

PRACTICA 1 PREDICCION

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- Se pide el mejor modelo de regresion para estimar la rentabilidad a 1 año:

1. Carga de datos:

En primer lugar, abrimos el csv y visualizamos por encima el mismo intuyendo que problemas podremos tener en cuanto a limpieza del archivo.

```
DS<-read.csv2("Fondos.csv")
getwd()

## [1] "/Users/fede/Desktop/DS/Prediccion"

vY<-DS$rent_1
vX<-cbind(1,DS[,])
```

Observamos que nuestro data frame de 500 observaciones y 30 variables, hay algunas que no resultan de interes para nuestro estudio y otras que desafortunadamente carecen de datos y no aparecen o aparecen como NA y que habra que eliminar para que no perturbe nuestro modelo.

2. Limpieza del fichero:

```
# Eliminamos las columnas que no son validas para nuestro estudio, y dejamos las que, a priori, nos van
DS<-DS[, -3]
DS<-DS[, -3]
DS<-DS[, -3]
DS<-DS[, -11]
DS<-DS[, -11]
DS<-DS[, -13]
DS<-DS[, -18]
DS<-DS[, -18]
DS<-DS[, -12]
DS<-DS[, -14]
DS<-DS[, -17]
DS<-DS[, -17]
```

```
# Tras esto, seguimos teniendo un problema clave que podria alterar nuestro modelo, que son los valores
library(rminer)
library(kknn)
DS=na.omit(DS)
cat("NA values:",sum(is.na(DS)),"\n")
```

```
## NA values: 0
```

3. Selecion del modelo:

```
regresion01<-lm(rent_1~ Inv_minima_inicial+ X1_Day_Return + X1_Week_Return + rent_1_mes + rent_3_meses +
  rent_6_meses + rent_en_el_anio + rent_10_anios +
  Capitaliz_media_bursatil + Sharpe_.3 + Volatilidad_3 + Com_Gestion + Com_deposito, data= DS)
summary(regresion01)
```

```
##
## Call:
## lm(formula = rent_1 ~ Inv_minima_inicial + X1_Day_Return + X1_Week_Return +
##   rent_1_mes + rent_3_meses + rent_6_meses + rent_en_el_anio +
##   rent_10_anios + Capitaliz_media_bursatil + Sharpe_.3 + Volatilidad_3 +
##   Com_Gestion + Com_deposito, data = DS)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.6529 -0.4908 -0.0068  0.5268  3.1810
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    -1.748e+00  3.202e-01  -5.458 2.25e-07 ***
## Inv_minima_inicial -4.523e-07  3.514e-07  -1.287 0.200323
## X1_Day_Return      6.234e-02  1.098e-01   0.568 0.571195
## X1_Week_Return    -2.281e-01  7.780e-02  -2.931 0.003968 **
## rent_1_mes       -6.759e-02  1.042e-01  -0.649 0.517508
## rent_3_meses      1.647e-01  7.322e-02   2.249 0.026144 *
## rent_6_meses     -2.033e-01  3.283e-02  -6.192 6.79e-09 ***
## rent_en_el_anio   9.046e-01  2.345e-02  38.581 < 2e-16 ***
## rent_10_anios     1.785e-01  6.211e-02   2.874 0.004715 **
## Capitaliz_media_bursatil 4.902e-06  4.785e-06   1.025 0.307411
## Sharpe_.3         1.430e+00  3.462e-01   4.131 6.31e-05 ***
## Volatilidad_3     -1.064e-01  3.073e-02  -3.463 0.000718 ***
## Com_Gestion       3.025e-01  2.017e-01   1.500 0.136089
## Com_deposito     -7.415e-01  1.036e+00  -0.716 0.475471
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.028 on 134 degrees of freedom
## Multiple R-squared:  0.9671, Adjusted R-squared:  0.9639
## F-statistic: 303.2 on 13 and 134 DF,  p-value: < 2.2e-16
```

```
# Nos quedamos con las variable mas significativas y construimos nuestro nuevo model con rent_6_meses,r
```

Nueva Regresion:

```
regresion02<-lm(rent_1~rent_6_meses + rent_en_el_anio + Sharpe_.3 + Volatilidad_3, DS)
summary(regresion02)
```

```
##
## Call:
## lm(formula = rent_1 ~ rent_6_meses + rent_en_el_anio + Sharpe_.3 +
##     Volatilidad_3, data = DS)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.8204 -0.5614  0.0270  0.5119  4.0533
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   -1.63982    0.24769   -6.620 6.72e-10 ***
## rent_6_meses   -0.18316    0.03194   -5.734 5.60e-08 ***
## rent_en_el_anio  0.90117    0.01960  45.989 < 2e-16 ***
## Sharpe_.3       2.15354    0.28443    7.571 4.17e-12 ***
## Volatilidad_3   -0.09763    0.02873   -3.398 0.000879 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.087 on 143 degrees of freedom
## Multiple R-squared:  0.9608, Adjusted R-squared:  0.9597
## F-statistic: 875.3 on 4 and 143 DF,  p-value: < 2.2e-16
```

