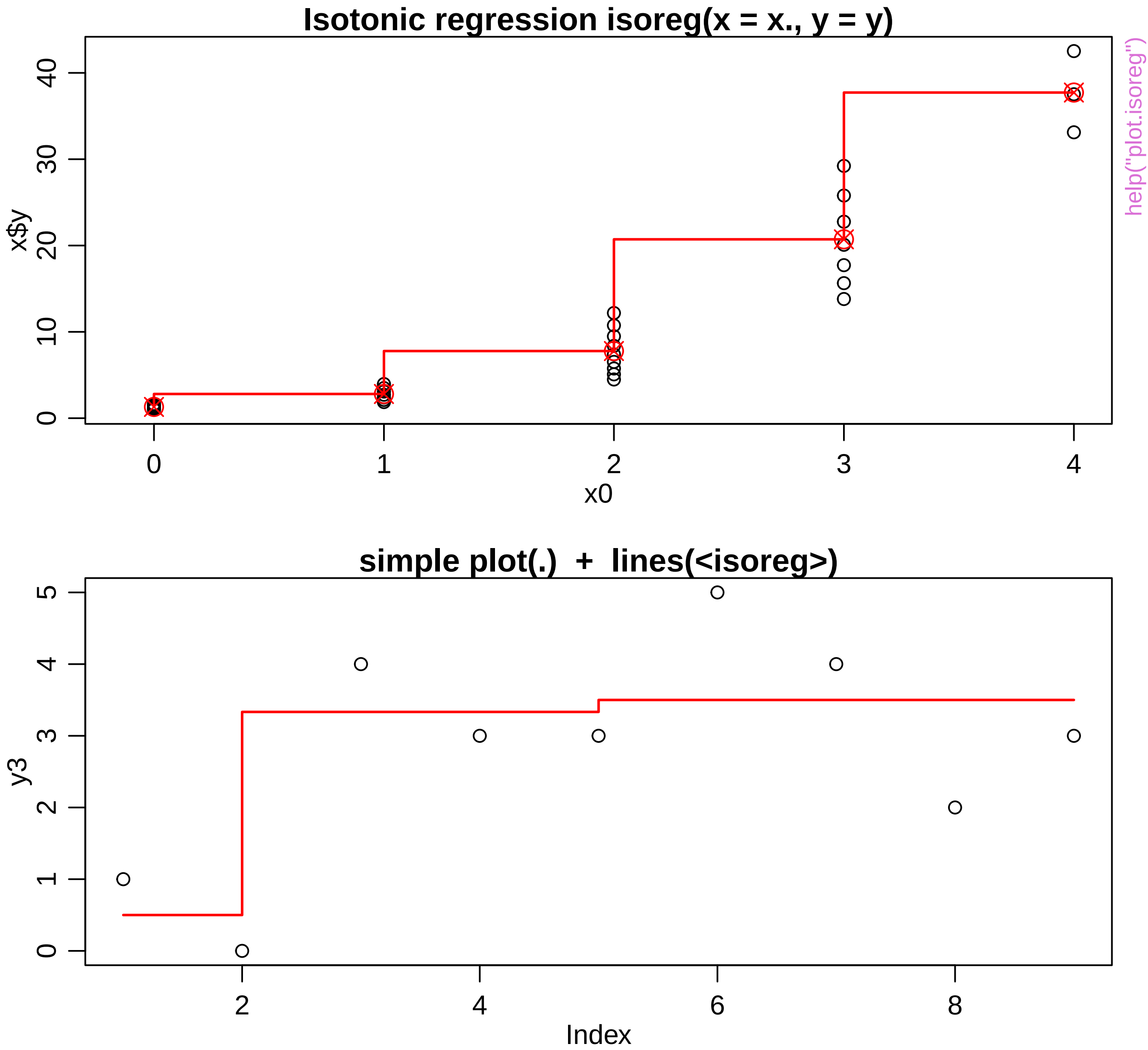

Srs5 & Srs1
Srs5 & Srs2
Srs5 & Srs3
Srs5 & Srs4
Srs6 & Srs1
Srs6 & Srs2
Srs6 & Srs3
Srs6 & Srs4
Srs7 & Srs1
Srs7 & Srs2
Srs7 & Srs3
Srs7 & Srs4
1.0
0.6
0.2
−0.2
−0.8
−0.4
0.0
Lag

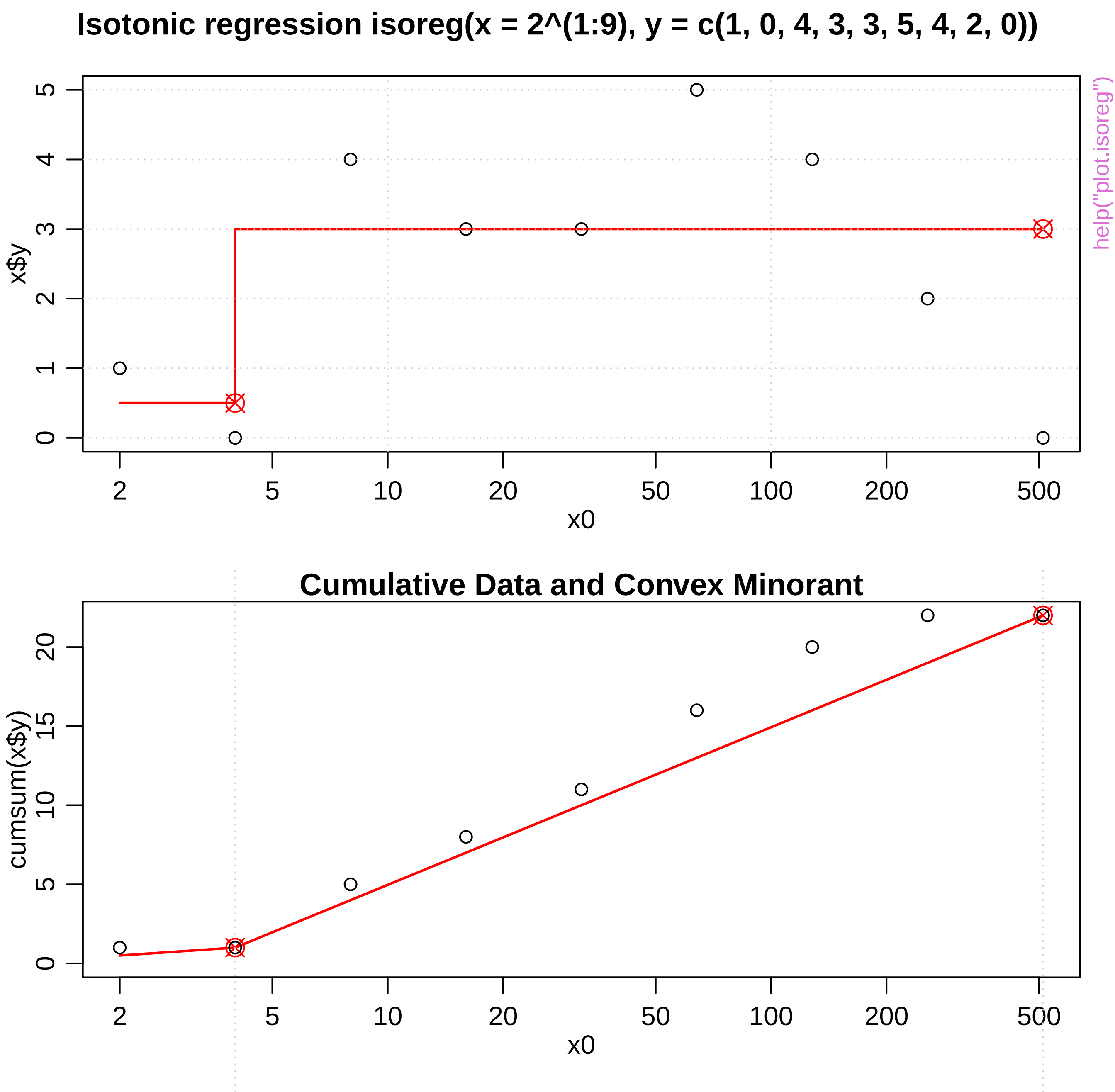
[2 , 1]


Series 5
Srs5 & Srs6
Srs5 & Srs7
Srs6 & Srs5
Series 6
Srs6 & Srs7
Srs7 & Srs5
Srs7 & Srs6
Series 7
Lag
[2 , 2]

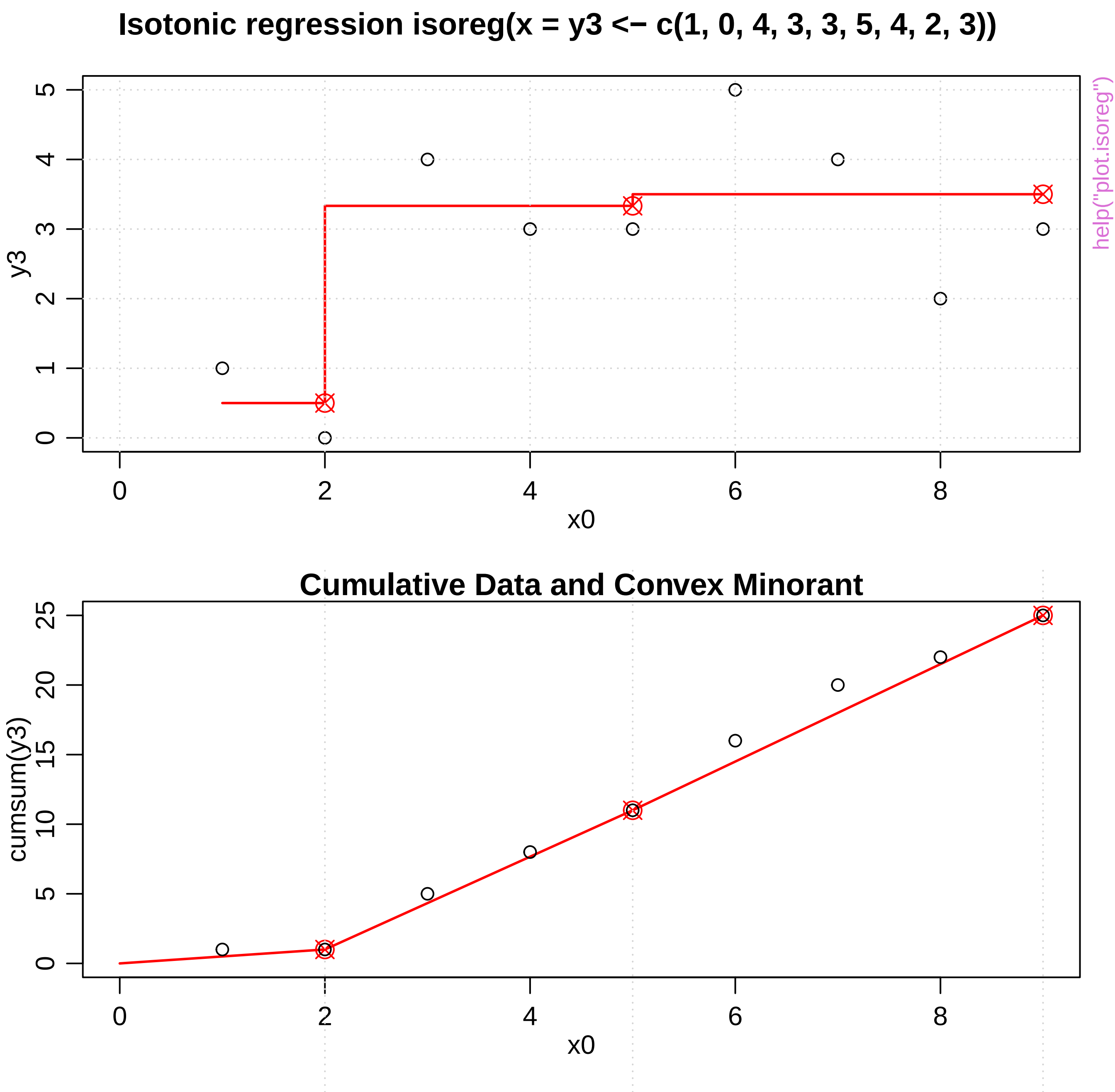


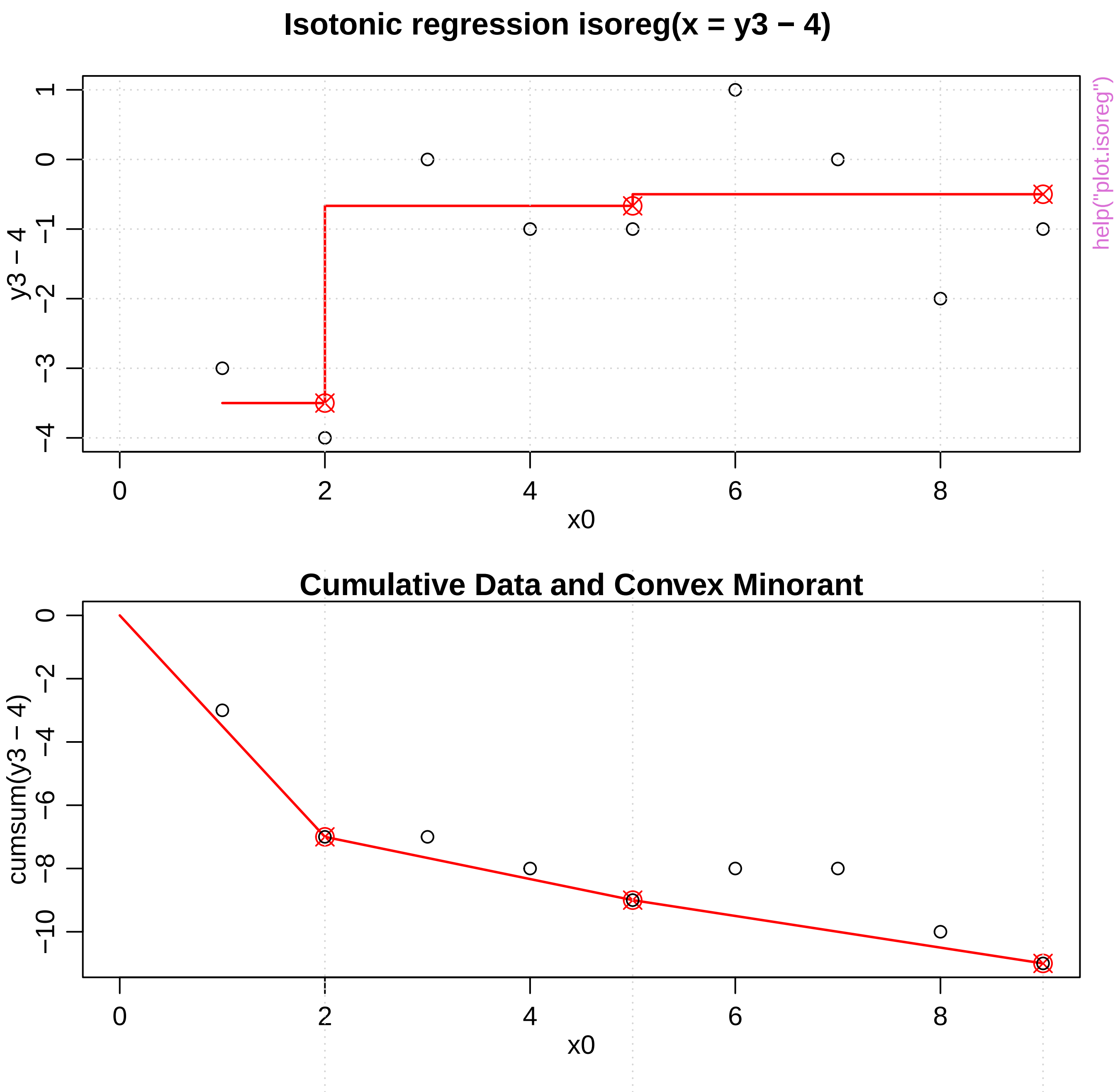
Isotonic regression isoreg(x = c(1, 0, 4, 3, 3, 5, 4, 2, 0))
x$y
x0
help("plot.isoreg")
Cumulative Data and Convex Minorant
cumsum(x$y)
x0

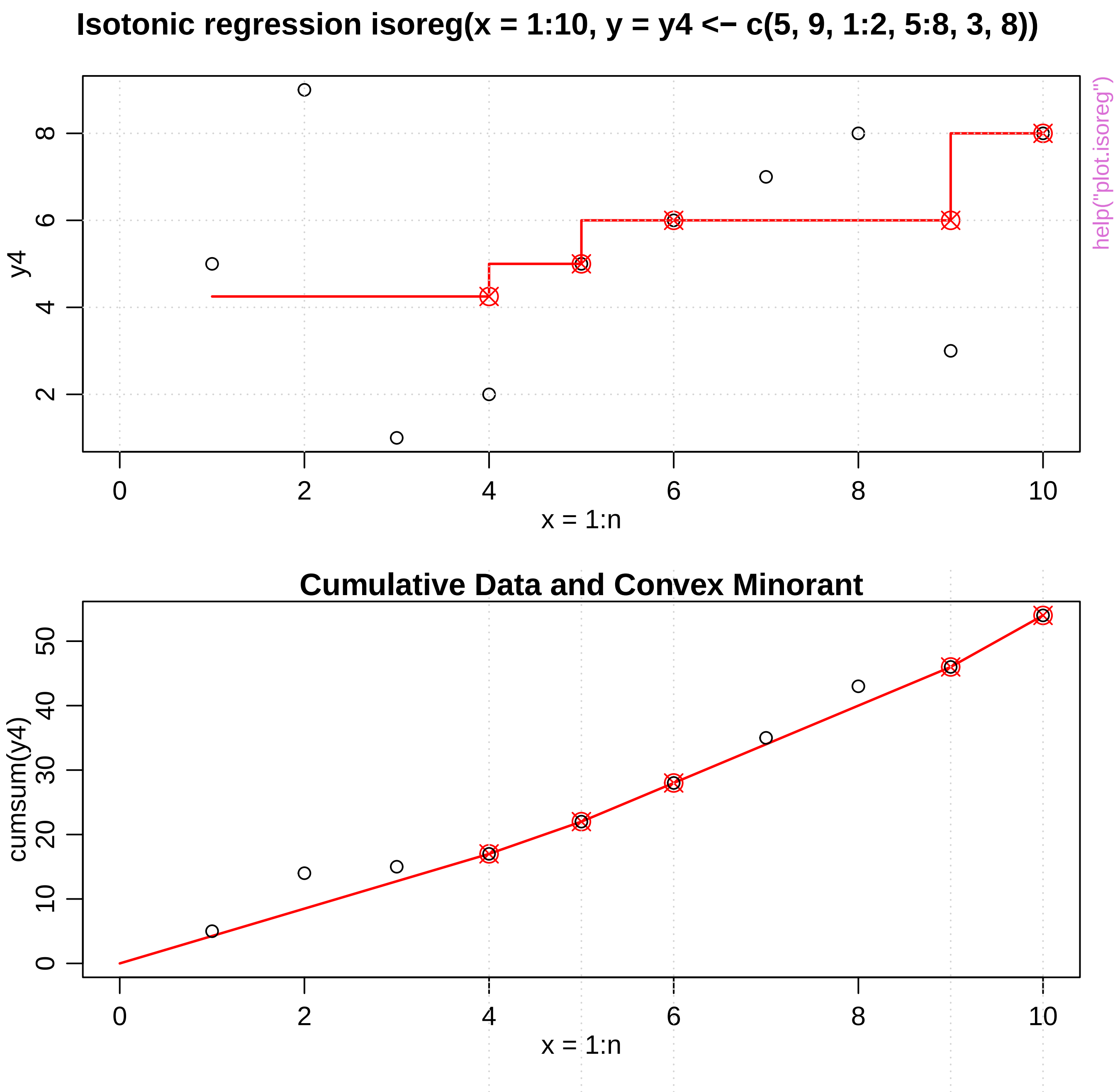

Isotonic regression isoreg(x = x., y = y)
x$y
0
10
20
30
40
0
1
2
3
4
x0
help("plot.isoreg")
simple plot(.) + lines(<isoreg>)
y3
0
1
2
3
4
5
2
4
6
8
Index

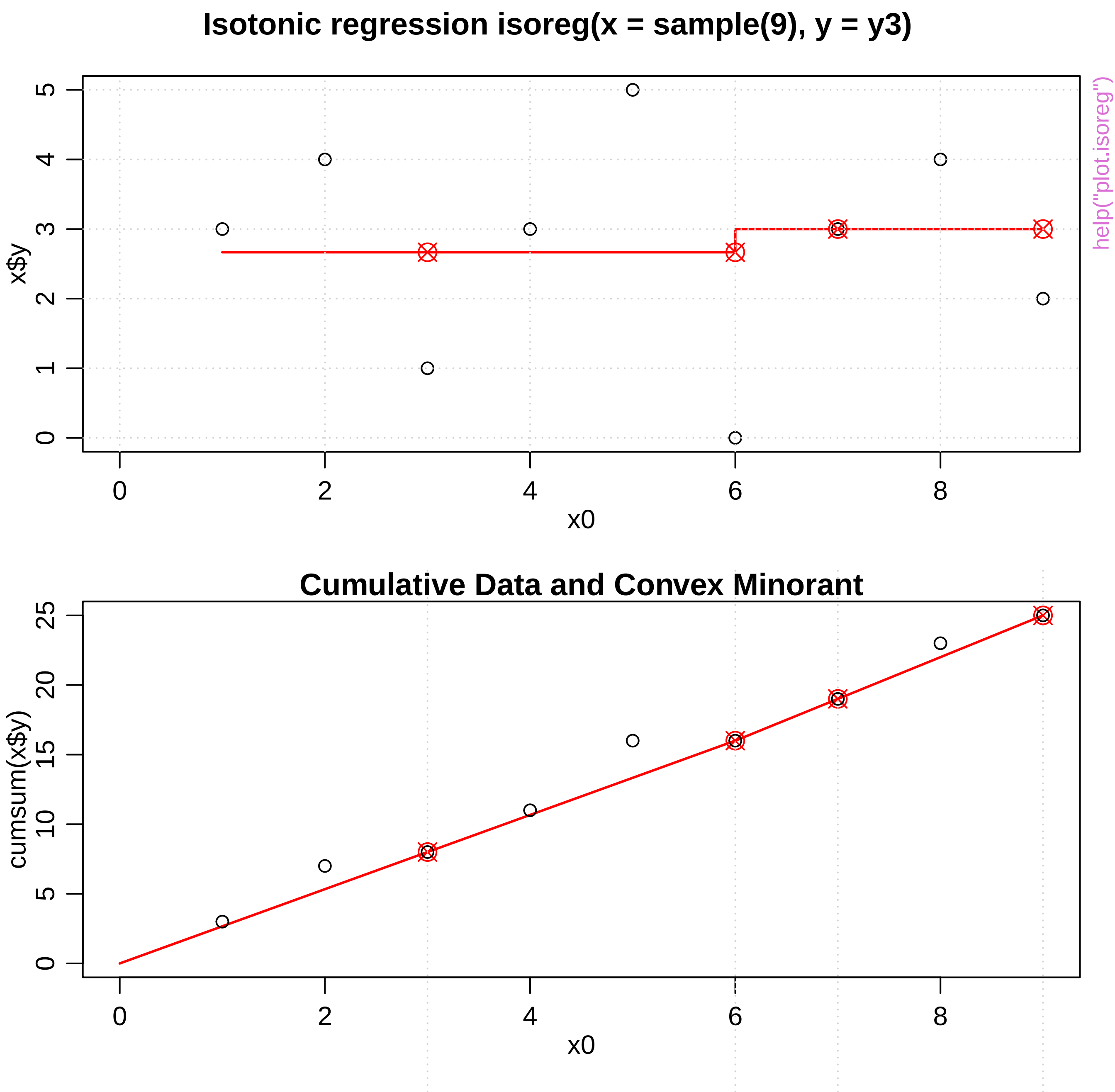


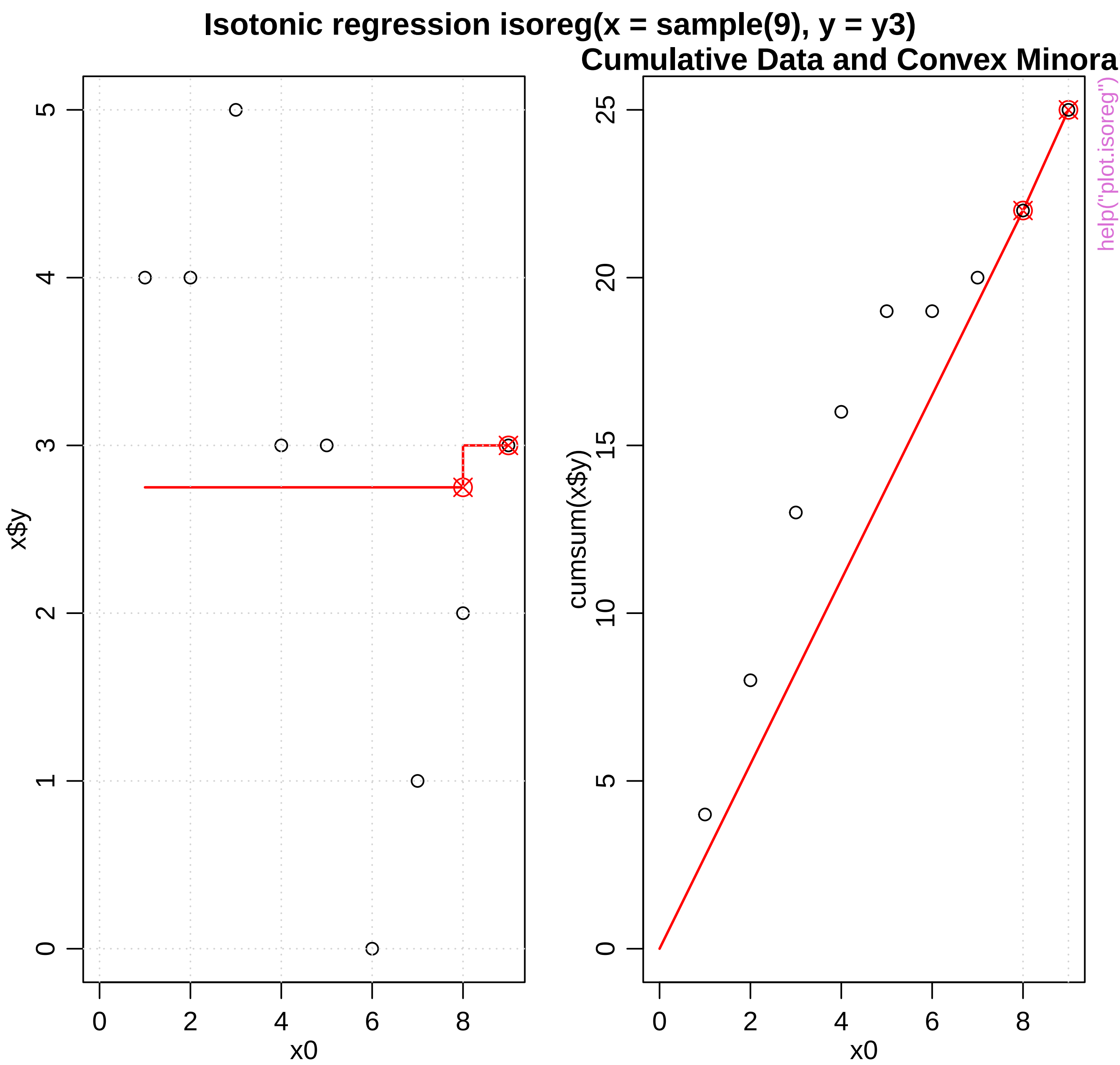
Isotonic regression isoreg(x = 2^(1:9), y = c(1, 0, 4, 3, 3, 5, 4, 2, 0))
x$y
0
1
2
3
4
5
2
5
10
20
50
100
200
500
x0
help("plot.isoreg")
Cumulative Data and Convex Minorant
cumsum(x$y)
0
5
10
15
20
2
5
10
20
50
100
200
500
x0


Isotonic regression isoreg(x = y3 <− c(1, 0, 4, 3, 3, 5, 4, 2, 3))
y3
x0
help("plot.isoreg")
Cumulative Data and Convex Minorant
cumsum(y3)
x0
0
2
4
6
8
0
1
2
3
4
5
0
5
10
15
20
25

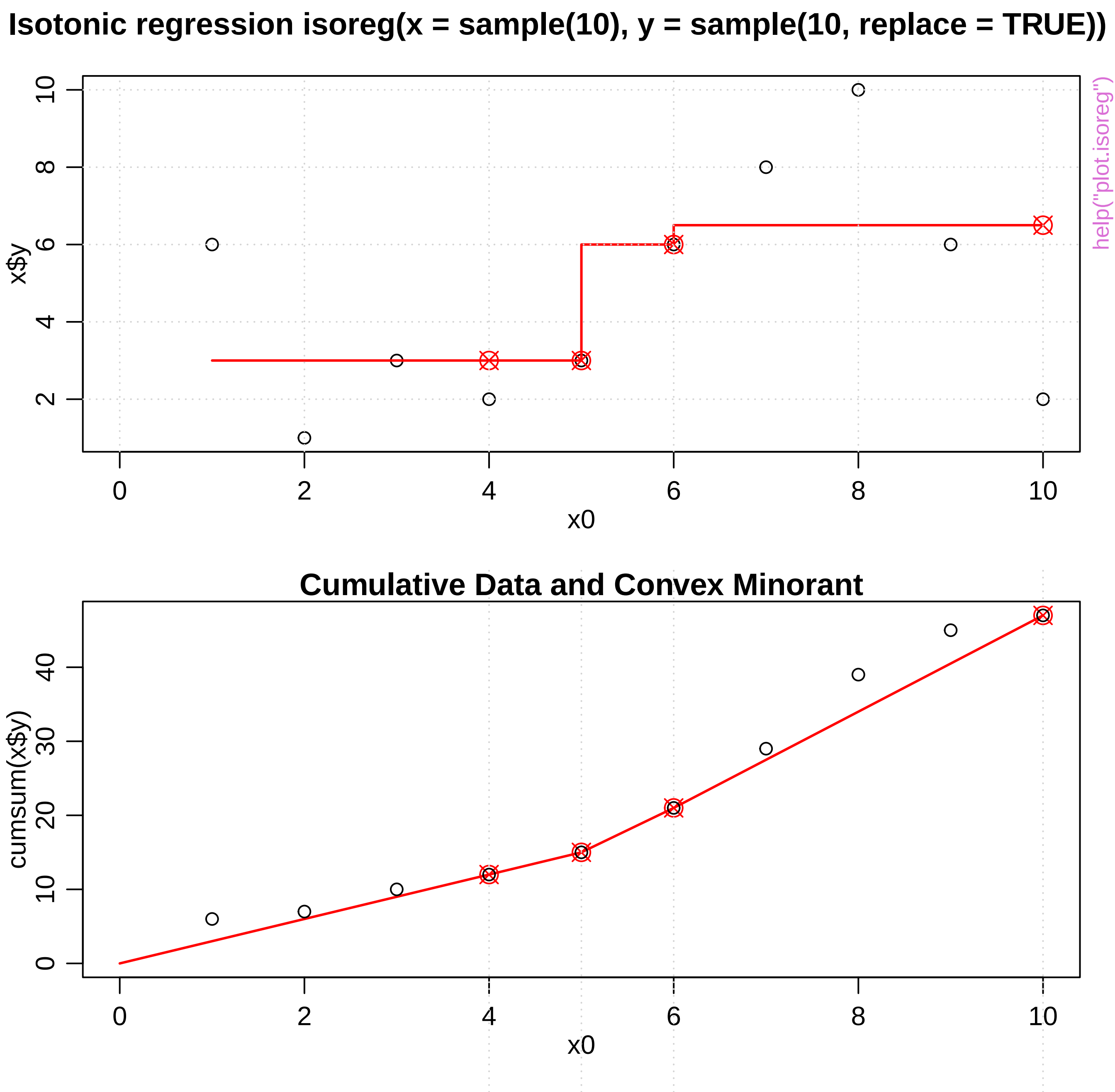

Isotonic regression isoreg(x = y3 − 4)
help("plot.isoreg")
y3 − 4
x0
Cumulative Data and Convex Minorant
cumsum(y3 − 4)
x0


Isotonic regression isoreg(x = 1:10, y = y4 <− c(5, 9, 1:2, 5:8, 3, 8))
y4
2
4
6
8
0
2
4
6
8
10
x = 1:n
help("plot.isoreg")
Cumulative Data and Convex Minorant
cumsum(y4)
0
10
20
30
40
50
0
2
4
6
8
10
x = 1:n

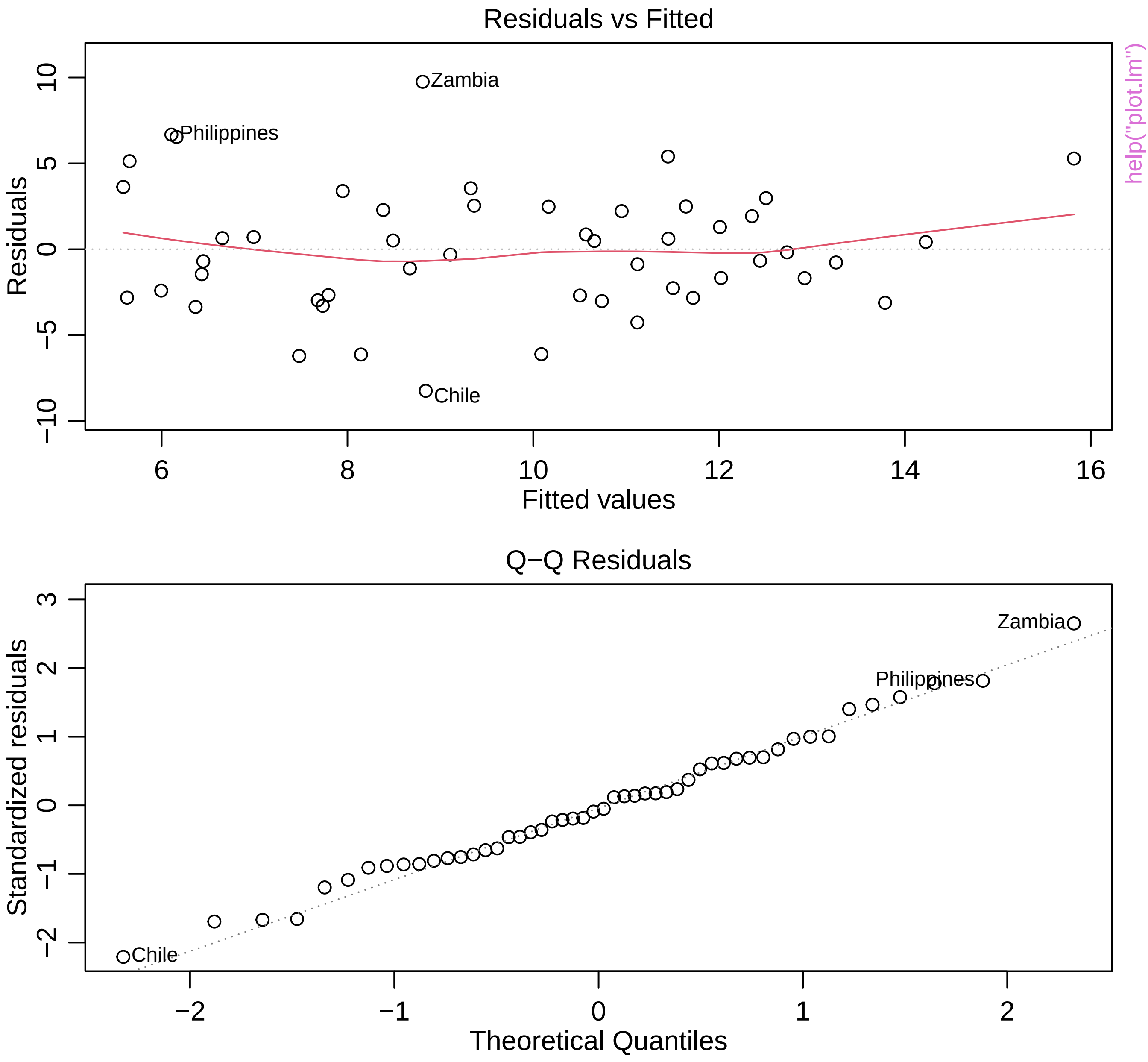

Isotonic regression isoreg(x = sample(9), y = y3)
x$y
x0
help("plot.isoreg")
Cumulative Data and Convex Minorant
cumsum(x$y)
x0

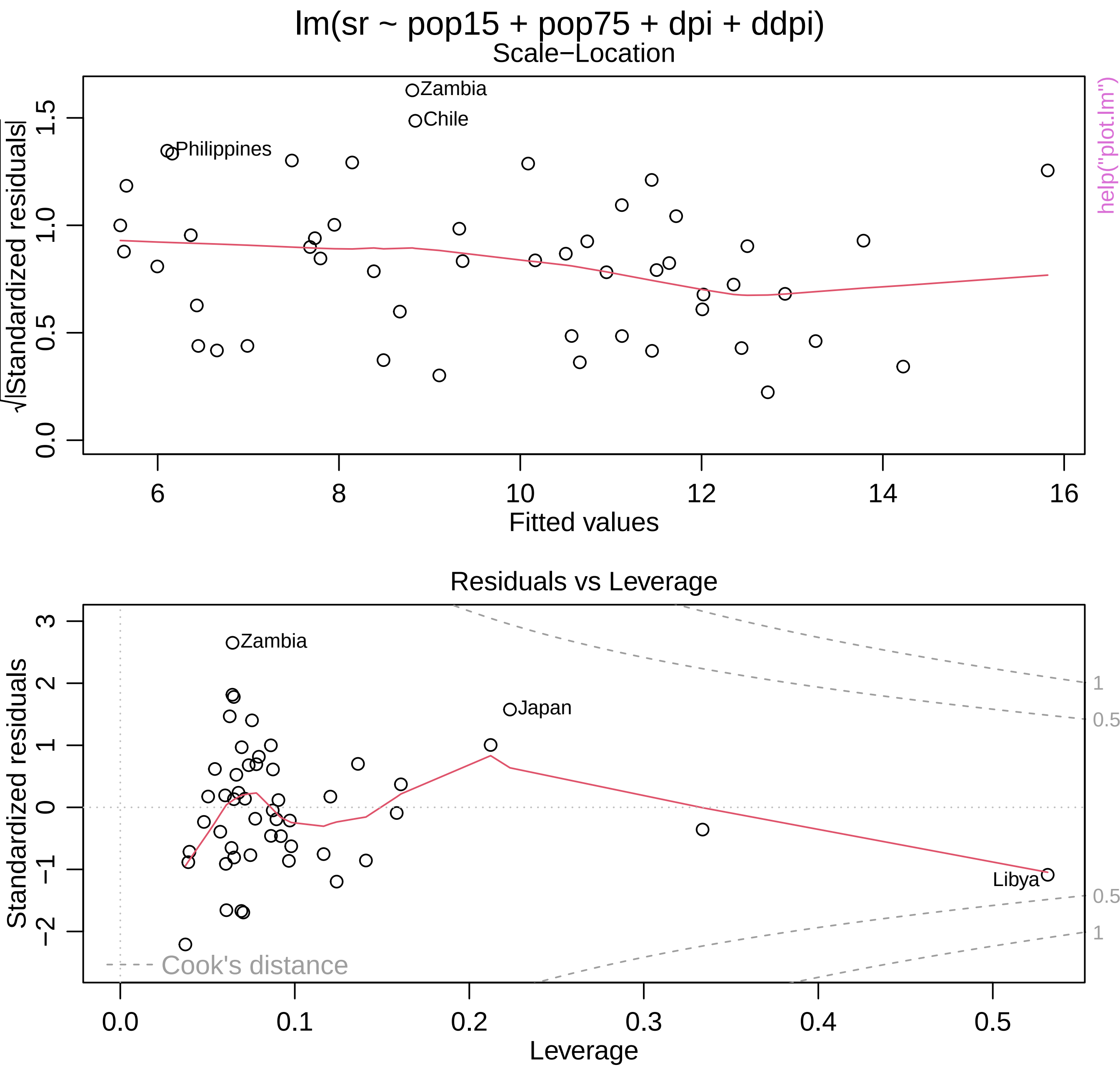


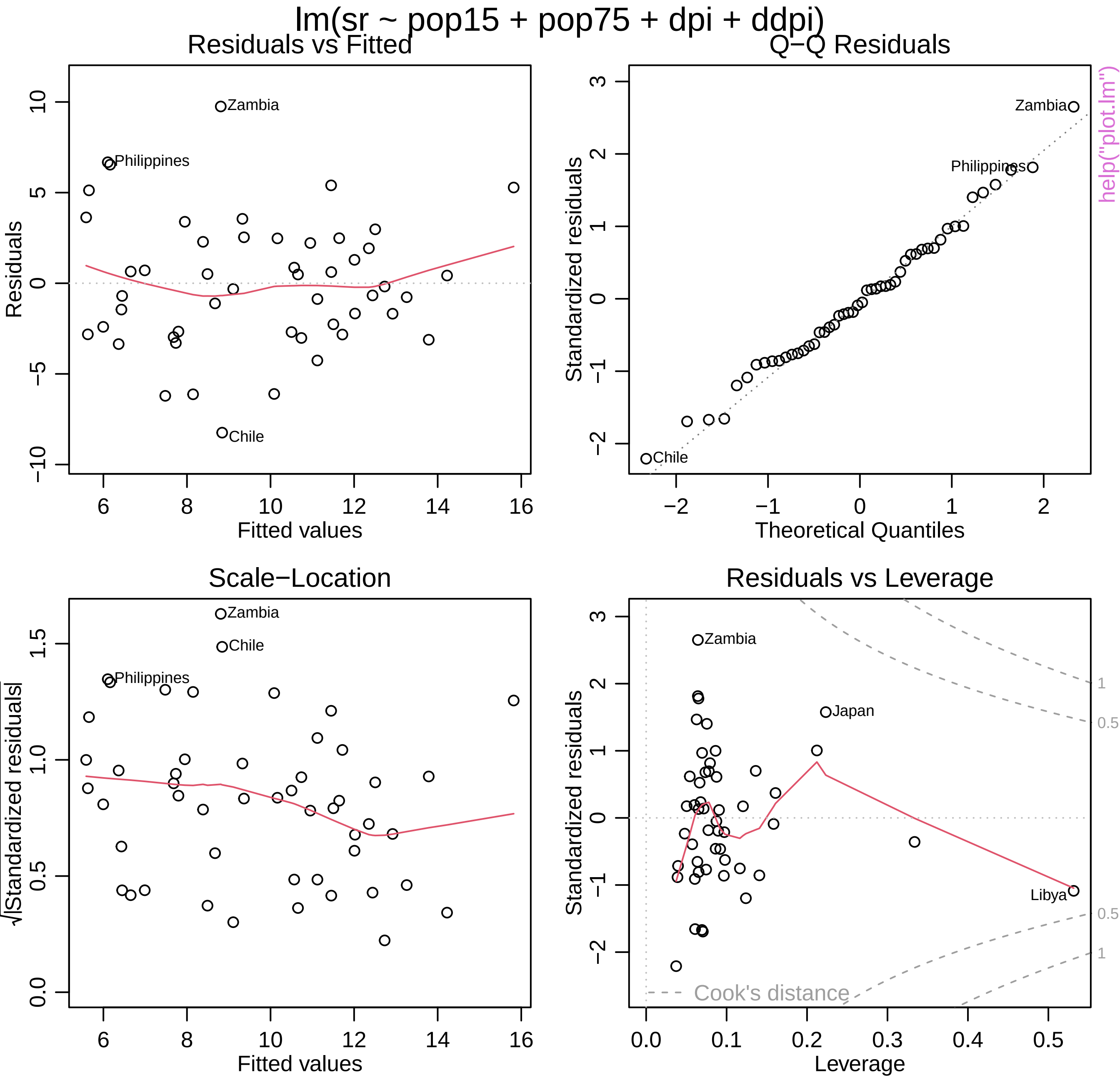
Isotonic regression isoreg(x = sample(9), y = y3)
Cumulative Data and Convex Minora
help("plot.isoreg")
x$y
x0
cumsum(x$y)
x0
0
1
2
3
4
5
0
2
4
6
8
0
5
10
15
20
25

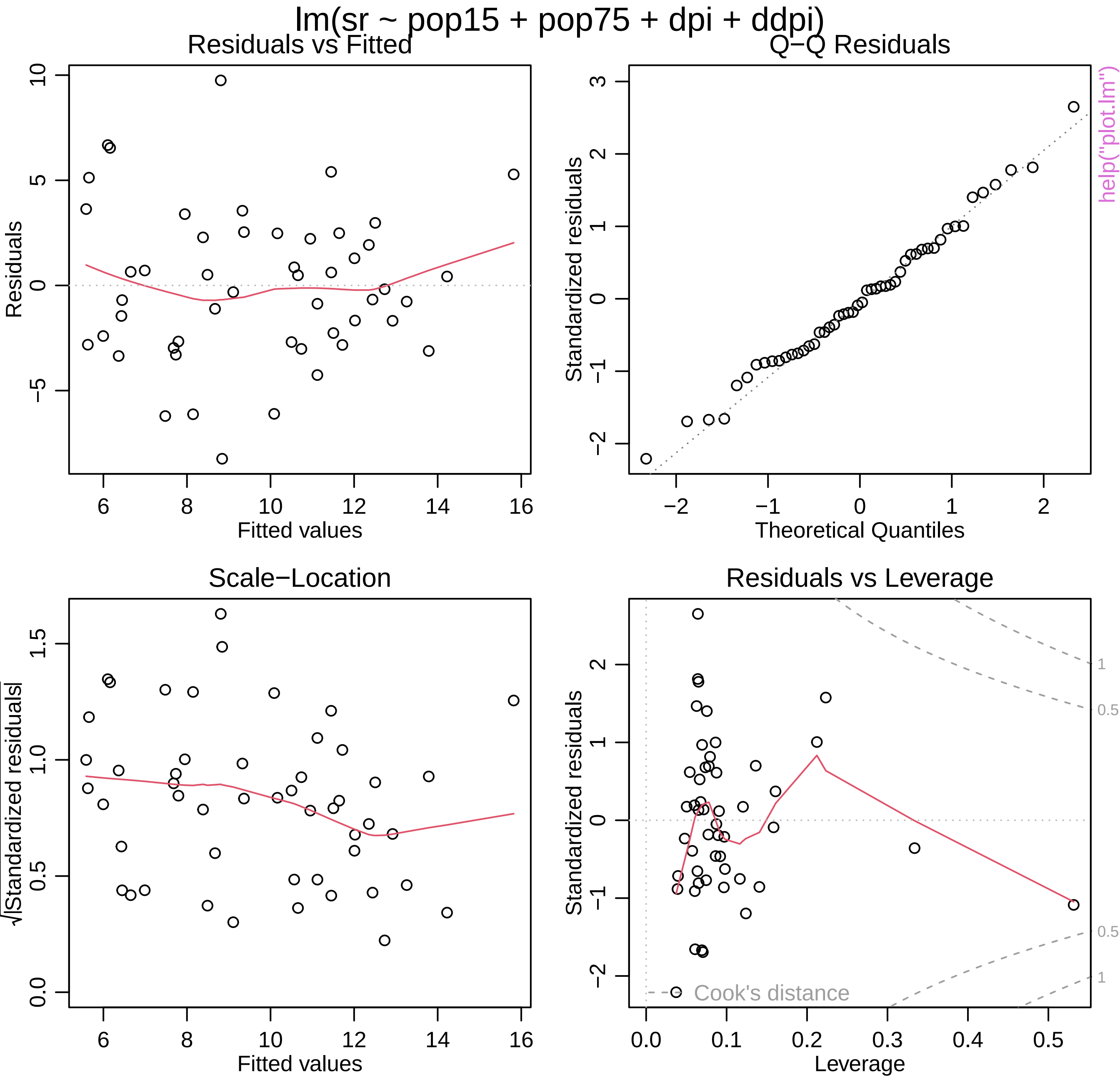


Isotonic regression isoreg(x = sample(10), y = sample(10, replace = TRUE))
x$y
x0
help("plot.isoreg")
Cumulative Data and Convex Minorant
cumsum(x$y)
x0

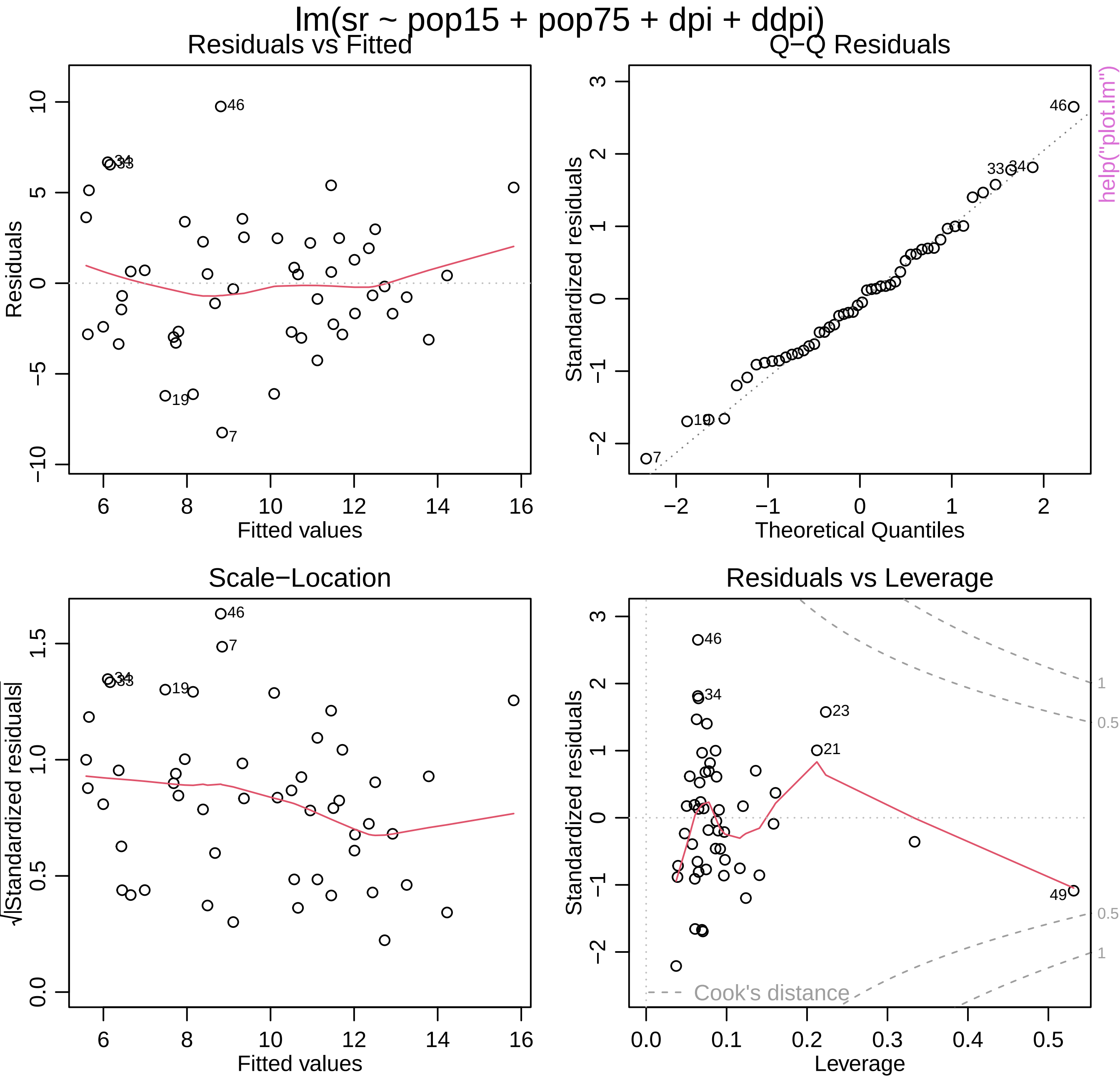

Residuals vs Fitted
Residuals
Fitted values
Zambia
Philippines
Chile
help("plot.lm")
Q−Q Residuals
Standardized residuals
Theoretical Quantiles
Zambia
Philippines
Chile


lm(sr ~ pop15 + pop75 + dpi + ddpi)
Scale−Location
Zambia
Chile
Philippines
√|Standardized residuals|
Fitted values
help("plot.lm")
Residuals vs Leverage
Zambia
Japan
Libya
Standardized residuals
Cook's distance
Leverage

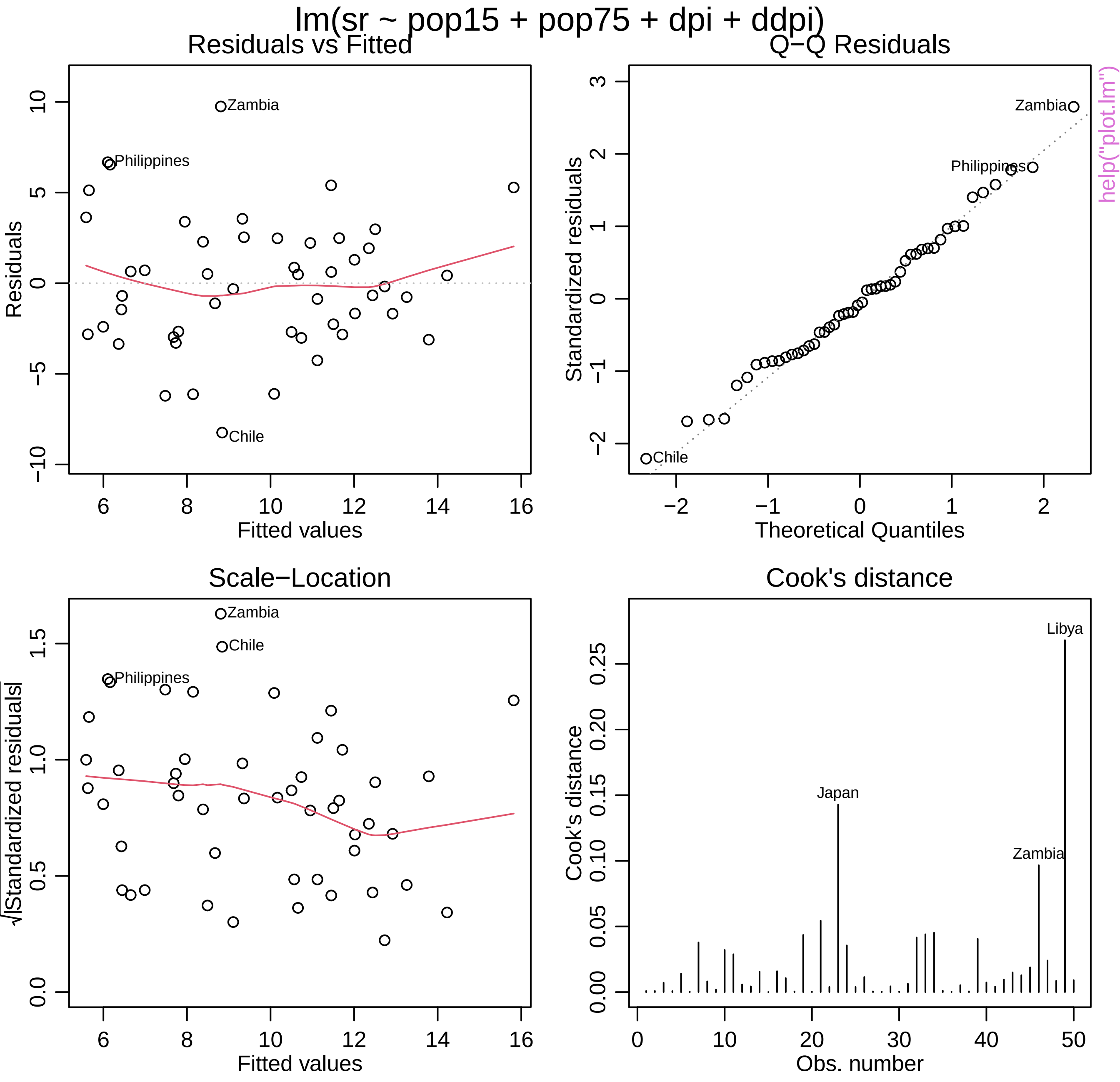

lm(sr ~ pop15 + pop75 + dpi + ddpi)
Residuals vs Fitted
Residuals
Fitted values
Zambia
Philippines
Chile
Q−Q Residuals
Standardized residuals
Theoretical Quantiles
help("plot.lm")
Scale−Location
√|Standardized residuals|
Residuals vs Leverage
Leverage
Japan
Libya
Cook's distance

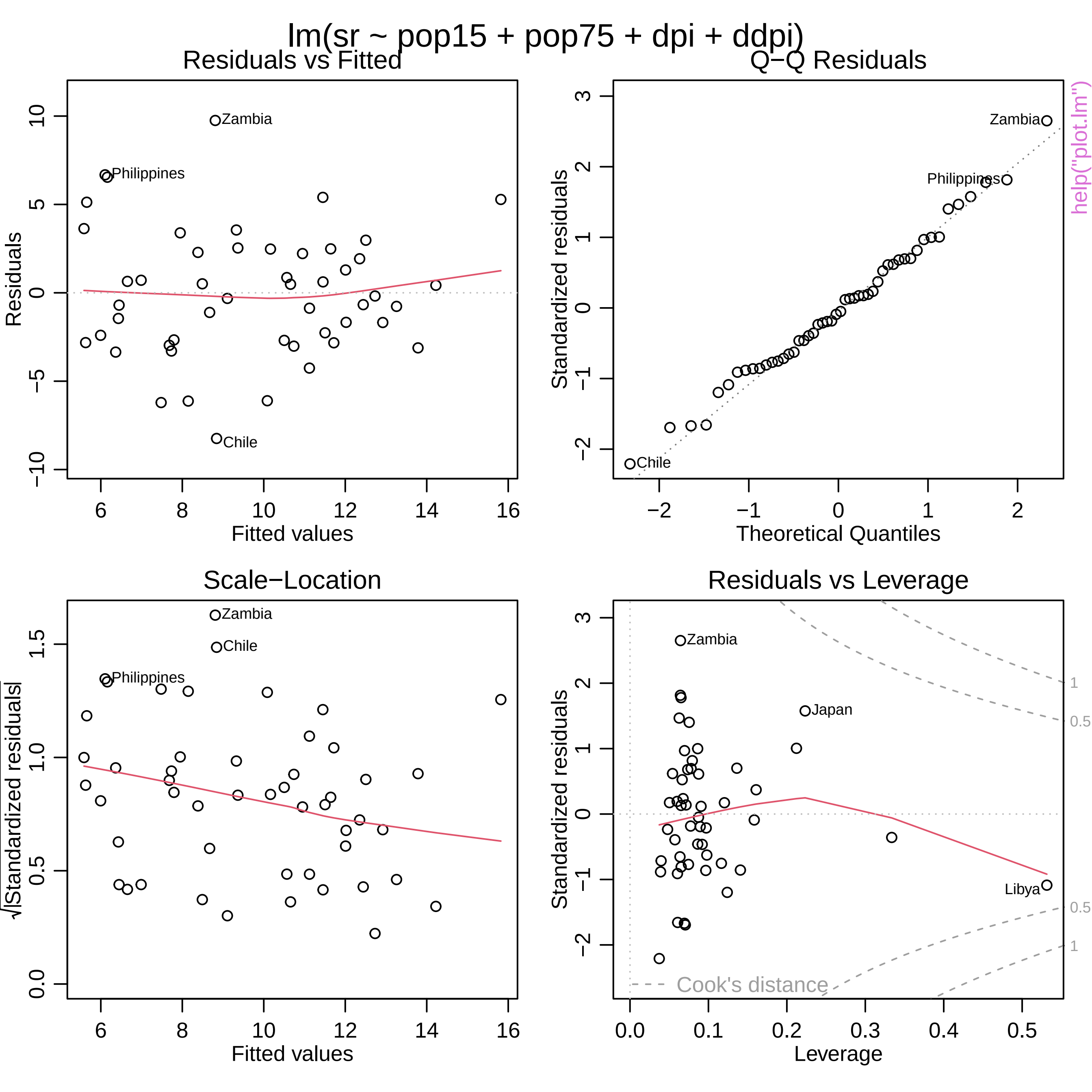


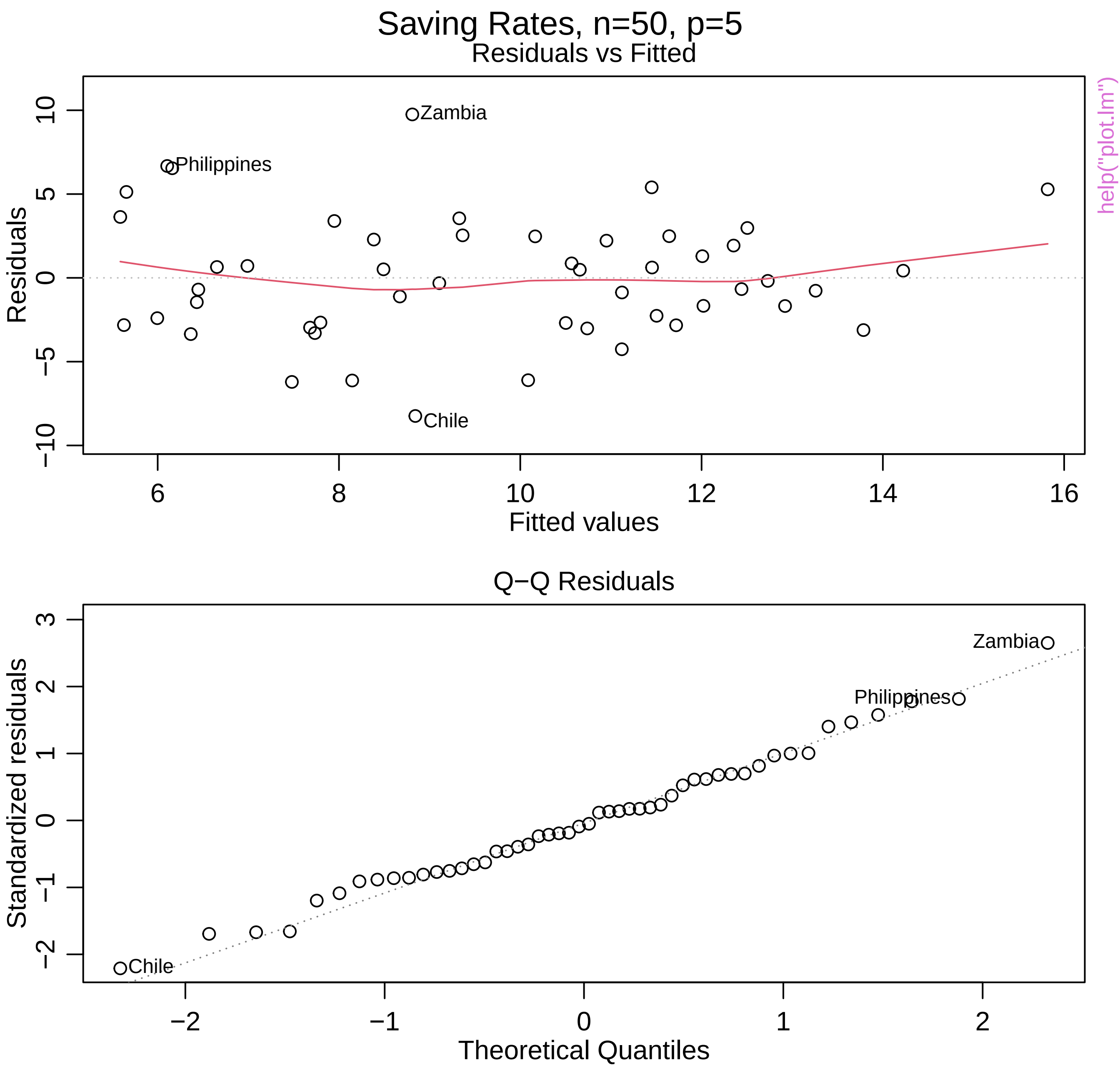
lm(sr ~ pop15 + pop75 + dpi + ddpi)
Residuals vs Fitted
Residuals
Fitted values
10
5
0
−5
6
8
10
12
14
16
Q−Q Residuals
Standardized residuals
Theoretical Quantiles
3
2
1
0
−1
−2
help("plot.lm")
Scale−Location
√|Standardized residuals|
Fitted values
1.5
1.0
0.5
0.0
Residuals vs Leverage
Standardized residuals
Leverage
0.0
0.1
0.2
0.3
0.4
0.5
Cook's distance
1
0.5



