Análisis discriminante lineal (LDA)

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2022-05-28

```
library(MASS)
```

Se cargan los datos Iris

```
Z<-as.data.frame(iris)
```

Se define la matriz de datos y la variable respesta con las ## clasificaciones.

```
x<-Z[,1:4]
y<-Z[,5]
```

Definir como n y p el número de flores y variables

```
n<-nrow(x)
p<-ncol(x)
```

Se aplica el AnÃ¡lisis discriminante lineal (LDA)

Cross validation (cv): clasificación óptima

```
lda.iris<-lda(y~.,data=x, CV=TRUE)
```

lda.iris$class contiene las clasificaciones hechas

por CV usando LDA.

```
lda.iris$class
```

```
##   [1] setosa     setosa     setosa     setosa     setosa     setosa
##   [7] setosa     setosa     setosa     setosa     setosa     setosa
##  [13] setosa     setosa     setosa     setosa     setosa     setosa
##  [19] setosa     setosa     setosa     setosa     setosa     setosa
##  [25] setosa     setosa     setosa     setosa     setosa     setosa
##  [31] setosa     setosa     setosa     setosa     setosa     setosa
##  [37] setosa     setosa     setosa     setosa     setosa     setosa
##  [43] setosa     setosa     setosa     setosa     setosa     setosa
##  [49] setosa     setosa     versicolor versicolor versicolor versicolor
##  [55] versicolor versicolor versicolor versicolor versicolor versicolor
##  [61] versicolor versicolor versicolor versicolor versicolor versicolor
##  [67] versicolor versicolor versicolor versicolor virginica  versicolor
```

```
##  [73] versicolor versicolor versicolor versicolor versicolor versicolor
##  [79] versicolor versicolor versicolor versicolor versicolor virginica
##  [85] versicolor versicolor versicolor versicolor versicolor versicolor
##  [91] versicolor versicolor versicolor versicolor versicolor versicolor
##  [97] versicolor versicolor versicolor versicolor virginica  virginica
## [103] virginica  virginica  virginica  virginica  virginica  virginica
## [109] virginica  virginica  virginica  virginica  virginica  virginica
## [115] virginica  virginica  virginica  virginica  virginica  virginica
## [121] virginica  virginica  virginica  virginica  virginica  virginica
## [127] virginica  virginica  virginica  virginica  virginica  virginica
## [133] virginica  versicolor virginica  virginica  virginica  virginica
## [139] virginica  virginica  virginica  virginica  virginica  virginica
## [145] virginica  virginica  virginica  virginica  virginica  virginica
## Levels: setosa versicolor virginica
```

Creación de la tabla de clasificaciones buenas y malas

```
table.lda<-table(y,lda.iris$class)
table.lda
```

```
##
## y             setosa versicolor virginica
##   setosa         50          0         0
##   versicolor      0         48         2
##   virginica       0          1        49
```

