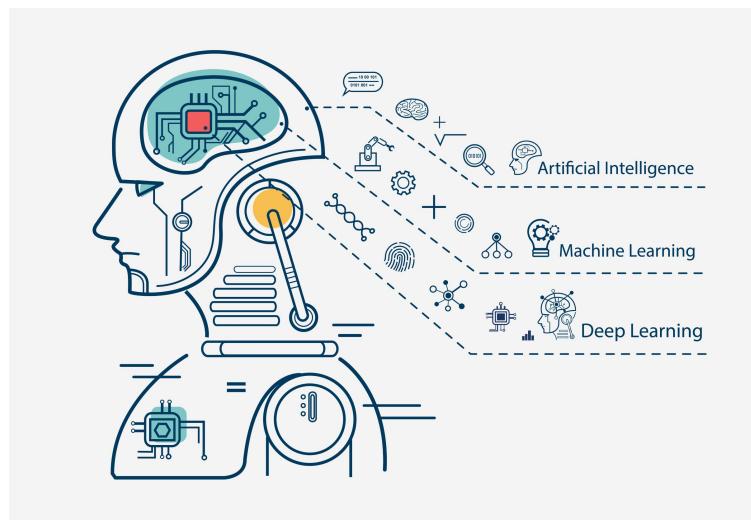


Proyecto final

COA-501 Herramientas de cómputo para investigadores (R y Python)

Iván F. Quiroz Ibáñez*

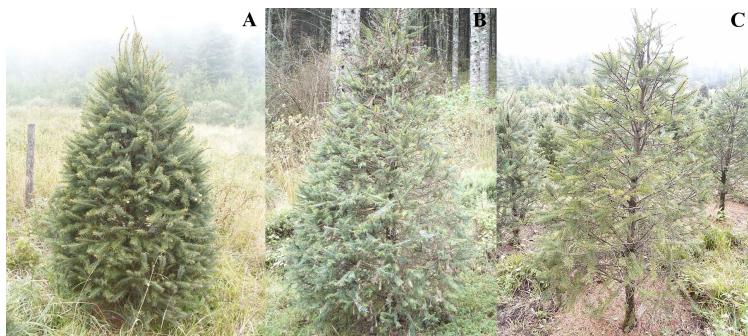
20 de noviembre de 2022



*IFIT-CP, quiroz.ivan@colpos.mx

0) Estudio de caso

Se cuenta con la base de datos de un experimento realizado en Puebla, dónde se evaluaron los efectos de fertilizantes y plaguicidas contra una enfermedad foliar conocida como tizón suizo en árboles de navidad de la especie Douglas-fir. Se tomaron variables como transparencia de copa, severidad, incidencia, longitud de brotes, área de acículas, etc. El objetivo del análisis es determinar la mejor técnica de machine learning o aprendizaje automático (Naive Bayes, K-NN y Random Forest) para clasificar la transparencia de copa en Douglas-fir.



Análisis de clasificación de la transparencia de copa en *Pseudotsuga menziesii* con técnicas de aprendizaje automatizado

Variables:

- Arbol= unidad experimental (UE)
- Bloque= Transparencia de copa asignada como baja,media y alta
- Longitud= distancia en grados, minutos y segundos que hay con respecto al meridiano principal, que es el meridiano de Greenwich (0°) de la UE
- Latitud= distancia en grados, minutos y segundos que hay con respecto al paralelo principal, que es el ecuador (0°)
- X_UTM= coordenada X en el sistema de coordenadas universal transversal de Mercator
- Y_UTM= coordenada Y en el sistema de coordenadas universal transversal de Mercator
- Altitud= distancia vertical de la UE respecto al nivel del mar
- AltRan= Rango de Altitud de las UE en dos categorías: Alta y Baja
- Fungicida= Tratamiento fungicida (Procloraz, Propiconazol o sin fungicida)
- Nutrimiento= Tratamiento fertilizante (Urea, Sulfato de potasio o sin fertilizante)
- Rep= repetición de la UE por tratamiento en un diseño experimental factorial en bloques generalizados
- Muestreo= número de muestreo de follaje (se realizaron 6)
- DDA= días después de la aplicación o del establecimiento del experimento
- Anio= edad del follaje o muestra
- AcicR= número de acículas retenidas de rama o muestra
- Abs= Número de cicatrices de acículas de la rama o muestra
- TotalAc= Total de acículas (AcicR + Abs)
- Inc= Incidencia del tizón suizo
- Sevmed= Severidad media del tizón suizo
- Sevmin= Severidad mínima del tizón suizo
- Sevmax= Severidad máxima del tizón suizo
- LonBrot= Longitud de la rama o muestrae en centímetros
- indcol= Índice de colonización (Inc * Sevmed)
- Afmed= Área media de acícula (Área de acículas en centímetros cuadrados por muestra)
- Afmax= Área máxima de acícula por muestra



- Afmin= Área mínima de acícula por muestra
- Aftotal= Suma de área de acículas por muestra
- CA= Abs expresada en porcentaje ($Abs*100/TotalAC$)
- RA= RA expresada en porcentaje ($RA*100/TotalAC$)
- Color= Categorías de color por cada muestra (Verde claro, verde oscuro y rojizo)
- trat= Interacción de tratamientos (Fungicida*Nutriamento)
- ABCPEIC= Área bajo la curva progreso de la enfermedad con el índice de colonización