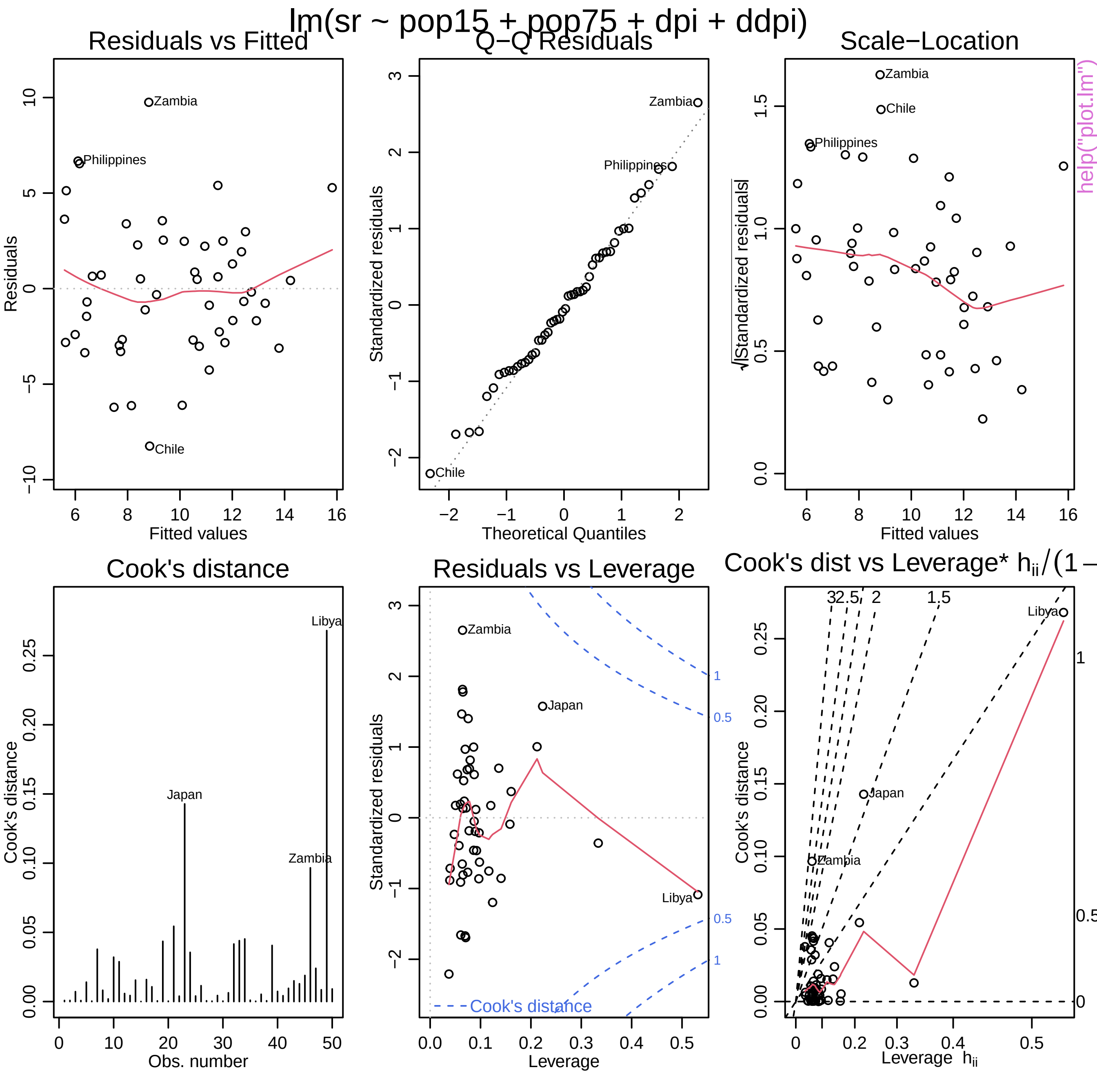
lm(sr ~ pop15 + pop75 + dpi + ddpi)
Residuals vs Fitted
Residuals
Fitted values
Q−Q Residuals
Standardized residuals
Theoretical Quantiles
help("plot.lm")
Scale−Location
√|Standardized residuals|
Fitted values
Residuals vs Leverage
Standardized residuals
Leverage
Cook's distance


lm(sr ~ pop15 + pop75 + dpi + ddpi)
Residuals vs Fitted
Residuals
Fitted values
Zambia
Philippines
Chile
Q−Q Residuals
Standardized residuals
Theoretical Quantiles
Zambia
Philippines
Chile
help("plot.lm")
Scale−Location
√|Standardized residuals|
Fitted values
Zambia
Chile
Philippines
Cook's distance
Cook's distance
Obs. number
Libya
Japan
Zambia

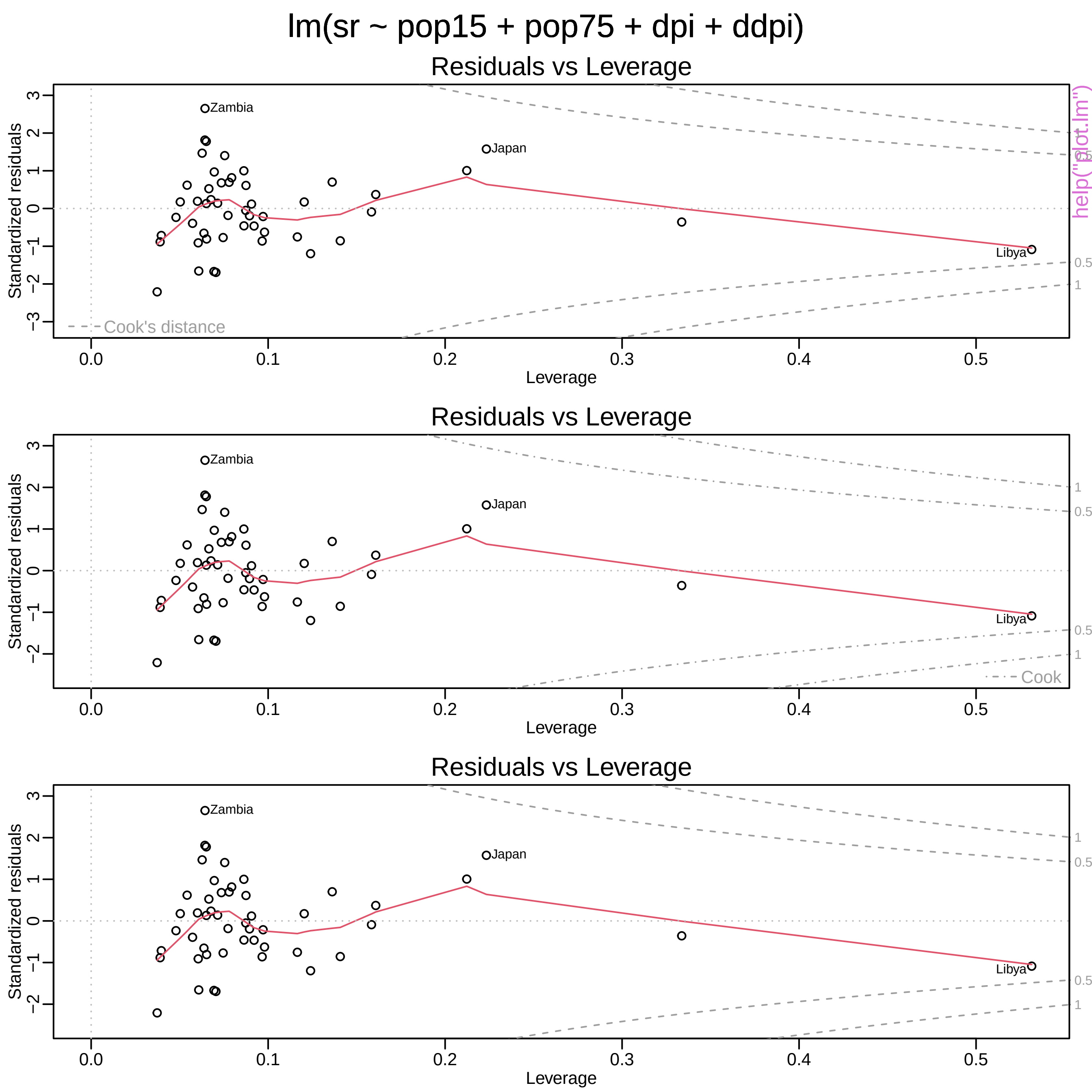

lm(sr ~ pop15 + pop75 + dpi + ddpi)
Residuals vs Fitted
Residuals
Fitted values
Zambia
Philippines
Chile
Q−Q Residuals
Standardized residuals
Theoretical Quantiles
help("plot.lm")
Scale−Location
√|Standardized residuals|
Residuals vs Leverage
Japan
Libya
Cook's distance
Leverage

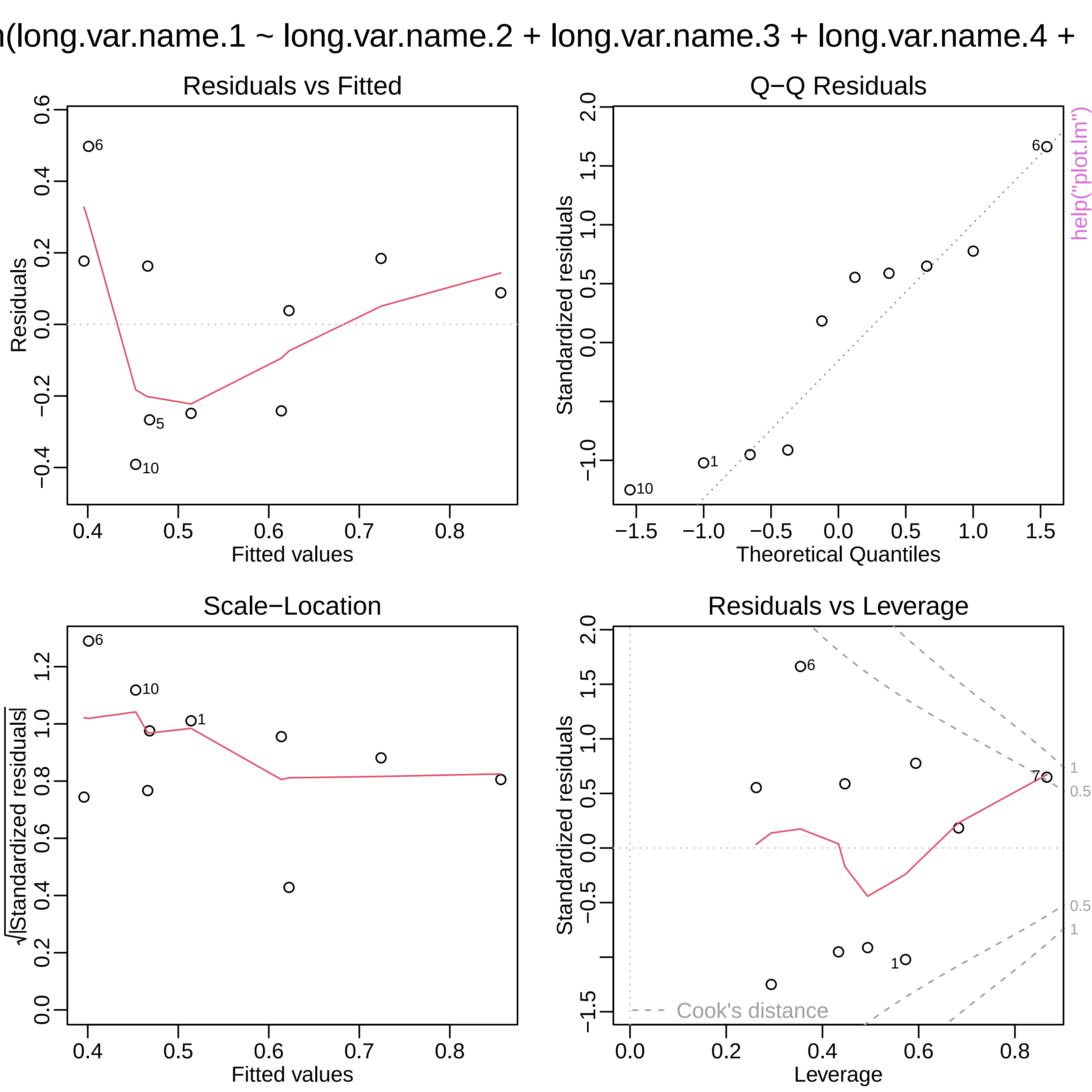


Saving Rates, n=50, p=5
Residuals vs Fitted
Residuals
10
5
0
−5
−10
Zambia
Philippines
Chile
6
8
10
12
14
16
Fitted values
help("plot.lm")
Q−Q Residuals
Standardized residuals
3
2
1
0
−1
−2
Zambia
Philippines
Chile
−2
−1
0
1
2
Theoretical Quantiles

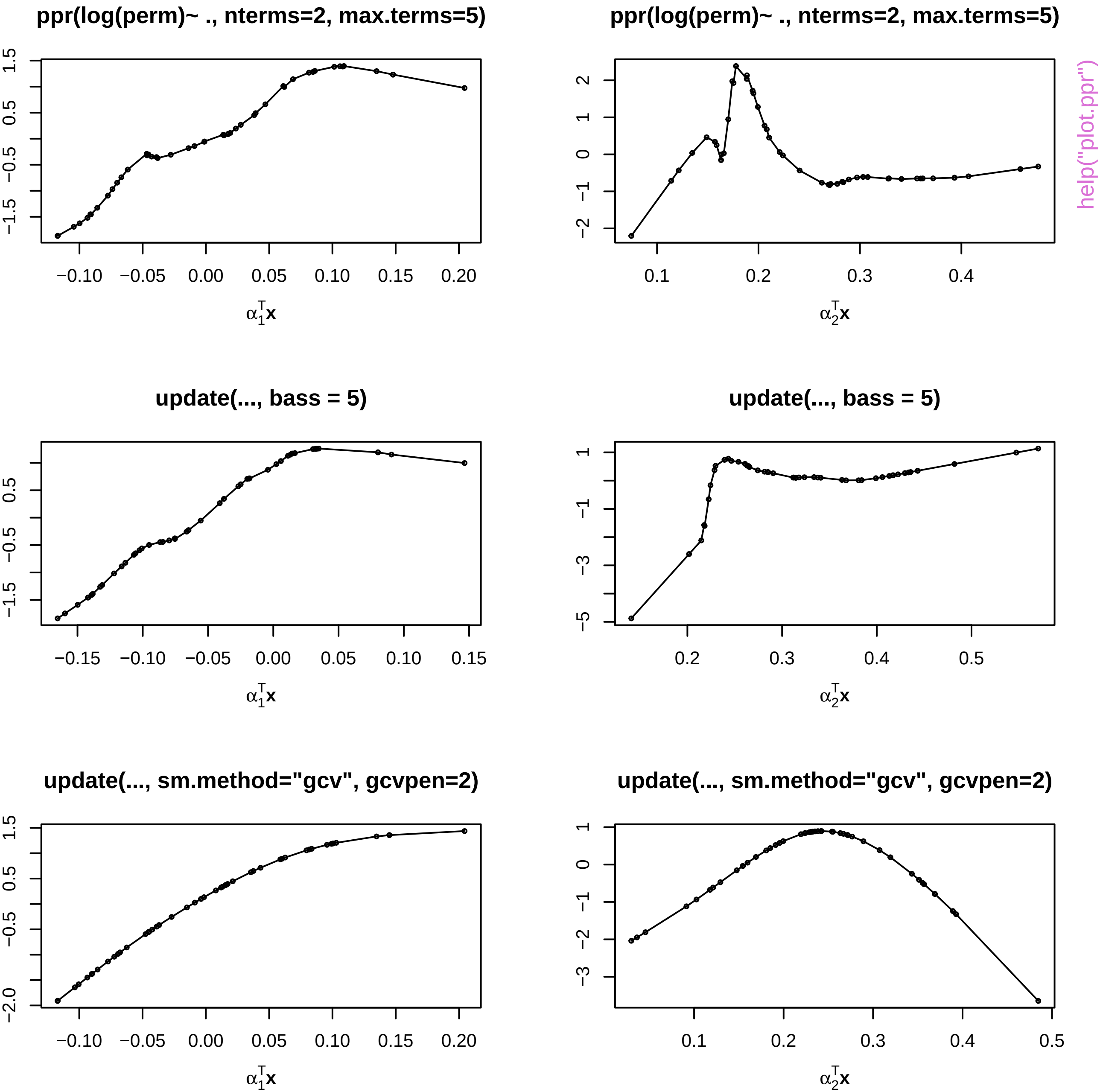


lm(sr ~ pop15 + pop75 + dpi + ddpi)
Residuals vs Fitted
Residuals
Fitted values
Zambia
Philippines
Chile
Q−Q Residuals
Standardized residuals
Theoretical Quantiles
Scale−Location
√|Standardized residuals|
help("plot.lm")
Cook's distance
Obs. number
Japan
Libya
Residuals vs Leverage
Leverage
Cook's distance
Cook's dist vs Leverage* h_ii/(1 −
Leverage h_ii

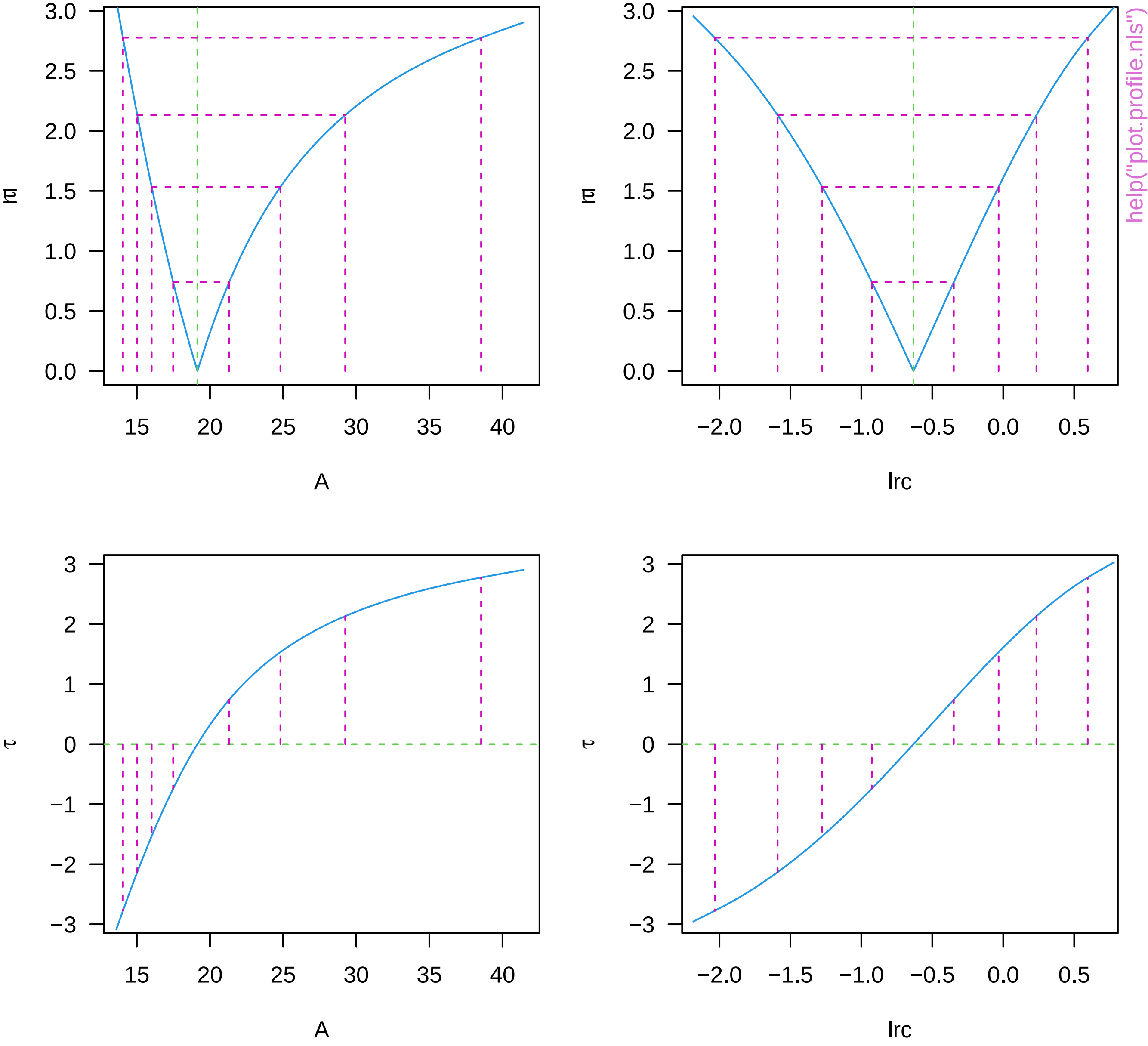

lm(sr ~ pop15 + pop75 + dpi + ddpi)
Residuals vs Leverage
Standardized residuals
Leverage
Zambia
Japan
Libya
Cook's distance
help("plot.lm")
0.5
1
Residuals vs Leverage
Standardized residuals
Leverage
Zambia
Japan
Libya
Cook
1
0.5
0.5
1
Residuals vs Leverage
Standardized residuals
Leverage
Zambia
Japan
Libya
1
0.5
0.5
1



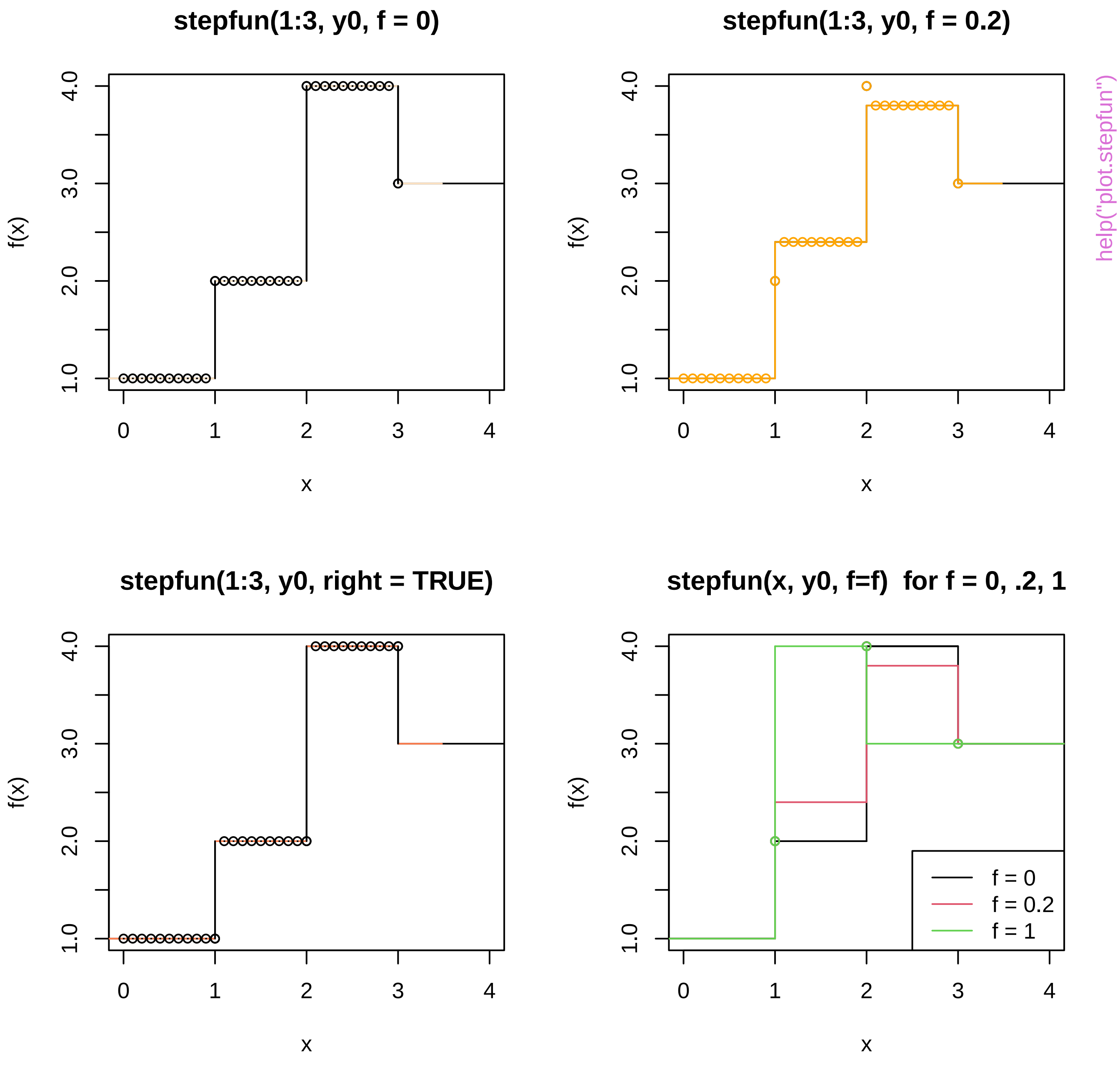
n(long.var.name.1 ~ long.var.name.2 + long.var.name.3 + long.var.name.4 +
Residuals vs Fitted
Residuals
Fitted values
Q−Q Residuals
Standardized residuals
Theoretical Quantiles
help("plot.lm")
Scale−Location
√|Standardized residuals|
Fitted values
Residuals vs Leverage
Standardized residuals
Leverage
Cook's distance


ppr(log(perm)~ ., nterms=2, max.terms=5)
1.5
0.5
−0.5
−1.5
−0.10
−0.05
0.00
0.05
0.10
0.15
0.20
$\alpha_1^T\mathbf{x}$
ppr(log(perm)~ ., nterms=2, max.terms=5)
2
1
0
−1
−2
0.1
0.2
0.3
0.4
$\alpha_2^T\mathbf{x}$
help("plot.ppr")
update(..., bass = 5)
0.5
−0.5
−1.5
−0.15
−0.10
−0.05
0.00
0.05
0.10
0.15
$\alpha_1^T\mathbf{x}$
update(..., bass = 5)
1
−1
−3
−5
0.2
0.3
0.4
0.5
$\alpha_2^T\mathbf{x}$
update(..., sm.method="gcv", gcvpen=2)
1.5
0.5
−0.5
−2.0
−0.10
−0.05
0.00
0.05
0.10
0.15
0.20
$\alpha_1^T\mathbf{x}$
update(..., sm.method="gcv", gcvpen=2)
1
0
−1
−2
−3
0.1
0.2
0.3
0.4
0.5
$\alpha_2^T\mathbf{x}$

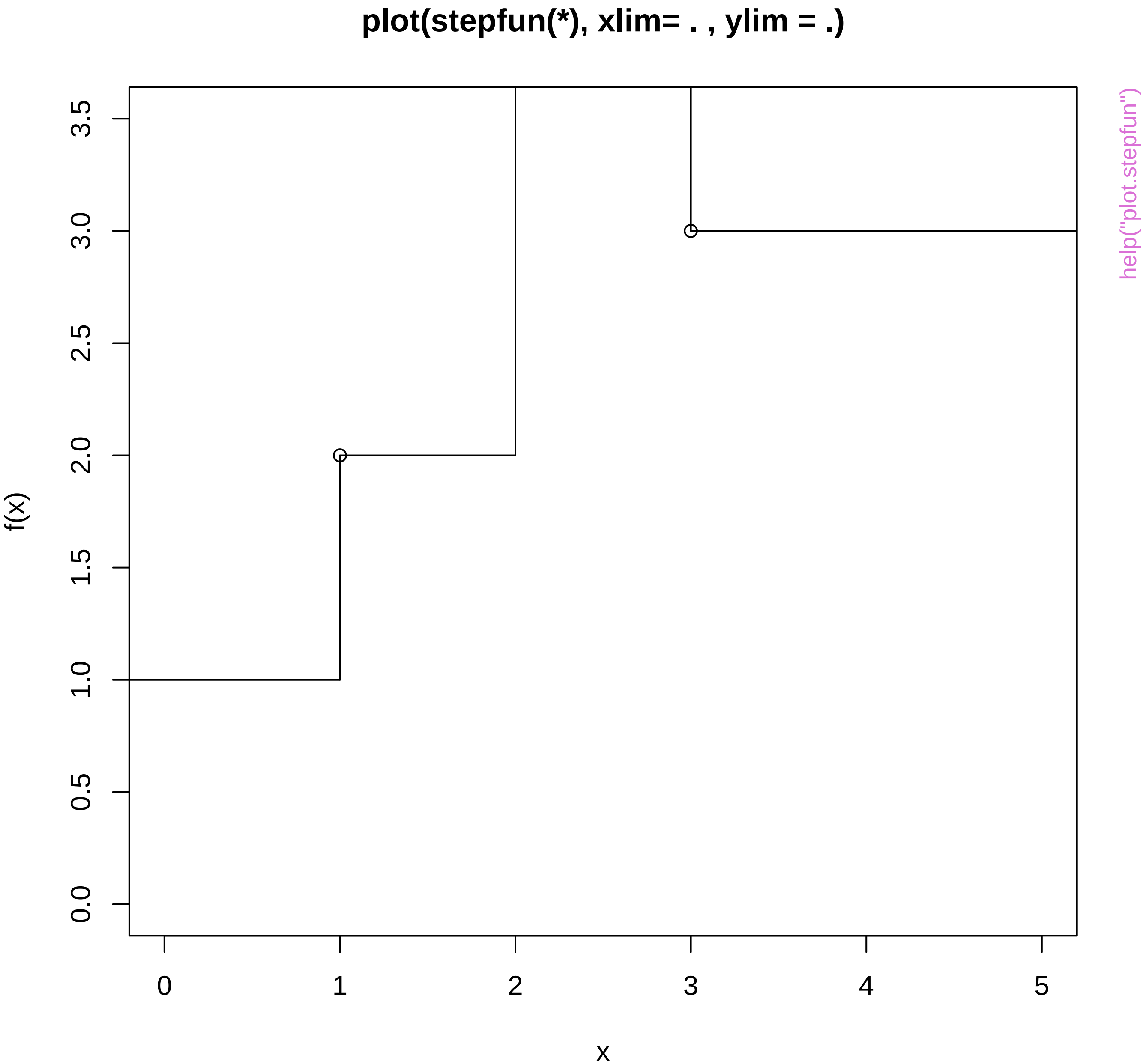
Confidence intervals based on the profile sum of squares

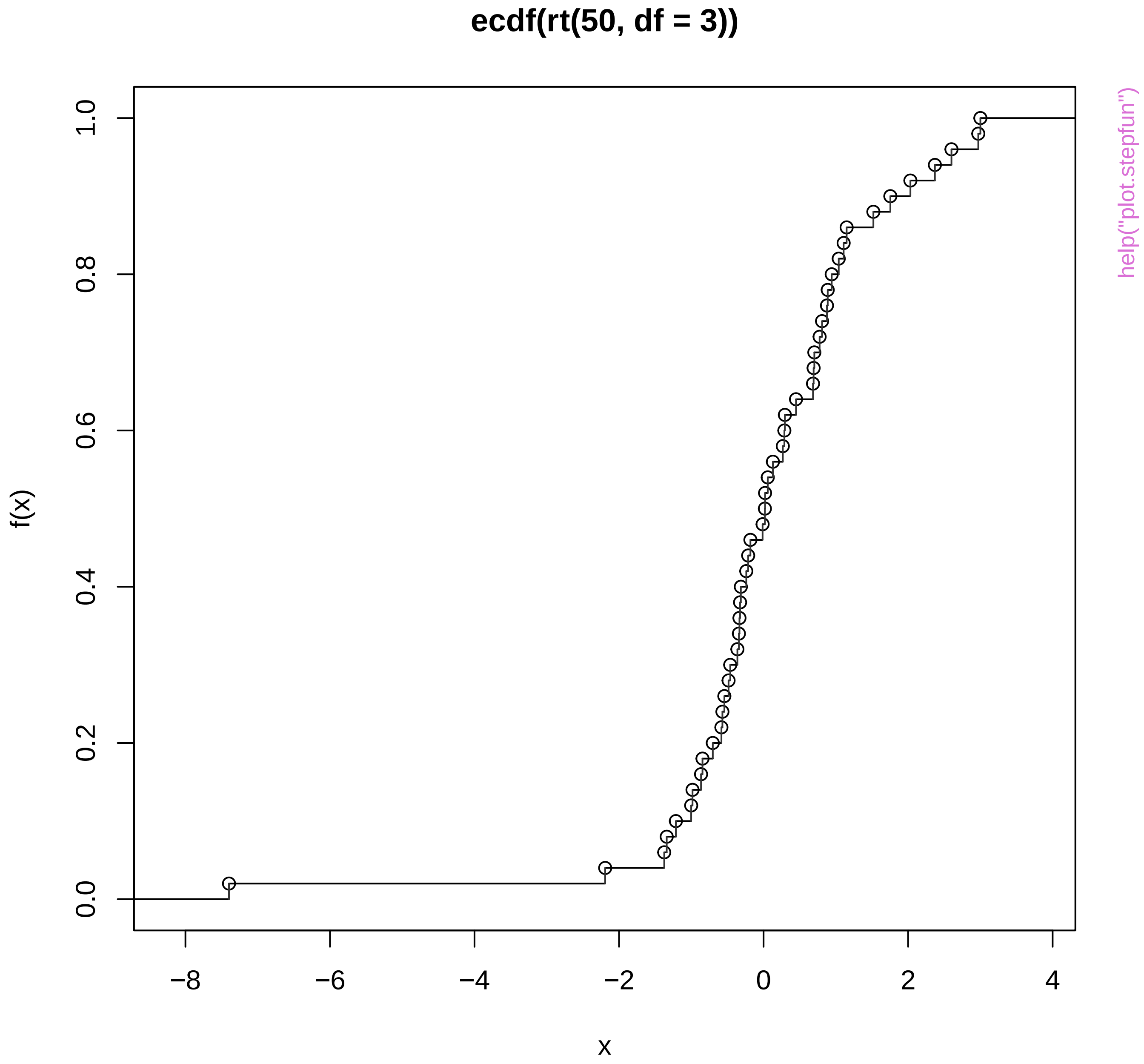


BOD data − confidence levels of 50%, 80%, 90% and 95%

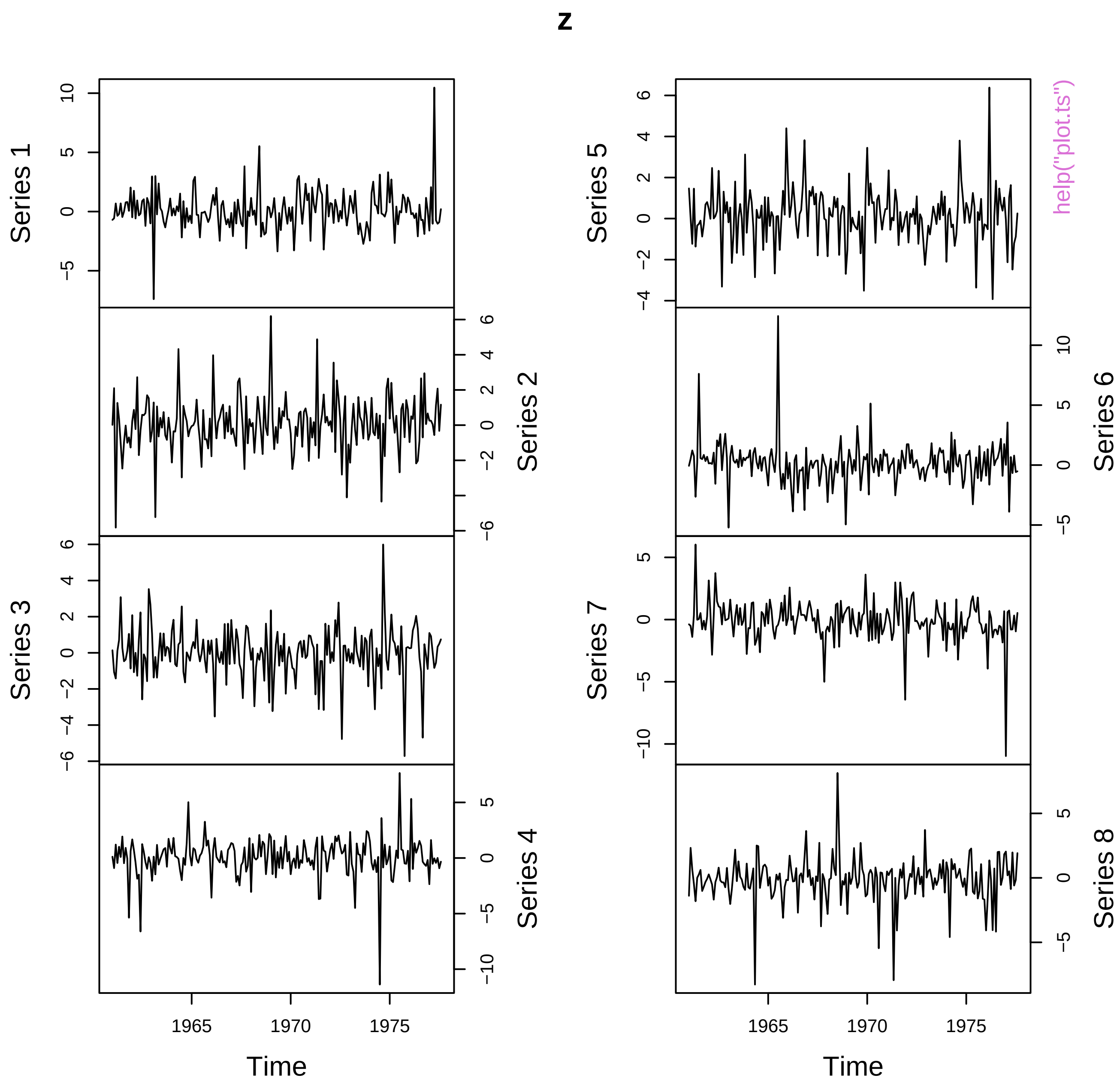


stepfun(1:3, y0, f = 0)
stepfun(1:3, y0, f = 0.2)
stepfun(1:3, y0, right = TRUE)
stepfun(x, y0, f=f) for f = 0, .2, 1
f(x)
x
1.0
2.0
3.0
4.0
0
1
2
3
4
f = 0
f = 0.2
f = 1
help("plot.stepfun")

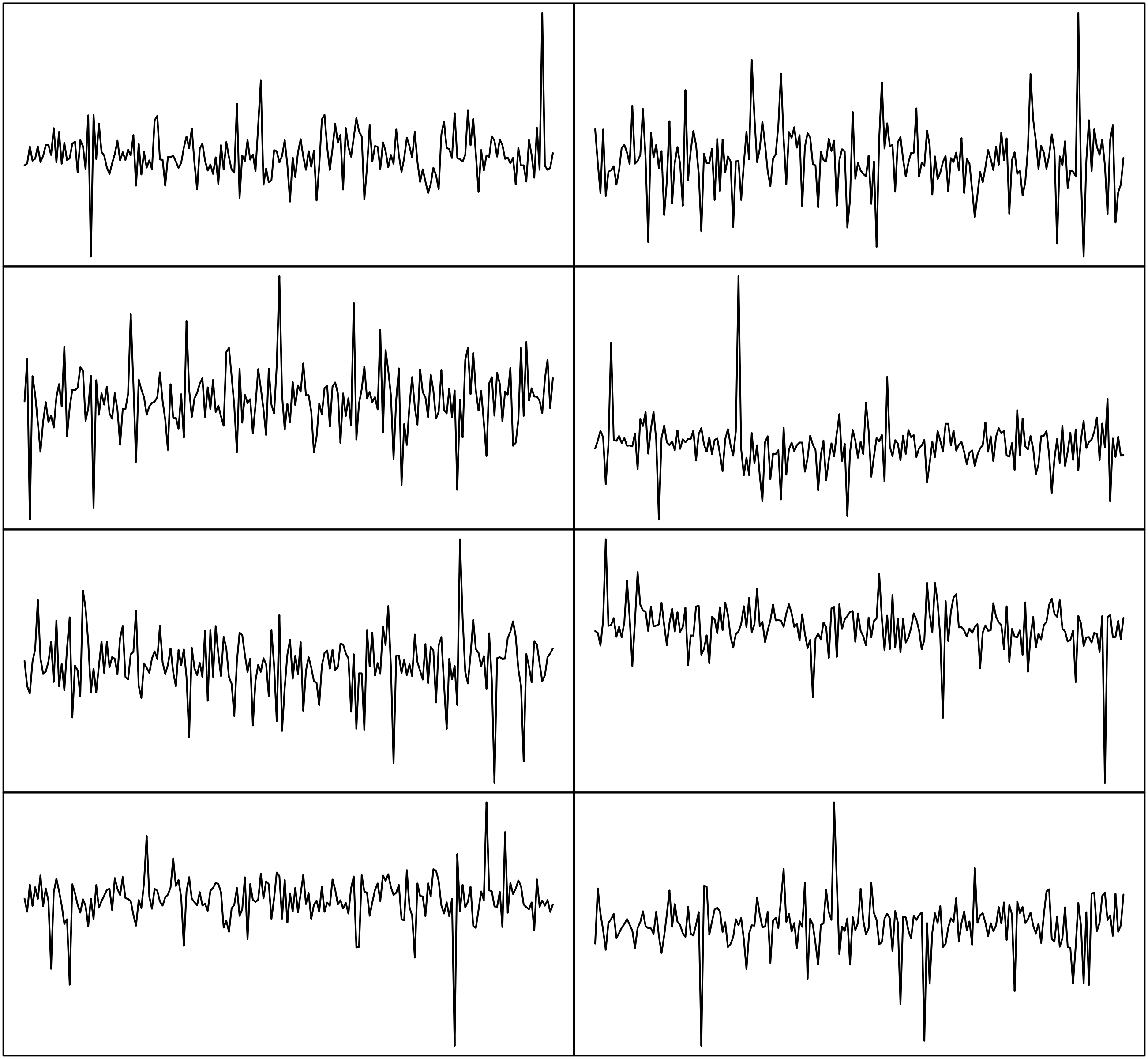

plot(stepfun(*), xlim= . , ylim = .)
f(x)
x
0
1
2
3
4
5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
help("plot.stepfun")

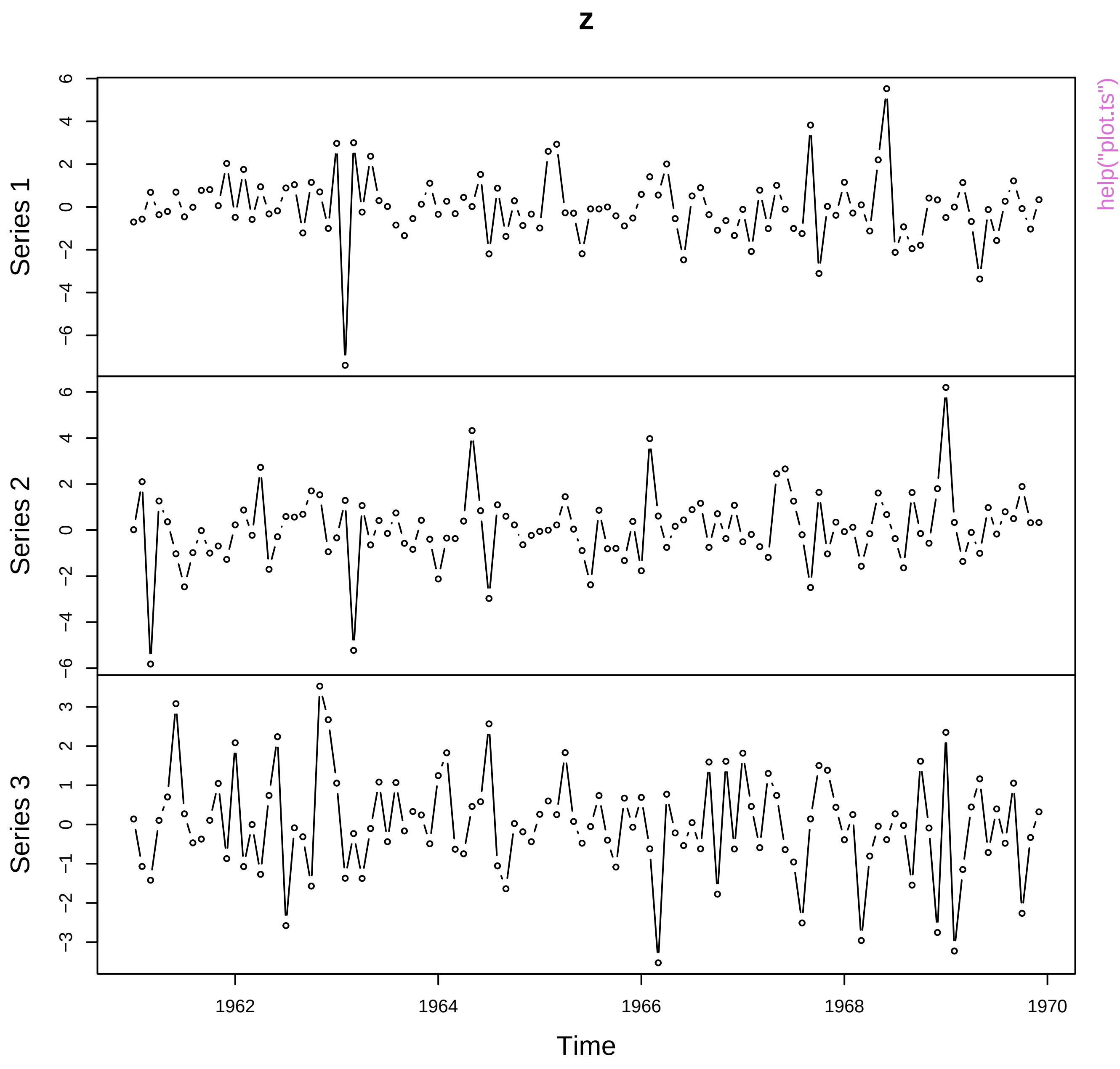


ecdf(rt(50, df = 3))
f(x)
0.0
0.2
0.4
0.6
0.8
1.0
−8
−6
−4
−2
0
2
4
x
help("plot.stepfun")

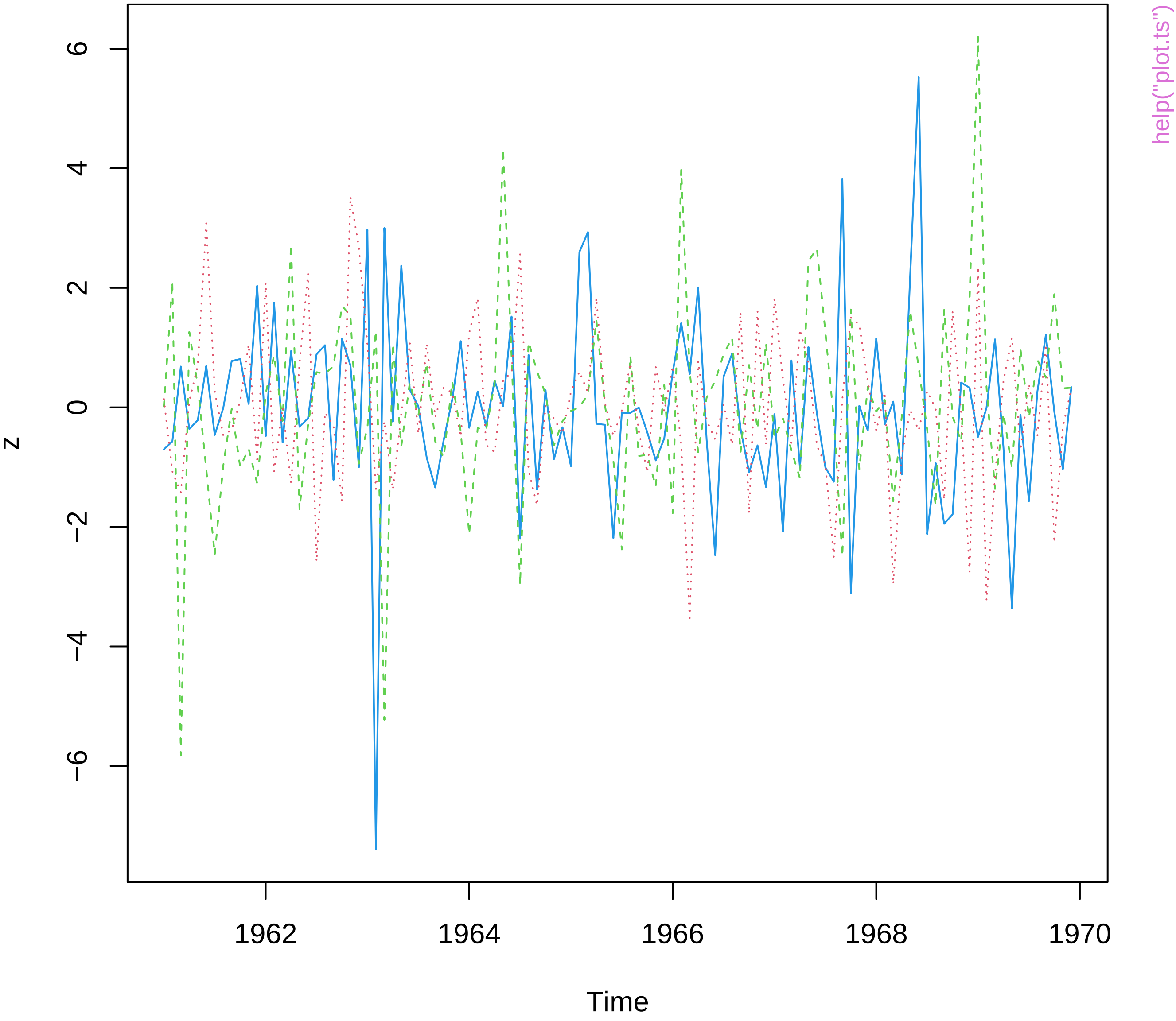

z
Series 1
Series 2
Series 3
Series 4
Series 5
Series 6
Series 7
Series 8
help("plot.ts")
1965
1970
1975
Time

plot(ts(..), axes=FALSE, ann=FALSE, frame.plot=TRUE, mar..., oma...)

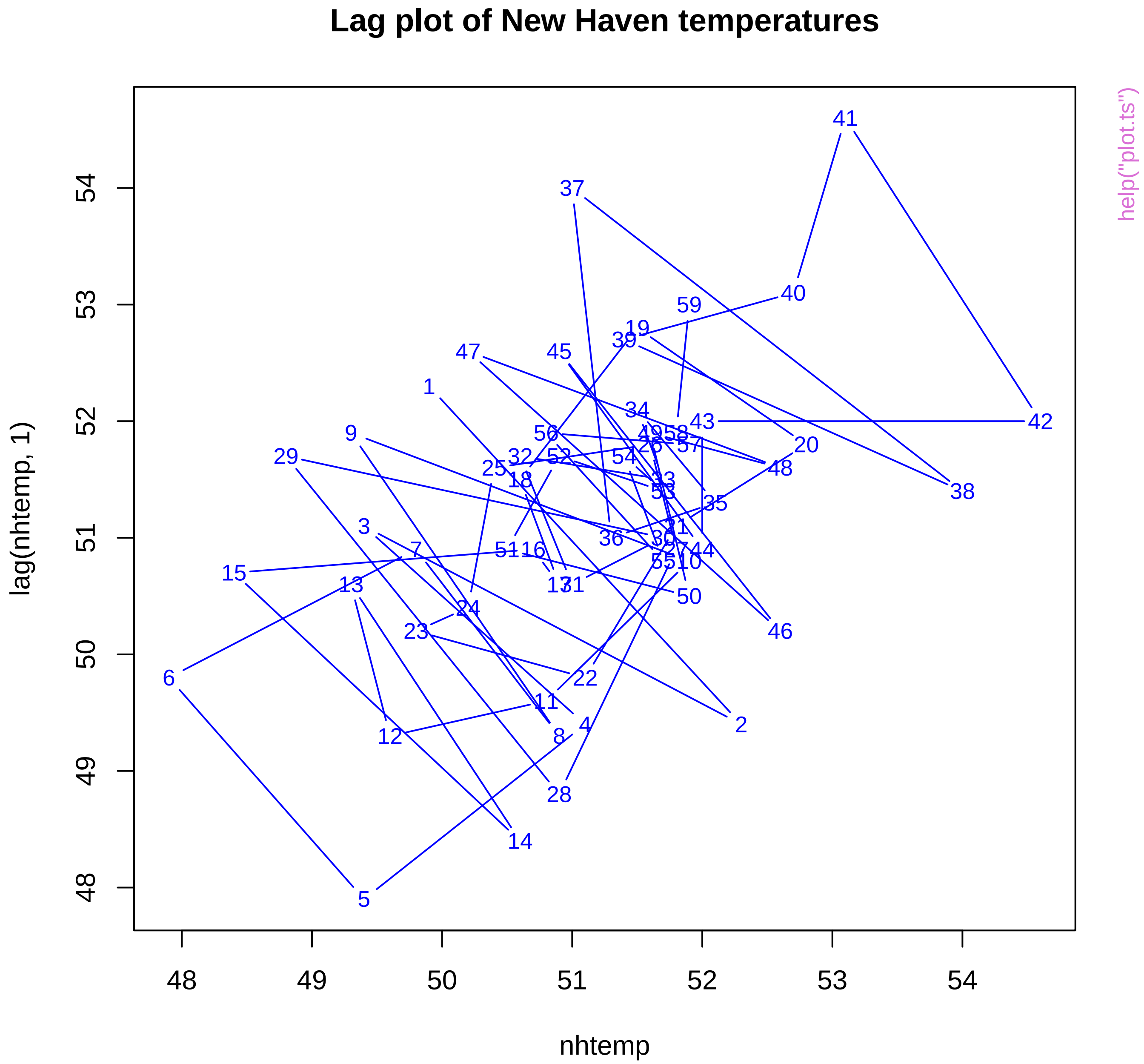




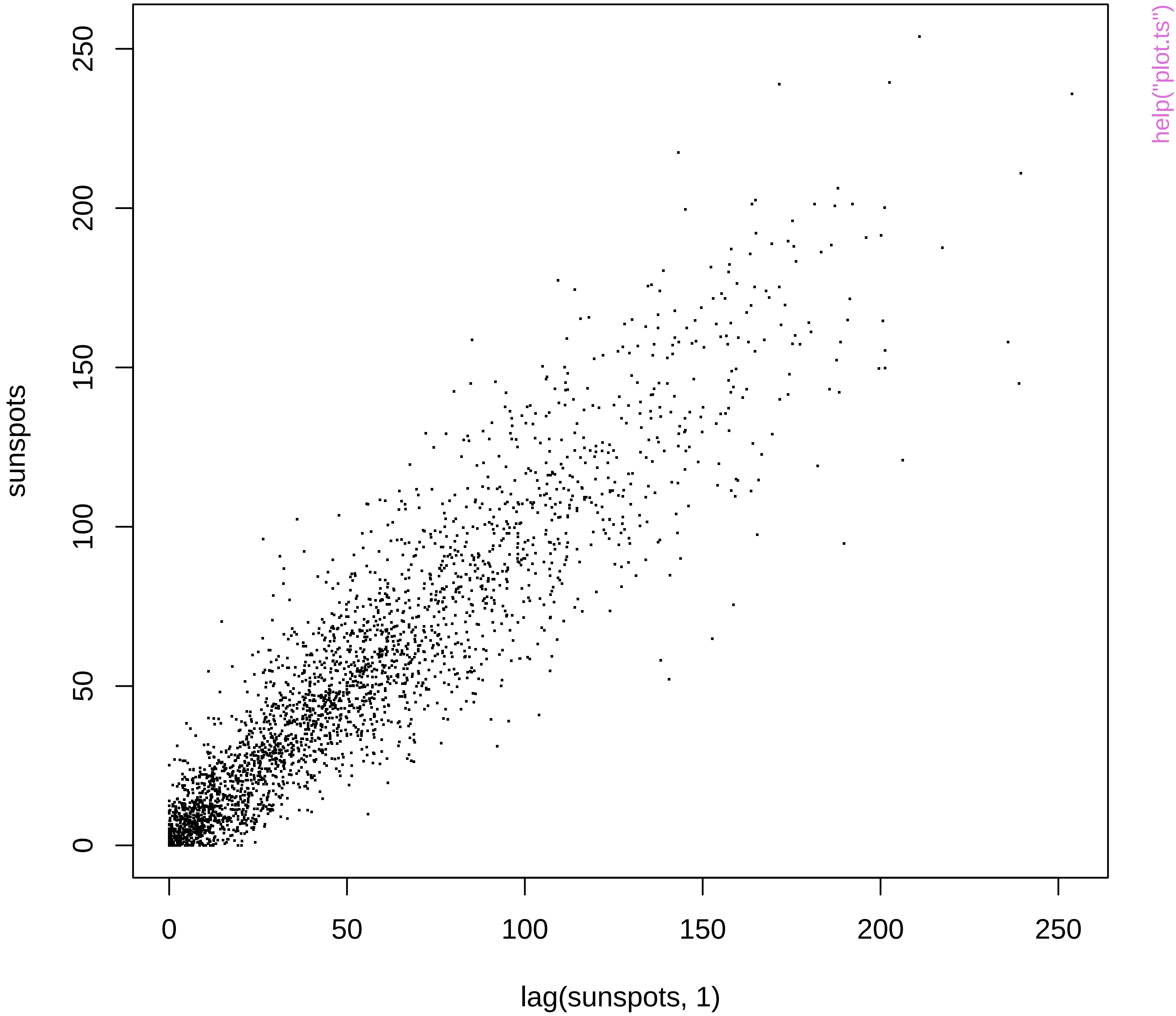
z
Series 1
Series 2
Series 3
Time
1962
1964
1966
1968
1970
help("plot.ts")

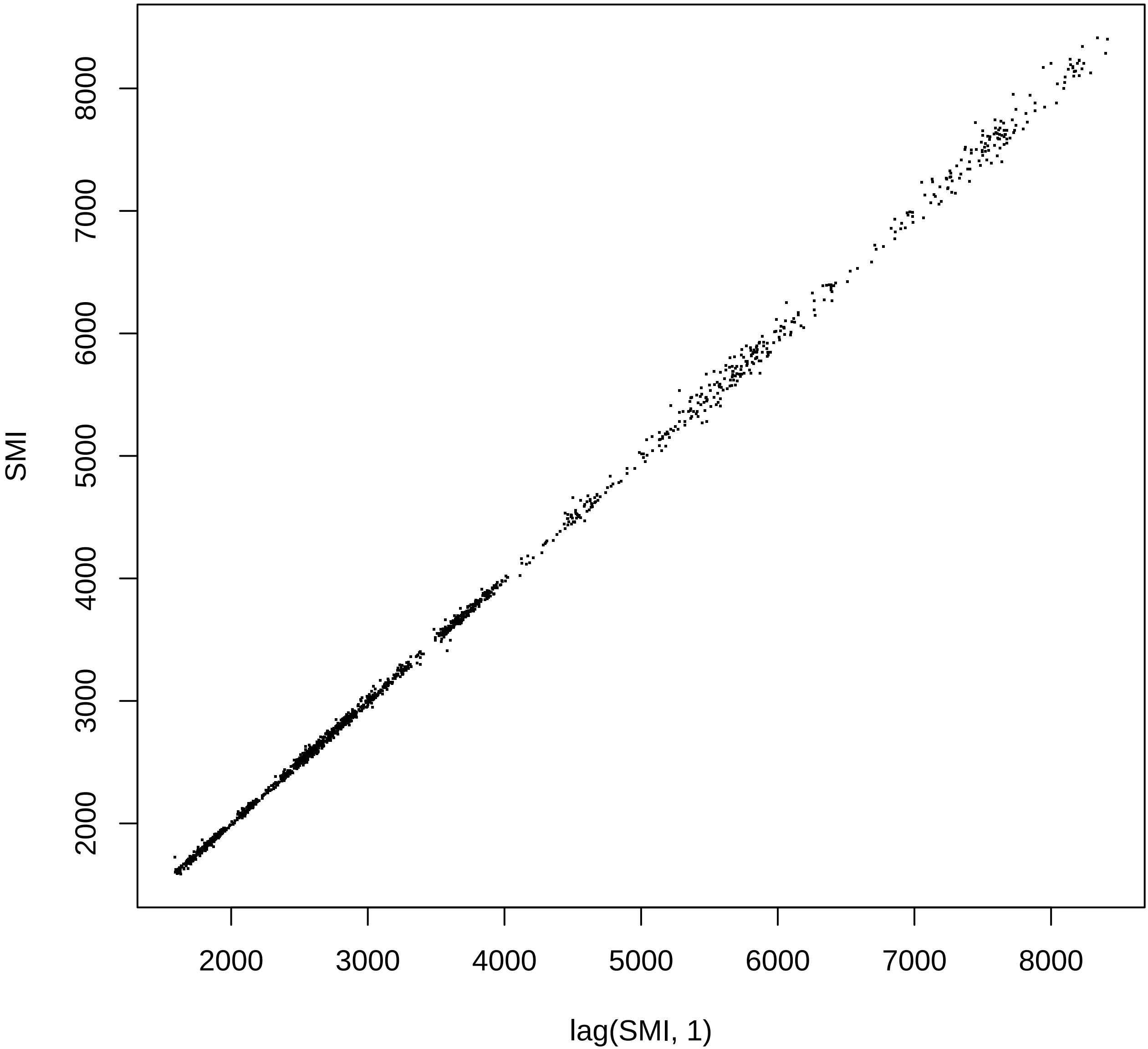


z
6
4
2
0
−2
−4
−6
1962
1964
1966
1968
1970
Time
help("plot.ts")