Hay 3 mal clasificados

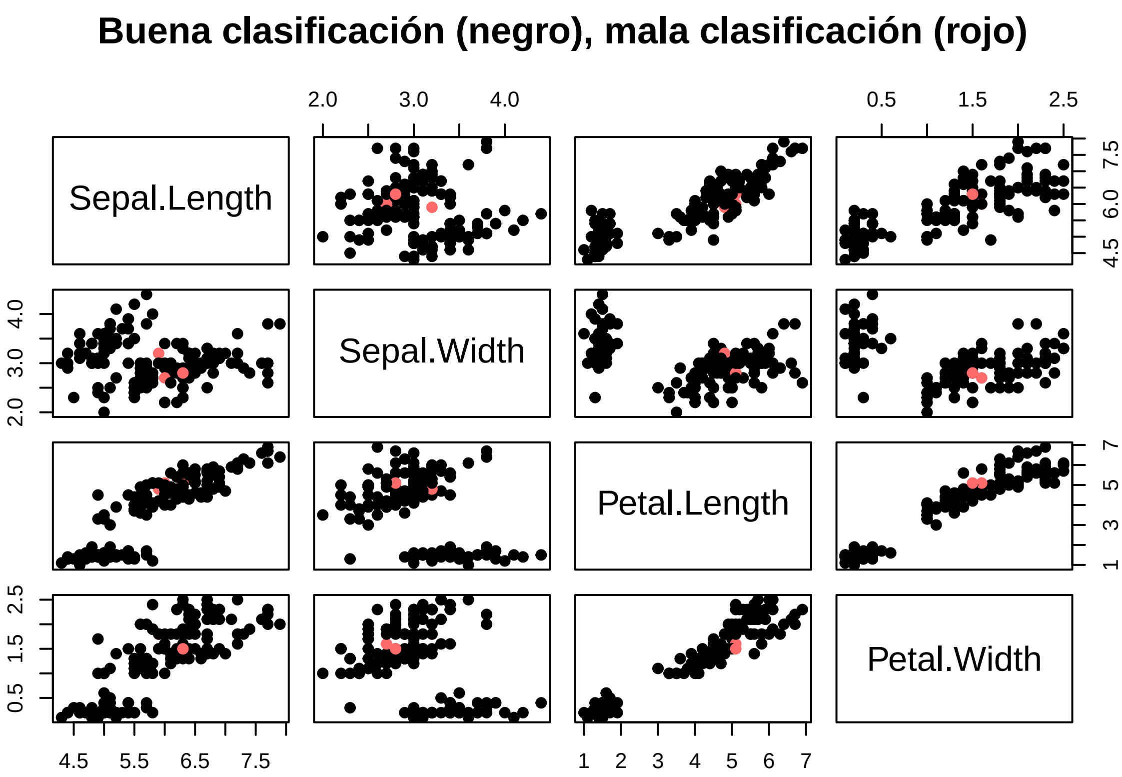
Proporción de errores

```
mis.lda<- n-sum(y==lda.iris$class)
mis.lda/n
```

```
## [1] 0.02
```

scater plot

```
col.lda.iris<-c("indianred1","black")[1*(y==lda.iris$class)+1]
pairs(x,main="Buena clasificación (negro), mala clasificación (rojo)",
      pch=19,col=col.lda.iris)
```



Buenas clasificaciones en negro y malas en rojo

Probabilidad de pertenencia a uno de los tres grupos

```
lda.iris$posterior
```

```
##          setosa   versicolor    virginica
## 1   1.000000e+00 5.087494e-22 4.385241e-42
## 2   1.000000e+00 9.588256e-18 8.888069e-37
## 3   1.000000e+00 1.983745e-19 8.606982e-39
## 4   1.000000e+00 1.505573e-16 5.101765e-35
## 5   1.000000e+00 2.075670e-22 1.739832e-42
## 6   1.000000e+00 5.332271e-21 8.674906e-40
## 7   1.000000e+00 1.498839e-18 3.999205e-37
## 8   1.000000e+00 5.268133e-20 1.983027e-39
## 9   1.000000e+00 2.280729e-15 1.293376e-33
## 10  1.000000e+00 1.504085e-18 5.037348e-38
## 11  1.000000e+00 1.296140e-23 4.023338e-44
## 12  1.000000e+00 2.171874e-18 3.223111e-37
## 13  1.000000e+00 1.996136e-18 6.109118e-38
## 14  1.000000e+00 1.604055e-19 2.549802e-39
## 15  1.000000e+00 2.843397e-31 1.593594e-54
## 16  1.000000e+00 2.330545e-28 3.074132e-49
## 17  1.000000e+00 5.136116e-25 3.269819e-45
## 18  1.000000e+00 5.747697e-21 2.253825e-40
## 19  1.000000e+00 2.187125e-22 4.069438e-42
## 20  1.000000e+00 3.297882e-22 9.802494e-42
## 21  1.000000e+00 1.757286e-19 8.150916e-39
## 22  1.000000e+00 2.027767e-20 3.730752e-39
```

