Projeto - Detecção de Fraude

Raphael Serra de Oliveira

6/30/2020

Carregando Bibliotecas e Objetos do Script Auxiliar

```r
library(readr)
library(knitr)
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```r
library(ggplot2)
library(caret)
```

```
## Loading required package: lattice
```

```r
library(lubridate)
```

```
##
## Attaching package: 'lubridate'

## The following objects are masked from 'package:dplyr':
##
##     intersect, setdiff, union

## The following objects are masked from 'package:base':
##
##     date, intersect, setdiff, union
```

```r
library(gridExtra)
```

```
##
## Attaching package: 'gridExtra'

## The following object is masked from 'package:dplyr':
##
##     combine
```

```r
library(randomForest)
```

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

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

##
## Attaching package: 'randomForest'

## The following object is masked from 'package:gridExtra':
##
##     combine

## The following object is masked from 'package:ggplot2':
##
##     margin

## The following object is masked from 'package:dplyr':
##
##     combine
```

```
library(DMwR)
```

```
## Loading required package: grid

## Registered S3 method overwritten by 'quantmod':
##   method            from
##   as.zoo.data.frame zoo
```

```
library(ROCR)
library(e1071)
source("src/Tools.R")
```

Carregando dados de treino

```
# Carregando dados de treino
train_sample <- read_csv("train_sample.csv")
```

```
## Parsed with column specification:
## cols(
##   ip = col_double(),
##   app = col_double(),
##   device = col_double(),
##   os = col_double(),
##   channel = col_double(),
##   click_time = col_datetime(format = ""),
##   attributed_time = col_datetime(format = ""),
##   is_attributed = col_double()
## )
```

```
# Algumas informações úteis sobre o dataset
dim(train_sample)
```

```
## [1] 100000      8
```

```
str(train_sample)
```

```
## tibble [100,000 x 8] (S3: spec_tbl_df/tbl_df/tbl/data.frame)
##  $ ip             : num [1:100000] 87540 105560 101424 94584 68413 ...
##  $ app            : num [1:100000] 12 25 12 13 12 3 1 9 2 3 ...
##  $ device         : num [1:100000] 1 1 1 1 1 1 1 1 2 1 ...
##  $ os             : num [1:100000] 13 17 19 13 1 17 17 25 22 19 ...
##  $ channel        : num [1:100000] 497 259 212 477 178 115 135 442 364 135 ...
```

```
##  $ click_time     : POSIXct[1:100000], format: "2017-11-07 09:30:38" "2017-11-07 13:40:27" ...
##  $ attributed_time: POSIXct[1:100000], format: NA NA ...
##  $ is_attributed  : num [1:100000] 0 0 0 0 0 0 0 0 0 0 ...
##  - attr(*, "spec")=
##   .. cols(
##   ..   ip = col_double(),
##   ..   app = col_double(),
##   ..   device = col_double(),
##   ..   os = col_double(),
##   ..   channel = col_double(),
##   ..   click_time = col_datetime(format = ""),
##   ..   attributed_time = col_datetime(format = ""),
##   ..   is_attributed = col_double()
##   .. )
```

Feature Selection

```
train_sample <- train_sample %>%
                  mutate(wday = as.factor(weekdays(click_time, abbreviate=T))) %>%
                  mutate(hour = hour(click_time)) %>%
                  select(-c(click_time)) %>%
                  add_count(ip, wday, hour) %>% rename("nip_day_h" = n) %>%
                  add_count(ip, hour, channel) %>% rename("nip_h_chan" = n) %>%
                  add_count(ip, hour, os) %>% rename("nip_h_osr" = n) %>%
                  add_count(ip, hour, app) %>% rename("nip_h_app" = n) %>%
                  add_count(ip, hour, device) %>% rename("nip_h_dev" = n) %>%
                  select(-c(ip, attributed_time))
```

Análise Exploratória

