Practica_Clasificación_1

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Introducción

El objetivo de esta práctica es realizar los ejercicios 4 y 5 del fichero de Prácticas de la Semana 1, sobre regresión logística y el ejercicio 4, los apartados (i) y (iii) del ejercicio 4, con respecto a la semana dos, relacionada con análisis discriminante.

```r
library(foreign)
library(nnet) # multinomial
library(stargazer)
library(ISLR)
library(Deducer)
library(pscl)
library(wooldridge)
library(MASS)
library(ISLR)
library(DAAG)
library(pastecs)
library(klaR)
library(corrplot)
```

Prácticas Semana 1

Ejercicio 4

4. La encuesta Wage del paquete ISLR contiene información sobre salarios y otras variables para un grupo de 3000 trabajadores hombres de la región Mid-Atlantic de USA.

(i)Construir un modelo de regresión logística para explicar la variable health de las variables age, race, education y logwage

```r
#Construcción del modelo de regresión logística


reg.logs <- glm(health ~ age + race + education + logwage, data=Wage,
                family=binomial(logit))

# Datos residuales del modelo de regresión lineal simple (diferencia
entre los datos observados de la variable dependiente y y los valores
ajustados ŷ)
```

```r
head(reg.logs$residuals,20)

##    231655     86582    161300    155159     11443    376662    450601 
377954 
## -4.329341  1.207812 -3.806592  1.231090 -2.173620  1.344103  1.409162 
-4.453001 
##    228963     81404    302778    305706      8690    153561    449654 
447660 
##  1.351297  1.552778 -3.529053  1.450687  1.426741  1.192407  1.568257 
1.621238 
##    160191    230312    301585    153682 
##  1.335697  1.145579 -3.749377  1.350546

#Medida de bondad de ajuste de un modelo lineal generalizado.

reg.logs$deviance

## [1] 3378.41

#La desviación nula muestra qué tan bien se predice la variable de 
respuesta mediante un modelo que incluye solo la intersección

head(reg.logs$null.deviance,20)

## [1] 3591.187

head(reg.logs$coefficients,20)

##                   (Intercept)                           age 
##                   -2.19222715                   -0.03514899 
##                  race2. Black                  race3. Asian 
##                   -0.03604936                   -0.17160044 
##                  race4. Other           education2. HS Grad 
##                   -0.41408867                    0.08208608 
##     education3. Some College     education4. College Grad 
##                    0.25867828                    0.63781151 
## education5. Advanced Degree                       logwage 
##                    0.87664718                    0.93275222

head(reg.logs$fitted.values,20)

##    231655     86582    161300    155159     11443    376662    450601 
377954 
## 0.7690179 0.8279437 0.7372978 0.8122882 0.5399379 0.7439908 0.7096416 
0.7754323 
##    228963     81404    302778    305706      8690    153561    449654 
447660 
## 0.7400300 0.6440072 0.7166378 0.6893285 0.7008979 0.8386398 0.6376506 
0.6168127 
##    160191    230312    301585    153682 
## 0.7486730 0.8729211 0.7332890 0.7404415
```

```
summary(reg.logs) #para resumir sus datos, valores mínimos, máximos,
cuantiles, p-values, nivel de significancia, etc.

##
## Call:
## glm(formula = health ~ age + race + education + logwage, family =
binomial(logit),
##     data = Wage)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.3091  -1.2063   0.6590   0.8436   1.7613
##
## Coefficients:
##                              Estimate Std. Error z value Pr(>|z|)
## (Intercept)                 -2.192227   0.621535  -3.527  0.00042 ***
## age                         -0.035149   0.003718  -9.455  < 2e-16 ***
## race2. Black                -0.036049   0.138152  -0.261  0.79414
## race3. Asian                -0.171600   0.180124  -0.953  0.34075
## race4. Other                -0.414089   0.351048  -1.180  0.23817
## education2. HS Grad          0.082086   0.146255   0.561  0.57462
## education3. Some College     0.258678   0.159104   1.626  0.10398
## education4. College Grad     0.637812   0.166661   3.827  0.00013 ***
## education5. Advanced Degree  0.876647   0.198000   4.428 9.53e-06 ***
## logwage                      0.932752   0.141471   6.593 4.30e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 3591.2  on 2999  degrees of freedom
## Residual deviance: 3378.4  on 2990  degrees of freedom
## AIC: 3398.4
##
## Number of Fisher Scoring iterations: 4
```

