# Análisis de Regresión Logística, Probit y Bootstrap

Carlos

2025-04-03

#### Contents

## 0.1 Carga de Datos

### 0.2 Modelo de Regresión Logística

```
modelo <- glm(y ~ x, family = binomial)</pre>
summary(modelo)
##
## Call:
## glm(formula = y ~ x, family = binomial)
##
## Coefficients:
              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -0.23758 0.75048 -0.317
## x
              -0.05311
                          0.02064 - 2.573
                                            0.0101 *
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## (Dispersion parameter for binomial family taken to be 1)
##
##
      Null deviance: 29.065 on 20 degrees of freedom
## Residual deviance: 12.332 on 19 degrees of freedom
## AIC: 16.332
##
## Number of Fisher Scoring iterations: 6
plot(x, y, pch = 19, col = ifelse(y == 1, "blue", "red"),
     main = "Logistic Regression Fit", xlab = "x = Auto Time - Bus Time", ylab = "P(car)")
curve(predict(modelo, data.frame(x = sort(x)), type = "response"),
     add = TRUE, col = "darkgreen", lwd = 2)
```

```
legend("bottomright", legend = c("Observado 1", "Observado 0", "Curva logística"),
       col = c("blue", "red", "darkgreen"), pch = c(19, 19, NA), lty = c(NA, NA, 1))
regresion_logit_probit_con_apendices_limpios_files/figure-latex/unnamed-chunk-2-1.pdf
     Ajuste por Mínimos Cuadrados No Lineales (NLS)
0.3
b0_init <- coef(modelo)[1]
b1_init <- coef(modelo)[2]</pre>
modelo_nls <- nls(</pre>
 y \sim 1 / (1 + exp(-(b0 + b1 * x))),
 start = list(b0 = b0_init , b1 = b1_init)
summary(modelo_nls)
##
## Formula: y \sim 1/(1 + \exp(-(b0 + b1 * x)))
## Parameters:
       Estimate Std. Error t value Pr(>|t|)
## b0
       -188.344 744010.283
                                  0
                                            1
         -7.197 27886.344
## b1
                                  0
                                            1
##
## Residual standard error: 0.2294 on 19 degrees of freedom
## Number of iterations to convergence: 16
## Achieved convergence tolerance: 4.887e-06
plot(x, y, pch = 19, col = ifelse(y == 1, "blue", "red"),
    main = "Comparación de Métodos de Ajuste", xlab = "x = Auto Time - Bus Time", ylab = "P(car)")
x_sorted <- sort(x)</pre>
lines(x_sorted, predict(modelo, type = "response")[order(x)], col = "darkgreen", lwd = 2)
b0_nls <- coef(modelo_nls)["b0"]
b1_nls <- coef(modelo_nls)["b1"]
p_nls <- 1 / (1 + exp(-(b0_nls + b1_nls * x_sorted)))</pre>
lines(x_sorted, p_nls, col = "purple", lwd = 2, lty = 2)
legend("bottomleft", legend = c("GLM (Verosimilitud)", "NLS (Minimos Cuadrados)"),
       col = c("darkgreen", "purple"), lty = c(1, 2), lwd = 2, cex = 0.5)
```

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#### 0.4 Modelo Probit

```
modelo_probit <- glm(y ~ x, family = binomial(link = "probit"))</pre>
summary(modelo probit)
##
## Call:
## glm(formula = y ~ x, family = binomial(link = "probit"))
##
## Coefficients:
##
               Estimate Std. Error z value Pr(>|z|)
## (Intercept) -0.06443
                           0.40068 -0.161 0.87224
               -0.03000
                           0.01029 -2.915 0.00355 **
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## (Dispersion parameter for binomial family taken to be 1)
##
##
       Null deviance: 29.065 on 20 degrees of freedom
## Residual deviance: 12.330 on 19 degrees of freedom
## AIC: 16.33
## Number of Fisher Scoring iterations: 7
plot(x, y, pch = 19, col = ifelse(y == 1, "blue", "red"),
    main = "Ajuste de Regresión Probit", xlab = "x = Auto Time - Bus Time", ylab = "P(car)")
x_{seq} \leftarrow seq(min(x), max(x), length.out = 100)
lines(x seq, predict(modelo probit, newdata = data.frame(x = x seq), type = "response"),
      col = "orange", lwd = 2)
legend("bottomleft", legend = c("Observado 1", "Observado 0", "Curva Probit"),
       col = c("blue", "red", "orange"), pch = c(19, 19, NA), lty = c(NA, NA, 1), lwd = 2, cex = 0.8)
regresion logit probit con apendices limpios files/figure-latex/unnamed-chunk-4-1.pdf
```

#### 0.5 Comparación: Logit vs Probit

```
col = c("blue", "red", "darkgreen", "orange"),
pch = c(19, 19, NA, NA), lty = c(NA, NA, 1, 2), lwd = 2, cex = 0.5)

regresion_logit_probit_con_apendices_limpios_files/figure-latex/unnamed-chunk-5-1.pdf
```

### 0.6 Bootstrap + Modelos

```
datos <- data.frame(auto_time, bus_time, x = auto_time - bus_time, y)</pre>
set.seed(123)
bootstrap_sample <- datos[sample(1:nrow(datos), size = 100, replace = TRUE), ]
x_btsp <- bootstrap_sample$x</pre>
y_btsp <- bootstrap_sample$y</pre>
modelo_btstrap <- glm(y_btsp ~ x_btsp, family = binomial)</pre>
summary(modelo_btstrap)
##
## Call:
## glm(formula = y_btsp ~ x_btsp, family = binomial)
## Coefficients:
               Estimate Std. Error z value Pr(>|z|)
                           0.41264 -1.263
                                               0.207
## (Intercept) -0.52119
## x btsp
               -0.06812
                           0.01300 -5.240 1.61e-07 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## (Dispersion parameter for binomial family taken to be 1)
##
##
       Null deviance: 138.589 on 99 degrees of freedom
## Residual deviance: 45.803 on 98 degrees of freedom
## AIC: 49.803
## Number of Fisher Scoring iterations: 6
plot(x_btsp, y_btsp, pch = 19, col = ifelse(y_btsp == 1, "blue", "red"),
     main = "Logistic Regression Fit (Bootstrap)", xlab = "x = Auto Time - Bus Time", ylab = "P(car)")
x_{seq_btsp} \leftarrow seq(min(x_btsp), max(x_btsp), length.out = 100)
lines(x_seq_btsp, predict(modelo_btstrap, newdata = data.frame(x_btsp = x_seq_btsp), type = "response")
      col = "darkgreen", lwd = 2)
legend("bottomleft", legend = c("Observado 1", "Observado 0", "Curva logística"),
       col = c("blue", "red", "darkgreen"), pch = c(19, 19, NA), lty = c(NA, NA, 1), lwd = 2, cex = 0.8
```

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#### 0.7 Conclusión General

Ambos modelos, logit y probit, son útiles para clasificación binaria. El modelo logit tiene una curva más empinada en el centro, mientras que el probit es más suave en los extremos. La técnica de bootstrap refuerza la validez de los estimadores obtenidos.

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