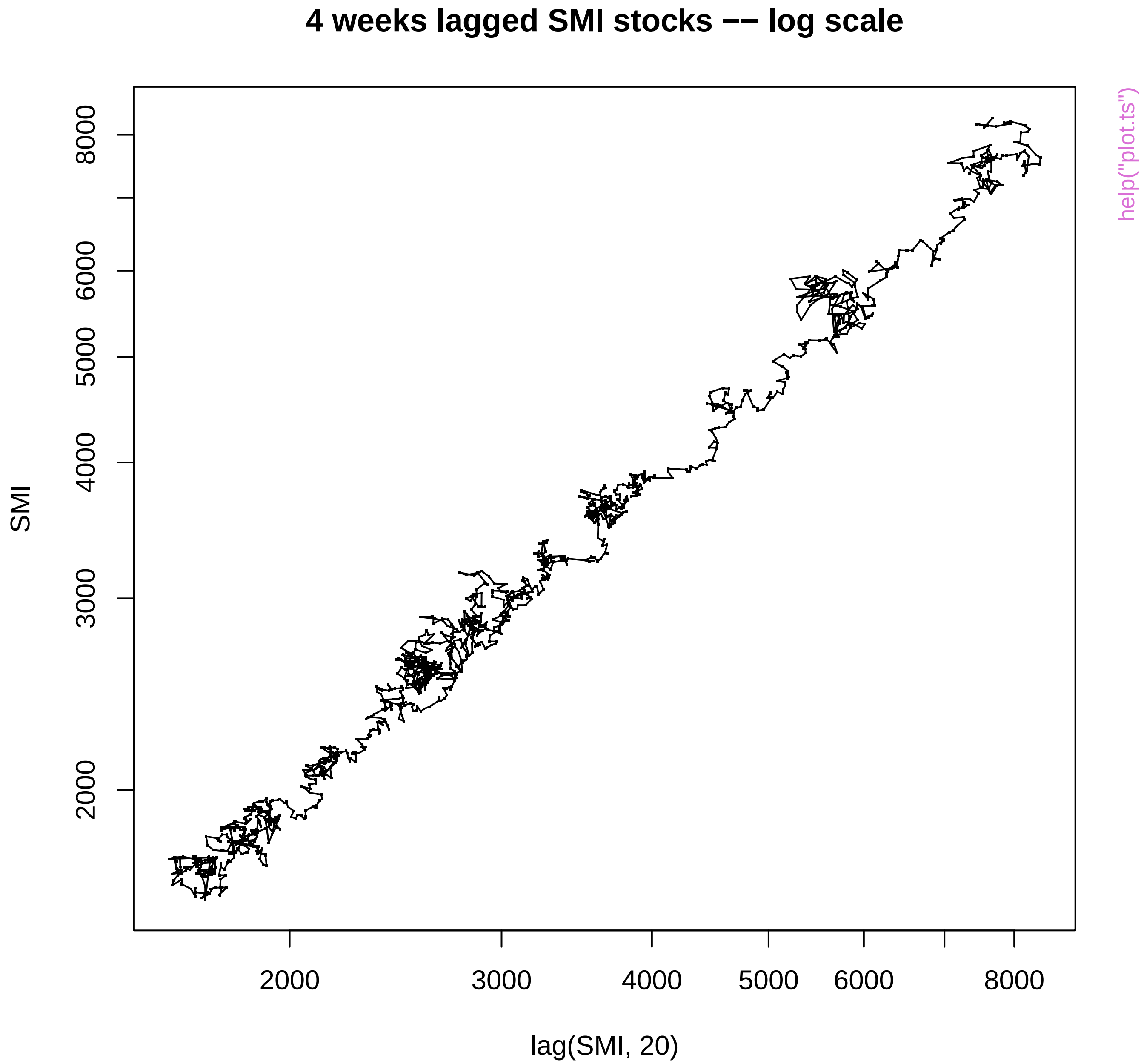
Lag plot of New Haven temperatures
lag(nhtemp, 1)
nhtemp
48
49
50
51
52
53
54
help("plot.ts")

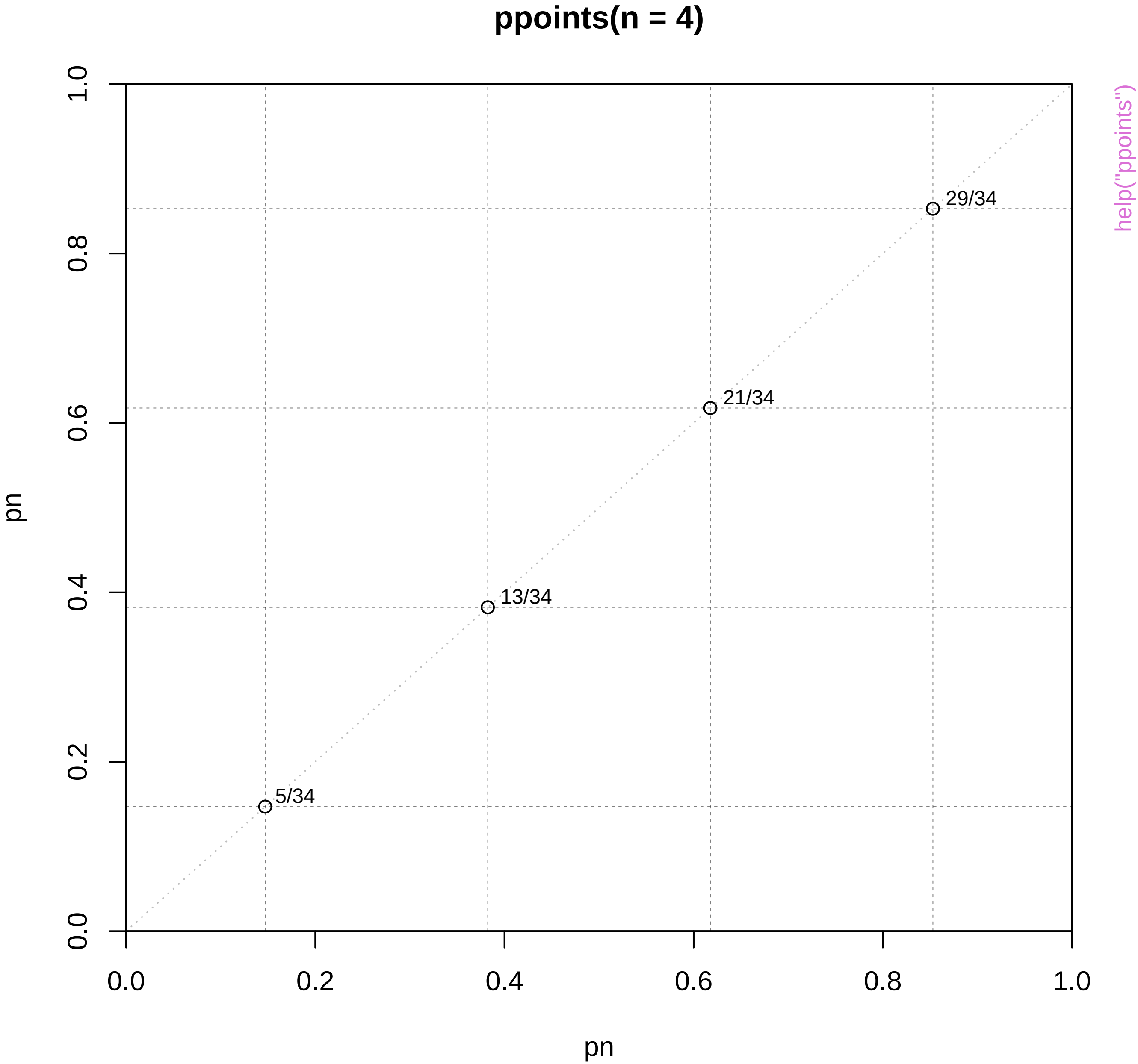

sunspots
lag(sunspots, 1)
0
50
100
150
200
250
help("plot.ts")

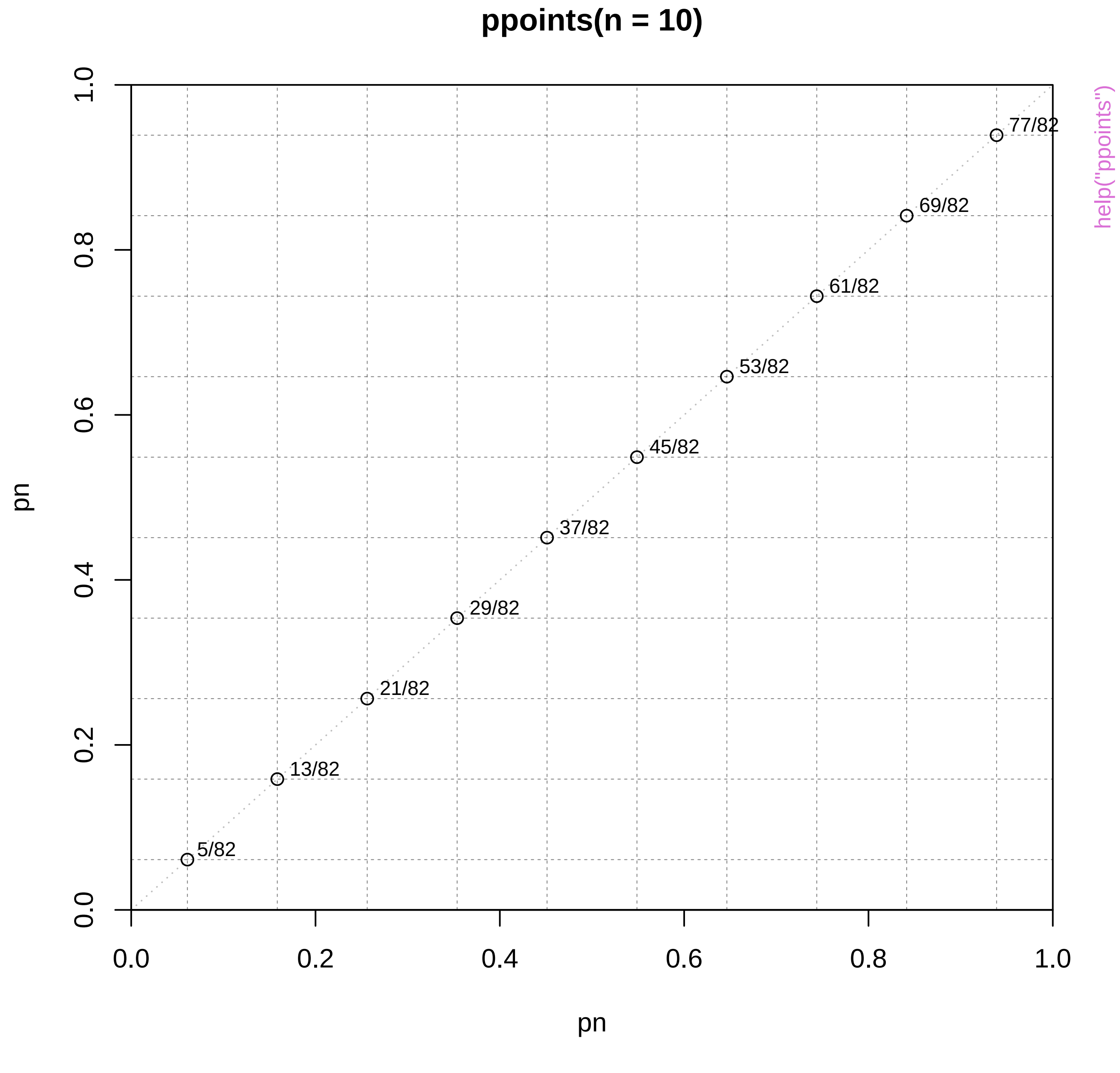


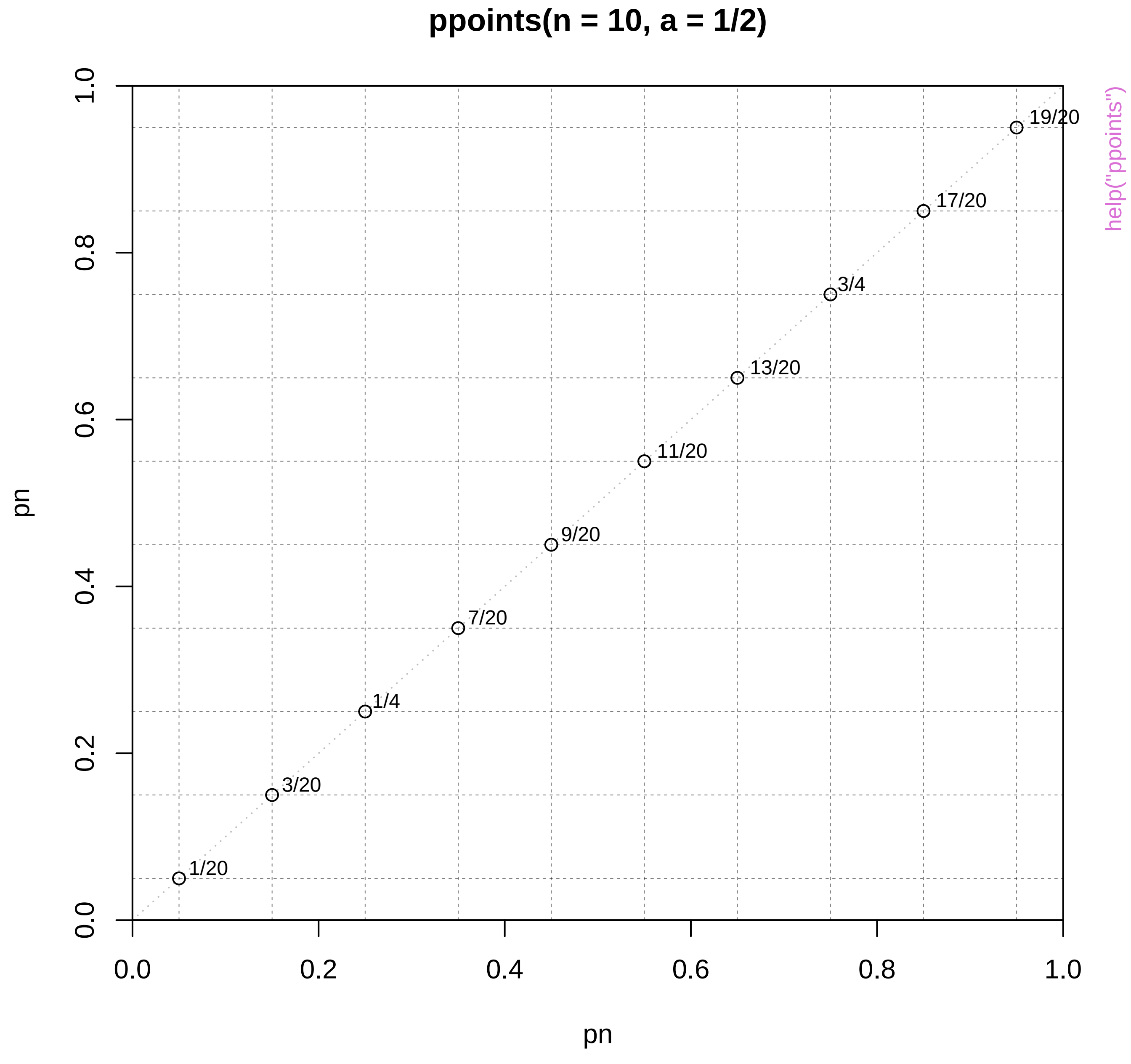
SMI
8000
7000
6000
5000
4000
3000
2000
2000
3000
4000
5000
6000
7000
8000
lag(SMI, 1)

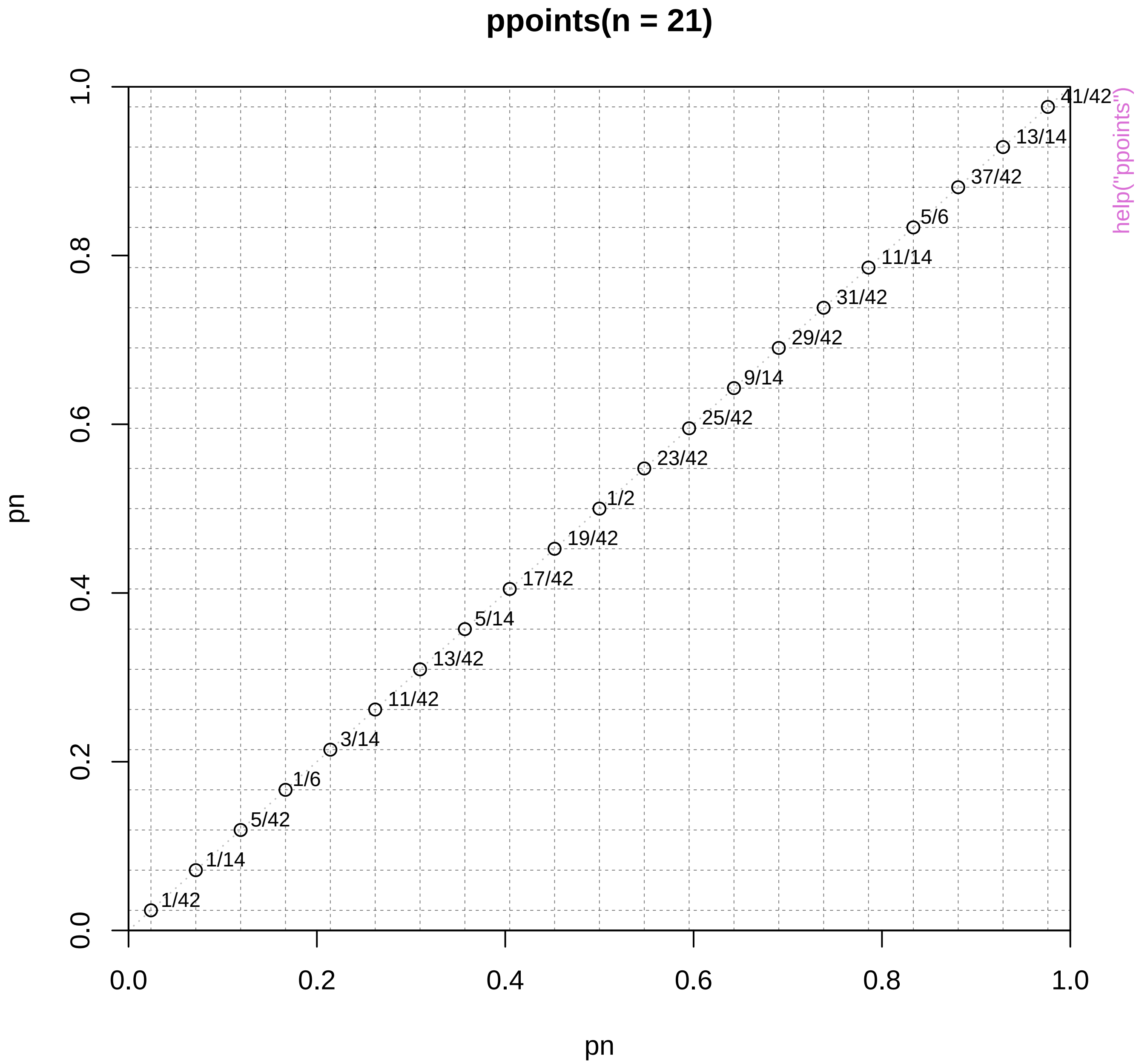
help("plot.ts")

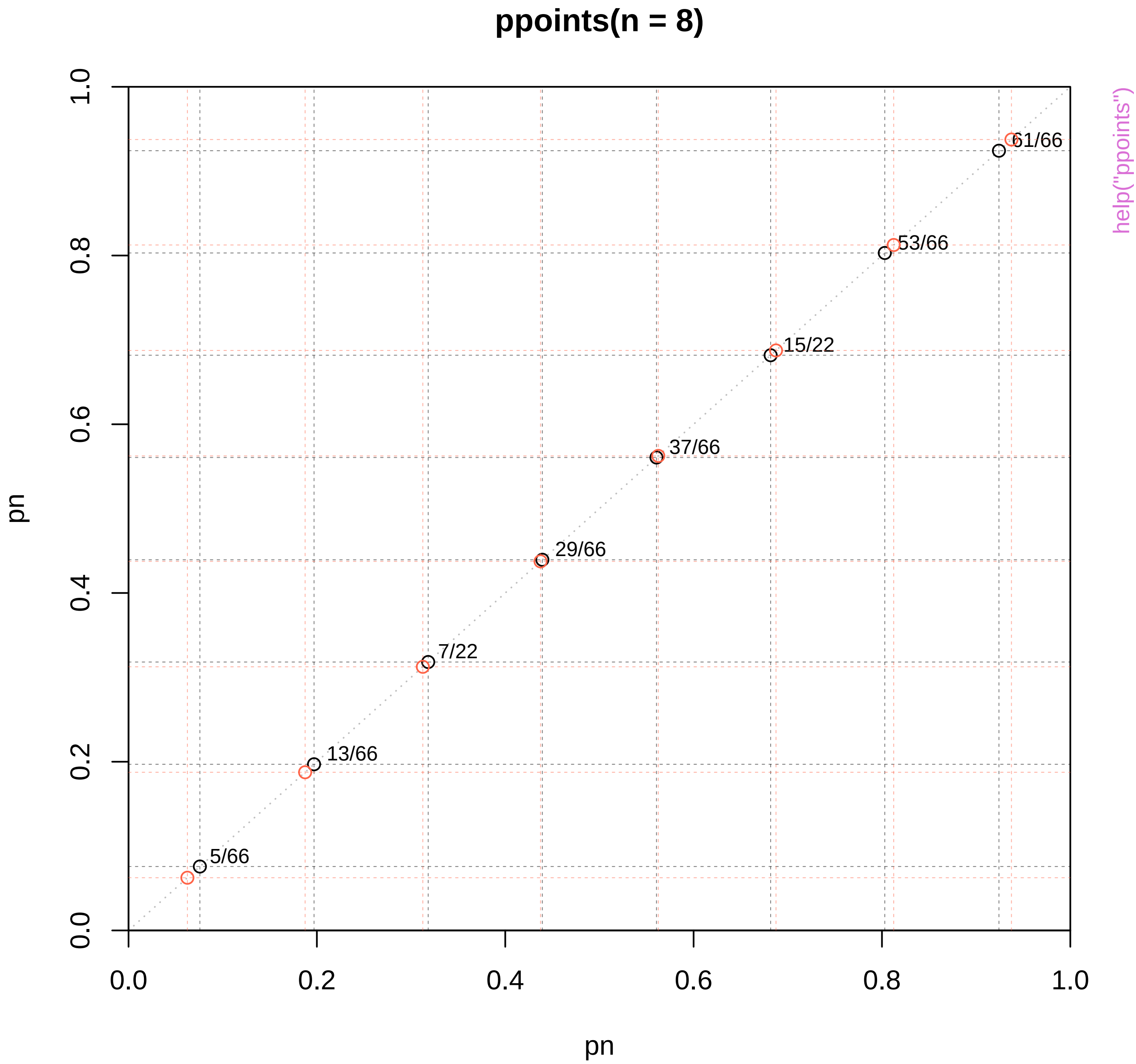

4 weeks lagged SMI stocks -- log scale
SMI
8000
6000
5000
4000
3000
2000
lag(SMI, 20)
2000
3000
4000
5000
6000
8000
help("plot.ts")

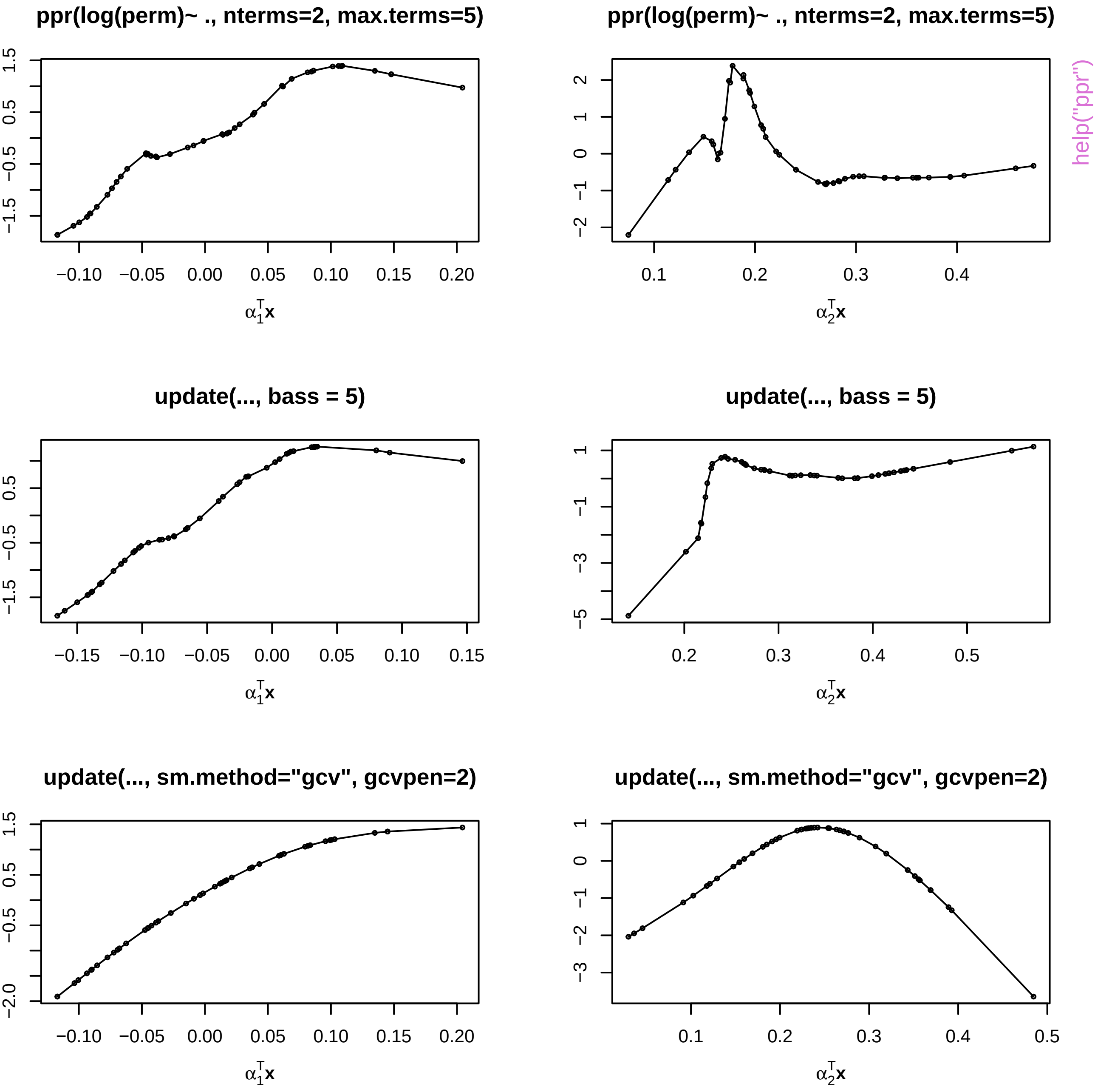

ppoints(n = 4)
help("ppoints")
pn
pn
0.0
0.2
0.4
0.6
0.8
1.0
0.0
0.2
0.4
0.6
0.8
1.0
5/34
13/34
21/34
29/34

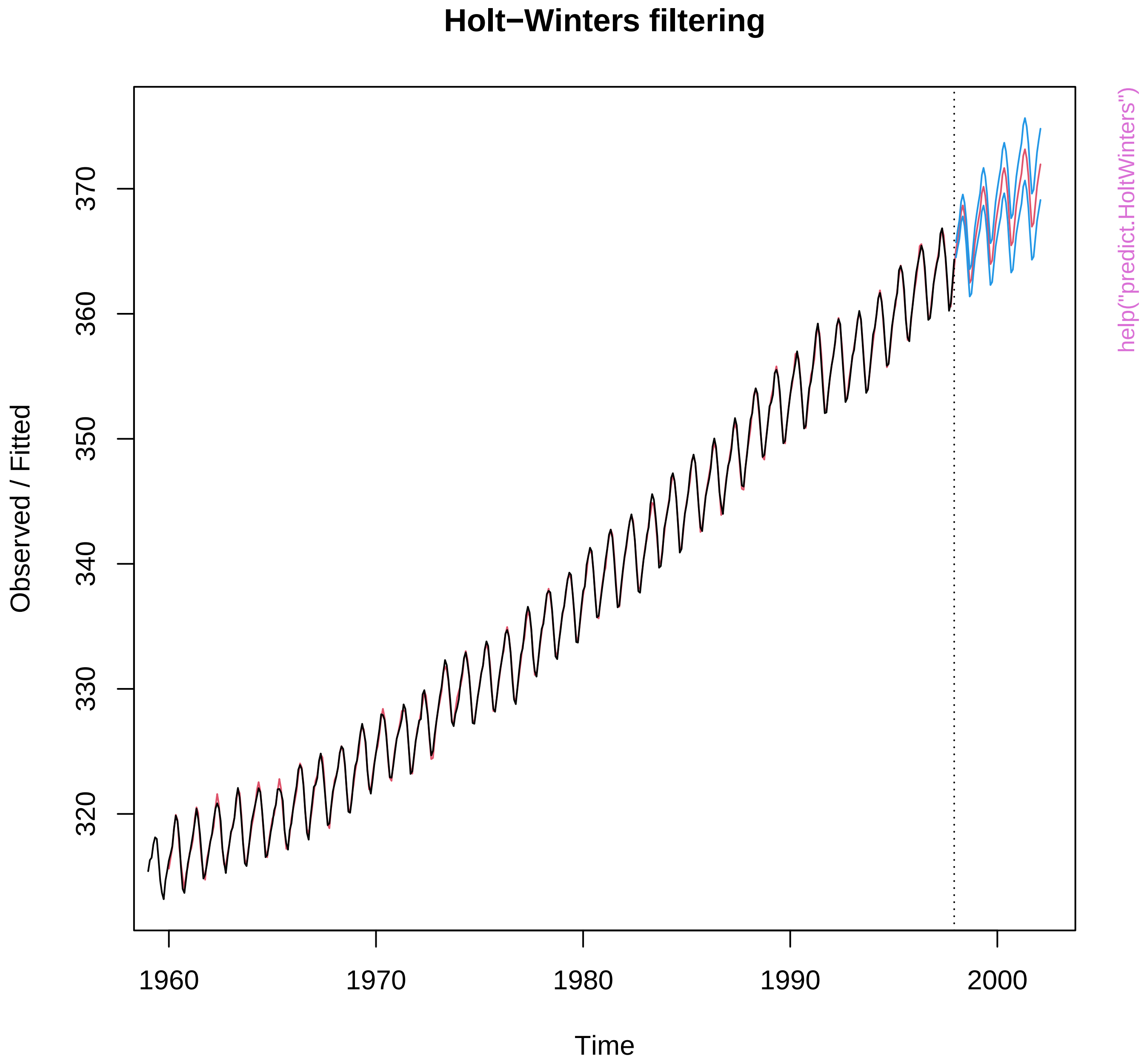

ppoints(n = 10)
5/82
13/82
21/82
29/82
37/82
45/82
53/82
61/82
69/82
77/82
0.0
0.2
0.4
0.6
0.8
1.0
pn
pn
help("ppoints")


ppoints(n = 10, a = 1/2)
1/20
3/20
1/4
7/20
9/20
11/20
13/20
3/4
17/20
19/20
0.0
0.2
0.4
0.6
0.8
1.0
pn
pn
help("ppoints")

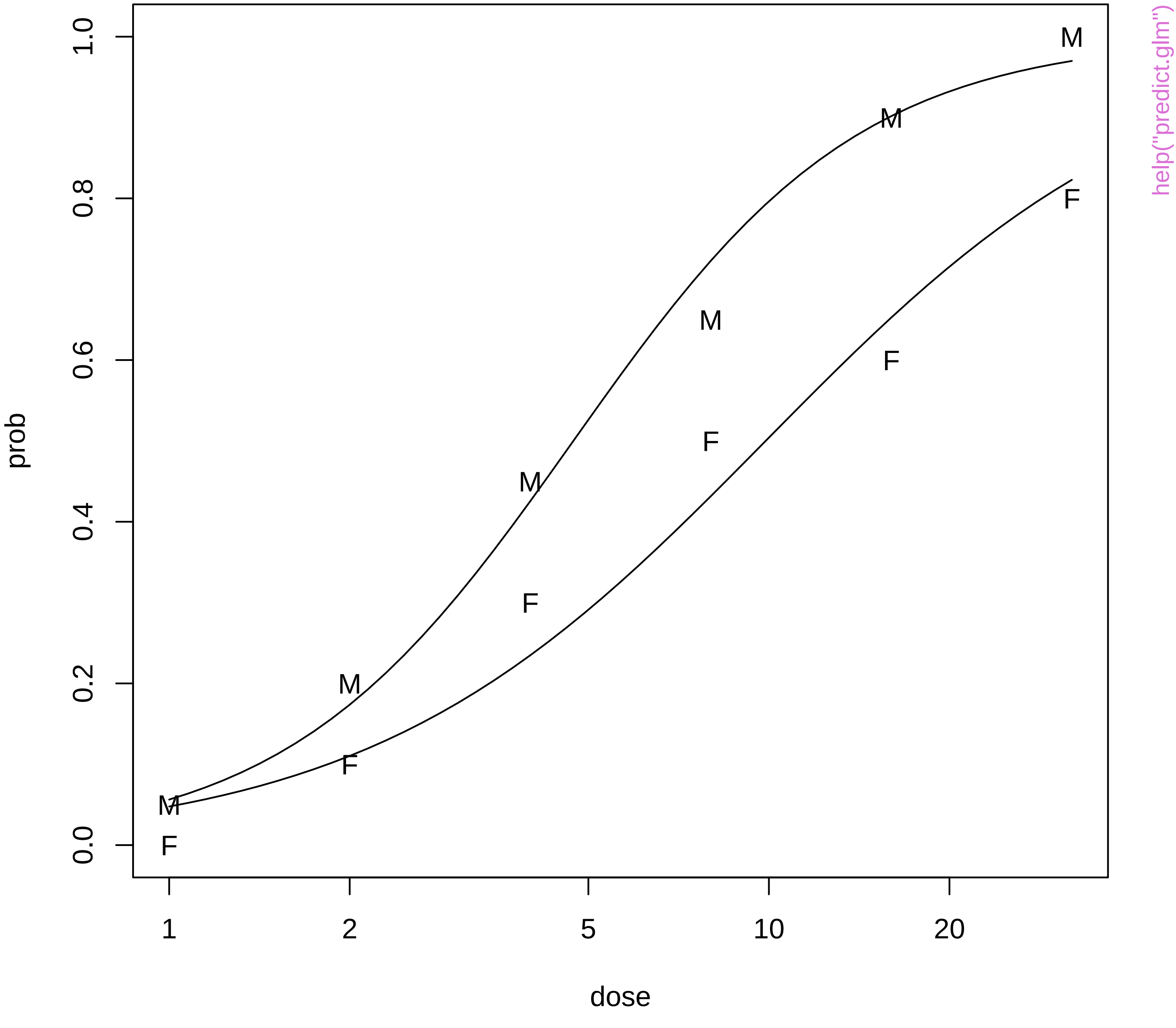

ppoints(n = 21)
pn
pn
0.0
0.2
0.4
0.6
0.8
1.0
0.0
0.2
0.4
0.6
0.8
1.0
1/42
1/14
5/42
1/6
3/14
11/42
13/42
5/14
17/42
19/42
1/2
23/42
25/42
9/14
29/42
31/42
11/14
5/6
37/42
13/14
41/42
help("ppoints")

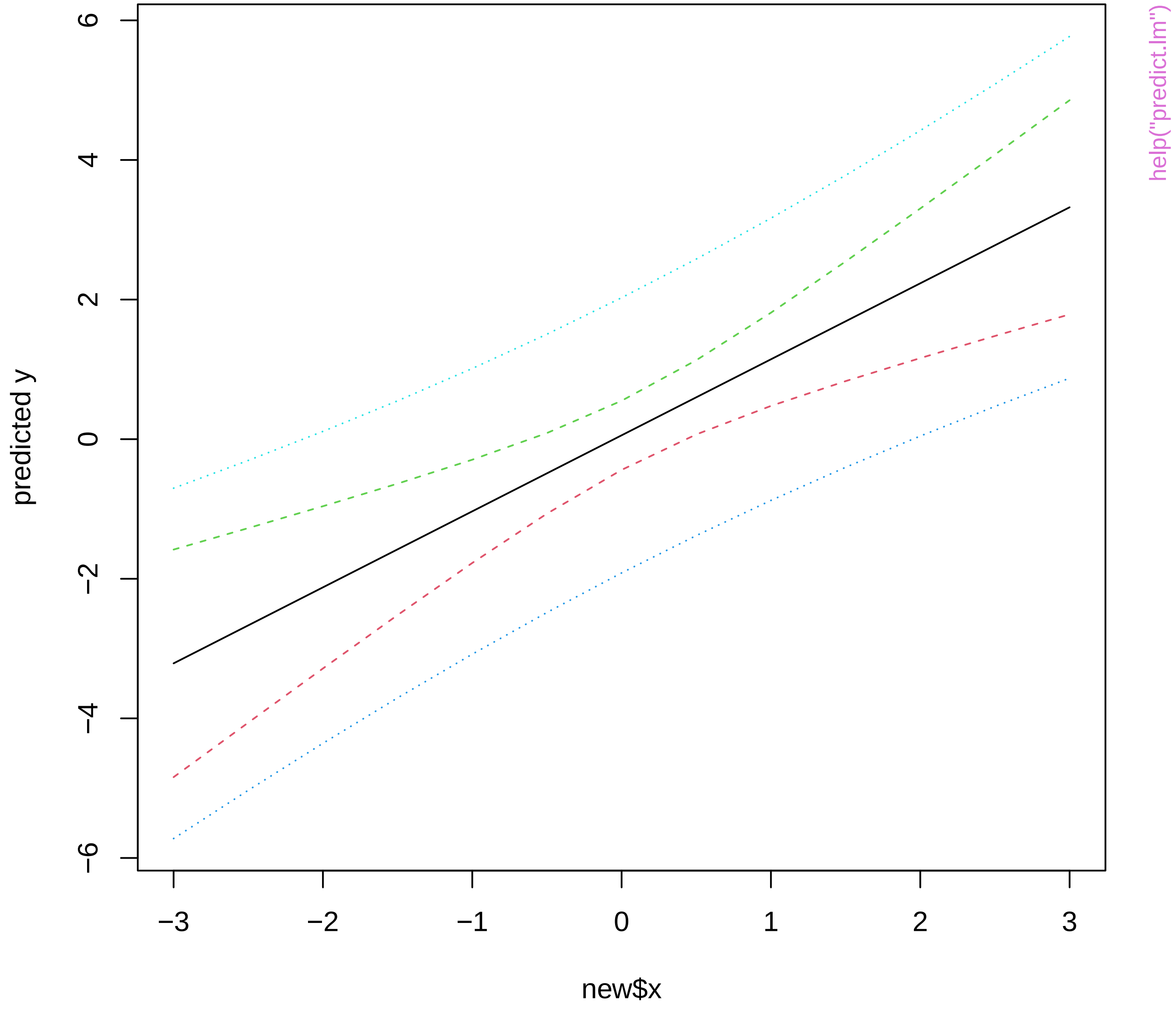

ppoints(n = 8)
5/66
13/66
7/22
29/66
37/66
15/22
53/66
61/66
0.0
0.2
0.4
0.6
0.8
1.0
pn
pn
help("ppoints")


ppr(log(perm)~ ., nterms=2, max.terms=5)
ppr(log(perm)~ ., nterms=2, max.terms=5)
update(..., bass = 5)
update(..., bass = 5)
update(..., sm.method="gcv", gcvpen=2)
update(..., sm.method="gcv", gcvpen=2)
$\alpha_1^T\mathbf{x}$
$\alpha_2^T\mathbf{x}$
help("ppr")

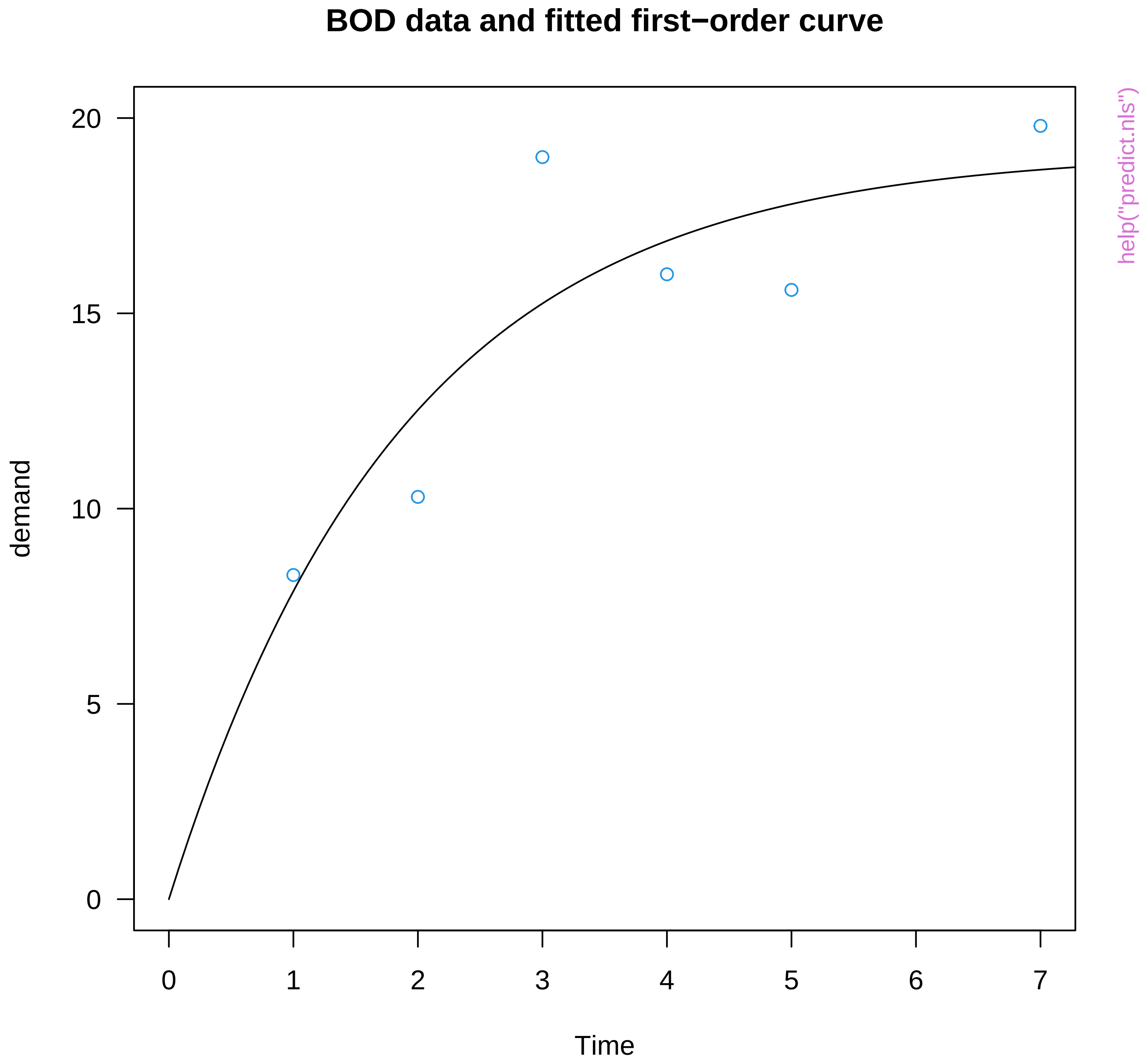


Holt−Winters filtering
Observed / Fitted
Time
320
330
340
350
360
370
1960
1970
1980
1990
2000
help("predict.HoltWinters")

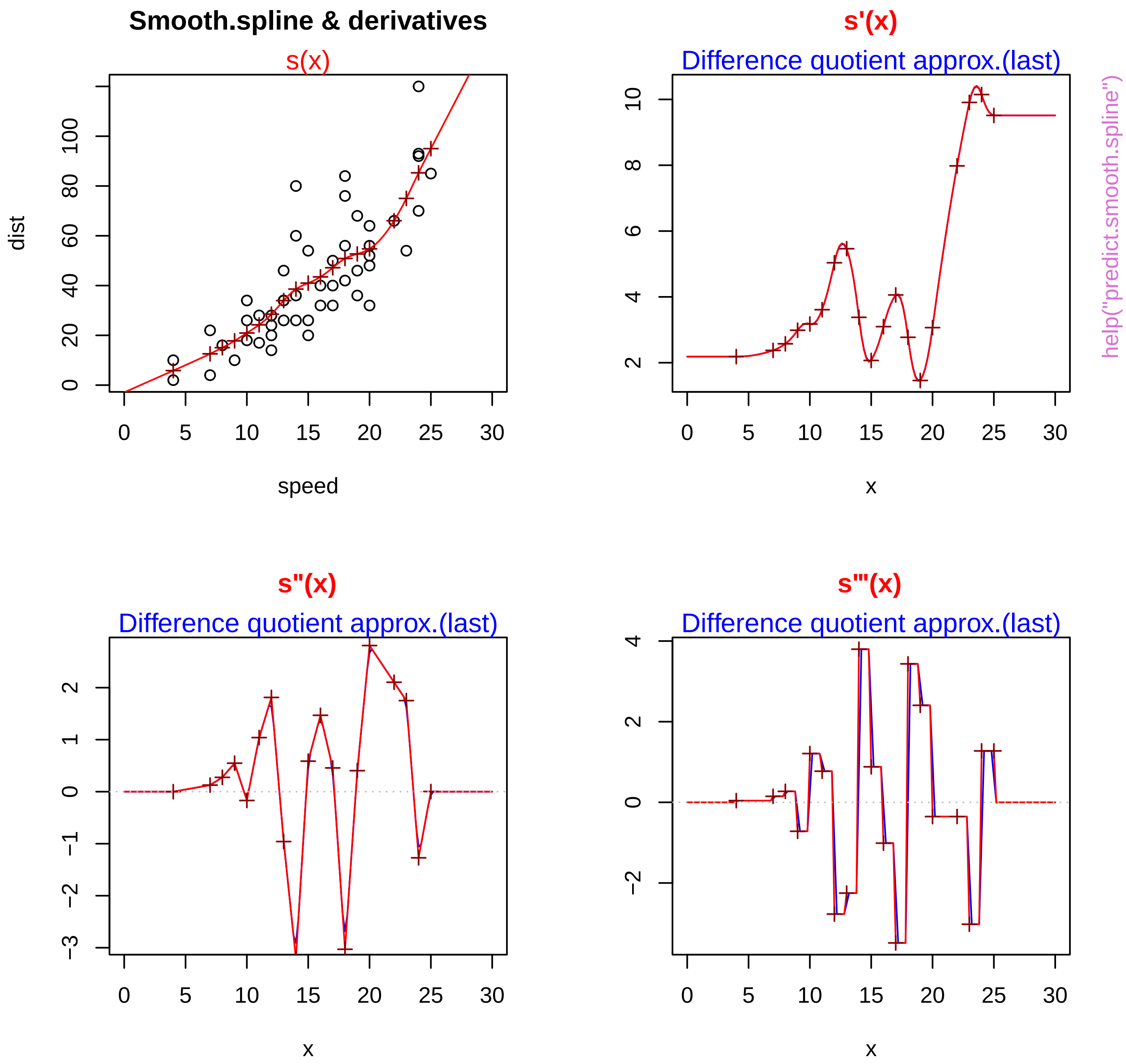

prob
1.0
0.8
0.6
0.4
0.2
0.0
1
2
5
10
20
dose
M
F
help("predict.glm")

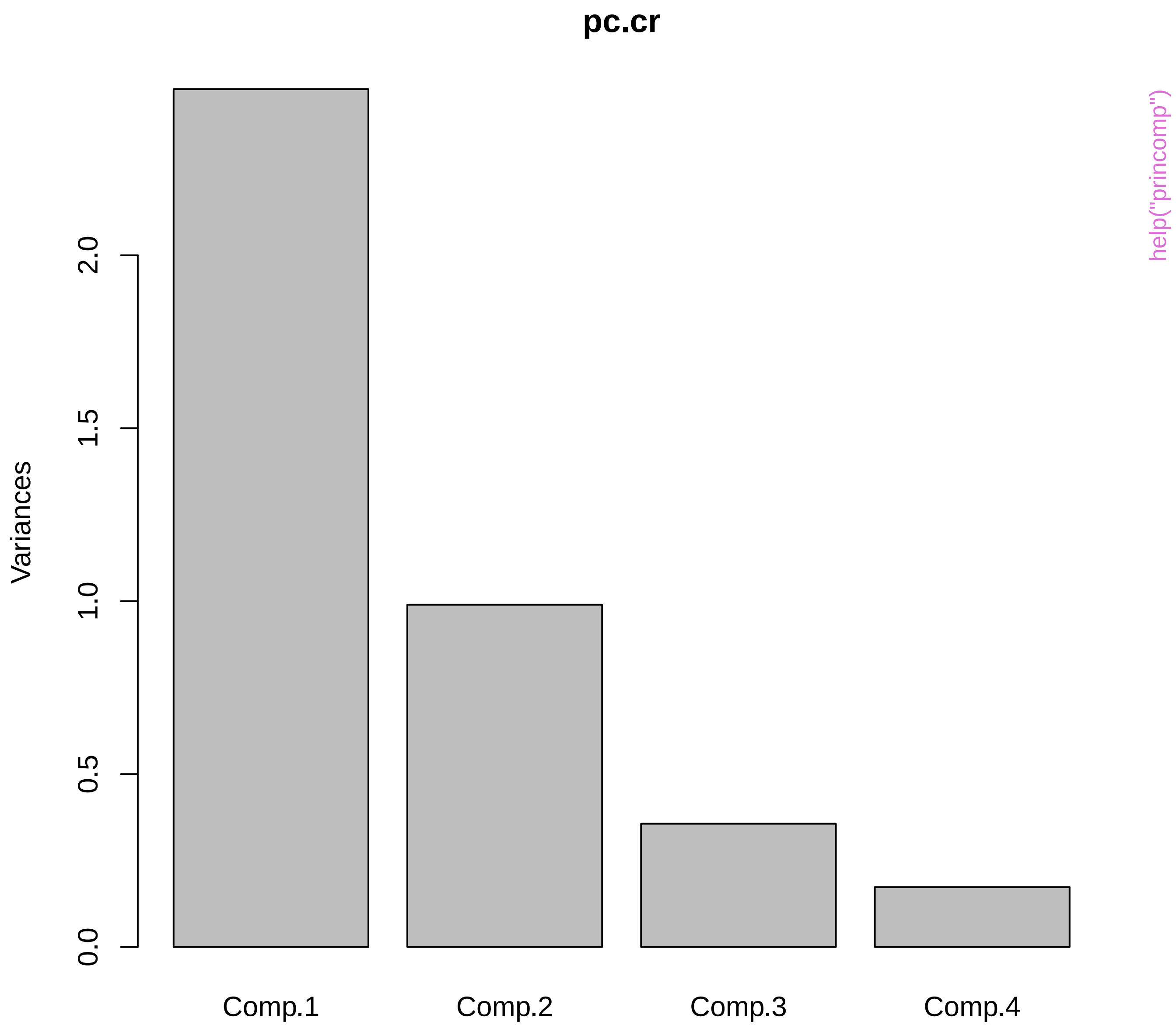


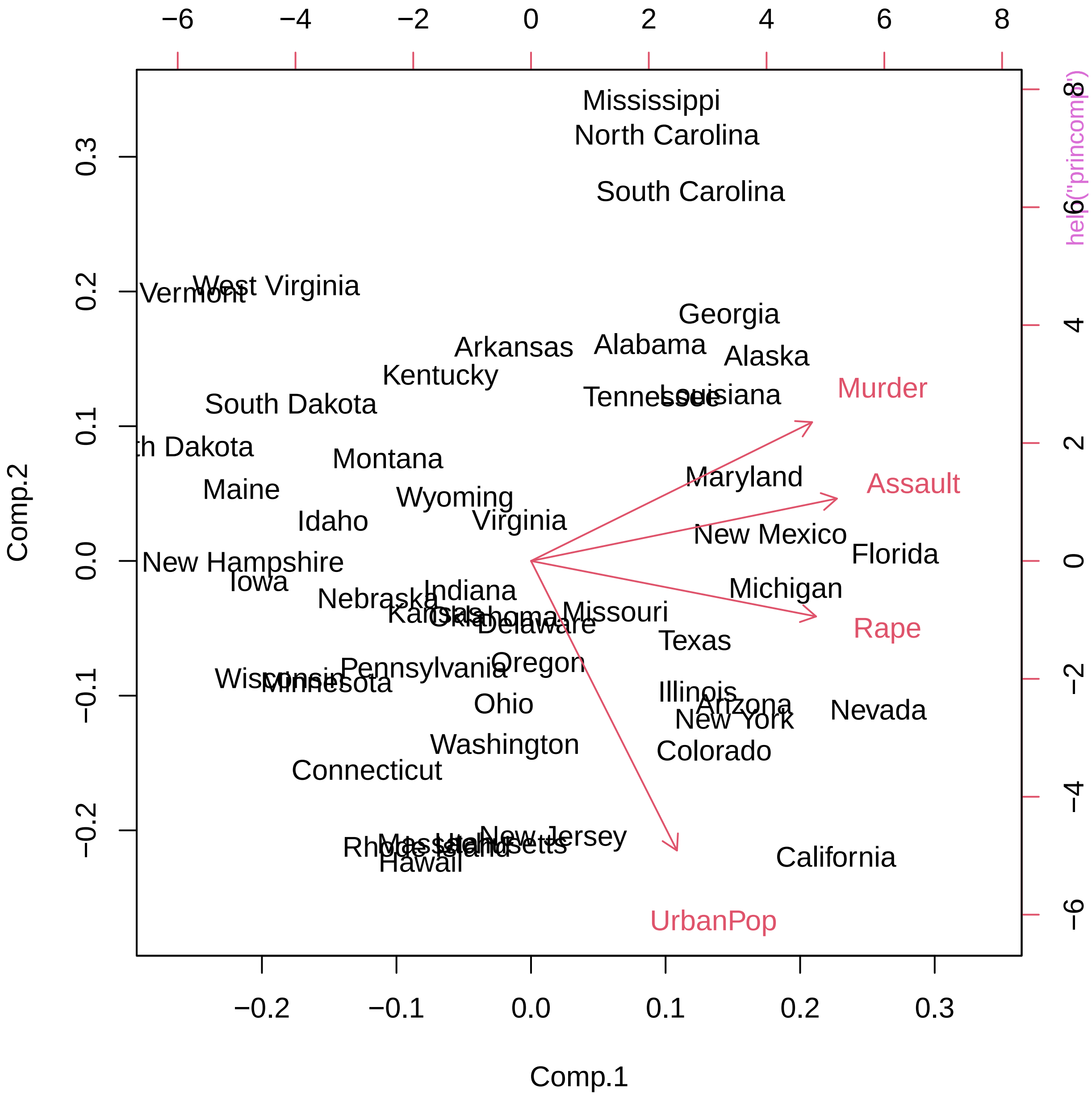
−6
−4
−2
0
2
4
6
predicted y
−3
−2
−1
0
1
2
3
new$x
help("predict.lm")



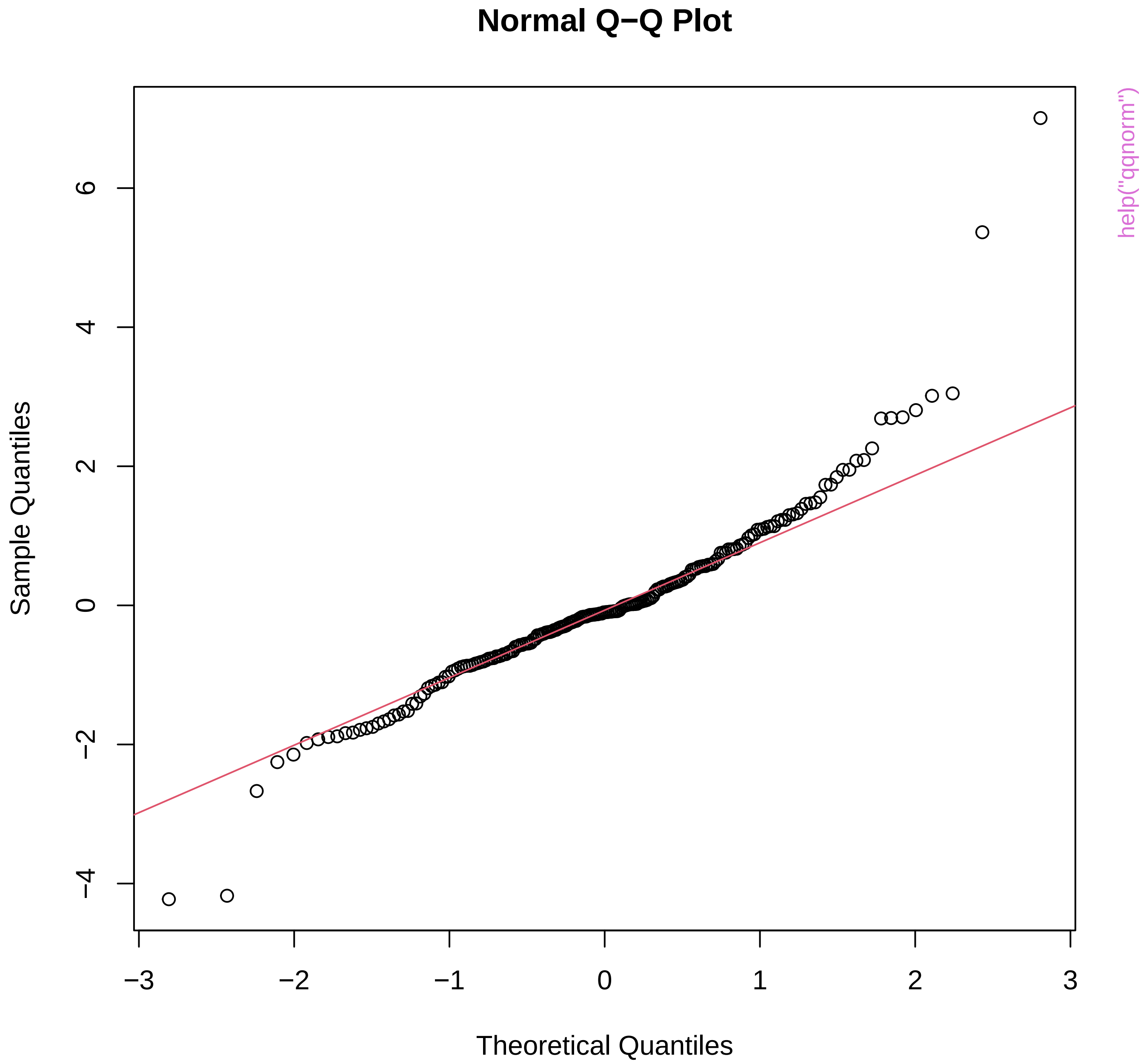
BOD data and fitted first−order curve
demand
Time
0
5
10
15
20
0
1
2
3
4
5
6
7
help("predict.nls")

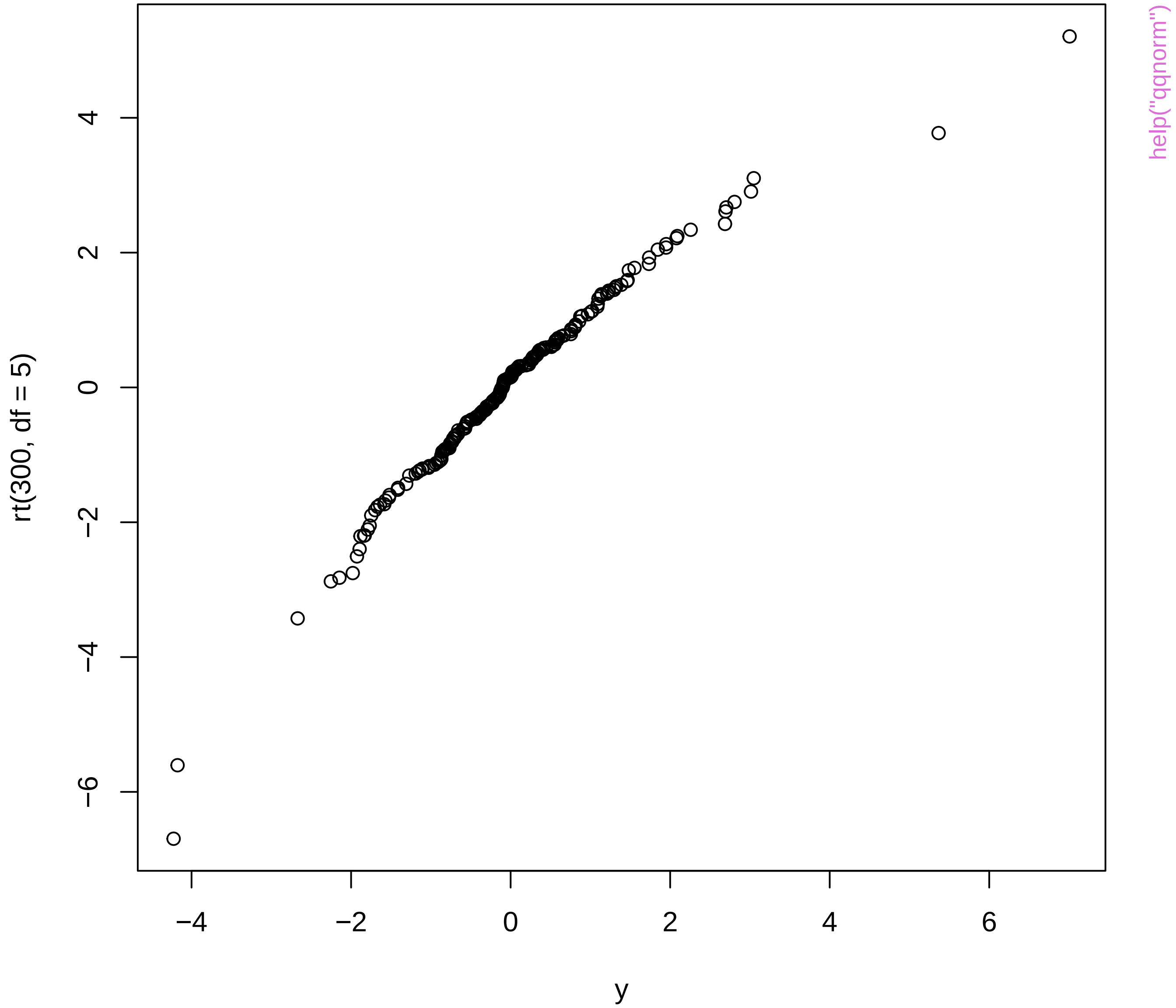

Smooth.spline & derivatives
s(x)
dist
speed
s'(x)
Difference quotient approx.(last)
x
help("predict.smooth.spline")
s"(x)
Difference quotient approx.(last)
x
s'''(x)
Difference quotient approx.(last)
x


pc.cr
Variances
0.0
0.5
1.0
1.5
2.0
Comp.1
Comp.2
Comp.3
Comp.4
help("princomp")

