# Actividad 7.- Regresión Logistica

José Carlos Sánchez Gómez

2024-11-08

```
library(ISLR)
library(tidyverse)
```

```
## ── Attaching core tidyverse packages ──────────────────────────
tidyverse 2.0.0 ──
## ✔ dplyr     1.1.4     ✔ readr     2.1.5
## ✔ forcats   1.0.0     ✔ stringr   1.5.1
## ✔ ggplot2   3.5.1     ✔ tibble    3.2.1
## ✔ lubridate 1.9.3     ✔ tidyr     1.3.1
## ✔ purrr     1.0.2
## ── Conflicts ──────────────────────────────────────────
tidyverse_conflicts() ──
## ✖ dplyr::filter() masks stats::filter()
## ✖ dplyr::lag()    masks stats::lag()
## ℹ Use the conflicted package (<http://conflicted.r-lib.org/>) to force
all conflicts to become errors
```

```
head(Weekly)
```

```
##   Year   Lag1   Lag2   Lag3   Lag4   Lag5    Volume  Today Direction
## 1 1990  0.816  1.572 -3.936 -0.229 -3.484 0.1549760 -0.270      Down
## 2 1990 -0.270  0.816  1.572 -3.936 -0.229 0.1485740 -2.576      Down
## 3 1990 -2.576 -0.270  0.816  1.572 -3.936 0.1598375  3.514        Up
## 4 1990  3.514 -2.576 -0.270  0.816  1.572 0.1616300  0.712        Up
## 5 1990  0.712  3.514 -2.576 -0.270  0.816 0.1537280  1.178        Up
## 6 1990  1.178  0.712  3.514 -2.576 -0.270 0.1544440 -1.372      Down
```

```
glimpse(Weekly)
```

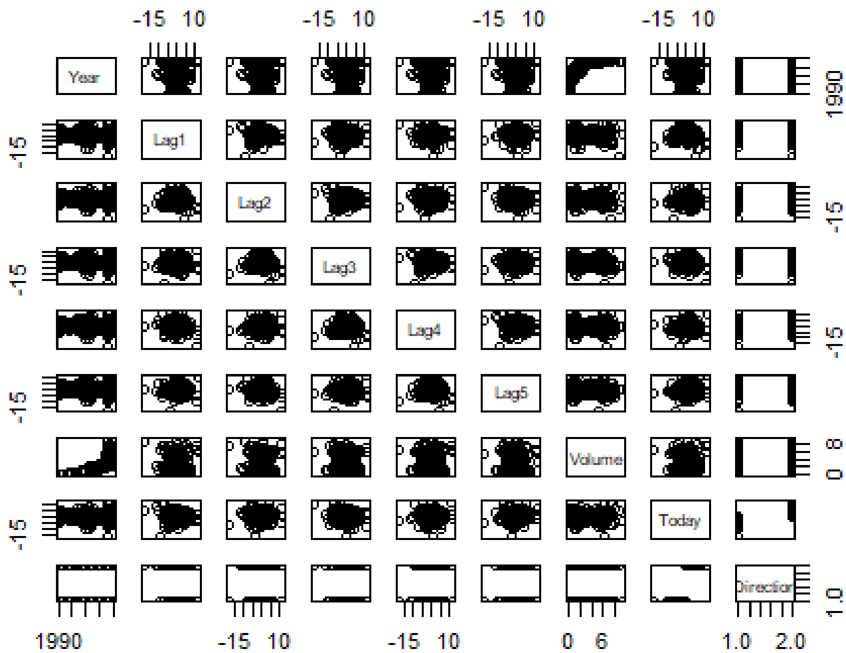
```
## Rows: 1,089
## Columns: 9
## $ Year      <dbl> 1990, 1990, 1990, 1990, 1990, 1990, 1990, 1990,
1990, 1990, …
## $ Lag1      <dbl> 0.816, -0.270, -2.576, 3.514, 0.712, 1.178, -1.372,
0.807, 0…
## $ Lag2      <dbl> 1.572, 0.816, -0.270, -2.576, 3.514, 0.712, 1.178, -
1.372, 0…
## $ Lag3      <dbl> -3.936, 1.572, 0.816, -0.270, -2.576, 3.514, 0.712,
1.178, -…
## $ Lag4      <dbl> -0.229, -3.936, 1.572, 0.816, -0.270, -2.576, 3.514,
0.712, …
## $ Lag5      <dbl> -3.484, -0.229, -3.936, 1.572, 0.816, -0.270, -
```

```
2.576, 3.514,…
## $ Volume    <dbl> 0.1549760, 0.1485740, 0.1598375, 0.1616300,
0.1537280, 0.154…
## $ Today     <dbl> -0.270, -2.576, 3.514, 0.712, 1.178, -1.372, 0.807,
0.041, 1…
## $ Direction <fct> Down, Down, Up, Up, Up, Down, Up, Up, Up, Down,
Down, Up, Up…
```