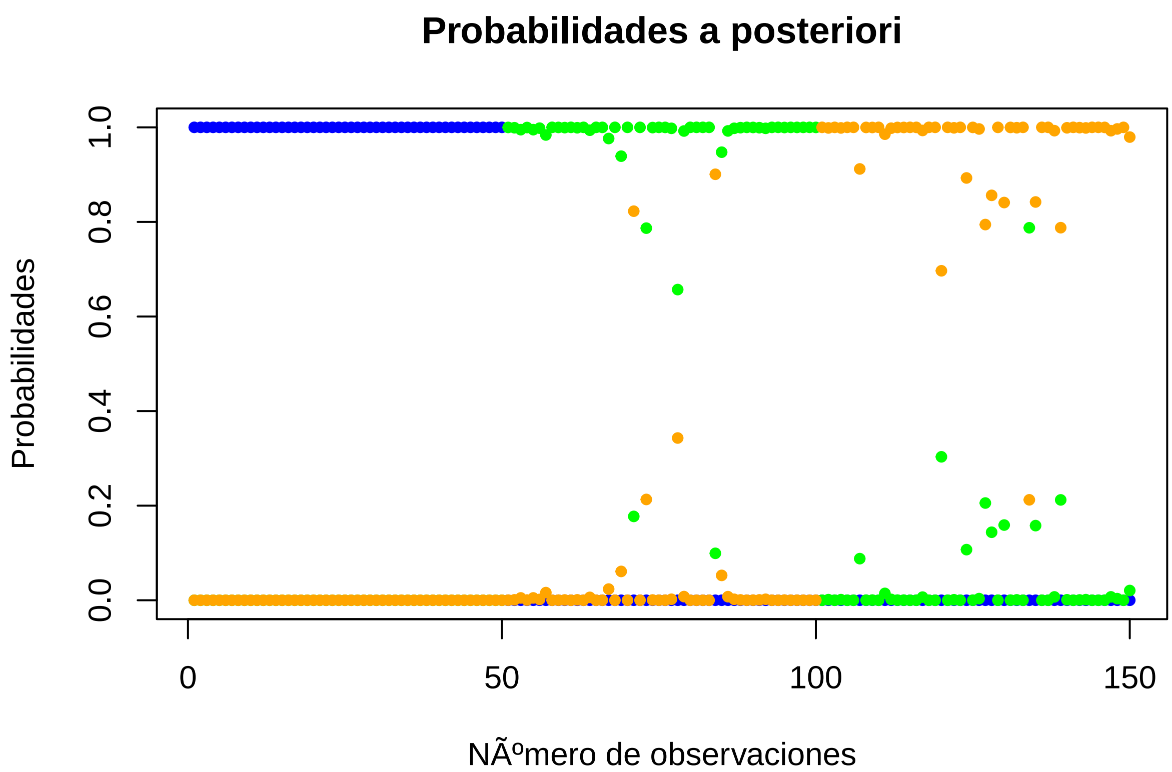
```
## 23  1.000000e+00 5.650696e-25 6.509776e-46
## 24  1.000000e+00 8.618517e-15 7.014744e-32
## 25  1.000000e+00 1.520334e-15 1.857885e-33
## 26  1.000000e+00 2.936141e-16 8.159510e-35
## 27  1.000000e+00 4.557392e-17 5.510803e-35
## 28  1.000000e+00 2.079675e-21 2.831513e-41
## 29  1.000000e+00 1.232321e-21 1.082692e-41
## 30  1.000000e+00 1.153050e-16 4.267126e-35
## 31  1.000000e+00 2.584595e-16 9.537258e-35
## 32  1.000000e+00 2.878754e-19 5.473623e-38
## 33  1.000000e+00 2.247070e-27 4.047137e-49
## 34  1.000000e+00 2.620949e-29 1.970538e-51
## 35  1.000000e+00 1.493279e-17 2.047516e-36
## 36  1.000000e+00 2.146308e-21 1.550216e-41
## 37  1.000000e+00 1.673983e-24 1.322398e-45
## 38  1.000000e+00 3.810942e-23 9.131835e-44
## 39  1.000000e+00 5.423320e-17 1.146137e-35
## 40  1.000000e+00 2.414191e-20 6.552342e-40
## 41  1.000000e+00 1.417602e-21 3.569675e-41
## 42  1.000000e+00 8.956712e-11 4.968454e-28
## 43  1.000000e+00 2.125837e-18 2.395462e-37
## 44  1.000000e+00 1.101293e-15 1.403899e-32
## 45  1.000000e+00 2.285363e-17 5.214629e-35
## 46  1.000000e+00 2.087086e-16 1.027948e-34
## 47  1.000000e+00 2.588201e-22 3.634491e-42
## 48  1.000000e+00 3.643000e-18 4.504970e-37
## 49  1.000000e+00 3.000767e-23 1.346233e-43
## 50  1.000000e+00 3.171862e-20 7.860312e-40
## 51  3.157725e-18 9.998716e-01 1.284247e-04
## 52  1.753919e-19 9.991816e-01 8.184018e-04
## 53  2.551962e-22 9.951044e-01 4.895626e-03
## 54  2.742687e-22 9.995996e-01 4.004477e-04
## 55  4.854978e-23 9.951404e-01 4.859638e-03
## 56  9.575747e-23 9.982973e-01 1.702702e-03
## 57  4.467689e-22 9.838631e-01 1.613691e-02
## 58  5.922943e-14 9.999999e-01 8.584221e-08
## 59  8.088509e-20 9.998655e-01 1.344590e-04
## 60  1.767441e-20 9.994314e-01 5.686054e-04
## 61  3.330661e-18 9.999987e-01 1.314516e-06
## 62  8.331100e-20 9.991631e-01 8.369389e-04
## 63  4.614428e-18 9.999989e-01 1.117671e-06
## 64  1.290071e-23 9.939163e-01 6.083745e-03
## 65  5.229707e-14 9.999984e-01 1.593028e-06
## 66  3.393529e-17 9.999528e-01 4.721492e-05
## 67  7.983370e-24 9.763990e-01 2.360097e-02
## 68  3.119288e-16 9.999991e-01 8.659241e-07
## 69  3.847473e-28 9.390462e-01 6.095377e-02
## 70  1.678698e-17 9.999966e-01 3.360127e-06
## 71  1.302246e-28 1.772727e-01 8.227273e-01
## 72  1.113263e-16 9.999902e-01 9.801197e-06
## 73  1.634947e-29 7.868347e-01 2.131653e-01
## 74  3.331093e-22 9.995073e-01 4.926830e-04
## 75  1.013127e-17 9.999741e-01 2.594176e-05
## 76  2.949236e-18 9.999081e-01 9.193549e-05
```

```