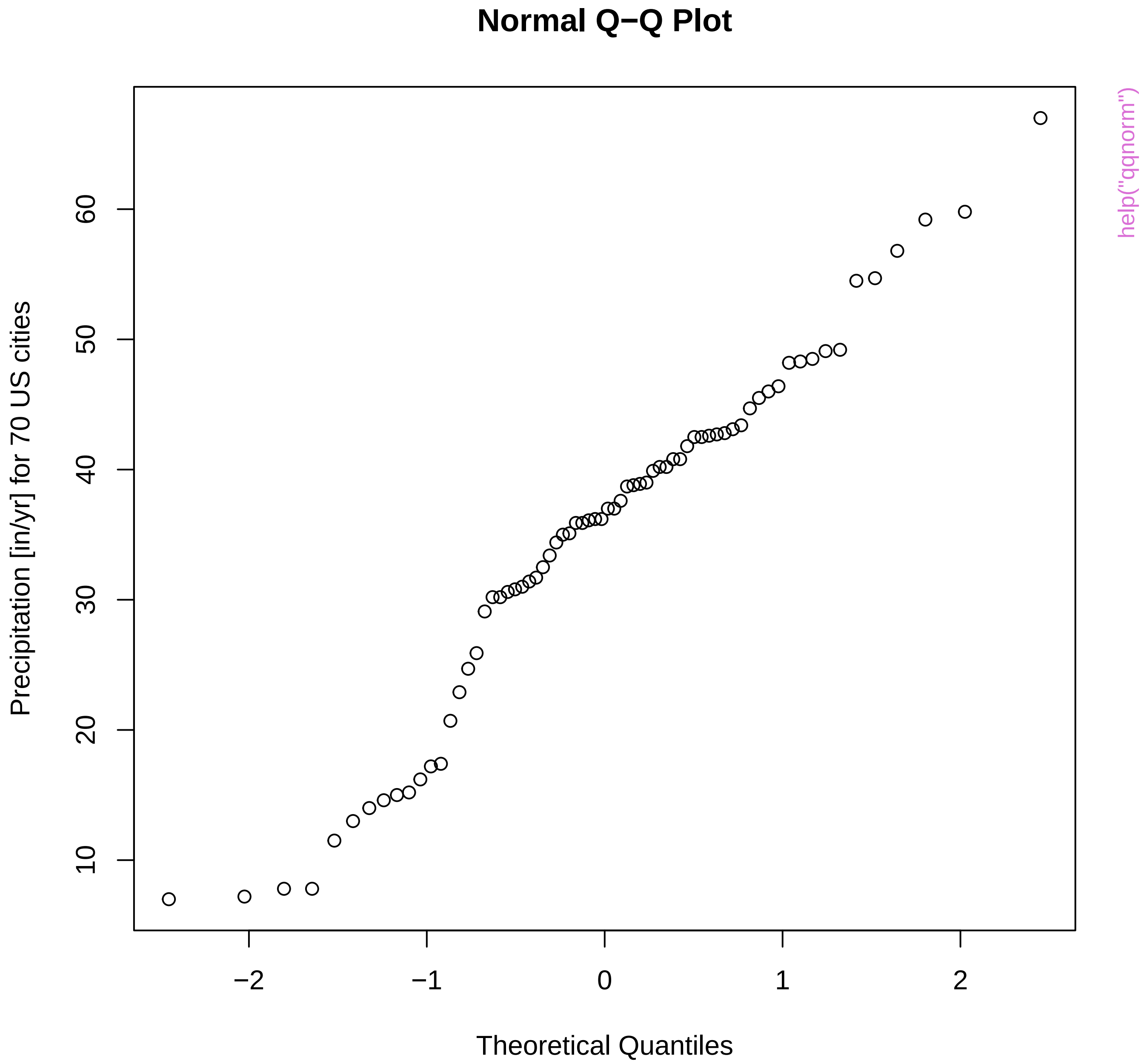


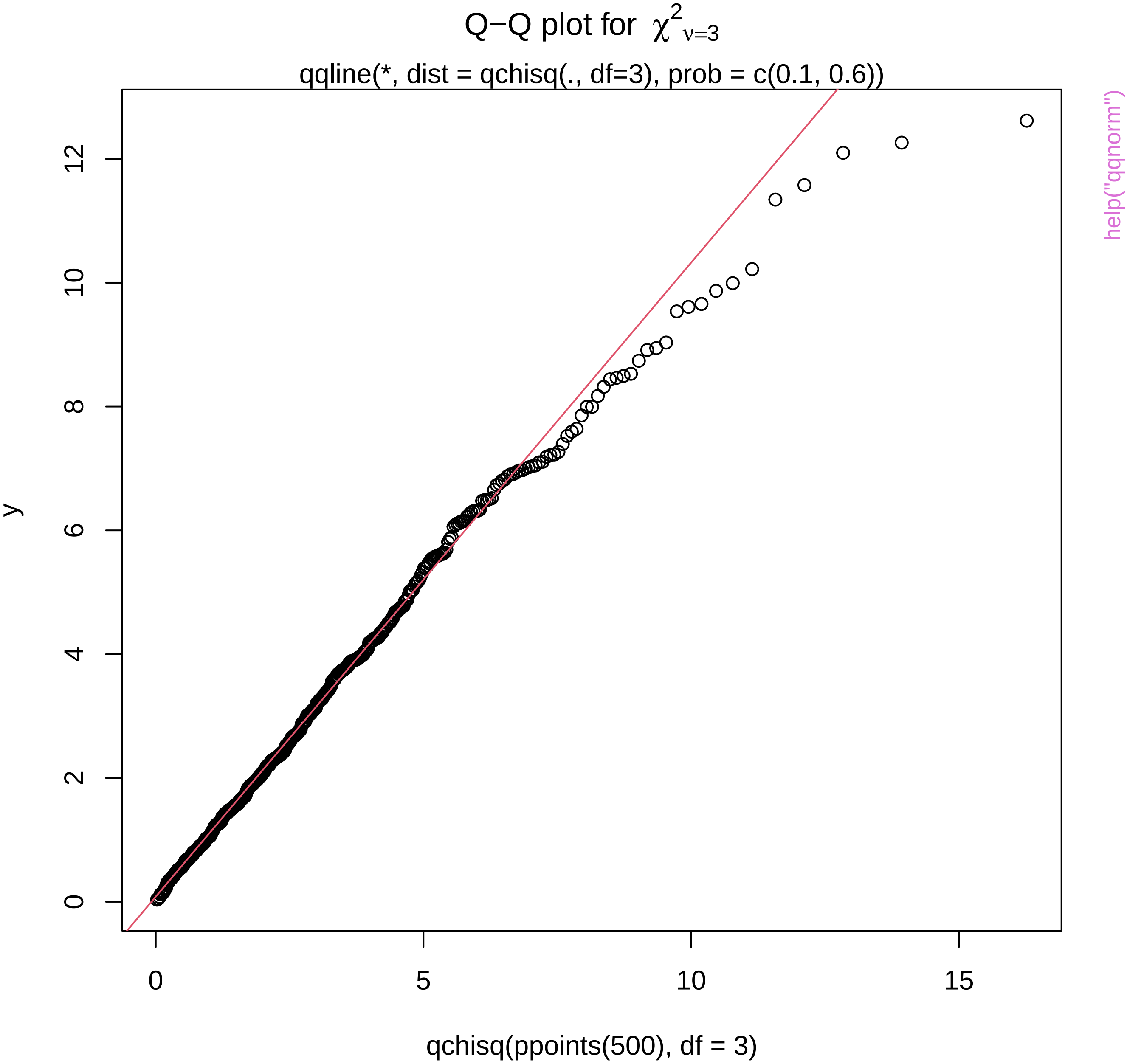
Comp.1
Comp.2
−0.2
−0.1
0.0
0.1
0.2
0.3
−6
−4
−2
0
2
4
6
8
Murder
Assault
Rape
UrbanPop
Mississippi
North Carolina
South Carolina
Vermont
West Virginia
Georgia
Arkansas
Alabama
Alaska
Kentucky
Tennessee
Louisiana
South Dakota
th Dakota
Montana
Maryland
Maine
Wyoming
Idaho
Virginia
New Mexico
Florida
New Hampshire
Iowa
Indiana
Nebraska
Kansas
Oklahoma
Delaware
Missouri
Michigan
Texas
Wisconsin
Minnesota
Pennsylvania
Oregon
Illinois
Arizona
New York
Nevada
Ohio
Washington
Colorado
Connecticut
New Jersey
Rhode Island
Massachusetts
Utah
Hawaii
California


Normal Q−Q Plot
Sample Quantiles
Theoretical Quantiles
−4
−2
0
2
4
6
−3
−2
−1
0
1
2
3
help("qqnorm")

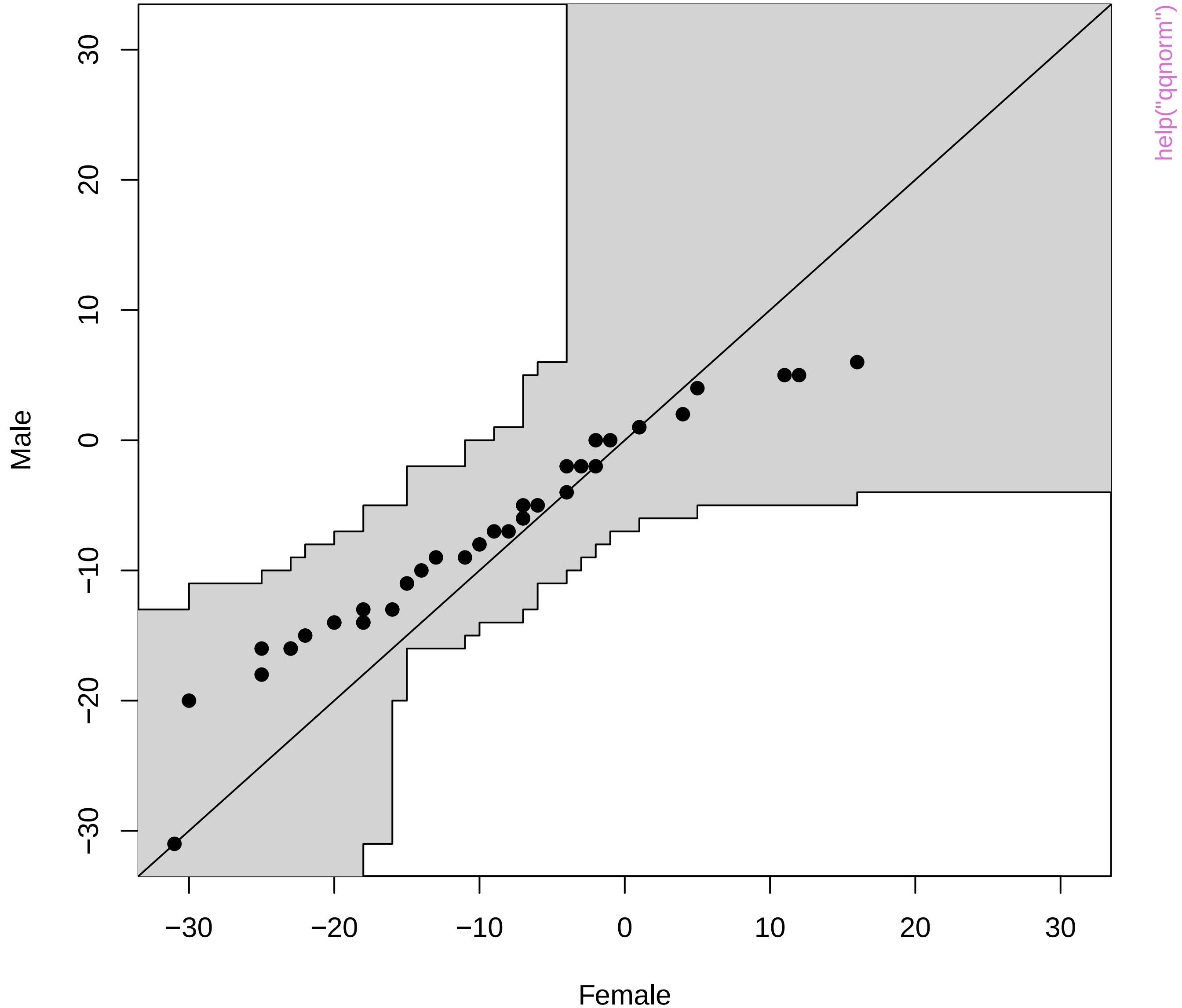


rt(300, df = 5)
4
2
0
−2
−4
−6
−4
−2
0
2
4
6
y
help("qqnorm")

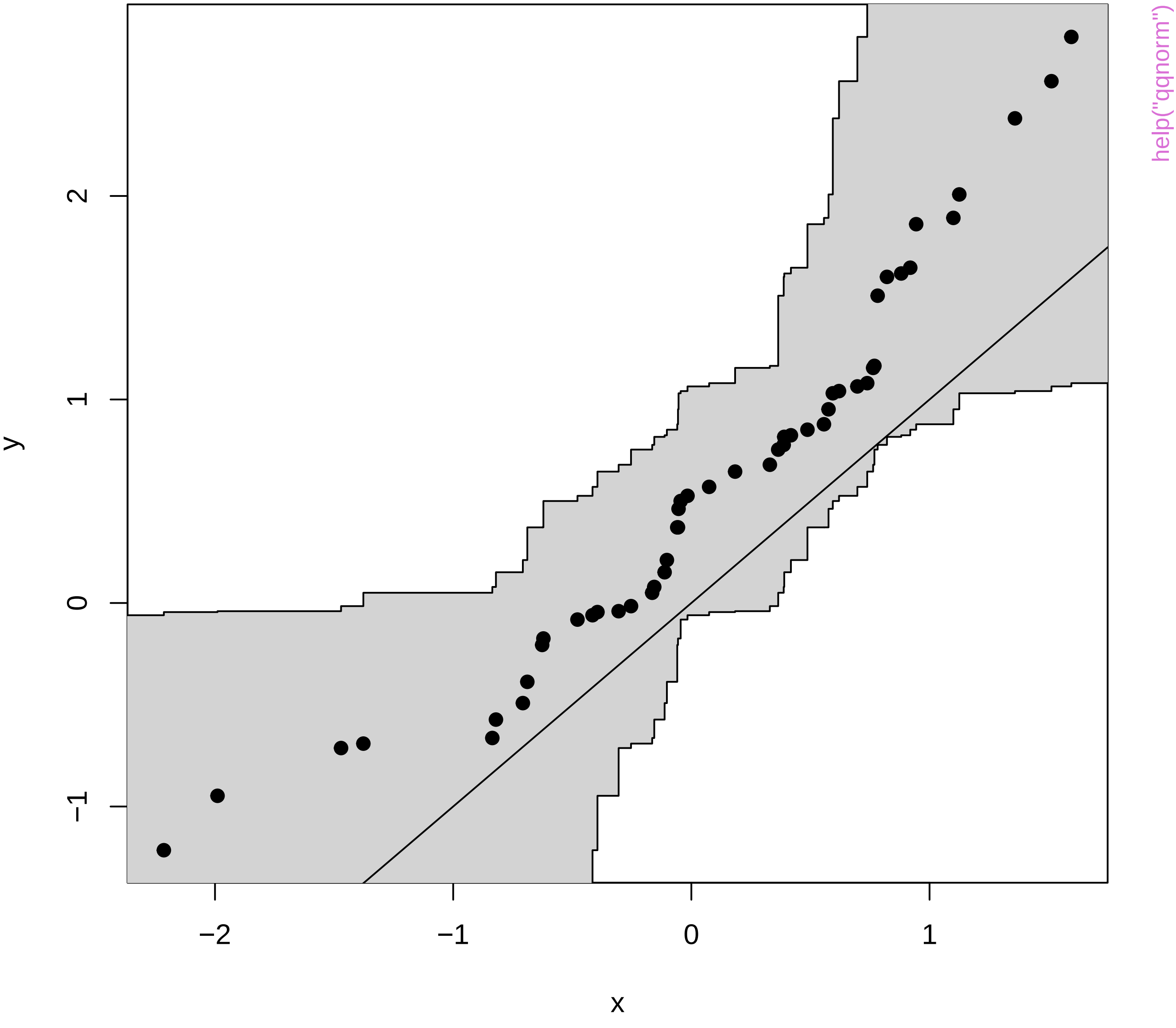

Normal Q−Q Plot
Precipitation [in/yr] for 70 US cities
Theoretical Quantiles
help("qqnorm")
10
20
30
40
50
60
−2
−1
0
1
2



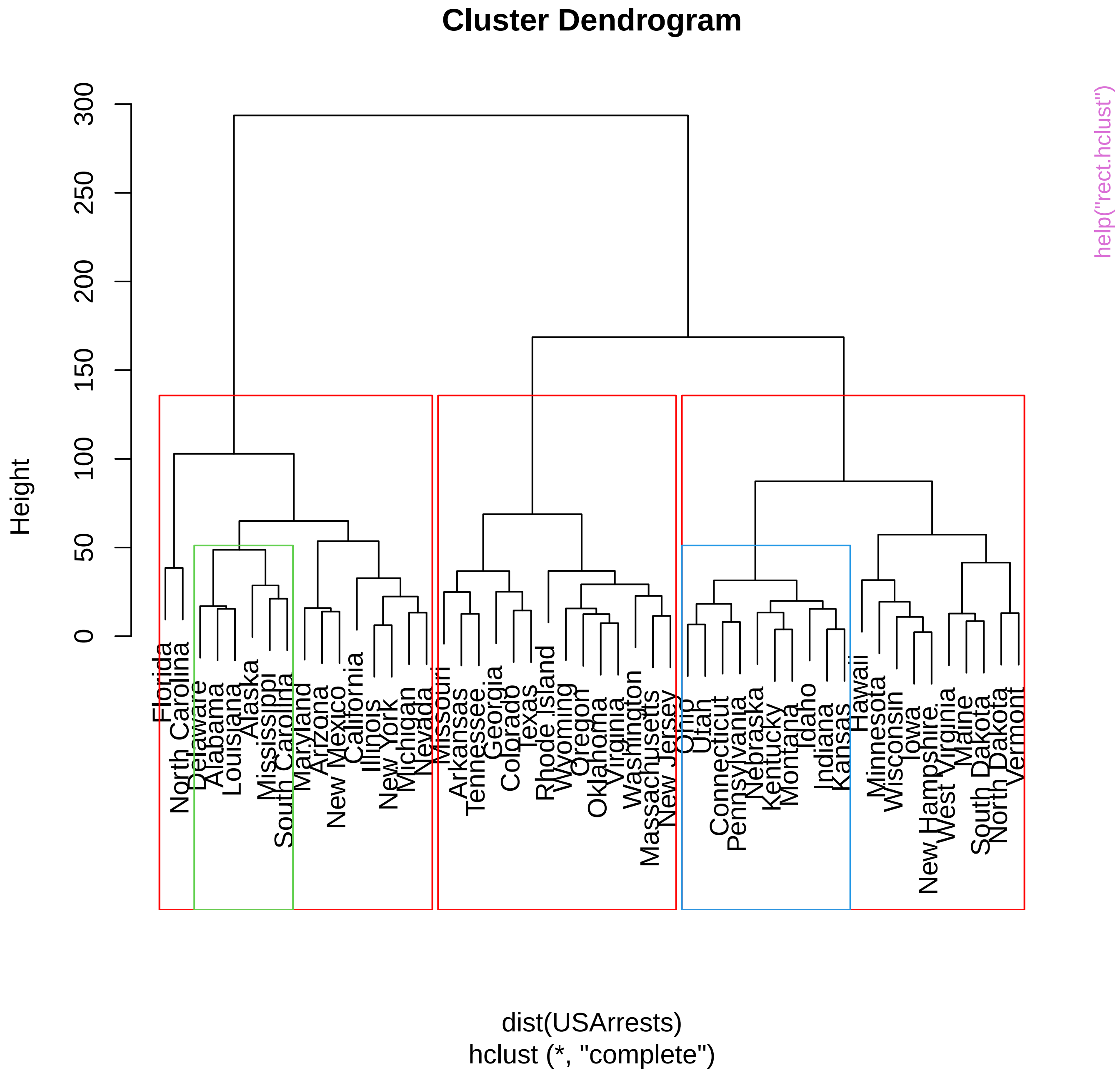
Q−Q plot for $\chi^2_{\nu=3}$
qqline(*, dist = qchisq(., df=3), prob = c(0.1, 0.6))
help("qqnorm")
y
0
2
4
6
8
10
12
0
5
10
15
qchisq(ppoints(500), df = 3)

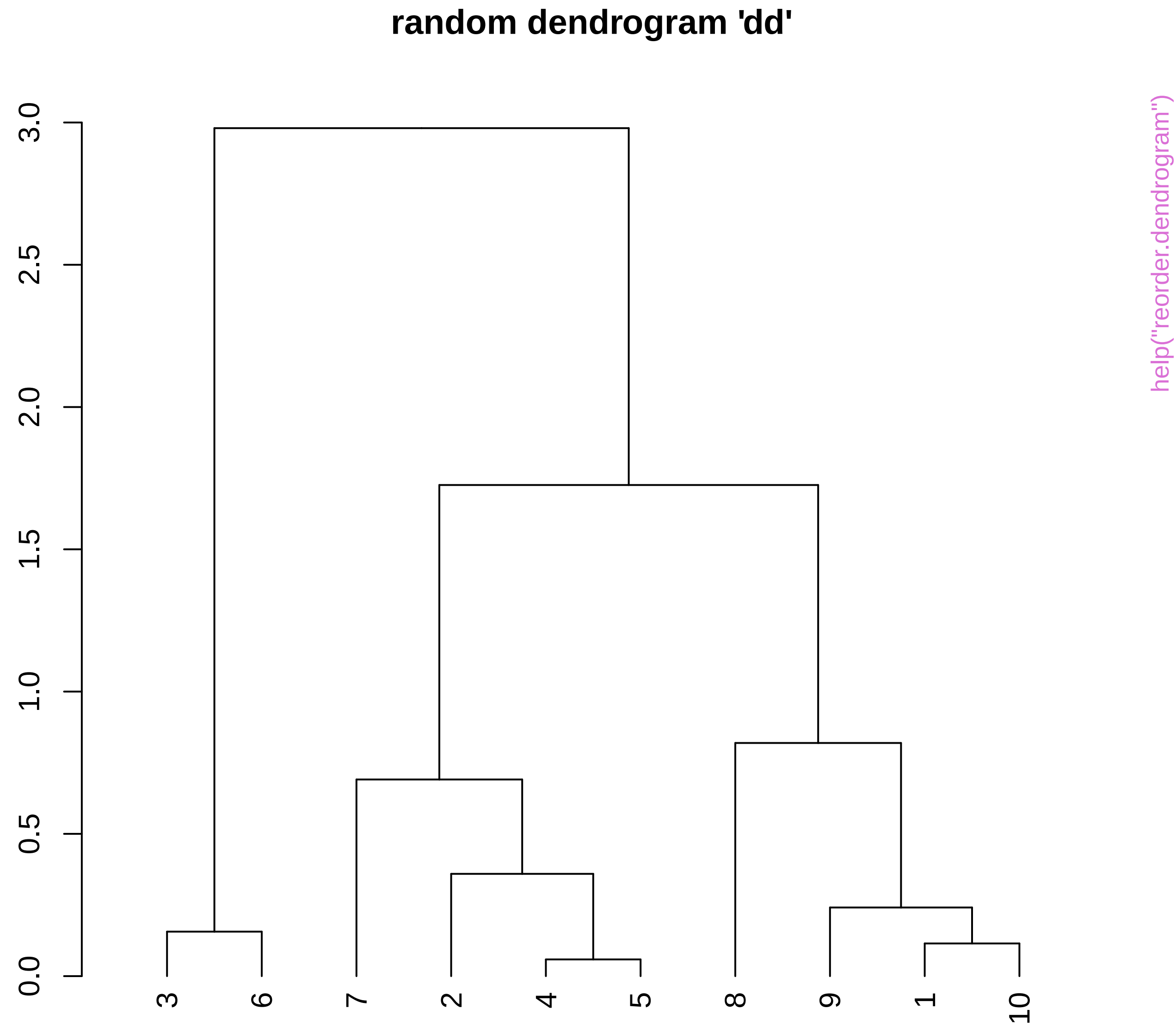


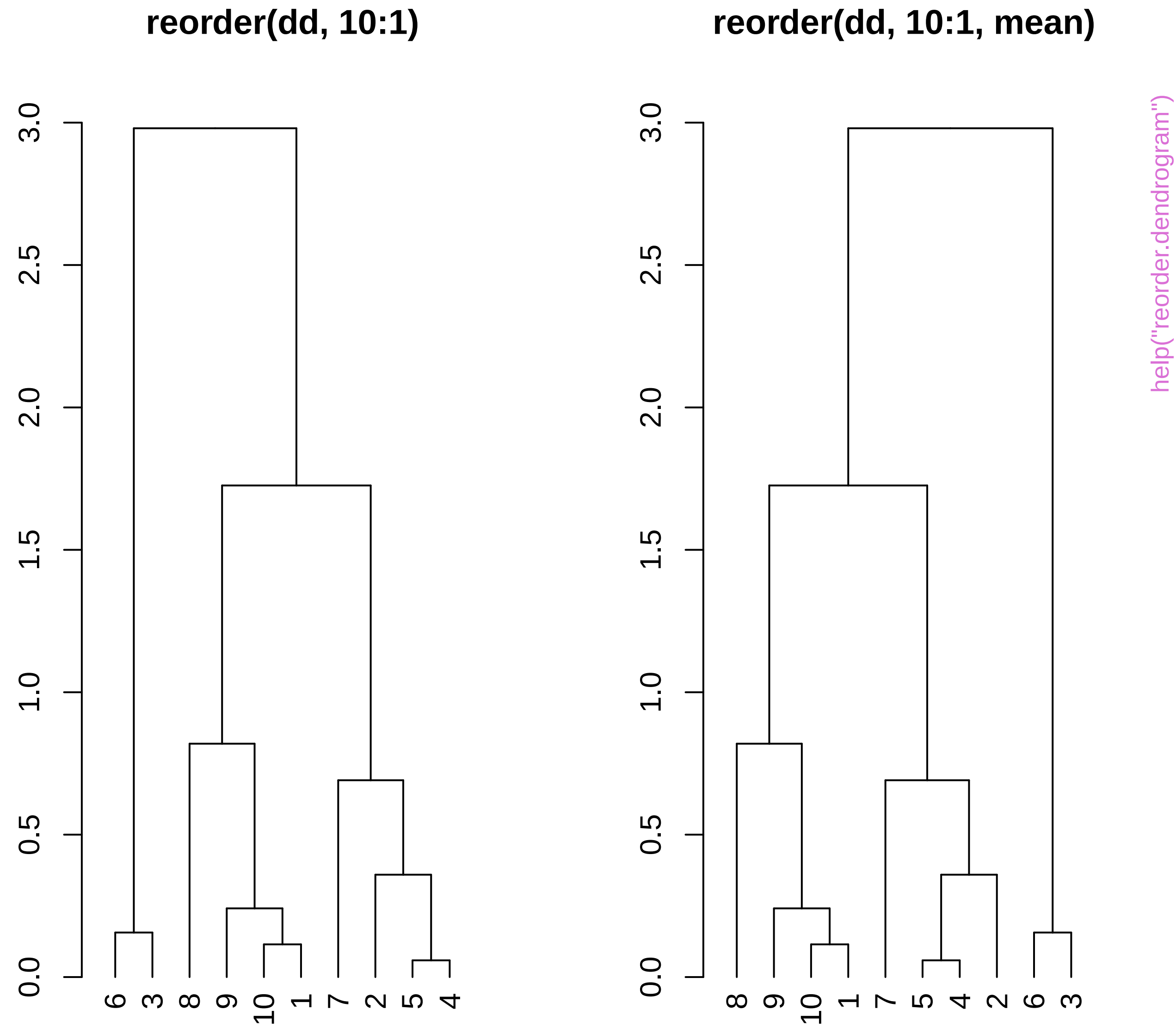
Male
Female
30
20
10
0
−10
−20
−30
−30
−20
−10
0
10
20
30
help("qqnorm")

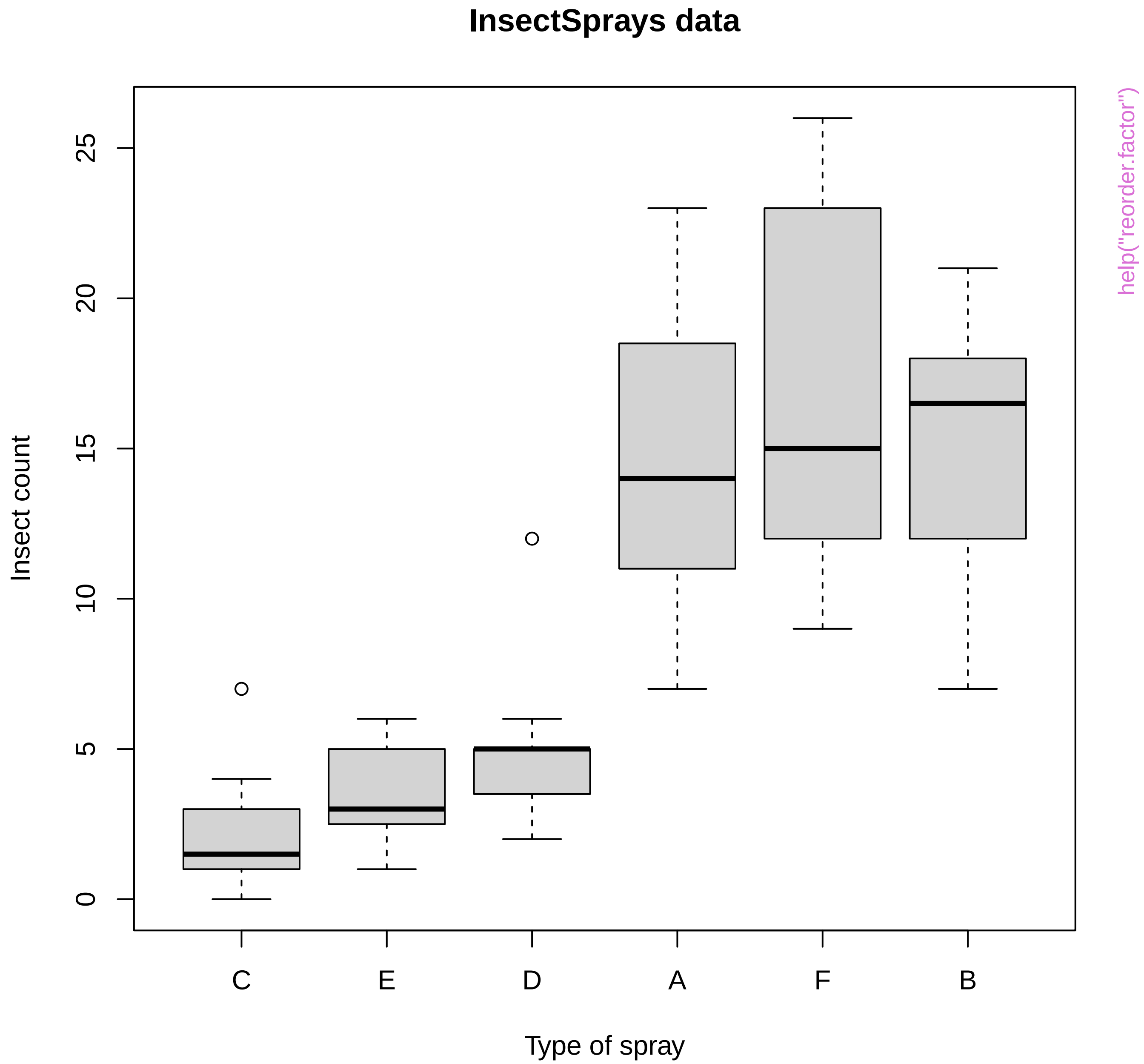


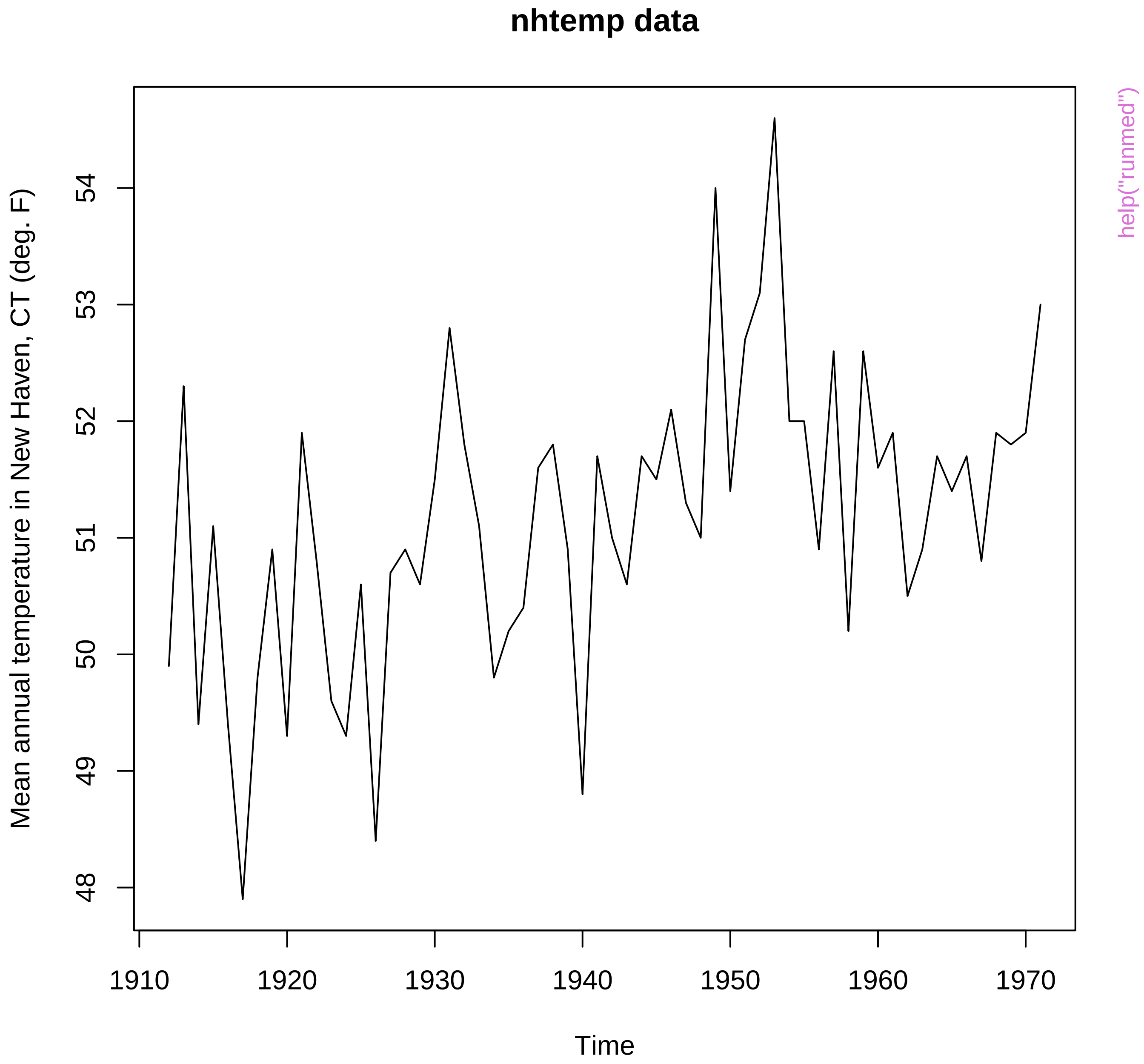
2
1
0
−1
y
−2
−1
0
1
x
help("qqnorm")


Cluster Dendrogram
Height
0
50
100
150
200
250
300
Florida
North Carolina
Delaware
Alabama
Louisiana
Alaska
Mississippi
South Carolina
Maryland
Arizona
New Mexico
California
Illinois
New York
Michigan
Nevada
Missouri
Arkansas
Tennessee
Georgia
Colorado
Texas
Rhode Island
Wyoming
Oregon
Oklahoma
Virginia
Washington
Massachusetts
New Jersey
Ohio
Utah
Connecticut
Pennsylvania
Nebraska
Kentucky
Montana
Idaho
Indiana
Kansas
Hawaii
Minnesota
Wisconsin
Iowa
New Hampshire
West Virginia
Maine
South Dakota
North Dakota
Vermont
dist(USArrests)
hclust (*, "complete")
help("rect.hclust")

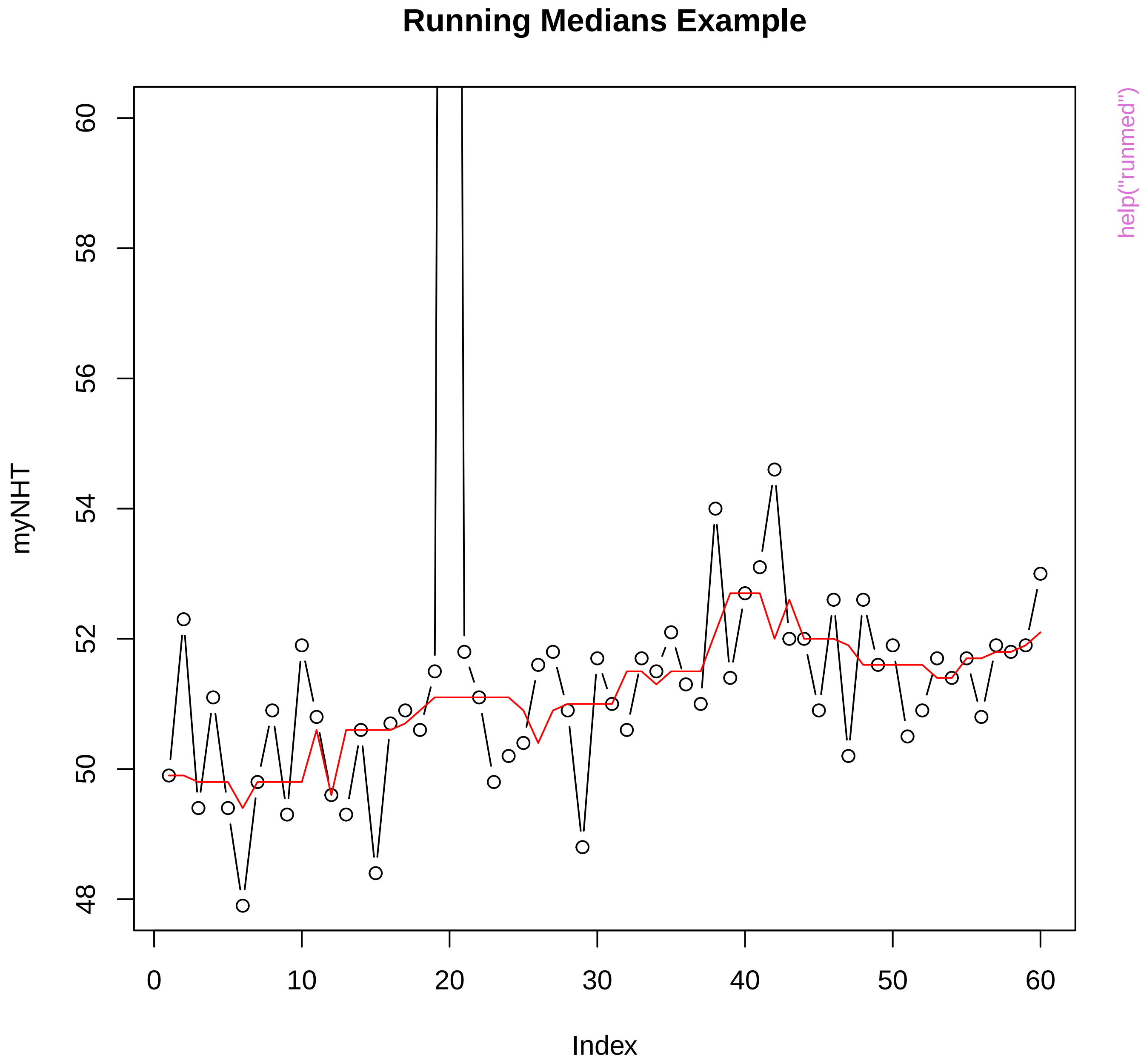

random dendrogram 'dd'
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3
6
7
2
4
5
8
9
1
10
help("reorder.dendrogram")

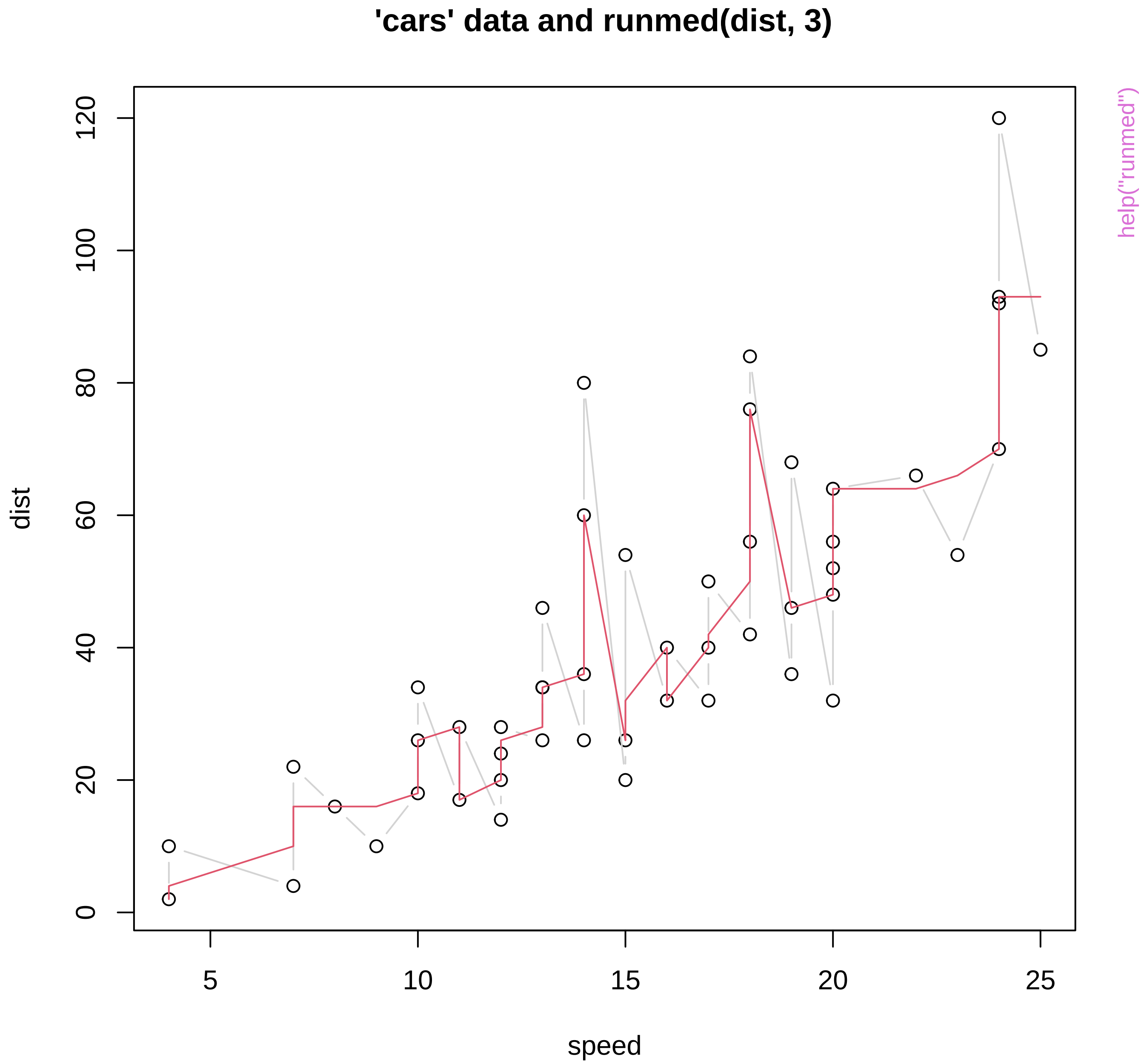

reorder(dd, 10:1)
reorder(dd, 10:1, mean)
0.0
0.5
1.0
1.5
2.0
2.5
3.0
6 3 8 9 10 1 7 2 5 4
8 9 10 1 7 5 4 2 6 3
help("reorder.dendrogram")

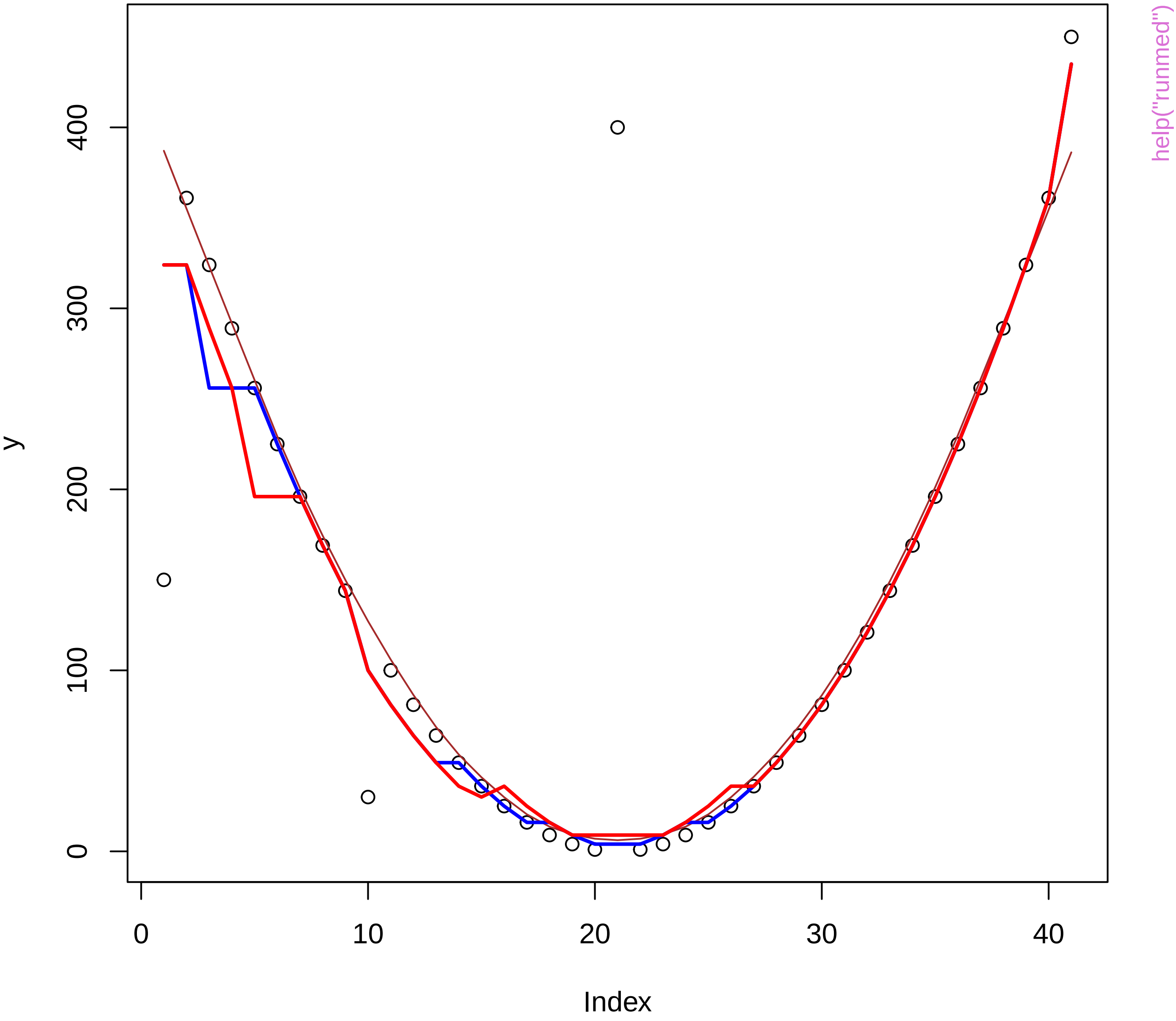

InsectSprays data
Insect count
0
5
10
15
20
25
C
E
D
A
F
B
Type of spray
help("reorder.factor")



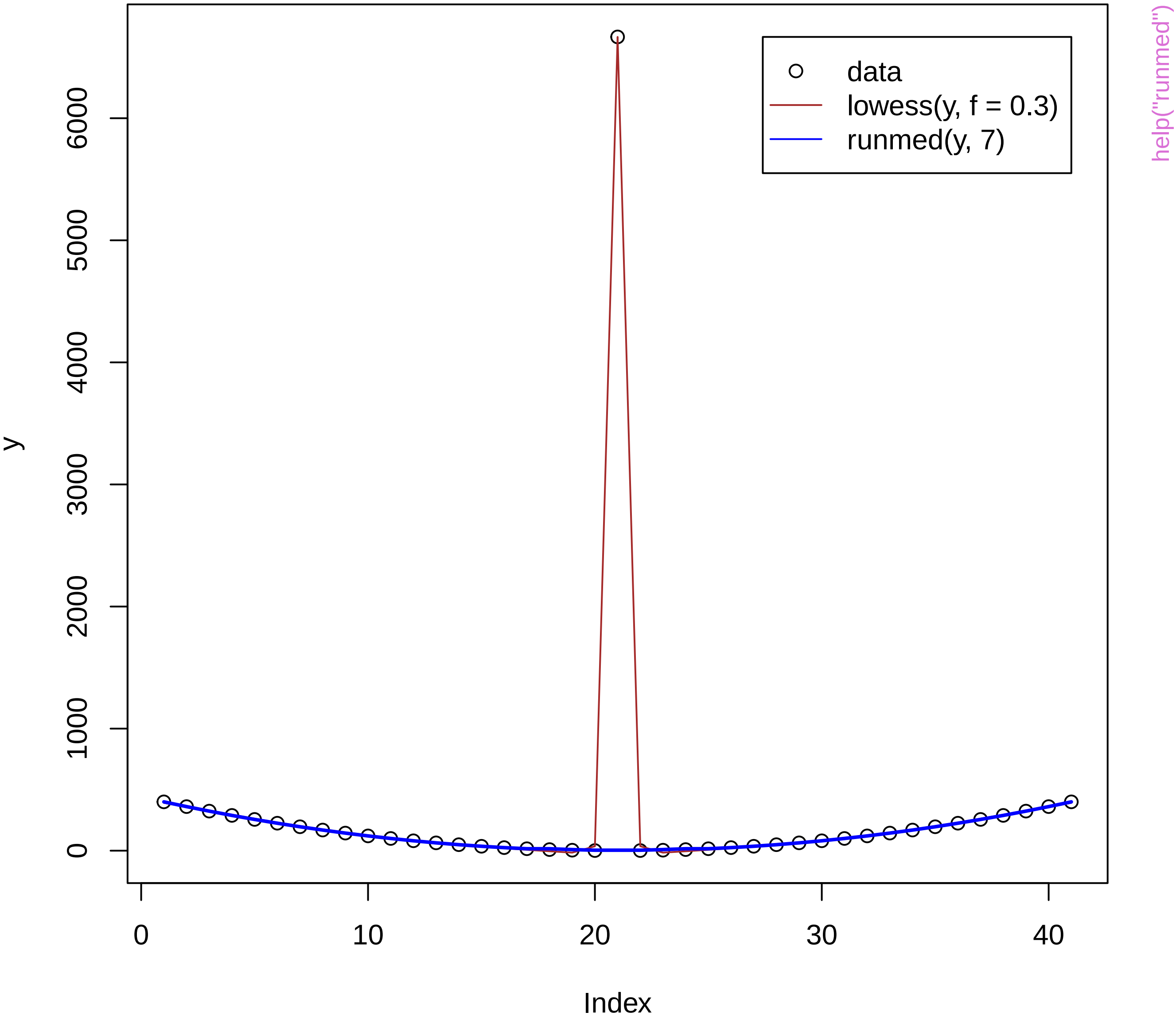
nhtemp data
Mean annual temperature in New Haven, CT (deg. F)
48
49
50
51
52
53
54
1910
1920
1930
1940
1950
1960
1970
Time
help("runmed")

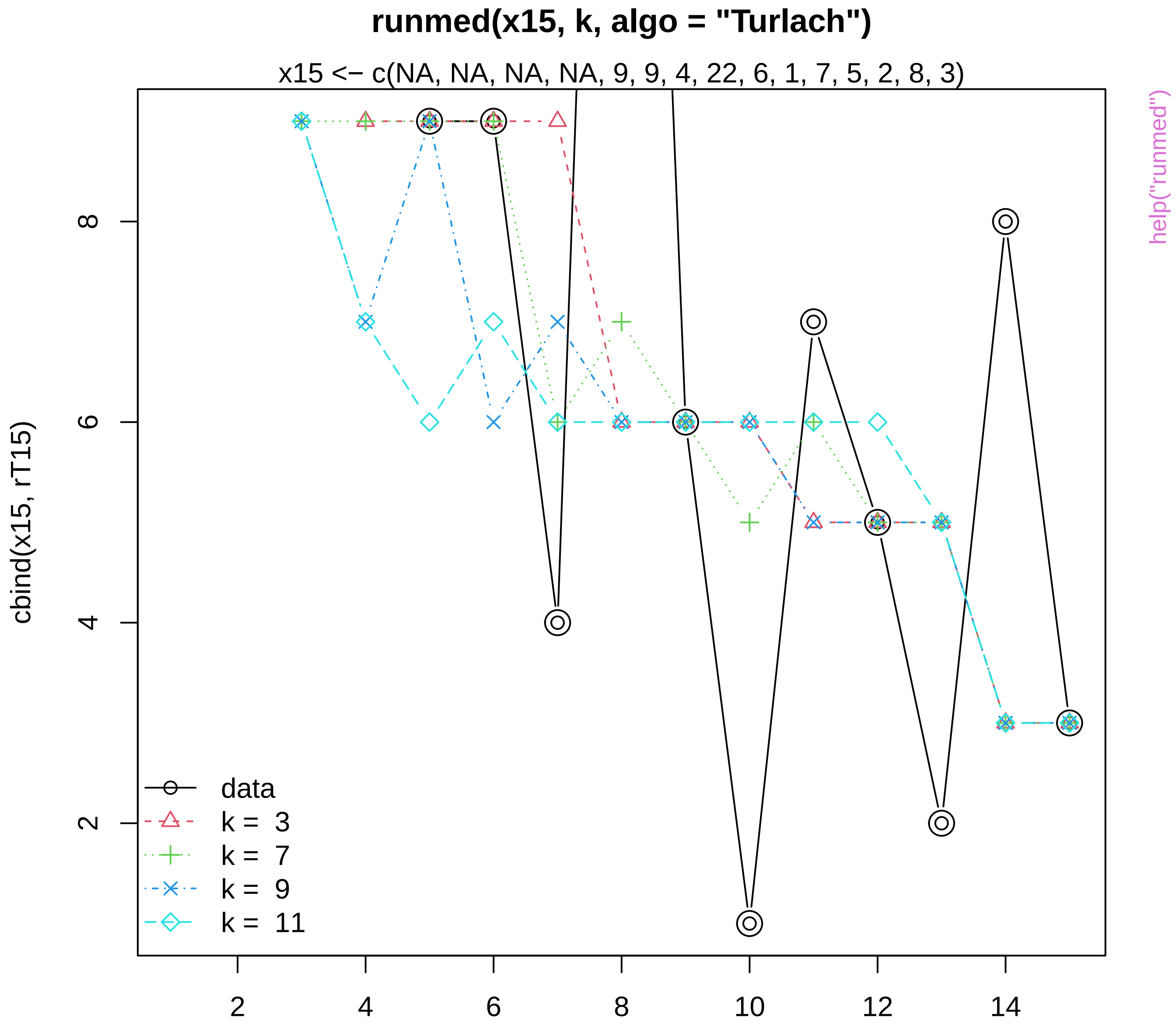

Running Medians Example
myNHT
Index
48
50
52
54
56
58
60
0
10
20
30
40
50
60
help("runmed")

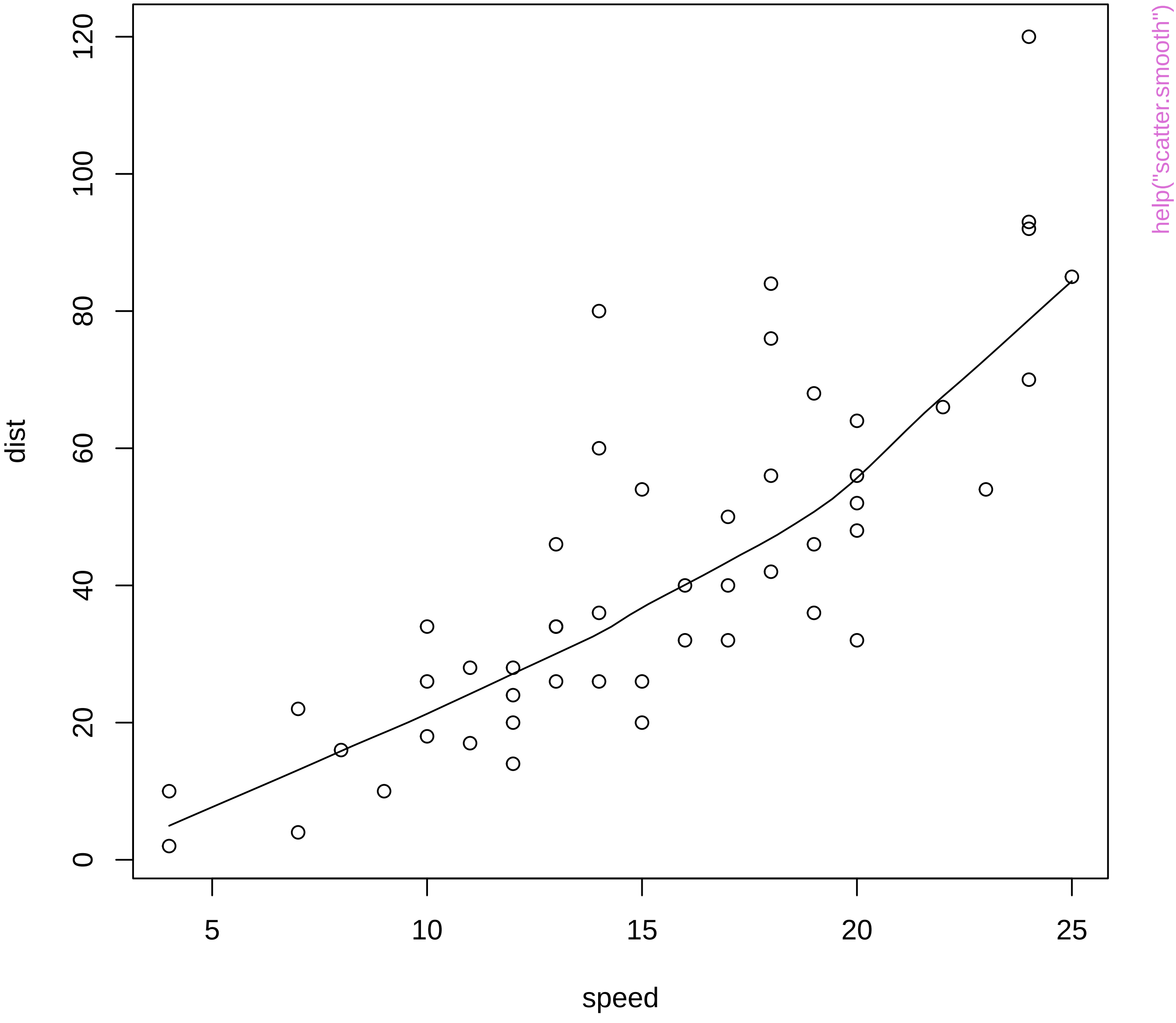

'cars' data and runmed(dist, 3)
dist
0
20
40
60
80
100
120
speed
5
10
15
20
25
help("runmed")



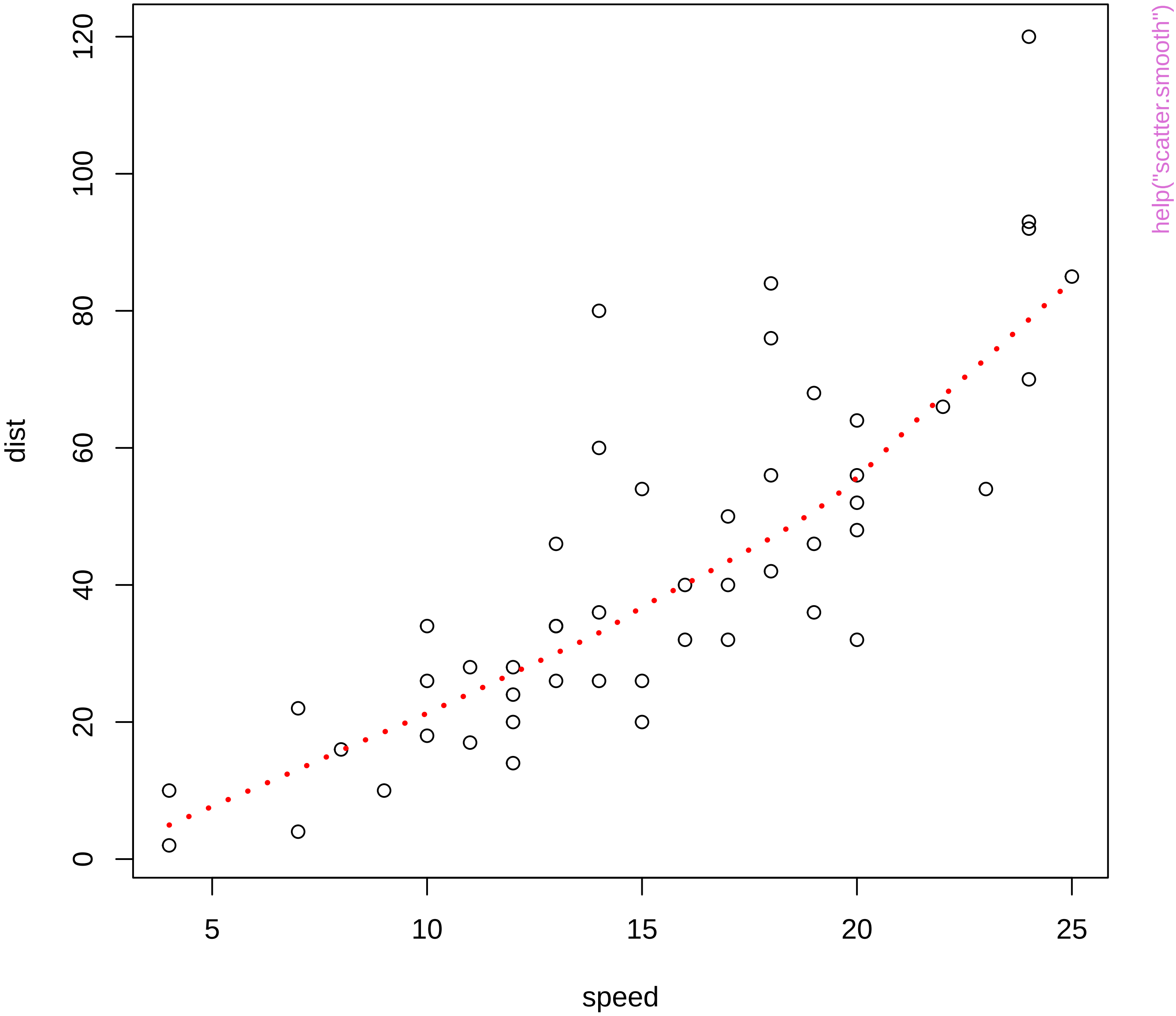
help("runmed")
y
0
100
200
300
400
0
10
20
30
40
Index


data
lowess(y, f = 0.3)
runmed(y, 7)
y
0
1000
2000
3000
4000
5000
6000
Index
0
10
20
30
40
help("runmed")

