Bosques aleatorios (clasificacion)

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#Bosques Aleatorios (clasificacion)

```
dataset = read.csv("Social_Network_Ads.csv")
dataset = dataset[,3:5]
```

```
dataset$Purchased = factor(dataset$Purchased, levels = c(0,1))
```

Dividir dataset en conjunto de entranmiento y conjunto de test

```
library(caTools)
```

```
## Warning: package 'caTools' was built under R version 4.0.5
```

```
set.seed(123)
split = sample.split(dataset$Purchased, SplitRatio = 0.75)
```

```
training_set = subset(dataset, split == TRUE)
training_set
```

```
##     Age EstimatedSalary Purchased
## 1    19           19000         0
## 3    26           43000         0
## 6    27           58000         0
## 7    27           84000         0
## 8    32          150000         1
## 10   35           65000         0
## 11   26           80000         0
## 13   20           86000         0
## 14   32           18000         0
## 15   18           82000         0
## 16   29           80000         0
## 17   47           25000         1
## 21   45           22000         1
## 23   48           41000         1
## 24   45           22000         1
## 25   46           23000         1
## 26   47           20000         1
## 27   49           28000         1
## 28   47           30000         1
## 30   31           18000         0
## 31   31           74000         0
## 33   21           16000         0
## 36   35           27000         0
```

```
## 37   33            28000          0
## 39   26            72000          0
## 40   27            31000          0
## 41   27            17000          0
## 42   33            51000          0
## 43   35           108000          0
## 44   30            15000          0
## 47   25            79000          0
## 49   30           135000          1
## 50   31            89000          0
## 51   24            32000          0
## 53   29            83000          0
## 54   35            23000          0
## 55   27            58000          0
## 56   24            55000          0
## 57   23            48000          0
## 58   28            79000          0
## 59   22            18000          0
## 60   32           117000          0
## 61   27            20000          0
## 62   25            87000          0
## 63   23            66000          0
## 64   32           120000          1
## 65   59            83000          0
## 67   24            19000          0
## 68   23            82000          0
## 70   31            68000          0
## 71   25            80000          0
## 72   24            27000          0
## 73   20            23000          0
## 76   34           112000          1
## 77   18            52000          0
## 78   22            27000          0
## 79   28            87000          0
## 80   26            17000          0
## 81   30            80000          0
## 83   20            49000          0
## 88   28            85000          0
## 90   35            50000          0
## 91   22            81000          0
## 92   30           116000          0
## 93   26            15000          0
## 94   29            28000          0
## 95   29            83000          0
## 96   35            44000          0
## 97   35            25000          0
## 98   28           123000          1
## 99   35            73000          0
## 100  28            37000          0
## 101  27            88000          0
## 102  28            59000          0
## 105  19            21000          0
## 106  21            72000          0
## 110  38            80000          0
```

```
## 111  39           71000         0
## 112  37           71000         0
## 113  38           61000         0
## 114  37           55000         0
## 115  42           80000         0
## 116  40           57000         0
## 118  36           52000         0
## 119  40           59000         0
## 120  41           59000         0
## 121  36           75000         0
## 122  37           72000         0
## 123  40           75000         0
## 125  41           51000         0
## 128  26           32000         0
## 129  30           17000         0
## 130  26           84000         0
## 132  33           31000         0
## 133  30           87000         0
## 135  28           55000         0
## 136  23           63000         0
## 137  20           82000         0
## 138  30          107000         1
## 140  19           25000         0
## 141  19           85000         0
## 142  18           68000         0
## 143  35           59000         0
## 144  30           89000         0
## 145  34           25000         0
## 146  24           89000         0
## 147  27           96000         1
## 149  29           61000         0
## 150  20           74000         0
## 151  26           15000         0
## 152  41           45000         0
## 153  31           76000         0
## 155  40           47000         0
## 157  46           59000         0
## 158  29           75000         0
## 160  32          135000         1
## 161  32          100000         1
## 164  35           38000         0
## 165  33           69000         0
## 166  18           86000         0
## 167  22           55000         0
## 168  35           71000         0
## 169  29          148000         1
## 171  21           88000         0
## 172  34          115000         0
## 173  26          118000         0
## 174  34           43000         0
## 177  35           47000         0
## 178  25           22000         0
## 179  24           23000         0
## 180  31           34000         0
```

```
## 181  26           16000         0
## 182  31           71000         0
## 183  32          117000         1
## 184  33           43000         0
## 185  33           60000         0
## 186  31           66000         0
## 187  20           82000         0
## 188  33           41000         0
## 189  35           72000         0
## 190  28           32000         0
## 191  24           84000         0
## 192  19           26000         0
## 194  19           70000         0
## 195  28           89000         0
## 196  34           43000         0
## 197  30           79000         0
## 198  20           36000         0
## 201  35           39000         0
## 202  49           74000         0
## 203  39          134000         1
## 204  41           71000         0
## 205  58          101000         1
## 206  47           47000         0
## 207  55          130000         1
## 209  40          142000         1
## 210  46           22000         0
## 211  48           96000         1
## 212  52          150000         1
## 214  35           58000         0
## 215  47           43000         0
## 216  60          108000         1
## 217  49           65000         0
## 218  40           78000         0
## 219  46           96000         0
## 220  59          143000         1
## 221  41           80000         0
## 222  35           91000         1
## 223  37          144000         1
## 225  35           60000         0
## 227  36          126000         1
## 231  35          147000         1
## 232  39           42000         0
## 233  40          107000         1
## 235  38          112000         0
## 238  37           80000         0
## 240  53          143000         1
## 242  38           59000         0
## 243  50           88000         1
## 244  56          104000         1
## 245  41           72000         0
## 246  51          146000         1
## 247  35           50000         0
## 248  57          122000         1
## 249  41           52000         0
```

```