## 77  7.224891e-23 9.979459e-01 2.054146e-03
## 78  2.386376e-27 6.569495e-01 3.430505e-01
## 79  4.473658e-23 9.922840e-01 7.716012e-03
## 80  7.145460e-12 1.000000e+00 1.241414e-08
## 81  1.333306e-17 9.999970e-01 3.044209e-06
## 82  1.119894e-15 9.999997e-01 2.916503e-07
## 83  1.748156e-16 9.999961e-01 3.876682e-06
## 84  1.125494e-33 9.924153e-02 9.007585e-01
## 85  1.191672e-24 9.474667e-01 5.253333e-02
## 86  1.983291e-20 9.924721e-01 7.527887e-03
## 87  4.531906e-21 9.980100e-01 1.989996e-03
## 88  2.035626e-23 9.993358e-01 6.642410e-04
## 89  7.813451e-18 9.999440e-01 5.603286e-05
## 90  8.212308e-21 9.998033e-01 1.967487e-04
## 91  6.631189e-23 9.992802e-01 7.197827e-04
## 92  7.049062e-22 9.979525e-01 2.047473e-03
## 93  4.490728e-18 9.999881e-01 1.188058e-05
## 94  2.600275e-14 9.999999e-01 8.745690e-08
## 95  6.422939e-21 9.996751e-01 3.248823e-04
## 96  2.159263e-17 9.999804e-01 1.956029e-05
## 97  3.823305e-19 9.998801e-01 1.199041e-04
## 98  2.089502e-18 9.999504e-01 4.963639e-05
## 99  9.013113e-11 1.000000e+00 9.943306e-09
## 100 6.167377e-19 9.999219e-01 7.813051e-05
## 101 1.335977e-53 3.188548e-09 1.000000e+00
## 102 9.949508e-38 1.209398e-03 9.987906e-01
## 103 1.950796e-42 2.774428e-05 9.999723e-01
## 104 3.081602e-38 1.232592e-03 9.987674e-01
## 105 5.411117e-46 1.807449e-06 9.999982e-01
## 106 5.887455e-50 5.662591e-07 9.999994e-01
## 107 1.203272e-32 8.794800e-02 9.120520e-01
## 108 1.774038e-42 1.735541e-04 9.998264e-01
## 109 1.924345e-42 2.617818e-04 9.997382e-01
## 110 1.851248e-46 1.352651e-07 9.999999e-01
## 111 4.379051e-32 1.446014e-02 9.855399e-01
## 112 2.052671e-37 1.776421e-03 9.982236e-01
## 113 9.704392e-39 2.172029e-04 9.997828e-01
## 114 2.386650e-40 2.251253e-04 9.997749e-01
## 115 8.048237e-46 8.410965e-07 9.999992e-01
## 116 1.008588e-39 2.840103e-05 9.999716e-01
## 117 2.811294e-35 6.595206e-03 9.934048e-01
## 118 7.282186e-45 1.296566e-06 9.999987e-01
## 119 1.004644e-64 2.647509e-10 1.000000e+00
## 120 3.160887e-33 3.033047e-01 6.966953e-01
## 121 1.719583e-42 6.688965e-06 9.999933e-01
## 122 6.252717e-37 9.870164e-04 9.990130e-01
## 123 2.627103e-51 7.704580e-07 9.999992e-01
## 124 1.504499e-31 1.070121e-01 8.929879e-01
## 125 3.688147e-39 9.571422e-05 9.999043e-01
## 126 2.426533e-36 3.398007e-03 9.966020e-01
## 127 3.865436e-30 2.055755e-01 7.944245e-01
## 128 3.606381e-30 1.437670e-01 8.562330e-01
## 129 8.371636e-44 1.376281e-05 9.999862e-01
## 130 2.937738e-32 1.589920e-01 8.410080e-01
```

```
## 131 6.294581e-42 1.714027e-04 9.998286e-01
## 132 5.466934e-36 7.736441e-04 9.992264e-01
## 133 1.208158e-45 3.051435e-06 9.999969e-01
## 134 5.464475e-29 7.876238e-01 2.123762e-01
## 135 9.884011e-35 1.578198e-01 8.421802e-01
## 136 6.515088e-46 1.990735e-06 9.999980e-01
## 137 2.840394e-44 7.895048e-07 9.999992e-01
## 138 7.160822e-35 7.053731e-03 9.929463e-01
## 139 1.782247e-29 2.122042e-01 7.877958e-01
## 140 3.640914e-36 9.289807e-04 9.990710e-01
## 141 5.881132e-45 1.108009e-06 9.999989e-01
## 142 2.122304e-35 6.157433e-04 9.993843e-01
## 143 9.949508e-38 1.209398e-03 9.987906e-01
## 144 9.585800e-46 9.978596e-07 9.999990e-01
## 145 2.206003e-46 2.038879e-07 9.999998e-01
## 146 1.133074e-38 8.851900e-05 9.999115e-01
## 147 8.781586e-36 7.084468e-03 9.929155e-01
## 148 7.108984e-35 3.342993e-03 9.966570e-01
## 149 3.096565e-40 1.338572e-05 9.999866e-01
## 150 3.585667e-33 2.058806e-02 9.794119e-01
```