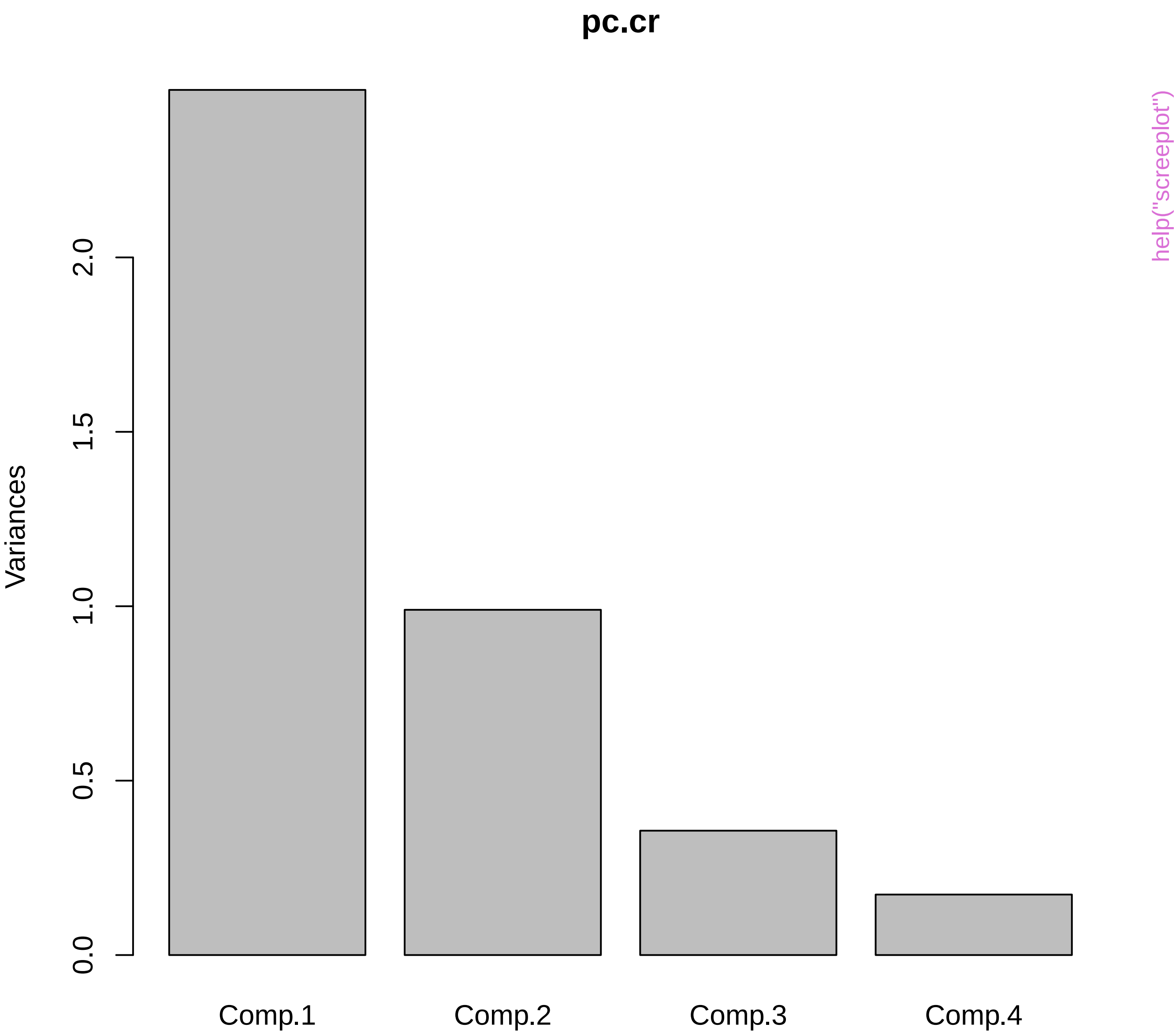

runmed(x15, k, algo = "Turlach")
x15 <- c(NA, NA, NA, NA, 9, 9, 4, 22, 6, 1, 7, 5, 2, 8, 3)
cbind(x15, rT15)
help("runmed")
data
k = 3
k = 7
k = 9
k = 11
2
4
6
8
10
12
14
2
4
6
8

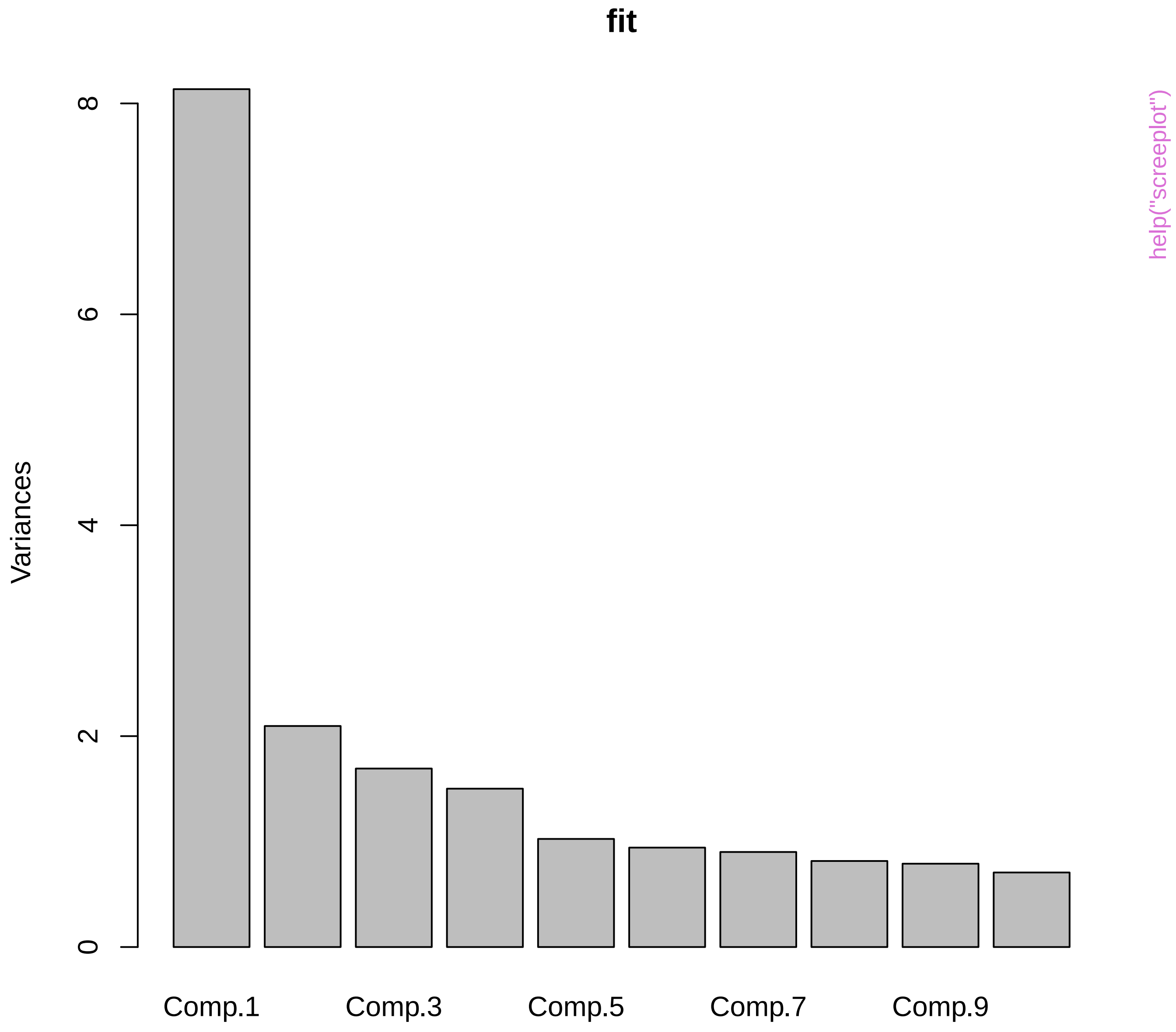


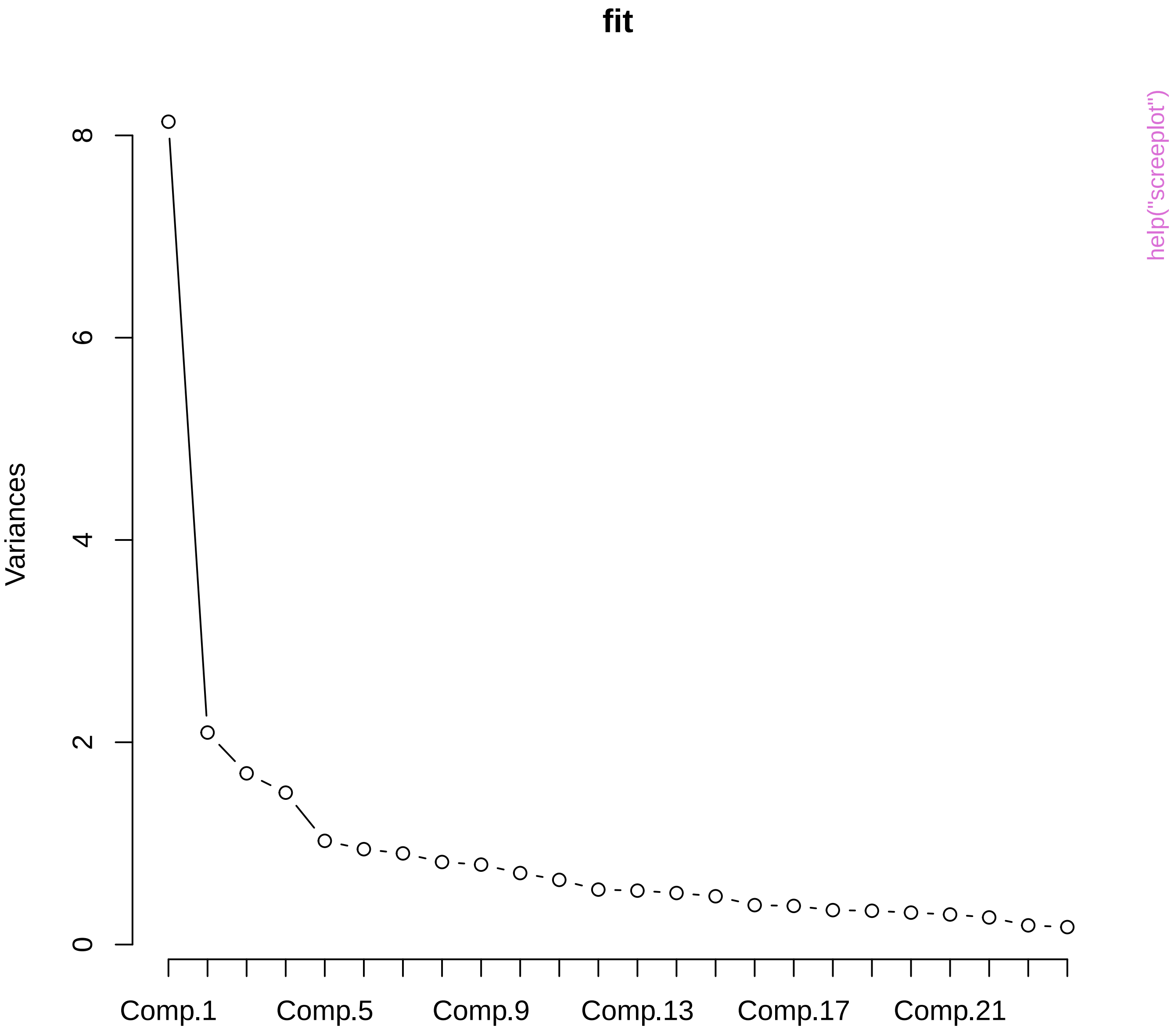
0
20
40
60
80
100
120
dist
5
10
15
20
25
speed
help("scatter.smooth")

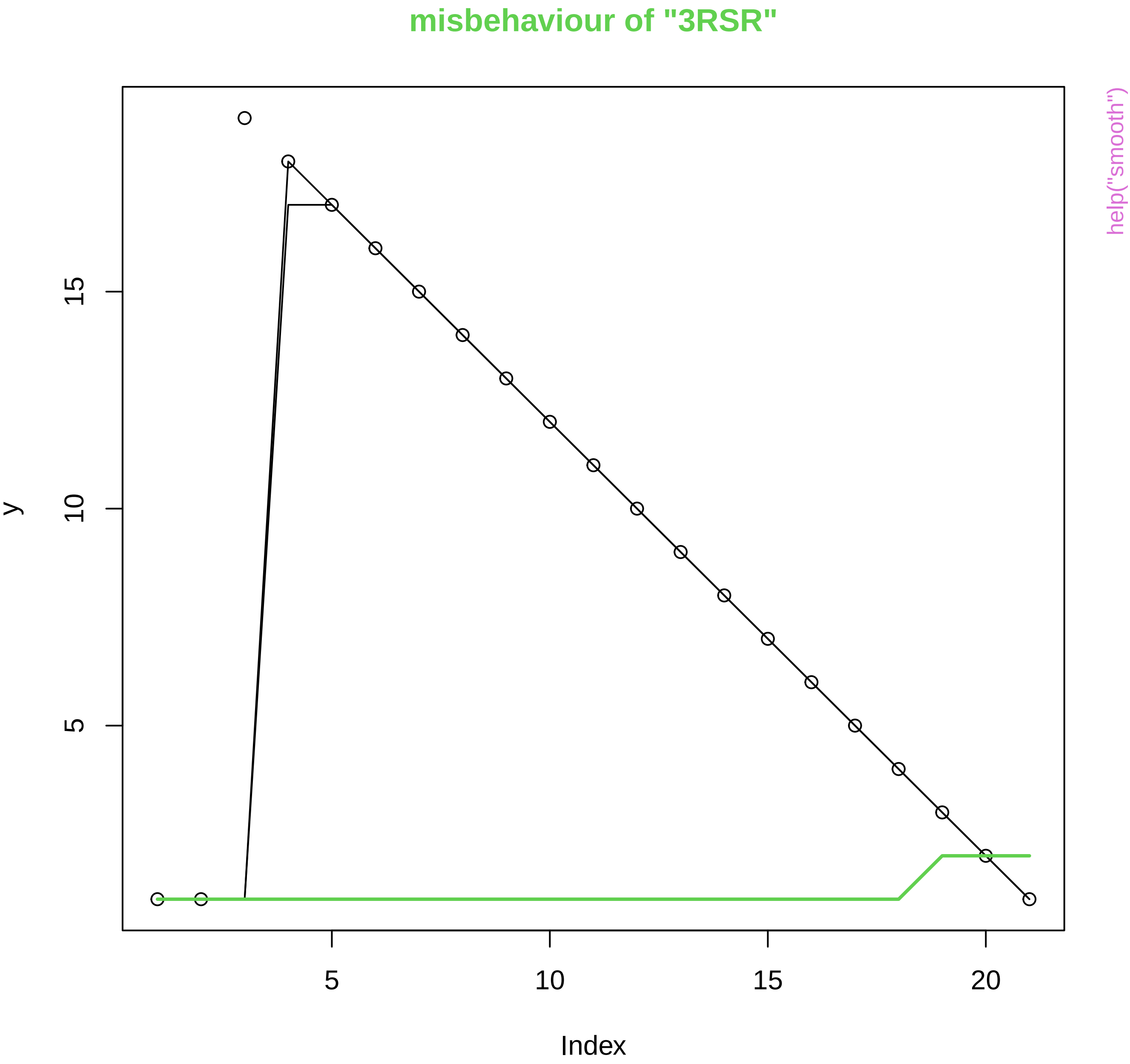


dist
0
20
40
60
80
100
120
5
10
15
20
25
speed
help("scatter.smooth")

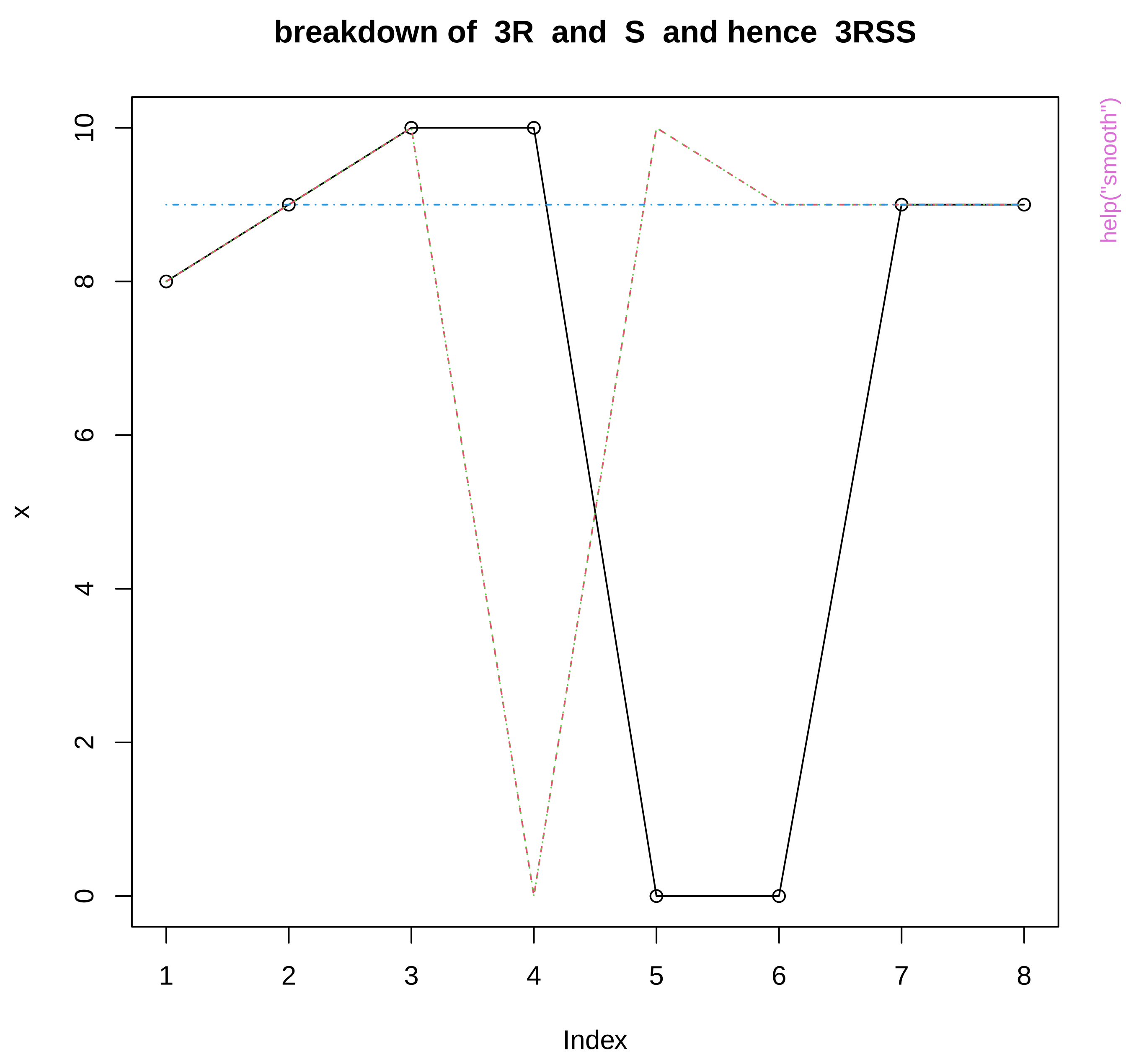

pc.cr
Variances
0.0
0.5
1.0
1.5
2.0
Comp.1
Comp.2
Comp.3
Comp.4
help("screeplot")

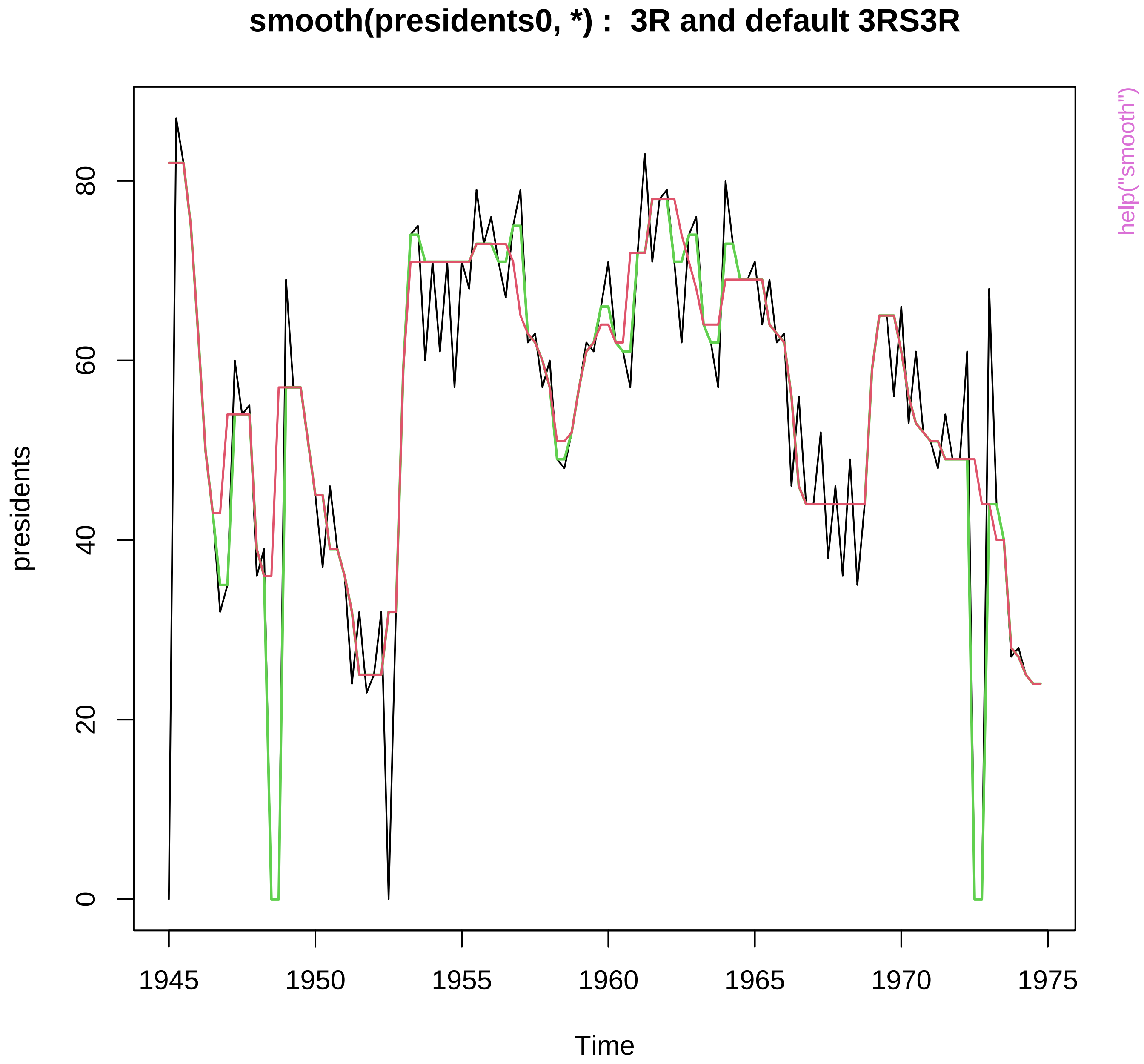

fit
Variances
0
2
4
6
8
Comp.1
Comp.3
Comp.5
Comp.7
Comp.9
help("screeplot")


fit
Variances
0
2
4
6
8
Comp.1
Comp.5
Comp.9
Comp.13
Comp.17
Comp.21
help("screeplot")

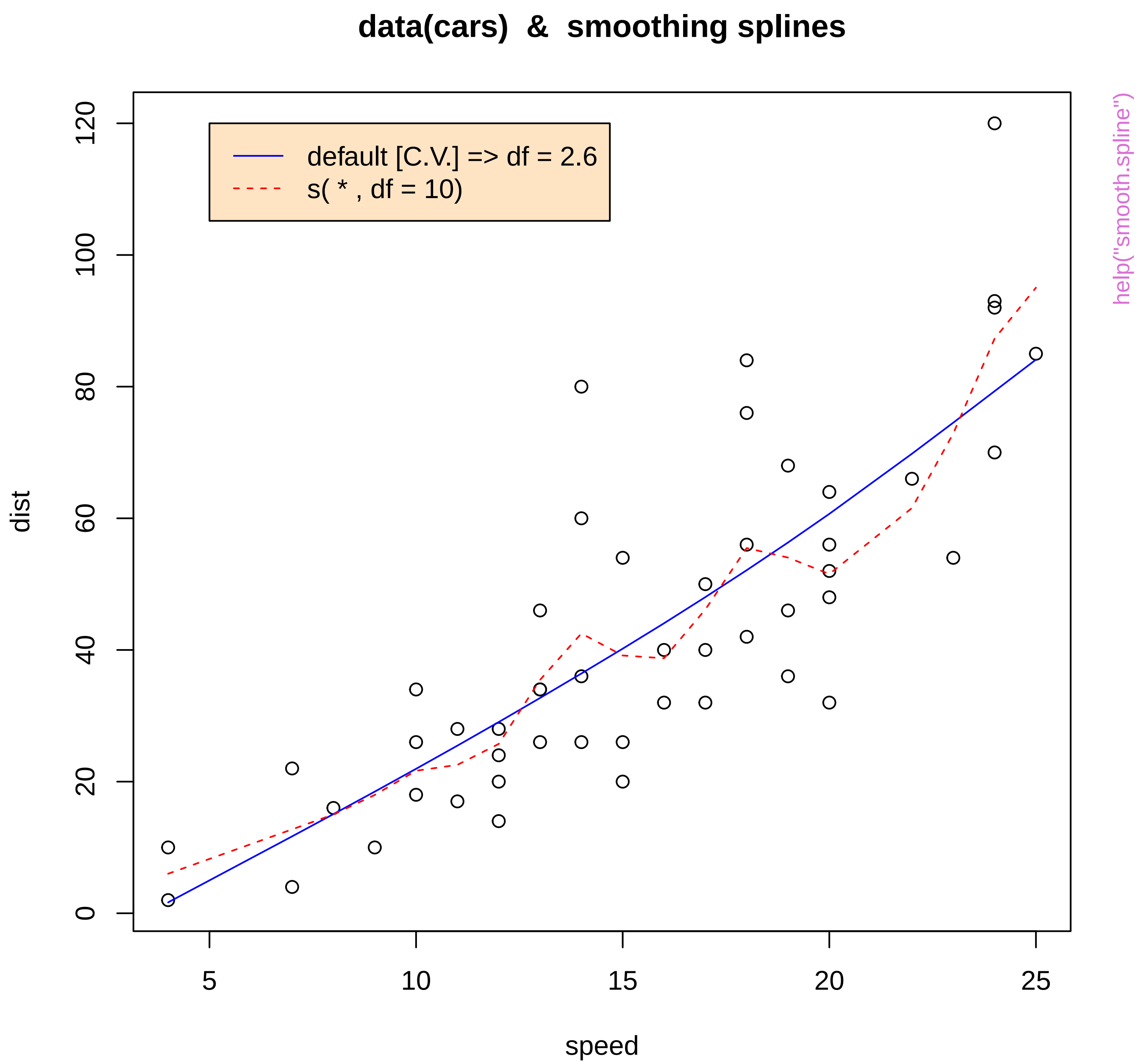


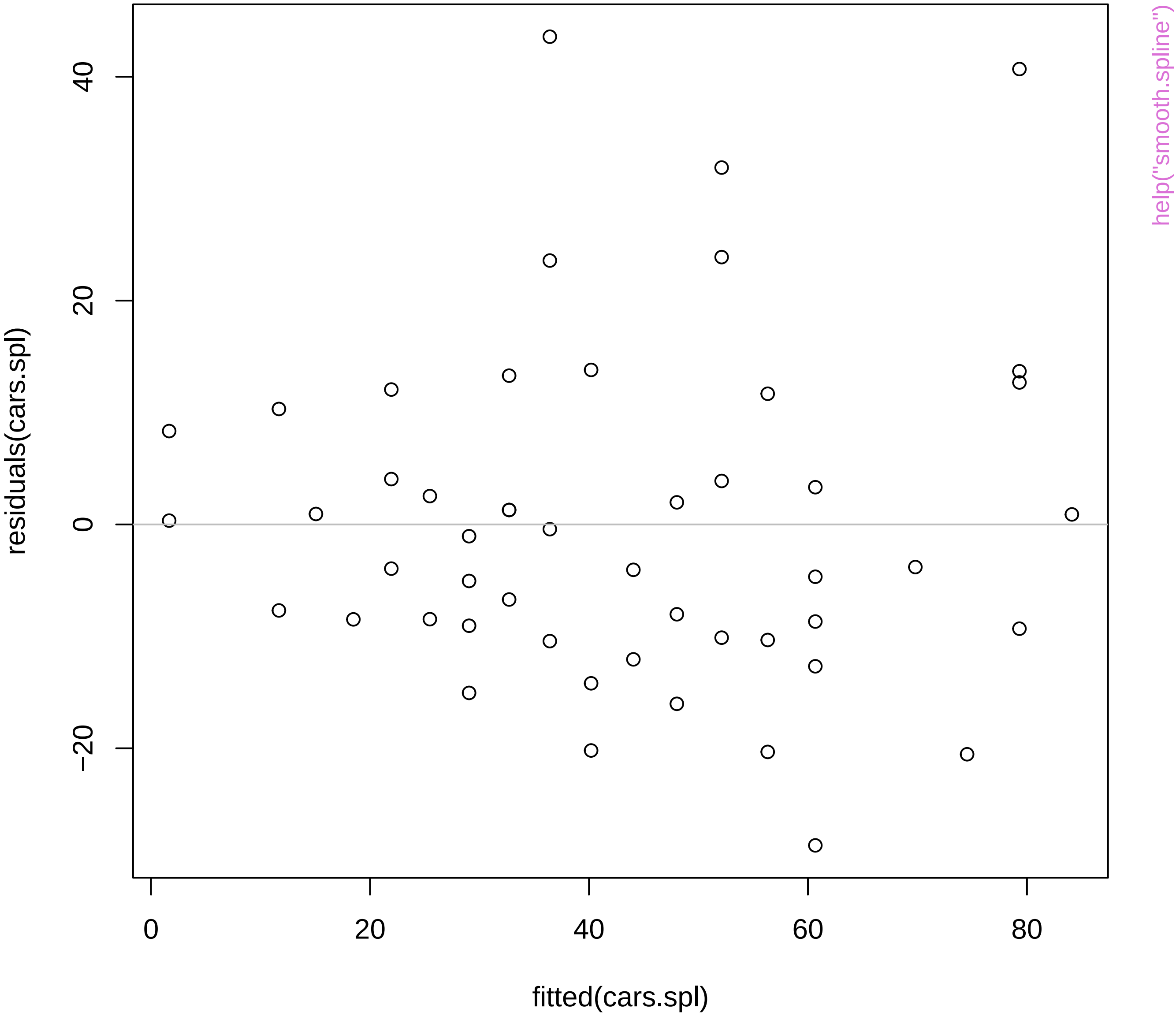
misbehaviour of "3RSR"
help("smooth")
y
Index
5
10
15
20
5
10
15

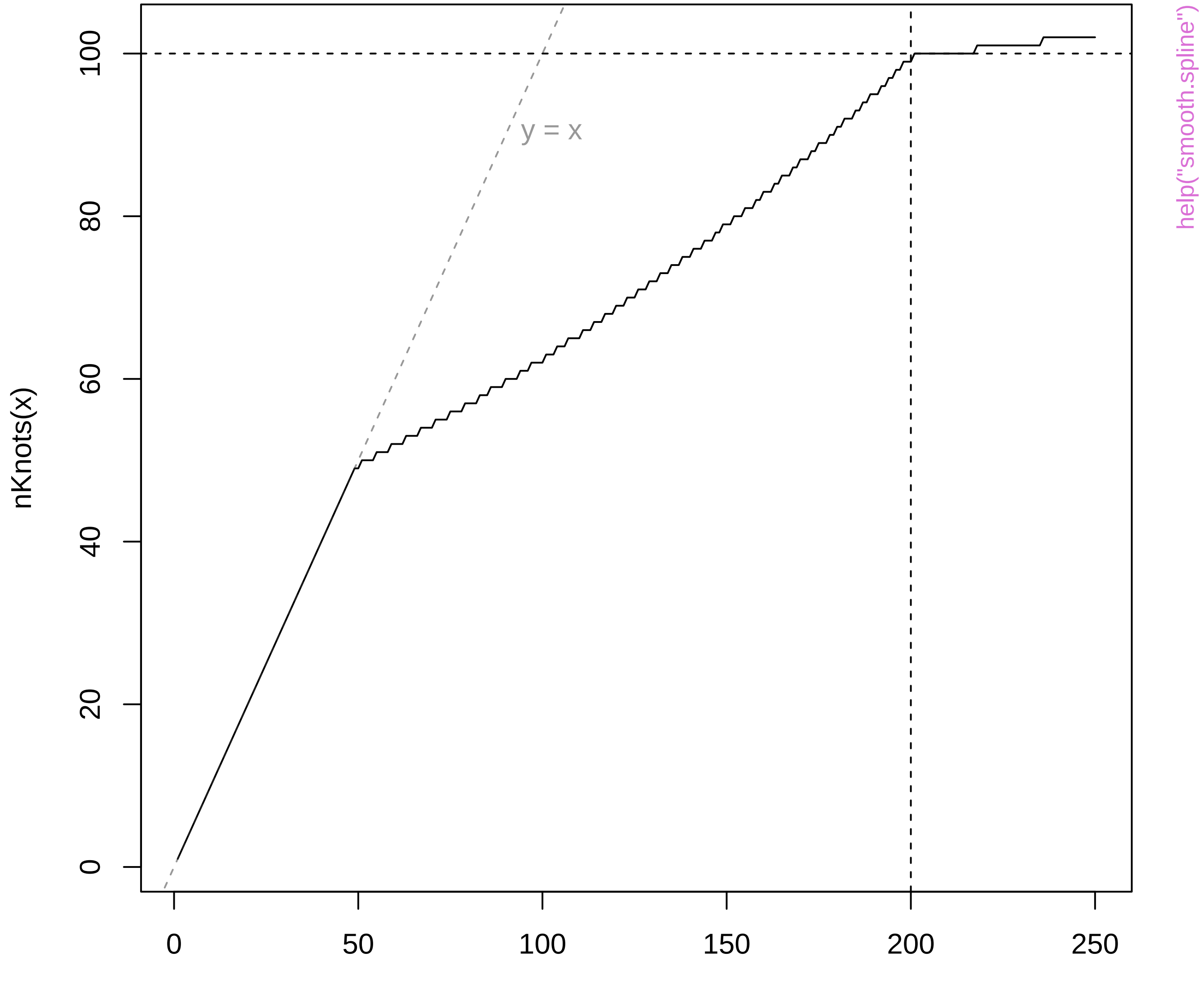

breakdown of 3R and S and hence 3RSS
x
Index
0
2
4
6
8
10
1
2
3
4
5
6
7
8
help("smooth")



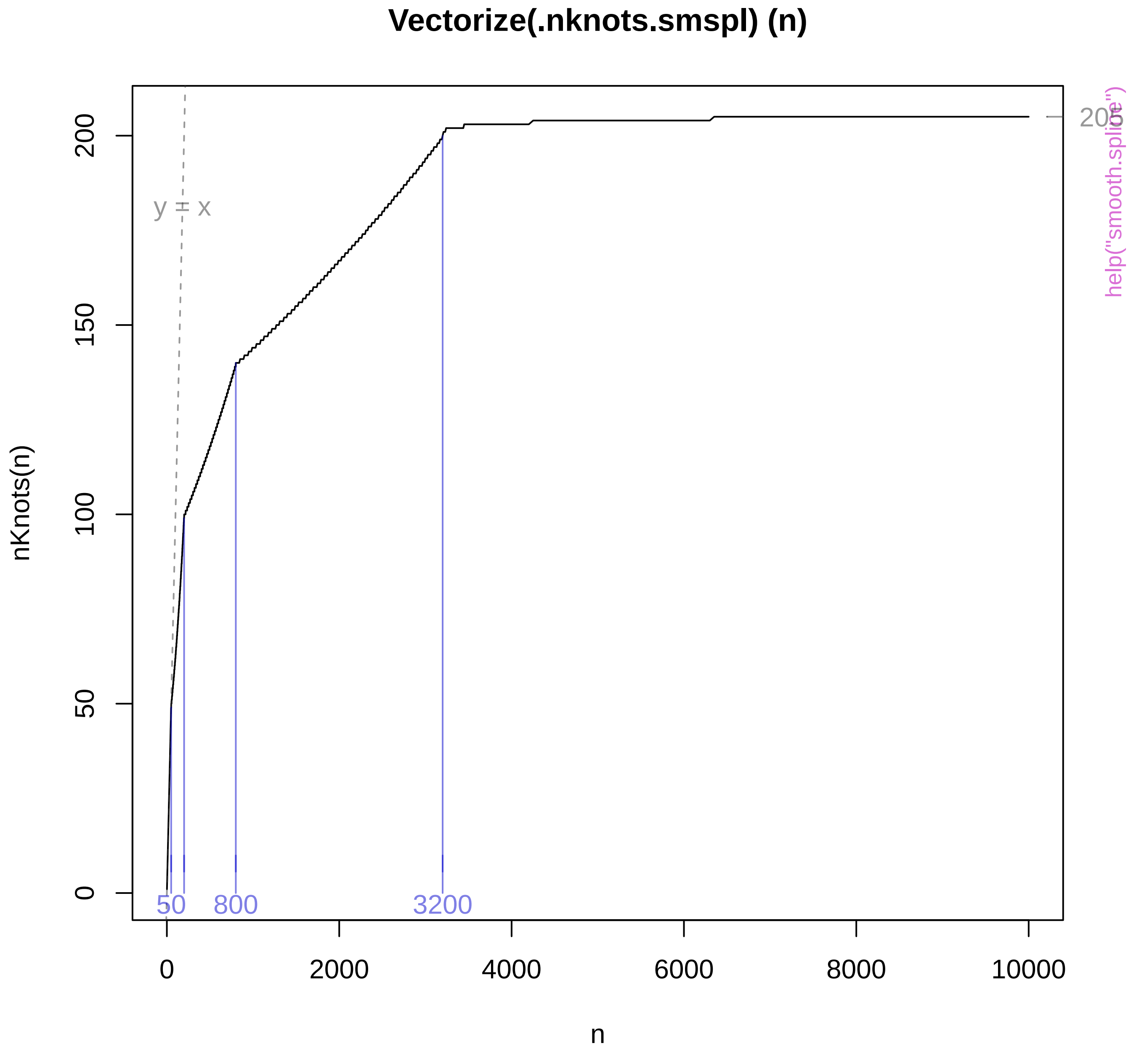
smooth(presidents0, *) : 3R and default 3RS3R
presidents
0
20
40
60
80
1945
1950
1955
1960
1965
1970
1975
Time
help("smooth")


data(cars) & smoothing splines
default [C.V.] => df = 2.6
s(* , df = 10)
help("smooth.spline")
dist
speed
0
20
40
60
80
100
120
5
10
15
20
25

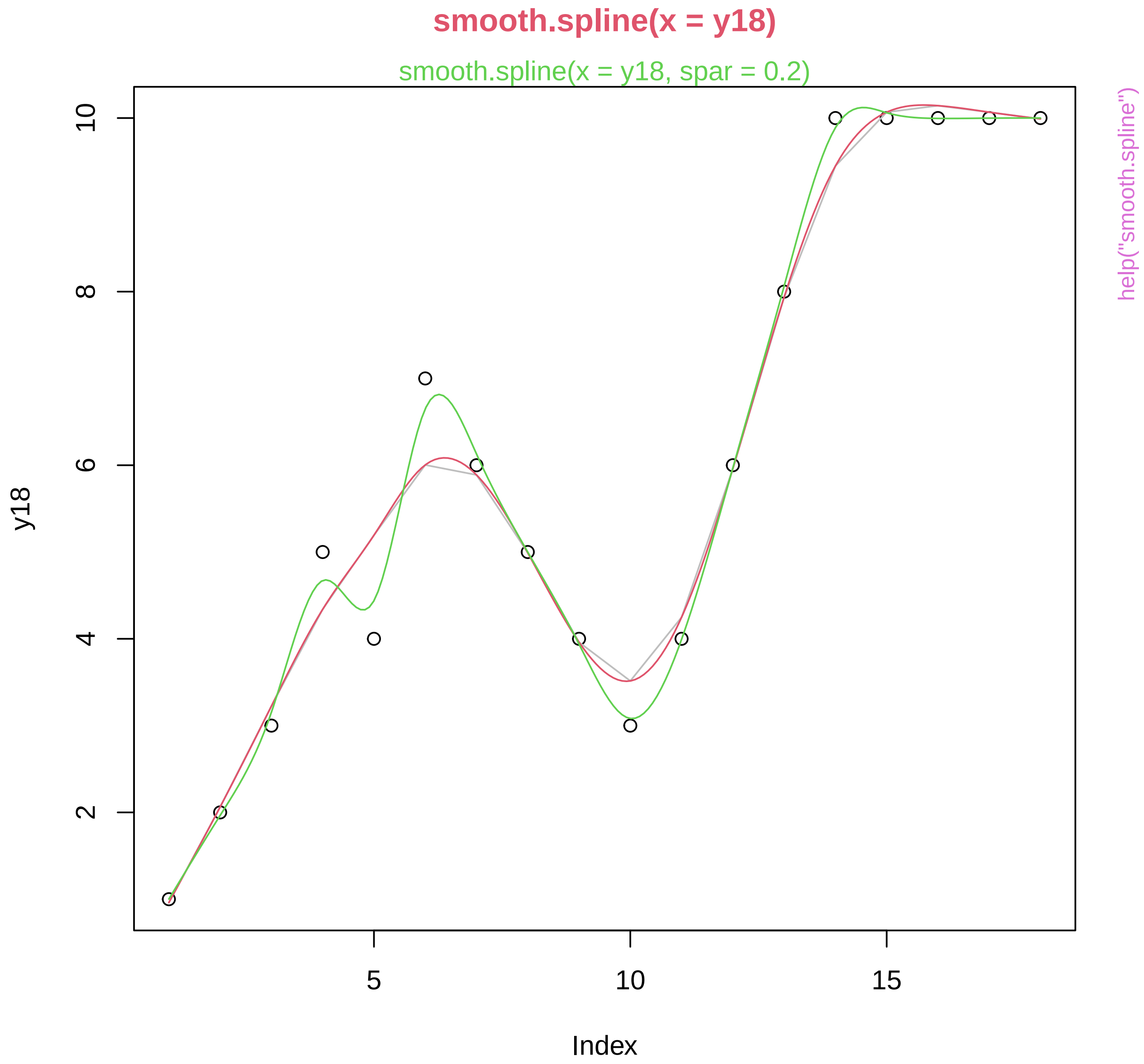

residuals(cars.spl)
fitted(cars.spl)
-20
0
20
40
0
20
40
60
80
help("smooth.spline")



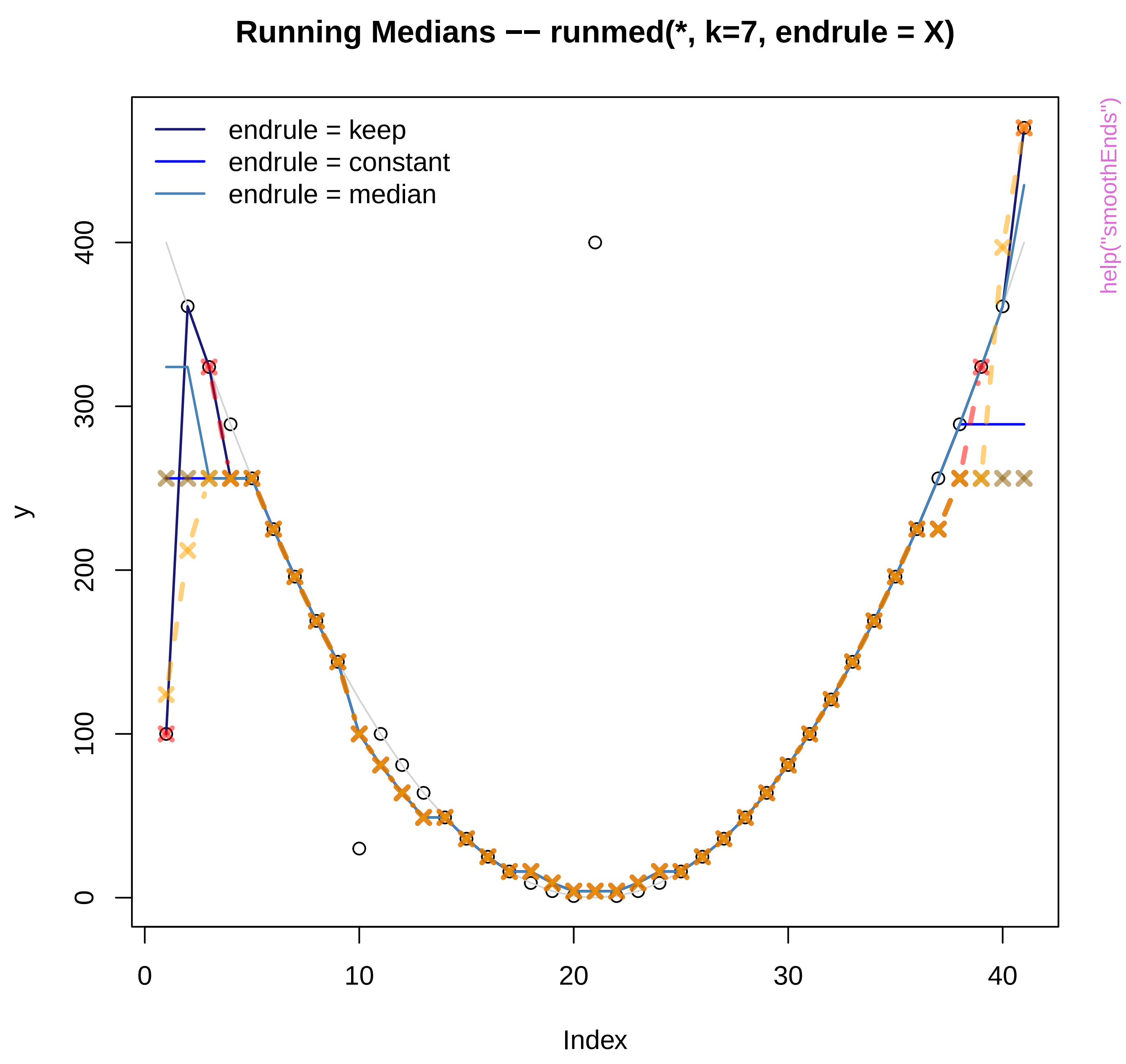
y = x
nKnots(x)
x
0
50
100
150
200
250
0
20
40
60
80
100
help("smooth.spline")



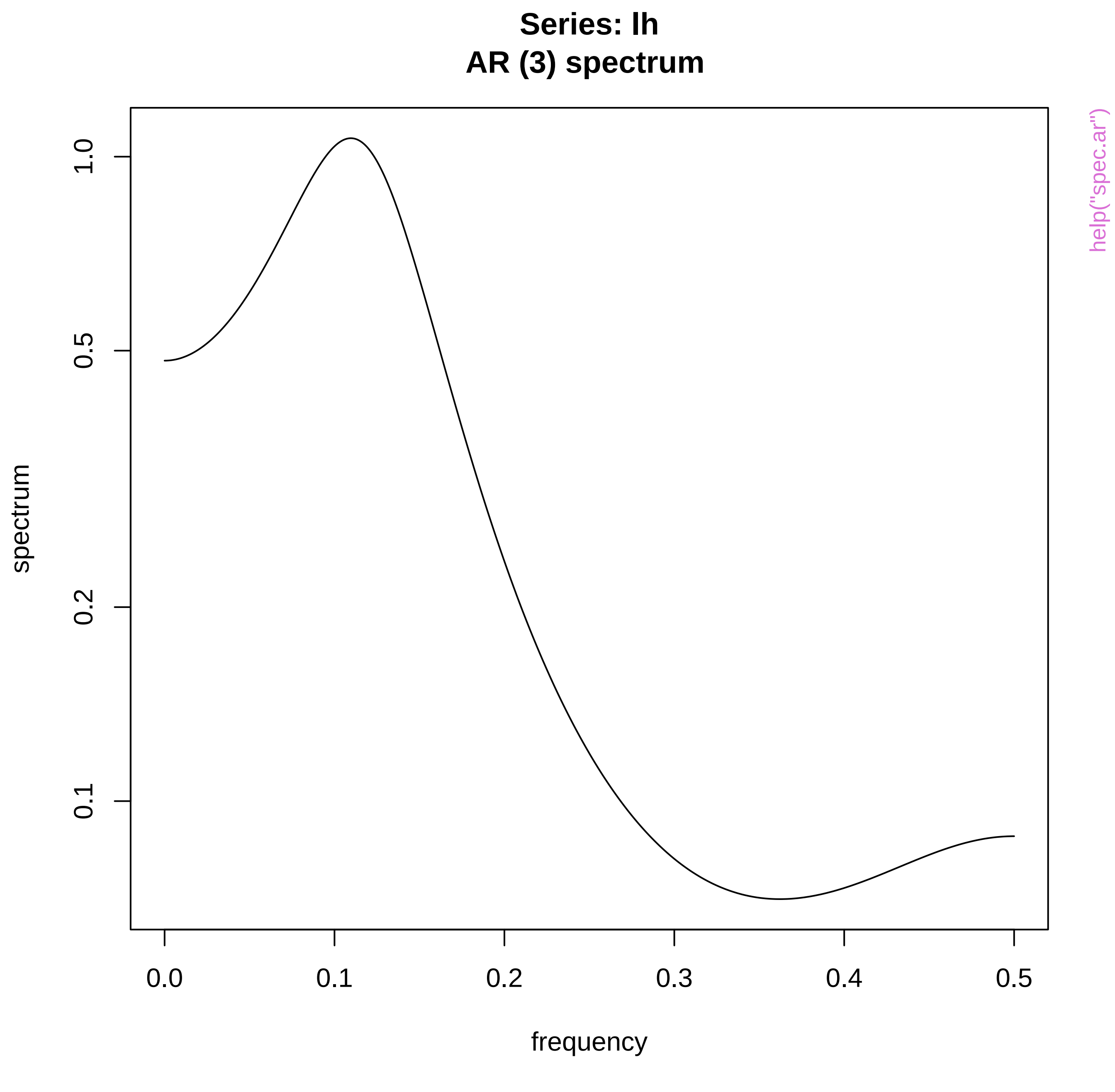
Vectorize(.nknots.smspl) (n)
nKnots(n)
n
0
50
100
150
200
0
2000
4000
6000
8000
10000
y = x
50
800
3200
205
help("smooth.spline")

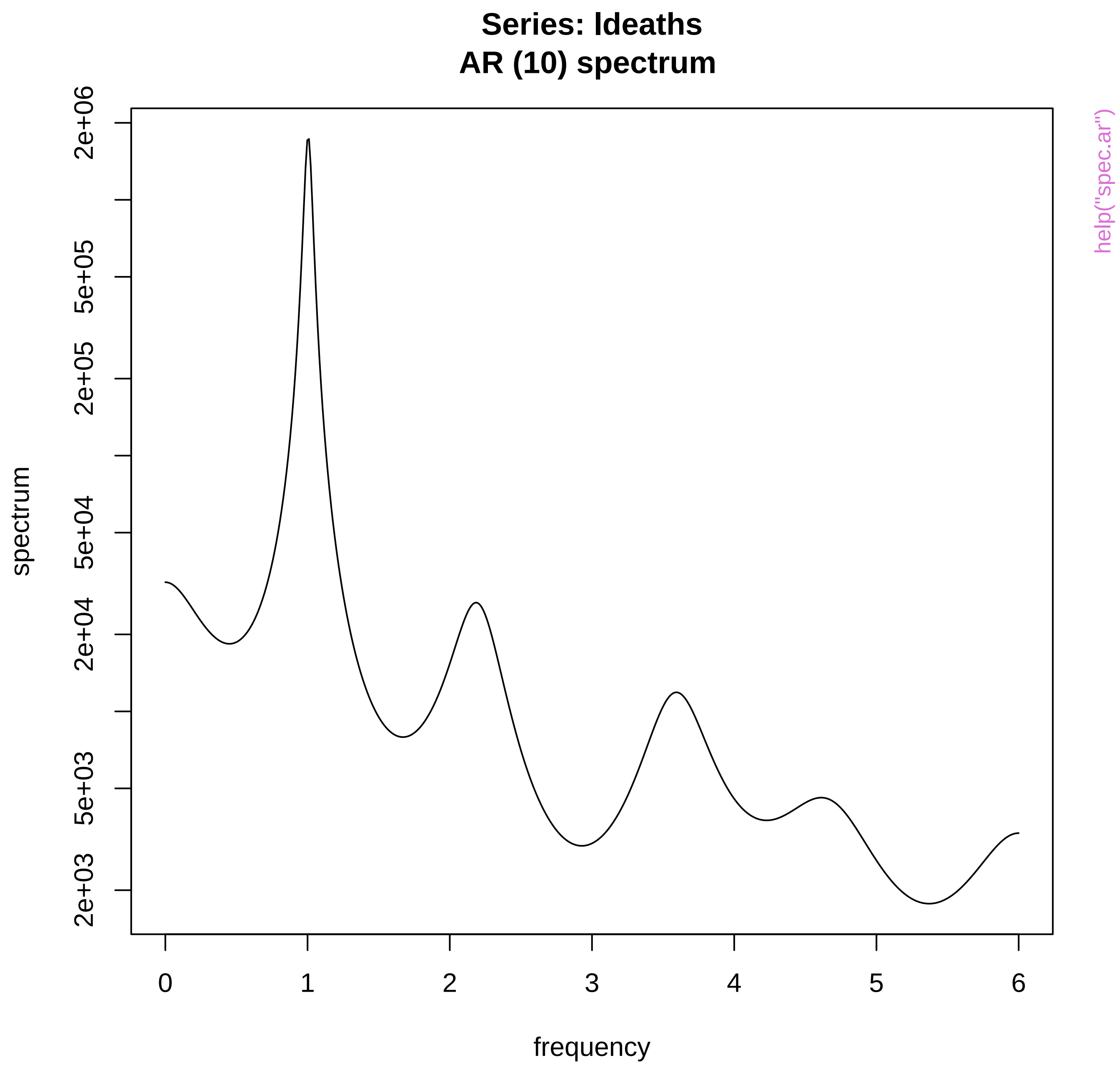


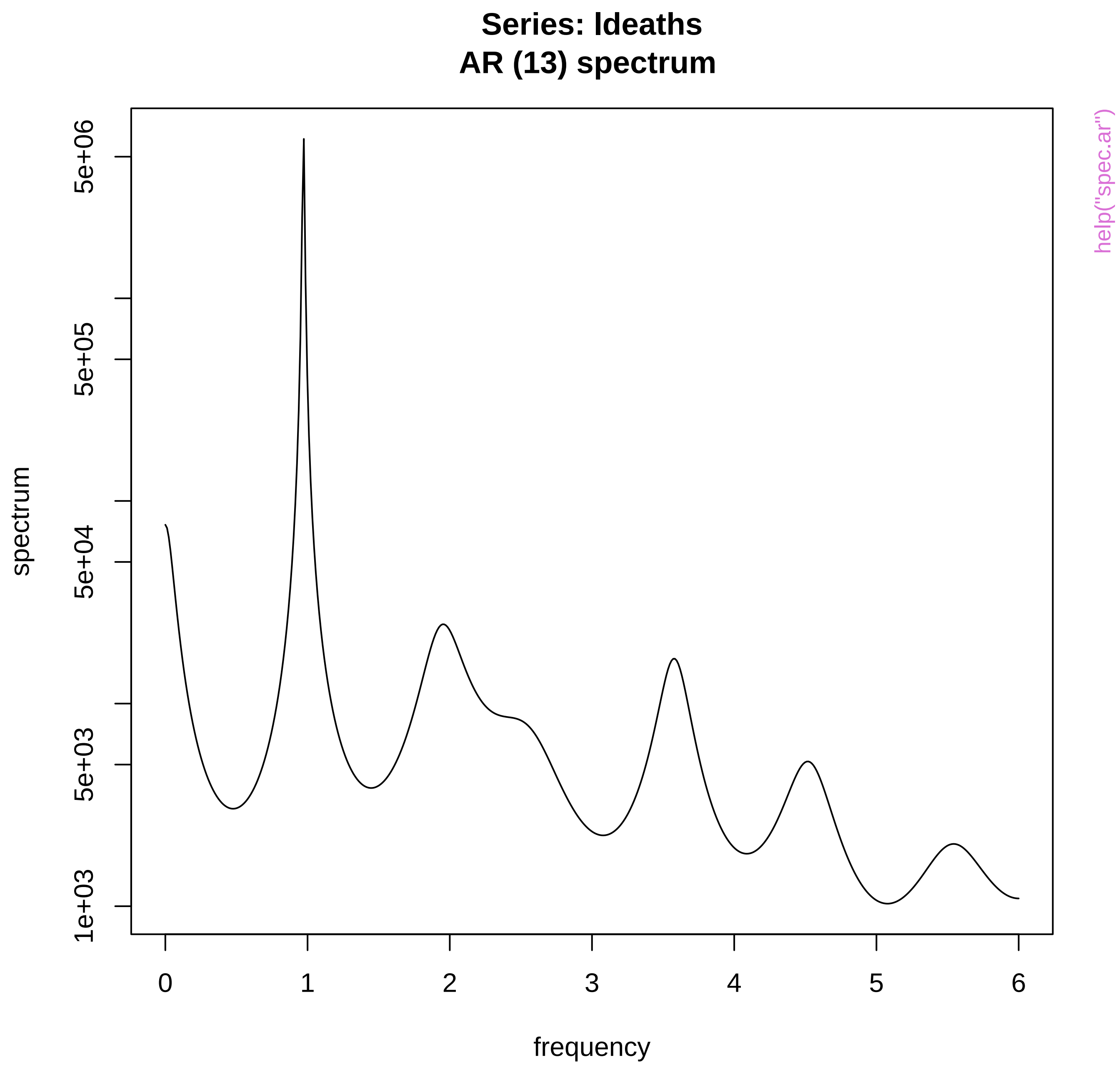
smooth.spline(x = y18)
smooth.spline(x = y18, spar = 0.2)
help("smooth.spline")
y18
Index
2
4
6
8
10
5
10
15

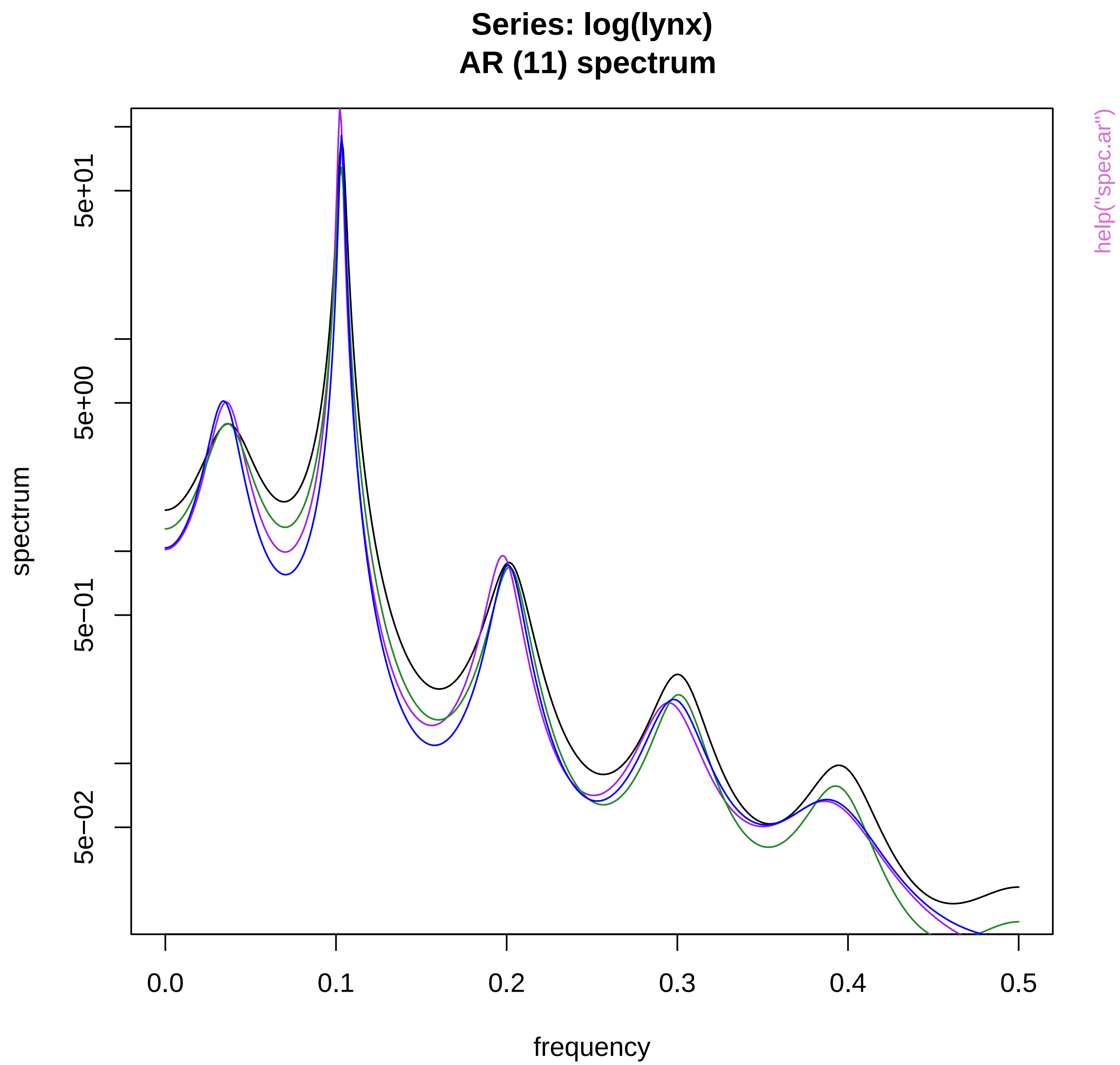


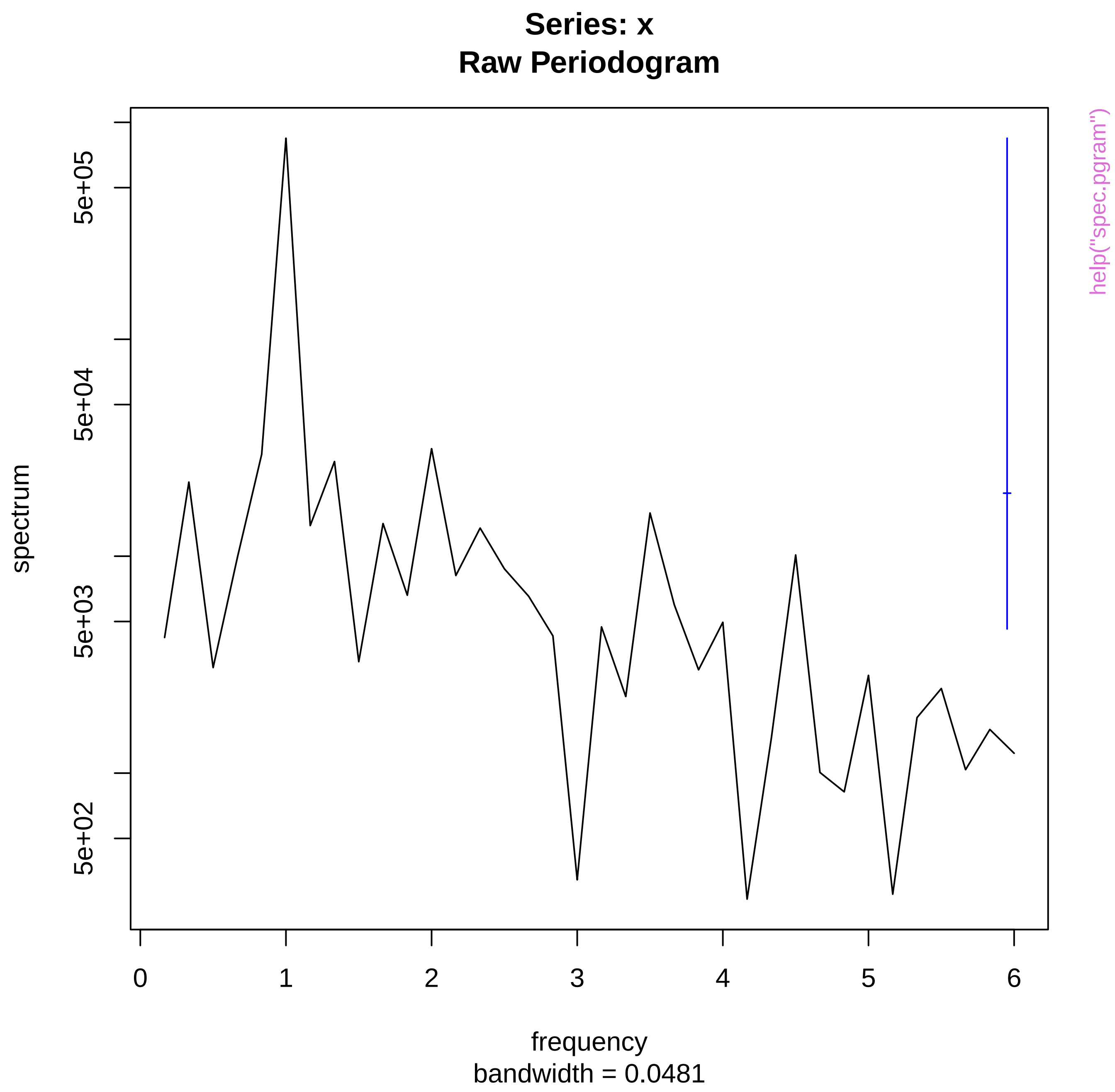
Running Medians -- runmed(*, k=7, endrule = X)
endrule = keep
endrule = constant
endrule = median
help("smoothEnds")
y
Index
0
100
200
300
400
0
10
20
30
40