1) Base de datos y AED

```
#base de datos
summary(base)
```

```
##      Arbol      Bloque      Longitud      Latitud      X_UTM
## 1     : 12     Alta :216    Min. :-97.99    Min. :19.72   Min. :605708
## 2     : 12     Baja :216   1st Qu.:-97.99   1st Qu.:19.72  1st Qu.:605724
## 3     : 12   Media:216   Median :-97.99   Median :19.72  Median :605732
## 4     : 12           Mean :-97.99   Mean  :19.72  Mean  :605732
## 5     : 12           3rd Qu.:-97.99  3rd Qu.:19.72 3rd Qu.:605741
## 6     : 12           Max. :-97.99   Max. :19.72  Max. :605759
## (Other):576
##      Y_UTM      Altitud      AltRan      Fungicida Nutriemento      Rep
##  Min.  :2180985  Min.  :2973  Alta:312  1:216    1:216    Min.  :1.0
##  1st Qu.:2181009 1st Qu.:2979  Baja:336  2:216    2:216    1st Qu.:1.0
##  Median :2181025 Median :2982           3:216    3:216    Median :1.5
##  Mean   :2181027 Mean   :2985           NA's    NA's    Mean   :1.5
##  3rd Qu.:2181039 3rd Qu.:2991           NA's    NA's    3rd Qu.:2.0
##  Max.   :2181087 Max.   :2994           NA's    NA's    Max.   :2.0
##
##      Muestreo DDA      Anio      AcicR      Abs
## 1:108    0 :108 2016:324  Min.  : 30.00  Min.  : 0.00
## 2:108    63 :108 2017:324  1st Qu.: 83.75 1st Qu.: 0.00
## 3:108    91 :108           Median :101.00 Median : 2.00
## 4:108   119:108           Mean   :103.14 Mean  : 6.91
## 5:108   147:108           3rd Qu.:121.00 3rd Qu.: 8.00
## 6:108   175:108           Max.   :225.00 Max.  :104.00
##          NA's   :24       NA's   :24       NA's   :24
##
##      TotalAc      Inc      Sevmed      Sevmin
##  Min.  : 36.0  Min.  :0.0000  Min.  :0.00000  Min.  :0.00000
##  1st Qu.: 91.0 1st Qu.:0.0000  1st Qu.:0.00000  1st Qu.:0.00000
##  Median :108.0 Median :0.2667  Median :0.01483 Median :0.00000
##  Mean   :110.1 Mean   :0.4584  Mean   :0.12498 Mean  :0.06102
##  3rd Qu.:128.0 3rd Qu.:0.9667 3rd Qu.:0.24258 3rd Qu.:0.10333
##  Max.   :225.0 Max.   :1.0000  Max.   :0.61900 Max.  :0.50667
##  NA's   :24     NA's   :24     NA's   :24     NA's   :24
##
##      Sevmax      LonBrot      indcol      Afmed
##  Min.  :0.00000  Min.  : 3.300  Min.  : 0.00  Min.  :0.1322
##  1st Qu.:0.00000 1st Qu.: 7.000  1st Qu.: 0.00  1st Qu.:0.2610
##  Median :0.07333 Median : 8.450  Median : 0.46  Median :0.3096
##  Mean   :0.20214 Mean   : 8.629  Mean   :11.72  Mean  :0.3117
##  3rd Qu.:0.40083 3rd Qu.: 9.963 3rd Qu.:22.85 3rd Qu.:0.3577
##  Max.   :0.90667 Max.   :23.400  Max.   :61.90  Max.  :0.6133
```



```
##  NA's   :24      NA's   :24      NA's   :24      NA's   :24
##    Afmax      Afmin      Aftotal     CA
##  Min.   :0.152  Min.   :0.0910  Min.   : 3.966  Min.   : 0.000
##  1st Qu.:0.300 1st Qu.:0.2087 1st Qu.: 7.831 1st Qu.: 0.000
##  Median :0.352 Median :0.2470 Median : 9.287 Median : 1.646
##  Mean   :0.358 Mean   :0.2486 Mean   : 9.350 Mean   : 6.178
##  3rd Qu.:0.411 3rd Qu.:0.2870 3rd Qu.:10.730 3rd Qu.: 7.692
##  Max.   :0.849 Max.   :0.4440 Max.   :18.398 Max.   :64.662
##  NA's   :24      NA's   :24      NA's   :24      NA's   :24
##    RA        Color       trat      ABCPEIC
##  Min.   : 35.34  Min.   :1.000  11   : 72  Min.   : 0.0000
##  1st Qu.: 92.31 1st Qu.:1.000  12   : 72  1st Qu.: 0.0000
##  Median : 98.35 Median :2.000  13   : 72  Median : 0.1925
##  Mean   : 93.82 Mean   :1.694  21   : 72  Mean   : 326.8269
##  3rd Qu.:100.00 3rd Qu.:2.000  22   : 72  3rd Qu.: 683.7950
##  Max.   :100.00 Max.   :3.000  23   : 72  Max.   :2850.9250
##  NA's   :24      NA's   :24      (Other):216
```

```
class(base)

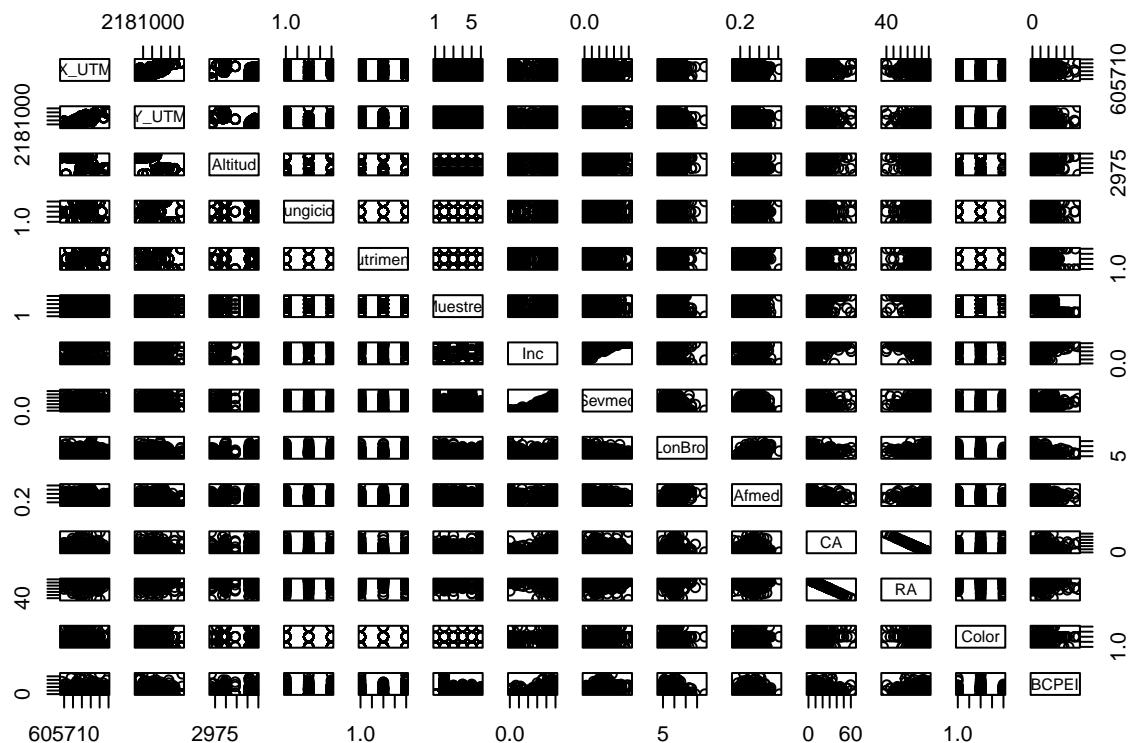
## [1] "data.frame"

str(base)

## 'data.frame':   648 obs. of  32 variables:
## $ Arbol     : Factor w/ 54 levels "1","2","3","4",...: 1 2 3 4 5 6 7 8 9 10 ...
## $ Bloque    : Factor w/ 3 levels "Alta","Baja",...: 1 1 1 1 1 1 1 1 1 1 ...
## $ Longitud   : num -98 -98 -98 -98 -98 ...
## $ Latitud    : num 19.7 19.7 19.7 19.7 19.7 ...
## $ X_UTM     : num 605748 605744 605740 605754 605742 ...
## $ Y_UTM     : num 2181070 2181057 2181039 2181034 2181026 ...
## $ Altitud    : num 2979 2979 2980 2980 2984 ...
## $ AltRan     : Factor w/ 2 levels "Alta","Baja": 2 2 2 2 2 1 1 1 1 1 ...
## $ Fungicida  : Factor w/ 3 levels "1","2","3": 1 1 2 1 2 1 1 2 2 3 ...
## $ Nutrimiento: Factor w/ 3 levels "1","2","3": 1 2 2 2 1 3 3 3 2 1 ...
## $ Rep        : int 1 1 1 2 1 1 2 1 2 1 ...
## $ Muestreo   : Factor w/ 6 levels "1","2","3","4",...: 1 1 1 1 1 1 1 1 1 1 ...
## $ DDA        : Factor w/ 6 levels "0","63","91",...: 1 1 1 1 1 1 1 1 1 1 ...
## $ Anio       : Factor w/ 2 levels "2016","2017": 1 1 1 1 1 1 1 1 1 1 ...
## $ AcicR     : int 74 129 69 33 98 71 68 44 92 92 ...
## $ Abs        : int 25 2 2 6 20 15 3 5 4 15 ...
## $ TotalAc   : int 99 131 71 39 118 86 71 49 96 107 ...
## $ Inc        : num 0.9 1 0.767 1 1 ...
## $ Sevmed    : num 0.15 0.331 0.347 0.351 0.384 ...
## $ Sevmin    : num 0 0.137 0 0.21 0.197 ...
## $ Sevmax    : num 0.4 0.667 0.583 0.573 0.56 ...
## $ LonBrot   : num 7.25 12.9 5.1 3.9 9.25 5 6.8 4.5 7.7 9.55 ...
## $ indcol    : num 13.5 33.1 26.6 35.1 38.4 ...
## $ Afmed     : num 0.239 0.374 0.196 0.37 0.362 ...
## $ Afmax     : num 0.275 0.436 0.217 0.411 0.482 ...
## $ Afmin     : num 0.194 0.308 0.163 0.286 0.29 ...
## $ Aftotal   : num 7.18 11.23 5.88 11.1 10.87 ...
## $ CA         : num 25.25 1.53 2.82 15.38 16.95 ...
```

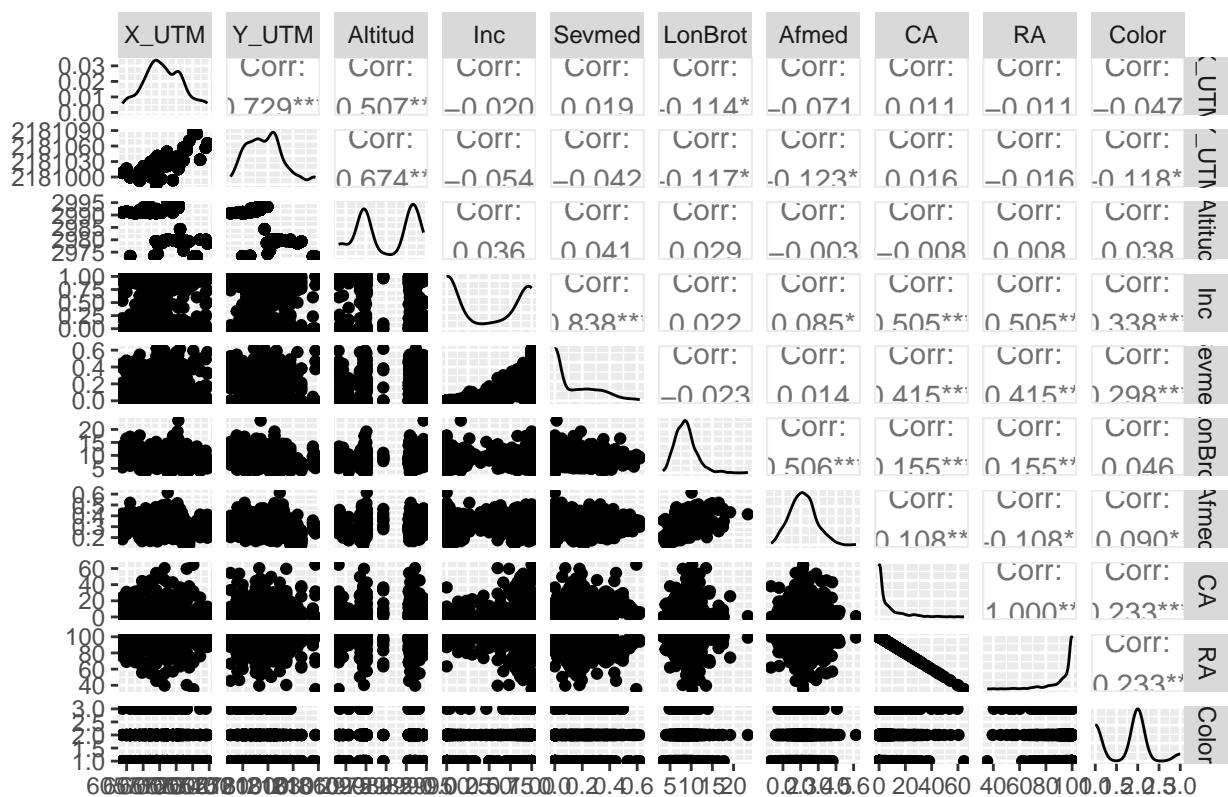
```
## $ RA      : num  74.7 98.5 97.2 84.6 83.1 ...
## $ Color   : int  1 1 1 1 1 1 1 1 1 1 ...
## $ trat    : Factor w/ 9 levels "11","12","13",...: 1 2 5 2 4 3 3 6 5 7 ...
## $ ABCPEIC : num  0 0 0 0 0 0 0 0 0 0 ...
```

```
#matriz de diagramas de dispersion  
pairs(base[,c(5,6,7,9,10,12,18,19,22,24,28:30,32)])  
  
library(GGally)
```