## 250  35           97000         1
## 251  44           39000         0
## 252  37           52000         0
## 253  48          134000         1
## 254  37          146000         1
## 256  52           90000         1
## 257  41           72000         0
## 258  40           57000         0
## 259  58           95000         1
## 260  45          131000         1
## 261  35           77000         0
## 262  36          144000         1
## 263  55          125000         1
## 267  40           75000         0
## 268  37           74000         0
## 269  47          144000         1
## 270  40           61000         0
## 271  43          133000         0
## 272  59           76000         1
## 275  57           26000         1
## 276  57           74000         1
## 277  38           71000         0
## 278  49           88000         1
## 279  52           38000         1
## 280  50           36000         1
## 282  35           61000         0
## 283  37           70000         1
## 284  52           21000         1
## 285  48          141000         0
## 287  37           62000         0
## 288  48          138000         1
## 289  41           79000         0
## 290  37           78000         1
## 291  39          134000         1
## 293  55           39000         1
## 294  37           77000         0
## 295  35           57000         0
## 296  36           63000         0
## 297  42           73000         1
## 298  43          112000         1
## 300  46          117000         1
## 301  58           38000         1
## 303  37          137000         1
## 304  37           79000         1
## 306  42           54000         0
## 308  47          113000         1
## 309  36          125000         1
## 311  42           70000         0
## 312  39           96000         1
## 313  38           50000         0
## 314  49          141000         1
## 315  39           79000         0
## 317  54          104000         1
## 318  35           55000         0
```

```
## 319  45           32000         1
## 320  36           60000         0
## 321  52          138000         1
## 322  53           82000         1
## 323  41           52000         0
## 325  48          131000         1
## 327  41           72000         0
## 328  42           75000         0
## 329  36          118000         1
## 330  47          107000         1
## 331  38           51000         0
## 333  42           65000         0
## 334  40           65000         0
## 335  57           60000         1
## 336  36           54000         0
## 337  58          144000         1
## 338  35           79000         0
## 340  39          122000         1
## 342  35           75000         0
## 344  47           51000         1
## 345  47          105000         1
## 346  41           63000         0
## 348  54          108000         1
## 349  39           77000         0
## 350  38           61000         0
## 351  38          113000         1
## 352  37           75000         0
## 354  37           57000         0
## 355  36           99000         1
## 356  60           34000         1
## 357  54           70000         1
## 358  41           72000         0
## 359  40           71000         1
## 360  42           54000         0
## 361  43          129000         1
## 362  53           34000         1
## 365  42          104000         1
## 366  59           29000         1
## 370  54           26000         1
## 371  60           46000         1
## 374  59          130000         1
## 375  37           80000         0
## 376  46           32000         1
## 377  46           74000         0
## 378  42           53000         0
## 379  41           87000         1
## 381  42           64000         0
## 382  48           33000         1
## 384  49           28000         1
## 385  57           33000         1
## 386  56           60000         1
## 387  49           39000         1
## 388  39           71000         0
## 390  48           35000         1
```

```
## 391  48           33000         1
## 393  45           45000         1
## 394  60           42000         1
## 396  46           41000         1
## 397  51           23000         1
## 398  50           20000         1
## 399  36           33000         0
```

```
testing_set = subset(dataset, split == FALSE)
testing_set
```

```
##     Age EstimatedSalary Purchased
## 2    35           20000         0
## 4    27           57000         0
## 5    19           76000         0
## 9    25           33000         0
## 12   26           52000         0
## 18   45           26000         1
## 19   46           28000         1
## 20   48           29000         1
## 22   47           49000         1
## 29   29           43000         0
## 32   27          137000         1
## 34   28           44000         0
## 35   27           90000         0
## 38   30           49000         0
## 45   28           84000         0
## 46   23           20000         0
## 48   27           54000         0
## 52   18           44000         0
## 66   24           58000         0
## 69   22           63000         0
## 74   33          113000         0
## 75   32           18000         0
## 82   39           42000         0
## 84   35           88000         0
## 85   30           62000         0
## 86   31          118000         1
## 87   24           55000         0
## 89   26           81000         0
## 103  32           86000         0
## 104  33          149000         1
## 107  26           35000         0
## 108  27           89000         0
## 109  26           86000         0
## 117  35           75000         0
## 124  35           53000         0
## 126  39           61000         0
## 127  42           65000         0
## 131  31           58000         0
## 134  21           68000         0
## 139  28           59000         0
## 148  41           30000         0
## 154  36           50000         0
## 156  31           15000         0
```

```
## 159  26           30000         0
## 162  25           90000         0
## 163  37           33000         0
## 170  29           47000         0
## 175  34           72000         0
## 176  23           28000         0
## 193  29           43000         0
## 199  26           80000         0
## 200  35           22000         0
## 208  52          114000         0
## 213  59           42000         0
## 224  60          102000         1
## 226  37           53000         0
## 228  56          133000         1
## 229  40           72000         0
## 230  42           80000         1
## 234  49           86000         1
## 236  46           79000         1
## 237  40           57000         0
## 239  46           82000         0
## 241  42          149000         1
## 255  50           44000         0
## 264  35           72000         0
## 265  48           90000         1
## 266  42          108000         1
## 273  60           42000         1
## 274  39          106000         1
## 281  59           88000         1
## 286  37           93000         1
## 292  49           89000         1
## 299  45           79000         0
## 302  48           74000         1
## 305  40           60000         0
## 307  51          134000         0
## 310  38           50000         0
## 316  39           75000         1
## 324  48           30000         1
## 326  41           60000         0
## 332  48          119000         1
## 339  38           55000         0
## 341  53          104000         1
## 343  38           65000         0
## 347  53           72000         1
## 353  42           90000         1
## 363  47           50000         1
## 364  42           79000         0
## 367  58           47000         1
## 368  46           88000         1
## 369  38           71000         0
## 372  60           83000         1
## 373  39           73000         0
## 380  58           23000         1
## 383  44          139000         1
## 389  47           34000         1
```

```
## 392  47           23000         1
## 395  39           59000         0
## 400  49           36000         1
```