(ii)Bondad de ajuste mediante test LR y pseudoR2 de McFadden

```
#Bondad de ajuste LR test

#Generalizamos el modelo de regresión lineal con las variables health,
age, race, education y logwage

model_all <- glm(health ~ age + race + education + logwage, data=Wage,
family = binomial(link = logit))

summary(model_all)

##
## Call:
## glm(formula = health ~ age + race + education + logwage, family =
```

```
binomial(link = logit),
##     data = Wage)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.3091  -1.2063   0.6590   0.8436   1.7613
##
## Coefficients:
##                              Estimate Std. Error z value Pr(>|z|)
## (Intercept)                 -2.192227   0.621535  -3.527  0.00042 ***
## age                         -0.035149   0.003718  -9.455  < 2e-16 ***
## race2. Black                -0.036049   0.138152  -0.261  0.79414
## race3. Asian                -0.171600   0.180124  -0.953  0.34075
## race4. Other                -0.414089   0.351048  -1.180  0.23817
## education2. HS Grad          0.082086   0.146255   0.561  0.57462
## education3. Some College     0.258678   0.159104   1.626  0.10398
## education4. College Grad     0.637812   0.166661   3.827  0.00013 ***
## education5. Advanced Degree  0.876647   0.198000   4.428 9.53e-06 ***
## logwage                      0.932752   0.141471   6.593 4.30e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 3591.2  on 2999  degrees of freedom
## Residual deviance: 3378.4  on 2990  degrees of freedom
## AIC: 3398.4
##
## Number of Fisher Scoring iterations: 4
```

```
# Modelo de regresión lineal para la variable health

model_health <- glm(health ~ 1, data=Wage, family = binomial(link =
logit))

#test anova
anova(reg.logs,test="Chisq")
```

```
## Analysis of Deviance Table
##
## Model: binomial, link: logit
##
## Response: health
##
## Terms added sequentially (first to last)
##
##
##           Df Deviance Resid. Df Resid. Dev  Pr(>Chi)
## NULL                       2999     3591.2
## age        1   58.041      2998     3533.1 2.567e-14 ***
```

```
## race       3    5.909      2995     3527.2    0.1161
## education  4  104.289      2991     3422.9 < 2.2e-16 ***
## logwage    1   44.539      2990     3378.4 2.494e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# Odds

exp(coef(model_all))
```

```
##                 (Intercept)                         age
##                   0.1116678                   0.9654616
##                 race2. Black                race3. Asian
##                   0.9645927                   0.8423157
##                 race4. Other          education2. HS Grad
##                   0.6609423                   1.0855493
##    education3. Some College    education4. College Grad
##                   1.2952170                   1.8923350
## education5. Advanced Degree                     logwage
##                   2.4028299                   2.5414943
```

```
# Intervalos de confianza

confint(model_all)
```

```
## Waiting for profiling to be done...
```

```
##                                   2.5 %      97.5 %
## (Intercept)                 -3.41500441 -0.97719004
## age                         -0.04247619 -0.02789839
## race2. Black                -0.30410307  0.23795441
## race3. Asian                -0.51903665  0.18838458
## race4. Other                -1.09411041  0.29252909
## education2. HS Grad         -0.20621174  0.36753703
## education3. Some College    -0.05426872  0.56981917
## education4. College Grad     0.31063209  0.96436564
## education5. Advanced Degree  0.49054822  1.26736804
## logwage                      0.65687962  1.21177242
```

```
# Pseudo R2 McFadden
pR2(model_all)
```

```
## fitting null model for pseudo-r2
```

```
##           llh       llhNull            G2      McFadden          r2ML
## -1.689205e+03 -1.795594e+03  2.127775e+02  5.924990e-02  6.846901e-02
##          r2CU
##  9.810443e-02
```

```
# McFadden = 0.05925

# Calculo directo McFadden
```

```r
1-model_all$deviance/model_health$deviance
```

```
## [1] 0.0592499
```

(iii)Matriz de confusión y curva ROC

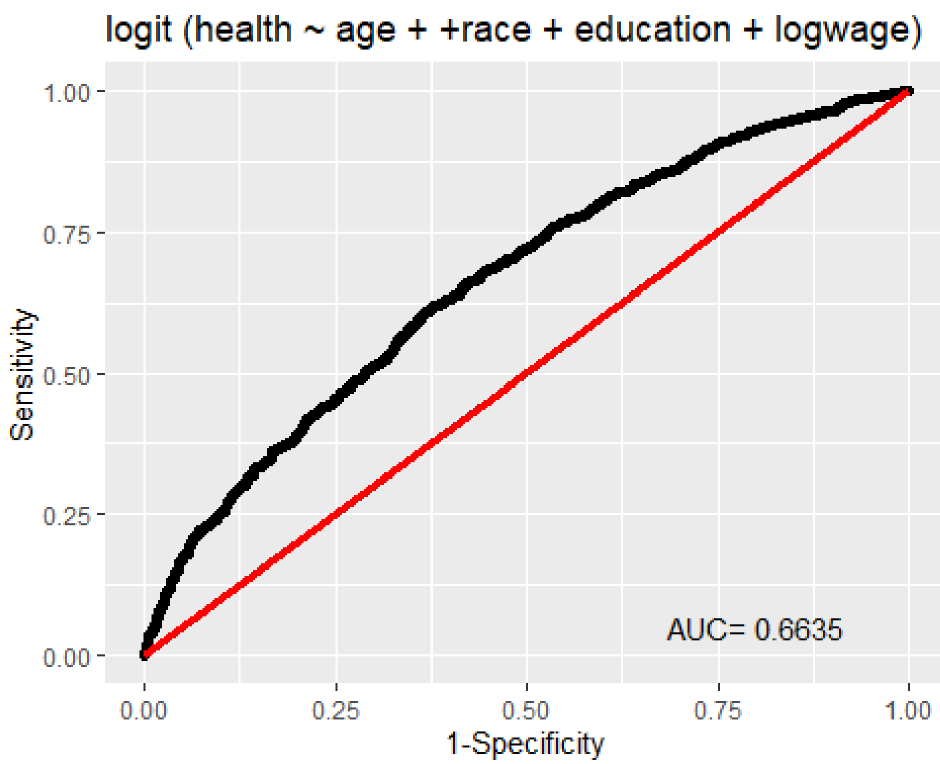
```r
#Matriz de confusión

fit.pred <- ifelse(model_all$fitted.values>0.5,1,0)
tabla<-table(fit.pred, Wage$health)
tabla
```

```
##
## fit.pred 1. <=Good 2. >=Very Good
##        0        88             73
##        1       770           2069
```

```r
(tabla[1,1]+tabla[2,2])/sum(tabla)
```

```
## [1] 0.719
```

```r
#curva ROC

model2 <- glm(health ~ age++race+education+logwage, data=Wage, family =
binomial(link = logit))

model2 <- glm(formula=health ~ age++race+education+logwage,data=Wage,
family = binomial(link = logit), na.action=na.omit)
rocplot(model2)
```




```
#la curva aparece representada en negro
```

Práctica 5

El conjunto de datos happines, del paquete wooldridge, proporciona información sobre el nivel de felicidad de una muestra 17131 individuos encuestados entre 1994 y 2006. Los datos también incluyen información acerca de una serie de características sociodemográfica de los encuestados.

