Script Análisis exploratorios

Introducción a la estadística inferencial

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R.1

ESTE EJEMPLO ES DE DATOS DE EVERITT 04 P. 17. CONSISTE EN INFORMACIÓN SOBRE CONTAMINACIÓN AMBIENTAL EN EU EN ZONAS METROPOLITANAS.

Llamo los datos (ojo que Everitt los tiene en formato dat, si están como txt, hay que llamarlos con read.table)

```
airpoll<-source("chap2airpoll.dat")$value
ap <- data.frame(airpoll)
write.csv(ap, "apdf.csv")
adf <- read.csv("airpoll.csv", header = T, sep = ";") #tabla con dato faltante
```

```
attach(airpoll)
airpoll
```

```
##           Rainfall Education Popden Nonwhite NOX SO2 Mortality
## akronOH         36      11.4   3243      8.8  15  59     921.9
```

```
## albanyNY       35       11.0   4281       3.5  10  39      997.9
## allenPA        44        9.8   4260       0.8   6  33      962.4
## atlantGA       47       11.1   3125      27.1   8  24      982.3
## baltimMD       43        9.6   6441      24.4  38 206     1071.0
## birmhmAL       53       10.2   3325      38.5  32  72     1030.0
## bostonMA       43       12.1   4679       3.5  32  62      934.7
## bridgeCT       45       10.6   2140       5.3   4   4      899.5
## bufaloNY       36       10.5   6582       8.1  12  37     1002.0
## cantonOH       36       10.7   4213       6.7   7  20      912.3
## chatagTN       52        9.6   2302      22.2   8  27     1018.0
## chicagIL       33       10.9   6122      16.3  63 278     1025.0
## cinnciOH       40       10.2   4101      13.0  26 146      970.5
## clevelOH       35       11.1   3042      14.7  21  64      986.0
## colombOH       37       11.9   4259      13.1   9  15      958.8
## dallasTX       35       11.8   1441      14.8   1   1      860.1
## daytonOH       36       11.4   4029      12.4   4  16      936.2
## denverCO       15       12.2   4824       4.7   8  28      871.8
## detrotMI       31       10.8   4834      15.8  35 124      959.2
## flintMI        30       10.8   3694      13.1   4  11      941.2
## ftwortTX       31       11.4   1844      11.5   1   1      891.7
## grndraMI       31       10.9   3226       5.1   3  10      871.3
## grnborNC       42       10.4   2269      22.7   3   5      971.1
## hartfdCT       43       11.5   2909       7.2   3  10      887.5
## houstnTX       46       11.4   2647      21.0   5   1      952.5
## indianIN       39       11.4   4412      15.6   7  33      968.7
## kansasMO       35       12.0   3262      12.6   4   4      919.7
## lancasPA       43        9.5   3214       2.9   7  32      844.1
```

```
## losangCA        11        12.1   4700        7.8 319 130      861.8
## louisvKY        30         9.9   4474       13.1  37 193      989.3
## memphsTN        50        10.4   3497       36.7  18  34     1006.0
## miamiFL         60        11.5   4657       13.5   1   1      861.4
## milwauWI        30        11.1   2934        5.8  23 125      929.2
## minnplMN        25        12.1   2095        2.0  11  26      857.6
## nashvlTN        45        10.1   2082       21.0  14  78      961.0
## newhvnCT        46        11.3   3327        8.8   3   8      923.2
## neworlLA        54         9.7   3172       31.4  17   1     1113.0
## newyrkNY        42        10.7   7462       11.3  26 108      994.6
## philadPA        42        10.5   6092       17.5  32 161     1015.0
## pittsbPA        36        10.6   3437        8.1  59 263      991.3
## portldOR        37        12.0   3387        3.6  21  44      894.0
## provdcRI        42        10.1   3508        2.2   4  18      938.5
## readngPA        41         9.6   4843        2.7  11  89      946.2
## richmdVA        44        11.0   3768       28.6   9  48     1026.0
## rochtrNY        32        11.1   4355        5.0   4  18      874.3
## stlousMO        34         9.7   5160       17.2  15  68      953.6
## sandigCA        10        12.1   3033        5.9  66  20      839.7
## sanfrnCA        18        12.2   4253       13.7 171  86      911.7
## sanjosCA        13        12.2   2702        3.0  32   3      790.7
## seatleWA        35        12.2   3626        5.7   7  20      899.3
## springMA        45        11.1   1883        3.4   4  20      904.2
## syracuNY        38        11.4   4923        3.8   5  25      950.7
## toledoOH        31        10.7   3249        9.5   7  25      972.5
## uticaNY         40        10.3   1671        2.5   2  11      912.2
## washDC          41        12.3   5308       25.9  28 102      968.8
```

```
## wichtaKS       28      12.1   3665      7.5   2   1     823.8
## wilmtnDE       45      11.3   3152     12.1  11  42    1004.0
## worctrMA       45      11.1   3678      1.0   3   8     895.7
## yorkPA         42       9.0   9699      4.8   8  49     911.8
## youngsOH       38      10.7   3451     11.7  13  39     954.4
```

```r
names(airpoll)
```

```
## [1] "Rainfall"  "Education" "Popden"    "Nonwhite"  "NOX"       "SO2"
## [7] "Mortality"
```

Exploración Univariada

Comenzamos por ver el vector de medias y varianzas

#mean(airpoll) #sd(airpoll)^2

```r
summary(airpoll)
```

```
##     Rainfall       Education         Popden         Nonwhite
##  Min.   :10.00   Min.   : 9.00   Min.   :1441   Min.   : 0.80
##  1st Qu.:32.75   1st Qu.:10.40   1st Qu.:3104   1st Qu.: 4.95
##  Median :38.00   Median :11.05   Median :3567   Median :10.40
##  Mean   :37.37   Mean   :10.97   Mean   :3866   Mean   :11.87
##  3rd Qu.:43.25   3rd Qu.:11.50   3rd Qu.:4520   3rd Qu.:15.65
##  Max.   :60.00   Max.   :12.30   Max.   :9699   Max.   :38.50
##       NOX               SO2           Mortality
##  Min.   :  1.00   Min.   :  1.00   Min.   : 790.7
##  1st Qu.:  4.00   1st Qu.: 11.00   1st Qu.: 898.4
```