Escalado de datos

Standardisation

$$x_{stand} = \frac{x - mean(x)}{sd(x)}$$

```
training_set[,1:2] = scale(training_set[,1:2])
testing_set[,1:2]= scale(testing_set[,1:2])
```

Ajustar el modelo de Regresión Logística con el conjunto de entrenamiento y hacer las predicciones con el conjunto testing

```
library(randomForest)
```

```
## Warning: package 'randomForest' was built under R version 4.0.5
```

```
## randomForest 4.6-14
```

```
## Type rfNews() to see new features/changes/bug fixes.
```

```
classifier = randomForest(x = training_set[, -3],
                          y = training_set$Purchased,
                          ntree = 10)
```

```
y_pred = predict(classifier, newdata = testing_set[,-3])
y_pred
```

```
##   2   4   5   9  12  18  19  20  22  29  32  34  35  38  45  46  48  52  66  69
##   0   0   0   0   0   0   1   1   0   0   0   0   0   0   0   0   0   0   0   0
##  74  75  82  84  85  86  87  89 103 104 107 108 109 117 124 126 127 131 134 139
##   1   0   0   1   0   1   0   0   0   1   0   0   0   0   0   0   0   0   0   0
## 148 154 156 159 162 163 170 175 176 193 199 200 208 213 224 226 228 229 230 234
##   0   0   0   0   0   0   0   0   0   0   0   0   1   1   1   0   1   0   0   1
## 236 237 239 241 255 264 265 266 273 274 281 286 292 299 302 305 307 310 316 324
##   1   0   0   1   0   0   1   1   1   1   1   1   1   0   0   0   1   0   0   1
## 326 332 339 341 343 347 353 363 364 367 368 369 372 373 380 383 389 392 395 400
##   0   1   0   1   0   1   1   0   0   1   0   0   1   0   1   0   1   1   0   1
## Levels: 0 1
```

Comparar uno a uno los resultados predichos con los esperados no es una buena técnica por lo que se construye la matriz de confusión