Utilizamos el Best Subset para comprobar que hemos elegido bien nuestras variables:

```
library(leaps)
regfit.full=regsubsets(rent_1~ Inv_minima_inicial+ X1_Day_Return + X1_Week_Return + rent_1_mes + rent_
    rent_6_meses + rent_en_el_anio + rent_10_anios +
    Capitaliz_media_bursatil + Sharpe_.3 + Volatilidad_3 + Com_Gestion + Com_deposito, data= DS)
reg.summary=summary(regfit.full)
reg.summary
```

```
## Subset selection object
## Call: regsubsets.formula(rent_1 ~ Inv_minima_inicial + X1_Day_Return +
##     X1_Week_Return + rent_1_mes + rent_3_meses + rent_6_meses +
##     rent_en_el_anio + rent_10_anios + Capitaliz_media_bursatil +
##     Sharpe_.3 + Volatilidad_3 + Com_Gestion + Com_deposito, data = DS)
## 13 Variables (and intercept)
##              Forced in Forced out
## Inv_minima_inicial      FALSE      FALSE
## X1_Day_Return           FALSE      FALSE
## X1_Week_Return          FALSE      FALSE
## rent_1_mes             FALSE      FALSE
## rent_3_meses           FALSE      FALSE
## rent_6_meses           FALSE      FALSE
## rent_en_el_anio        FALSE      FALSE
## rent_10_anios          FALSE      FALSE
## Capitaliz_media_bursatil FALSE      FALSE
## Sharpe_.3              FALSE      FALSE
## Volatilidad_3          FALSE      FALSE
```

```
## Com_Gestion          FALSE      FALSE
## Com_deposito         FALSE      FALSE
## 1 subsets of each size up to 8
## Selection Algorithm: exhaustive
##      Inv_minima_inicial X1_Day_Return X1_Week_Return rent_1_mes
## 1 ( 1 ) " "           " "           " "           " "
## 2 ( 1 ) " "           " "           " "           " "
## 3 ( 1 ) " "           " "           " "           " "
## 4 ( 1 ) " "           " "           " "           " "
## 5 ( 1 ) " "           " "           " "           " "
## 6 ( 1 ) " "           " "           "*"           " "
## 7 ( 1 ) " "           " "           "*"           " "
## 8 ( 1 ) " "           " "           "*"           " "
##      rent_3_meses rent_6_meses rent_en_el_anio rent_10_anios
## 1 ( 1 ) " "           " "           "*"           " "
## 2 ( 1 ) " "           "*"           "*"           " "
## 3 ( 1 ) " "           "*"           "*"           " "
## 4 ( 1 ) " "           "*"           "*"           " "
## 5 ( 1 ) " "           "*"           "*"           "*"
## 6 ( 1 ) " "           "*"           "*"           "*"
## 7 ( 1 ) "*"           "*"           "*"           "*"
## 8 ( 1 ) "*"           "*"           "*"           "*"
##      Capitaliz_media_bursatil Sharpe_.3 Volatilidad_3 Com_Gestion
## 1 ( 1 ) " "           " "           " "           " "
## 2 ( 1 ) " "           " "           " "           " "
## 3 ( 1 ) " "           "*"           " "           " "
## 4 ( 1 ) " "           "*"           "*"           " "
## 5 ( 1 ) " "           "*"           "*"           " "
## 6 ( 1 ) " "           "*"           "*"           " "
## 7 ( 1 ) " "           "*"           "*"           " "
## 8 ( 1 ) " "           "*"           "*"           "*"
##      Com_deposito
## 1 ( 1 ) " "
## 2 ( 1 ) " "
## 3 ( 1 ) " "
## 4 ( 1 ) " "
## 5 ( 1 ) " "
## 6 ( 1 ) " "
## 7 ( 1 ) " "
## 8 ( 1 ) " "
```

```
reg.summary$bic
```

```
## [1] -351.5088 -401.1186 -447.7473 -454.2439 -455.0070 -458.4547 -458.0226
## [8] -456.2119
```

```
summary(regresion02)
```

```
##
## Call:
## lm(formula = rent_1 ~ rent_6_meses + rent_en_el_anio + Sharpe_.3 +
##     Volatilidad_3, data = DS)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
```

```
## -2.8204 -0.5614 0.0270 0.5119 4.0533
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   -1.63982    0.24769  -6.620 6.72e-10 ***
## rent_6_meses   -0.18316    0.03194  -5.734 5.60e-08 ***
## rent_en_el_anio 0.90117    0.01960  45.989 < 2e-16 ***
## Sharpe_.3       2.15354    0.28443   7.571 4.17e-12 ***
## Volatilidad_3   -0.09763    0.02873  -3.398 0.000879 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.087 on 143 degrees of freedom
## Multiple R-squared:  0.9608, Adjusted R-squared:  0.9597
## F-statistic: 875.3 on 4 and 143 DF, p-value: < 2.2e-16
```

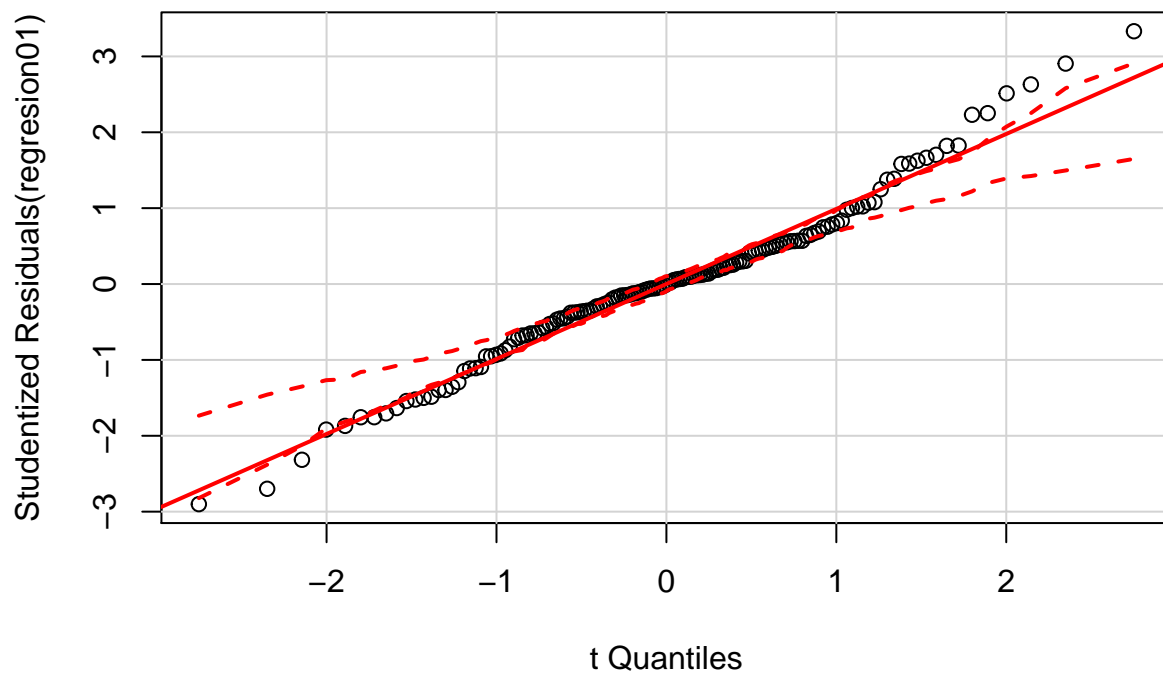
Finalmente nos decantamos por el modelo dos basandonos en significatividad de las variables, el alto

