EJEMPLO 1. CREDITOS

Historia crédito. BAD: Moroso, no moroso

$X_1,..,X_4$ ………. LOAN, MORTDUE, CLAGE, CLNO

~~Test de Igualdad de Medias~~

```
                      Statistics        F df1 df2 Pr
Wilks Lambda            0.377179 55.73007   4 135  0
Pillai Trace            0.622821 55.73007   4 135  0
Hoteling-Lawley Trace   1.651261 55.73007   4 135  0
Roy Greatest Root       1.651261 55.73007   4 135  0
```

~~Test de Mardia de Multinormalidad por grupos~~

```
grupos: Moroso
    kappa1    pvalsim     kappa2   pvalkurt              n
16.4509769  0.6882819 -1.5057794  0.1321238     55.0000000
------------------------------------------------------------
grupos: No moroso
     kappa1     pvalsim      kappa2    pvalkurt           n
26.18812374  0.15968824 -1.83298187  0.06680527 85.00000000
```

DISCRIMINANTE LINEAL

Call:

lda(BAD ~ LOAN + MORTDUE + CLAGE + CLNO, data = credit1)

```
Prior probabilities of groups:

   Moroso No moroso

0.3928571 0.6071429

Group means:

              LOAN  MORTDUE    CLAGE     CLNO

Moroso    13774.55 50982.20 142.0774 19.65455

No moroso 17929.41 62384.15 258.6129 19.58824


Coefficients of linear discriminants (ES LO QUE EN CLASE SE LLAMO
FUNCION DE CLASIFICACION.:

                  LD1

LOAN     5.563021e-05

MORTDUE  1.832424e-05

CLAGE    1.859608e-02

CLNO    -7.712388e-02
```

Predicción

```
                Pred1

            Moroso No moroso

  Moroso        45        10

  No moroso      0        85
```

~~Test de Homogeneidad de Variancias~~

```
      Statistic df           Pr

Box.M  47.88681 10 6.509141e-07

adj.M  46.29599 10 1.267556e-06
```

DISCRIMINANTE CUADRATICO

Call:

```
qda(BAD ~ LOAN + MORTDUE + CLAGE + CLNO, data = credit1)


Prior probabilities of groups:
   Moroso No moroso
0.3928571 0.6071429


Group means:
              LOAN  MORTDUE    CLAGE     CLNO
Moroso    13774.55 50982.20 142.0774 19.65455
No moroso 17929.41 62384.15 258.6129 19.58824
```

Predicción

```
     pred2
            Moroso No moroso
  Moroso        46         9
  No moroso      0        85
```

DISCRIMINANTE LOGISTICO

```
Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -1.076e+01  2.484e+00  -4.334 1.47e-05 ***
LOAN         1.453e-04  6.420e-05   2.262  0.02367 *
MORTDUE      5.992e-05  1.826e-05   3.281  0.00103 **
CLAGE        4.634e-02  9.145e-03   5.067 4.04e-07 ***
CLNO        -2.369e-01  7.499e-02  -3.160  0.00158 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 187.603  on 139  degrees of freedom
Residual deviance:  68.497  on 135  degrees of freedom
AIC: 78.497
Number of Fisher Scoring iterations: 7
```

Predicción

```
          pred3
              0  1
  Moroso     47  8
  No moroso   2 83
```

EJEMPLO INVEST (YA USADO EN CLUSTER)

Grupo: el país tiene o no tiene Grado Inversor

X_1, X_2, X_3, X_4, X_5….. INDICE PAIS, DEUDA/PBI, PBIPERCAPITA, INFLACION, CRECMIENTOPBI

~~Test de Igualdad de Medias~~

	Statistics	F	df1	df2	Pr
Wilks Lambda	0.3962623	16.97704	7	78	1.971756e-13
Pillai Trace	0.6037377	16.97704	7	78	1.971756e-13
Hoteling-Lawley Trace	1.5235808	16.97704	7	78	1.971756e-13
Roy Greatest Root	1.5235808	16.97704	7	78	1.971756e-13

~~Test de Homogeneidad de Variancias~~

	Statistic	df	Pr
Box.M	388.5175	28	0
adj.M	352.2176	28	0

~~Test de Mardia de Multinormalidad por grupos~~

grupos: 0

kappa1	pvalsim	kappa2	pvalkurt	n
2.307879e+02	1.221245e-15	5.909363e+00	3.434339e-09	34

----

grupos: 1

kappa1	pvalsim	kappa2	pvalkurt	n
1.852117e+02	1.371679e-09	-4.400827e-01	6.598772e-01	52