(i)Estimar el modelo de regresión lineal incluye como variable dependiente a la variable binaria vhappy, que toma valor 1 si el encuestado afirma ser muy feliz y 0 en el caso contrario, y como independientes la variables años de educación (educ), ingreso (income), mujer(female) y desempleado (unem10).

```
#modelo de regresión lineal

modelo_RL <- glm(vhappy ~ educ + income + female + unem10, data =
happiness,family=binomial)

summary(modelo_RL)#resumen de los datos del modelo

##
## Call:
```

```
## glm(formula = vhappy ~ educ + income + female + unem10, family =
binomial,
##     data = happiness)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.0065  -0.9478  -0.7661   1.3935   2.2115
##
## Coefficients:
##                        Estimate Std. Error z value Pr(>|z|)
## (Intercept)           -0.930041   0.229074  -4.060 4.91e-05 ***
## educ                   0.015733   0.008054   1.953 0.050762 .
## income$1000 to 2999   -0.364266   0.302788  -1.203 0.228961
## income$3000 to 3999   -0.653166   0.338111  -1.932 0.053383 .
## income$4000 to 4999   -0.639649   0.338067  -1.892 0.058481 .
## income$5000 to 5999   -0.303040   0.290866  -1.042 0.297479
## income$6000 to 6999   -1.117017   0.336860  -3.316 0.000913 ***
## income$7000 to 7999   -0.663001   0.299159  -2.216 0.026677 *
## income$8000 to 9999   -0.524492   0.261885  -2.003 0.045203 *
## income$10000 - 14999 -0.273140   0.222475  -1.228 0.219547
## income$15000 - 19999 -0.419422   0.225573  -1.859 0.062976 .
## income$20000 - 24999 -0.108122   0.221141  -0.489 0.624893
## income$25000 or more  0.173741   0.209284   0.830 0.406443
## female                 0.025440   0.044800   0.568 0.570126
## unem10                -0.480592   0.049717  -9.666  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 12196  on 9962  degrees of freedom
## Residual deviance: 11906  on 9948  degrees of freedom
##   (7174 observations deleted due to missingness)
## AIC: 11936
##
## Number of Fisher Scoring iterations: 4
```

(ii) Estimar el modelo del apartado anterior por medio de regresión logística. Con las variables anteriores, seleccionar el mejor modelo mediantes stepAIC

```r
#modelo de regresión y estimación AIC
modelo_RL <- glm(vhappy ~ educ + income + female + unem10, data =
happiness,
                                 family = binomial(logit))
#estudio de AIC
modelo_RL_AIC <- stepAIC(modelo_RL, trace = TRUE)
```

```
## Start:  AIC=11936.46
## vhappy ~ educ + income + female + unem10
##
##            Df Deviance   AIC
```

```
## - female  1     11907 11935
## <none>          11906 11936
## - educ    1     11910 11938
## - unem10  1     12003 12031
## - income 11     12031 12039
##
## Step:  AIC=11934.78
## vhappy ~ educ + income + unem10
##
##          Df Deviance   AIC
## <none>          11907 11935
## - educ    1     11911 11937
## - unem10  1     12004 12030
## - income 11     12031 12037
```

```
#test anova
modelo_RL_AIC$anova
```

```
## Stepwise Model Path
## Analysis of Deviance Table
##
## Initial Model:
## vhappy ~ educ + income + female + unem10
##
## Final Model:
## vhappy ~ educ + income + unem10
##
##
##       Step Df  Deviance Resid. Df Resid. Dev      AIC
## 1                            9948   11906.46 11936.46
## 2 - female  1 0.3225805      9949   11906.78 11934.78
```

```
#resumen de los datos obtenidos
summary(modelo_RL_AIC)
```

```
##
## Call:
## glm(formula = vhappy ~ educ + income + unem10, family =
binomial(logit),
##     data = happiness)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.0019  -0.9527  -0.7688   1.3919   2.2108
##
## Coefficients:
##                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)           -0.91469    0.22746  -4.021 5.78e-05 ***
## educ                   0.01583    0.00805   1.967  0.04923 *
## income$1000 to 2999   -0.36518    0.30280  -1.206  0.22780
## income$3000 to 3999   -0.65074    0.33808  -1.925  0.05425 .
```

```
## income$4000 to 4999  -0.63922    0.33807  -1.891  0.05865 .
## income$5000 to 5999  -0.30158    0.29086  -1.037  0.29980
## income$6000 to 6999  -1.11528    0.33684  -3.311  0.00093 ***
## income$7000 to 7999  -0.66114    0.29913  -2.210  0.02709 *
## income$8000 to 9999  -0.52434    0.26188  -2.002  0.04526 *
## income$10000 - 14999 -0.27254    0.22247  -1.225  0.22056
## income$15000 - 19999 -0.42041    0.22556  -1.864  0.06235 .
## income$20000 - 24999 -0.11002    0.22112  -0.498  0.61879
## income$25000 or more  0.17002    0.20918   0.813  0.41635
## unem10               -0.48129    0.04970  -9.684  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 12196  on 9962  degrees of freedom
## Residual deviance: 11907  on 9949  degrees of freedom
##   (7174 observations deleted due to missingness)
## AIC: 11935
##
## Number of Fisher Scoring iterations: 4
```

(iii) Predecir con el modelo de regresión logística y con el modelo de regresión lineal la probabilidad de ser muy feliz de una mujer con 18 años de educación, que trabaja y tieen un intreso superior a 25000$ anuales (income=$25000 or more)

```
#Añadimos los parámetros que indica el enunciado para realizar el
filtrado y guardarlos en una nueva variable.

predict_RL <- data.frame(educ = 18, income = '$25000 or more', female =
1, unem10 = 0)

predict <- predict(modelo_RL, newdata = predict_RL, type = 'response')

predict

##         1
## 0.3899168
```

Prácticas Semana 2

4. El fichero de datos spam7. Los datos consisten en 4601 elementos de correo electŕonico,de los cuales 1813 elementos se identificaron como spam. El fichero contiene las siguientes variables:

- crl.tot total length of words in capitals.