3. Diagnosis:

Ahora comprobamos normalidad:

```
library(car)
qqPlot(regression01, labels=row.names(DS), id.method="identify",
        simulate=TRUE, main="Q-Q Plot")
```

Q-Q Plot



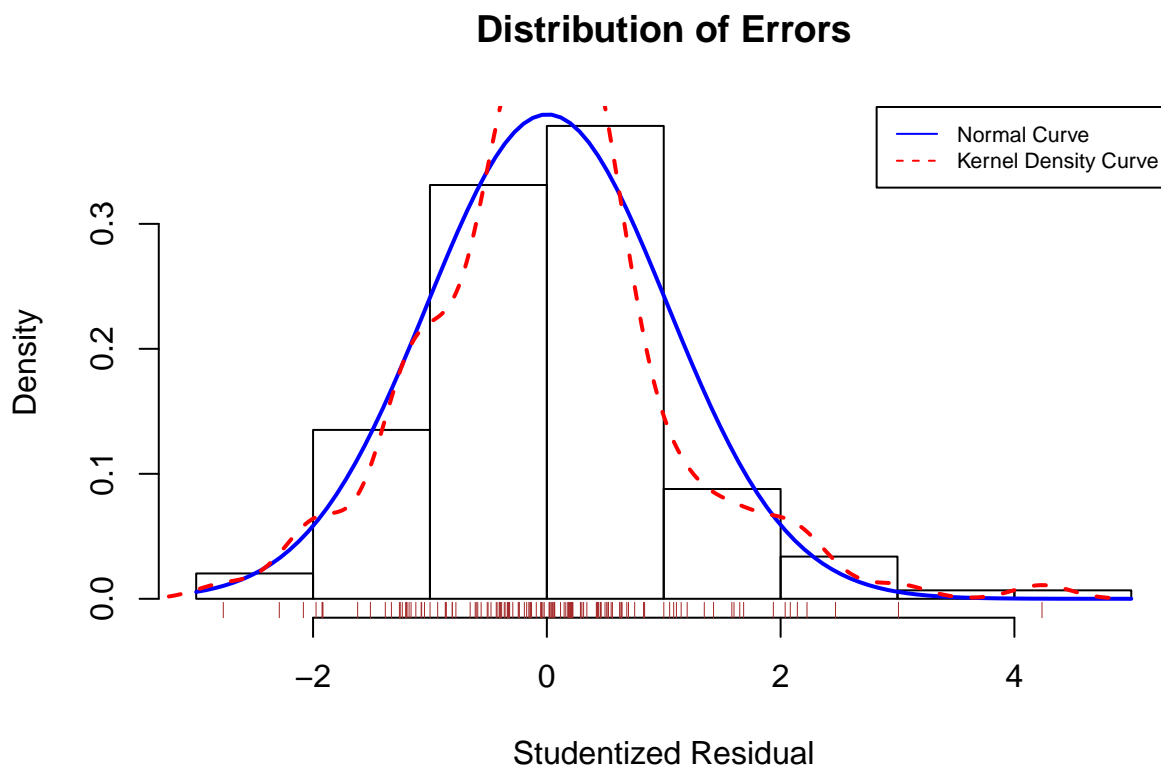
```
residplot <- function(fit, nbreaks=10) {
  z <- rstudent(fit)
  hist(z, breaks=nbreaks, freq=FALSE,
```

```

    xlab="Studentized Residual",
    main="Distribution of Errors")
rug(jitter(z), col="brown")
curve(dnorm(x, mean=mean(z), sd=sd(z)),
      add=TRUE, col="blue", lwd=2)
lines(density(z)$x, density(z)$y,
      col="red", lwd=2, lty=2)
legend("topright",
      legend = c( "Normal Curve", "Kernel Density Curve"),
      lty=1:2, col=c("blue","red"), cex=.7)
}

residplot(regresion02)