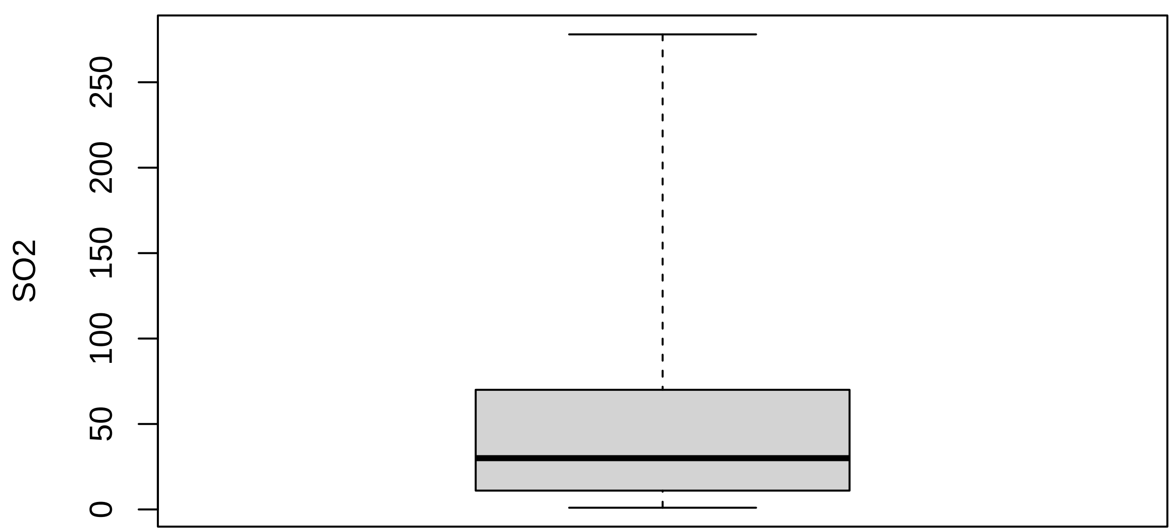
```
##  Median :  9.00   Median : 30.00   Median : 943.7
##  Mean   : 22.65   Mean   : 53.77   Mean   : 940.4
##  3rd Qu.: 23.75   3rd Qu.: 69.00   3rd Qu.: 983.2
##  Max.   :319.00   Max.   :278.00   Max.   :1113.0
```

```
summary(airpoll$SO2)
```

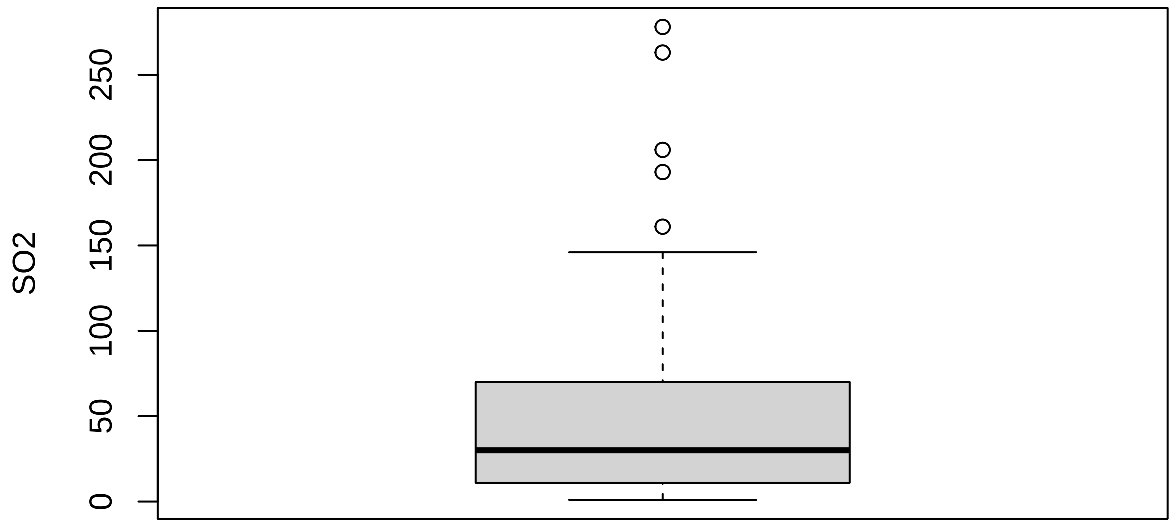
```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    1.00   11.00   30.00   53.77   69.00  278.00
```

vease la diferencia entre la media y la mediana para reconocer desviaciones, calculese el intervalo intercuartiles (3er-1er).

```
#windows()
boxplot(SO2, range=0, ylab="SO2") # en este caso, los "bigotes" del boxplot ubican el má
```



```r
boxplot(SO2, ylab="SO2") #en este caso, la función se ejecuta con range = 1.5 por defect
```




```r
iqSO2<-69-11
iqSO2
```

```
## [1] 58
```

Una buena regla de dedo para identificar datos atípicos es: que los puntos que caen mas allá del 3er+1.5(intercuartil) o mas bajo que 1er-1.5(intercuartil) son valores atípicos.

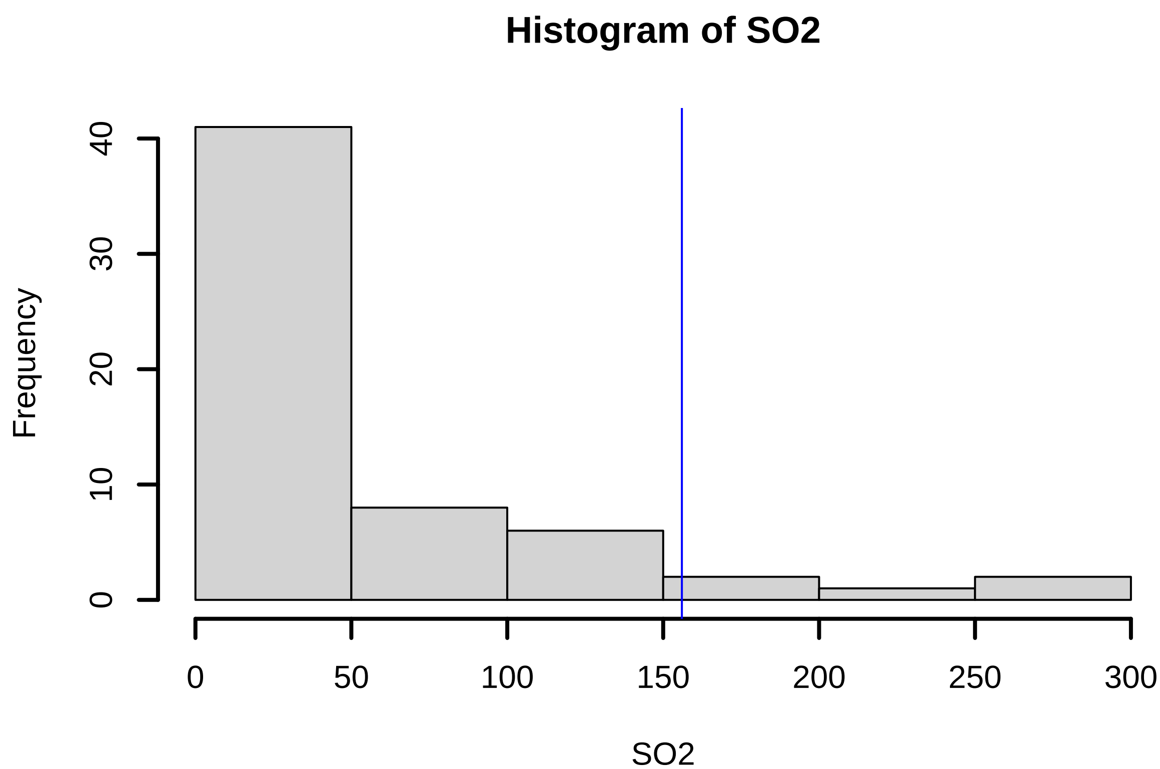
```r
atipicossup<-69+(iqSO2*1.5)
  atipicossup
```

```
## [1] 156
```

```r
atipicosinf<-abs(11-(iqSO2*1.5))
  atipicosinf
```

```
## [1] 76
```

```r
hist(SO2,lwd=2)
abline(v = 156, col = "blue")
```




```r
airpoll
```

```
##            Rainfall Education Popden Nonwhite NOX SO2 Mortality
## akronOH          36      11.4   3243      8.8  15  59     921.9
## albanyNY         35      11.0   4281      3.5  10  39     997.9
## allenPA          44       9.8   4260      0.8   6  33     962.4
```