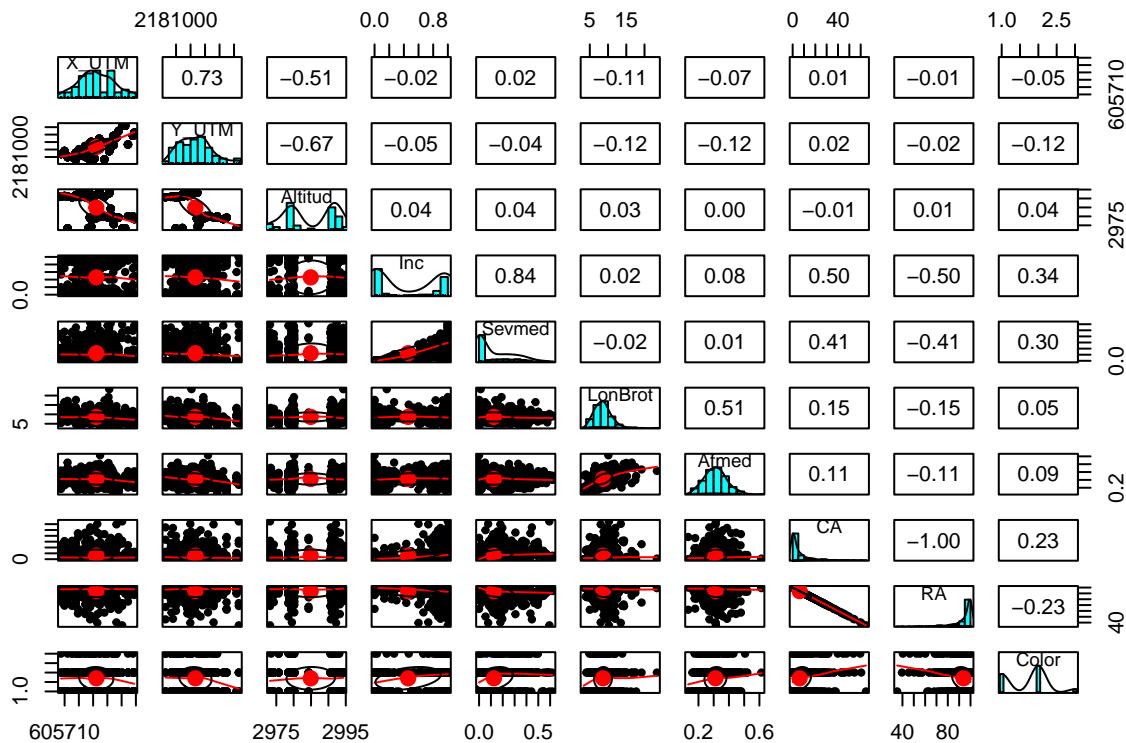


```
ggpairs(base[,c(5,6,7,18,19,22,24,28:30)],  
       title="correlograma con ggpairs")
```

correlograma con ggpairs



```
psych::pairs.panels(base[,c(5,6,7,18,19,22,24,28:30)])
```



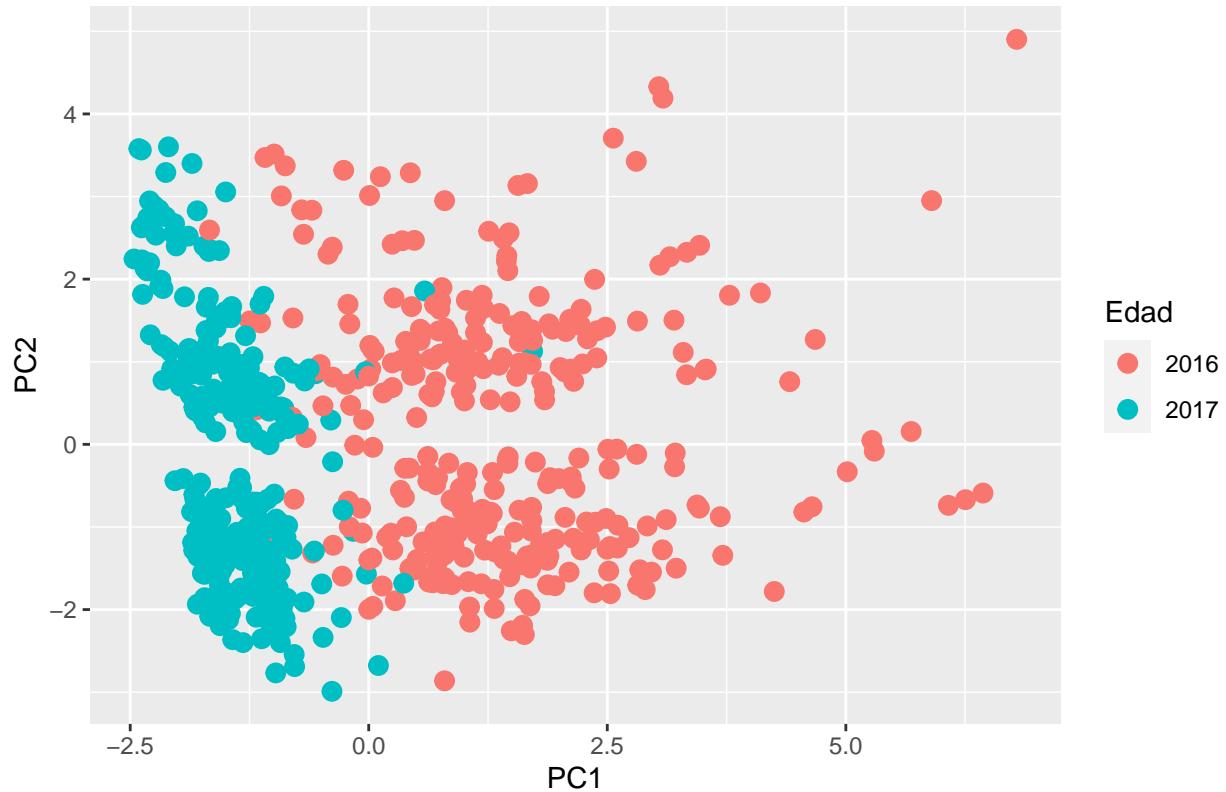
```
base.pc<- na.omit(base[,c(14,2,5,6,7,18,19,22,24,28:30)])
```

```
#Análisis de componentes principales
pca <- prcomp(base.pc[,-c(1,2)], scale = T, center=T)
summary(pca)
```

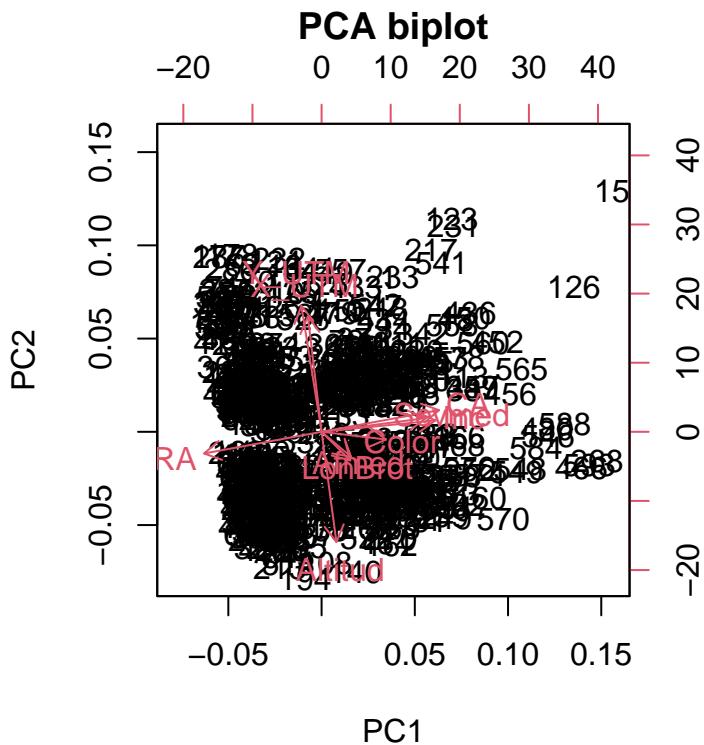
```
## Importance of components:
##                 PC1    PC2    PC3    PC4    PC5    PC6    PC7
## Standard deviation   1.7451 1.5196 1.2216 1.0107 0.88496 0.70241 0.69614
## Proportion of Variance 0.3045 0.2309 0.1492 0.1021 0.07832 0.04934 0.04846
## Cumulative Proportion 0.3045 0.5354 0.6847 0.7868 0.86512 0.91446 0.96292
##                  PC8    PC9    PC10
## Standard deviation   0.46896 0.38840 1.265e-10
## Proportion of Variance 0.02199 0.01509 0.000e+00
## Cumulative Proportion 0.98491 1.00000 1.000e+00
```

```
#biplot
library(ggplot2)
Edad <- as.factor(base.pc$Anio)
plot4 <- ggplot(base.pc, aes(x = pca$x[,1], y = pca$x[,2], colour = Edad)) +
  geom_point(size=3) + xlab("PC1") + ylab("PC2")+
  ggtitle("PCA por Edad del follaje")
plot4
```

PCA por Edad del follaje



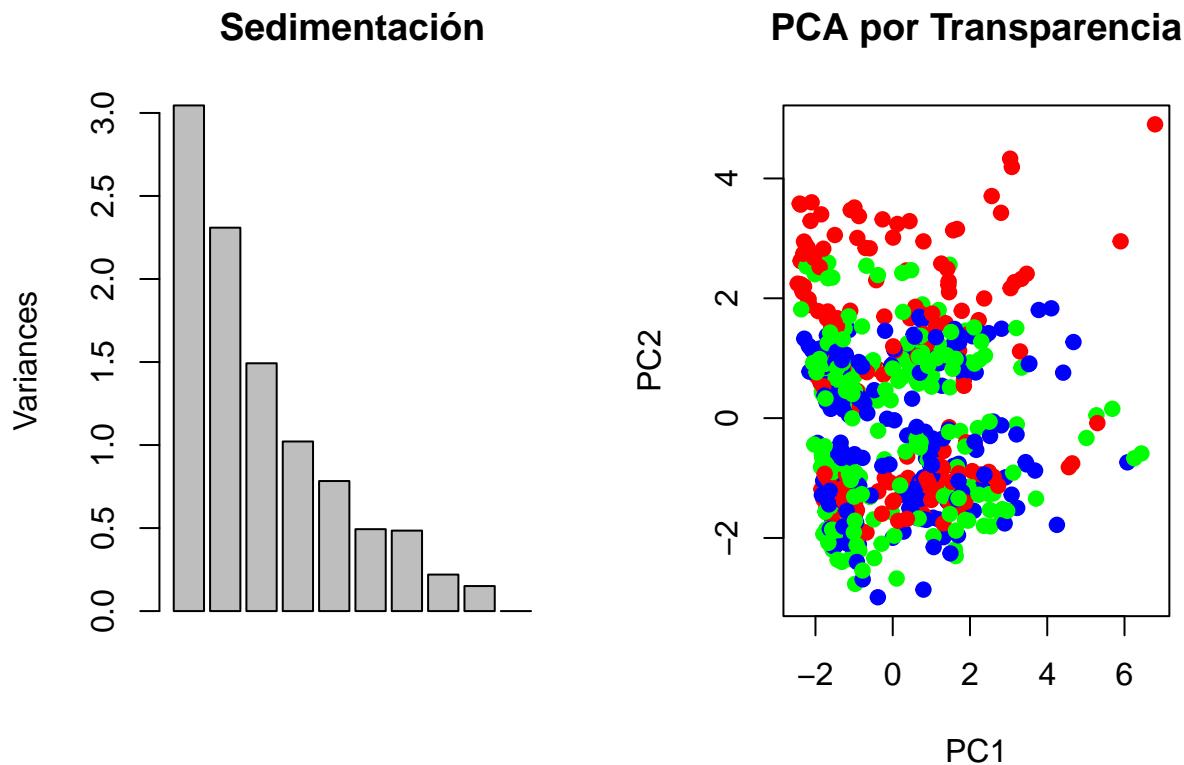
```
biplot(pca, main="PCA biplot")
```



```
par(mfrow = c(1,2))
plot(pca, main="Sedimentaci?n")

colores <- function(vec){
  # la funci?n rainbow() devuelve un vector que contiene el n?mero de colores distintos
  col <- rainbow(length(unique(vec)))
  return(col[as.numeric(as.factor(vec))])
}

plot(pca$x[,c(1, 2)], col = colores(base.pc$Bloque),
  pch = 19,
  xlab = "PC1",
  ylab = "PC2", main="PCA por Transparencia")
```



```
dev.off()
```

```
## null device
##      1
```