```



podemos observar como los residuos obtenidos de la regresion02 se distribuyen normalmente. Seguidamente realizamos el test de Jarque Bera para corroborarlo. #

```
library(fBasics)
```

```
## Loading required package: timeDate
```

```
## Loading required package: timeSeries
```

```
##
```

```
## Rmetrics Package fBasics
```

```
## Analysing Markets and calculating Basic Statistics
```

```
## Copyright (C) 2005-2014 Rmetrics Association Zurich
```

```
## Educational Software for Financial Engineering and Computational Science
```

```
## Rmetrics is free software and comes with ABSOLUTELY NO WARRANTY.
```

```
## https://www.rmetrics.org --- Mail to: info@rmetrics.org
##
## Attaching package: 'fBasics'
## The following object is masked from 'package:car':
##
##      densityPlot
vResid=resid(regresion02)
library(timeDate)
library(timeSeries)
jbTest(vResid)

## Warning in interpp.old(x, y, z, xo, yo, ncp = 0, extrap = FALSE, duplicate
## = "median", : interpp.old() is deprecated, future versions will only
## provide interpp()

## Warning in interpp.old(x, y, z, xo, yo, ncp = 0, extrap = FALSE, duplicate
## = "median", : interpp.old() is deprecated, future versions will only
## provide interpp()

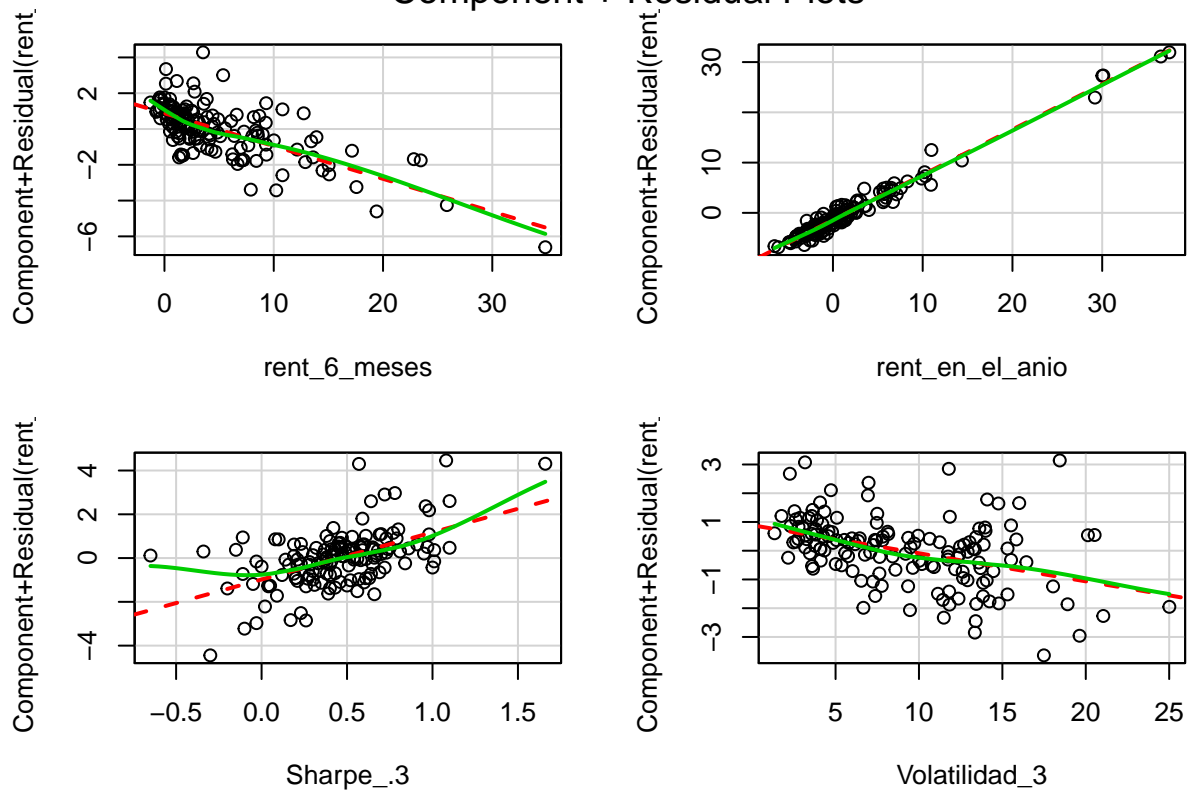
##
## Title:
## Jarque - Bera Normality Test
##
## Test Results:
##   PARAMETER:
##     Sample Size: 148
##   STATISTIC:
##     LM: 15.1
##     ALM: 17.128
##   P VALUE:
##     LM p-value: 0.006
##     ALM p-value: 0.006
##     Asymptotic: 0.001
##
## Description:
## Sat Oct 28 16:08:44 2017 by user:
shapiro.test(vResid)

##
## Shapiro-Wilk normality test
##
## data:  vResid
## W = 0.97605, p-value = 0.01085
```

Realizando ambos Test comprobamos que no podemos rechazar la Hipotesis Nula y por tanto los residuos de esta regresion se distribuyen siguiendo una normal.

```
crPlots(regresion02)
```