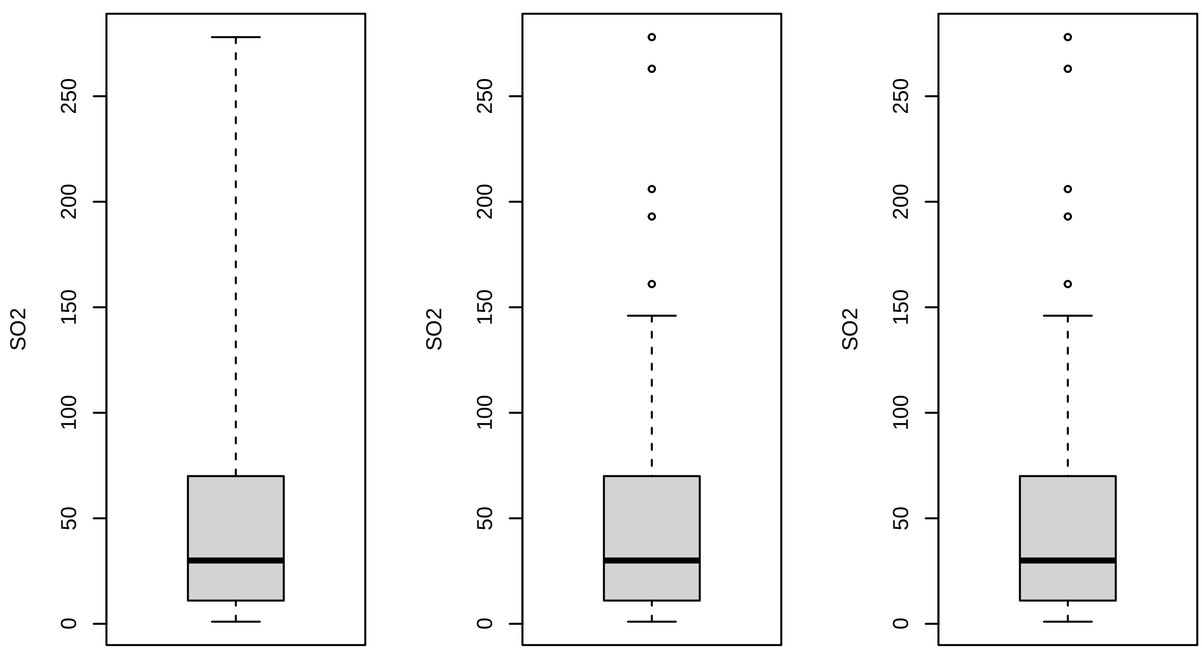
```
## atlantGA       47       11.1   3125      27.1   8  24      982.3
## baltimMD       43        9.6   6441      24.4  38 206     1071.0
## birmhmAL       53       10.2   3325      38.5  32  72     1030.0
## bostonMA       43       12.1   4679       3.5  32  62      934.7
## bridgeCT       45       10.6   2140       5.3   4   4      899.5
## bufaloNY       36       10.5   6582       8.1  12  37     1002.0
## cantonOH       36       10.7   4213       6.7   7  20      912.3
## chatagTN       52        9.6   2302      22.2   8  27     1018.0
## chicagIL       33       10.9   6122      16.3  63 278     1025.0
## cinnciOH       40       10.2   4101      13.0  26 146      970.5
## clevelOH       35       11.1   3042      14.7  21  64      986.0
## colombOH       37       11.9   4259      13.1   9  15      958.8
## dallasTX       35       11.8   1441      14.8   1   1      860.1
## daytonOH       36       11.4   4029      12.4   4  16      936.2
## denverCO       15       12.2   4824       4.7   8  28      871.8
## detrotMI       31       10.8   4834      15.8  35 124      959.2
## flintMI        30       10.8   3694      13.1   4  11      941.2
## ftwortTX       31       11.4   1844      11.5   1   1      891.7
## grndraMI       31       10.9   3226       5.1   3  10      871.3
## grnborNC       42       10.4   2269      22.7   3   5      971.1
## hartfdCT       43       11.5   2909       7.2   3  10      887.5
## houstnTX       46       11.4   2647      21.0   5   1      952.5
## indianIN       39       11.4   4412      15.6   7  33      968.7
## kansasMO       35       12.0   3262      12.6   4   4      919.7
## lancasPA       43        9.5   3214       2.9   7  32      844.1
## losangCA       11       12.1   4700       7.8 319 130      861.8
## louisvKY       30        9.9   4474      13.1  37 193      989.3
```

```
## memphsTN       50    10.4  3497    36.7  18  34    1006.0
## miamiFL        60    11.5  4657    13.5   1   1     861.4
## milwauWI       30    11.1  2934     5.8  23 125     929.2
## minnplMN       25    12.1  2095     2.0  11  26     857.6
## nashvlTN       45    10.1  2082    21.0  14  78     961.0
## newhvnCT       46    11.3  3327     8.8   3   8     923.2
## neworlLA       54     9.7  3172    31.4  17   1    1113.0
## newyrkNY       42    10.7  7462    11.3  26 108     994.6
## philadPA       42    10.5  6092    17.5  32 161    1015.0
## pittsbPA       36    10.6  3437     8.1  59 263     991.3
## portldOR       37    12.0  3387     3.6  21  44     894.0
## provdcRI       42    10.1  3508     2.2   4  18     938.5
## readngPA       41     9.6  4843     2.7  11  89     946.2
## richmdVA       44    11.0  3768    28.6   9  48    1026.0
## rochtrNY       32    11.1  4355     5.0   4  18     874.3
## stlousMO       34     9.7  5160    17.2  15  68     953.6
## sandigCA       10    12.1  3033     5.9  66  20     839.7
## sanfrnCA       18    12.2  4253    13.7 171  86     911.7
## sanjosCA       13    12.2  2702     3.0  32   3     790.7
## seatleWA       35    12.2  3626     5.7   7  20     899.3
## springMA       45    11.1  1883     3.4   4  20     904.2
## syracuNY       38    11.4  4923     3.8   5  25     950.7
## toledoOH       31    10.7  3249     9.5   7  25     972.5
## uticaNY        40    10.3  1671     2.5   2  11     912.2
## washDC         41    12.3  5308    25.9  28 102     968.8
## wichtaKS       28    12.1  3665     7.5   2   1     823.8
## wilmtnDE       45    11.3  3152    12.1  11  42    1004.0
```

```
## worctrMA        45       11.1    3678       1.0    3    8      895.7
## yorkPA          42        9.0    9699       4.8    8   49      911.8
## youngsOH        38       10.7    3451      11.7   13   39      954.4
```