Interpretación: De acuerdo con el AED y ACP se seleccionaron las variables transparencia de copa, coordenadas UTM (X y Y), altitud, incidencia, severidad, longitud de brote, área de acícula, acículas caídas, acículas retenidas y color de acícula, para implementar las técnicas de ML.

2) Random Forest

```
library(randomForest)
library(caret)

#Getting Data
base_rf <- na.omit(base[,c(2,5,6,7,18,19,22,24,28:30)])

base_rf$Bloque <- as.factor(base_rf$Bloque)
table(base_rf$Bloque)

## 
## Alta  Baja Media
##   200   216   208
```



```
#Data Partition
set.seed(123)
ind <- sample(2, nrow(base_rf), replace = TRUE, prob = c(0.7, 0.3))
train <- base_rf[ind==1,]
test <- base_rf[ind==2,]

#Random Forest in R
rf <- randomForest(Bloque~, data=train, proximity=TRUE)
rf

##
## Call:
##   randomForest(formula = Bloque ~ ., data = train, proximity = TRUE)
##           Type of random forest: classification
##                   Number of trees: 500
##   No. of variables tried at each split: 3
##
##           OOB estimate of error rate: 2.28%
## Confusion matrix:
##      Alta Baja Media class.error
## Alta    132    4     1  0.03649635
## Baja      0   160     0  0.00000000
## Media     4     1   136  0.03546099

#Confusion Matrix and Statistics
p1 <- predict(rf, train)
confusionMatrix(p1, train$Bloque)

## Confusion Matrix and Statistics
##
## Reference
## Prediction Alta Baja Media
## Alta    137    0     0
## Baja      0   160     0
## Media     0     0   141
##
## Overall Statistics
##
##           Accuracy : 1
##           95% CI : (0.9916, 1)
##   No Information Rate : 0.3653
##   P-Value [Acc > NIR] : < 2.2e-16
##
##           Kappa : 1
##
##   Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##           Class: Alta Class: Baja Class: Media
## Sensitivity          1.0000      1.0000      1.0000
## Specificity          1.0000      1.0000      1.0000
## Pos Pred Value       1.0000      1.0000      1.0000
```



```
## Neg Pred Value      1.0000      1.0000      1.0000
## Prevalence          0.3128      0.3653      0.3219
## Detection Rate     0.3128      0.3653      0.3219
## Detection Prevalence 0.3128      0.3653      0.3219
## Balanced Accuracy   1.0000      1.0000      1.0000
```

```
(tab1 <- table(p1, train$Bloque))
```

```
##
## p1      Alta Baja Media
## Alta    137   0   0
## Baja     0   160   0
## Media    0   0   141
```

```
1 - sum(diag(tab1)) / sum(tab1)
```

```
## [1] 0
```

```
#error del 0%
```

```
p2 <- predict(rf, test)
confusionMatrix(p2, test$Bloque)
```

```
## Confusion Matrix and Statistics
##
##             Reference
## Prediction Alta Baja Media
## Alta       60   0   0
## Baja        2   56   0
## Media       1   0   67
##
## Overall Statistics
##
##                 Accuracy : 0.9839
##                   95% CI : (0.9536, 0.9967)
## No Information Rate : 0.3602
## P-Value [Acc > NIR] : < 2.2e-16
##
##                 Kappa : 0.9758
##
## McNemar's Test P-Value : NA
##
## Statistics by Class:
##
##                         Class: Alta Class: Baja Class: Media
## Sensitivity            0.9524      1.0000      1.0000
## Specificity           1.0000      0.9846      0.9916
## Pos Pred Value        1.0000      0.9655      0.9853
## Neg Pred Value        0.9762      1.0000      1.0000
## Prevalence            0.3387      0.3011      0.3602
## Detection Rate        0.3226      0.3011      0.3602
```

```
## Detection Prevalence      0.3226      0.3118      0.3656
## Balanced Accuracy        0.9762      0.9923      0.9958
```

```
(tab2 <- table(p2, test$Bloque))
```

```
##
## p2      Alta Baja Media
##   Alta     60    0    0
##   Baja      2   56    0
##   Media     1    0   67
```

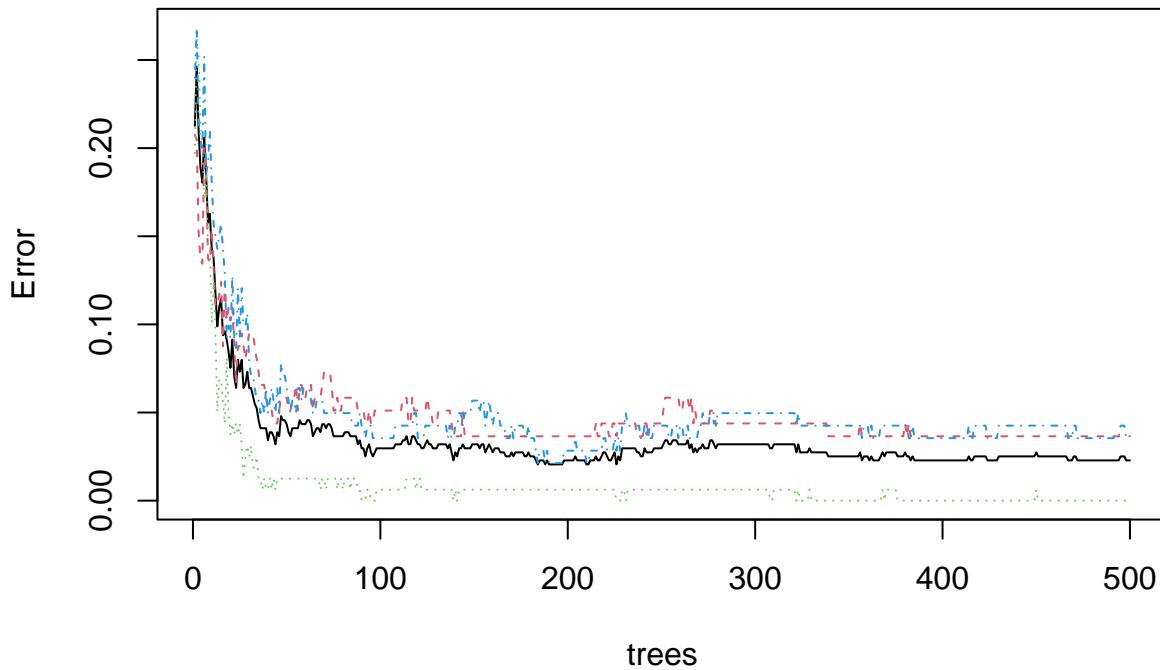
```
1 - sum(diag(tab2)) / sum(tab2)
```

```
## [1] 0.01612903
```

```
#error del 0%
```

```
#Error rate of Random Forest
plot(rf)
```

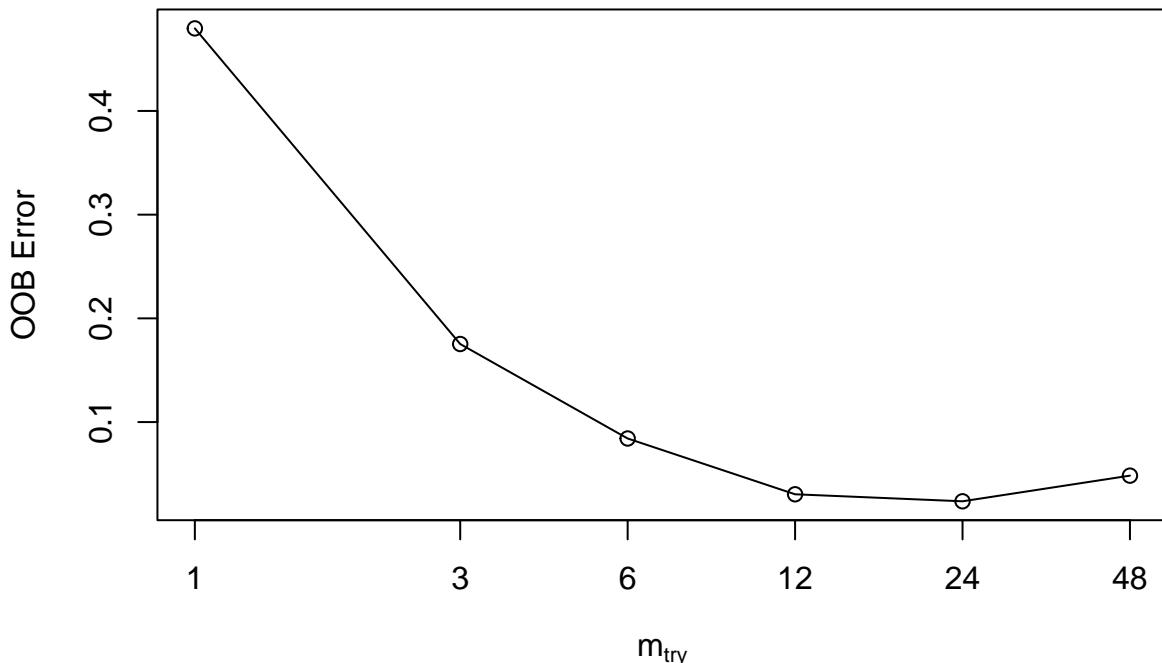
rf



```
#Tune mtry (Número de variables aleatorias utilizadas en cada árbol)
```

```
t <- tuneRF(train[,-1], train[,1],  
            stepFactor = 0.5,  
            plot = TRUE,  
            ntreeTry = 5,  
            trace = TRUE,  
            improve = 0.05)
```