Component + Residual Plots



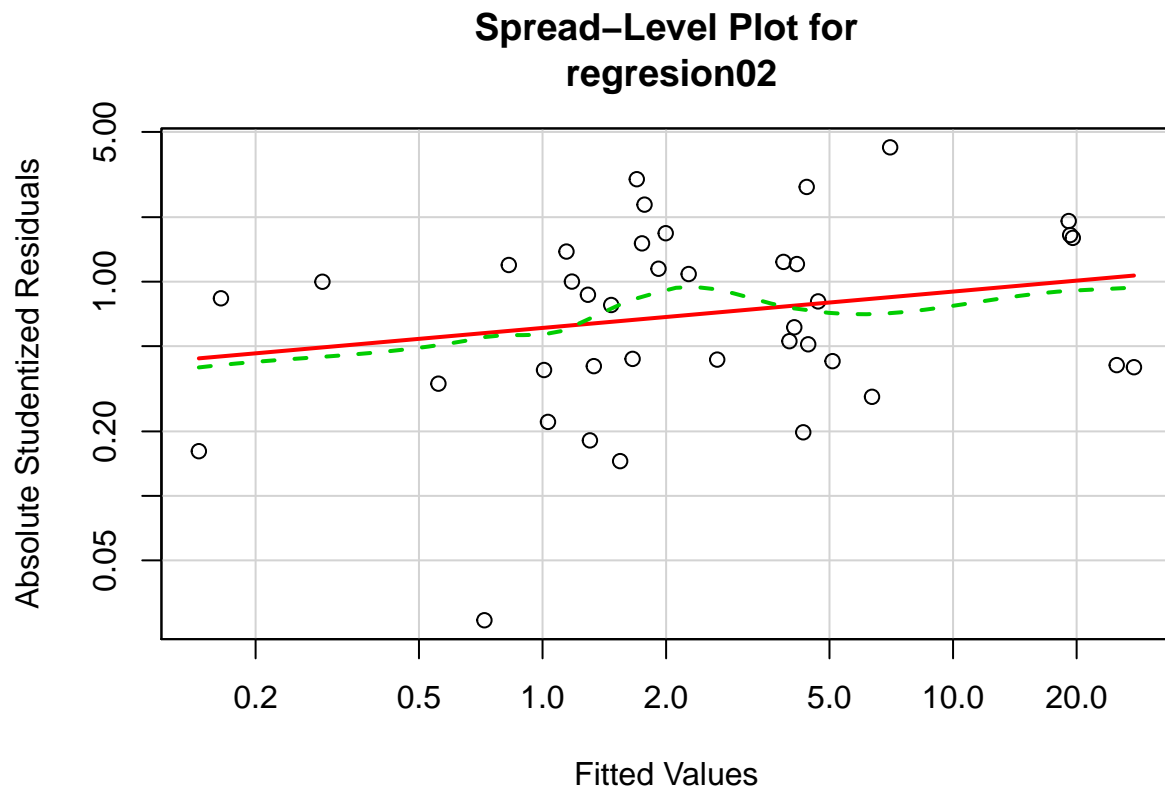
el proximo paso es comprobar la varianza de las observaciones es o no constante (homocedasticidad o heterocedasticidad). Para ello utilizamos el test de Breusch-Pagan en donde la H_0 implica homocedasticidad.

```
ncvTest(regression02)
```

```
## Non-constant Variance Score Test
## Variance formula: ~ fitted.values
## Chisquare = 6.017495    Df = 1    p = 0.01416474
```

```
spreadLevelPlot(regression02)
```

```
## Warning in spreadLevelPlot.lm(regression02): 109 negative fitted values
## removed
```

```
##
## Suggested power transformation: 0.8303391
```

En este primer caso de regresion02 podemos concluir que la variación de las observaciones es constante, ya que no podemos rechazar la H_0 .

Seguidamente realizamos el test de validación global en nuestro modelo:

```
# Regresion3
library(gvlma)
gvmodel <- gvlma(regresion02)
summary(gvmodel)

##
## Call:
## lm(formula = rent_1 ~ rent_6_meses + rent_en_el_anio + Sharpe_.3 +
##     Volatilidad_3, data = DS)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.8204 -0.5614  0.0270  0.5119  4.0533
##
## Coefficients:
```

```
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)   -1.63982    0.24769  -6.620 6.72e-10 ***
## rent_6_meses  -0.18316    0.03194  -5.734 5.60e-08 ***
## rent_en_el_anio 0.90117    0.01960  45.989 < 2e-16 ***
## Sharpe_.3      2.15354    0.28443   7.571 4.17e-12 ***
## Volatilidad_3  -0.09763    0.02873  -3.398 0.000879 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.087 on 143 degrees of freedom
## Multiple R-squared:  0.9608, Adjusted R-squared:  0.9597
## F-statistic: 875.3 on 4 and 143 DF,  p-value: < 2.2e-16
##
##
## ASSESSMENT OF THE LINEAR MODEL ASSUMPTIONS
## USING THE GLOBAL TEST ON 4 DEGREES-OF-FREEDOM:
## Level of Significance = 0.05
##
## Call:
## gvlma(x = regresion02)
##
##               Value p-value              Decision
## Global Stat      22.28287 0.000176 Assumptions NOT satisfied!
## Skewness          4.63147 0.031391 Assumptions NOT satisfied!
## Kurtosis          10.46829 0.001214 Assumptions NOT satisfied!
## Link Function      0.06065 0.805473 Assumptions acceptable.
## Heteroscedasticity 7.12246 0.007612 Assumptions NOT satisfied!
```

4. Multicolinealidad:

Seguimos comprobando la validez de nuestro modelo, comprobando si existe correlacion entre las variables explicativas (mulicolinealidad) mediante el Test VIF (Factor de inflacion de la varianza).

```
# Regresion3
vif(regresion02)

##      rent_6_meses rent_en_el_anio      Sharpe_.3      Volatilidad_3
##      4.158433      2.296332      1.037553      2.555556

sqrt(vif(regresion02)) > 2

##      rent_6_meses rent_en_el_anio      Sharpe_.3      Volatilidad_3
##      TRUE      FALSE      FALSE      FALSE
```

Con el resultado del Test VIF concluimos que, en regresion02, la variable rentabilidad 6 meses presenta multicolinealidad.