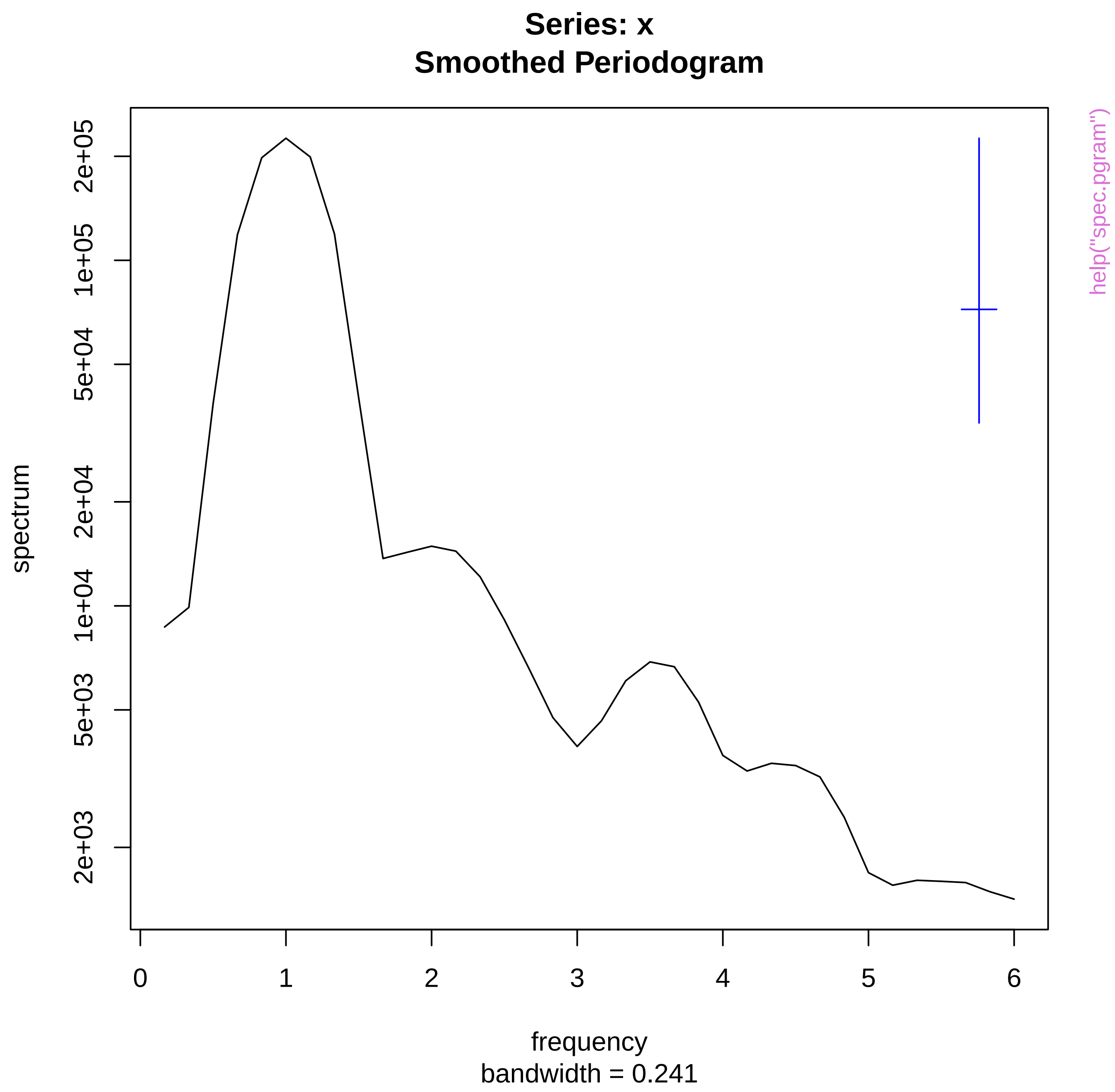

Series: lh
AR (3) spectrum
1.0
0.5
0.2
0.1
spectrum
0.0
0.1
0.2
0.3
0.4
0.5
frequency
help("spec.ar")

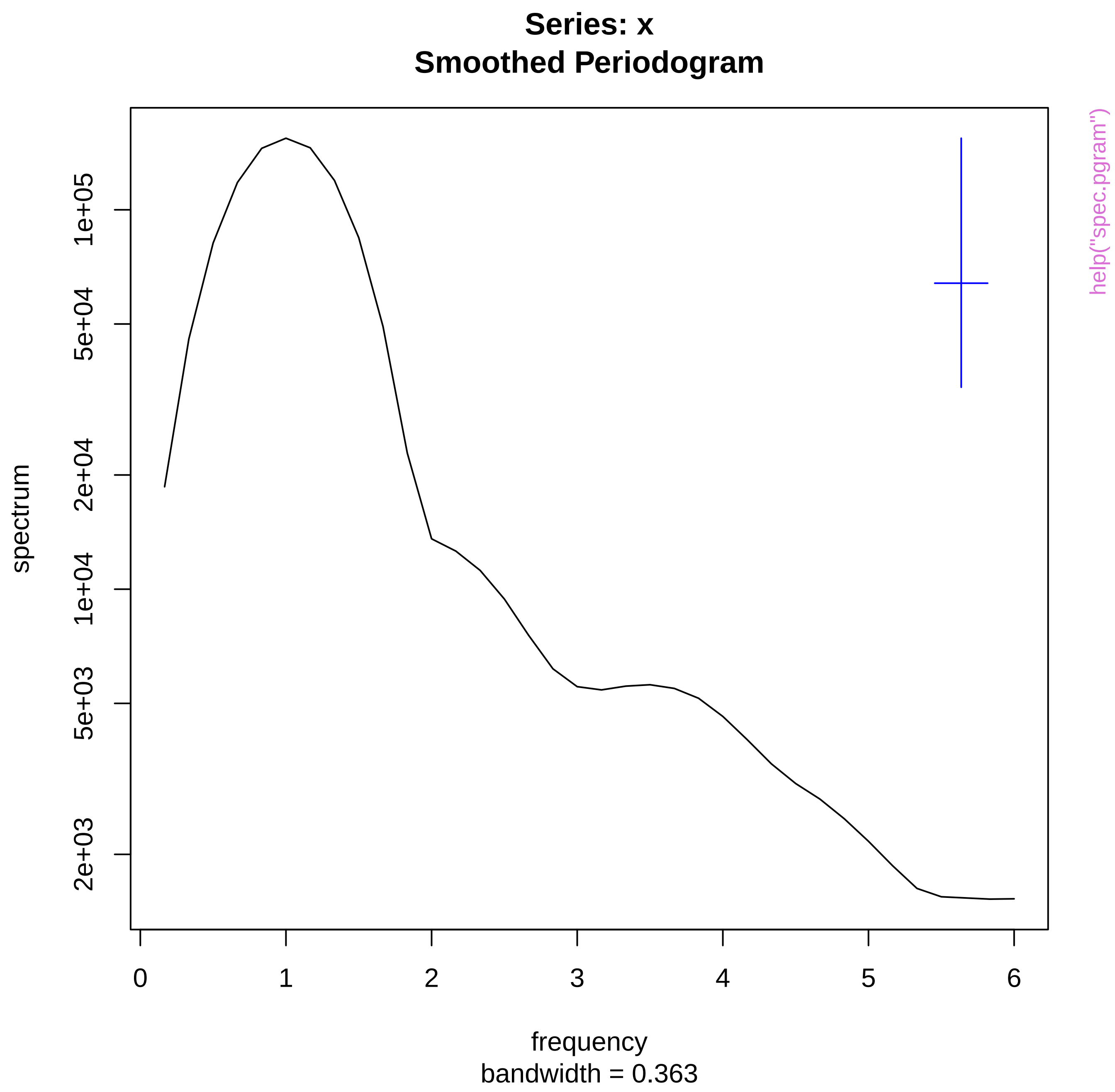

Series: ldeaths
AR (10) spectrum
spectrum
2e+06
5e+05
2e+05
5e+04
2e+04
5e+03
2e+03
0
1
2
3
4
5
6
frequency
help("spec.ar")

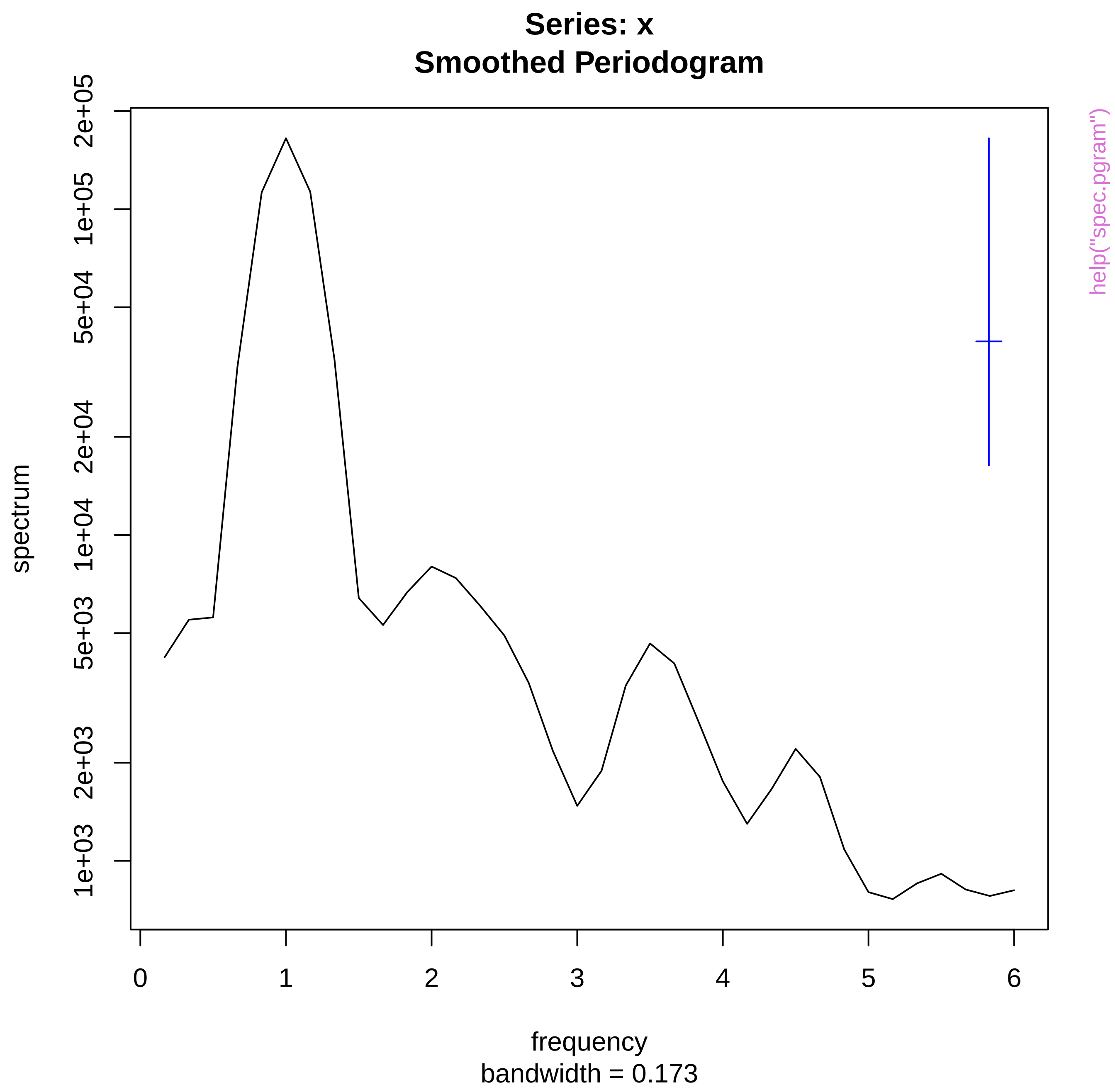

Series: ldeaths
AR (13) spectrum
spectrum
frequency
5e+06
5e+05
5e+04
5e+03
1e+03
0
1
2
3
4
5
6
help("spec.ar")

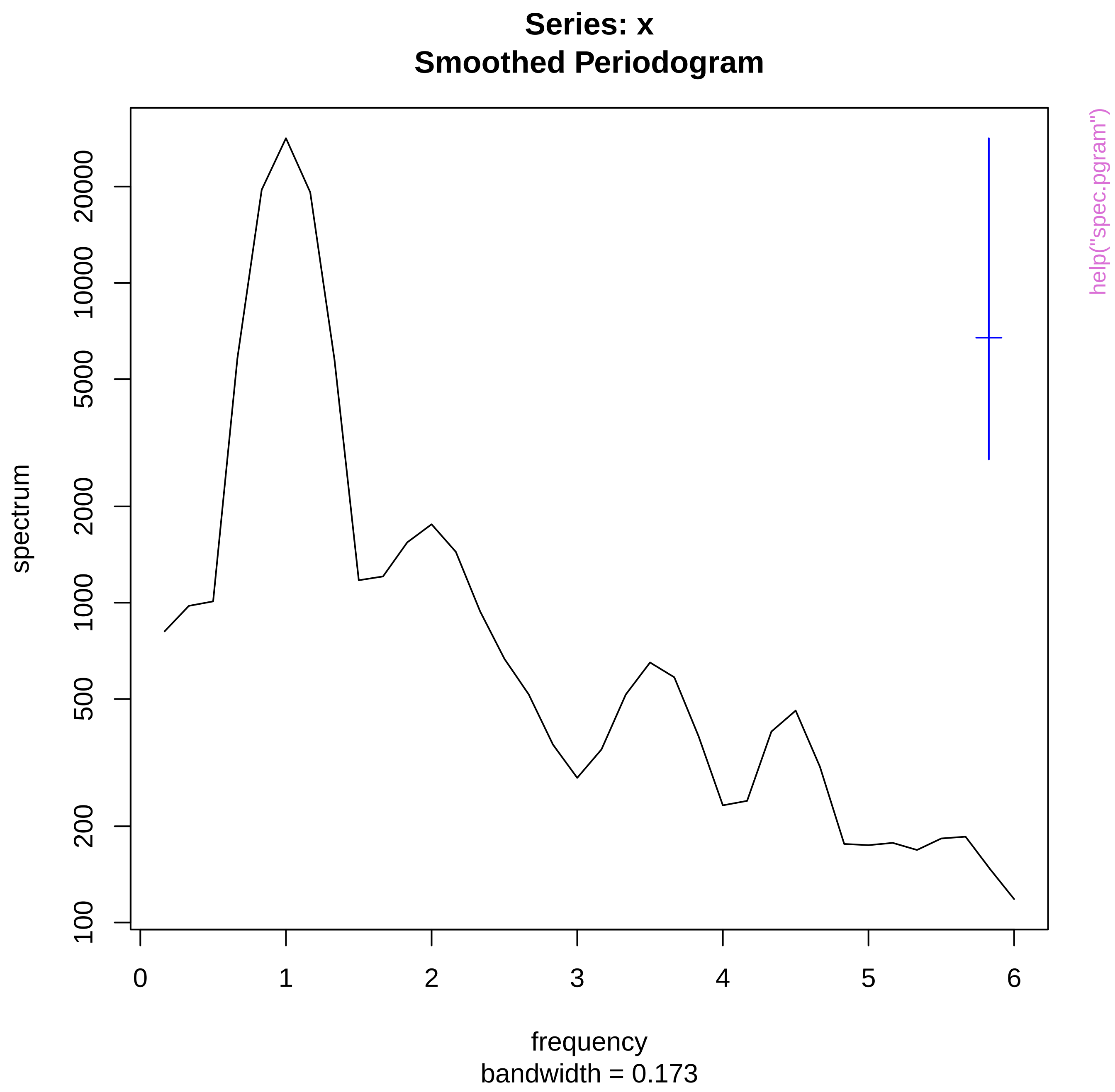

Series: log(lynx)
AR (11) spectrum
spectrum
5e+01
5e+00
5e−01
5e−02
0.0
0.1
0.2
0.3
0.4
0.5
frequency
help("spec.ar")


Series: x
Raw Periodogram
spectrum
5e+05
5e+04
5e+03
5e+02
0
1
2
3
4
5
6
frequency
bandwidth = 0.0481
help("spec.pgram")

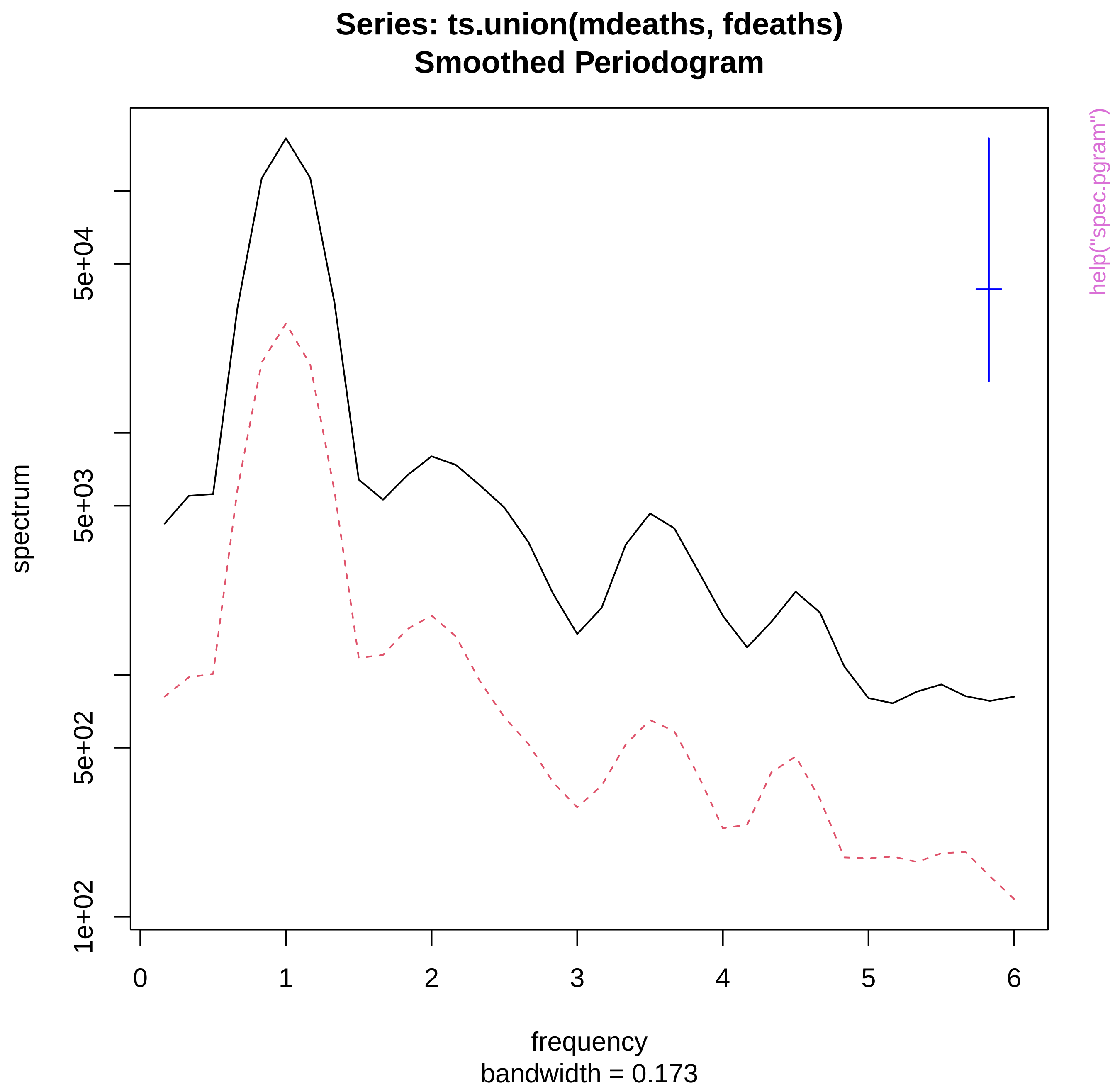

Series: x
Smoothed Periodogram
spectrum
2e+05
1e+05
5e+04
2e+04
1e+04
5e+03
2e+03
0
1
2
3
4
5
6
frequency
bandwidth = 0.241
help("spec.pgram")

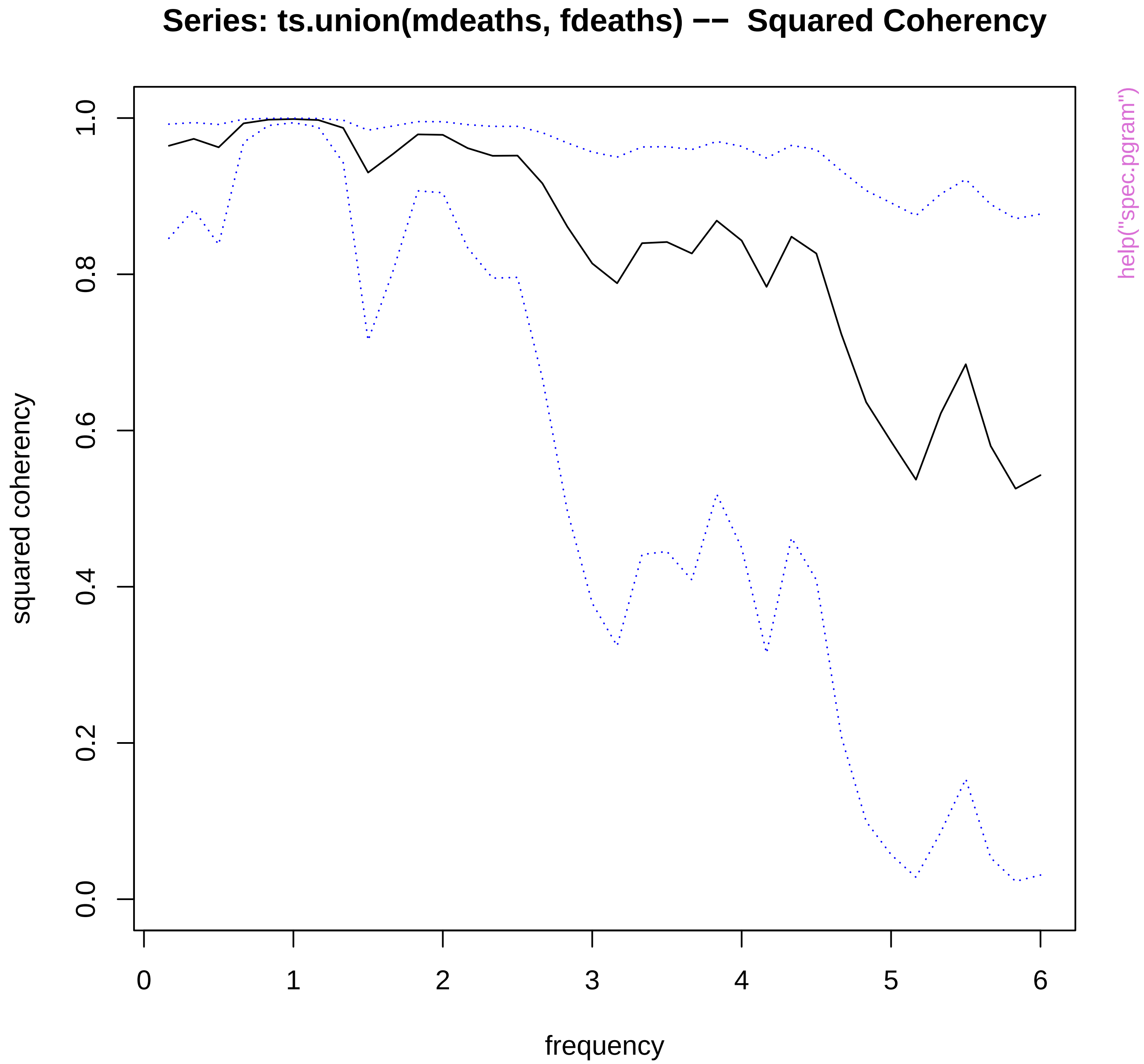

Series: x
Smoothed Periodogram
spectrum
1e+05
5e+04
2e+04
1e+04
5e+03
2e+03
0
1
2
3
4
5
6
frequency
bandwidth = 0.363
help("spec.pgram")


Series: x
Smoothed Periodogram
spectrum
2e+05
1e+05
5e+04
2e+04
1e+04
5e+03
2e+03
1e+03
0
1
2
3
4
5
6
frequency
bandwidth = 0.173
help("spec.pgram")

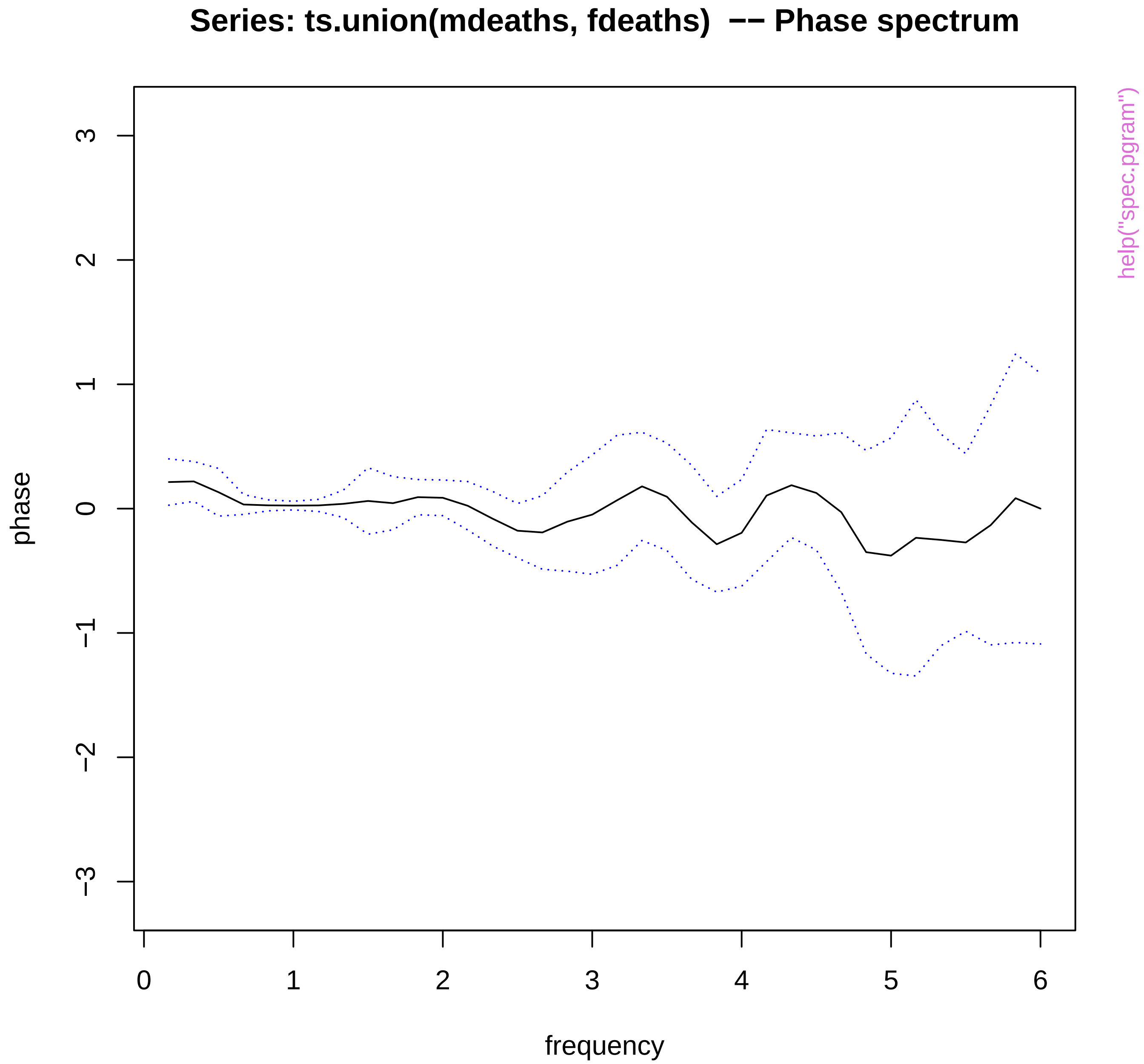


Series: x
Smoothed Periodogram
spectrum
100
200
500
1000
2000
5000
10000
20000
0
1
2
3
4
5
6
frequency
bandwidth = 0.173
help("spec.pgram")

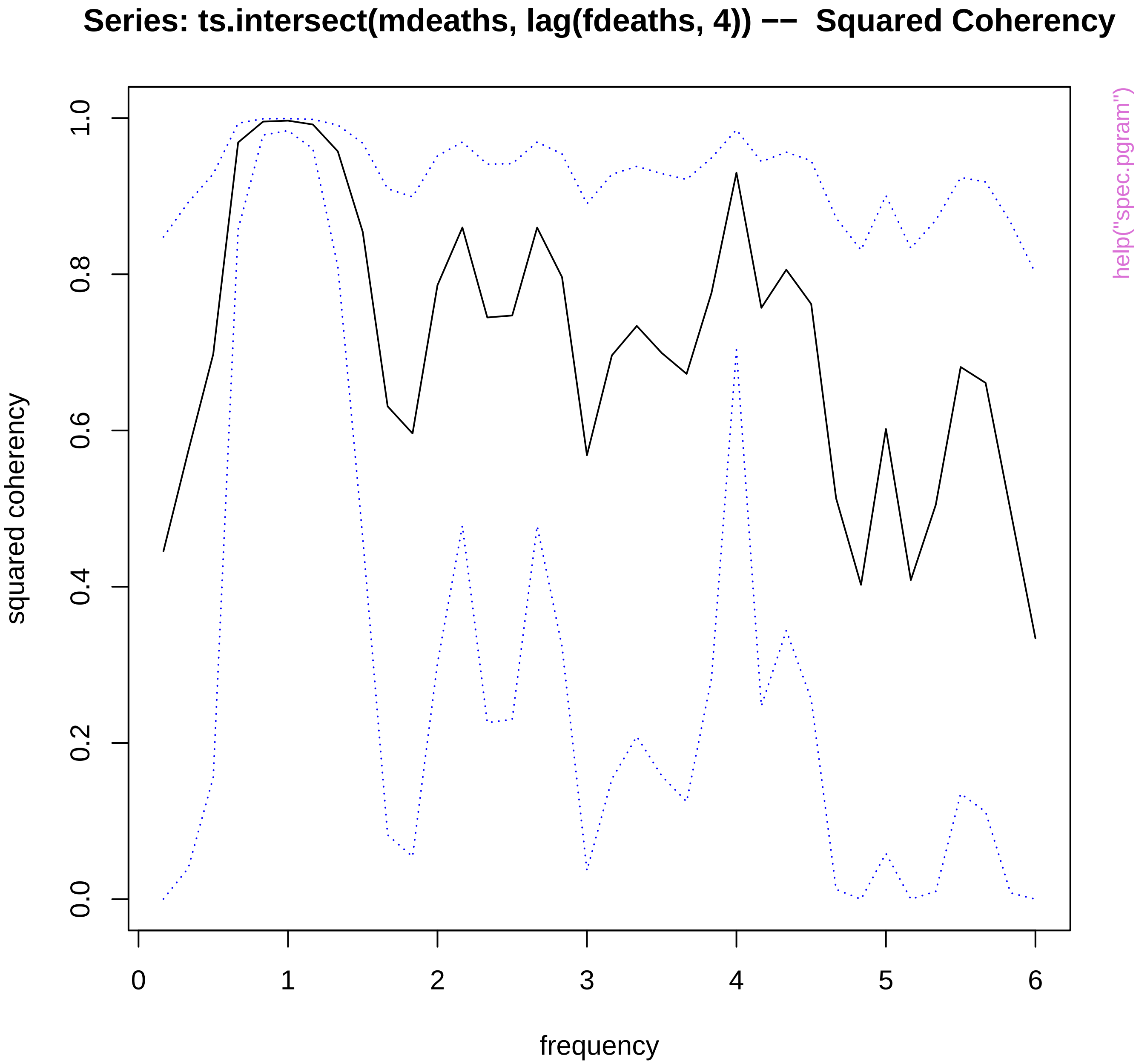

Series: ts.union(mdeaths, fdeaths)
Smoothed Periodogram
spectrum
1e+02
5e+02
5e+03
5e+04
0
1
2
3
4
5
6
frequency
bandwidth = 0.173
help("spec.pgram")

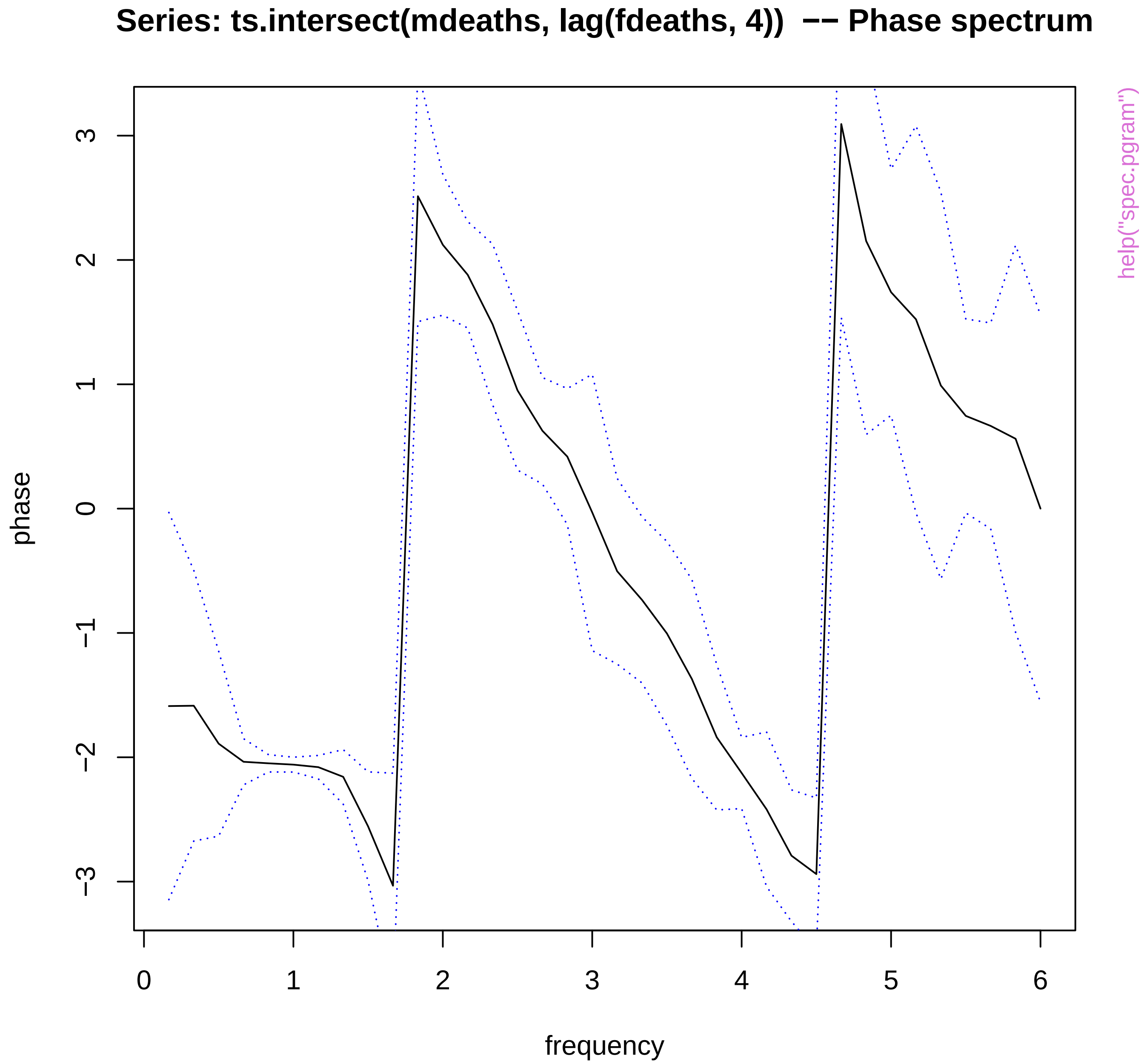


Series: ts.union(mdeaths, fdeaths) -- Squared Coherency
squared coherency
frequency
0.0
0.2
0.4
0.6
0.8
1.0
0
1
2
3
4
5
6
help("spec.pgram")

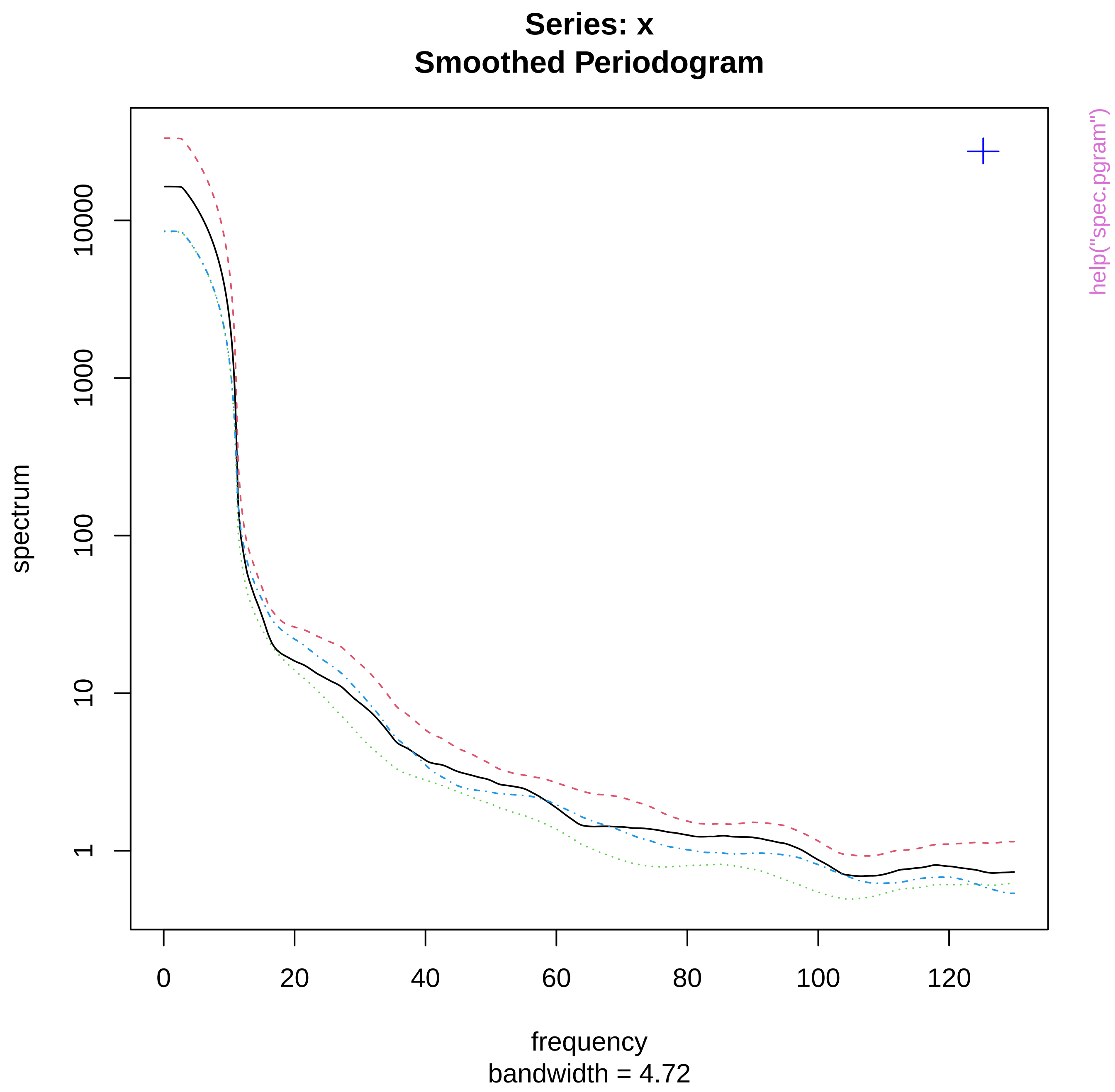


Series: ts.union(mdeaths, fdeaths) -- Phase spectrum
phase
frequency
3
2
1
0
−1
−2
−3
0
1
2
3
4
5
6
help("spec.pgram")

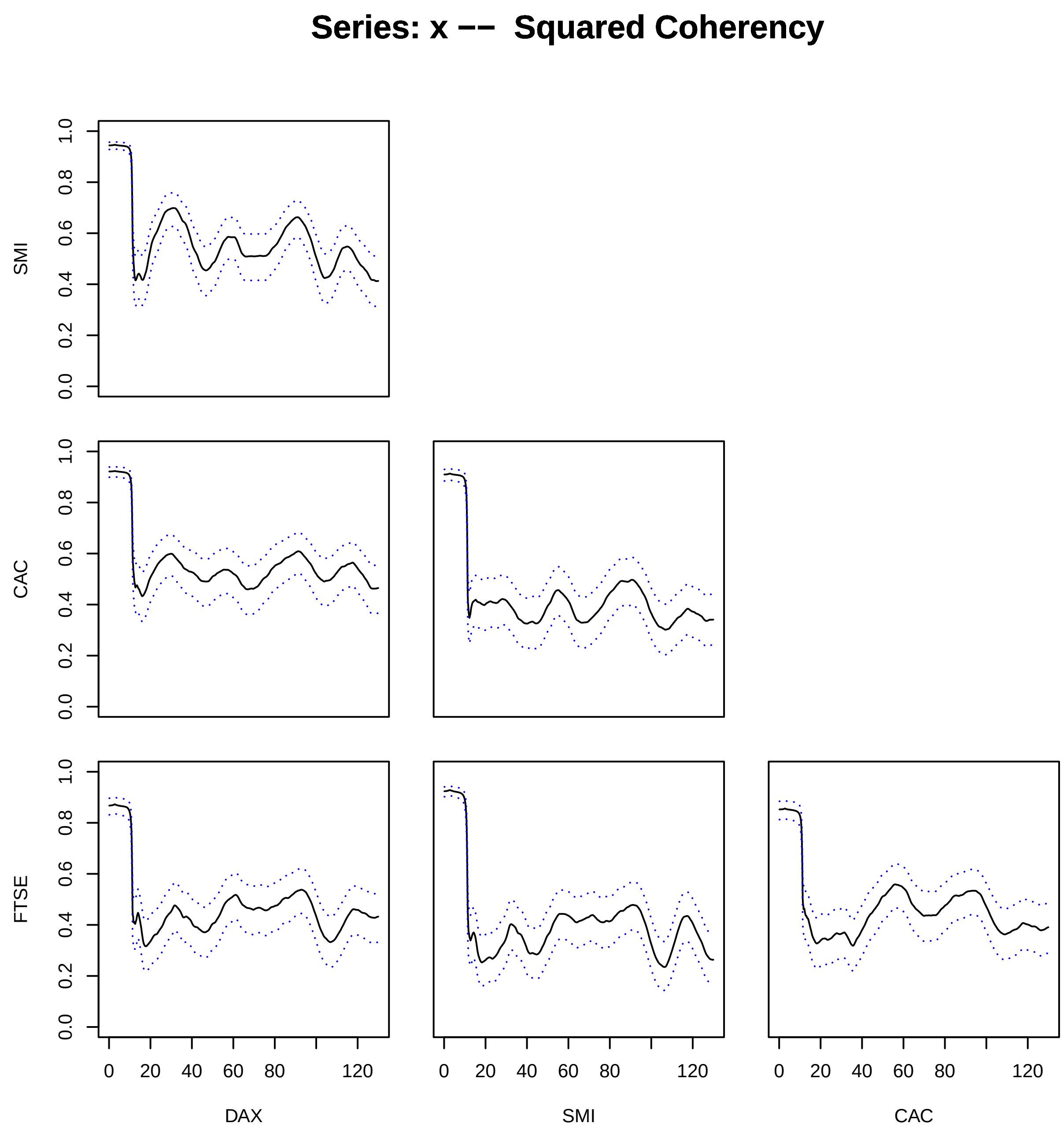

Series: ts.intersect(mdeaths, lag(fdeaths, 4)) -- Squared Coherency
squared coherency
frequency
0.0
0.2
0.4
0.6
0.8
1.0
0
1
2
3
4
5
6
help("spec.pgram")



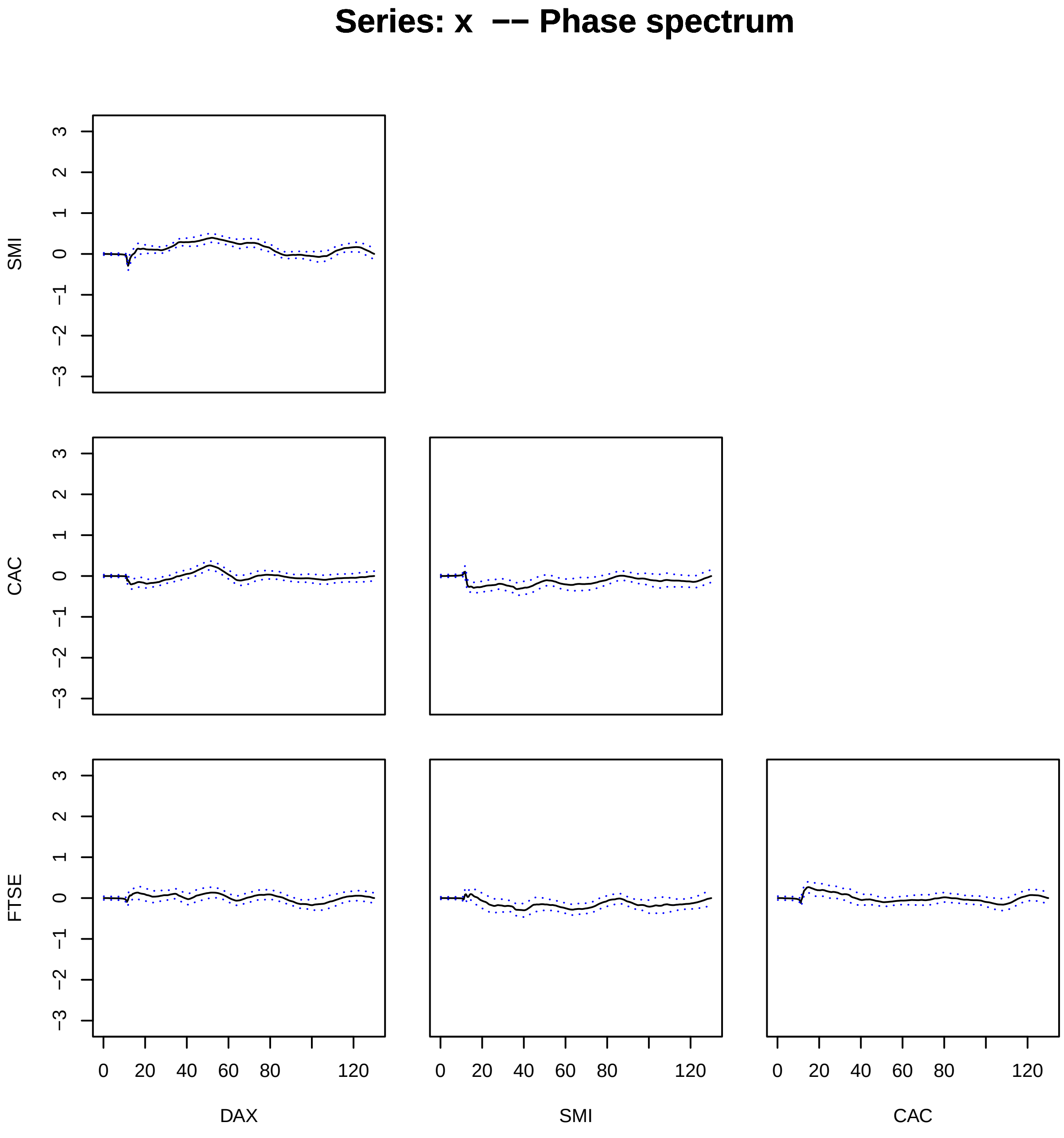
Series: ts.intersect(mdeaths, lag(fdeaths, 4)) -- Phase spectrum
phase
frequency
3
2
1
0
−1
−2
−3
0
1
2
3
4
5
6
help("spec.pgram")

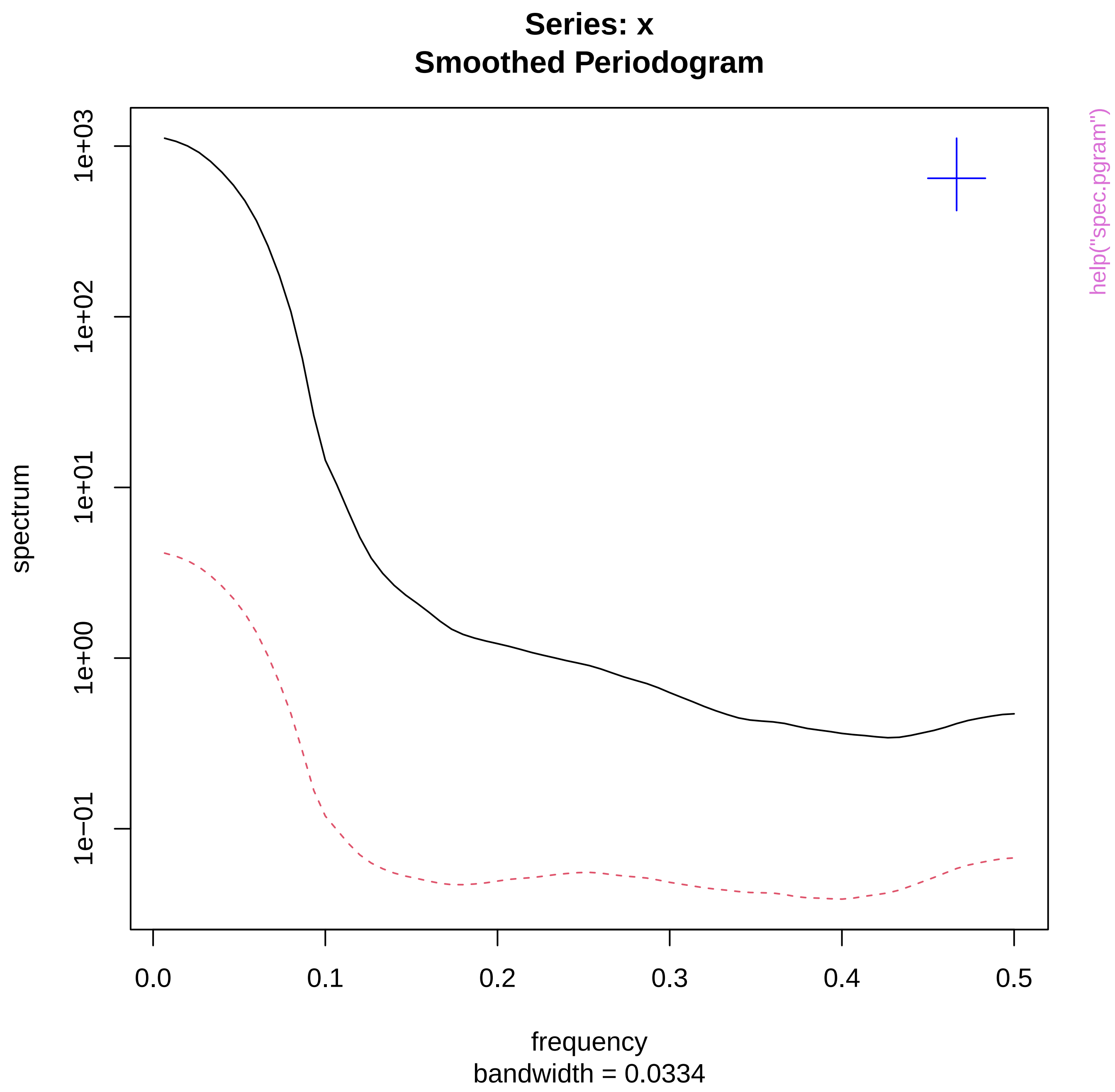


Series: x
Smoothed Periodogram
spectrum
10000
1000
100
10
1
0
20
40
60
80
100
120
frequency
bandwidth = 4.72
help("spec.pgram")

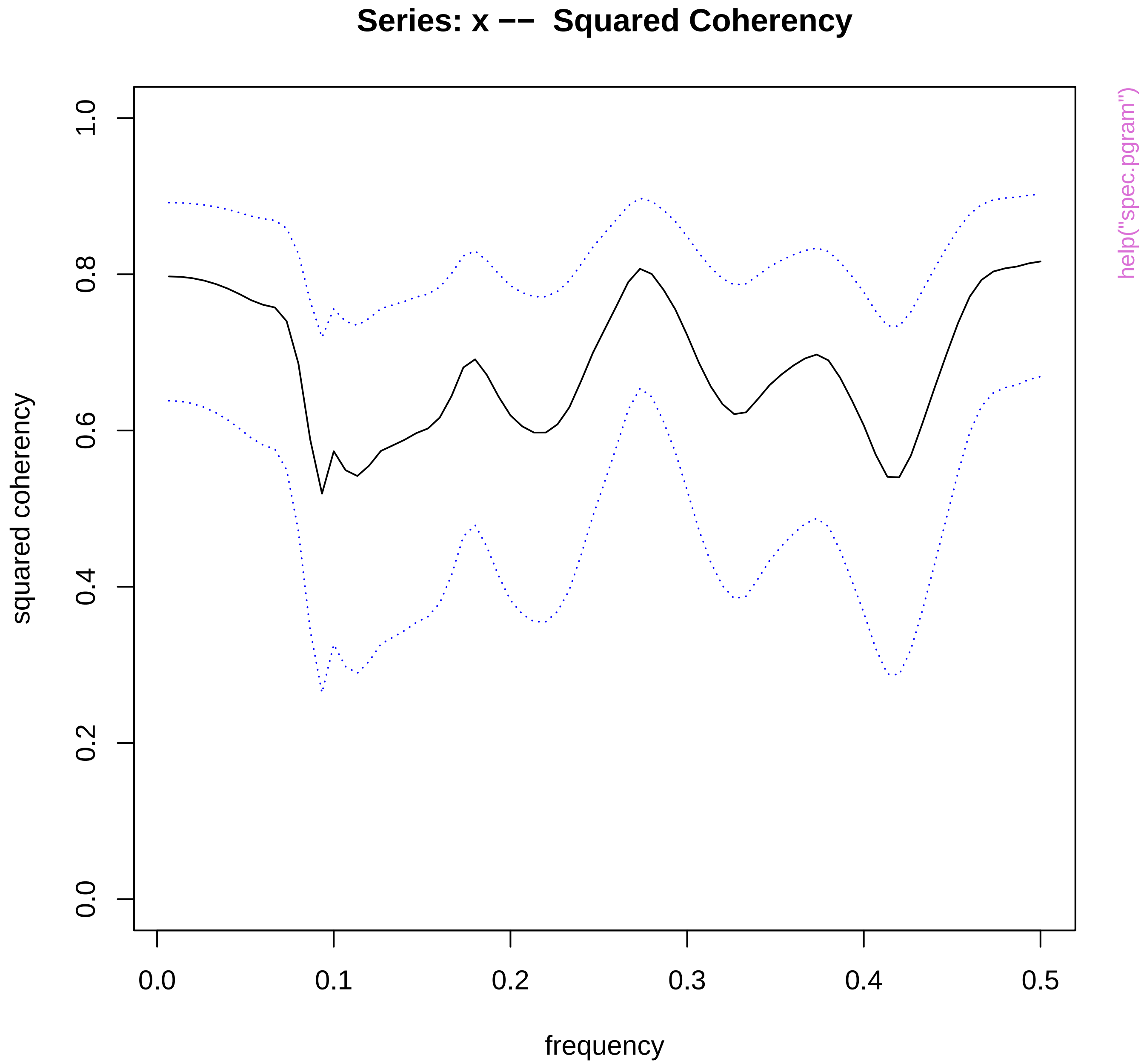


Series: x -- Squared Coherency
SMI
CAC
FTSE
DAX
SMI
CAC
0.0
0.2
0.4
0.6
0.8
1.0
0
20
40
60
80
120

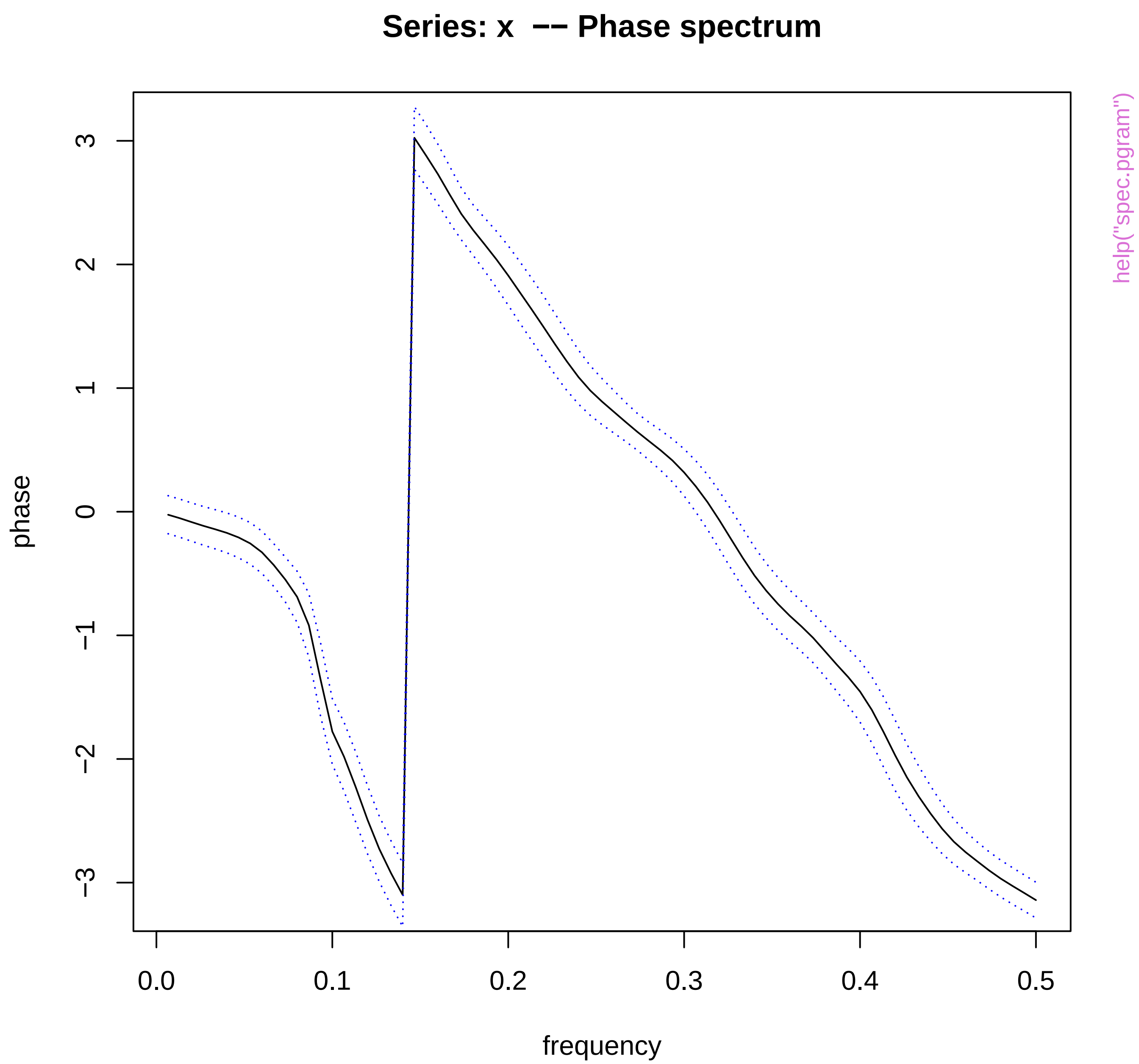

Series: x -- Phase spectrum
SMI
CAC
FTSE
DAX
SMI
CAC
3
2
1
0
−1
−2
−3
0
20
40
60
80
120