```
# Número de valores únicos por variável
unique_values <- as.data.frame(lapply(train_sample, function(x)length(unique(x))))
unique_values
```

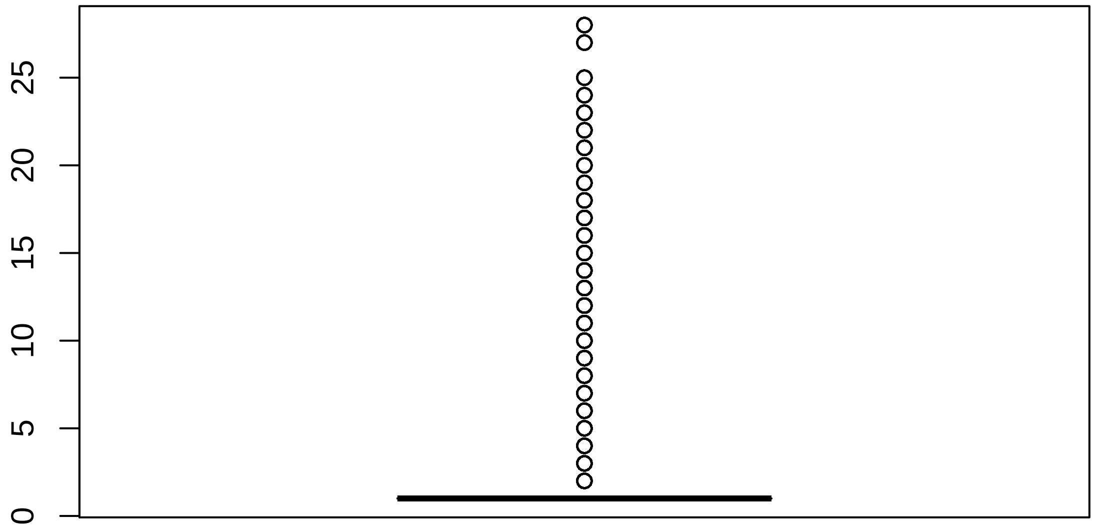
```
##   app device  os channel is_attributed wday hour nip_day_h nip_h_chan nip_h_osr
## 1 161    100 130     161             2    4   24        27          9        16
##   nip_h_app nip_h_dev
## 1        12        39
```

```
# Verificando valores missing
sapply(train_sample, function(x) sum(is.na(x)))
```

```
##           app        device            os       channel is_attributed
##             0             0             0             0             0
##          wday          hour     nip_day_h    nip_h_chan     nip_h_osr
##             0             0             0             0             0
##     nip_h_app     nip_h_dev
##             0             0
```

```
# Visualizando a distribuição e os outliers das variáveis criadas durante
# o processo de feature selection

# Os boxplots não nos traz tanta informação visual nesse caso,
# pois os valores de primeiro quartil, mediana e terceiro quartil
# estão muito próximo. Porém é interessante notar a presença
```

```r
# dos outliers
boxplot(train_sample$nip_day_h)
```



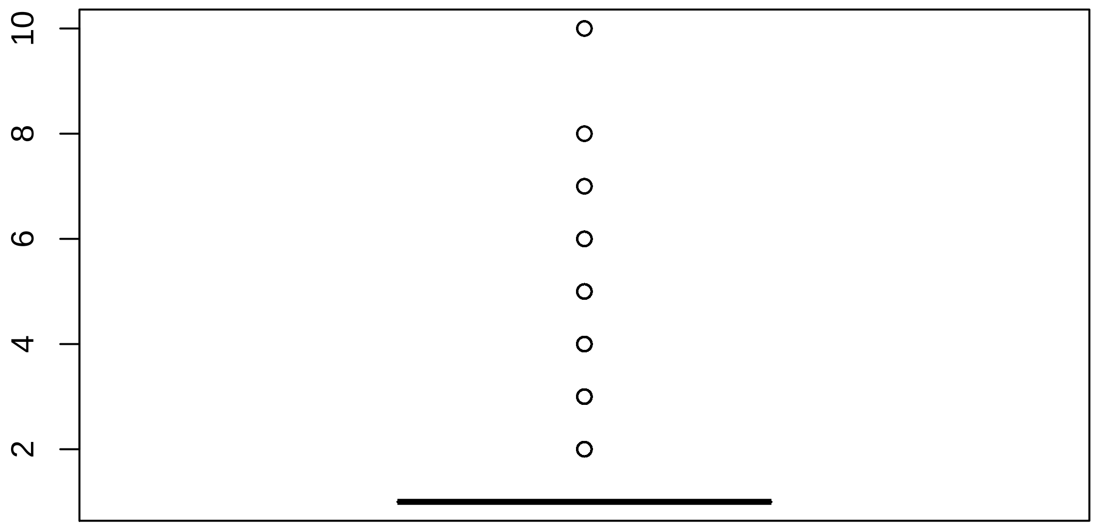