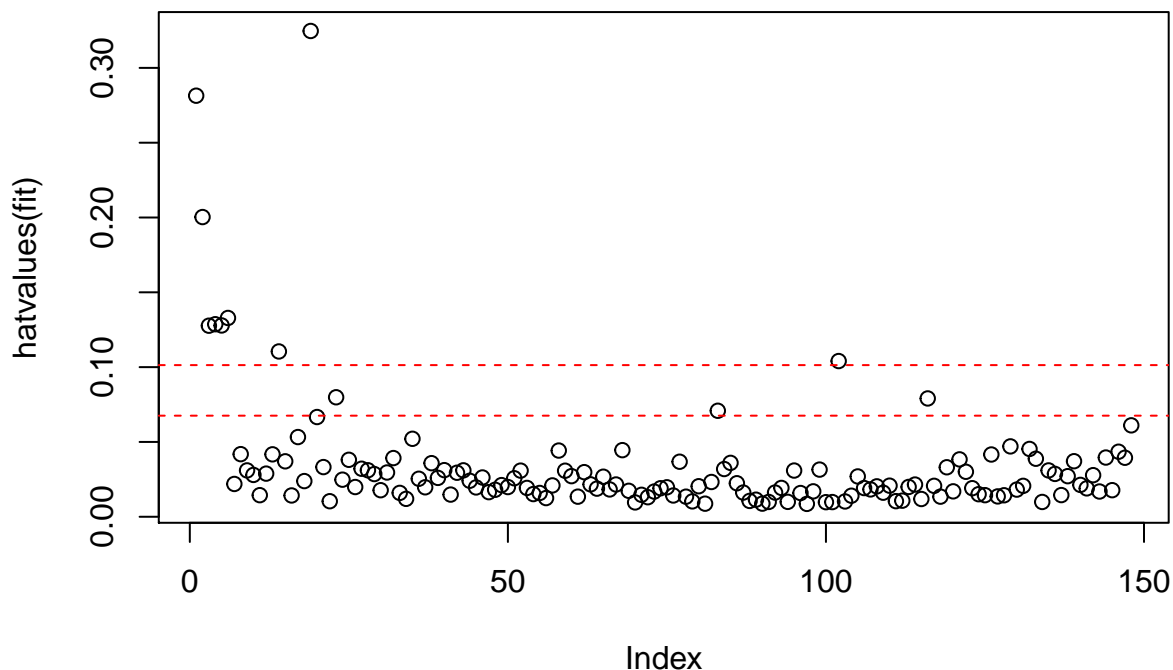
5. Identificación de observaciones anomalas:

```
outlierTest(regresion02)
```

```
##      rstudent unadjusted p-value Bonferonni p  
## 6  4.23603      4.0695e-05    0.0060229
```

```
hat.plot <- function(fit) {  
  p <- length(coefficients(fit))  
  n <- length(fitted(fit))  
  plot(hatvalues(fit), main="Index Plot of Hat Values")  
  abline(h=c(2,3)*p/n, col="red", lty=2)  
  identify(1:n, hatvalues(fit), names(hatvalues(fit)))  
}  
hat.plot(regresion02)
```

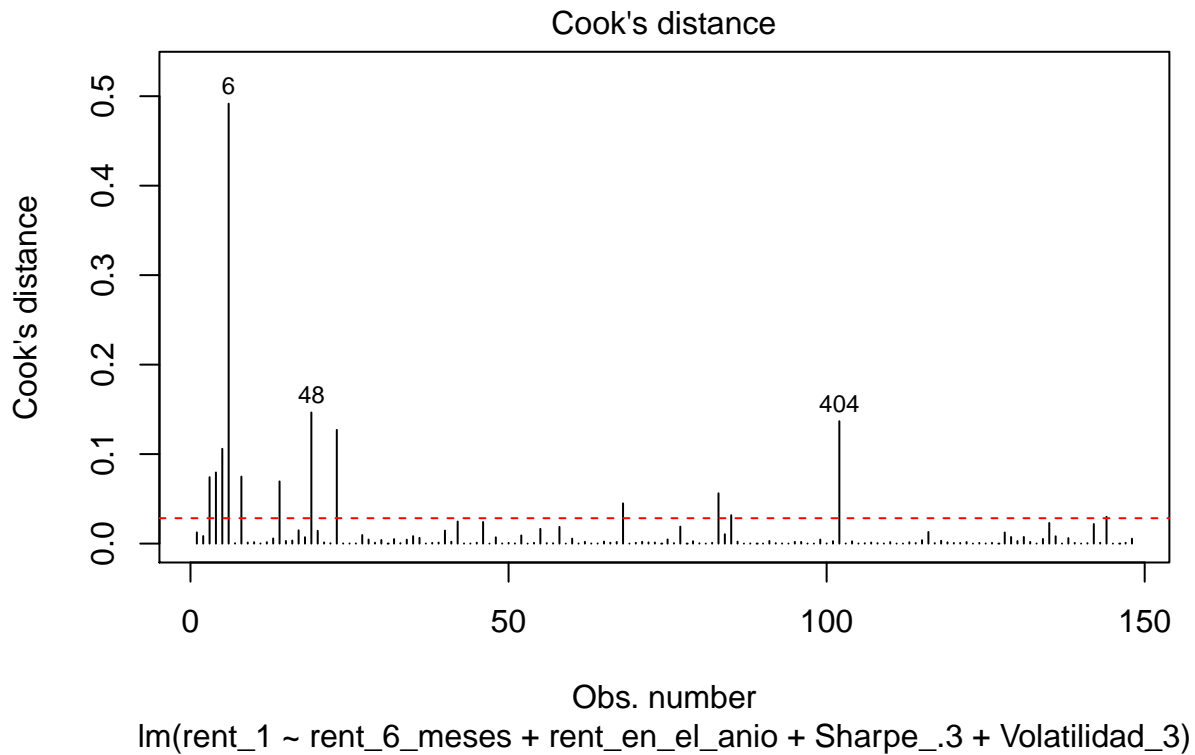
Index Plot of Hat Values



```
## integer(0)
```