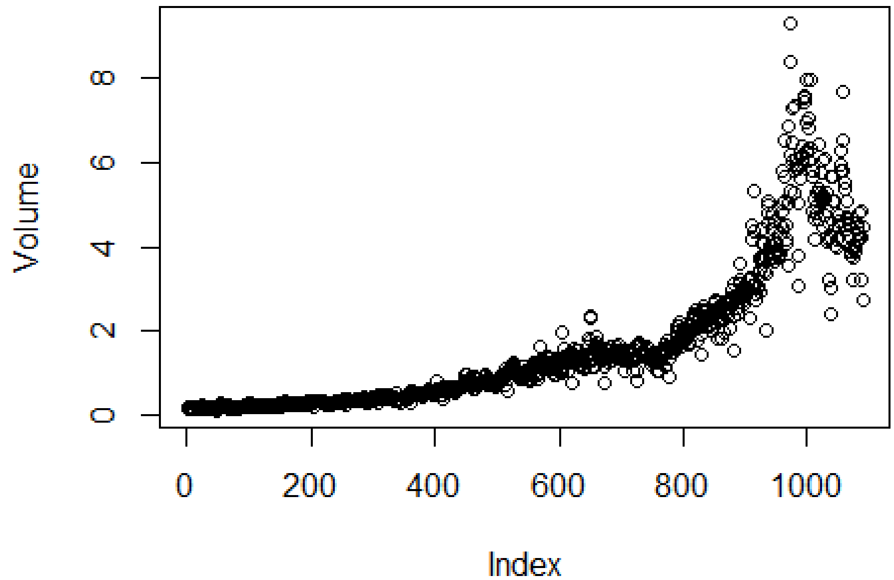
```
summary(Weekly)
```

```
##       Year           Lag1               Lag2               Lag3
##  Min.   :1990   Min.   :-18.1950   Min.   :-18.1950   Min.   :-18.1950
##  1st Qu.:1995   1st Qu.: -1.1540   1st Qu.: -1.1540   1st Qu.: -1.1580
##  Median :2000   Median :  0.2410   Median :  0.2410   Median :  0.2410
##  Mean   :2000   Mean   :  0.1506   Mean   :  0.1511   Mean   :  0.1472
##  3rd Qu.:2005   3rd Qu.:  1.4050   3rd Qu.:  1.4090   3rd Qu.:  1.4090
##  Max.   :2010   Max.   : 12.0260   Max.   : 12.0260   Max.   : 12.0260
##       Lag4               Lag5              Volume            Today
##  Min.   :-18.1950   Min.   :-18.1950   Min.   :0.08747   Min.   :-
18.1950
##  1st Qu.: -1.1580   1st Qu.: -1.1660   1st Qu.:0.33202   1st Qu.: -
1.1540
##  Median :  0.2380   Median :  0.2340   Median :1.00268   Median :
0.2410
##  Mean   :  0.1458   Mean   :  0.1399   Mean   :1.57462   Mean   :
0.1499
##  3rd Qu.:  1.4090   3rd Qu.:  1.4050   3rd Qu.:2.05373   3rd Qu.:
1.4050
##  Max.   : 12.0260   Max.   : 12.0260   Max.   :9.32821   Max.   :
12.0260
##  Direction
##  Down:484
##  Up  :605
##
##
##
##
```

```
pairs(Weekly)
```