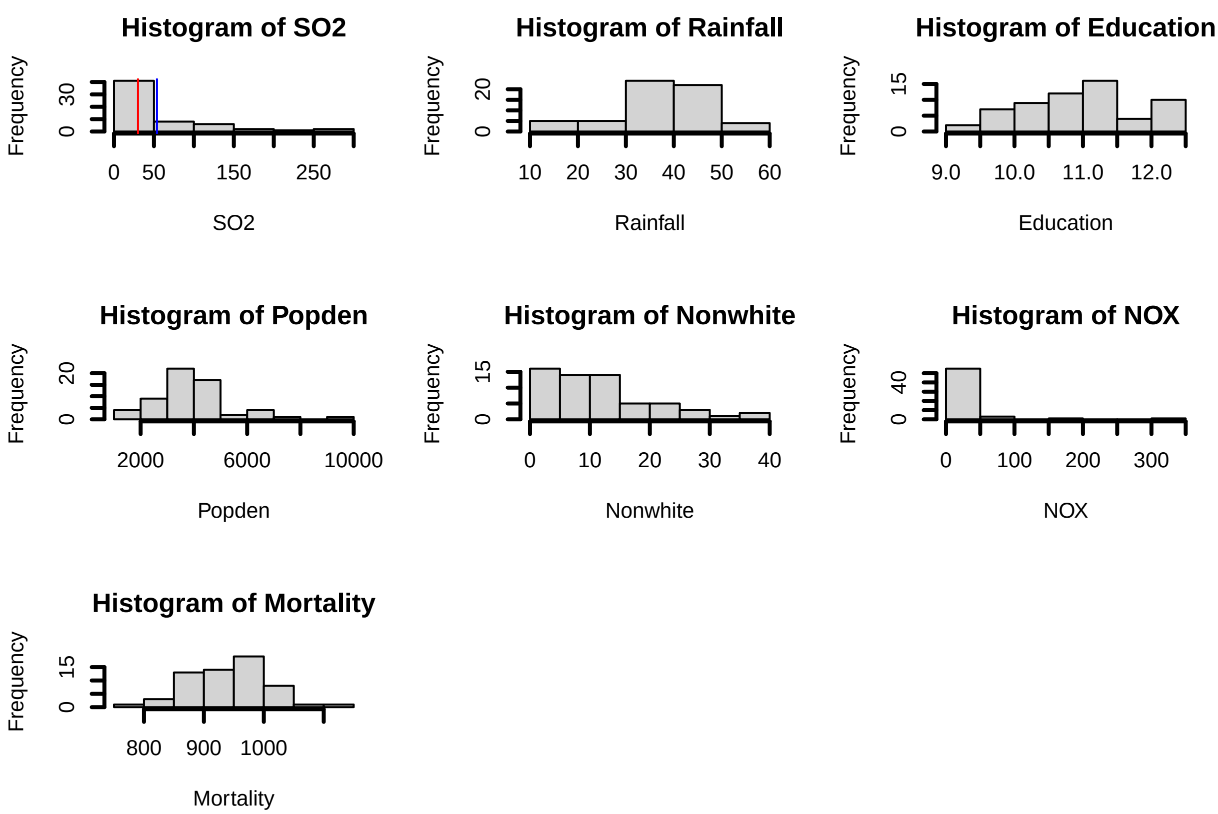
¿Cuales son los valores atípicos para SO2? Ahora veamos lo que considera R como atípicos por default

```
par(mfrow=c(1,3))
boxplot(SO2, range=0, ylab="SO2")
boxplot(SO2, ylab="SO2")
boxplot(SO2, range=1.5, ylab="SO2")
```