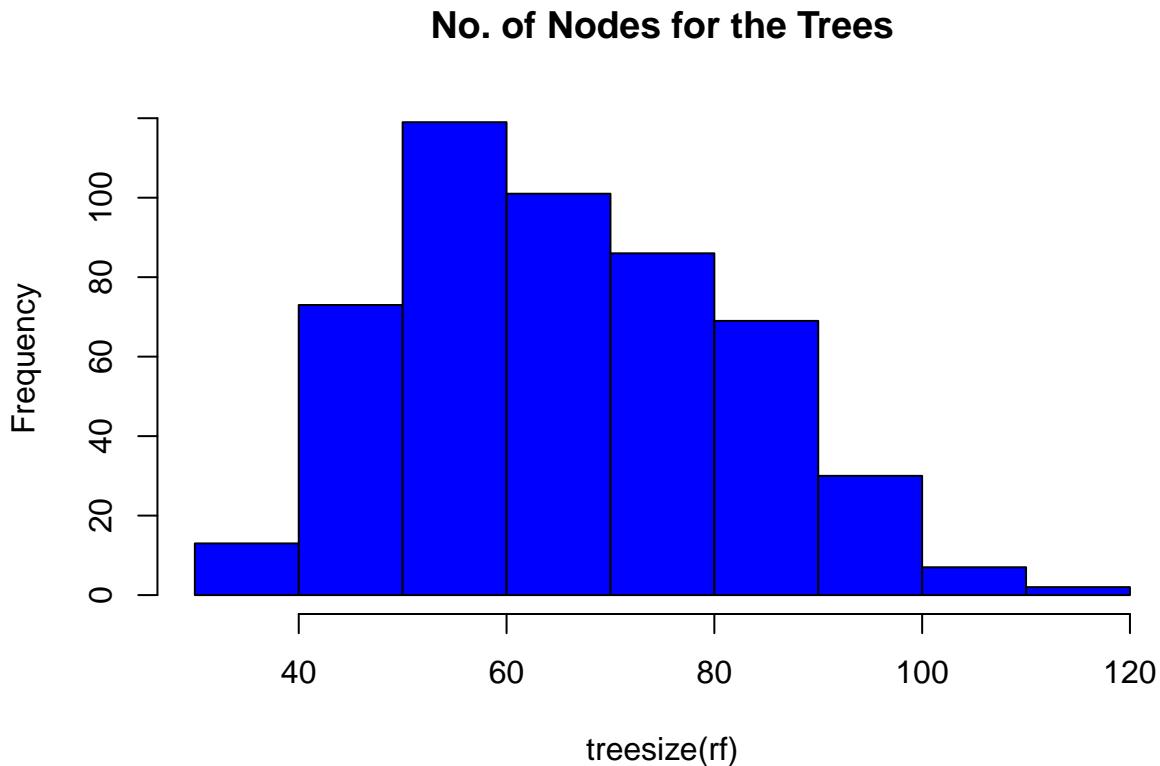
```
## mtry = 3 OOB error = 17.53%  
## Searching left ...  
## mtry = 6      OOB error = 8.42%  
## 0.519802 0.05  
## mtry = 12     OOB error = 3.04%  
## 0.6390171 0.05  
## mtry = 24     OOB error = 2.36%  
## 0.2224409 0.05  
## mtry = 48     OOB error = 4.83%  
## -1.04665 0.05  
## Searching right ...  
## mtry = 1      OOB error = 47.96%  
## -19.30272 0.05
```



```
#mtry=6
```

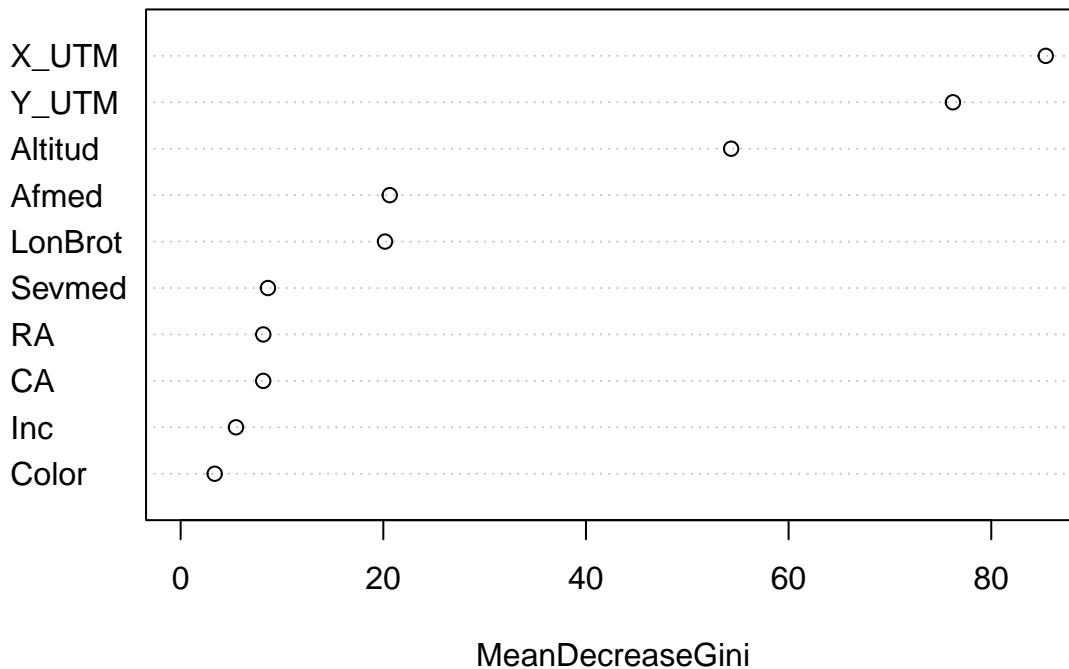
```
#No. of nodes for the trees
```

```
hist(treesize(rf),  
      main = "No. of Nodes for the Trees",  
      col = "blue")
```



```
#media de 60 árboles  
  
#Variable Importance  
varImpPlot(rf,  
            sort = T,  
            n.var = 10,  
            main = "Top 10 - Importancia de Variables")
```

Top 10 – Importancia de Variables

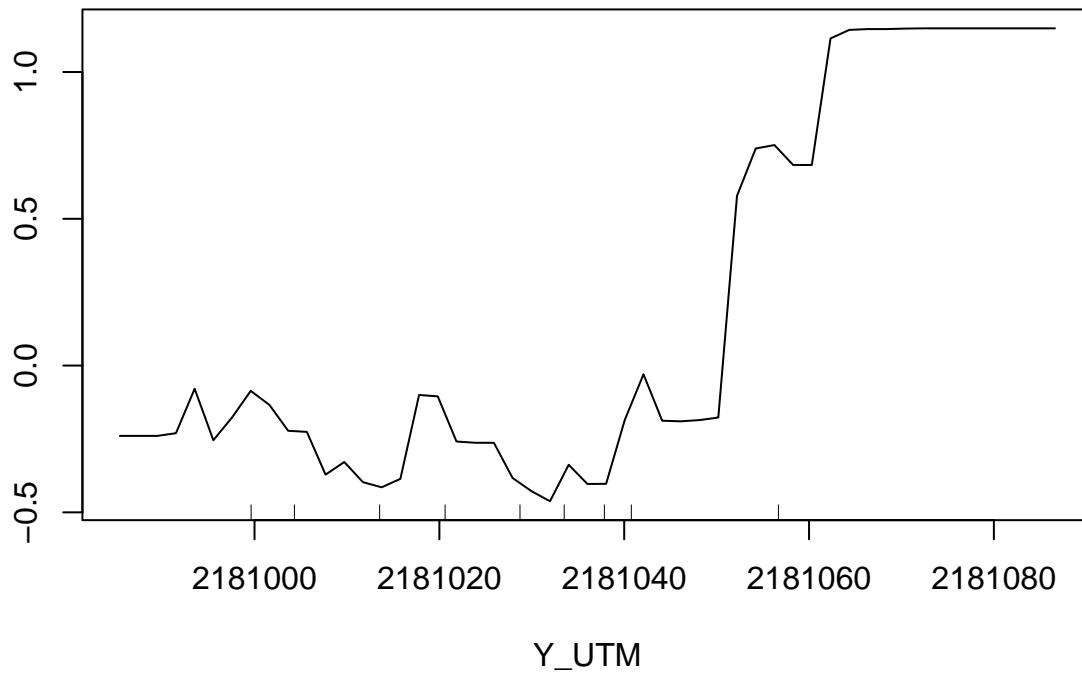


```
importance(rf)
```

```
##          MeanDecreaseGini
## X_UTM      85.378578
## Y_UTM      76.219320
## Altitud    54.328330
## Inc        5.457896
## Sevmed    8.613401
## LonBrot   20.168919
## Afmed     20.634459
## CA         8.147649
## RA         8.153187
## Color      3.360461
```

```
#Partial Dependence Plot
partialPlot(rf, train, Y_UTM, "Alta")
```

Partial Dependence on Y_UTM



Interpretación: se obtuvo una precisión del 98% y un valor $\kappa = 0.98$, una mtry (Número de variables aleatorias utilizadas en cada árbol) de 6, 60 nodos promedio por árbol, las variables de mayor peso son las coordenadas UTM (X y Y).