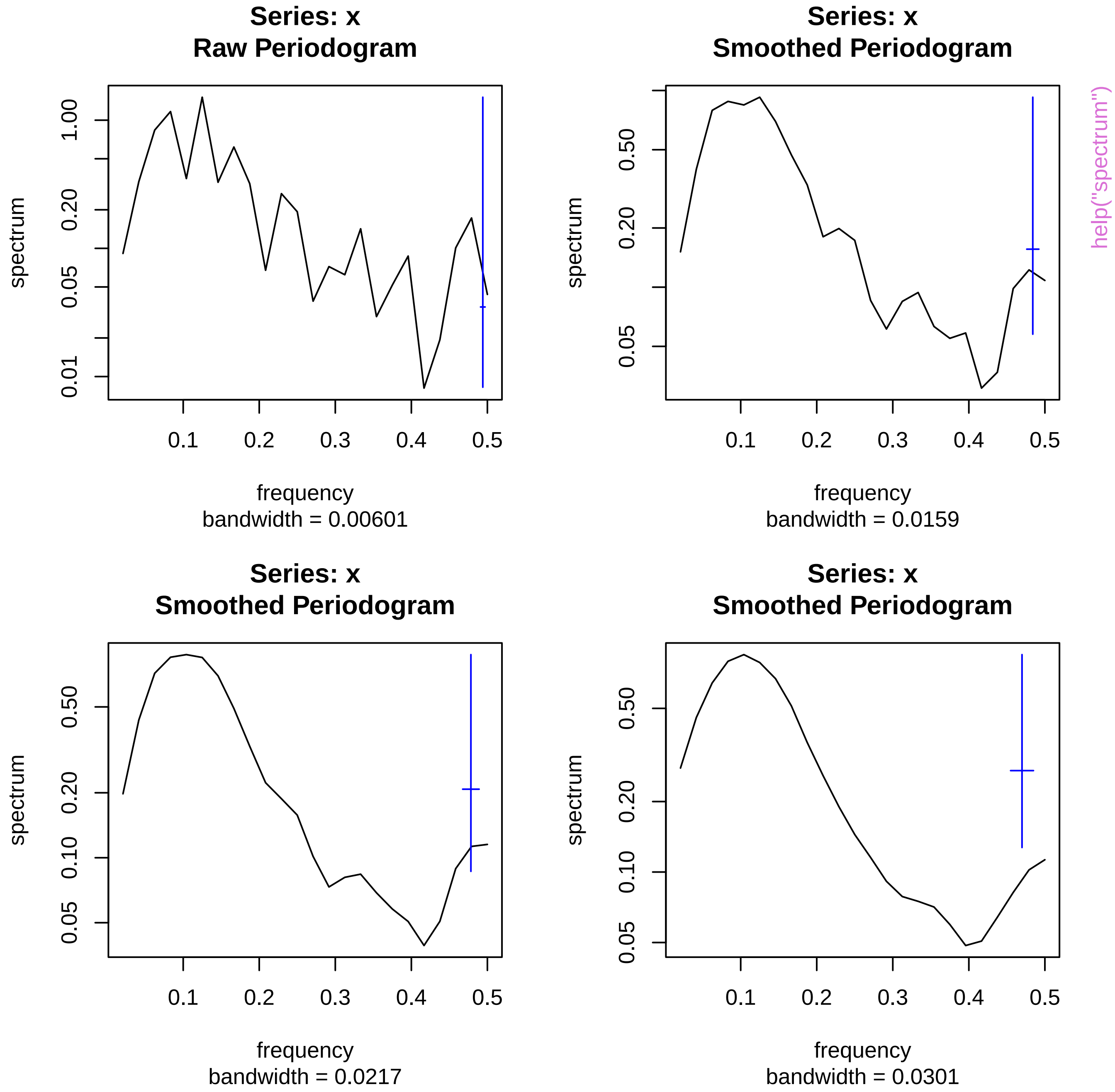


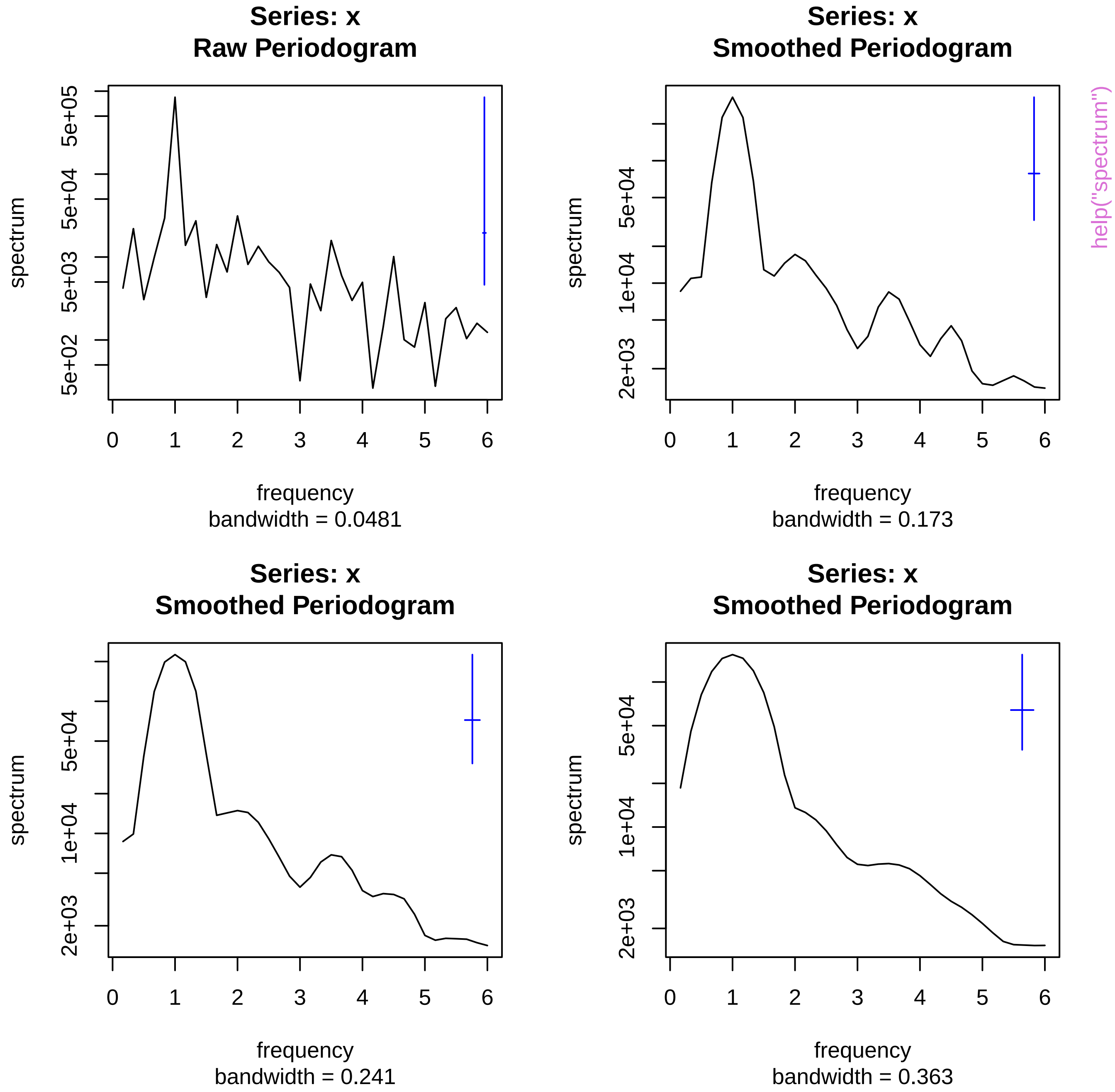
Series: x
Smoothed Periodogram
spectrum
1e+03
1e+02
1e+01
1e+00
1e−01
0.0
0.1
0.2
0.3
0.4
0.5
frequency
bandwidth = 0.0334
help("spec.pgram")

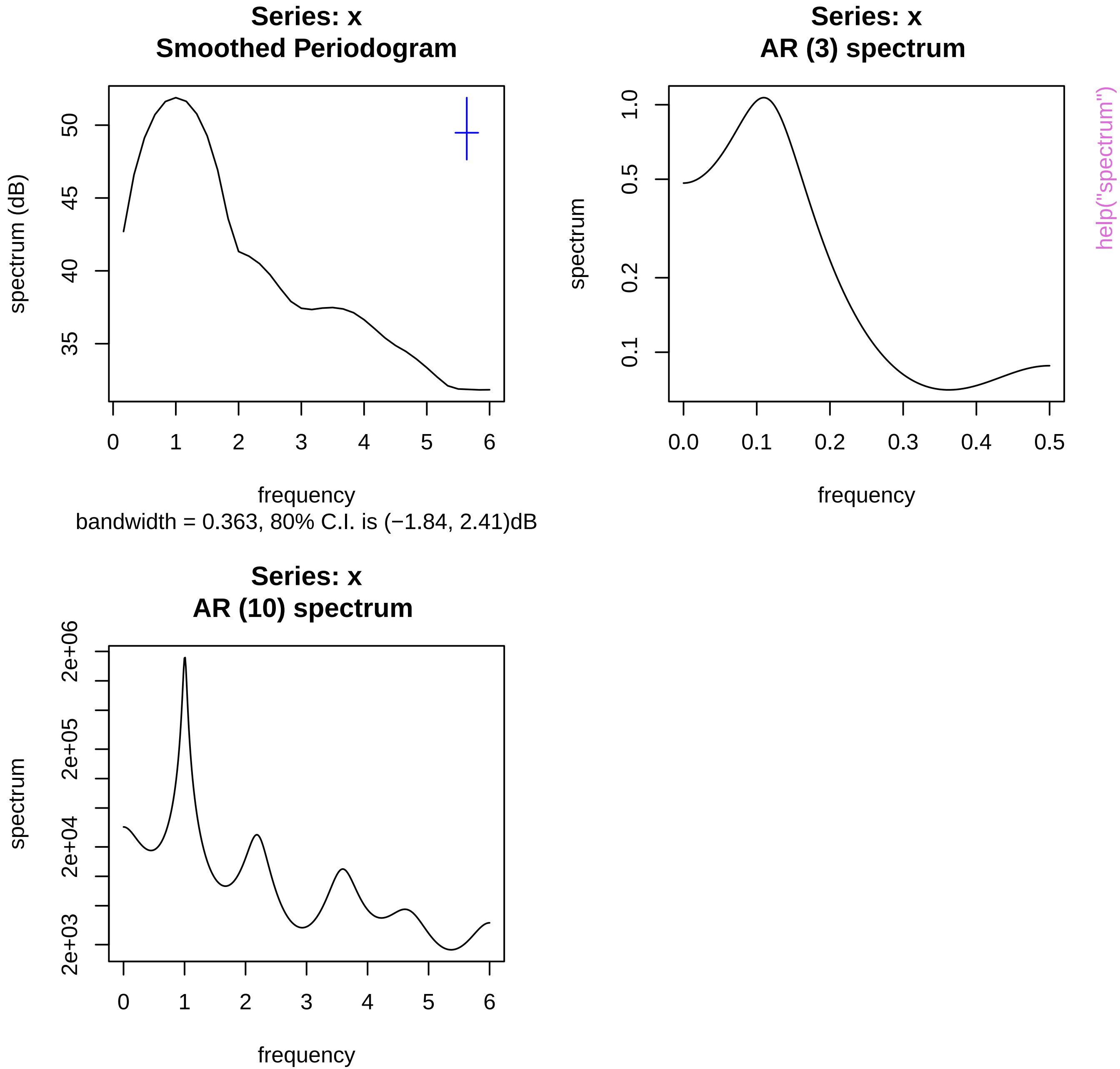


Series: x -- Squared Coherency
squared coherency
frequency
0.0
0.2
0.4
0.6
0.8
1.0
0.0
0.1
0.2
0.3
0.4
0.5
help("spec.pgram")

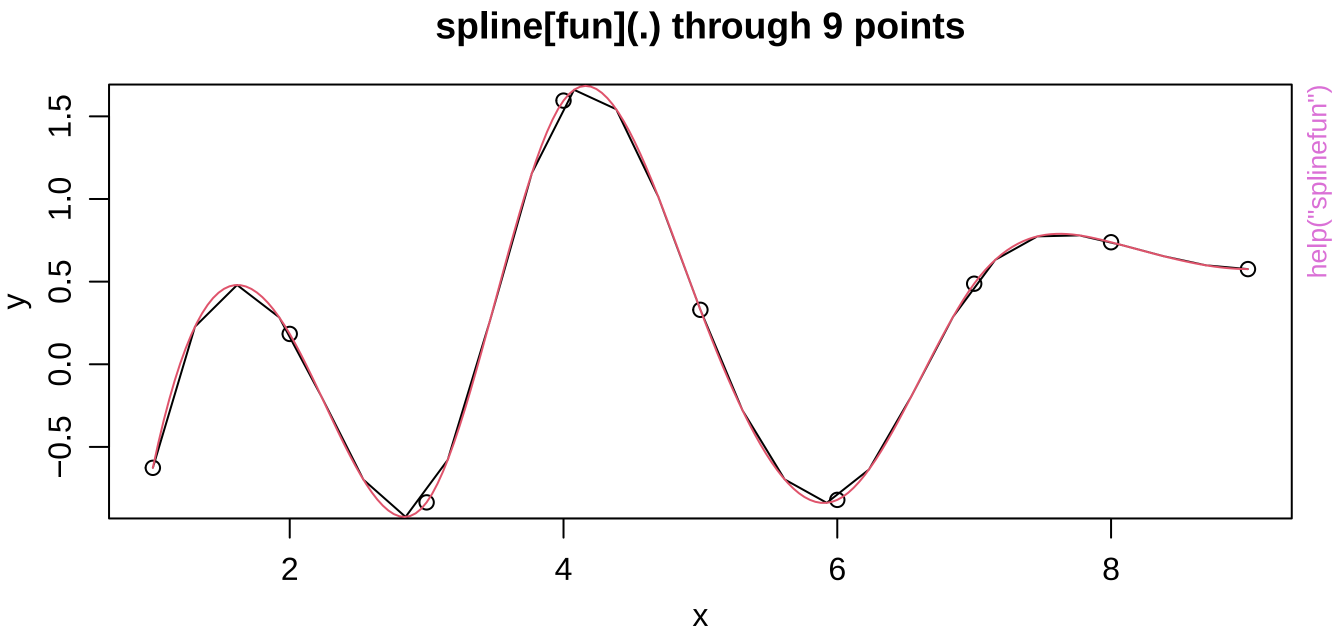

Series: x −− Phase spectrum
phase
frequency
3
2
1
0
−1
−2
−3
0.0
0.1
0.2
0.3
0.4
0.5
help("spec.pgram")

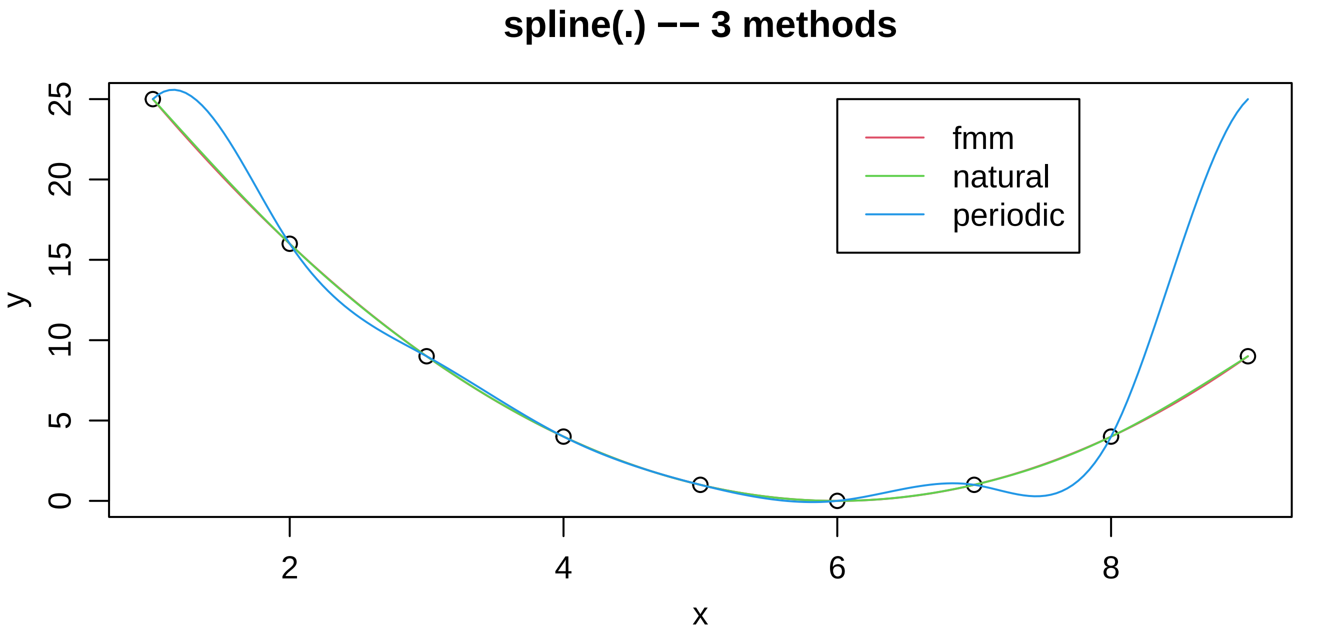

Series: x
Raw Periodogram
spectrum
0.01
0.05
0.20
1.00
0.1
0.2
0.3
0.4
0.5
frequency
bandwidth = 0.00601
Series: x
Smoothed Periodogram
spectrum
0.05
0.20
0.50
0.1
0.2
0.3
0.4
0.5
frequency
bandwidth = 0.0159
help("spectrum")
Series: x
Smoothed Periodogram
spectrum
0.05
0.10
0.20
0.50
0.1
0.2
0.3
0.4
0.5
frequency
bandwidth = 0.0217
Series: x
Smoothed Periodogram
spectrum
0.05
0.10
0.20
0.50
0.1
0.2
0.3
0.4
0.5
frequency
bandwidth = 0.0301

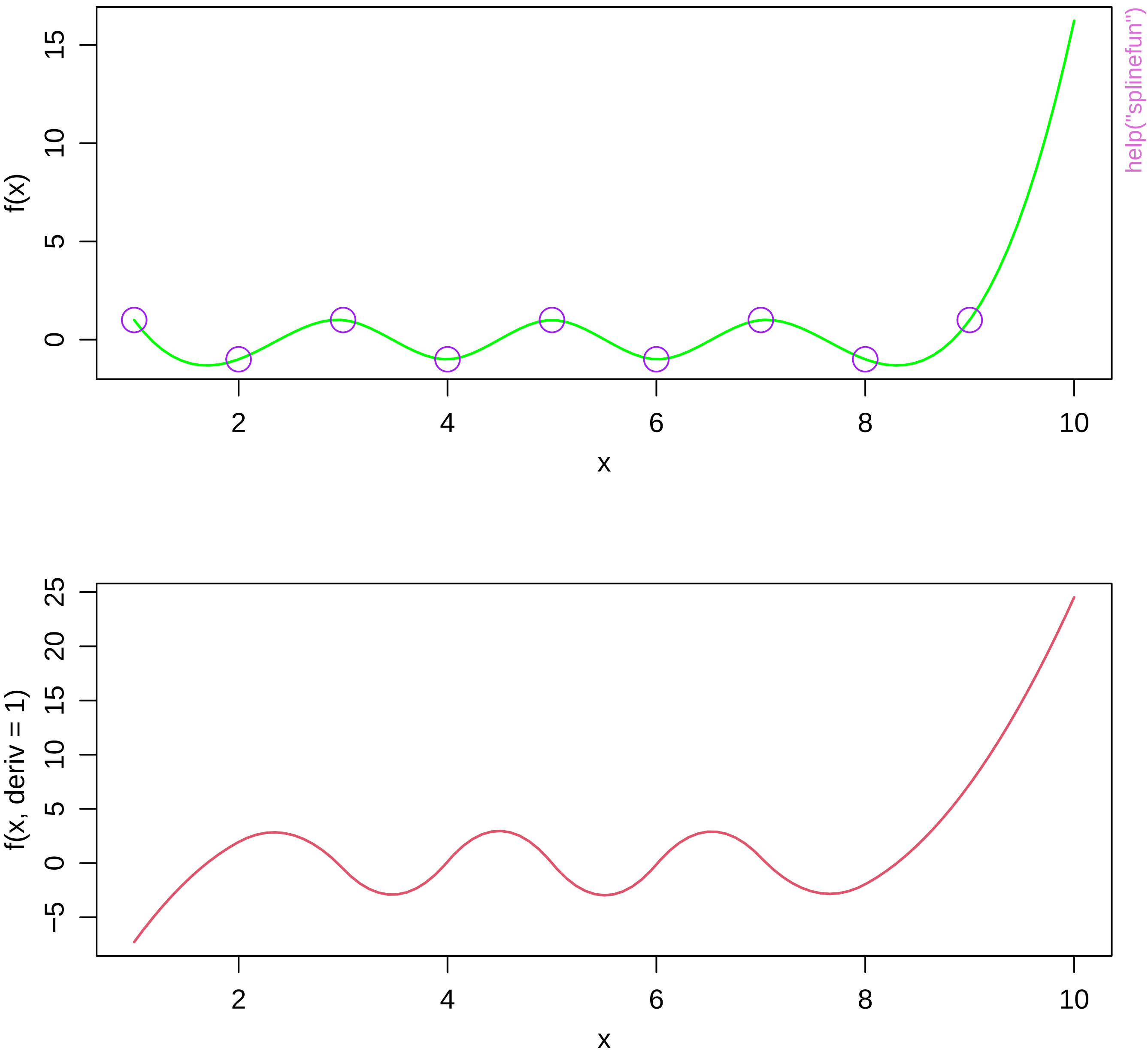

Series: x
Raw Periodogram
spectrum
5e+02
5e+03
5e+04
5e+05
0
1
2
3
4
5
6
frequency
bandwidth = 0.0481
Series: x
Smoothed Periodogram
spectrum
2e+03
1e+04
5e+04
frequency
bandwidth = 0.173
help("spectrum")
Series: x
Smoothed Periodogram
spectrum
2e+03
1e+04
5e+04
frequency
bandwidth = 0.241
Series: x
Smoothed Periodogram
spectrum
2e+03
1e+04
5e+04
frequency
bandwidth = 0.363



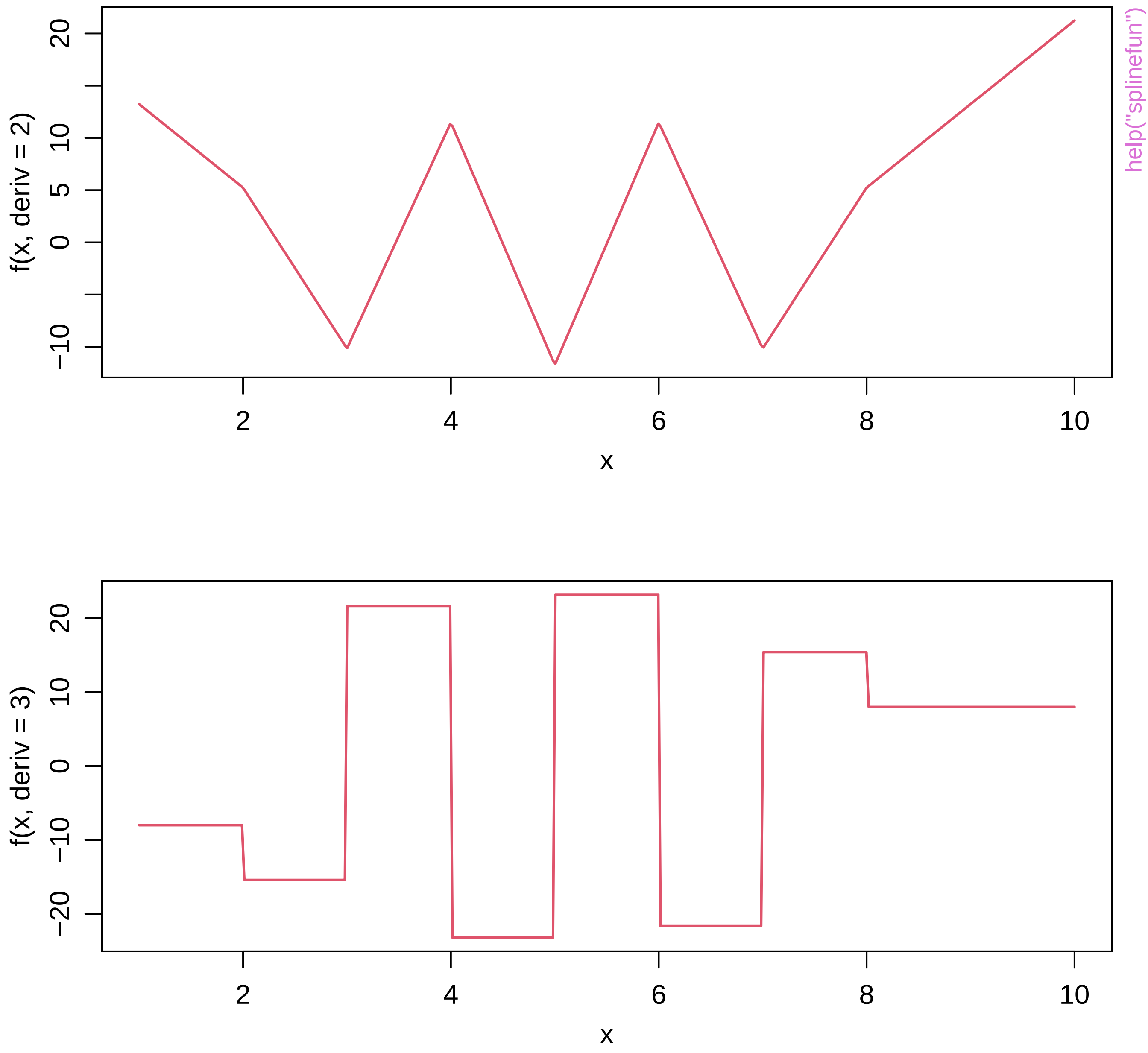
Series: x
Smoothed Periodogram
spectrum (dB)
35
40
45
50
0
1
2
3
4
5
6
frequency
bandwidth = 0.363, 80% C.I. is (−1.84, 2.41)dB
Series: x
AR (3) spectrum
spectrum
0.1
0.2
0.5
1.0
0.0
0.1
0.2
0.3
0.4
0.5
frequency
help("spectrum")
Series: x
AR (10) spectrum
spectrum
2e+03
2e+04
2e+05
2e+06
0
1
2
3
4
5
6
frequency


spline[fun](.) through 9 points
help("splinefun")
y
x
−0.5
0.0
0.5
1.0
1.5
2
4
6
8

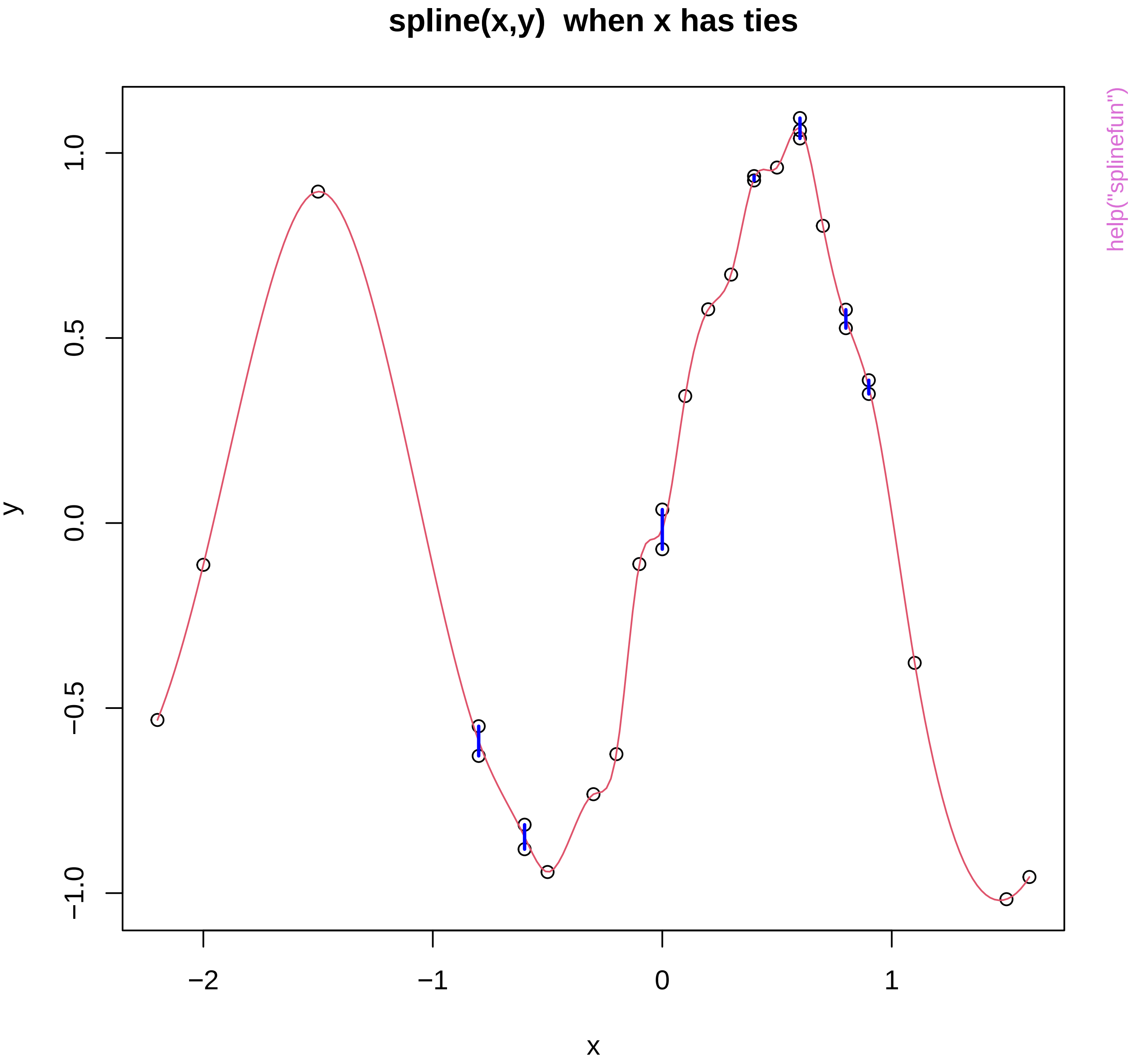

spline(.) −− 3 methods
fmm
natural
periodic
y
x
0
5
10
15
20
25
2
4
6
8



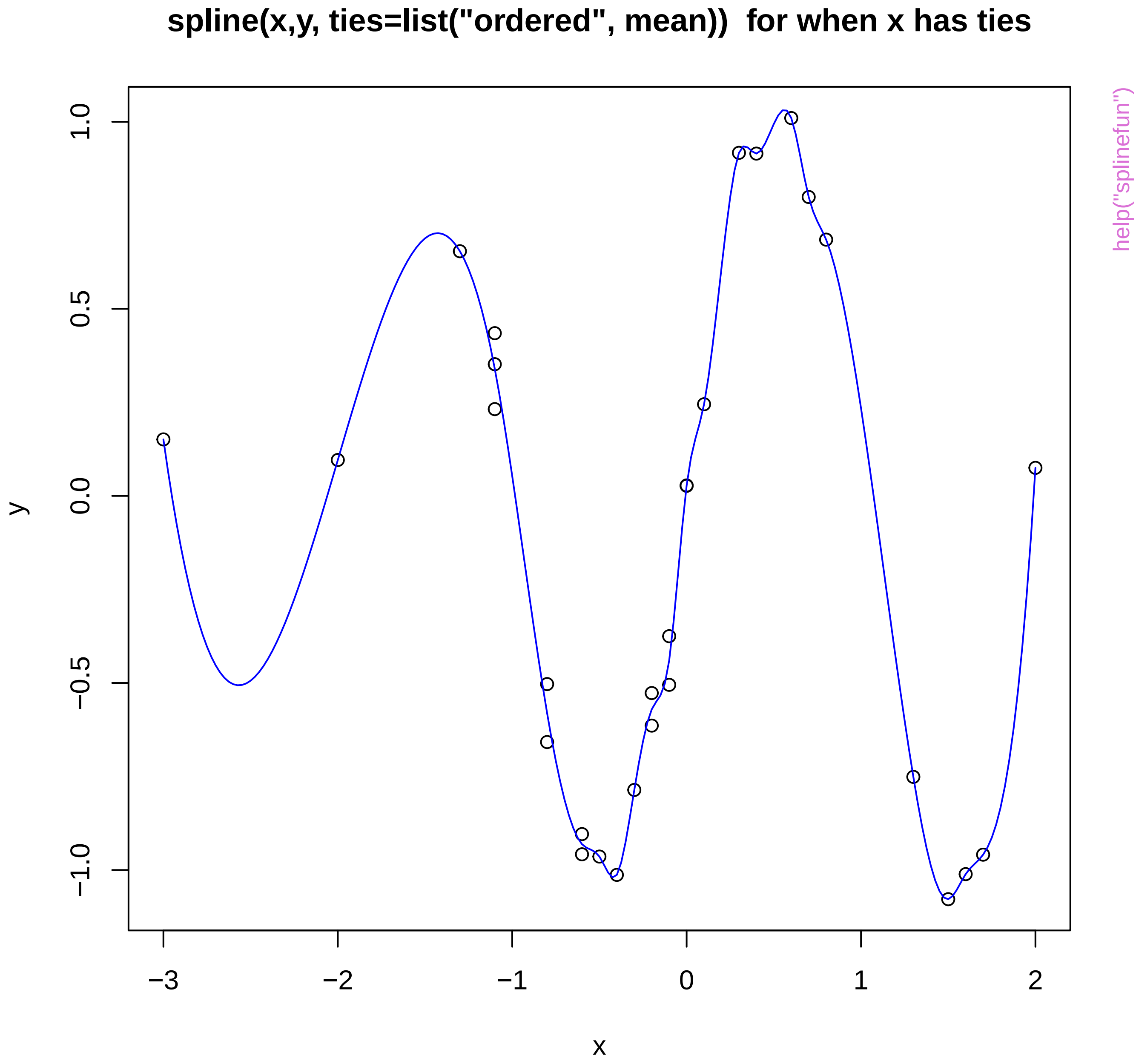
help("splinefun")
f(x)
0
5
10
15
2
4
6
8
10
x
f(x, deriv = 1)
−5
0
5
10
15
20
25
2
4
6
8
10
x

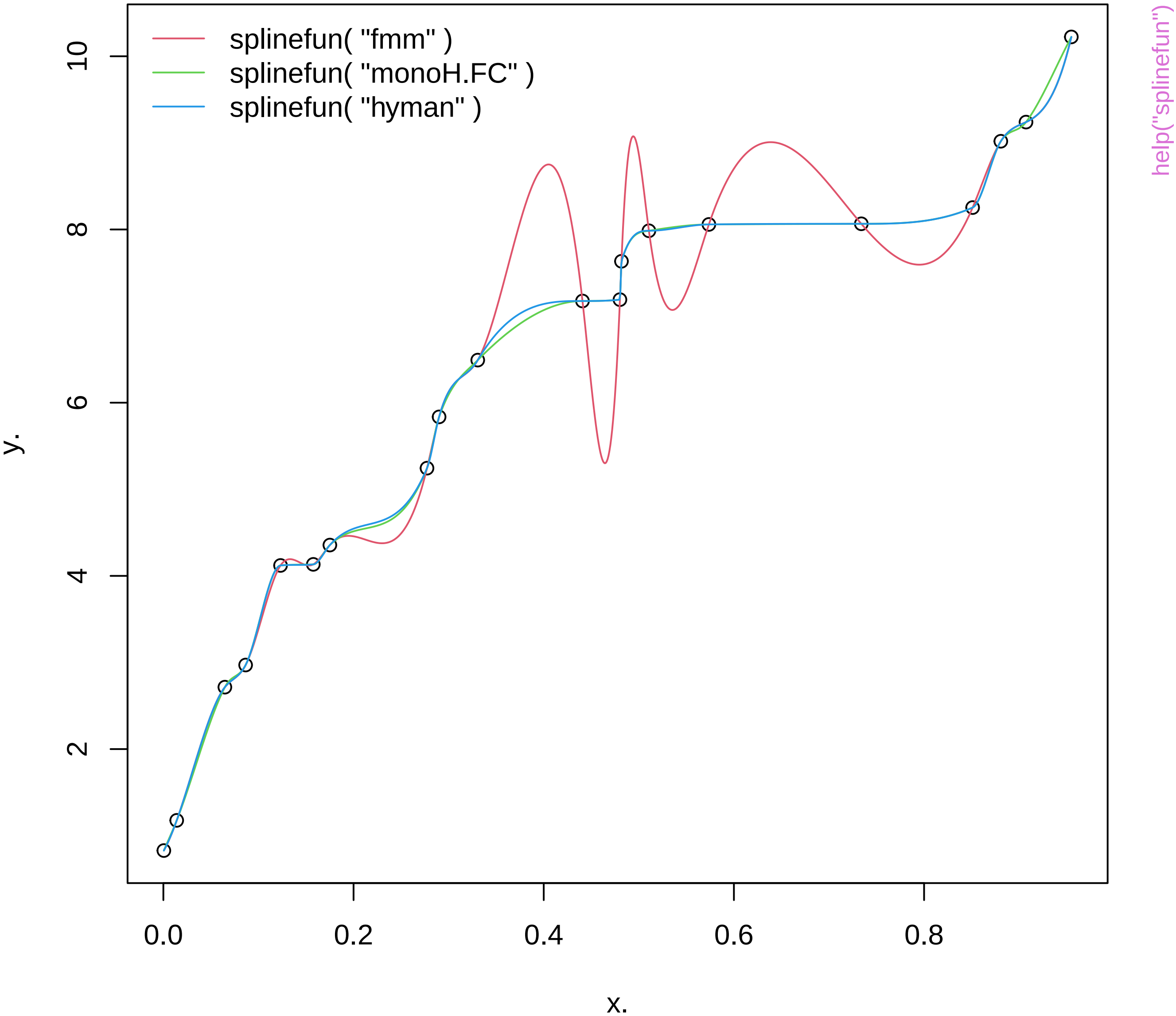


f(x, deriv = 2)
20
10
5
0
−10
2
4
6
8
10
x
help("splinefun")
f(x, deriv = 3)
20
10
0
−10
−20
2
4
6
8
10
x

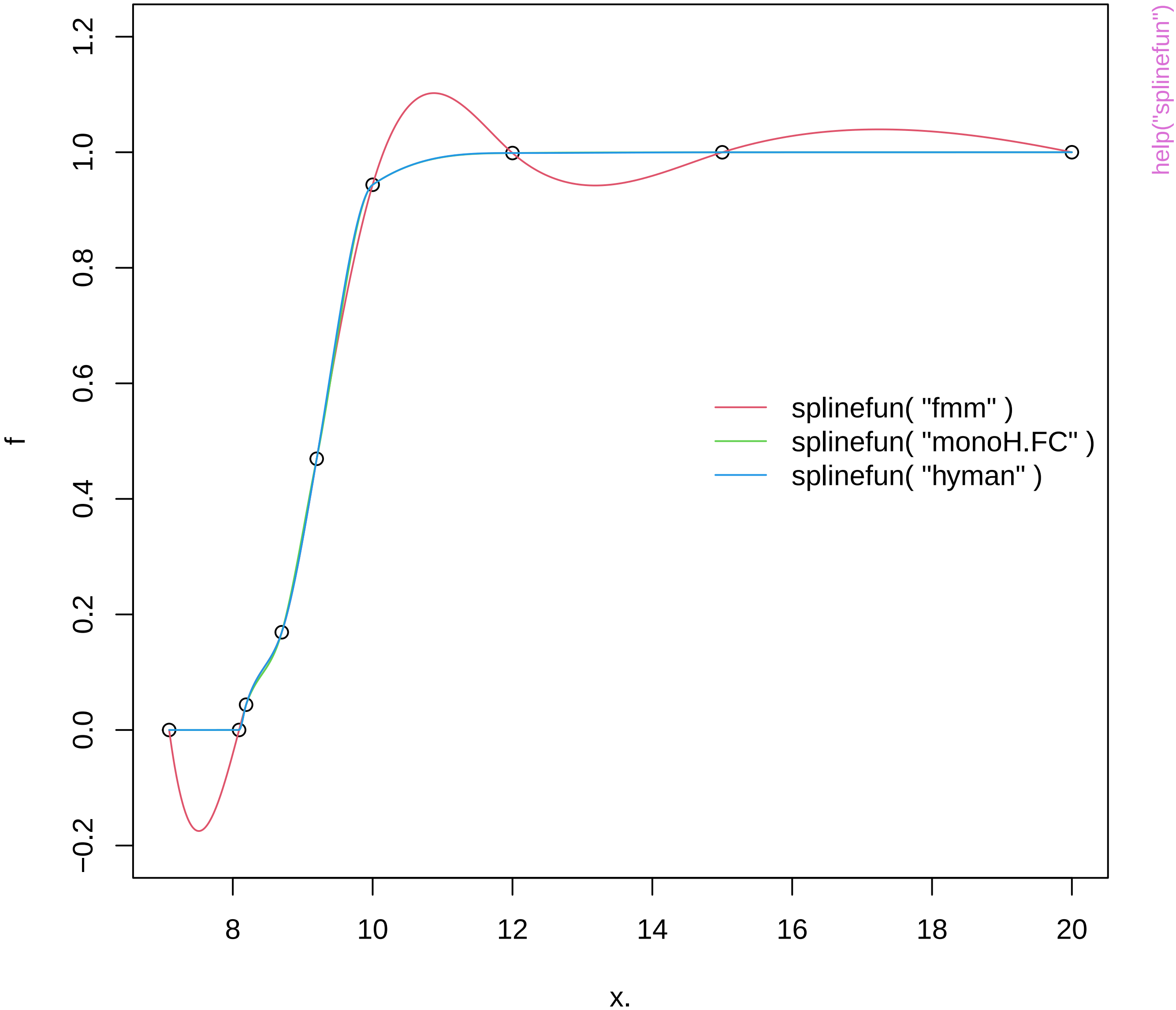


spline(x,y) when x has ties
y
x
1.0
0.5
0.0
−0.5
−1.0
−2
−1
0
1
help("splinefun")

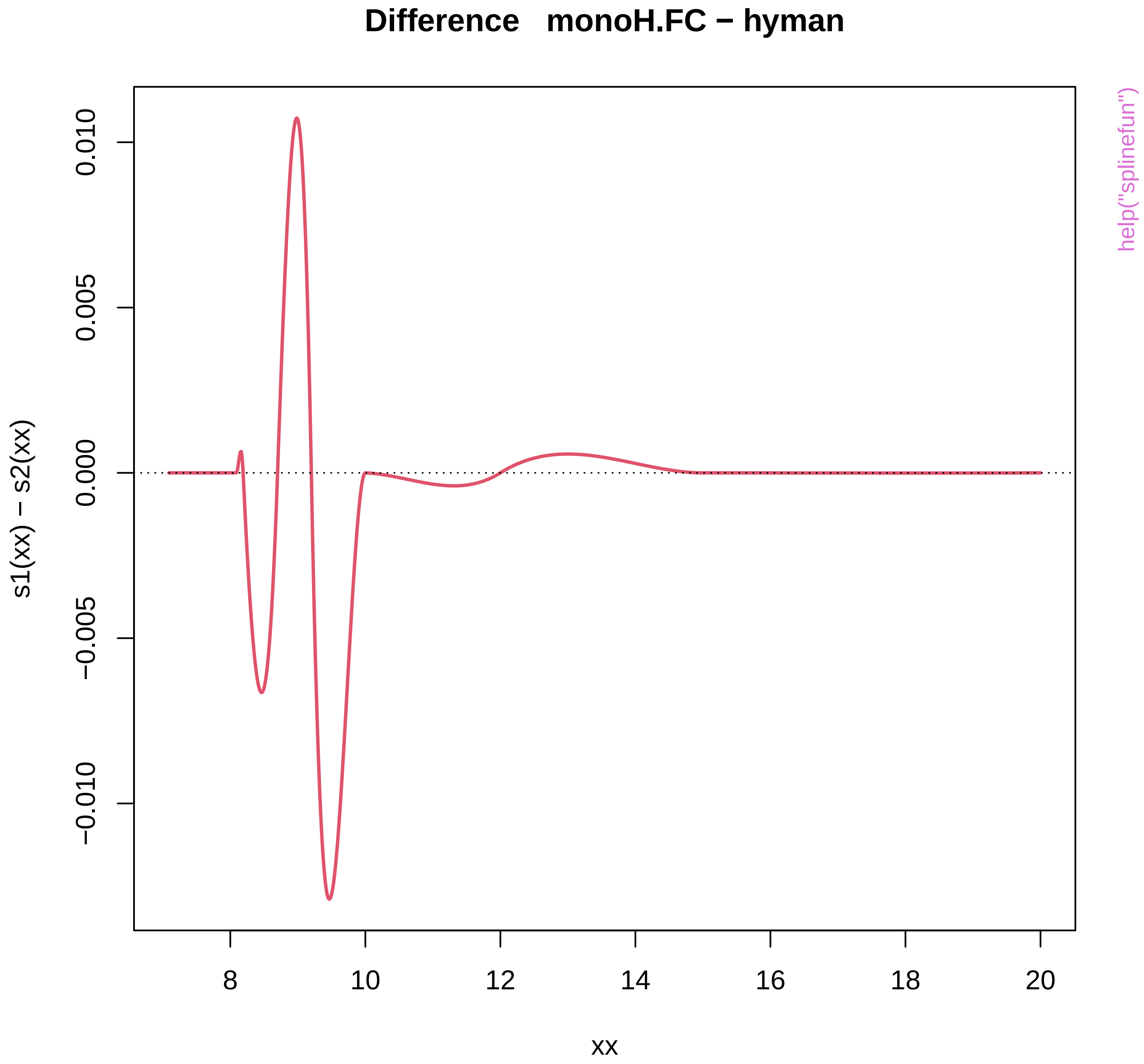

spline(x,y, ties=list("ordered", mean)) for when x has ties
help("splinefun")
y
x
1.0
0.5
0.0
−0.5
−1.0
−3
−2
−1
0
1
2

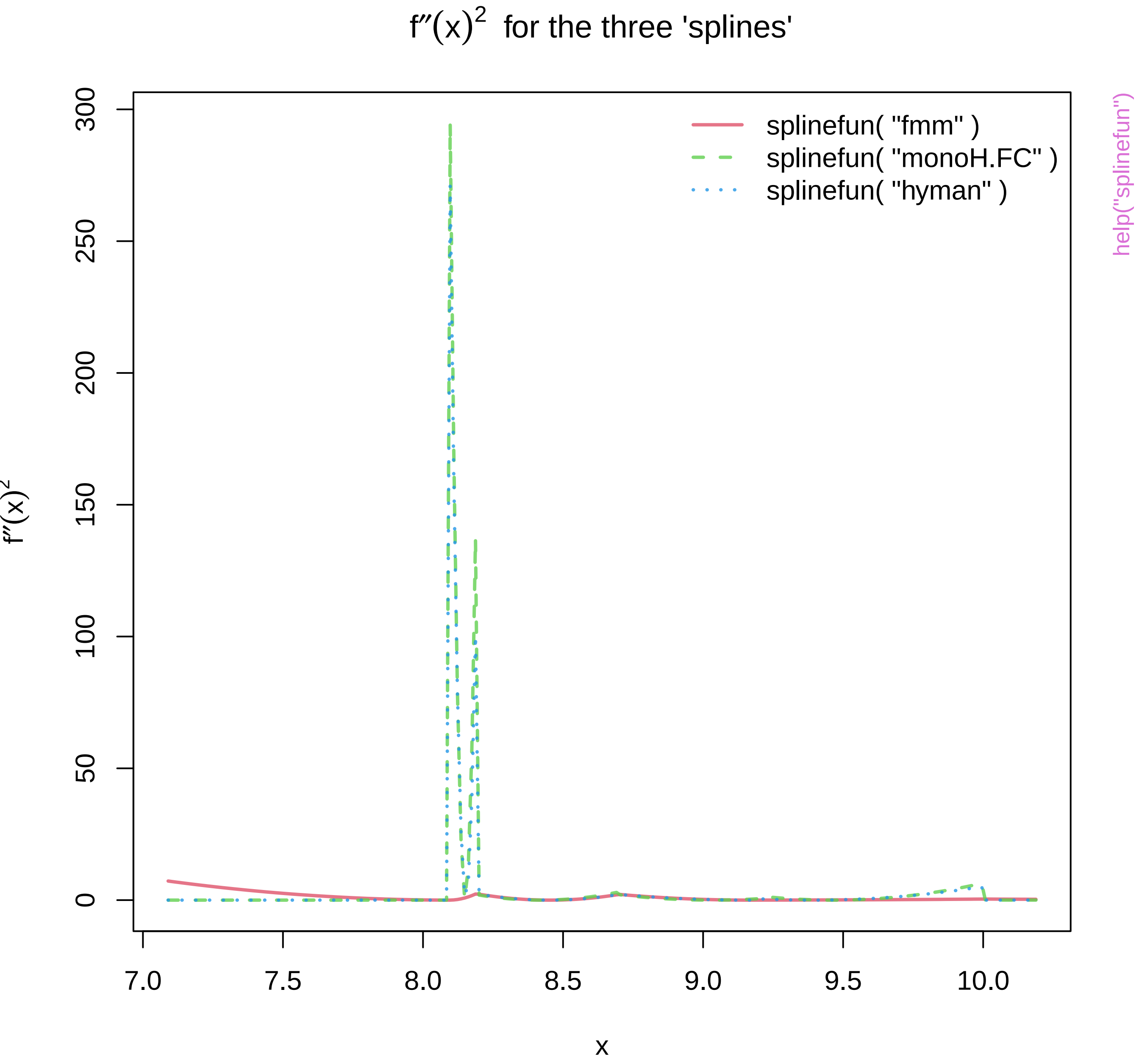


splinefun("fmm")
splinefun("monoH.FC")
splinefun("hyman")
help("splinefun")
y.
x.
0.0
0.2
0.4
0.6
0.8
2
4
6
8
10

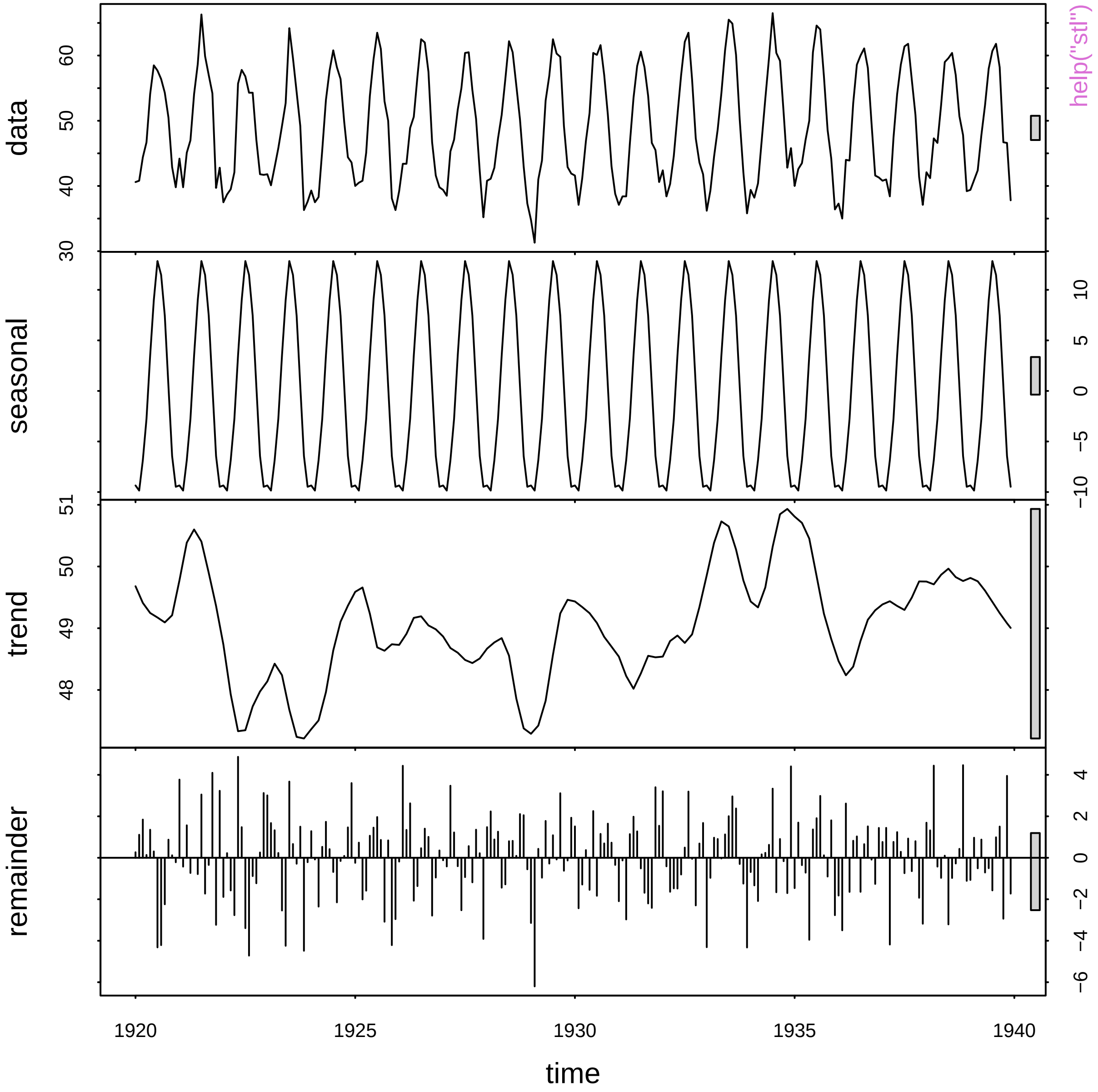


splinefun("fmm")
splinefun("monoH.FC")
splinefun("hyman")
f
x.
−0.2
0.0
0.2
0.4
0.6
0.8
1.0
1.2
8
10
12
14
16
18
20
help("splinefun")

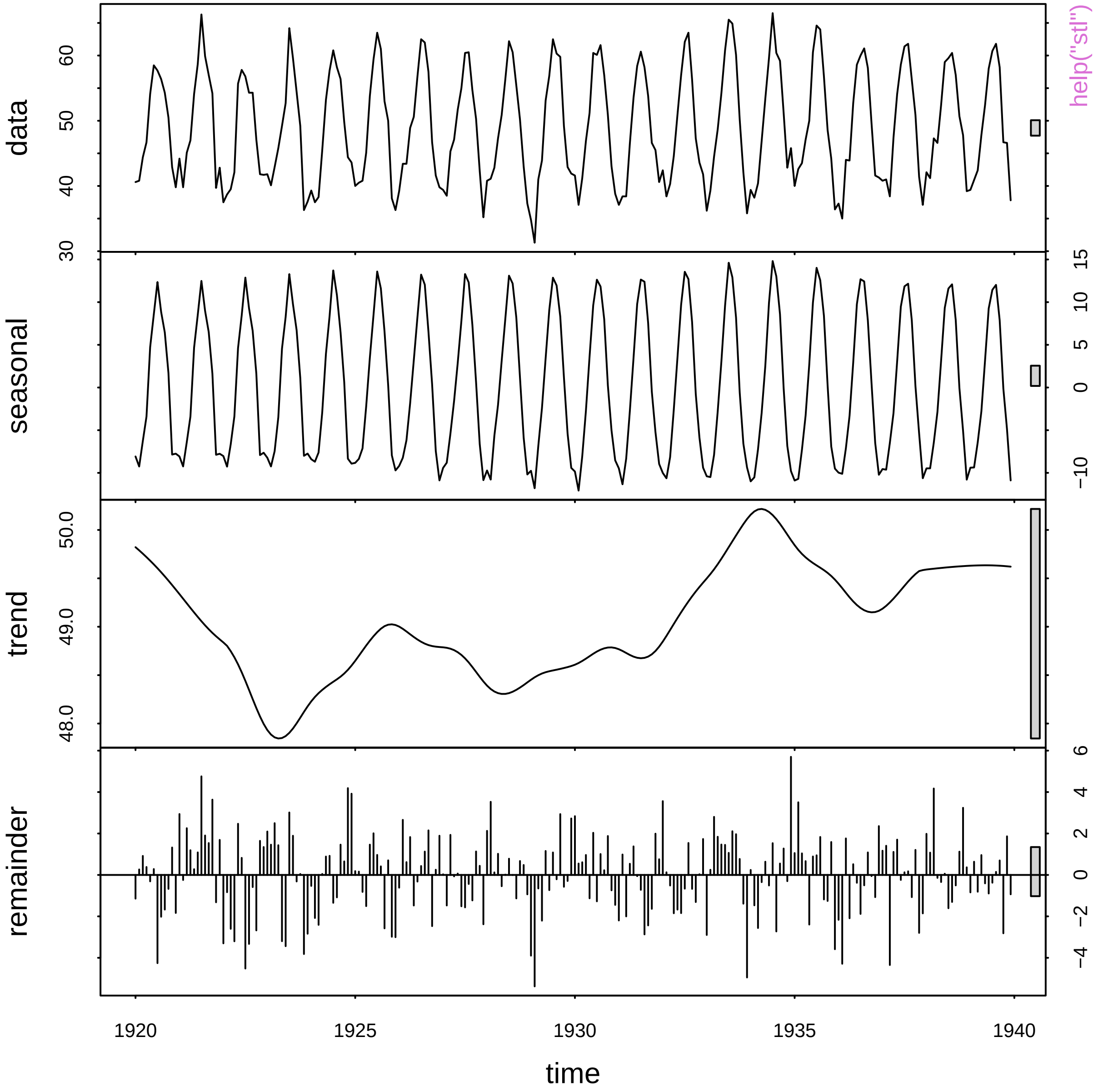

Difference   monoH.FC − hyman
s1(xx) − s2(xx)
0.010
0.005
0.000
−0.005
−0.010
8
10
12
14
16
18
20
xx
help("splinefun")



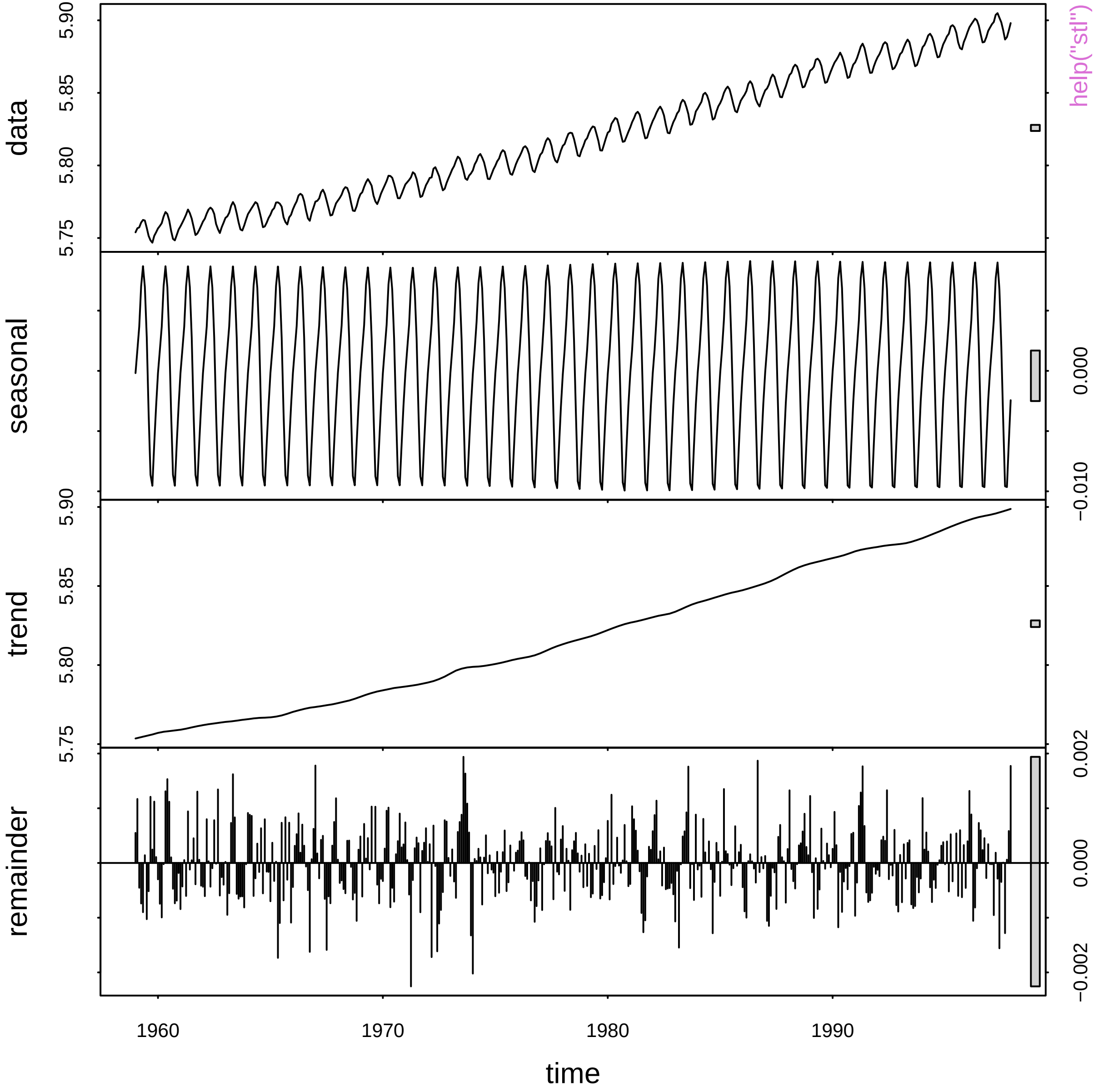
$f''(x)^2$ for the three 'splines'
splinefun("fmm")
splinefun("monoH.FC")
splinefun("hyman")
help("splinefun")
0
50
100
150
200
250
300
$f''(x)^2$
7.0
7.5
8.0
8.5
9.0
9.5
10.0
x



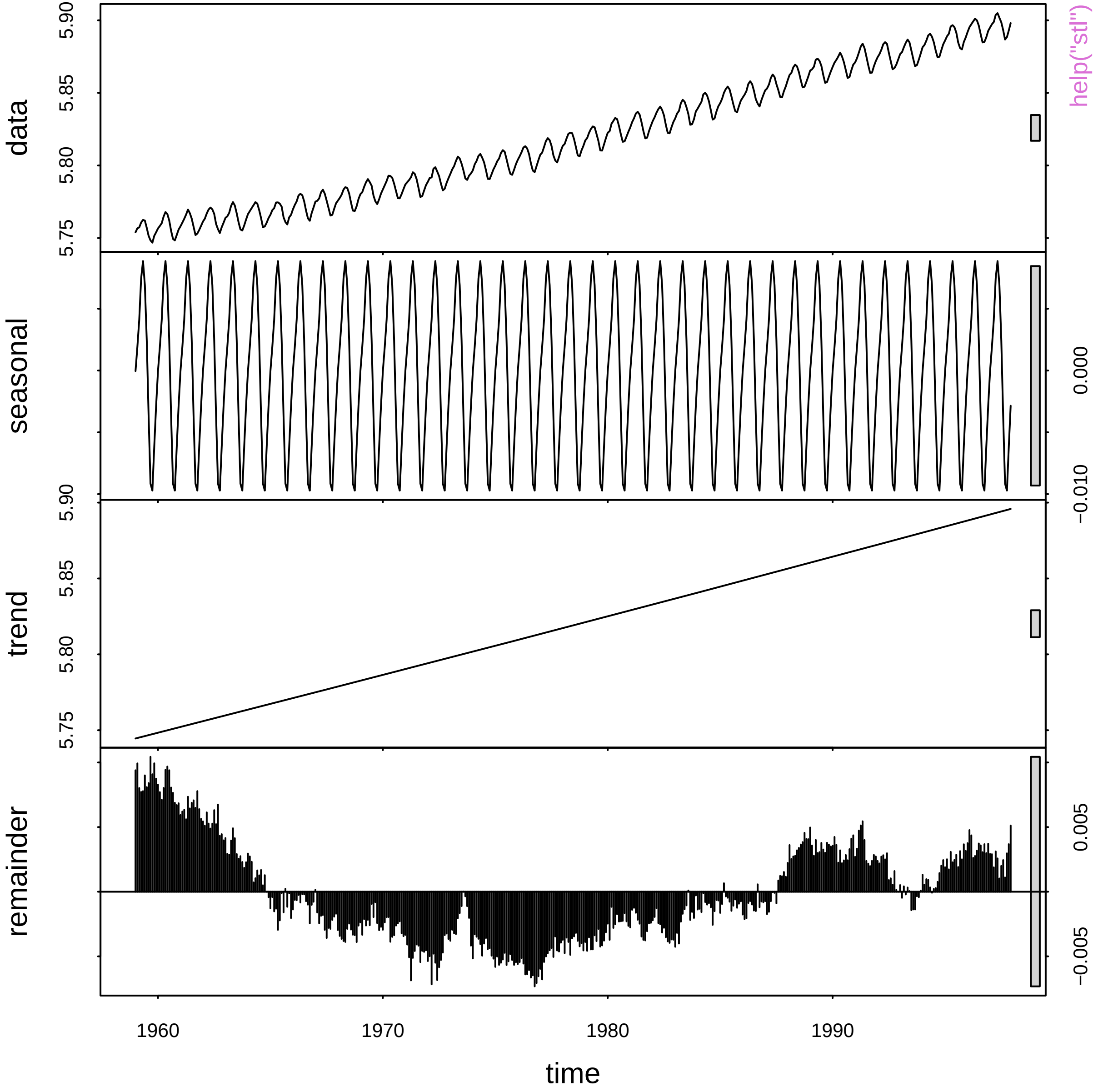
data
seasonal
trend
remainder
help("stl")
30
40
50
60
−10
−5
0
5
10
48
49
50
51
−6
−4
−2
0
2
4
1920
1925
1930
1935
1940
time