LOGISTICO

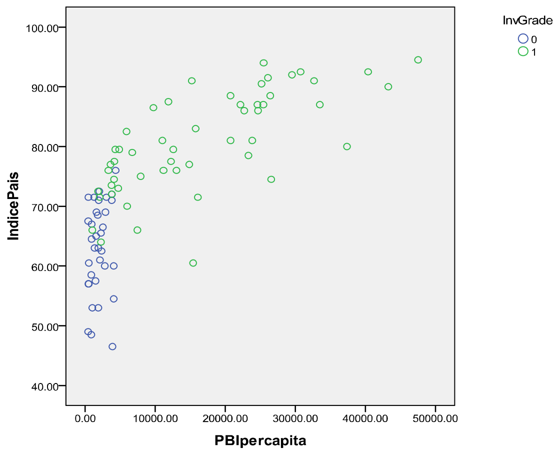
Coefficients:

```
              Estimate Std. Error z value Pr(>|z|)
(Intercept)  -1.368e+01  9.035e+00  -1.514   0.1301
IndicePais    1.857e-01  1.353e-01   1.372   0.1700
DPBI         -3.234e-02  2.470e-02  -1.309   0.1904
PBIpercapita  1.080e-03  5.522e-04   1.956   0.0504 .
Inflacion    -4.277e-01  2.318e-01  -1.845   0.0650 .
CrecimPBI     2.441e-01  3.045e-01   0.802   0.4227
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 115.426  on 85  degrees of freedom
Residual deviance:  23.771  on 80  degrees of freedom
AIC: 35.771

Number of Fisher Scoring iterations: 10
```




```
SALIDA CON MENOS VARIABLES
                 Estimate Std. Error z value Pr(>|z|)
(Intercept)  -1.806e+01  6.477e+00  -2.788  0.00531 **
IndicePais    2.235e-01  9.395e-02   2.379  0.01738 *
PBIpercapita  6.607e-04  2.897e-04   2.280  0.02258 *

    Null deviance: 115.426  on 85  degrees of freedom
Residual deviance:  34.503  on 83  degrees of freedom
AIC: 40.503
```

Predicción

```
                 InvGrade
SCOR1        0            1
    0      0.89       0.12
    1      0.06       0.94
```

EJEMPLO BAJO PESO DEL Niño AL NACER

Se desea explicar el bajo peso de los niños al nacer.

PESO: 1, SI TIENE BAJO PESO, 0 SI NO

Se tienen características de la madres: edad (AGE), peso(LWT), cantidad visitas al médico (FTV), fuma(SMOKE), historia de hipertensión (HT), molestias uterinas(UI)

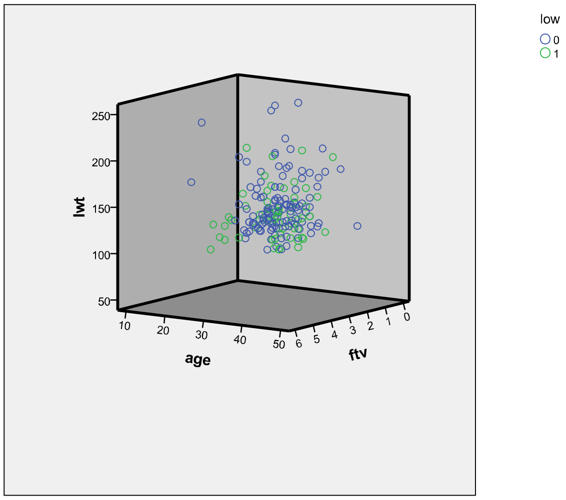
Test apara discriminante lineal con 3 variable, edad, peso y cantidad visitas

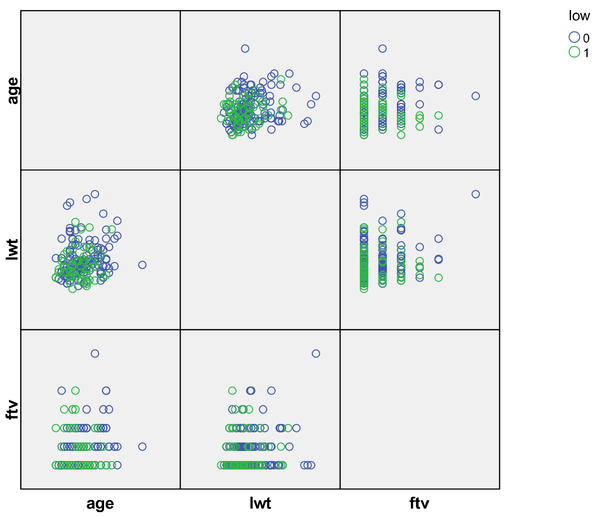
testes(peso[,c(2,3,9)], peso[,1])

~~Test de Igualdad de Medias~~

	Statistics	F	df1	df2	Pr
Wilks Lambda	0.96264931	2.39266	3	185	0.06997377
Pillai Trace	0.03735069	2.39266	3	185	0.06997377
Hoteling-Lawley Trace	0.03879990	2.39266	3	185	0.06997377
Roy Greatest Root	0.03879990	2.39266	3	185	0.06997377