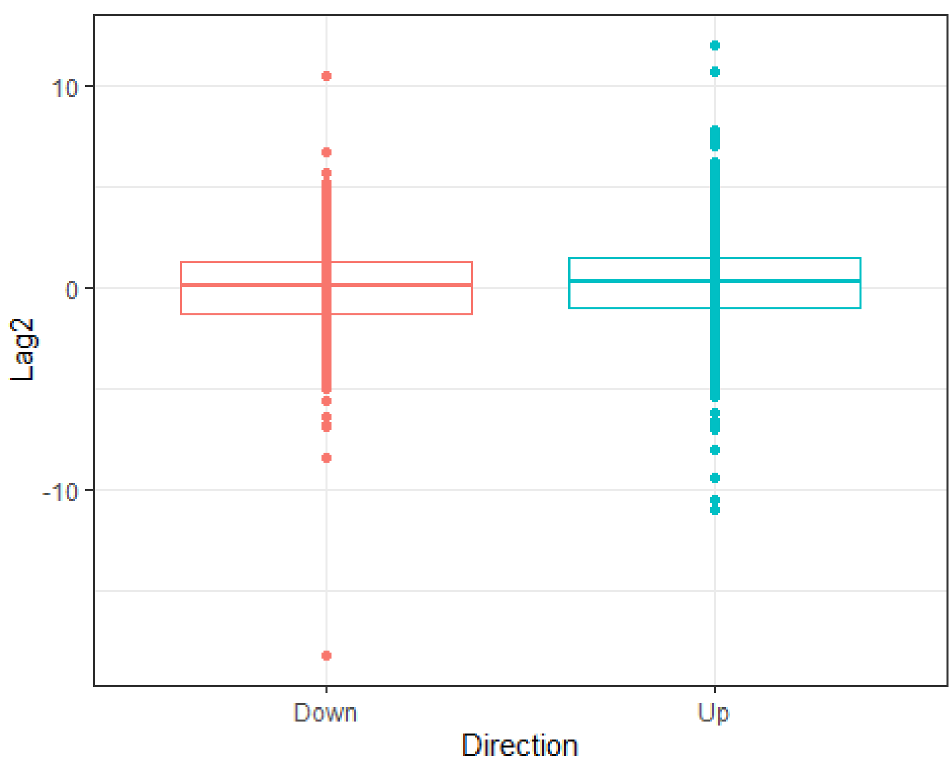



```
cor(Weekly[, -9])

##               Year         Lag1        Lag2        Lag3         Lag4
## Year    1.00000000 -0.032289274 -0.03339001 -0.03000649 -0.031127923
## Lag1   -0.03228927  1.000000000 -0.07485305  0.05863568 -0.071273876
## Lag2   -0.03339001 -0.074853051  1.00000000 -0.07572091  0.058381535
## Lag3   -0.03000649  0.058635682 -0.07572091  1.00000000 -0.075395865
## Lag4   -0.03112792 -0.071273876  0.05838153 -0.07539587  1.000000000
## Lag5   -0.03051910 -0.008183096 -0.07249948  0.06065717 -0.075675027
## Volume  0.84194162 -0.064951313 -0.08551314 -0.06928771 -0.061074617
## Today  -0.03245989 -0.075031842  0.05916672 -0.07124364 -0.007825873
##                Lag5      Volume        Today
## Year   -0.030519101  0.84194162 -0.032459894
## Lag1   -0.008183096 -0.06495131 -0.075031842
## Lag2   -0.072499482 -0.08551314  0.059166717
## Lag3    0.060657175 -0.06928771 -0.071243639
## Lag4   -0.075675027 -0.06107462 -0.007825873
## Lag5    1.000000000 -0.05851741  0.011012698
## Volume -0.058517414  1.00000000 -0.033077783
## Today   0.011012698 -0.03307778  1.000000000

attach(Weekly)
plot(Volume)
```