3) Naive Bayes

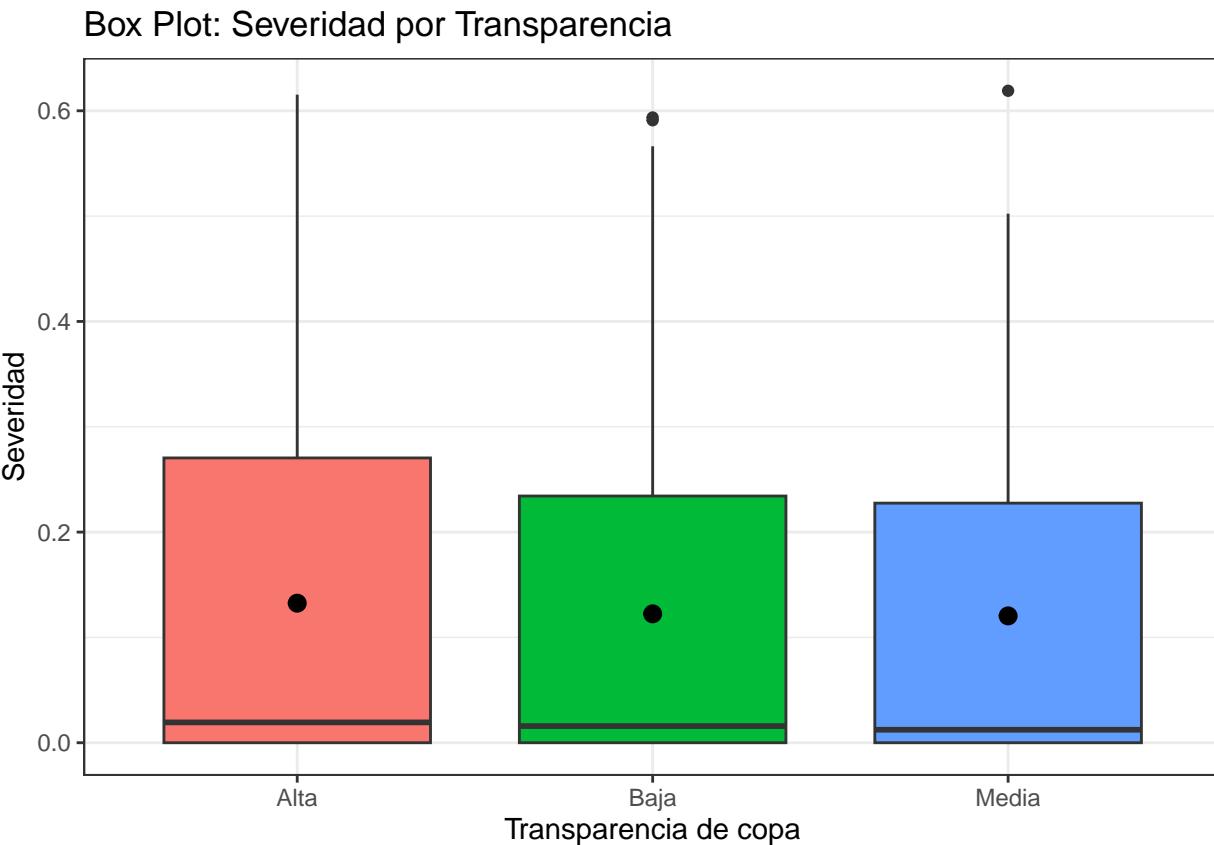
```
#clasificacion en datos poco correlacionados
#https://www.r-bloggers.com/2021/04/naive-bayes-classification-in-r/
#Para segmentar imagenes (severidad)
#https://plantcv.readthedocs.io/en/latest/tutorials/machine_learning_tutorial/
library(naivebayes)
library(dplyr)
library(ggplot2)

base_nb <- na.omit(base[,c(2,5,6,7,18,19,22,24,28:30)])

#Dplyr
base_nb$Bloque <- as.factor(base_nb$Bloque)
table(base_nb$Bloque)

##
##  Alta  Baja Media
##  200   216   208
```

```
base_nb %>%
  ggplot(aes(x=base_nb$Bloque,
             y=base_nb$Sevmed, fill = base_nb$Bloque)) +
  geom_boxplot() +theme_bw() +stat_summary(fun="mean")+
  ggtitle("Box Plot: Severidad por Transparencia")+
  xlab("Transparencia de copa") + ylab("Severidad")+
  theme(legend.position="none")
```



```
#particion de datos
set.seed(1234)
ind <- sample(2, nrow(base_nb), replace = T, prob = c(0.7, 0.3))
train_nb <- base_nb[ind == 1,]
test_nb <- base_nb[ind == 2,]

nb <- naive_bayes(Bloque ~ ., data = train_nb, usekernel = T)

## ===== Naive Bayes =====
## Call:
## naive_bayes(formula = Bloque ~ ., data = train_nb, usekernel = T)
##
```



```
## -----
## 
## Laplace smoothing: 0
## 
## -----
## 
## A priori probabilities:
## 
##      Alta      Baja      Media
## 0.3294931 0.3525346 0.3179724
## 
## -----
## 
## Tables:
## 
## -----
## :::: X_UTM:::Alta (KDE)
## -----
## 
## Call:
## density.default(x = x, na.rm = TRUE)
## 
## Data: x (143 obs.); Bandwidth 'bw' = 4.234
## 
##      x              y
## Min. :605708  Min. :6.845e-05
## 1st Qu.:605724  1st Qu.:5.646e-03
## Median :605740  Median :1.531e-02
## Mean   :605740  Mean   :1.563e-02
## 3rd Qu.:605756  3rd Qu.:2.251e-02
## Max.   :605772  Max.   :3.999e-02
## 
## -----
## :::: X_UTM:::Baja (KDE)
## -----
## 
## Call:
## density.default(x = x, na.rm = TRUE)
## 
## Data: x (153 obs.); Bandwidth 'bw' = 3.012
## 
##      x              y
## Min. :605698  Min. :0.00000586
## 1st Qu.:605716  1st Qu.:0.0035397
## Median :605733  Median :0.0080609
## Mean   :605733  Mean   :0.0145803
## 3rd Qu.:605750  3rd Qu.:0.0230454
## Max.   :605767  Max.   :0.0516069
## 
## -----
## :::: X_UTM:::Media (KDE)
## -----
## 
## Call:
```



```
## density.default(x = x, na.rm = TRUE)
##
## Data: x (138 obs.); Bandwidth 'bw' = 3.566
##
##      x          y
## Min. :605699  Min. :7.663e-05
## 1st Qu.:605713 1st Qu.:7.099e-03
## Median :605727 Median :2.061e-02
## Mean   :605727 Mean   :1.823e-02
## 3rd Qu.:605740 3rd Qu.:2.765e-02
## Max.  :605754  Max.  :3.286e-02
##
## -----
## :::: Y_UTM::Alta (KDE)
## -----
##
## Call:
## density.default(x = x, na.rm = TRUE)
##
## Data: x (143 obs.); Bandwidth 'bw' = 8.552
##
##      x          y
## Min. :2180968  Min. :1.452e-05
## 1st Qu.:2181004 1st Qu.:1.747e-03
## Median :2181040 Median :7.805e-03
## Mean   :2181040 Mean   :6.930e-03
## 3rd Qu.:2181076 3rd Qu.:1.125e-02
## Max.  :2181112  Max.  :1.466e-02
##
## -----
## :::: Y_UTM::Baja (KDE)
## -----
##
## Call:
## density.default(x = x, na.rm = TRUE)
##
## Data: x (153 obs.); Bandwidth 'bw' = 6.059
##
##      x          y
## Min. :2180967  Min. :2.968e-05
## 1st Qu.:2180994 1st Qu.:2.931e-03
## Median :2181021 Median :7.321e-03
## Mean   :2181021 Mean   :9.275e-03
## 3rd Qu.:2181048 3rd Qu.:1.296e-02
## Max.  :2181075  Max.  :2.738e-02
##
## -----
## :::: Y_UTM::Media (KDE)
## -----
##
## Call:
## density.default(x = x, na.rm = TRUE)
##
## Data: x (138 obs.); Bandwidth 'bw' = 5.663
```



```
##  
##      x          y  
## Min.   :2180983   Min.   :5.218e-05  
## 1st Qu.:2181003   1st Qu.:4.901e-03  
## Median :2181024   Median  :1.382e-02  
## Mean    :2181024   Mean    :1.195e-02  
## 3rd Qu.:2181045   3rd Qu.:1.862e-02  
## Max.    :2181066   Max.    :2.012e-02  
##  
## -----  
## :::: Altitud::Alta (KDE)  
## -----  
##  
## Call:  
## density.default(x = x, na.rm = TRUE)  
##  
## Data: x (143 obs.); Bandwidth 'bw' = 2.165  
##  
##      x          y  
## Min.   :2967   Min.   :8.123e-05  
## 1st Qu.:2975   1st Qu.:7.206e-03  
## Median :2983   Median  :1.904e-02  
## Mean    :2983   Mean    :3.037e-02  
## 3rd Qu.:2991   3rd Qu.:5.454e-02  
## Max.    :3000   Max.    :8.754e-02  
##  
## -----  
## :::: Altitud::Baja (KDE)  
## -----  
##  
## Call:  
## density.default(x = x, na.rm = TRUE)  
##  
## Data: x (153 obs.); Bandwidth 'bw' = 2.301  
##  
##      x          y  
## Min.   :2967   Min.   :0.0001377  
## 1st Qu.:2976   1st Qu.:0.0068304  
## Median :2984   Median  :0.0229024  
## Mean    :2984   Mean    :0.0295464  
## 3rd Qu.:2993   3rd Qu.:0.0524126  
## Max.    :3001   Max.    :0.0725437  
##  
## -----  
## :::: Altitud::Media (KDE)  
## -----  
##  
## Call:  
## density.default(x = x, na.rm = TRUE)  
##  
## Data: x (138 obs.); Bandwidth 'bw' = 2.332  
##  
##      x          y  
## Min.   :2966   Min.   :0.0001916
```



```
## 1st Qu.:2975   1st Qu.:0.0078593
## Median :2983   Median :0.0223586
## Mean   :2983   Mean   :0.0298194
## 3rd Qu.:2992   3rd Qu.:0.0515802
## Max.    :3000   Max.   :0.0763652
##
## -----
## :::: Inc:::Alta (KDE)
## -----
## Call:
## density.default(x = x, na.rm = TRUE)
##
## Data: x (143 obs.); Bandwidth 'bw' = 0.1516
##
##          x                  y
## Min.   :-0.45489   Min.   :0.007724
## 1st Qu.: 0.02255   1st Qu.:0.184333
## Median : 0.50000   Median :0.430753
## Mean   : 0.50000   Mean   :0.522644
## 3rd Qu.: 0.97745   3rd Qu.:0.877189
## Max.   : 1.45489   Max.   :1.250835
##
## -----
## :::: Inc:::Baja (KDE)
## -----
## Call:
## density.default(x = x, na.rm = TRUE)
##
## Data: x (153 obs.); Bandwidth 'bw' = 0.147
##
##          x                  y
## Min.   :-0.44114   Min.   :0.008662
## 1st Qu.: 0.02943   1st Qu.:0.234846
## Median : 0.50000   Median :0.439232
## Mean   : 0.50000   Mean   :0.530306
## 3rd Qu.: 0.97057   3rd Qu.:0.877922
## Max.   : 1.44114   Max.   :1.208382
##
## -----
## :::: Inc:::Media (KDE)
## -----
## Call:
## density.default(x = x, na.rm = TRUE)
##
## Data: x (138 obs.); Bandwidth 'bw' = 0.1492
##
##          x                  y
## Min.   :-0.44755   Min.   :0.00673
## 1st Qu.: 0.02622   1st Qu.:0.17381
## Median : 0.50000   Median :0.42338
## Mean   : 0.50000   Mean   :0.52670
```



```
## 3rd Qu.: 0.97378   3rd Qu.:0.84646
## Max.     : 1.44755   Max.    :1.41405
##
## -----
## :::: Sevmed::Alta (KDE)
## -----
## Call:
## density.default(x = x, na.rm = TRUE)
##
## Data: x (143 obs.); Bandwidth 'bw' = 0.05544
##
##          x                  y
## Min.    :-0.16632  Min.    :0.00084
## 1st Qu.: 0.07067  1st Qu.:0.21204
## Median  : 0.30767  Median  :1.00329
## Mean    : 0.30767  Mean    :1.05316
## 3rd Qu.: 0.54466  3rd Qu.:1.22723
## Max.    : 0.78166  Max.    :3.88998
##
## -----
## :::: Sevmed::Baja (KDE)
## -----
## Call:
## density.default(x = x, na.rm = TRUE)
##
## Data: x (153 obs.); Bandwidth 'bw' = 0.05547
##
##          x                  y
## Min.    :-0.16640  Min.    :0.001247
## 1st Qu.: 0.06522  1st Qu.:0.321627
## Median  : 0.29683  Median  :0.890326
## Mean    : 0.29683  Mean    :1.077629
## 3rd Qu.: 0.52845  3rd Qu.:1.361567
## Max.    : 0.76007  Max.    :3.893333
##
## -----
## :::: Sevmed::Media (KDE)
## -----
## Call:
## density.default(x = x, na.rm = TRUE)
##
## Data: x (138 obs.); Bandwidth 'bw' = 0.0524
##
##          x                  y
## Min.    :-0.15720  Min.    :0.00182
## 1st Qu.: 0.04698  1st Qu.:0.42085
## Median  : 0.25117  Median  :0.97273
## Mean    : 0.25117  Mean    :1.22230
## 3rd Qu.: 0.45535  3rd Qu.:1.23741
## Max.    : 0.65953  Max.    :4.53500
##
```



```
## -----
## # ... and 5 more tables
## -----
## -----
```

```
#plot(nb)

#Prediccion
p <- predict(nb, train_nb, type = 'prob')
head(cbind(p, train_nb))

##      Alta     Baja     Media Bloque    X_UTM    Y_UTM Altitud     Inc
## 1 0.9787447 0.01850964 0.002745704 Alta 605747.9 2181070 2979.3 0.9000000
## 2 0.4113505 0.53406359 0.054585864 Alta 605744.3 2181057 2979.3 1.0000000
## 3 0.6491587 0.25629479 0.094546554 Alta 605740.2 2181039 2979.5 0.7666667
## 4 0.8842636 0.11442525 0.001311104 Alta 605754.5 2181034 2980.0 1.0000000
## 6 0.8065772 0.14937314 0.044049685 Alta 605727.7 2181021 2992.3 1.0000000
## 7 0.7160262 0.07648249 0.207491317 Alta 605724.3 2181003 2990.8 1.0000000
##      Sevmed LonBrot Afmed      CA      RA Color
## 1 0.1503333    7.25 0.2393667 25.252525 74.74747    1
## 2 0.3310000   12.90 0.3744867  1.526718 98.47328    1
## 3 0.3466667    5.10 0.1960667  2.816901 97.18310    1
## 4 0.3510000    3.90 0.3699000 15.384615 84.61538    1
## 6 0.2486667    5.00 0.2253667 17.441860 82.55814    1
## 7 0.4033333    6.80 0.2549333  4.225352 95.77465    1

#Confusion Matrix - train data
p1 <- predict(nb, train_nb)
(tab1 <- table(p1, train_nb$Bloque))

## 
## p1      Alta Baja Media
##   Alta    91   19   20
##   Baja    19   97   26
##   Media   33   37   92

1 - sum(diag(tab1)) / sum(tab1) #error del 35%
```

```
## [1] 0.3548387

#Confusion Matrix - test data
p2 <- predict(nb, test_nb)
(tab2 <- table(p2, test_nb$Bloque))

## 
## p2      Alta Baja Media
##   Alta    28   14   13
##   Baja    12   30   22
##   Media   17   19   35
```