```r
# Podemos ver que a média de clicks por ip em um mesmo dia e hora é aproximadamente 1.
# Portanto os outliers podem indicar a ação de bots.
summary(train_sample$nip_day_h)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
##   1.000   1.000   1.000   1.493   1.000  28.000
```

```r
sd(train_sample$nip_day_h)
```

```
## [1] 2.020593
```

```r
# O mesmo padrão se repete para as outra variáveis
boxplot(train_sample$nip_h_chan)
```



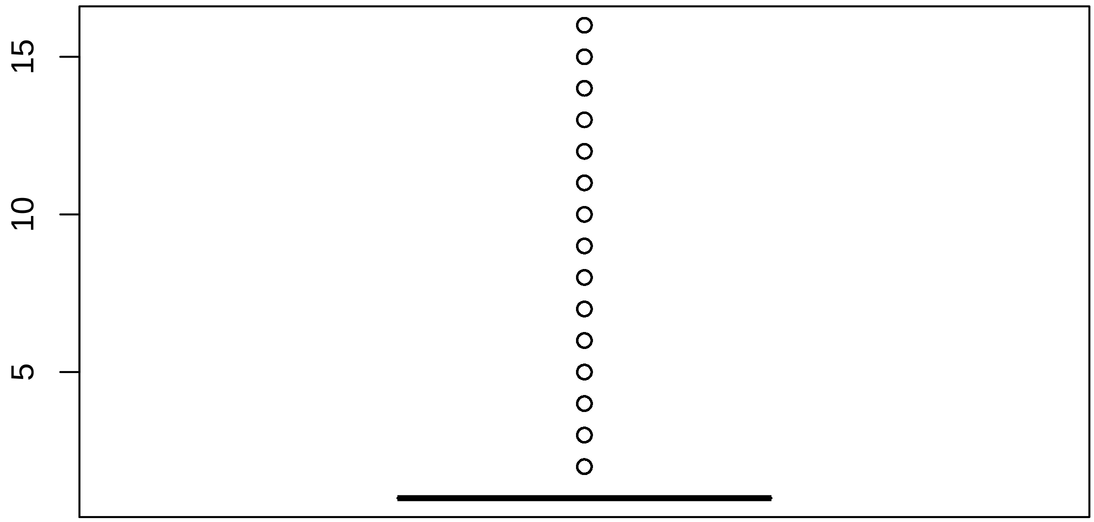

```r
summary(train_sample$nip_h_chan)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
##   1.000   1.000   1.000   1.054   1.000  10.000
```