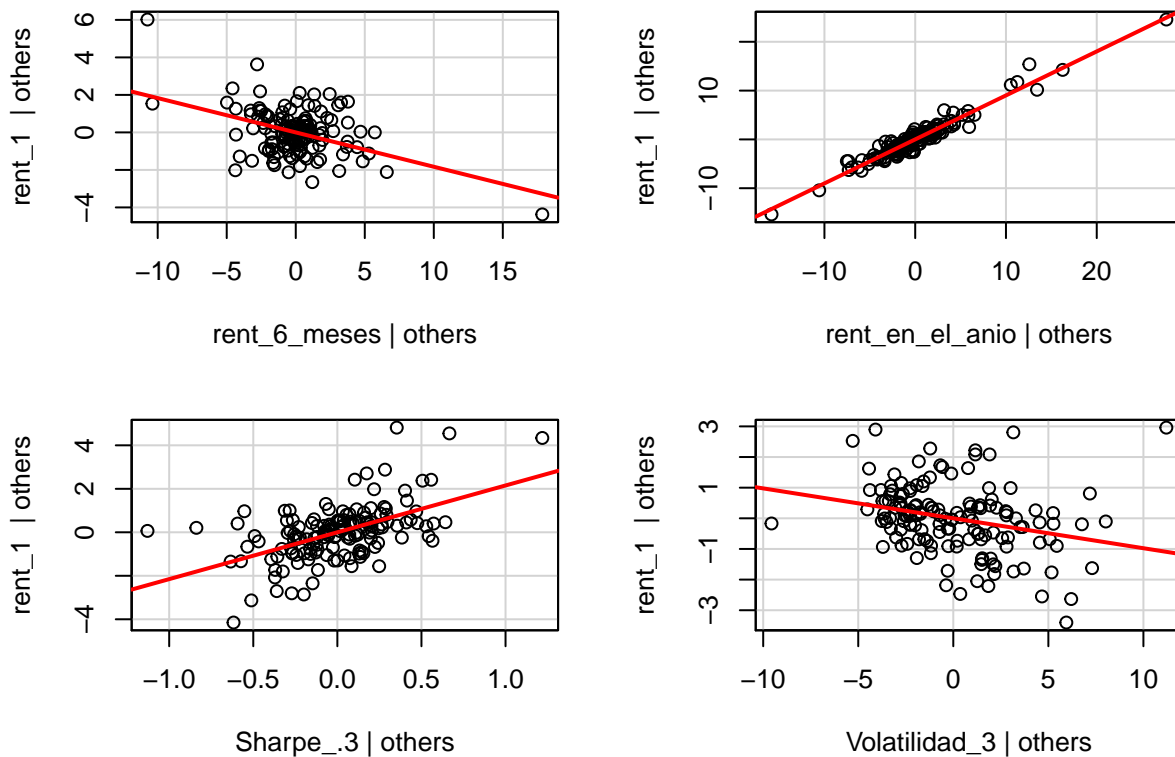
```
#Tambien observamos los valores influyentes:
```

```
cutoff <- 4/(nrow(DS)-length(regresion02$coefficients)-2)  
plot(regresion02, which=4, cook.levels=cutoff)  
abline(h=cutoff, lty=2, col="red")
```

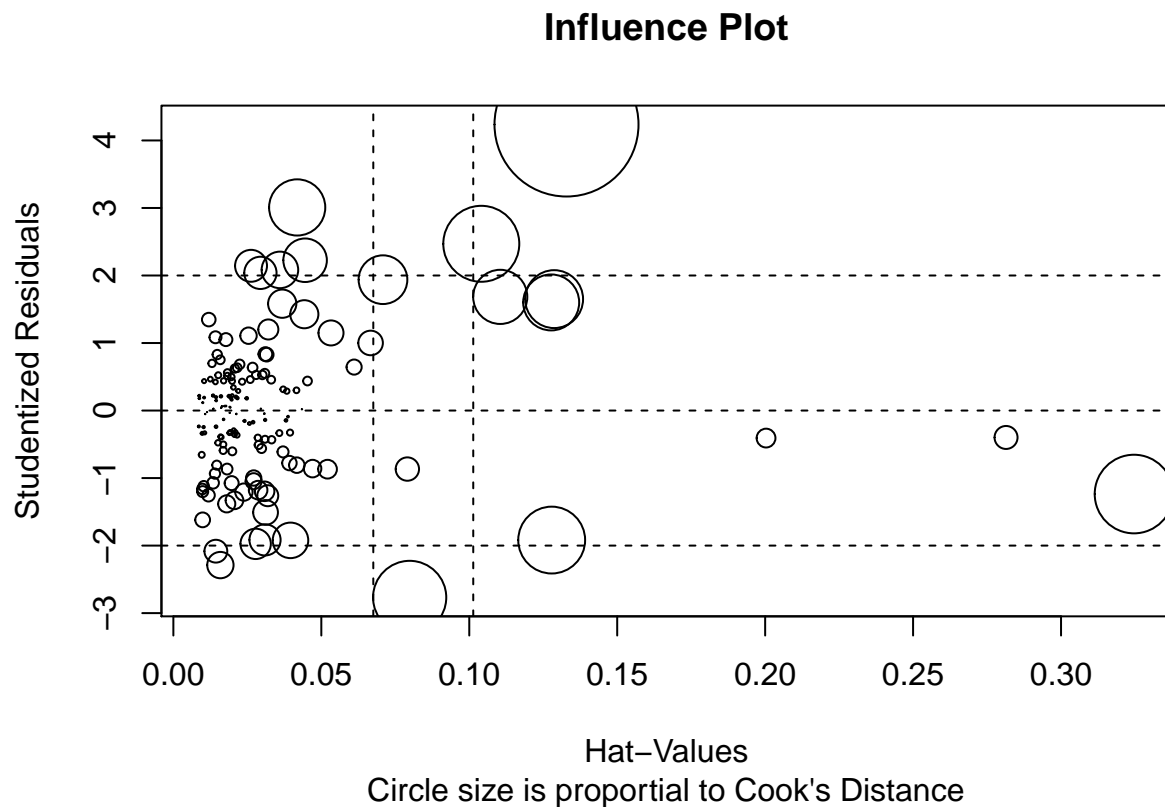


```
avPlots(regression02, ask=FALSE, id.method="identify")
```

Added-Variable Plots



```
influencePlot(regression02, id.method="identify", main="Influence Plot",
  sub="Circle size is proportional to Cook's Distance" )
```