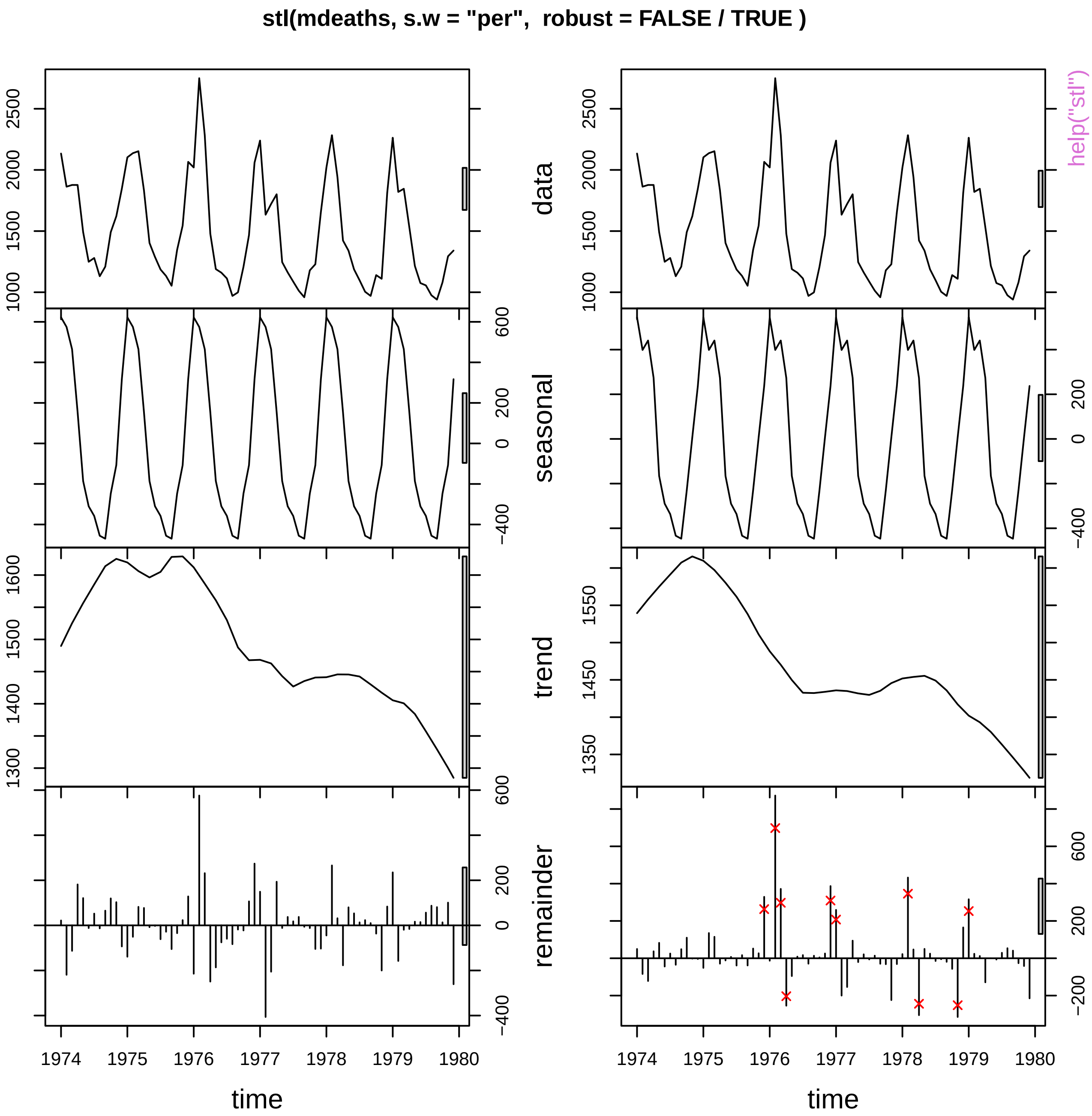
data
seasonal
trend
remainder
help("stl")
30
40
50
60
15
10
5
0
−10
48.0
49.0
50.0
6
4
2
0
−2
−4
1920
1925
1930
1935
1940
time



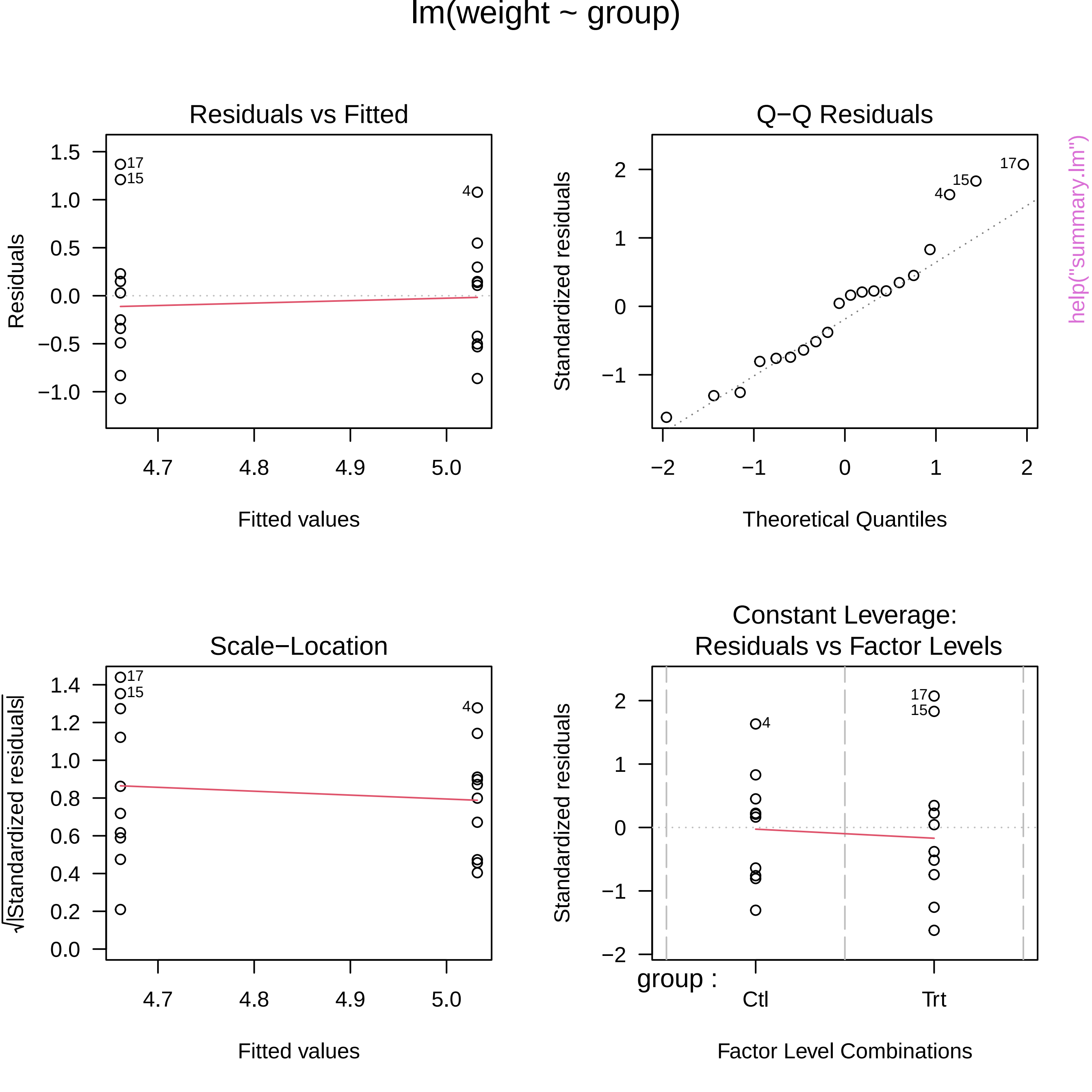
data
seasonal
trend
remainder
time
help("stl")
5.75
5.80
5.85
5.90
0.000
-0.010
0.002
-0.002
1960
1970
1980
1990

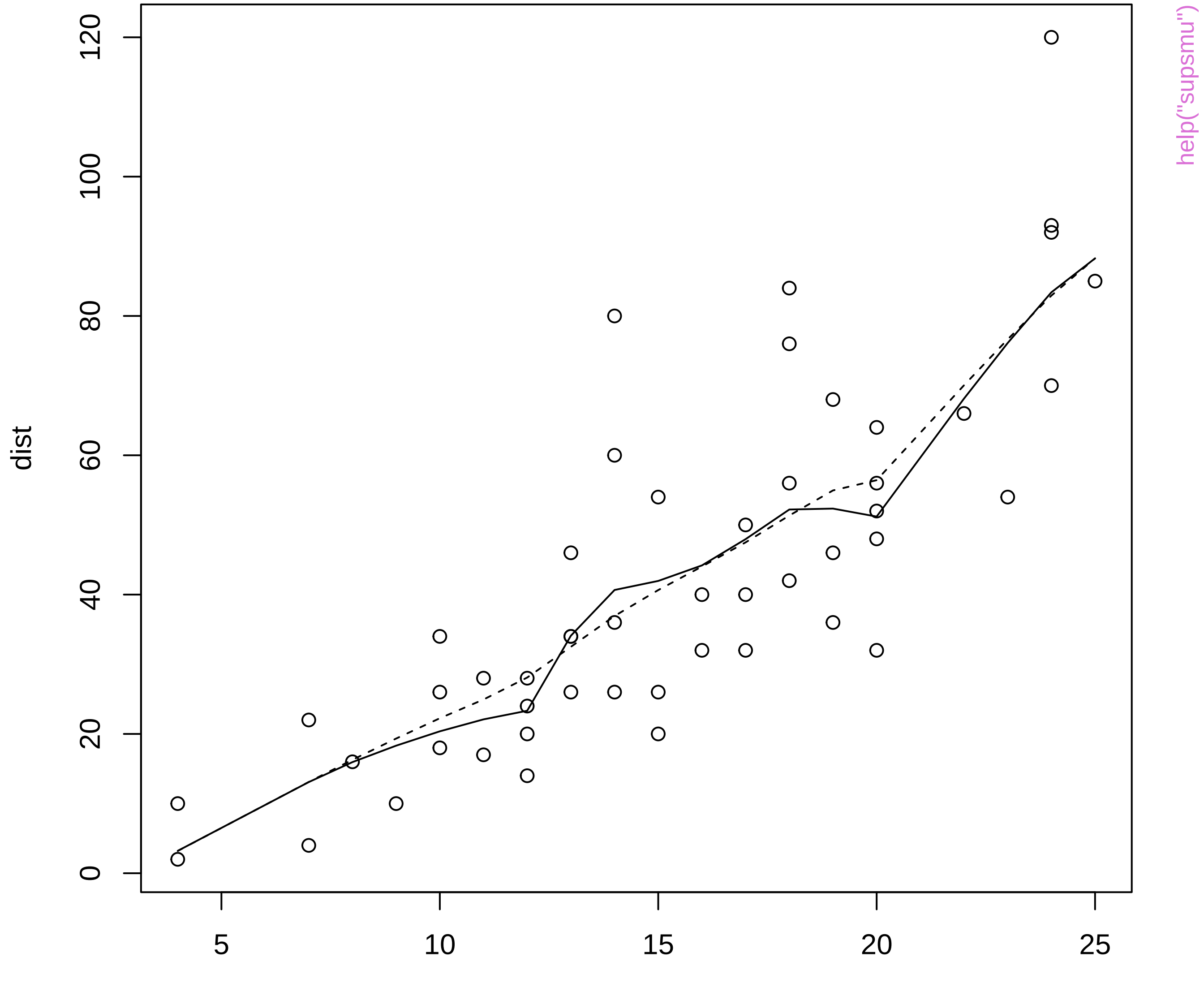


data
seasonal
trend
remainder
5.75
5.80
5.85
5.90
0.000
−0.010
0.005
−0.005
1960
1970
1980
1990
time
help("stl")

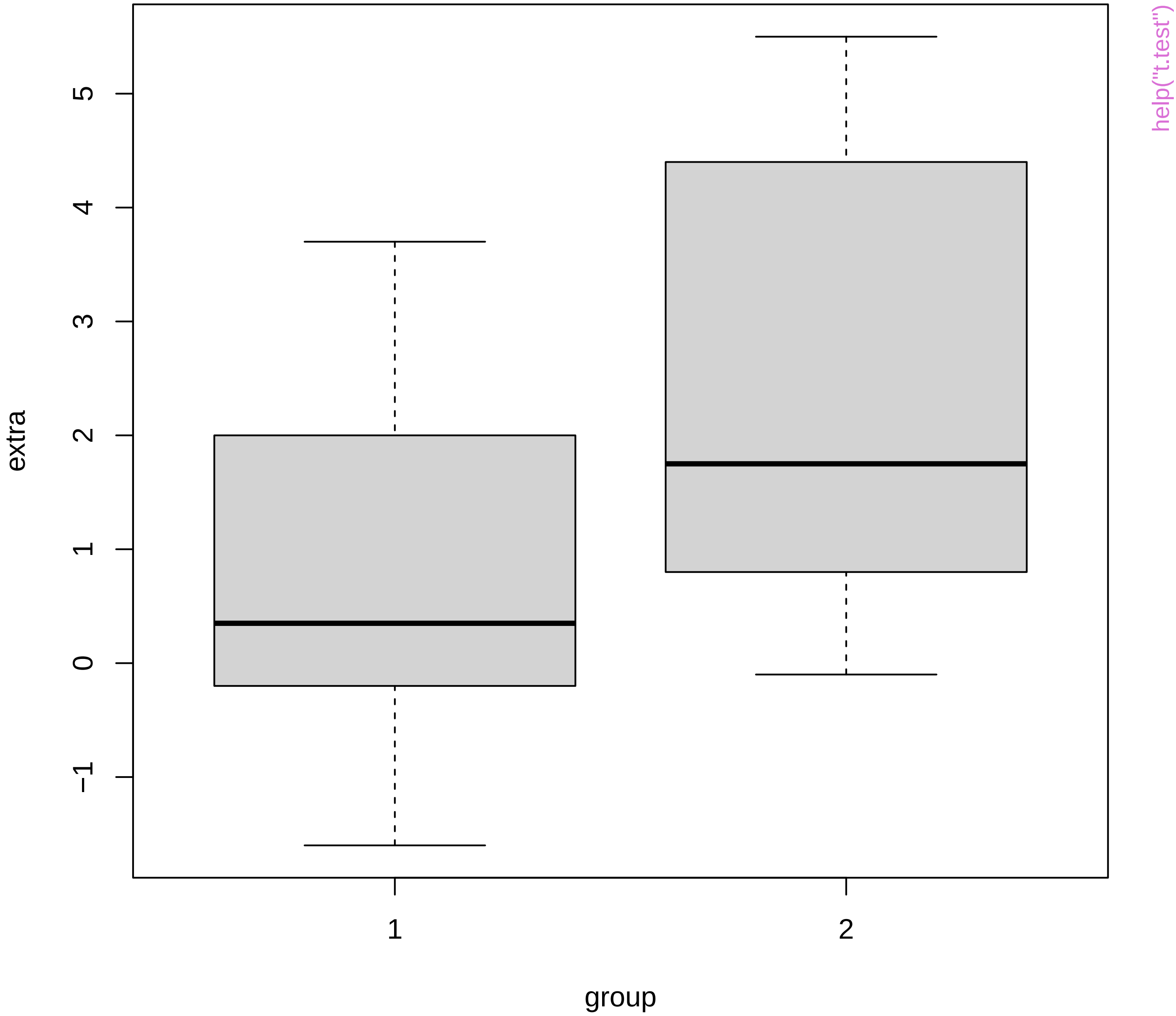


stl(mdeaths, s.w = "per", robust = FALSE / TRUE)
data
seasonal
trend
remainder
time
time
1974
1975
1976
1977
1978
1979
1980
help("stl")

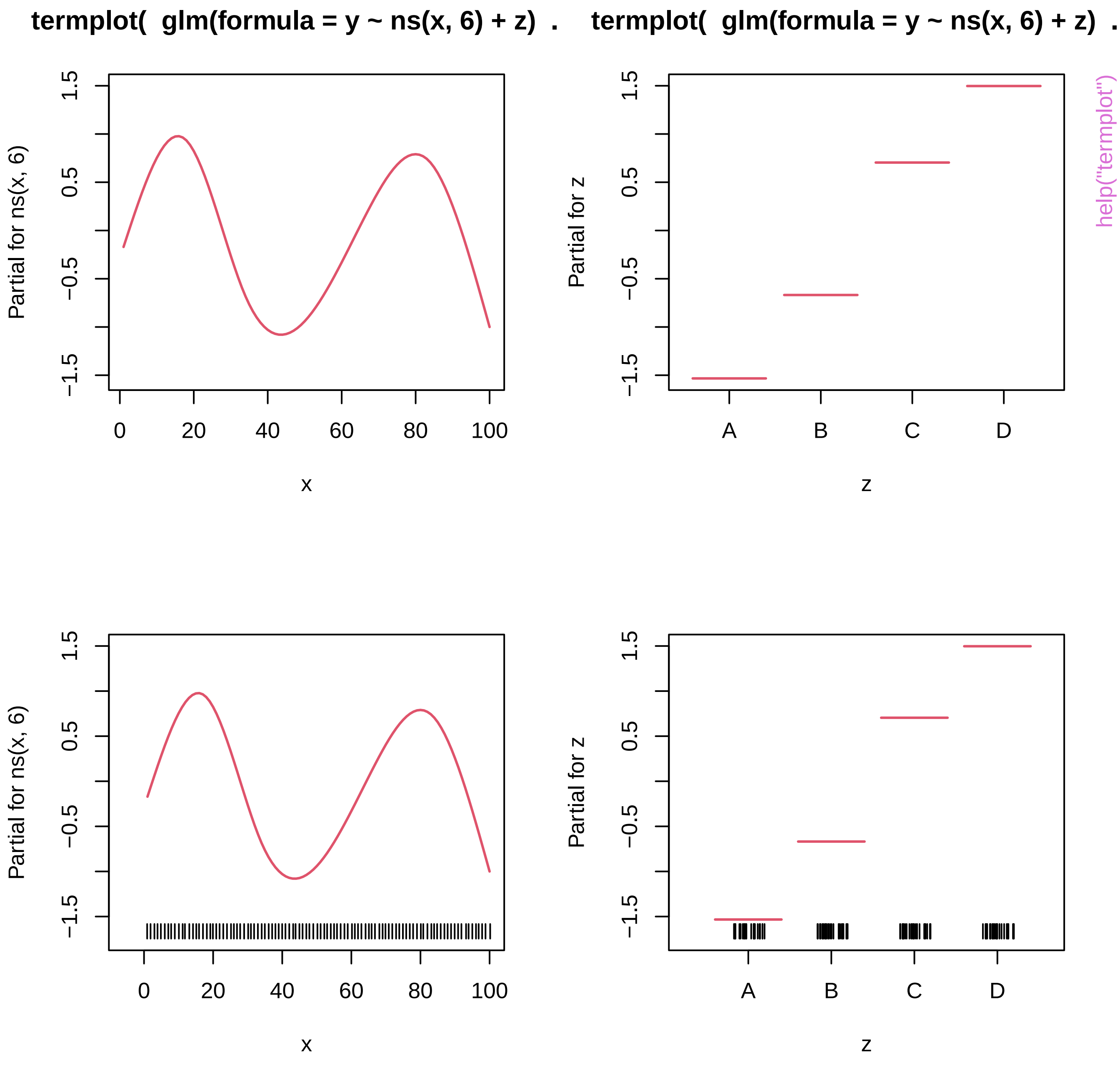

lm(weight ~ group)
Residuals vs Fitted
Residuals
Fitted values
1.5
1.0
0.5
0.0
−0.5
−1.0
4.7
4.8
4.9
5.0
17
15
4
Q−Q Residuals
Standardized residuals
Theoretical Quantiles
2
1
0
−1
−2
17
15
4
help("summary.lm")
Scale−Location
√|Standardized residuals|
Fitted values
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
17
15
4
Constant Leverage:
Residuals vs Factor Levels
Standardized residuals
group :
Ctl
Trt
Factor Level Combinations
17
15
4



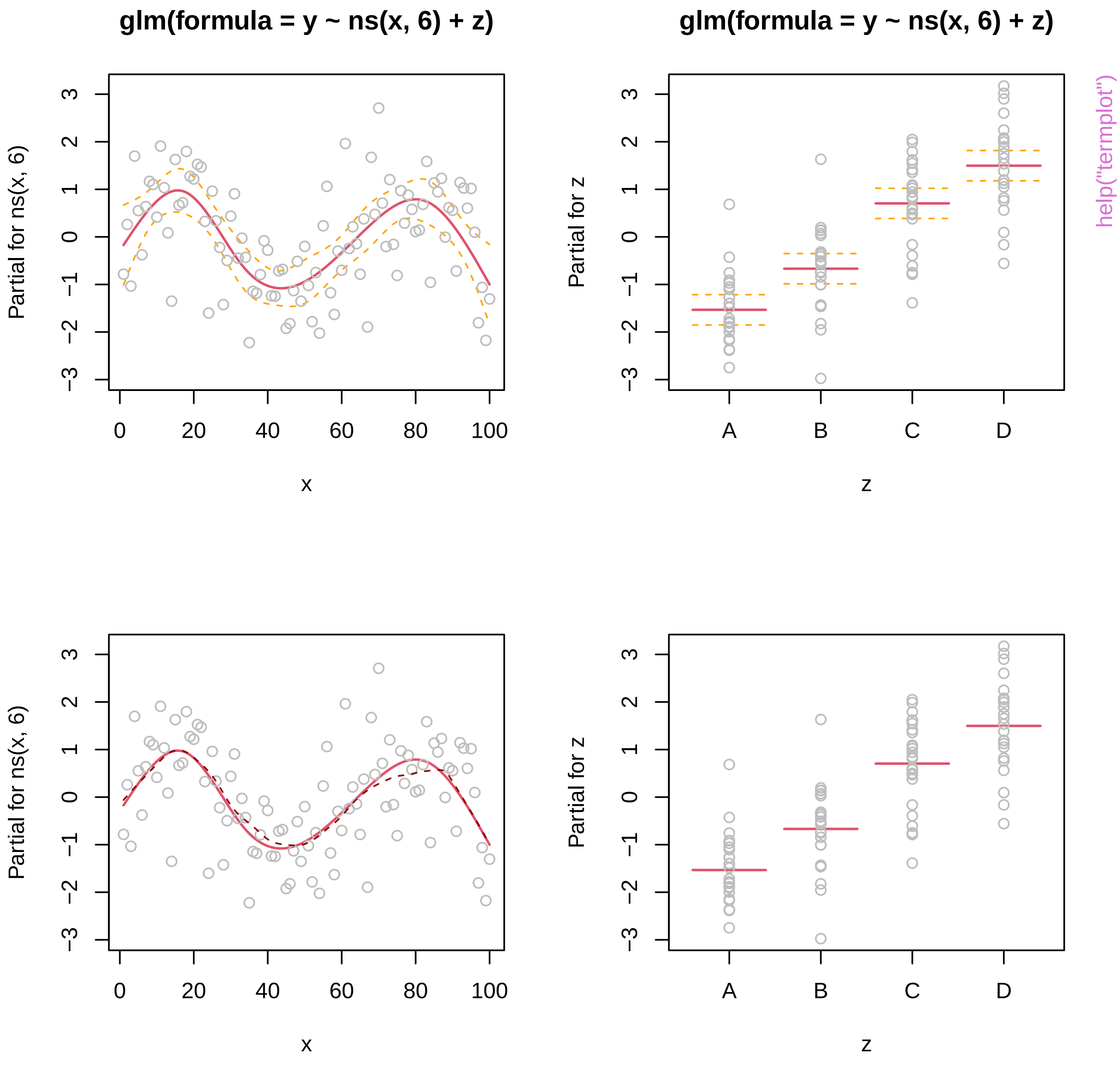
dist
speed
0
20
40
60
80
100
120
5
10
15
20
25
help("supsmu")



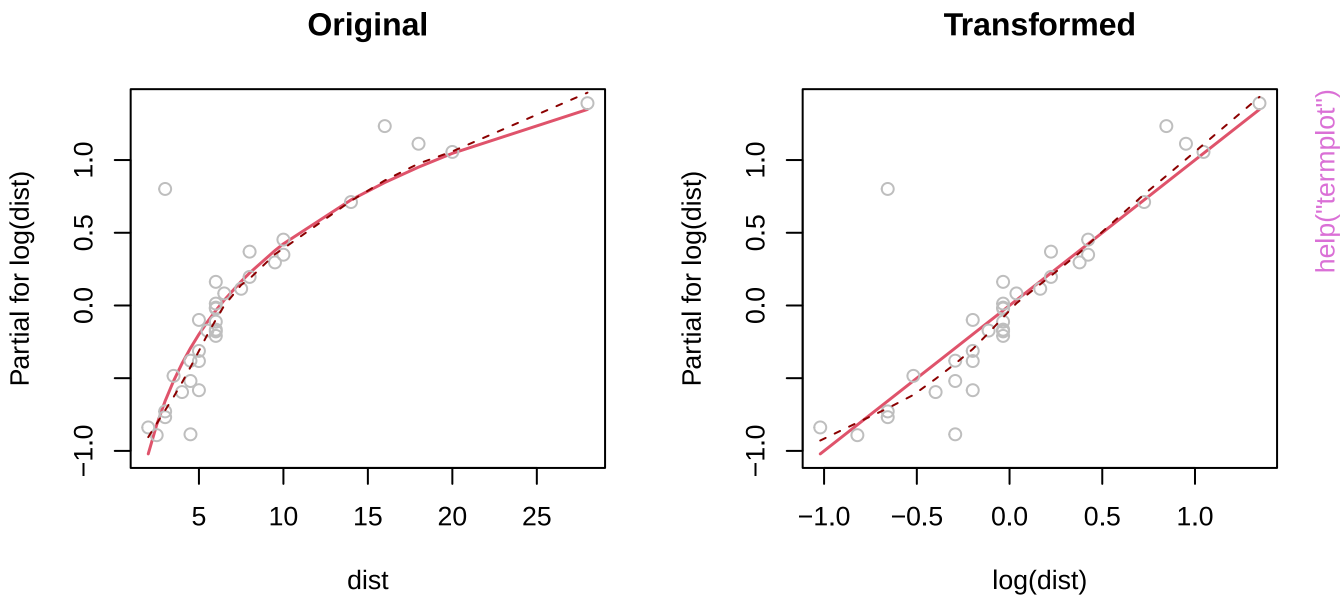
extra
5
4
3
2
1
0
−1
1
2
group
help("t.test")

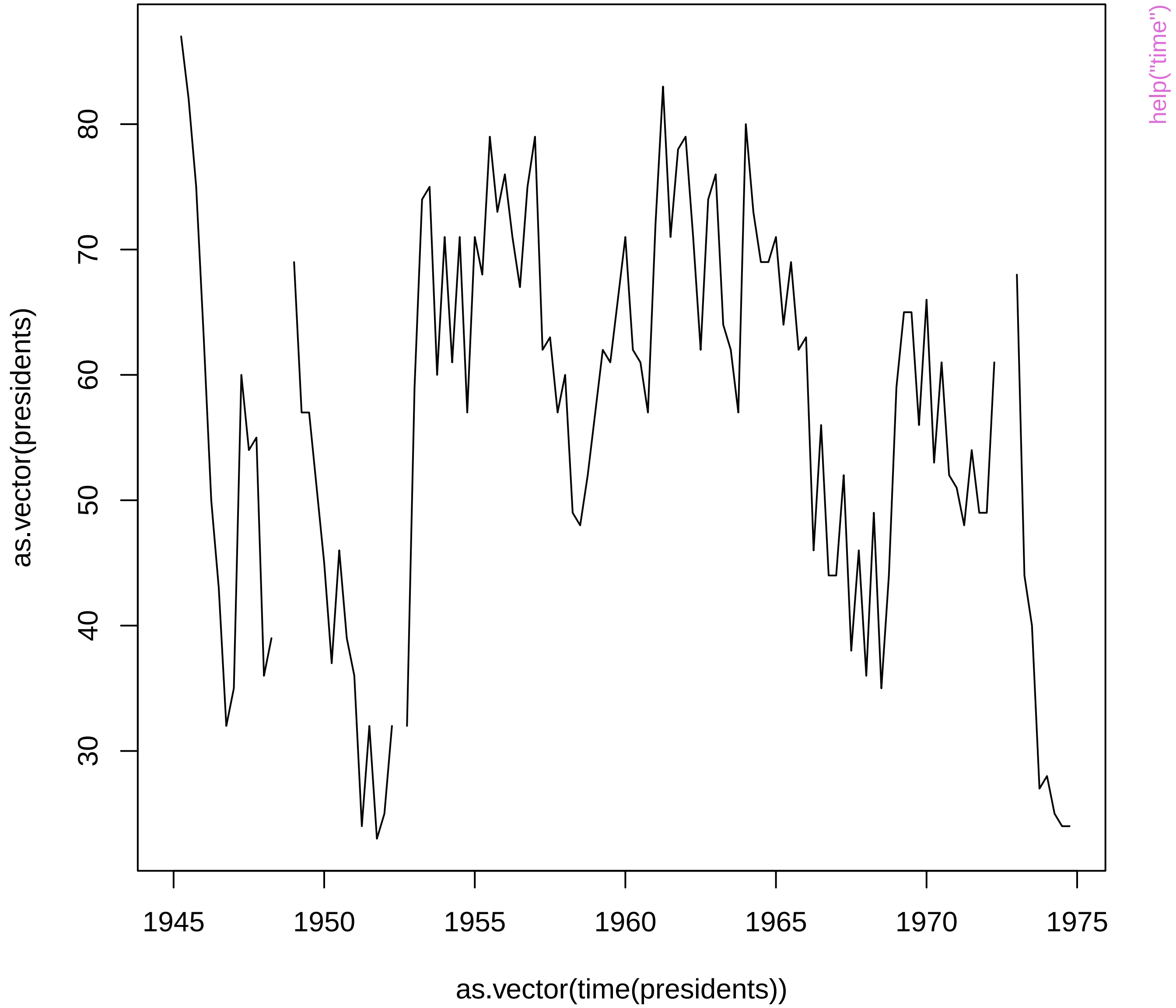


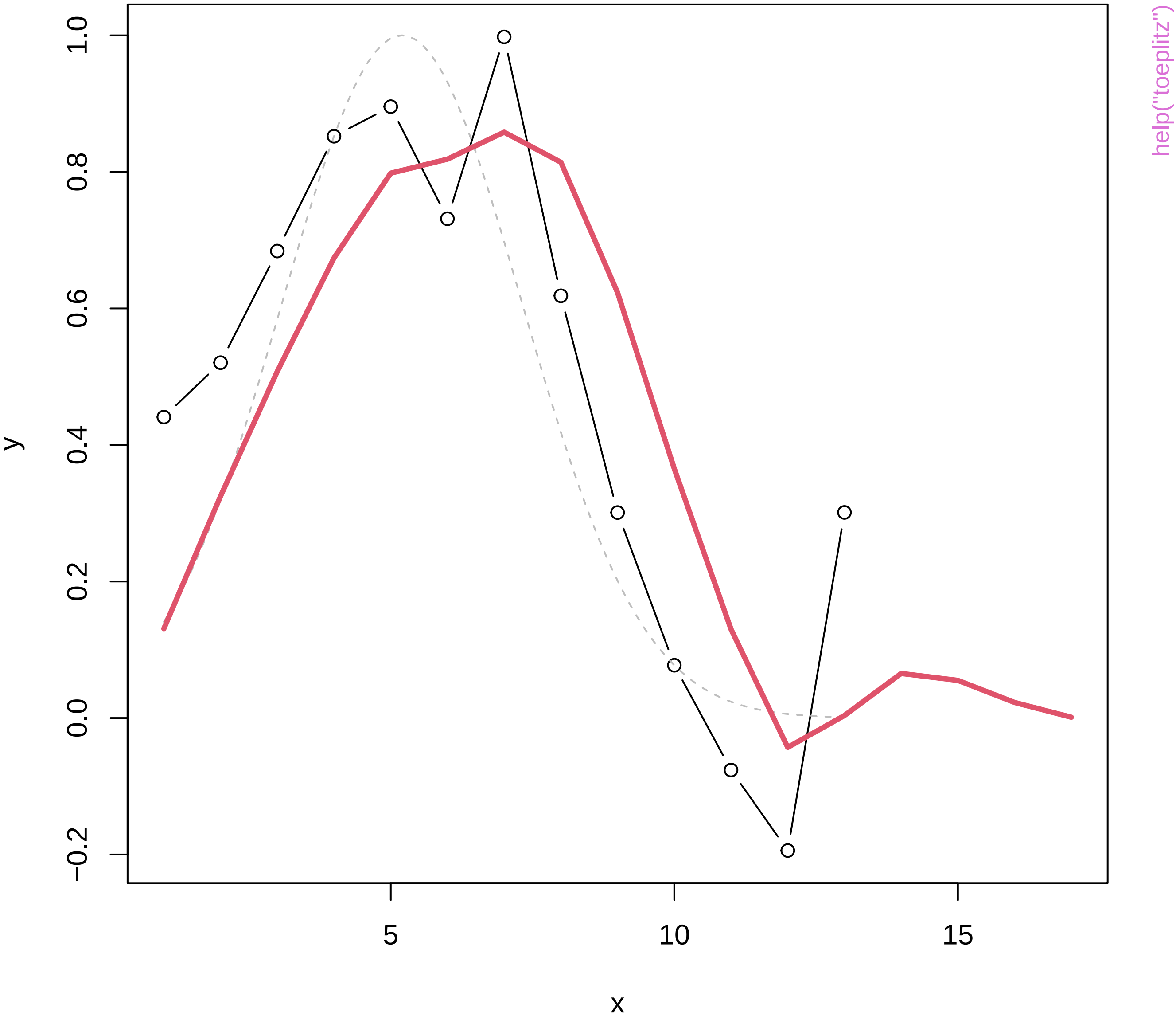
termplot(glm(formula = y ~ ns(x, 6) + z) .
termplot(glm(formula = y ~ ns(x, 6) + z) .
help("termplot")
Partial for ns(x, 6)
x
Partial for z
z
−1.5
−0.5
0.5
1.5
0
20
40
60
80
100
A
B
C
D



glm(formula = y ~ ns(x, 6) + z)
glm(formula = y ~ ns(x, 6) + z)
Partial for ns(x, 6)
Partial for z
x
z
help("termplot")

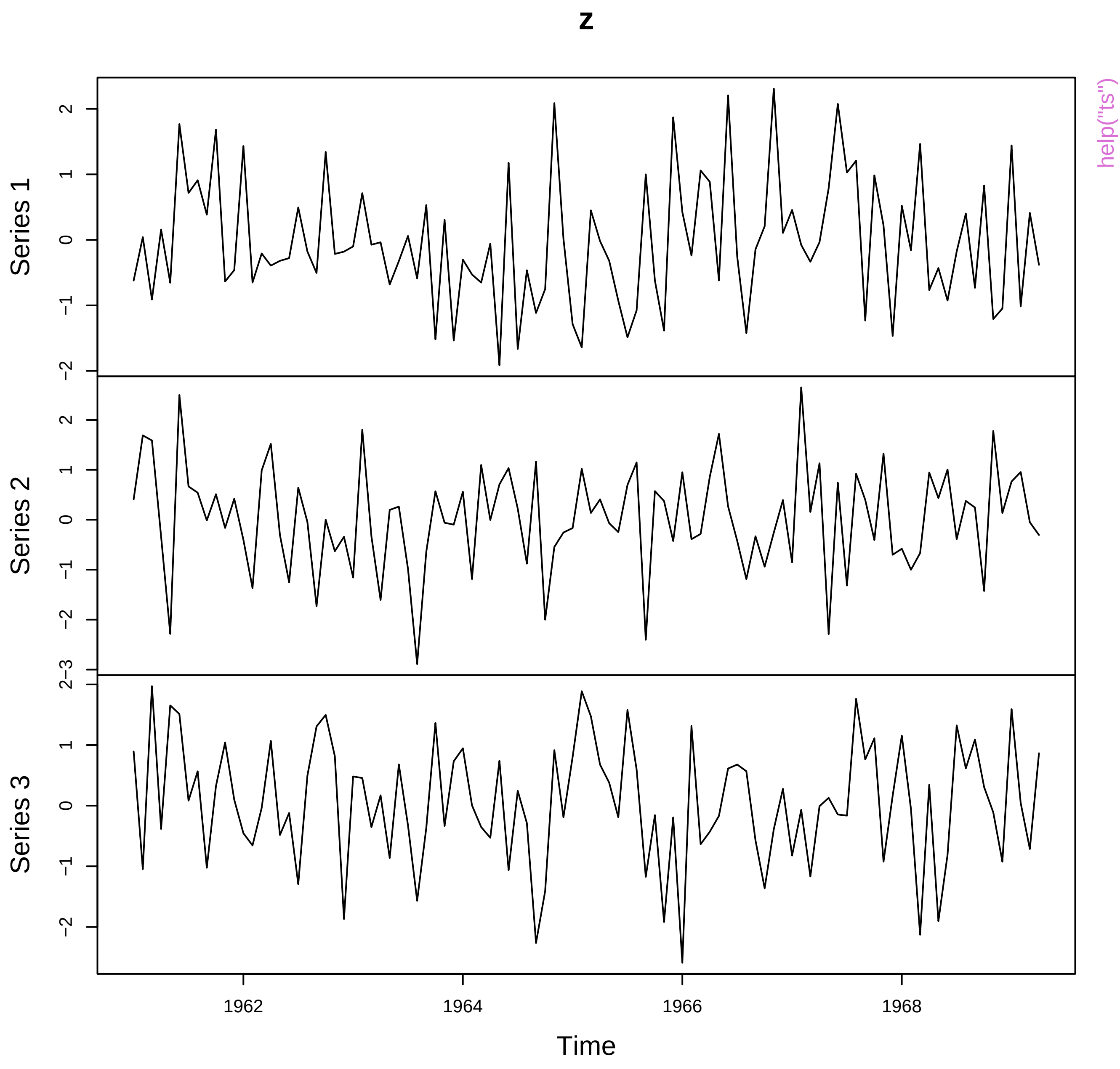

Original
Transformed
Partial for log(dist)
dist
log(dist)
help("termplot")
5
10
15
20
25
−1.0
−0.5
0.0
0.5
1.0

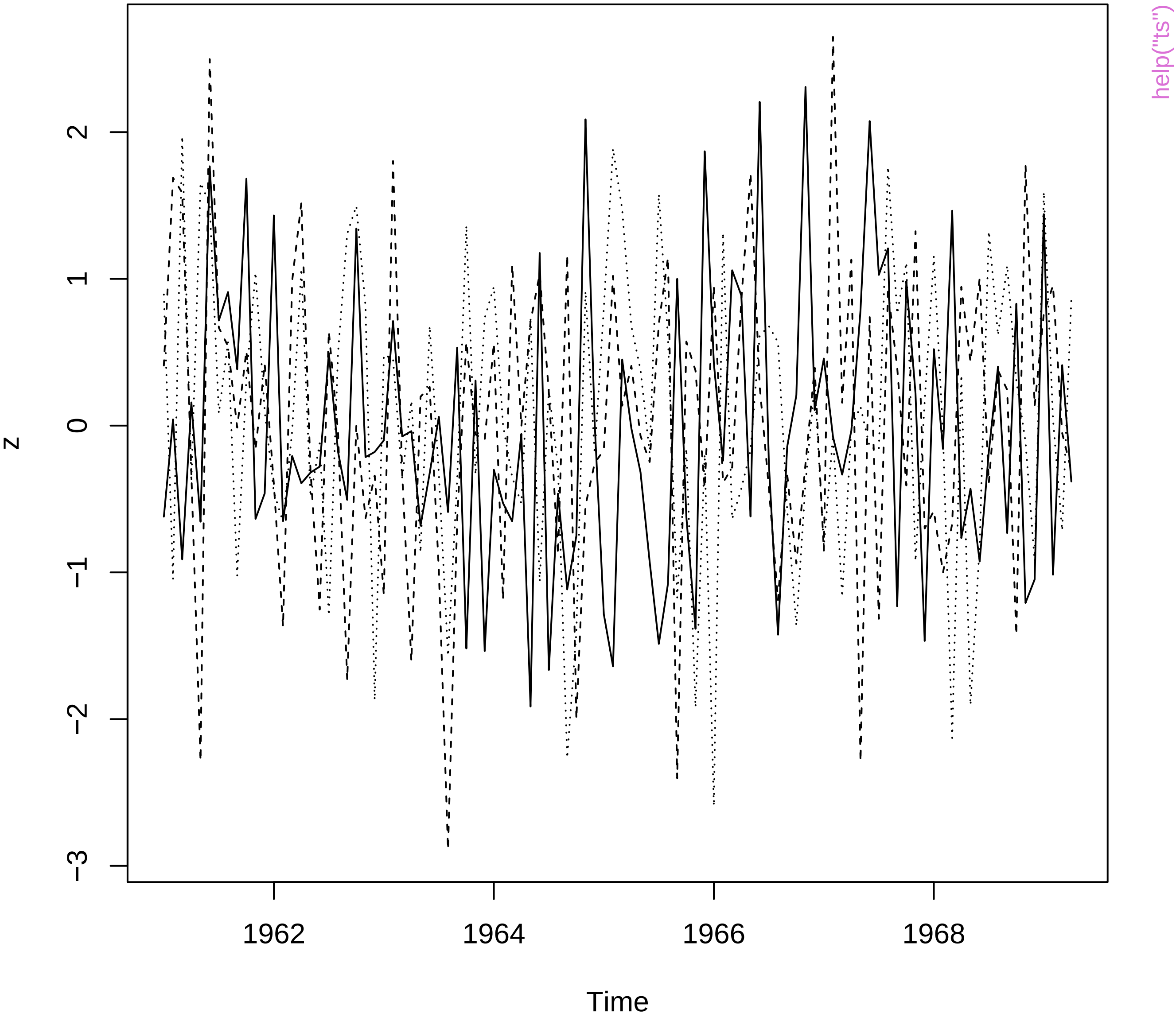

as.vector(presidents)
30
40
50
60
70
80
1945
1950
1955
1960
1965
1970
1975
as.vector(time(presidents))
help("time")



1.0
0.8
0.6
0.4
0.2
0.0
−0.2
y
5
10
15
x
help("toeplitz")

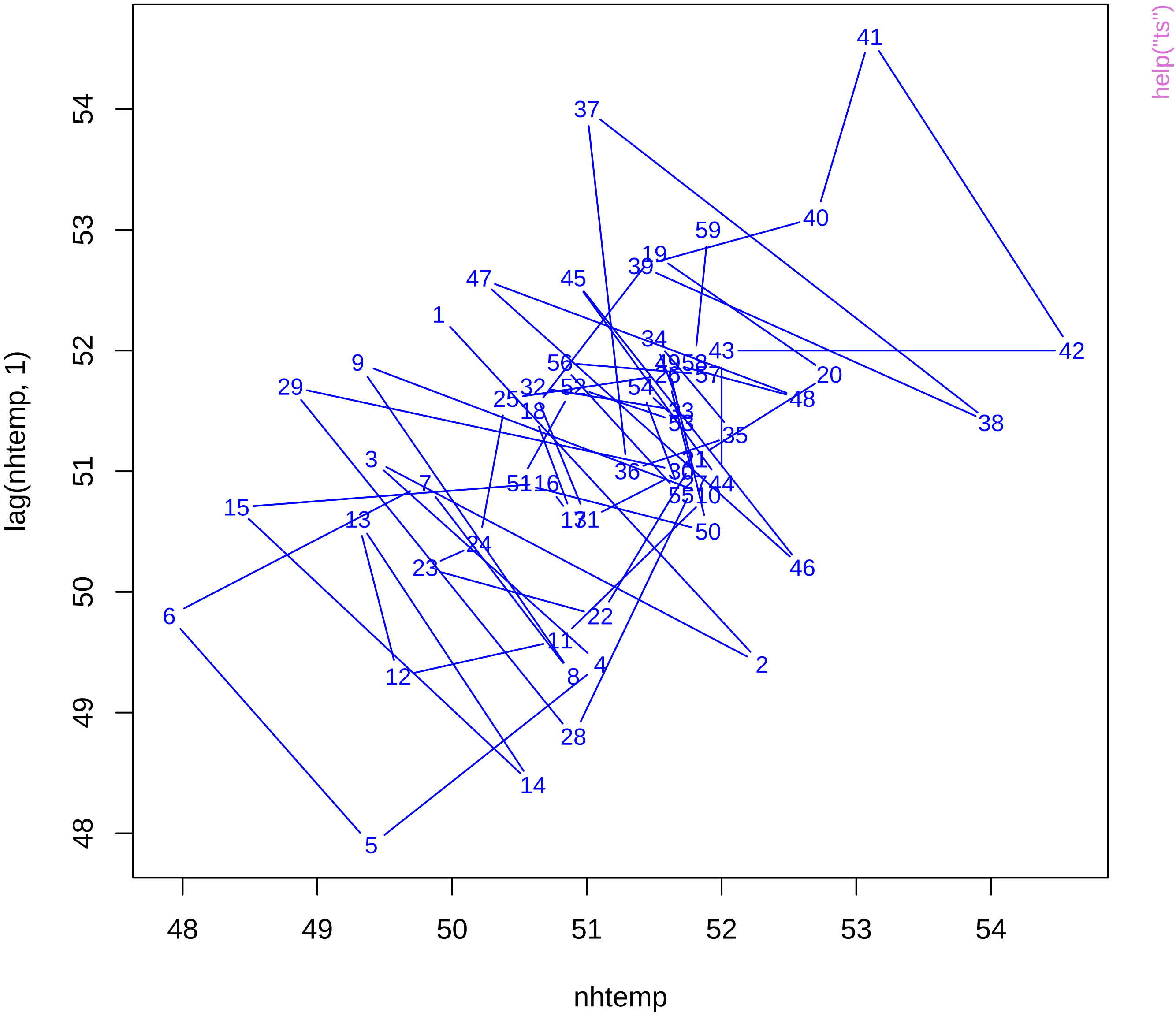
gnp
0
20
40
60
80
100
1956
1958
1960
1962
Time
help("ts")

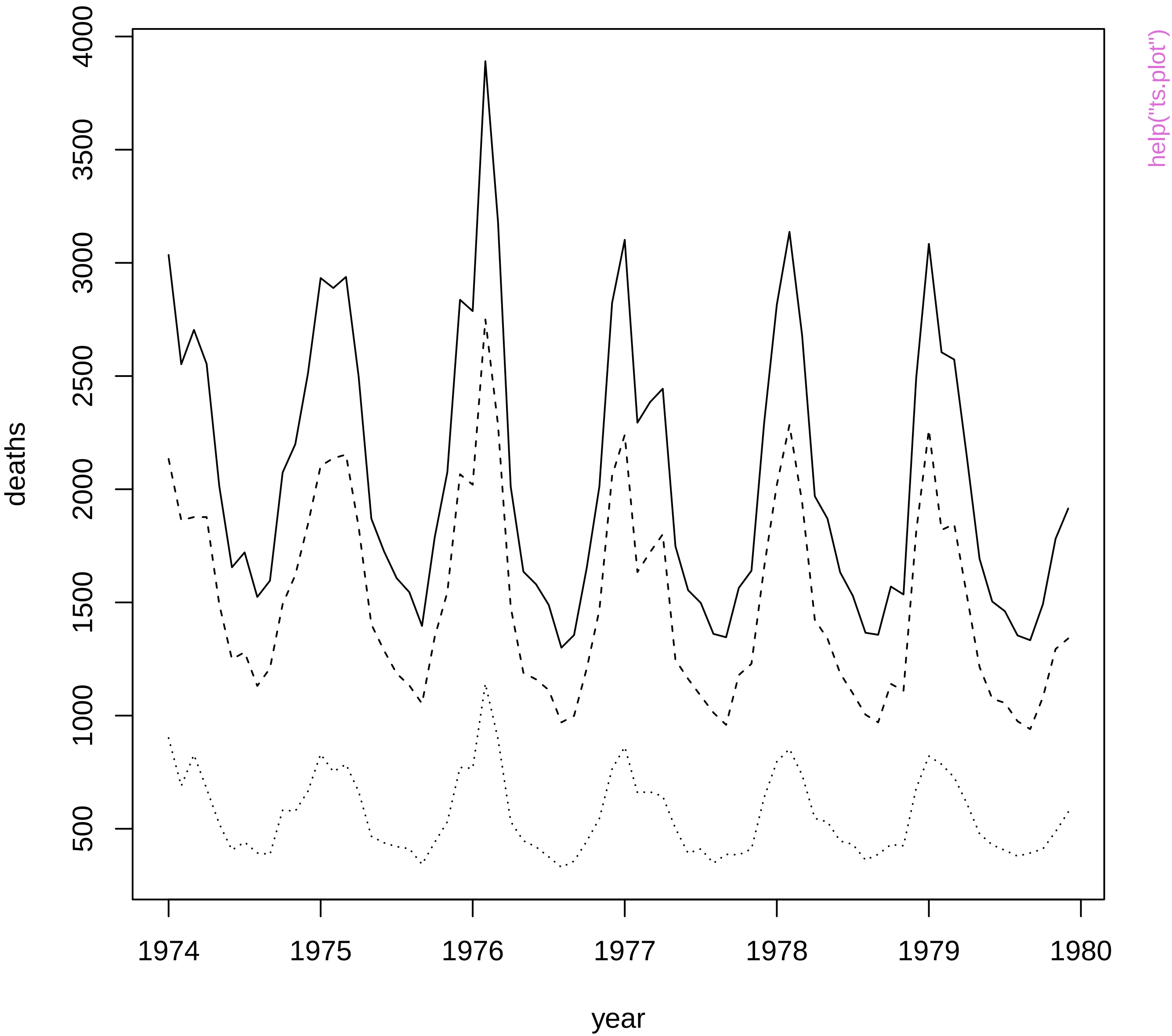

z
Series 1
Series 2
Series 3
Time
1962
1964
1966
1968
help("ts")

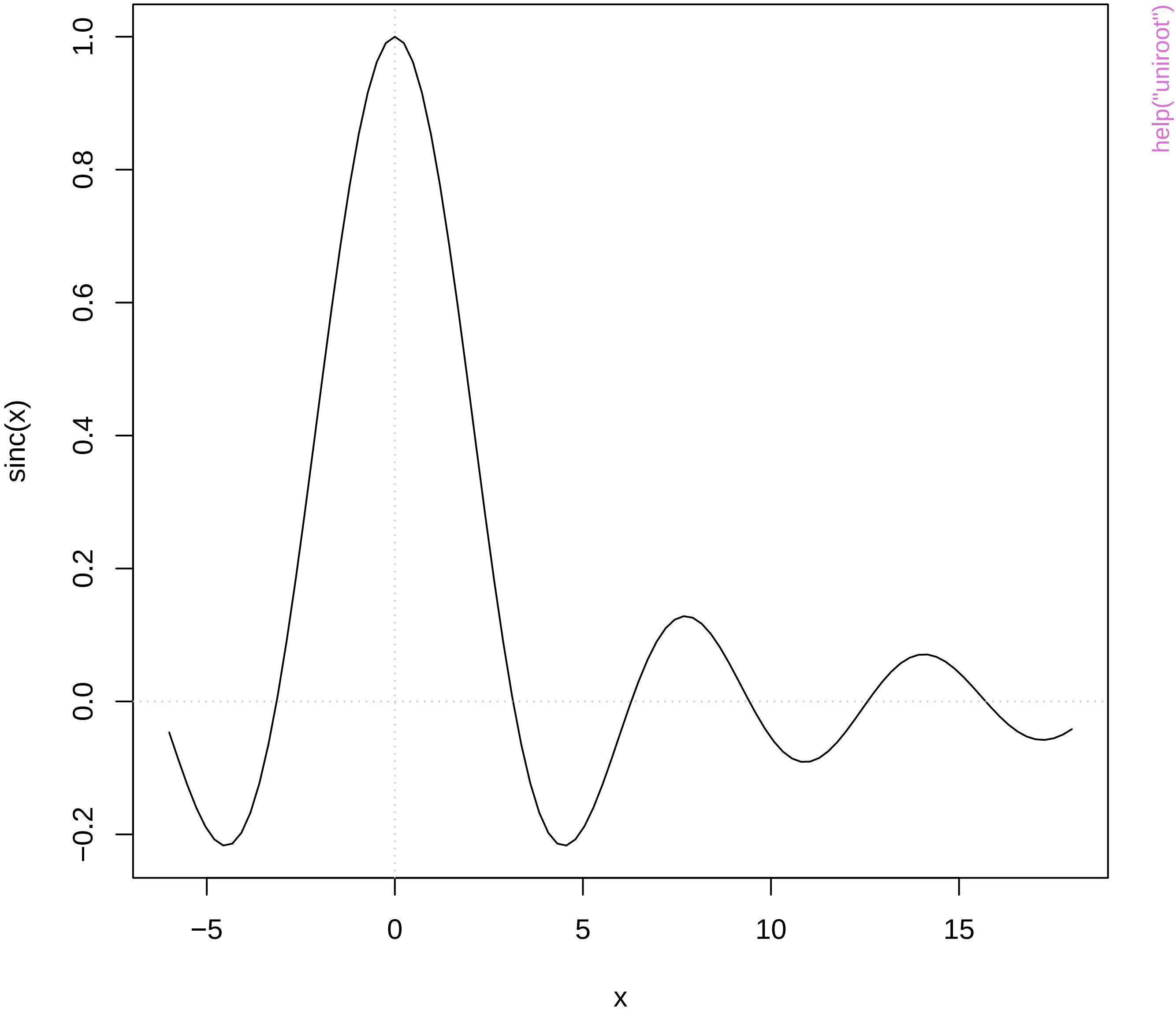


z
2
1
0
−1
−2
−3
1962
1964
1966
1968
Time
help("ts")

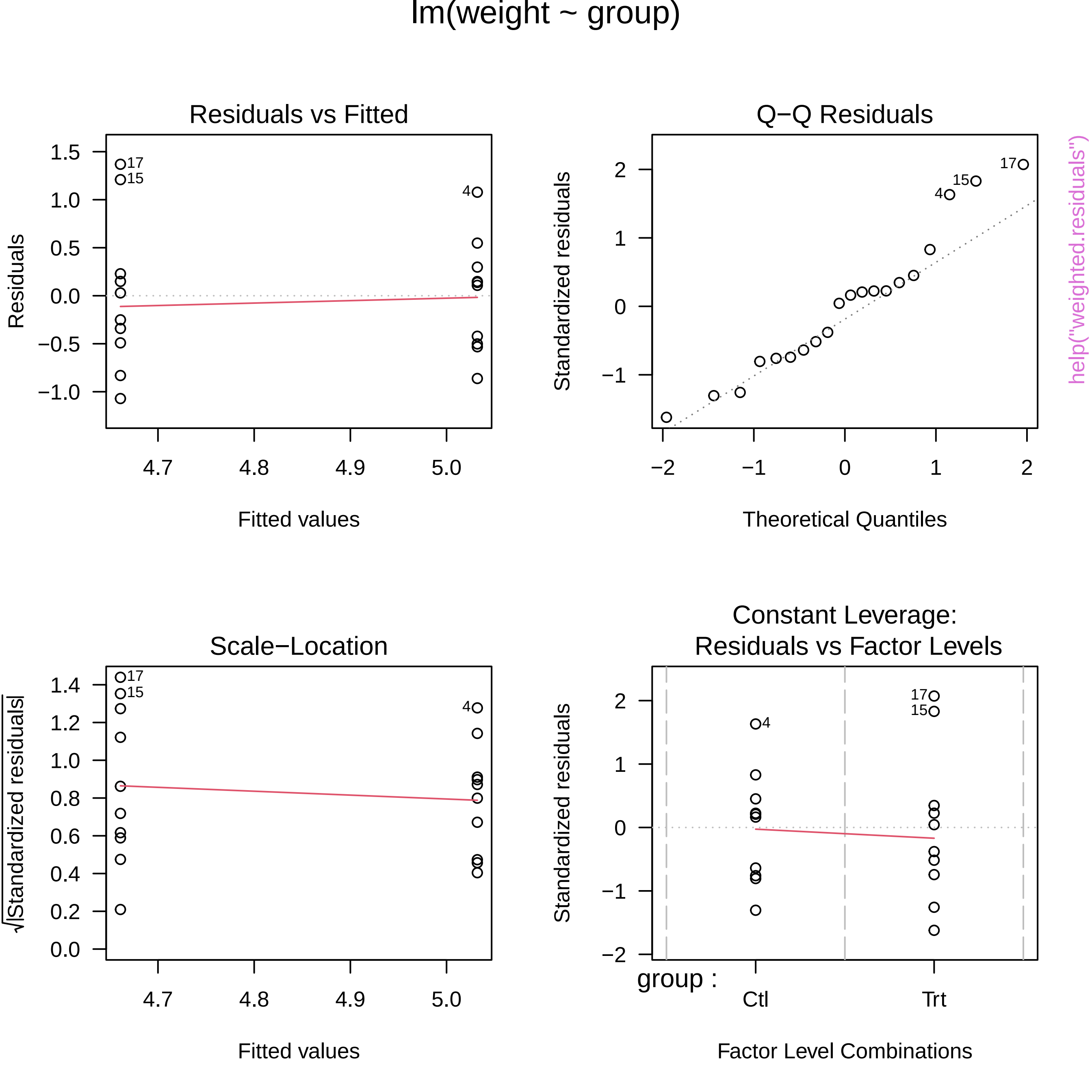
Lag plot of New Haven temperatures

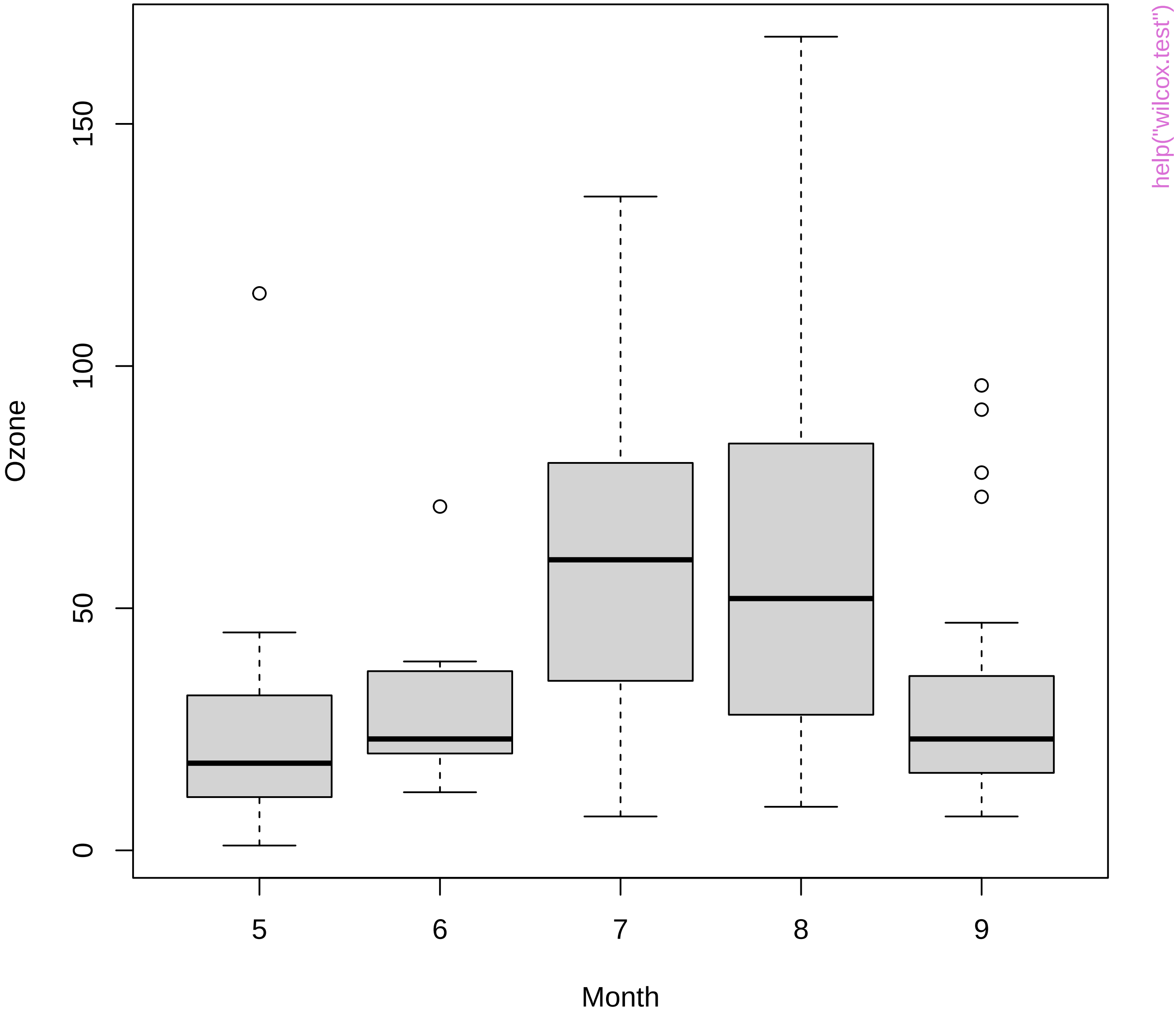



deaths
4000
3500
3000
2500
2000
1500
1000
500
1974
1975
1976
1977
1978
1979
1980
year
help("ts.plot")



sinc(x)
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−5
0
5
10
15
x
help("uniroot")


lm(weight ~ group)
Residuals vs Fitted
Residuals
Fitted values
Q−Q Residuals
Standardized residuals
Theoretical Quantiles
help("weighted.residuals")
Scale−Location
√|Standardized residuals|
Fitted values
Constant Leverage:
Residuals vs Factor Levels
Standardized residuals
group :
Ctl
Trt
Factor Level Combinations



Ozone
0
50
100
150
5
6
7
8
9
Month
help("wilcox.test")