```r
sd(train_sample$nip_h_chan)
```

```
## [1] 0.3332162
```

```r
boxplot(train_sample$nip_h_osr)
```



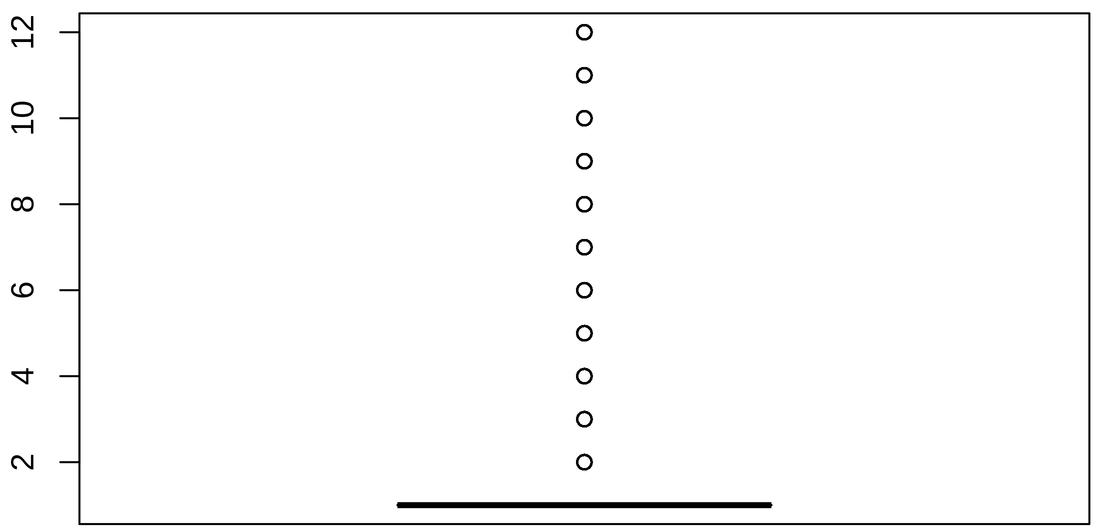

```r
summary(train_sample$nip_h_osr)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   1.000   1.000   1.154   1.000  16.000
```

```r
sd(train_sample$nip_h_osr)
```

```
## [1] 0.8607566
```

```r
boxplot(train_sample$nip_h_app)
```



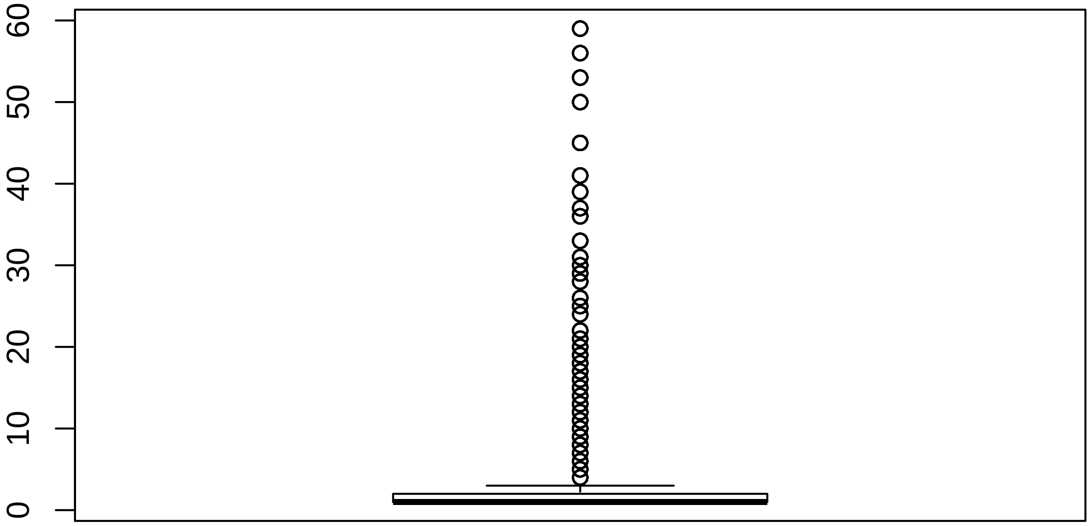

```r
summary(train_sample$nip_h_app)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   1.000   1.000   1.145   1.000  12.000
```