- dollar number of occurrences of the $ symbol.
- bang number of occurrences of the ! symbol.
- money number of occurrences of the word ”money”.
- n000 number of occurrences of the string ”000”.
- make number of occurrences of the word ”make”.
- yesno outcome variable, a factor with levels n not spam, y spam.

(i) Realizar un an´alisis descriptivo de las variables explicativas

```
#Lectura de datos del fichero de datos spam7

spam7 <- spam7

str(spam7)

## 'data.frame':    4601 obs. of  7 variables:
##  $ crl.tot: num  278 1028 2259 191 191 ...
##  $ dollar : num  0 0.18 0.184 0 0 0 0.054 0 0.203 0.081 ...
##  $ bang   : num  0.778 0.372 0.276 0.137 0.135 0 0.164 0 0.181 0.244
...
##  $ money  : num  0 0.43 0.06 0 0 0 0 0 0.15 0 ...
##  $ n000   : num  0 0.43 1.16 0 0 0 0 0 0 0.19 ...
##  $ make   : num  0 0.21 0.06 0 0 0 0 0 0.15 0.06 ...
##  $ yesno  : Factor w/ 2 levels "n","y": 2 2 2 2 2 2 2 2 2 2 ...

head(spam7)

##   crl.tot dollar  bang money n000 make yesno
## 1     278  0.000 0.778  0.00 0.00 0.00     y
## 2    1028  0.180 0.372  0.43 0.43 0.21     y
## 3    2259  0.184 0.276  0.06 1.16 0.06     y
## 4     191  0.000 0.137  0.00 0.00 0.00     y
## 5     191  0.000 0.135  0.00 0.00 0.00     y
## 6      54  0.000 0.000  0.00 0.00 0.00     y

colnames(spam7) #el nombre de todas las columnas

## [1] "crl.tot" "dollar"  "bang"    "money"   "n000"    "make"
"yesno"

attach(spam7)
#resumen de los datos y de sus variables.
summary(spam7)

##     crl.tot             dollar             bang             money
##  Min.   :    1.0   Min.   :0.00000   Min.   : 0.0000   Min.   :
0.00000
##  1st Qu.:   35.0   1st Qu.:0.00000   1st Qu.: 0.0000   1st Qu.:
0.00000
##  Median :   95.0   Median :0.00000   Median : 0.0000   Median :
0.00000
```

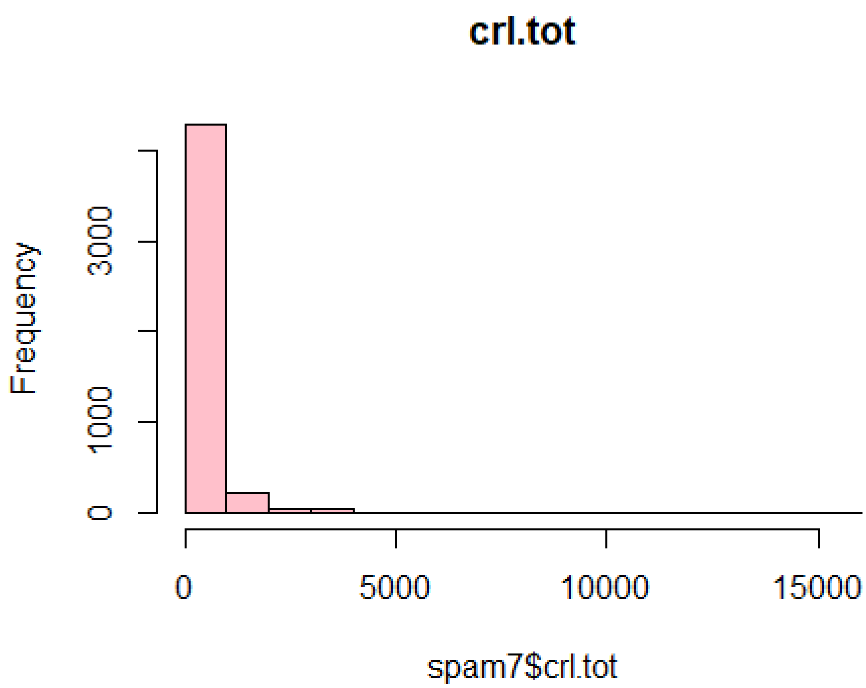
```
##  Mean   :  283.3   Mean   :0.07581   Mean   : 0.2691   Mean   :
0.09427
##  3rd Qu.:  266.0   3rd Qu.:0.05200   3rd Qu.: 0.3150   3rd Qu.:
0.00000
##  Max.   :15841.0   Max.   :6.00300   Max.   :32.4780   Max.
:12.50000
##       n000              make        yesno
##  Min.   :0.0000   Min.   :0.0000   n:2788
##  1st Qu.:0.0000   1st Qu.:0.0000   y:1813
##  Median :0.0000   Median :0.0000
##  Mean   :0.1016   Mean   :0.1046
##  3rd Qu.:0.0000   3rd Qu.:0.0000
##  Max.   :5.4500   Max.   :4.5400
```

```
stat.desc(spam7)
```