Veamos las distribuciones de todas

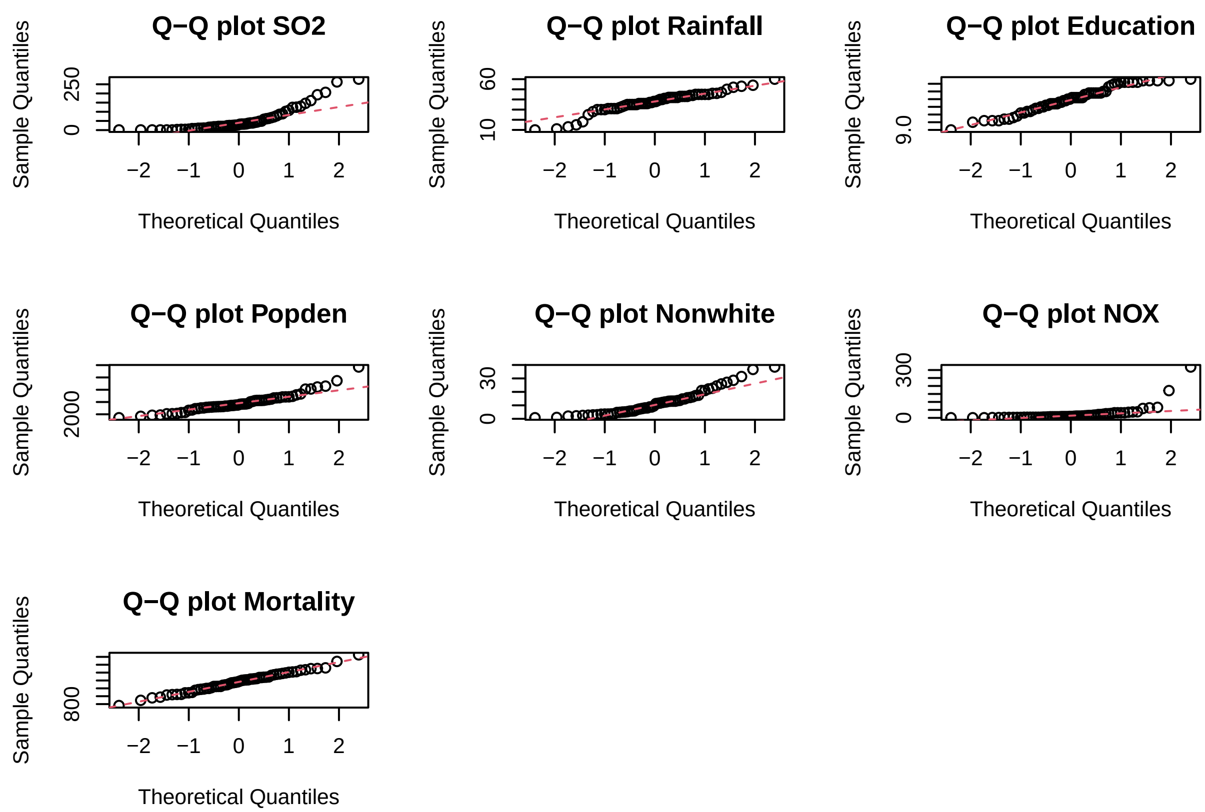
```r
par(mfrow=c(3,3))
hist(SO2,lwd=2); abline(v = c(53.77, 30), col = c("blue", "red"))
hist(Rainfall,lwd=2)
hist(Education,lwd=2)
hist(Popden,lwd=2)
hist(Nonwhite,lwd=2)
hist(NOX,lwd=2)
hist(Mortality,lwd=2)
```



¿reconocen desviaciones negativas o positivas? Son normales?

```r
par(mfrow=c(3,3))
qqnorm(SO2, main="Q-Q plot SO2"); qqline(SO2, col = 2, lty = 2)
qqnorm(Rainfall, main="Q-Q plot Rainfall"); qqline(Rainfall, col = 2, lty = 2)
```

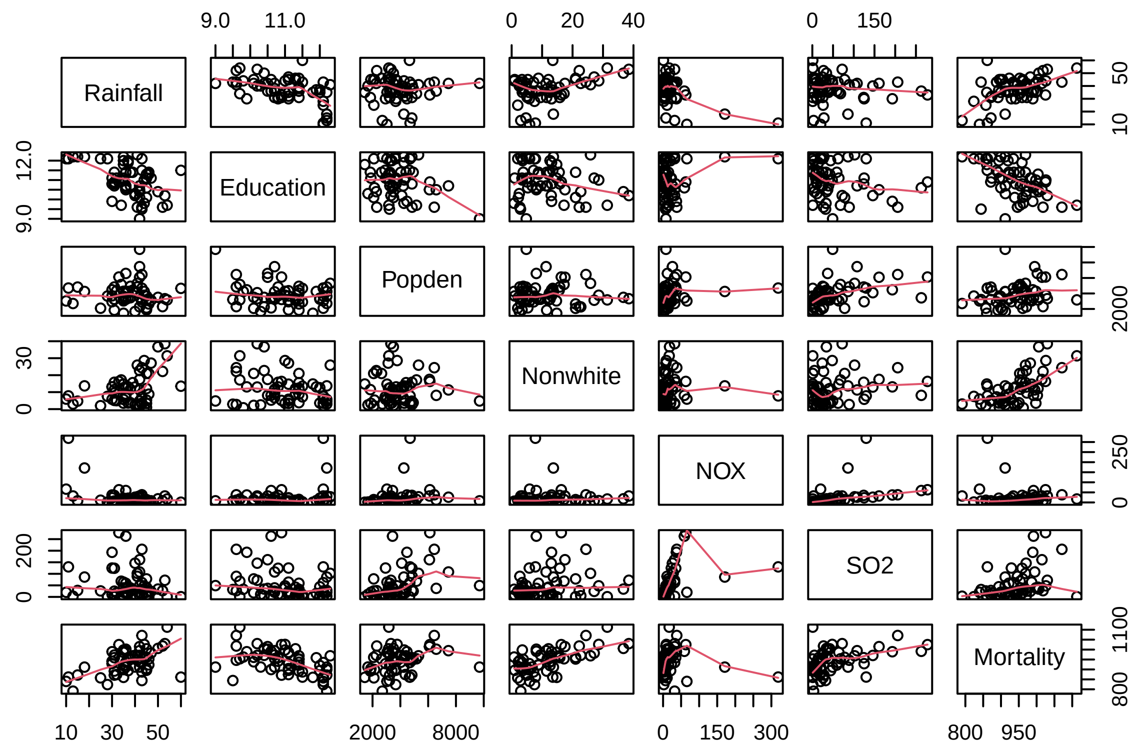
```
qqnorm(Education, main="Q-Q plot Education"); qqline(Education, col = 2, lty = 2)
qqnorm(Popden, main="Q-Q plot Popden"); qqline(Popden, col = 2, lty = 2)
qqnorm(Nonwhite, main="Q-Q plot Nonwhite"); qqline(Nonwhite, col = 2, lty = 2)
qqnorm(NOX, main="Q-Q plot NOX"); qqline(NOX, col = 2, lty = 2)
qqnorm(Mortality, main="Q-Q plot Mortality"); qqline(Mortality, col = 2, lty = 2)
```