```r
sd(train_sample$nip_h_app)
```

```
## [1] 0.7217136
```

```r
boxplot(train_sample$nip_h_dev)
```




```r
summary(train_sample$nip_h_dev)
```

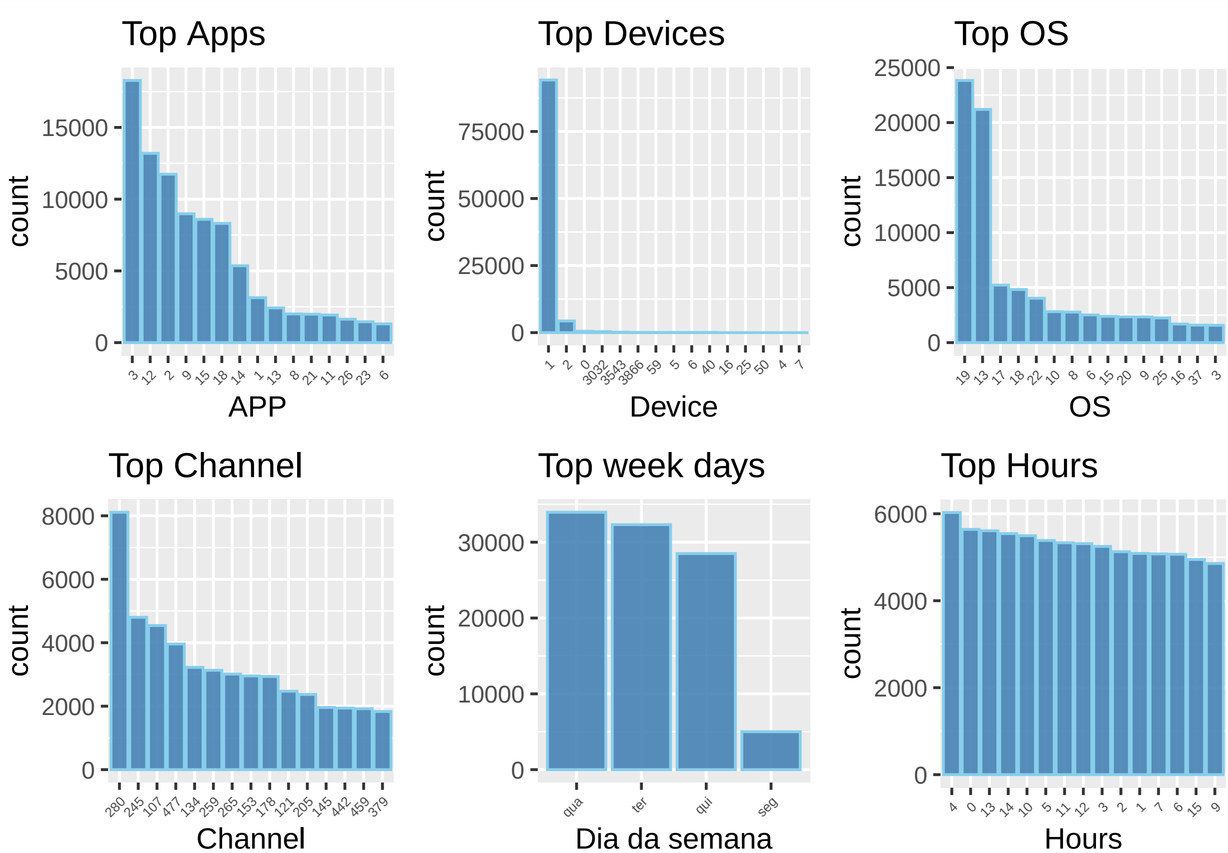
```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   1.000   1.000   2.054   2.000  59.000
```