p2

```
## [1] Baja Baja Alta Baja Media Media Baja Media Alta Alta Baja Alta
## [13] Media Alta Media Baja Media Media Media Media Baja Media Baja Baja
## [25] Baja Baja Alta Media Baja Alta Alta Baja Alta Alta Media Baja
## [37] Baja Baja Baja Baja Media Alta Media Alta Media Alta Media Media
## [49] Media Media Media Alta Media Alta Baja Baja Media Alta Baja Media
## [61] Alta Baja Media Alta Media Media Baja Media Media Alta Alta Baja
## [73] Baja Alta Media Baja Media Baja Alta Alta Media Media Media Alta
## [85] Media Media Baja Media Alta Baja Baja Media Media Alta Baja Baja
## [97] Baja Media Media Media Alta Alta Baja Baja Media Alta Media Alta
## [109] Baja Media Alta Alta Alta Media Media Alta Media Alta Alta Baja
## [121] Media Baja Media Media Alta Alta Media Alta Alta Media Baja Baja
## [133] Baja Baja Baja Media Media Baja Media Baja Baja Alta Media Media
## [145] Alta Alta Baja Media Media Media Alta Alta Baja Alta Baja Media
## [157] Alta Alta Media Alta Alta Alta Media Baja Baja Baja Baja Media
## [169] Baja Media Baja Baja Baja Baja Baja Baja Alta Baja Alta Media
## [181] Alta Alta Media Media Media Baja Baja Media Baja Media Baja Media
## Levels: Alta Baja Media
```

```
1 - sum(diag(tab2)) / sum(tab2) #error del 51%
```

```
## [1] 0.5105263
```

```
library(caret)
confusionMatrix(p2,test_nb$Bloque)
```

```
## Confusion Matrix and Statistics
##
##             Reference
## Prediction Alta Baja Media
##     Alta     28   14   13
##     Baja     12   30   22
##     Media    17   19   35
##
## Overall Statistics
##
##                 Accuracy : 0.4895
##                 95% CI : (0.4164, 0.5629)
##     No Information Rate : 0.3684
##     P-Value [Acc > NIR] : 0.0004302
##
##                 Kappa : 0.2309
##
## McNemar's Test P-Value : 0.8238127
##
## Statistics by Class:
##
##                         Class: Alta Class: Baja Class: Media
## Sensitivity                  0.4912      0.4762      0.5000
## Specificity                   0.7970      0.7323      0.7000
## Pos Pred Value                 0.5091      0.4688      0.4930
```

```
## Neg Pred Value      0.7852      0.7381      0.7059
## Prevalence         0.3000      0.3316      0.3684
## Detection Rate    0.1474      0.1579      0.1842
## Detection Prevalence 0.2895      0.3368      0.3737
## Balanced Accuracy  0.6441      0.6042      0.6000
```

Interpretación: se obtuvo una precisión de 49% y un valor de $\kappa=0.23$. En general esta técnica no fue tan buena para clasificar la transparencia de copa.

4) K-NN

```
#https://rpubs.com/JairoAyala/601703

library(kknn)

base_knn <- na.omit(base[,c(2,5,6,7,9,10,12,18,19,22,24,28:30,32)])
```

```
base_knn$Bloque <- as.factor(base_knn$Bloque)
table(base_knn$Bloque)
```

```
##
```

```
## Alta Baja Media
## 200 216 208
```

```
set.seed(2020)
muestra <- sample(1:624, 437)
train_knn <- base_knn[muestra,] #70%
test_knn <- base_knn[-muestra,] #30%
dim(train_knn) [1]
```

```
## [1] 437
```

```
dim(test_knn) [1]
```

```
## [1] 187
```

```
knn <- train.kknn(Bloque~ ., data = train_knn, kmax = 9)
knn
```

```
##
```

```
## Call:
## train.kknn(formula = Bloque ~ ., data = train_knn, kmax = 9)
##
```

```
## Type of response variable: nominal
## Minimal misclassification: 0.5102975
## Best kernel: optimal
## Best k: 9
```



```
entre <- predict(knn, train_knn[,-1])
tt  <- table(train_knn[,1],entre)
tt
```

```
##          entre
##          Alta Baja Media
## Alta     129    5    5
## Baja      16   122   15
## Media      7    7   131
```

```
precision <- (sum(diag(tt)))/sum(tt)
precision
```

```
## [1] 0.8741419
```

#precisión del 100 % en datos de entrenamiento

```
#Precisión test de prueba
pred <- predict(knn, test_knn[,-1])
table <- table(test_knn[,1],pred)
table
```

```
##          pred
##          Alta Baja Media
## Alta     35    13    13
## Baja      13   29    21
## Media     12    16   35
```

```
clas <- (sum(diag(table)))/sum(table)
clas
```

```
## [1] 0.5294118
```

#Precisión del 53% de datos de prueba

```
#matriz de confusión con la prueba
library(caret)
confusionMatrix(pred,test_knn$Bloque)
```

```
## Confusion Matrix and Statistics
##
##          Reference
## Prediction Alta Baja Media
## Alta       35   13   12
## Baja       13   29   16
## Media      13   21   35
##
## Overall Statistics
```



```
##                                     Accuracy : 0.5294
##                               95% CI : (0.4552, 0.6026)
## No Information Rate : 0.3369
## P-Value [Acc > NIR] : 4.914e-08
##
##                                     Kappa : 0.294
##
## McNemar's Test P-Value : 0.8695
##
## Statistics by Class:
##
##          Class: Alta Class: Baja Class: Media
## Sensitivity          0.5738     0.4603     0.5556
## Specificity          0.8016     0.7661     0.7258
## Pos Pred Value       0.5833     0.5000     0.5072
## Neg Pred Value       0.7953     0.7364     0.7627
## Prevalence           0.3262     0.3369     0.3369
## Detection Rate       0.1872     0.1551     0.1872
## Detection Prevalence 0.3209     0.3102     0.3690
## Balanced Accuracy    0.6877     0.6132     0.6407
```

Interpretación: se obtuvo una precisión de 53% y un valor de $\kappa=0.30$. En general esta técnica no fue tan buena para clasificar la transparencia de copa.