Relaciones bivariadas

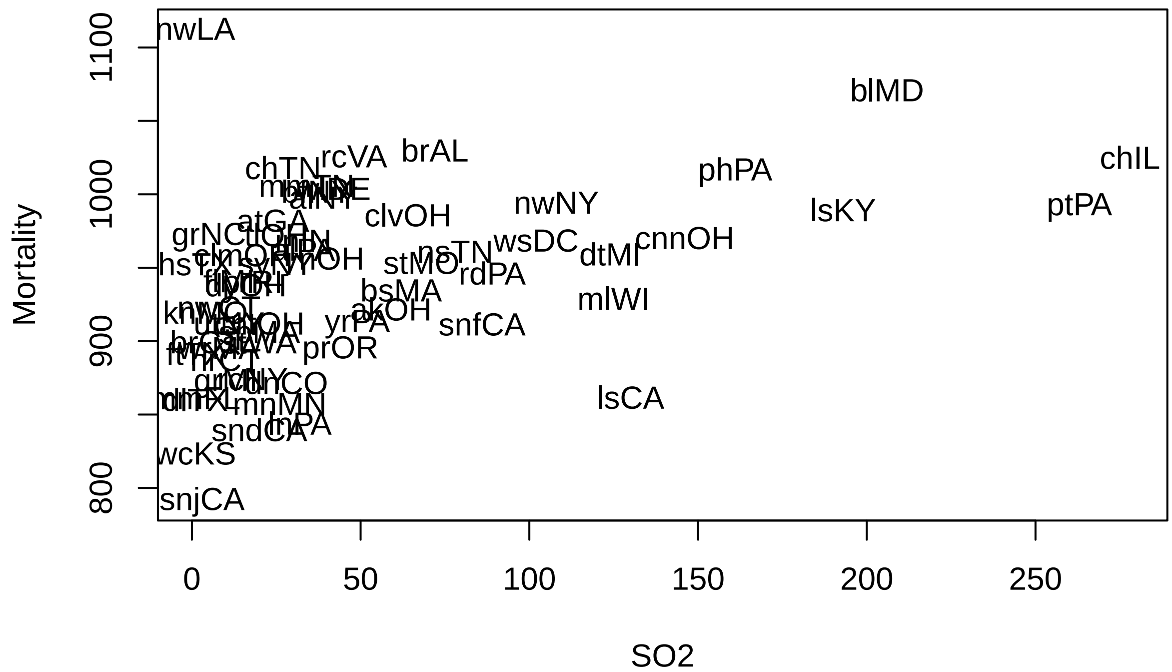
Veamos que relación hay entre las distintas variables. Aquí utilizo una función smoooth (regresión con pesos locales) que permite sugerir con los propios datos que tipo de relación pudieran tener.

```
pairs(airpoll, panel=panel.smooth)
```



veamos con mas detalle la relación SO2-mortalidad

```
nombres<-abbreviate(row.names(airpoll))
par(mfrow=c(1,1))
plot(SO2,Mortality,lwd=2,type="n")
text(SO2,Mortality,labels=nombres,lwd=2)
```




```r
detach(airpoll)
```

C.1

R.2 valores faltantes

```r
airpoldf <- read.table("datofalta.txt")
airpoldf
```

```
##           Rainfall Education Popden Nonwhite NOX SO2 Mortality
## akronOH         35      10.4   3242      7.8  14  58        NA
```

```
## albanyNY        28       4.0    4274       -3.5   3  32       990.9
## allenPA         43       8.8    4259       -0.2   5  32       961.4
## atlantGA        40       4.1    3118       20.1   1  17       975.3
## baltimMD        42       8.6    6440       23.4  37 205      1070.0
## birmhmAL        46       3.2    3318       31.5  25  65      1023.0
## bostonMA        42      11.1    4678        2.5  31  61       933.7
## bridgeCT        38       3.6    2133       -1.7  -3  -3       892.5
## bufaloNY        35       9.5    6581        7.1  11  36      1001.0
## cantonOH        29       3.7    4206       -0.3   0  13       905.3
## chatagTN        51       8.6    2301       21.2   7  26      1017.0
## chicagIL        26       3.9    6115        9.3  56 271      1018.0
## cinnciOH        39       9.2    4100       12.0  25 145       969.5
## clevelOH        28       4.1    3035        7.7  14  57       979.0
## colombOH        36      10.9    4258       12.1   8  14       957.8
## dallasTX        28       4.8    1434        7.8  -6  -6       853.1
## daytonOH        35      10.4    4028       11.4   3  15       935.2
## denverCO         8       5.2    4817       -2.3   1  21       864.8
## detrotMI        30       9.8    4833       14.8  34 123       958.2
## flintMI         23       3.8    3687        6.1  -3   4       934.2
## ftwortTX        30      10.4    1843       10.5   0   0       890.7
## grndraMI        24       3.9    3219       -1.9  -4   3       864.3
## grnborNC        41       9.4    2268       21.7   2   4       970.1
## hartfdCT        36       4.5    2902        0.2  -4   3       880.5
## houstnTX        45      10.4    2646       20.0   4   0       951.5
## indianIN        32       4.4    4405        8.6   0  26       961.7
## kansasMO        34      11.0    3261       11.6   3   3       918.7
## lancasPA        36       2.5    3207       -4.1   0  25       837.1
```

```
## losangCA      10       11.1   4699        6.8 318 129      860.8
## louisvKY      23        2.9   4467        6.1  30 186      982.3
## memphsTN      49        9.4   3496       35.7  17  33     1005.0
## miamiFL       53        4.5   4650        6.5  -6  -6      854.4
## milwauWI      29       10.1   2933        4.8  22 124      928.2
## minnplMN      18        5.1   2088       -5.0   4  19      850.6
## nashvlTN      44        9.1   2081       20.0  13  77      960.0
## newhvnCT      39        4.3   3320        1.8  -4   1      916.2
## neworlLA      53        8.7   3171       30.4  16   0     1112.0
## newyrkNY      35        3.7   7455        4.3  19 101      987.6
## philadPA      41        9.5   6091       16.5  31 160     1014.0
## pittsbPA      29        3.6   3430        1.1  52 256      984.3
## portldOR      36       11.0   3386        2.6  20  43      893.0
## provdcRI      35        3.1   3501       -4.8  -3  11      931.5
## readngPA      40        8.6   4842        1.7  10  88      945.2
## richmdVA      37        4.0   3761       21.6   2  41     1019.0
## rochtrNY      31       10.1   4354        4.0   3  17      873.3
## stlousMO      27        2.7   5153       10.2   8  61      946.6
## sandigCA       9       11.1   3032        4.9  65  19      838.7
## sanfrnCA      11        5.2   4246        6.7 164  79      904.7
## sanjosCA      12       11.2   2701        2.0  31   2      789.7
## seatleWA      28        5.2   3619       -1.3   0  13      892.3
## springMA      44       10.1   1882        2.4   3  19      903.2
## syracuNY      31        4.4   4916       -3.2  -2  18      943.7
## toledoOH      30        9.7   3248        8.5   6  24      971.5
## uticaNY       33        3.3   1664       -4.5  -5   4      905.2
## washDC        40       11.3   5307       24.9  27 101      967.8
```

```
## wichtaKS        21        5.1    3658        0.5   -5   -6      816.8
## wilmtnDE        44       10.3    3151       11.1   10   41     1003.0
## worctrMA        38        4.1    3671       -6.0   -4    1      888.7
## yorkPA          41        8.0    9698        3.8    7   48      910.8
## youngsOH        31        3.7    3444        4.7    6   32      947.4
```

```
attach(airpoldf)
```

Lo mas fácil la media

```
summary(Mortality)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##   789.7   892.4   943.7   936.6   977.1  1112.0       1
```