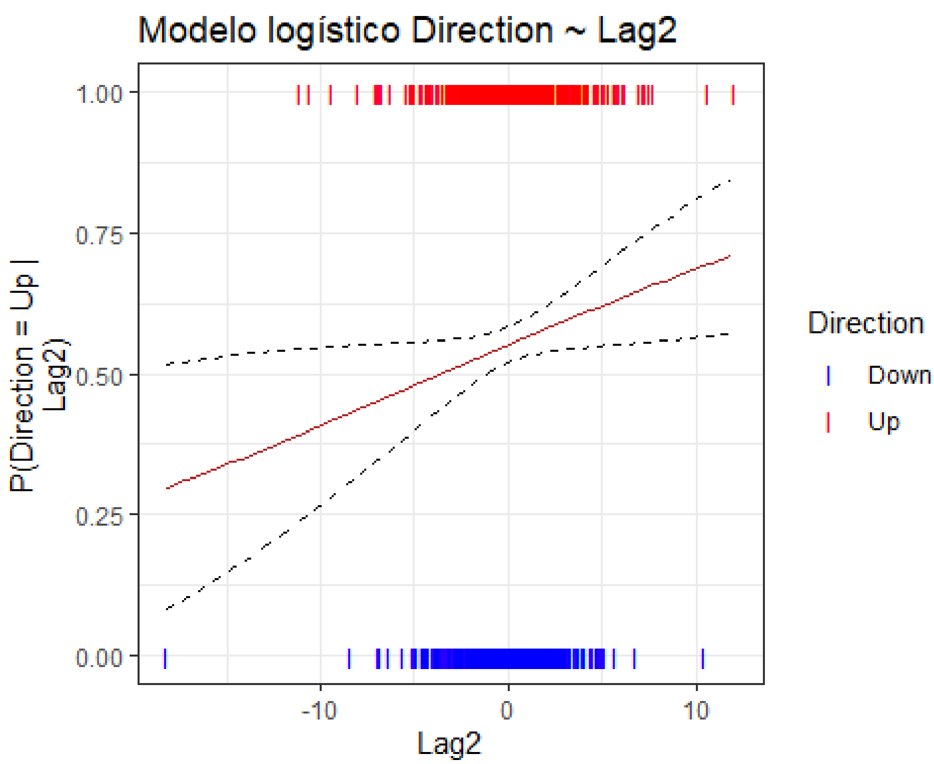

```
modelo.log.m <- glm(Direction ~ . -Today, data = Weekly, family =
binomial)
summary(modelo.log.m)

##
## Call:
## glm(formula = Direction ~ . - Today, family = binomial, data = Weekly)
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) 17.225822  37.890522   0.455   0.6494
## Year        -0.008500   0.018991  -0.448   0.6545
## Lag1        -0.040688   0.026447  -1.538   0.1239
## Lag2         0.059449   0.026970   2.204   0.0275 *
## Lag3        -0.015478   0.026703  -0.580   0.5622
## Lag4        -0.027316   0.026485  -1.031   0.3024
## Lag5        -0.014022   0.026409  -0.531   0.5955
## Volume       0.003256   0.068836   0.047   0.9623
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1496.2  on 1088  degrees of freedom
## Residual deviance: 1486.2  on 1081  degrees of freedom
## AIC: 1502.2
```

```
##
## Number of Fisher Scoring iterations: 4

contrasts(Direction)

##      Up
## Down  0
## Up    1

confint(object = modelo.log.m, level = 0.95)

## Waiting for profiling to be done...

##                     2.5 %      97.5 %
## (Intercept) -56.985558236 91.66680901
## Year         -0.045809580  0.02869546
## Lag1         -0.092972584  0.01093101
## Lag2          0.007001418  0.11291264
## Lag3         -0.068140141  0.03671410
## Lag4         -0.079519582  0.02453326
## Lag5         -0.066090145  0.03762099
## Volume       -0.131576309  0.13884038

ggplot(data = Weekly, mapping = aes(x = Direction, y = Lag2)) +
geom_boxplot(aes(color = Direction)) +
geom_point(aes(color = Direction)) +
theme_bw() +
theme(legend.position = "null")
```



```
datos.entrenamiento <- (Year < 2009)
datos.test <- Weekly[!datos.entrenamiento, ]
nrow(datos.entrenamiento) + nrow(datos.test)

## integer(0)

modelo.log.s <- glm(Direction ~ Lag2, data = Weekly,
family = binomial, subset = datos.entrenamiento)
summary(modelo.log.s)

##
## Call:
## glm(formula = Direction ~ Lag2, family = binomial, data = Weekly,
##     subset = datos.entrenamiento)
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.20326    0.06428   3.162  0.00157 **
## Lag2         0.05810    0.02870   2.024  0.04298 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1354.7  on 984  degrees of freedom
## Residual deviance: 1350.5  on 983  degrees of freedom
## AIC: 1354.5
##
## Number of Fisher Scoring iterations: 4

nuevos_puntos <- seq(from = min(Weekly$Lag2), to = max(Weekly$Lag2),by =
0.5)
predicciones <- predict(modelo.log.s, newdata = data.frame(Lag2 =
nuevos_puntos),se.fit = TRUE, type = "response")

CI_inferior <- predicciones$fit - 1.96 * predicciones$se.fit
CI_superior <- predicciones$fit + 1.96 * predicciones$se.fit
datos_curva <- data.frame(Lag2 = nuevos_puntos, probabilidad =
predicciones$fit, CI.inferior = CI_inferior, CI.superior = CI_superior)

Weekly$Direction <- ifelse(Weekly$Direction == "Down", yes = 0, no = 1)
ggplot(Weekly, aes(x = Lag2, y = Direction)) +
geom_point(aes(color = as.factor(Direction)), shape = "I", size = 3) +
geom_line(data = datos_curva, aes(y = probabilidad), color = "firebrick")
+
geom_line(data = datos_curva, aes(y = CI.superior), linetype = "dashed")
+
geom_line(data = datos_curva, aes(y = CI.inferior), linetype = "dashed")
+
labs(title = "Modelo logístico Direction ~ Lag2", y = "P(Direction = Up |
Lag2)", x = "Lag2") +
```

```
scale_color_manual(labels = c("Down", "Up"), values = c("blue", "red")) +
guides(color=guide_legend("Direction")) +
theme(plot.title = element_text(hjust = 0.5)) +
theme_bw()
```




```
anova(modelo.log.s, test = "Chisq")

## Analysis of Deviance Table
##
## Model: binomial, link: logit
##
## Response: Direction
##
## Terms added sequentially (first to last)
##
##
##      Df Deviance Resid. Df Resid. Dev Pr(>Chi)
## NULL                   984     1354.7
## Lag2  1   4.1666       983     1350.5  0.04123 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

prob.modelo <- predict(modelo.log.s, newdata = datos.test, type =
"response")
pred.modelo <- rep("Down", length(prob.modelo))
pred.modelo[prob.modelo > 0.5] <- "Up"
Direction.0910 = Direction[!datos.entrenamiento]
```

```r
matriz.confusion <- table(pred.modelo, Direction.0910)
matriz.confusion
```

```
##            Direction.0910
## pred.modelo Down Up
##        Down    9  5
##        Up     34 56
```