5) Curvas Receiver Operating Characteristic (ROC)

```
par(mfrow = c(1,3))
#Random forest

# Validation set assessment #2: ROC curves and AUC
# Needs to import ROCR package for ROC curve plotting:
library(ROCR)

# Calculate the probability of new observations belonging to each class
# prediction_for_roc_curve will be a matrix with dimensions data_set_size x number_of_classes
prediction_for_roc_curve <- predict(rf,test[,-1],type="prob")
# Use pretty colours:
pretty_colours <- c("#F8766D", "#00BA38", "#619cff")
# Specify the different classes
test$Bloque <- as.factor(test$Bloque)
classes <- levels(test$Bloque)
# For each class
for (i in 1:3)
{
  # Define which observations belong to class[i]
  true_values <- ifelse(test[,1]==classes[i],1,0)
  # Assess the performance of classifier for class[i]
  pred <- prediction(prediction_for_roc_curve[,i],true_values)
  perf <- performance(pred, "tpr", "fpr")
  if (i==1)
  {
    plot(perf,main="ROC Curve-Random Forest",col=pretty_colours[i])
```



```
}

else
{
  plot(perf,main="ROC Curve- Random Forest",col=pretty_colours[i],add=TRUE)
  abline (a = 0, b = 1, lty="dotted", lwd=2)
}
# Calculate the AUC and print it to screen
auc.perf <- performance(pred, measure = "auc")
print(auc.perf@y.values)
}

## [[1]]
## [1] 0.9993548
##
## [[1]]
## [1] 1
##
## [[1]]
## [1] 1

#Naive Bayes (ROC)

# Validation set assessment #2: ROC curves and AUC
# Needs to import ROOCR package for ROC curve plotting:
library(ROOCR)
# Calculate the probability of new observations belonging to each class
# prediction_for_roc_curve will be a matrix with dimensions data_set_size x number_of_classes
prediction_for_roc_curve <- predict(nb,test_nb[,-1],type="prob")
# Use pretty colours:
pretty_colours <- c("#F8766D","#00BA38","#619cff")
# Specify the different classes
test_nb$Bloque <- as.factor(test_nb$Bloque)
classes <- levels(test_nb$Bloque)
# For each class
for (i in 1:3)
{
  # Define which observations belong to class[i]
  true_values <- ifelse(test_nb[,1]==classes[i],1,0)
  # Assess the performance of classifier for class[i]
  pred <- prediction(prediction_for_roc_curve[,i],true_values)
  perf <- performance(pred, "tpr", "fpr")
  if (i==1)
  {
    plot(perf,main="ROC Curve-Naive Bayes",col=pretty_colours[i])
  }
  else
  {
    plot(perf,main="ROC Curve-Naive Bayes",col=pretty_colours[i],add=TRUE)
    abline (a = 0, b = 1, lty="dotted", lwd=2)
  }
  # Calculate the AUC and print it to screen
  auc.perf <- performance(pred, measure = "auc")
  print(auc.perf@y.values)
}
```



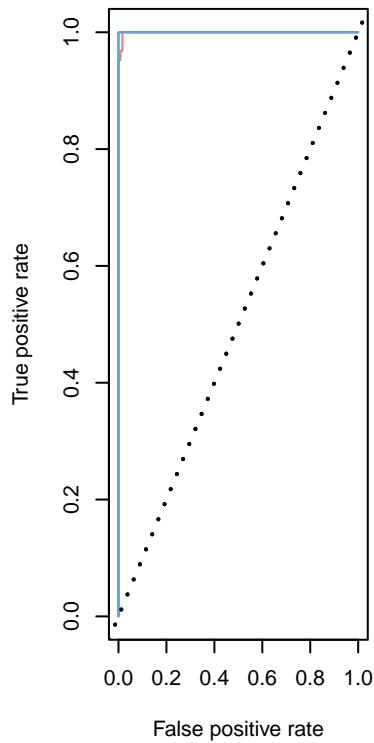
}

```
## [[1]]
## [1] 0.7632238
##
## [[1]]
## [1] 0.6860392
##
## [[1]]
## [1] 0.702381
```

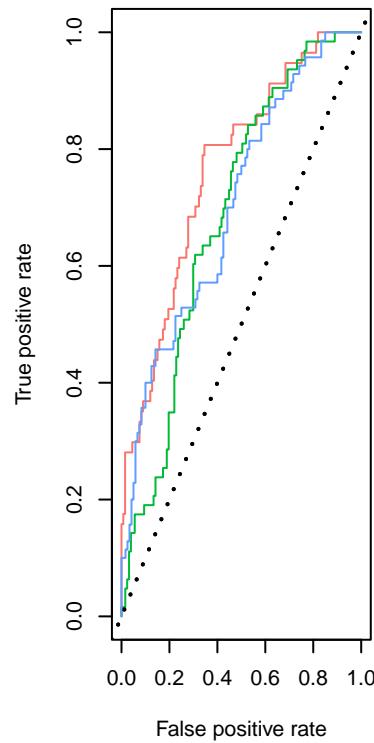
#KNN (ROC)

```
# Validation set assessment #2: ROC curves and AUC
# Needs to import ROCR package for ROC curve plotting:
library(ROCR)
# Calculate the probability of new observations belonging to each class
# prediction_for_roc_curve will be a matrix with dimensions data_set_size x number_of_classes
prediction_for_roc_curve <- predict(knn,test_knn[,-1],type="prob")
# Use pretty colours:
pretty_colours <- c("#F8766D", "#00BA38", "#619cff")
# Specify the different classes
test_knn$Bloque <- as.factor(test_knn$Bloque)
classes <- levels(test_knn$Bloque)
# For each class
for (i in 1:3)
{
  # Define which observations belong to class[i]
  true_values <- ifelse(test_knn[,1]==classes[i],1,0)
  # Assess the performance of classifier for class[i]
  pred <- prediction(prediction_for_roc_curve[,i],true_values)
  perf <- performance(pred, "tpr", "fpr")
  if (i==1)
  {
    plot(perf,main="ROC Curve - KNN",col=pretty_colours[i])
  }
  else
  {
    plot(perf,main="ROC Curve -KNN",col=pretty_colours[i],add=TRUE)
    abline (a = 0, b = 1, lty="dotted", lwd=2)
  }
  # Calculate the AUC and print it to screen
  auc.perf<- performance(pred, measure = "auc")
  print(auc.perf@y.values)
}
```

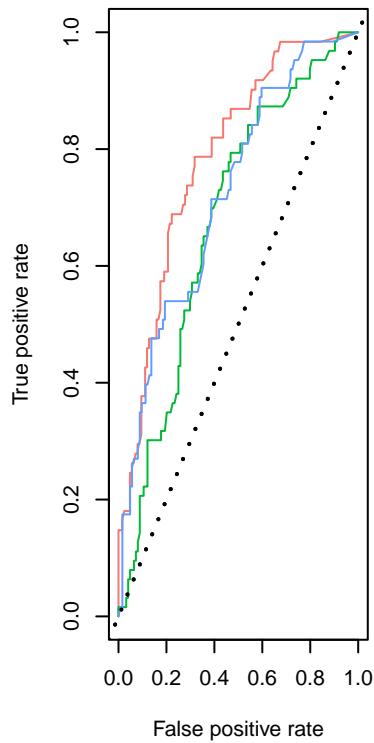
ROC Curve–Random Forest



ROC Curve–Naive Bayes



ROC Curve – KNN



```
## [[1]]
## [1] 0.7848686
##
## [[1]]
## [1] 0.6751792
##
## [[1]]
## [1] 0.7210061

dev.off()

## null device
##           1

#cuadro con valores de precision
p <- rbind(c(0.98,0.49,0.53))
k <- rbind(c(0.98,0.23,0.30))
r <- rbind(c(1.00, 0.70, 0.72))
pres <- rbind(p,k,r)
pres <- as.data.frame(pres)
colnames(pres) <- c("Random Forest", "Naive Bayes", "K-NN")
pres <- cbind(Métrica=c("Precisión(%)", "Kappa", "AUC-ROC"), pres)

library(gt)
pres %>% gt()
```

Métrica	Random Forest	Naive Bayes	K-NN
Precisión(%)	0.98	0.49	0.53
Kappa	0.98	0.23	0.30
AUC-ROC	1.00	0.70	0.72

Interpretación: De acuerdo la evaluación de las curvas ROC, es evidente que el mejor modelo para clasificar a la transparencia de copa de Douglas-fir fue Random Forest, ya que tuvo mayor cantidad de positivos verdaderos en comparación de Naive Bayes y K-NN, donde se pueden considerar que son modelos de regulares a malos.

Conclusiones: De acuerdo la evaluación de las curvas ROC, precisión y valor de kappa, es evidente que el mejor modelo para clasificar a la transparencia de copa de Douglas-fir fue Random Forest, además tuvo mayor cantidad de positivos verdaderos con sensibilidad, especificidad y precisión equilibrada en comparación de Naive Bayes y K-NN, donde se pueden considerar que son modelos de regulares a malos para clasificar la transparencia de copa.