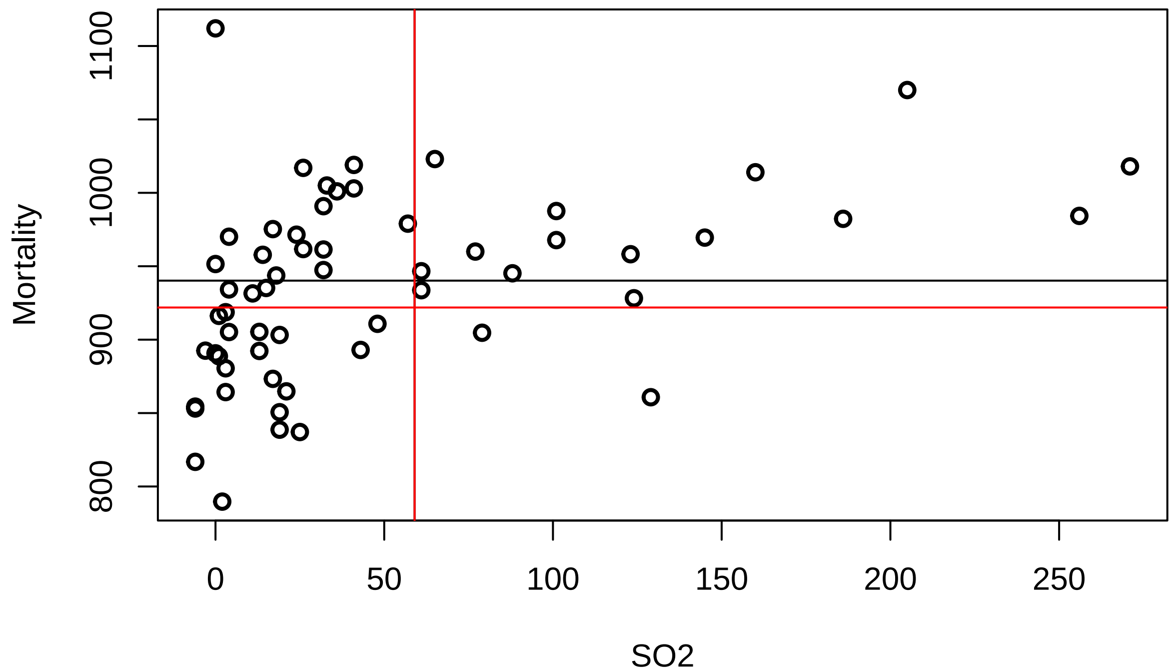
```
sum(is.na(Mortality))
```

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

Cual es el valor imputado? Cuales son los problemas asociados a esta imputación?

regresión mortalidad y SO2

```
par(mfrow=c(1,1))
plot(SO2,Mortality,lwd=2)
abline(v = 59, h = 940.2)
abline(v = 59, h = 921.9, col = "red")
```



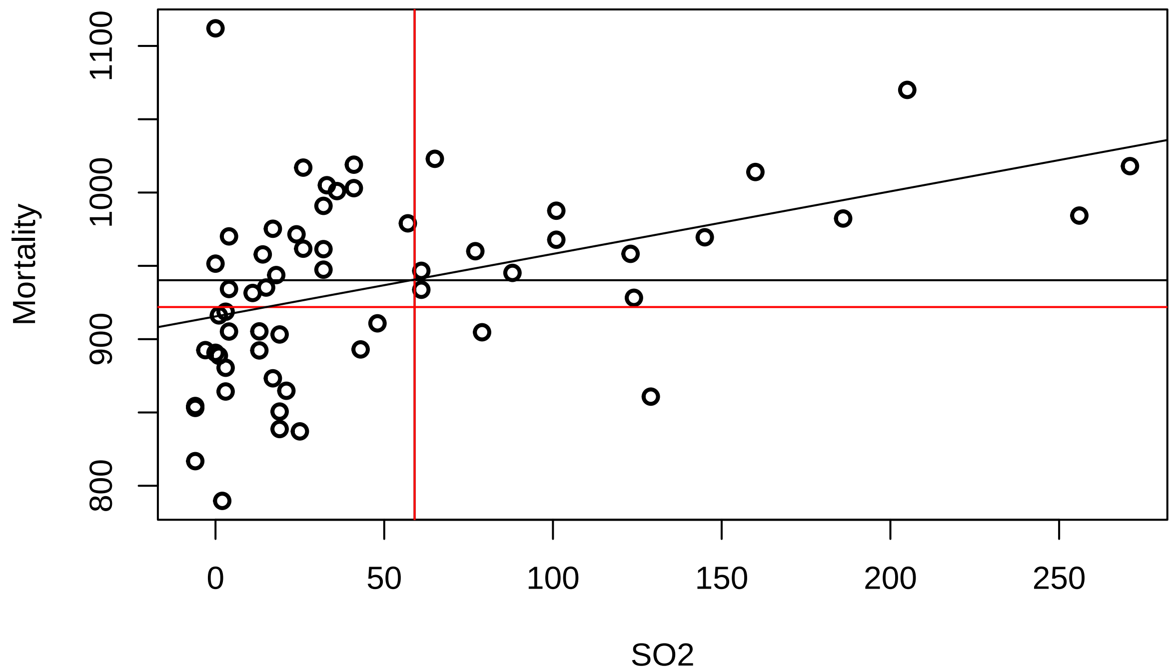

```r
regmort<-lm(Mortality~SO2)
summary(regmort)
```

```
##
## Call:
## lm(formula = Mortality ~ SO2)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -126.625  -38.213   -7.796   35.582  196.528
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
```

```
## (Intercept) 915.4721     9.4932  96.435  < 2e-16 ***
## SO2           0.4266     0.1177   3.624  0.00062 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 57.47 on 57 degrees of freedom
##   (1 observation deleted due to missingness)
## Multiple R-squared:  0.1872, Adjusted R-squared:  0.173
## F-statistic: 13.13 on 1 and 57 DF,  p-value: 0.0006196
```

```
m <-  (915.4720997 + (0.4266209*59))
```

```
par(mfrow=c(1,1))
plot(SO2,Mortality,lwd=2)
abline(v = 59, h = 940.2)
abline(v = 59, h = 921.9, col = "red")
abline(lm(Mortality~SO2))
```




```
predict(regmort, list(SO2=58))
```

```
##        1
## 940.2161
```