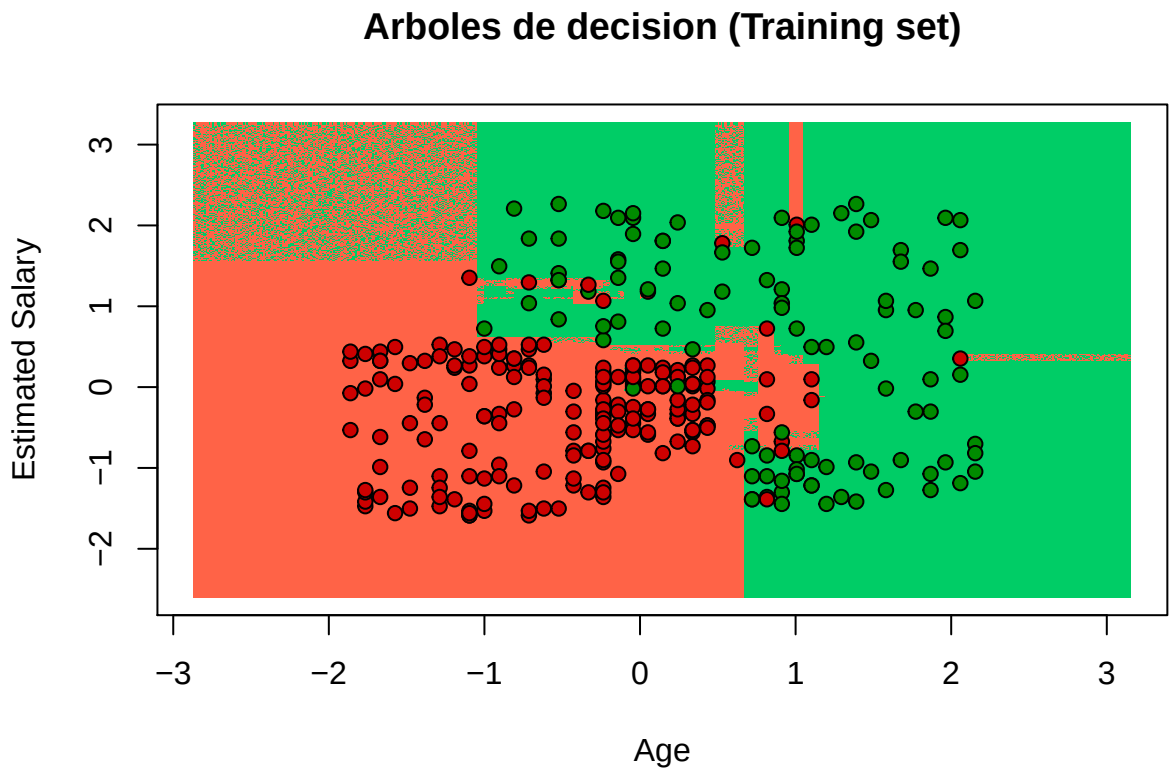
```
cm = table(testing_set[, 3], y_pred)
cm
```

```
##    y_pred
##      0  1
##   0 59  5
##   1  9 27
```

La diagonal principal es la cantidad de datos que son predichos correctamente.La diagonal secundaria son los fallos.

Visualización del conjunto de entranmiento

```
library(ElemStatLearn)
set = training_set
X1 = seq(min(set[, 1]) - 1, max(set[, 1]) + 1, by = 0.01)
X2 = seq(min(set[, 2]) - 1, max(set[, 2]) + 1, by = 0.01)
grid_set = expand.grid(X1, X2)
colnames(grid_set) = c('Age', 'EstimatedSalary')
y_grid = predict(classifier,
                 newdata = grid_set)
plot(set[, -3],
     main = 'Arboles de decision (Training set)',
     xlab = 'Age', ylab = 'Estimated Salary',
     xlim = range(X1), ylim = range(X2))
contour(X1, X2, matrix(as.numeric(y_grid), length(X1), length(X2)), add = TRUE)
points(grid_set, pch = '.', col = ifelse(y_grid == 1, 'springgreen3', 'tomato'))
points(set, pch = 21, bg = ifelse(set[, 3] == 1, 'green4', 'red3'))
```



Visualising the Test set results

```
library(ElemStatLearn)
set = testing_set
X1 = seq(min(set[, 1]) - 1, max(set[, 1]) + 1, by = 0.01)
X2 = seq(min(set[, 2]) - 1, max(set[, 2]) + 1, by = 0.01)
```

```
grid_set = expand.grid(X1, X2)
colnames(grid_set) = c('Age', 'EstimatedSalary')
y_grid = predict(classifier,
                 newdata = grid_set)
plot(set[, -3],
     main = 'Arboles de decision (Test set)',
     xlab = 'Age', ylab = 'Estimated Salary',
     xlim = range(X1), ylim = range(X2))
contour(X1, X2, matrix(as.numeric(y_grid), length(X1), length(X2)), add = TRUE)
points(grid_set, pch = '.', col = ifelse(y_grid == 1, 'springgreen3', 'tomato'))
points(set, pch = 21, bg = ifelse(set[, 3] == 1, 'green4', 'red3'))
```