Machine Learning and Forecasting Models

Part 3: Tree Based Models and Neural Networks

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Pacotes utilizados:

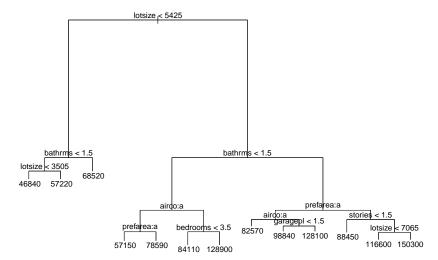
```
library(randomForest)
library(ggplot2)
library(reshape2)
library(tree)
library(gridExtra)
```

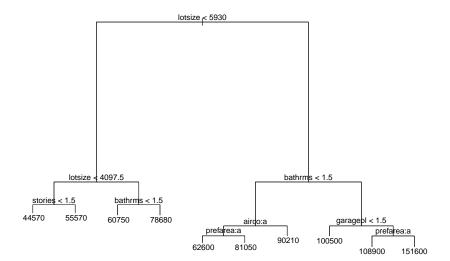
Banco de Dados

```
data(Housing,package="Ecdat")
```

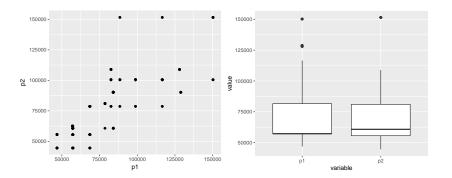
- ▶ The example dataset has 546 observations of sold houses,
- We want to forecast the selling price,
- ► Characteristics: Bedrooms, Bathrooms, garages, etc.

- First we will look at individual trees.
- Undertand the instability problem





```
pred = data.frame(p1 = predict(tree1, Housing) ,p2 = predict(tree2, Housing))
g1 = ggplot(data = pred) + geom_point(aes(p1, p2))
g2 = ggplot(data = melt(pred)) + geom_boxplot(aes(variable, value))
grid.arrange(g1, g2, ncol = 2)
```

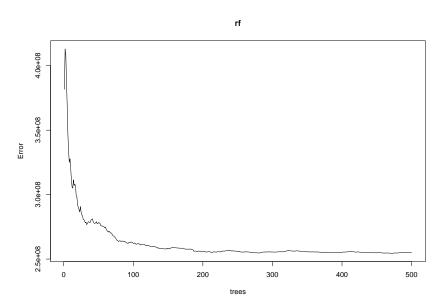


[1] 0.7986199

importance(rf)

```
##
            %IncMSE IncNodePurity
## lotsize 38.987281
                     91833371227
## bedrooms 18.999051 21343481145
## bathrms 35.276966 49194651344
## stories 23.667206
                     23954116988
## driveway 17.437953 7089694747
## recroom 11.851130 7108625124
## fullbase 14.564720 8772633419
## gashw 3.939987 5436730391
## airco
           22.258920
                     29073690740
## garagepl 14.813148
                     24827758850
## prefarea 18.183930
                     14785925617
```

plot(rf)



```
tr=getTree(rf,1)
tr[1:15,]
```

```
##
      left daughter right daughter split var split point status prediction
## 1
                   2
                                   3
                                             11
                                                         1.0
                                                                  -3
                                                                       68368.86
                   4
                                   5
                                              9
## 2
                                                         1.0
                                                                  -3
                                                                       63315.81
## 3
                   6
                                   7
                                              9
                                                         1.0
                                                                  -3
                                                                       86494.95
## 4
                   8
                                   9
                                              5
                                                         1.0
                                                                  -3
                                                                       56660.07
## 5
                  10
                                  11
                                                      5974.0
                                                                  -3
                                                                       78528.92
## 6
                  12
                                  13
                                              3
                                                         1.5
                                                                  -3
                                                                       74863.39
## 7
                                              4
                                                         1.5
                  14
                                  15
                                                                  -3
                                                                       98784.91
                                              2
## 8
                  16
                                  17
                                                         3.5
                                                                  -3
                                                                       45776.18
## 9
                                             10
                  18
                                  19
                                                         0.5
                                                                  -3
                                                                       59418.66
## 10
                  20
                                  21
                                             10
                                                         0.5
                                                                  -3
                                                                       67730.88
## 11
                  22
                                  23
                                              4
                                                         3.5
                                                                  -3
                                                                       92926.31
## 12
                  24
                                  25
                                              1
                                                      5450.0
                                                                  -3
                                                                       69273.17
## 13
                  26
                                  27
                                              4
                                                         1.5
                                                                  -3
                                                                       90143.33
## 14
                  28
                                  29
                                                         1.0
                                                                  -3
                                                                       79872.73
                                                         3.5
## 15
                  30
                                  31
                                                                  -3
                                                                      112206.45
```