```r
sd(train_sample$nip_h_dev)
```

```
## [1] 4.370674
```

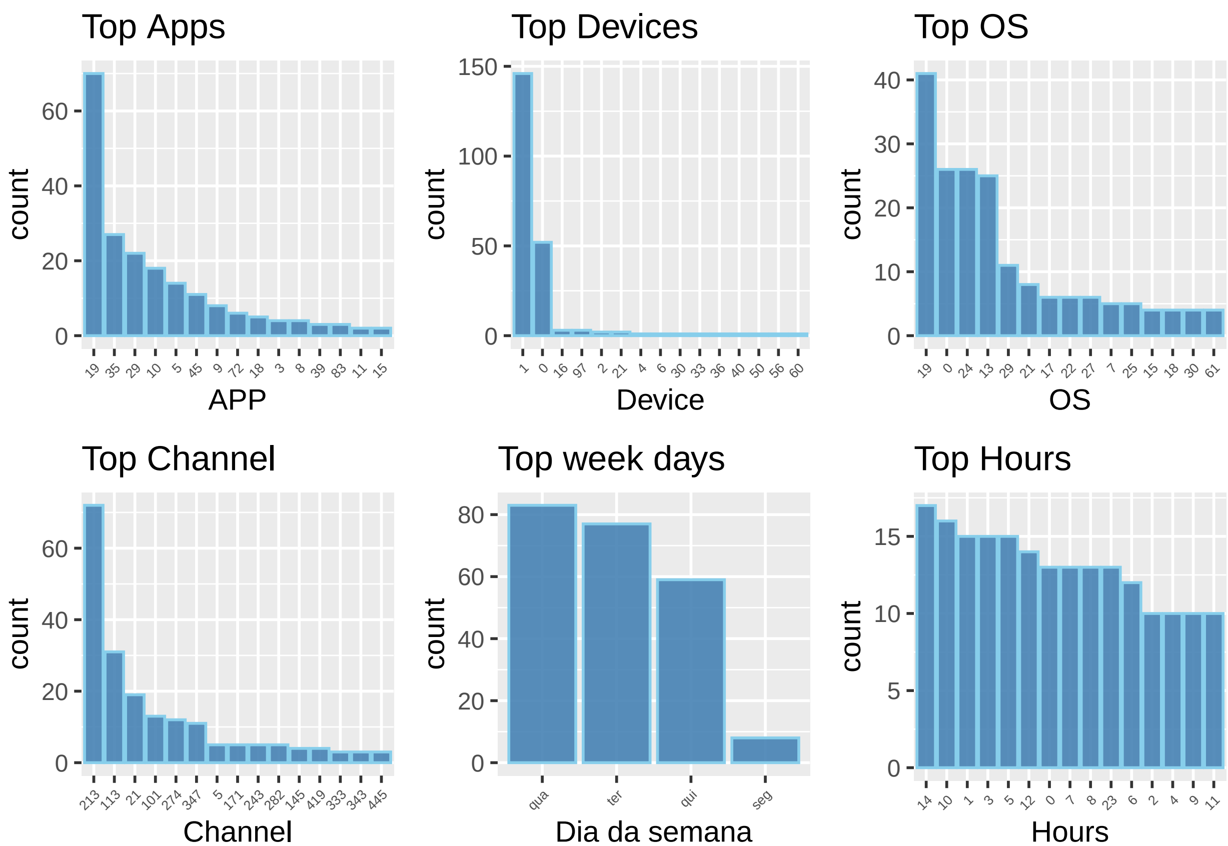
```r
# Plot de frequência das variáveis APP, Device, OS, Channel, Hora e Dia da semana
# filtrando dataset para dados ondenão houve download

h1 <- train_sample %>% group_by(app) %>% filter(is_attributed==FALSE) %>% summarise(count = n()) %>%
  arrange(desc(count)) %>% mutate(app = as.character(app)) %>% head(15) %>%
  ggplot(aes(x = reorder(app, -count), y=count)) + geom_bar(stat='identity', color='skyblue',
                                                            fill="steelblue", alpha=0.9) +
  ggtitle("Top Apps") + theme(axis.text.x=element_text(angle=45, hjust=1, size=4.5)) + labs(x = "APP")

h2 <- train_sample %>% group_by(device) %>% filter(is_attributed==FALSE) %>% summarise(count = n()) %>%
  arrange(desc(count)) %>% mutate(app = as.character(device)) %>% head(15) %>%
  ggplot(aes(x = reorder(device, -count), y=count)) + geom_bar(stat='identity', color='skyblue',
                                                               fill="steelblue", alpha=0.9) +
  ggtitle("Top Devices") + theme(axis.text.x=element_text(angle=45, hjust=1, size=4.5)) + labs(x = "Devi