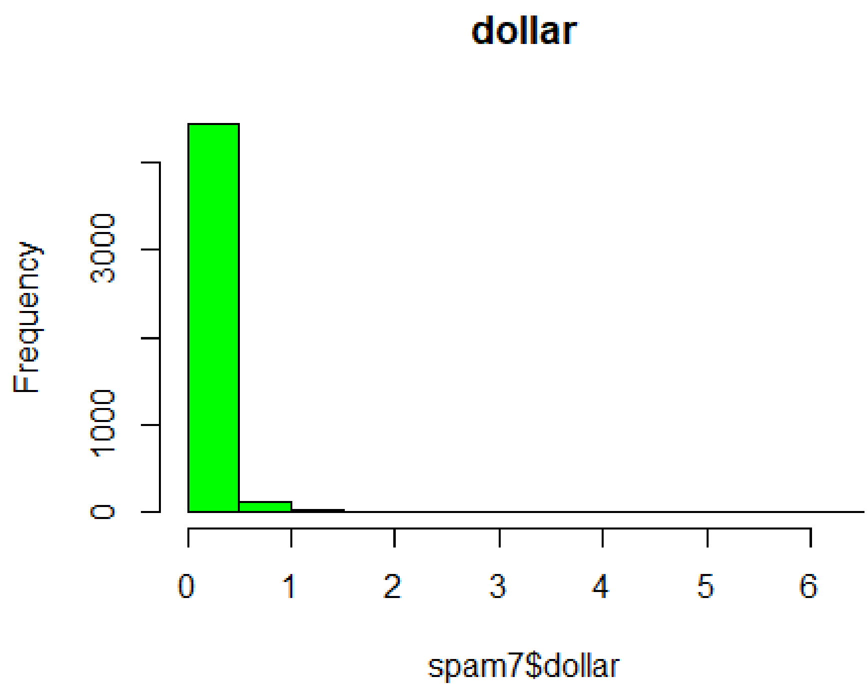
```
##                   crl.tot       dollar         bang        money
n000
## nbr.val      4.601000e+03 4.601000e+03 4.601000e+03 4.601000e+03
4.601000e+03
## nbr.null     0.000000e+00 3.201000e+03 2.343000e+03 3.866000e+03
3.922000e+03
## nbr.na       0.000000e+00 0.000000e+00 0.000000e+00 0.000000e+00
0.000000e+00
## min          1.000000e+00 0.000000e+00 0.000000e+00 0.000000e+00
0.000000e+00
## max          1.584100e+04 6.003000e+00 3.247800e+01 1.250000e+01
5.450000e+00
## range        1.584000e+04 6.003000e+00 3.247800e+01 1.250000e+01
5.450000e+00
## sum          1.303414e+06 3.488050e+02 1.237995e+03 4.337300e+02
4.676700e+02
## median       9.500000e+01 0.000000e+00 0.000000e+00 0.000000e+00
0.000000e+00
## mean         2.832893e+02 7.581069e-02 2.690709e-01 9.426864e-02
1.016453e-01
## SE.mean      8.939140e+00 3.624938e-03 1.202512e-02 6.525596e-03
5.164130e-03
## CI.mean.0.95 1.752500e+01 7.106619e-03 2.357500e-02 1.279330e-02
1.012417e-02
## var          3.676577e+05 6.045796e-02 6.653202e-01 1.959262e-01
1.227006e-01
## std.dev      6.063479e+02 2.458820e-01 8.156716e-01 4.426355e-01
3.502864e-01
## coef.var     2.140384e+00 3.243368e+00 3.031438e+00 4.695470e+00
3.446165e+00
##                      make yesno
## nbr.val      4.601000e+03    NA
## nbr.null     3.548000e+03    NA
## nbr.na       0.000000e+00    NA
```

```
## min          0.000000e+00    NA
## max          4.540000e+00    NA
## range        4.540000e+00    NA
## sum          4.810500e+02    NA
## median       0.000000e+00    NA
## mean         1.045534e-01    NA
## SE.mean      4.501762e-03    NA
## CI.mean.0.95 8.825614e-03    NA
## var          9.324324e-02    NA
## std.dev      3.053576e-01    NA
## coef.var     2.920591e+00    NA
```

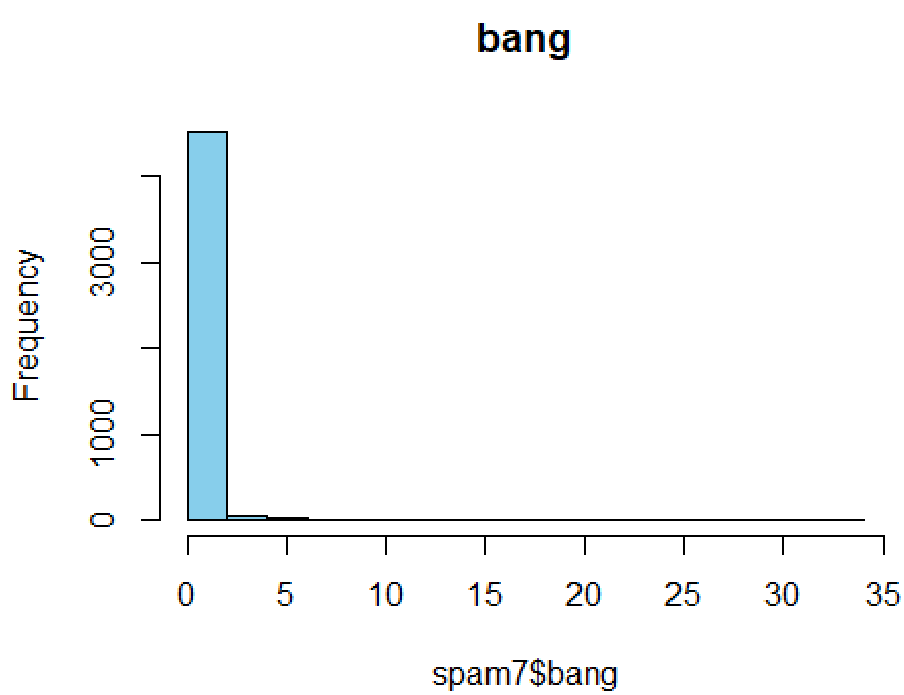
```
hist(spam7$crl.tot,col = "pink",main = "crl.tot" )
```