Gráfico de probabilidades

```
plot(1:n, lda.iris$posterior[,1],
     main="Probabilidades a posteriori",
     pch=20, col="blue",
     xlab="NÃºmero de observaciones", ylab="Probabilidades")
points(1:n,lda.iris$posterior[,2],
       pch=20, col="green")
points(1:n,lda.iris$posterior[,3],
       pch=20, col="orange")
```



LDA CON MATRIZ NUEVA

Se cargan los datos

```
input <- ("
especie pata abdomen organo_sexual
a 191 131 53
a 185 134 50
a 200 137 52
a 173 127 50
a 171 128 49
a 160 118 47
a 188 134 54
a 186 129 51
a 174 131 52
a 163 115 47
b 186 107 49
b 211 122 49
b 201 144 47
b 242 131 54
b 184 108 43
b 211 118 51
b 217 122 49
b 223 127 51
b 208 125 50
b 199 124 46
")
datos <- read.table(textConnection(input), header = TRUE)
datos$especie <- as.factor(datos$especie)
```

Se define la matriz de datos y la variable respesta con las ## clasificaciones.

```
x<-datos[,2:4]
y<-datos[,1]
```

Definir como n y p el número de flores y variables

```
n<-nrow(x)
p<-ncol(x)
```

Se aplica el Análisis discriminante lineal (LDA)

Cross validation (cv): clasificación óptima

```
lda.iris<-lda(y~.,data=x, CV=TRUE)
```

lda.iris$class contiene las clasificaciones hechas

por CV usando LDA.

```
lda.iris$class
```

```
##  [1] a a a a a a a a a a b a b b b b b b b b
## Levels: a b
```

Creación de la tabla de clasificaciones buenas y malas

```
table.lda<-table(y,lda.iris$class)
table.lda
```

```
##
## y    a  b
##   a 10  0
##   b  2  8
```