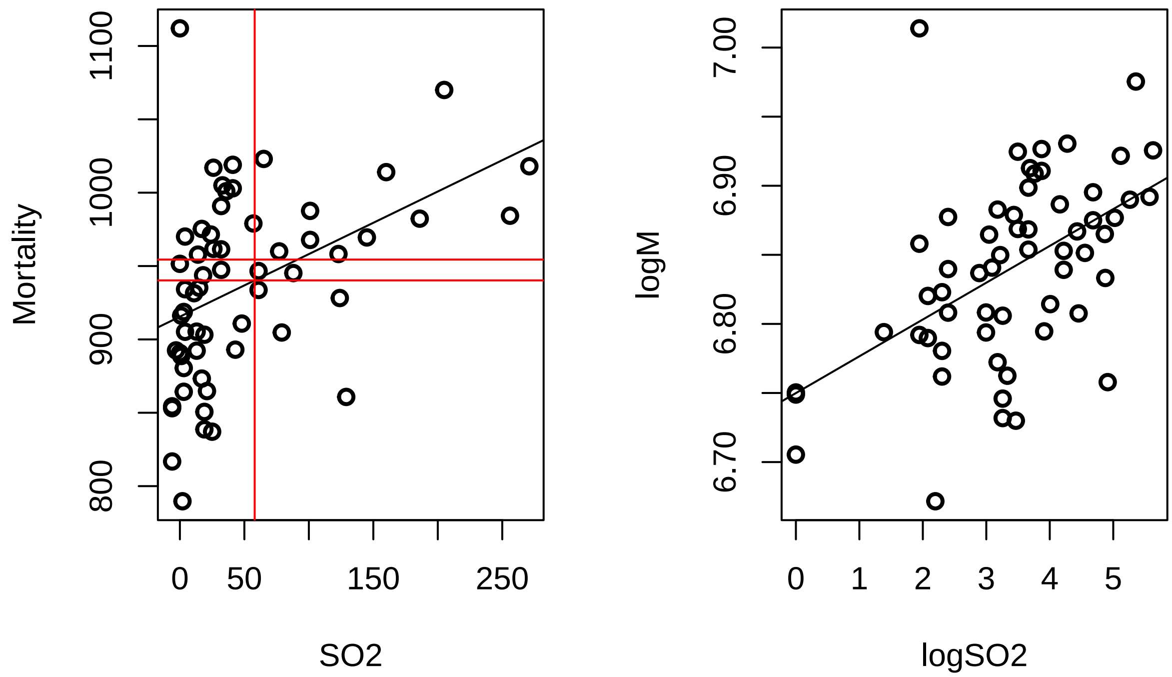
```
logM<-log(Mortality)
logSO2<-log(SO2+7)
loglog<-lm(logM~logSO2)
summary(loglog)
```

```
##
## Call:
## lm(formula = logM ~ logSO2)
```

```
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.136793 -0.030759  0.000398  0.029763  0.212163
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 6.749926   0.021463 314.487  < 2e-16 ***
## logSO2      0.026633   0.005928   4.493 3.48e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.05863 on 57 degrees of freedom
##   (1 observation deleted due to missingness)
## Multiple R-squared:  0.2615, Adjusted R-squared:  0.2486
## F-statistic: 20.19 on 1 and 57 DF,  p-value: 3.482e-05
```

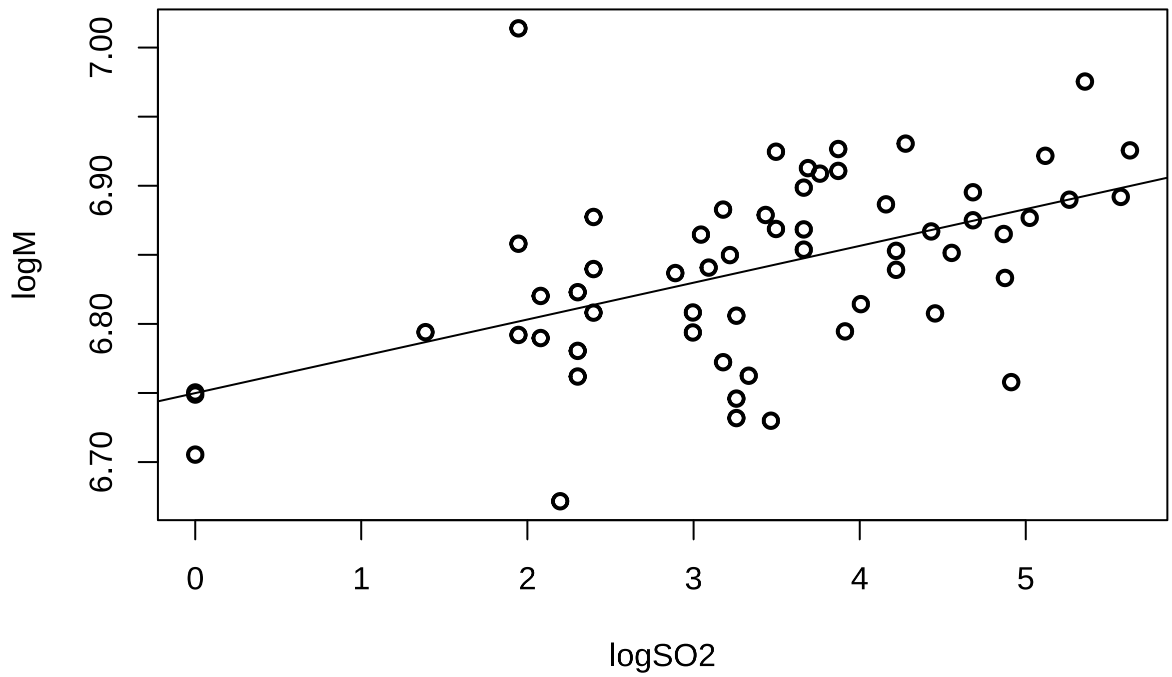
```r
par(mfrow=c(1,2))
plot(SO2,Mortality,lwd=2)
abline(regmort)
abline(v = 58, h = c(940.2161, 954.4211), col = "red")


plot(logSO2,logM,lwd=2)
abline(lm(logM~logSO2))
abline(v = 58, h = 940.2161, col = "red")
```




```
plot(logSO2,logM,lwd=2)

abline(lm(logM~logSO2))
```



el valor de SO2 que corresponde al valor faltante de mortalidad es 58. Como hemos generado un modelo de logaritmos a ambos lados de la ecuación sacamos el log del (SO2+7)

```
log(58+7)
```

```
## [1] 4.174387
```

Usamos la función predict para predecir el valor correspondiente de Mortalidad

```
predict(loglog, list(logSO2=4.174387))
```

```
##        1
## 6.861105
```

pero recordando que usamos logaritmos en el modelo, retrotransformamos con el antilog con base e (e elevado al numero que nos interesa retro transformar)

```r
exp(6.861105)
```

```
## [1] 954.4211
```

El valor predicho por regresión lineal es? Cuales son los problemas asociados a esta imputación?

fin