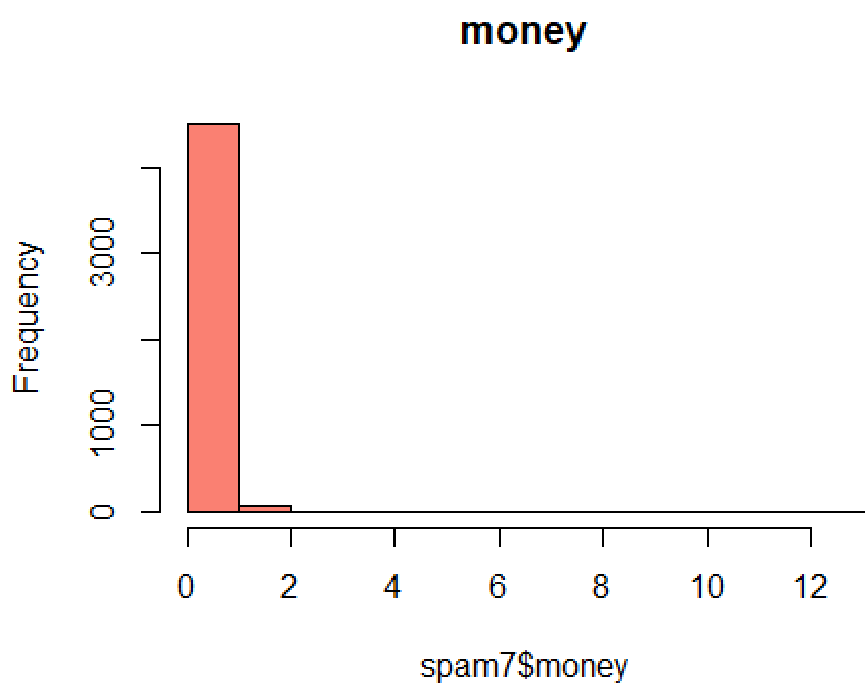

```
hist(spam7$dollar,col = "green",main = "dollar" )
```



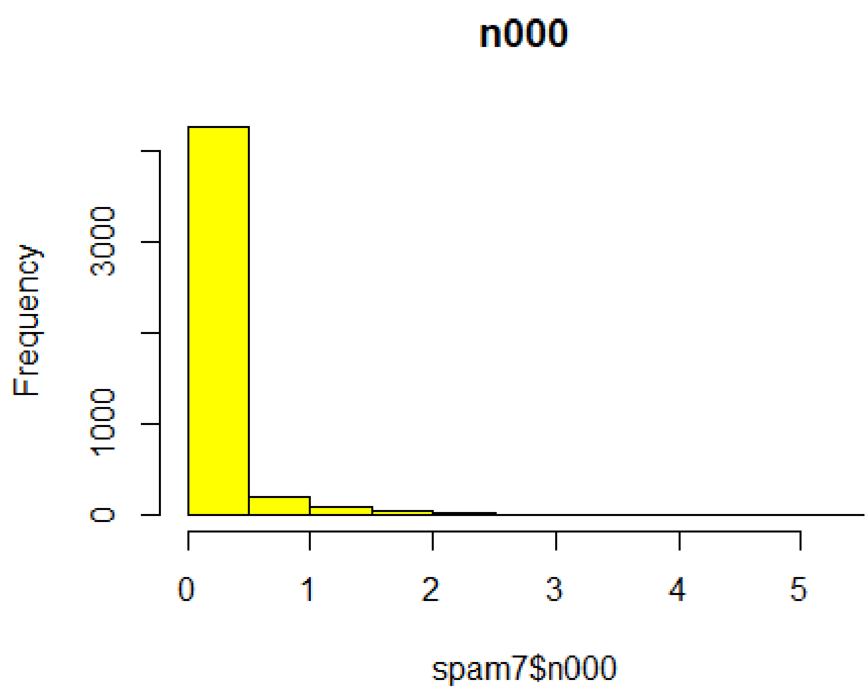

```
hist(spam7$bang,col = "skyblue",main = "bang" )
```