Parâmetros:

```
## [1] 0.9387345
```

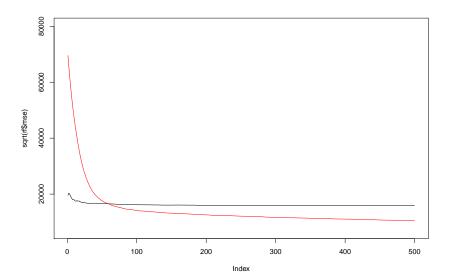
- The xgboost package is the best Boosting package in R.
- lt does not accept string variables.

```
library(xgboost)
Housing$driveway=ifelse(Housing$driveway=="yes",1,0)
Housing$recroom=ifelse(Housing$recroom=="yes",1,0)
Housing$fullbase=ifelse(Housing$fullbase=="yes",1,0)
Housing$gashw=ifelse(Housing$gashw=="yes",1,0)
Housing$airco=ifelse(Housing$prefarea=="yes",1,0)
Housing$prefarea=ifelse(Housing$prefarea=="yes",1,0)
```

- Boosting has more parameters to tune than Random Forests,
- It is also more sentive to the parameters,
- ▶ The Boosting trees are smaller, which makes the algorithm faster.

```
## [1]
      train-rmse:69552.265625
  [2]
      train-rmse:66458.945312
##
## [3]
      train-rmse:63567.464844
## [4] train-rmse:60744.230469
## [5]
      train-rmse:58109.117188
##
  [6]
      train-rmse:55612.960938
##
  [7]
      train-rmse:53253.890625
##
  [8]
      train-rmse:51042.558594
## [9]
      train-rmse:48997.394531
## [10] train-rmse:47070.867188
## [11] train-rmse:45213.398438
## [12] train-rmse:43488.046875
## [13] train-rmse:41873.070312
## [14] train-rmse:40309.351562
## [4E] +---: 20000 E00400
```

```
plot(sqrt(rf$mse),type="1",ylim=c(7000,80000))
lines(xgb$evaluation_log[,2],col=2)
```



```
mse_xgb = sqrt(mean((predict(xgb, x[outsamp, ]) - y[outsamp])^2))
mse_xgb

## [1] 18238.56

mse_rf

## [1] 15905.59
```

Boosting - examplo 2

- ▶ This second example is also on a Housing dataset. But in this case the dataset is bigger (5000 observations).
- ▶ Houses sold in Melbourne in 2016 and 2017.

Boosting - examplo 2

```
load("housing2.rda")
data$Distance=as.numeric(as.character(data$Distance))
x=as.matrix(data[,-2])
y=data[,2]
set.seed(1)
insamp=sample(1:nrow(data),3000)
outsamp=setdiff(1:nrow(data),insamp)
```

Boosting - exemplo 2

[1]

##

```
##
   [2]
       train-rmse: 1330780, 250000
## [3]
       train-rmse: 1274018, 250000
## [4]
       train-rmse: 1219418.000000
##
   [5]
       train-rmse: 1168791.875000
   [6]
##
       train-rmse:1120952.875000
   [7]
       train-rmse: 1074249.500000
##
##
   [8]
       train-rmse: 1030829.312500
## [9]
       train-rmse:990472.250000
## [10] train-rmse:953062.937500
   [11] train-rmse:915938.437500
## [12] train-rmse:881595.812500
## [13] train-rmse:849436.812500
  [14] train-rmse:818364.062500
  [15] train-rmse:789748.562500
   [16] train-rmse:761661.687500
##
  [17] train-rmse:735612.562500
  [18] train-rmse:710991.187500
## [19] train-rmse:686907.437500
```

train-rmse: 1389774.000000

Boosting - exemplo 2

[1] 304297.3

```
mse_xgb = sqrt(mean((predict(xgb, x[outsamp, ]) - y[outsamp])^2))
mse_rf = sqrt(mean((predict(rf, x[outsamp, ]) - y[outsamp])^2))
mse_rf

## [1] 322670.7
mse_xgb
```

- Dados de preços de casas explicados por número de quartos, latitude, longitude, número de banheiros, etc. Total de 8 variáveis explicativas.
- ▶ 5814 observações. 3000 de treino e 2814 de teste

```
library(h2o)
load("housing2.rda")
data$Distance=as.numeric(as.character(data$Distance))
set.seed(1)
training = sample(1:nrow(data),3000)
test = setdiff(1:nrow(data),training)
```

 O pacote h2o precisa ser iniciado em uma seção separada exclusiva

```
h2o.init(nthreads = -1)
```

Arguments:

- y: Name of the response variable,
- training_frame: data.frame with all variables,
- activation: Name of the activation function,
- epochs: How many times the algorithm goes through the data,
- train_samples_per_iteration: Number of observations evaluated per iteration,
- seed: seed for replication.

```
# = Calcular previsão
y_pred = h2o.predict(model, newdata = as.h2o(data[test,]))
y_pred = as.vector(y_pred)
## Fechar seção.
h2o.shutdown()
```

XGBoost as benchmark

Results

342720.7 304202.4

```
ann_e = sqrt(mean((y_pred-data$Price[test])^2))
xgb_e = sqrt(mean((y_pred_xgb-data$Price[test])^2))
c(ann=ann_e,xgb=xgb_e)
## ann xgb
```