No existe evidencia de que el vector de medias de los 2 grupos sea diferente. Esto lo podemos ver gráficamente


low
0
1
250
200
150
100
50
lwt
10
20
30
40
50
age
6
5
4
3
2
1
0
ftv


low
0
1
age
lwt
ftv
age
lwt
ftv

DISCRIMINANTE LOGISTICO CON TODAS LAS VARIABLES

```
Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)  0.480623   1.196888   0.402  0.68801
age         -0.029549   0.037031  -0.798  0.42489
lwt         -0.015424   0.006919  -2.229  0.02580 *
race2        1.272260   0.527357   2.413  0.01584 *
race3        0.880496   0.440778   1.998  0.04576 *
smoke        0.938846   0.402147   2.335  0.01957 *
ptl          0.543337   0.345403   1.573  0.11571
ht           1.863303   0.697533   2.671  0.00756 **
ui           0.767648   0.459318   1.671  0.09467 .
ftv          0.065302   0.172394   0.379  0.70484
```

Predicción

```
                 SCOR1
low          0         1
  0 0.9000000 0.1000000
  1 0.6101695 0.3898305
```

Otra salida

```
Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)  0.056276   0.937853   0.060  0.95215
lwt         -0.016732   0.006803  -2.459  0.01392 *
race2        1.324562   0.521464   2.540  0.01108 *
race3        0.926197   0.430386   2.152  0.03140 *
smoke        1.035831   0.392558   2.639  0.00832 **
ht           1.871416   0.690902   2.709  0.00676 **
ui           0.904974   0.447553   2.022  0.04317 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 234.67  on 188  degrees of freedom
Residual deviance: 204.22  on 182  degrees of freedom
AIC: 218.22

Number of Fisher Scoring iterations: 4
```

Clasificación (punto corte 0.5)

```
              SCOR2
low         0         1
  0 0.9000000 0.1000000
  1 0.6440678 0.3559322
```

Clasificación (punto corte 0.33)

```
              SCOR3
low         0         1
  0 0.7538462 0.2461538
  1 0.4237288 0.5762712
```

EJEMPLO VINO

Se tienen 3 grupos (3 cepas distintas de vino) y la concentración de 13 productos químicos diferentes (reflejado en 13 variables).

~~Test de Igualdad de Medias~~

```
Statistics                    F             df1 df2 Pr
Wilks Lambda           0.01934091  77.61987  26 326  0
Pillai Trace           1.70582080  73.15128  26 328  0
Hoteling-Lawley Trace 13.21020848  82.30976  26 324  0
Roy Greatest Root      9.08173944 114.56964  13 164  0
```

~~Test de Mardia de Multinormalidad por grupos~~

```
grupos: 1
     kappa1     pvalsim      kappa2    pvalkurt      n
489.2834848   0.1290062  -1.4231165   0.1547024      59
----------------------------------------------------------------------
grupos: 2
      kappa1      pvalsim       kappa2     pvalkurt  n
7.121859e+02 1.205702e-13 3.441382e+00 5.787517e-04  71
----------------------------------------------------------------------
grupos: 3
     kappa1     pvalsim      kappa2    pvalkurt       n
429.8665311   0.7958293  -1.5723031   0.1158803      48
```

```
Coefficients of linear discriminants(FUNCIONES DE CLASIFICACION VISTAS
EN CLASE)
             LD1           LD2
V2  -0.403399781  0.8717930699
V3   0.165254596  0.3053797325
V4  -0.369075256  2.3458497486
V5   0.154797889 -0.1463807654
V6  -0.002163496 -0.0004627565
V7   0.618052068 -0.0322128171
V8  -1.661191235 -0.4919980543
V9  -1.495818440 -1.6309537953
V10  0.134092628 -0.3070875776
V11  0.355055710  0.2532306865
V12 -0.818036073 -1.5156344987
V13 -1.157559376  0.0511839665
V14 -0.002691206  0.0028529846
```

Predicción

```
        pred1w
obs      1  2  3
  1     59  0  0
  2      0 71  0
  3      0  0 48
```

Clasificación cross validation

```
     pred1wC
       1  2  3
  1   59  0  0
  2    1 69  1
  3    0  0 48
```

~~Test de Homogeneidad de Variancias~~

```
      Statistic  df Pr
Box.M  764.8065 182  0
adj.M  684.2031 182  0
```

Clasificación con funciones cuadráticas

```
      pred2w
        1  2  3
  1    59  0  0
  2     1 70  0
  3     0  0 48
```

OTRO EJEMPLO PRESTAMOS

```
                  ~~Test de Igualdad de Medias~~

                      Statistics        F df1 df2 Pr
Wilks Lambda           0.7124707 39.89543   7 692  0
Pillai Trace           0.2875293 39.89543   7 692  0
Hoteling-Lawley Trace  0.4035665 39.89543   7 692  0
Roy Greatest Root      0.4035665 39.89543   7 692  0

                  ~~Test de Homogeneidad de Varianzas~~

      Statistic df Pr
Box.M  563.2906 28  0
adj.M  554.9823 28  0


                  ~~Test de Mardia de Multinormalidad por grupos~~

grupos: No
    kappa1    pvalsim     kappa2   pvalkurt   n
3254.15537    0.00000   58.19759    0.00000  517
------------------------------------------------------------------------------
grupos: Yes
    kappa1    pvalsim     kappa2   pvalkurt   n
3996.04829    0.00000   93.13884    0.00000  183
```