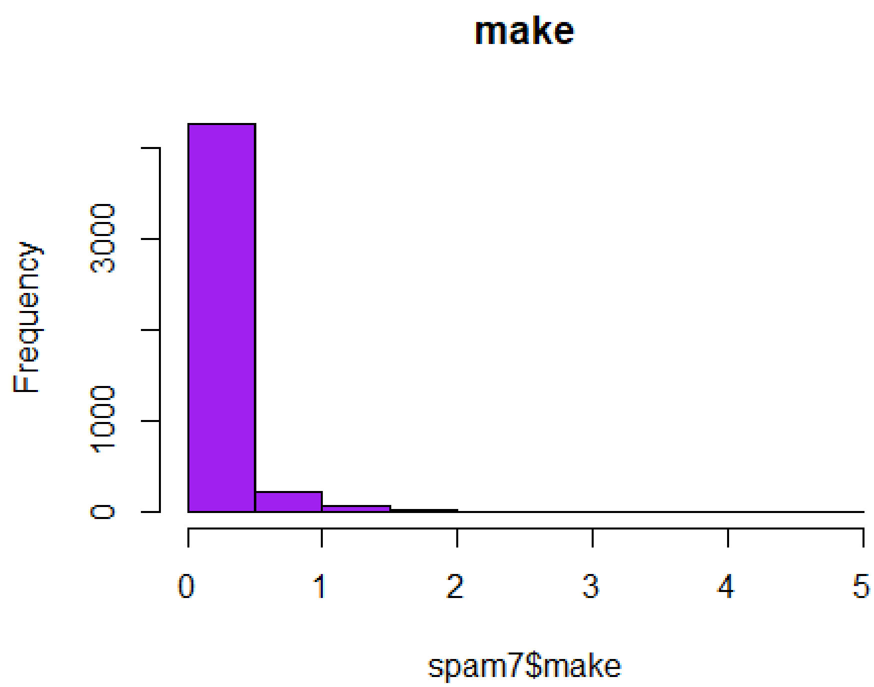

```
hist(spam7$money,col = "salmon",main = "money" )
```




```
hist(spam7$n000,col = "yellow",main = "n000" )
```




```
hist(spam7$make,col = "purple",main = "make" )
```




```
#Todas las variables se distribuyen de forma muy similar, solo crl.tot
muestra una mayor distribución de frecuencia.
```

(ii) Comparar los modelos LR, LDA y QDA mediante la matriz de confusíon. Realizar gráficosd partición

Se realiza los modelos LR, LDA y QDA para las variable dependiente Yesno y el resto. Después estos son utilizados para las matrices de confusión. Por último se crea el gráfico de partición LDA y QDA para representar dicho análisis.

```
#Modelo LR:

modelo_LR <- glm(yesno ~., data = spam7, family = binomial(link = logit))

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

result_LR <- predict(modelo_LR, newdata = spam7)

#Modelo LDA:

modelo_LDA <- lda(yesno ~., data = spam7)

modelo_LDA

## Call:
## lda(yesno ~ ., data = spam7)
##
```

```
## Prior probabilities of groups:
##         n         y 
## 0.6059552 0.3940448 
## 
## Group means:
##    crl.tot     dollar      bang      money        n000      make
## n 161.4709 0.01164849 0.1099835 0.01713773 0.007087518 0.0734792
## y 470.6194 0.17447821 0.5137126 0.21287921 0.247054606 0.1523387
## 
## Coefficients of linear discriminants:
##                  LD1
## crl.tot 0.0005832625
## dollar  1.6357112508
## bang    0.5229084780
## money   0.8295009511
## n000    1.5117933586
## make    0.1509208601
```

```r
#Modelo QDA:

modelo_QDA <- qda(yesno ~., data = spam7)
modelo_QDA
```

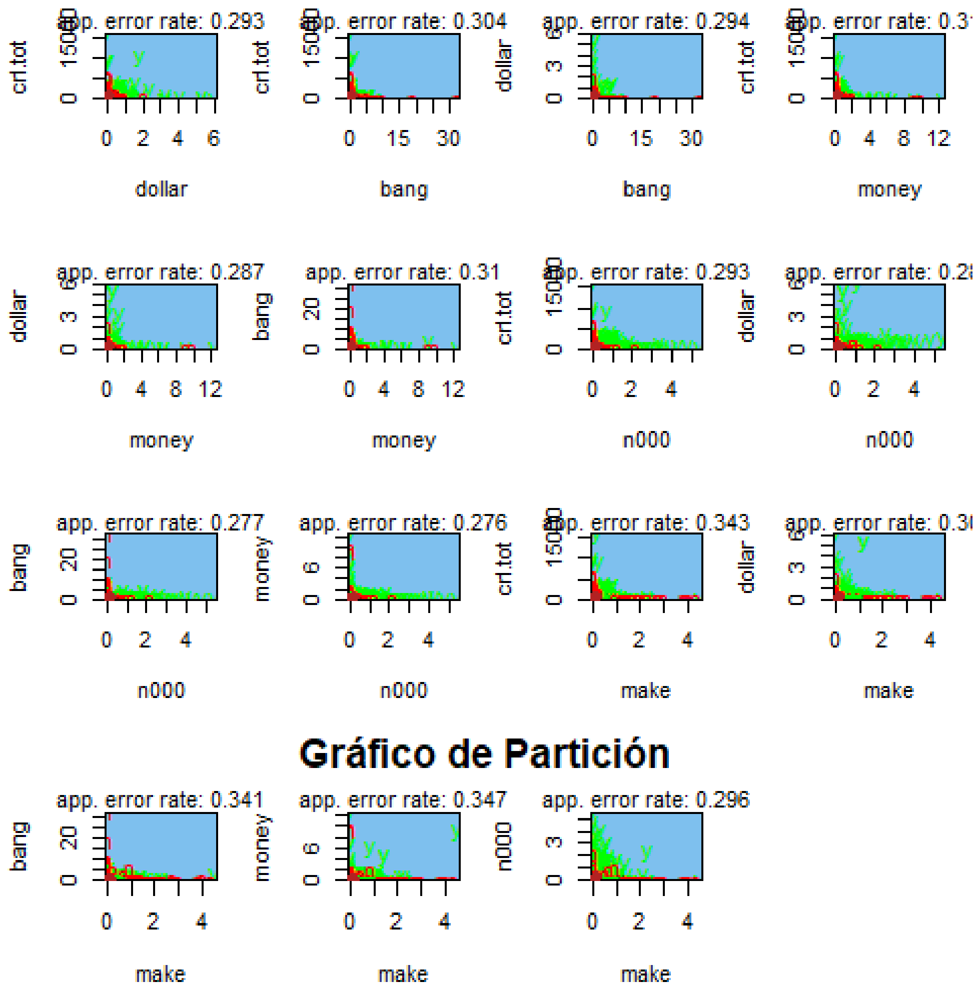
```
## Call:
## qda(yesno ~ ., data = spam7)
## 
## Prior probabilities of groups:
##         n         y 
## 0.6059552 0.3940448 
## 
## Group means:
##    crl.tot     dollar      bang      money        n000      make
## n 161.4709 0.01164849 0.1099835 0.01713773 0.007087518 0.0734792
## y 470.6194 0.17447821 0.5137126 0.21287921 0.247054606 0.1523387
```

```r
#Matriz de Confusión LDA:

result_LDA <- predict(modelo_LDA, newdata = spam7)
matrizLDA <- table(result_LDA$class, spam7$yesno)
matrizLDA
```

```
## 
##        n    y
##   n 2723 1015
##   y   65  798
```