Hay 2 mal clasificados

Proporción de errores

```
mis.lda<- n-sum(y==lda.iris$class)
mis.lda/n
```

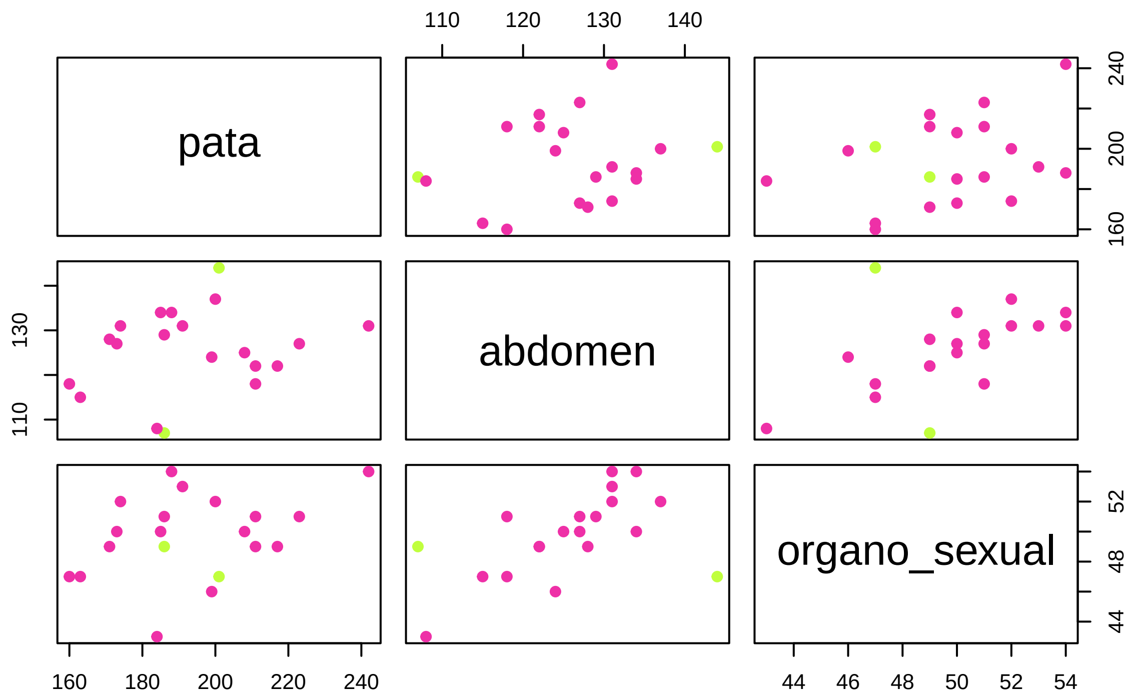
```
## [1] 0.1
```

Se obtiene un 10% de error de clasificación

scater plot

```
col.lda.iris<-c("olivedrab1","maroon2")[1*(y==lda.iris$class)+1]
pairs(x,main="Buena clasificación (Rosa), mala clasificación (Verde)",
      pch=19,col=col.lda.iris)
```

Buena clasificación (Rosa), mala clasificación (Verde)



Probabilidad de pertenencia a uno de los tres grupos

```
lda.iris$posterior
```

```
##               a            b
## 1  9.999944e-01 5.606981e-06
## 2  9.999257e-01 7.430403e-05
## 3  9.974377e-01 2.562308e-03
## 4  9.999996e-01 4.116591e-07
## 5  9.999989e-01 1.123620e-06
## 6  9.999891e-01 1.093188e-05
## 7  1.000000e+00 2.901861e-09
## 8  9.999384e-01 6.155360e-05
## 9  1.000000e+00 2.126082e-11
## 10 9.996688e-01 3.312218e-04
## 11 6.544243e-01 3.455757e-01
## 12 5.475623e-07 9.999995e-01
## 13 9.999997e-01 3.203539e-07
## 14 5.814853e-10 1.000000e+00
## 15 7.388358e-10 1.000000e+00
## 16 2.981347e-05 9.999702e-01
## 17 2.816404e-09 1.000000e+00
## 18 2.418569e-07 9.999998e-01
## 19 1.357653e-04 9.998642e-01
## 20 1.439840e-06 9.999986e-01
```

Gráfico de probabilidades

```
plot(1:n, lda.iris$posterior[,1],
     main="Probabilidades a posteriori",
     pch=20, col="orange",
     xlab="NÃºmero de observaciones", ylab="Probabilidades")
points(1:n,lda.iris$posterior[,2],
       pch=20, col="purple")
```