Observamos que tenemos una observacion anomala y la eliminamos del modelo:

```
DS<-DS[-6,]
regresion02<-lm(rent_1~rent_6_meses + rent_en_el_anio + Sharpe_.3 + Volatilidad_3, DS)
summary(regresion02)
```

```
##
## Call:
## lm(formula = rent_1 ~ rent_6_meses + rent_en_el_anio + Sharpe_.3 +
##     Volatilidad_3, data = DS)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.5230 -0.5764 -0.0059  0.5263  3.3260
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   -1.46471    0.23782  -6.159 7.12e-09 ***
## rent_6_meses   -0.13979    0.03189  -4.383 2.26e-05 ***
## rent_en_el_anio  0.88205    0.01907  46.253 < 2e-16 ***
## Sharpe_.3       2.04046    0.27027   7.550 4.82e-12 ***
## Volatilidad_3  -0.13424    0.02851  -4.709 5.86e-06 ***
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.028 on 142 degrees of freedom
## Multiple R-squared:  0.9639, Adjusted R-squared:  0.9629
## F-statistic: 948.8 on 4 and 142 DF,  p-value: < 2.2e-16
# Aunque el modelo no mejora demasiado ya que tan solo hemos eliminado una observacion. Comprobamos de
gvmodel <- gvlma(regresion02)
summary(gvmodel)

##
## Call:
## lm(formula = rent_1 ~ rent_6_meses + rent_en_el_anio + Sharpe_.3 +
##     Volatilidad_3, data = DS)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.5230 -0.5764 -0.0059  0.5263  3.3260
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   -1.46471    0.23782  -6.159 7.12e-09 ***
## rent_6_meses   -0.13979    0.03189  -4.383 2.26e-05 ***
## rent_en_el_anio  0.88205    0.01907  46.253 < 2e-16 ***
## Sharpe_.3       2.04046    0.27027   7.550 4.82e-12 ***
## Volatilidad_3  -0.13424    0.02851  -4.709 5.86e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.028 on 142 degrees of freedom
## Multiple R-squared:  0.9639, Adjusted R-squared:  0.9629
## F-statistic: 948.8 on 4 and 142 DF,  p-value: < 2.2e-16
##
##
## ASSESSMENT OF THE LINEAR MODEL ASSUMPTIONS
## USING THE GLOBAL TEST ON 4 DEGREES-OF-FREEDOM:
## Level of Significance = 0.05
##
## Call:
## gvlma(x = regresion02)
##
##              Value p-value              Decision
## Global Stat      9.726 0.04531 Assumptions NOT satisfied!
## Skewness         1.354 0.24455  Assumptions acceptable.
## Kurtosis         1.605 0.20519  Assumptions acceptable.
## Link Function    2.638 0.10431  Assumptions acceptable.
## Heteroscedasticity 4.128 0.04217 Assumptions NOT satisfied!
```

De esta manera sin el outlier se cumple los supuestos de asimetría y kurtosis.

Como penúltimo paso comparamos los modelos mediante los criterios AIC y de nuevo BIC:

```
AIC(regresion01,regresion02)
```

```
## Warning in AIC.default(regresion01, regresion02): models are not all fitted  
## to the same number of observations
```

```
##           df      AIC  
## regresion01 15 443.3684  
## regresion02  6 432.0759
```

```
BIC(regresion01,regresion02)
```

```
## Warning in BIC.default(regresion01, regresion02): models are not all fitted  
## to the same number of observations
```

```
##           df      BIC  
## regresion01 15 488.3266  
## regresion02  6 450.0185
```

```
# Comprobamos la mejora del modelo 02 con respecto al primero bajo ambos criterios de seleccion.
```

6. Cross Validation:

```
library(ISLR)  
set.seed(250)  
numData=nrow(DS)  
train=sample(numData ,numData/2)
```

```
regres.train =lm(rent_1~rent_6_meses + rent_en_el_anio + Sharpe_.3 + Volatilidad_3, DS ,subset =train )  
attach(DS)  
mean((rent_1-predict(regres.train ,Auto))[-train ]^2)
```

```
## Warning: 'newdata' had 392 rows but variables found have 147 rows
```

```
## [1] 1.401156
```

```
set.seed(251)
```

```
regres.train2 =lm(rent_1~rent_6_meses + rent_en_el_anio + Sharpe_.3 + Volatilidad_3, DS ,subset =train )  
mean((rent_1-predict(regres.train2 ,Auto))[-train ]^2)
```

```
## Warning: 'newdata' had 392 rows but variables found have 147 rows
```

```
## [1] 1.401156
```

Leave-one-out Cross Validation:

```
glm.fit1=glm(rent_1~rent_6_meses + rent_en_el_anio + Sharpe_.3 + Volatilidad_3, DS ,family = gaussian())
coef(glm.fit1)
```

```
##      (Intercept)      rent_6_meses rent_en_el_anio      Sharpe_.3
##      -1.4647074      -0.1397874      0.8820467      2.0404648
##      Volatilidad_3
##      -0.1342384
```

```
library (boot)
```

```
##
## Attaching package: 'boot'
##
## The following object is masked from 'package:car':
##
##      logit
```

```
cv.err =cv.glm(DS,glm.fit1)
cv.err$delta
```

```
## [1] 1.144061 1.143608
```

```
glm.fit2=glm(rent_1~rent_en_el_anio + Sharpe_.3 + Volatilidad_3, DS ,family = gaussian())
cv.err2 =cv.glm(DS,glm.fit2)
cv.err2$delta
```

```
## [1] 1.261463 1.261096
```

K-Fold Cross-Validation:

```
library (boot)
cv.err =cv.glm(DS,glm.fit1,K=10)
cv.err$delta
```

```
## [1] 1.167098 1.158525
```

```
glm.fit2=glm(rent_1~rent_en_el_anio + Sharpe_.3 + Volatilidad_3, DS ,family = gaussian())
cv.err2 =cv.glm(DS,glm.fit2,K=10)
cv.err2$delta
```

```
## [1] 1.283470 1.276506
```