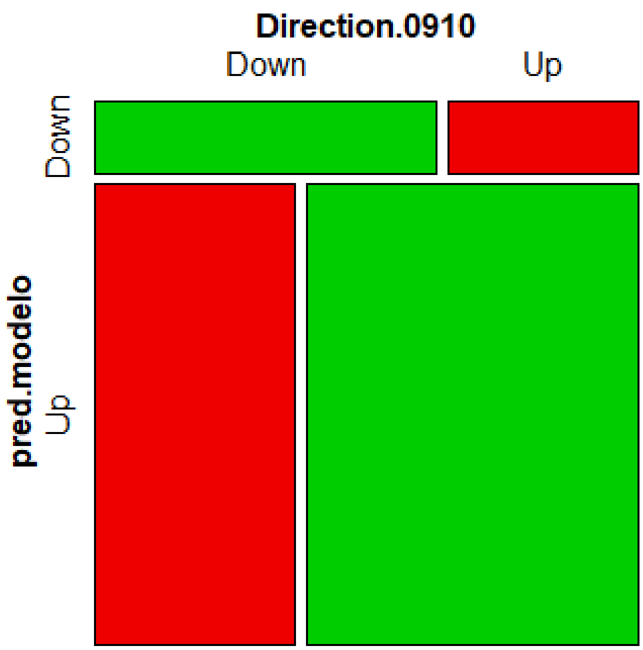
```r
library(vcd)
```

```
## Cargando paquete requerido: grid
```

```
##
## Adjuntando el paquete: 'vcd'
```

```
## The following object is masked from 'package:ISLR':
##
##     Hitters
```

```r
mosaic(matriz.confusion, shade = T, colorize = T,
gp = gpar(fill = matrix(c("green3", "red2", "red2", "green3"), 2, 2)))
```




```r
mean(pred.modelo == Direction.0910)
```

```
## [1] 0.625
```

La ecuación que podemos obtener dado el modelo es la siguiente: $\log\left(\frac{P(Direction)=1}{1-P(Direction=1)}\right) = 0.20326 \times 0.05810 \times Lag2$. Y la gráfica anterior, es la representación visual de la matriz de confusión. Esta son los resultados de nuestras predicciones. En el contexto del problema, esta gráfica representa la dirección del comportamiento de la bolsa (arriba o abajo). Esta gráfica nos muestra visualmente las ocasiones en las que el modelo adivina de manera correcta o erronea, y lo que debio de haber sido en realidad, haciendo más sencilla la tarea de detectar falsos verdaderos o verdaderos falsos.

Dados los resultados, podemos observar que este modelo creado no es bueno. Se puede observar que el modelo tiene un claro sesgo hacia predecir el valor de arriba, ya que este es el que más veces predijo, incluso cuando este era incorrecto. Para poder mejorar la predicción se podría hacer uso de más variables para que el modelo tenga más información de la cual poder aprender los patrones, y asi devolver un mejor resultado. O en el peor de los casos, probar con otros métodos alternativos como arboles de decision o bosques aleatorios.