h3 <- train_sample %>% group_by(os) %>% filter(is_attributed==FALSE) %>%  summarise(count = n())  %>%
  arrange(desc(count)) %>% mutate(app = as.character(os)) %>% head(15) %>%
  ggplot(aes(x = reorder(os, -count), y=count)) + geom_bar(stat='identity', color='skyblue',
                                                           fill="steelblue", alpha=0.9) +
  ggtitle("Top OS") + theme(axis.text.x=element_text(angle=45, hjust=1, size=4.5))  + labs(x = "OS")

h4 <- train_sample %>% group_by(channel) %>% filter(is_attributed==FALSE) %>% summarise(count = n()) %>%
  arrange(desc(count)) %>% mutate(app = as.character(channel)) %>% head(15) %>%
  ggplot(aes(x = reorder(channel, -count), y=count)) + geom_bar(stat='identity', color='skyblue',
```

```
                                                              fill="steelblue", alpha=0.9) +
  ggtitle("Top Channel") + theme(axis.text.x=element_text(angle=45, hjust=1, size=4.5)) + labs(x = "Cha

h5 <- train_sample %>% group_by(wday) %>% filter(is_attributed==FALSE) %>% summarise(count = n()) %>%
  arrange(desc(count)) %>% mutate(app = as.character(wday)) %>% head(15) %>%
  ggplot(aes(x = reorder(wday, -count), y=count)) + geom_bar(stat='identity', color='skyblue',
                                                           fill="steelblue", alpha=0.9) +
  ggtitle("Top week days") + theme(axis.text.x=element_text(angle=45, hjust=1, size=4.5)) +
  labs(x = "Dia da semana")

h6 <- train_sample %>% group_by(hour) %>% filter(is_attributed==FALSE) %>% summarise(count = n()) %>%
  arrange(desc(count)) %>% mutate(app = as.character(hour)) %>% head(15) %>%
  ggplot(aes(x = reorder(hour, -count), y=count)) + geom_bar(stat='identity', color='skyblue',
                                                           fill="steelblue", alpha=0.9) +
  ggtitle("Top Hours") + theme(axis.text.x=element_text(angle=45, hjust=1, size=4.5)) + labs(x = "Hours
#?element_text
grid.arrange(h1, h2, h3, h4, h5, h6, nrow = 2)
```




```
# Plot de frequência das variáveis APP, Device, OS, Channel, Hora e dia da semana filtrando o dataset
# para dados onde houve o download

h7 <- train_sample %>% filter(is_attributed==TRUE) %>% group_by(app) %>% summarise(count = n()) %>%
  arrange(desc(count)) %>% mutate(app = as.character(app)) %>% head(15) %>%
  ggplot(aes(x = reorder(app, -count), y=count)) + geom_bar(stat='identity', color='skyblue',
                                                         fill="steelblue", alpha=0.9) +
  ggtitle("Top Apps") + theme(axis.text.x=element_text(angle=45, hjust=1, size=4.5)) + labs(x = "APP")
```

```r
h8 <- train_sample %>% filter(is_attributed==TRUE) %>% group_by(device) %>% summarise(count = n()) %>%
  arrange(desc(count)) %>% mutate(app = as.character(device)) %>% head(15) %>%
  ggplot(aes(x = reorder(device, -count), y=count)) + geom_bar(stat='identity', color='skyblue',
                                                              fill="steelblue", alpha=0.9) +
  ggtitle("Top Devices") + theme(axis.text.x=element_text(angle=45, hjust=1, size=4.5)) + labs(x = "Devi

h9 <- train_sample %>% filter(is_attributed==TRUE) %>% group_by(os) %>% summarise(count = n()) %>%
  arrange(desc(count)) %>% mutate(app = as.character(os)) %>% head(15) %>%
  ggplot(aes(x = reorder(os, -count), y=count)) + geom_bar(stat='identity', color='skyblue',
                                                          fill="steelblue", alpha=0.9) +
  ggtitle("Top OS") + theme(axis.text.x=element_text(angle=45, hjust=1, size=4.5))  + labs(x = "OS")