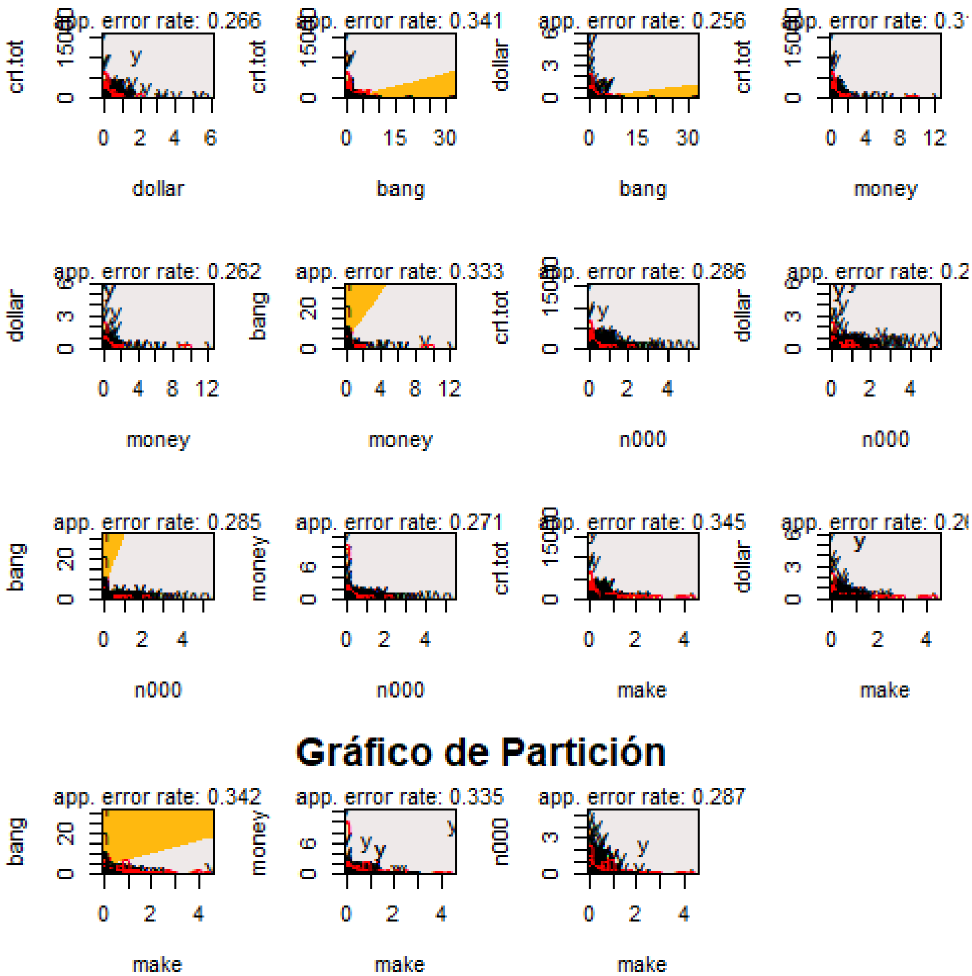
```r
#Matriz de Confusión QDA:

result_QDA <- predict(modelo_QDA, newdata = spam7)
matrizQDA <- table(result_QDA$class, spam7$yesno)
matrizQDA
```

```
##
##        n    y
##   n 2687 1003
##   y  101  810

#Gráfico de Partición LDA

  graf_PartLDA <- partimat(yesno ~., data = spam7,
method="lda",main="Gráfico de Partición",  col.correct="green",col.wrong
= "red"

, image.colors = c("darkgoldenrod1", "skyblue2"), col.mean = "firebrick")
```




```r
#Gráfico de Partición QDA

graf_PartQDA <- partimat(yesno ~., data = spam7,
```

```
method="qda",image.colors = c("darkgoldenrod1", "snow2"),main="Gráfico de Partición")
```



```r
# % de precisión del modelo QDA
sum(diag(matrizQDA))/sum(matrizQDA) #la precisión del modelo QDA. El resultado es de un 76% de precisión.

## [1] 0.7600522

# % de precisión del modelo LDA
sum(diag(matrizLDA))/sum(matrizLDA) #la precisión del modelo LDA. El resultado obtenido es muy próximo al anterior, 76,52%

## [1] 0.7652684
```

El color verde de estos gráficos representa el acierto y el rojo el error de cada una de las variables