h10 <- train_sample %>% filter(is_attributed==TRUE) %>% group_by(channel) %>% summarise(count = n()) %>%
  arrange(desc(count)) %>% mutate(app = as.character(channel)) %>% head(15) %>%
  ggplot(aes(x = reorder(channel, -count), y=count)) + geom_bar(stat='identity', color='skyblue',
                                                               fill="steelblue", alpha=0.9) +
  ggtitle("Top Channel") + theme(axis.text.x=element_text(angle=45, hjust=1, size=4.5)) + labs(x = "Chan

h11 <- train_sample %>% filter(is_attributed==TRUE) %>% group_by(wday) %>% summarise(count = n()) %>%
  arrange(desc(count)) %>% mutate(app = as.character(wday)) %>% head(15) %>%
  ggplot(aes(x = reorder(wday, -count), y=count)) + geom_bar(stat='identity', color='skyblue',
                                                            fill="steelblue", alpha=0.9) +
  ggtitle("Top week days") + theme(axis.text.x=element_text(angle=45, hjust=1, size=4.5)) + labs(x = "Da

h12 <- train_sample %>% filter(is_attributed==TRUE) %>% group_by(hour) %>% summarise(count = n()) %>%
  arrange(desc(count)) %>% mutate(app = as.character(hour)) %>% head(15) %>%
  ggplot(aes(x = reorder(hour, -count), y=count)) + geom_bar(stat='identity', color='skyblue',
                                                            fill="steelblue", alpha=0.9) +
  ggtitle("Top Hours") + theme(axis.text.x=element_text(angle=45, hjust=1, size=4.5)) + labs(x = "Hours

grid.arrange(h7, h8, h9, h10, h11, h12, nrow = 2)
```




```
# Podemos observas certas diferenças na utilização de aplicativo, dispositivo, hora e outros em relação
# aos dados onde tivemos o download e onde não tivemos o download.
```

Transformando variáveis em fator

```
train_sample <- to.factors(train_sample, factColNames)
str(train_sample)
```

```
## tibble [100,000 x 12] (S3: tbl_df/tbl/data.frame)
##  $ app          : num [1:100000] 12 25 12 13 12 3 1 9 2 3 ...
##  $ device       : num [1:100000] 1 1 1 1 1 1 1 1 2 1 ...
##  $ os           : num [1:100000] 13 17 19 13 1 17 17 25 22 19 ...
##  $ channel      : num [1:100000] 497 259 212 477 178 115 135 442 364 135 ...
##  $ is_attributed: Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
##  $ wday         : Factor w/ 4 levels "qua","qui","seg",..: 4 4 4 4 2 2 2 4 1 1 ...
##  $ hour         : Factor w/ 24 levels "0","1","2","3",..: 10 14 19 5 10 2 2 11 10 13 ...
##  $ nip_day_h    : int [1:100000] 1 4 1 1 1 1 1 1 1 1 ...
##  $ nip_h_chan   : int [1:100000] 1 1 1 1 1 1 1 1 1 1 ...
##  $ nip_h_osr    : int [1:100000] 1 1 1 1 1 1 1 1 1 1 ...
##  $ nip_h_app    : int [1:100000] 1 1 1 1 1 1 1 1 1 1 ...
##  $ nip_h_dev    : int [1:100000] 1 8 1 1 1 1 2 1 1 1 ...
```

Verificando balanceamento do dataset

```
table(train_sample$is_attributed)
```

```
##
```

```
##      0     1
## 99773   227
```

```r
prop.table(table(train_sample$is_attributed))
```

```
##
##       0       1
## 0.99773 0.00227
```

```r
# Dataset altamente desbalanceado

# Balanceamento do dataset
balanced_train_sample <- SMOTE(is_attributed ~ ., as.data.frame(train_sample), k = 3, perc.over = 400, p
table(balanced_train_sample$is_attributed)
```

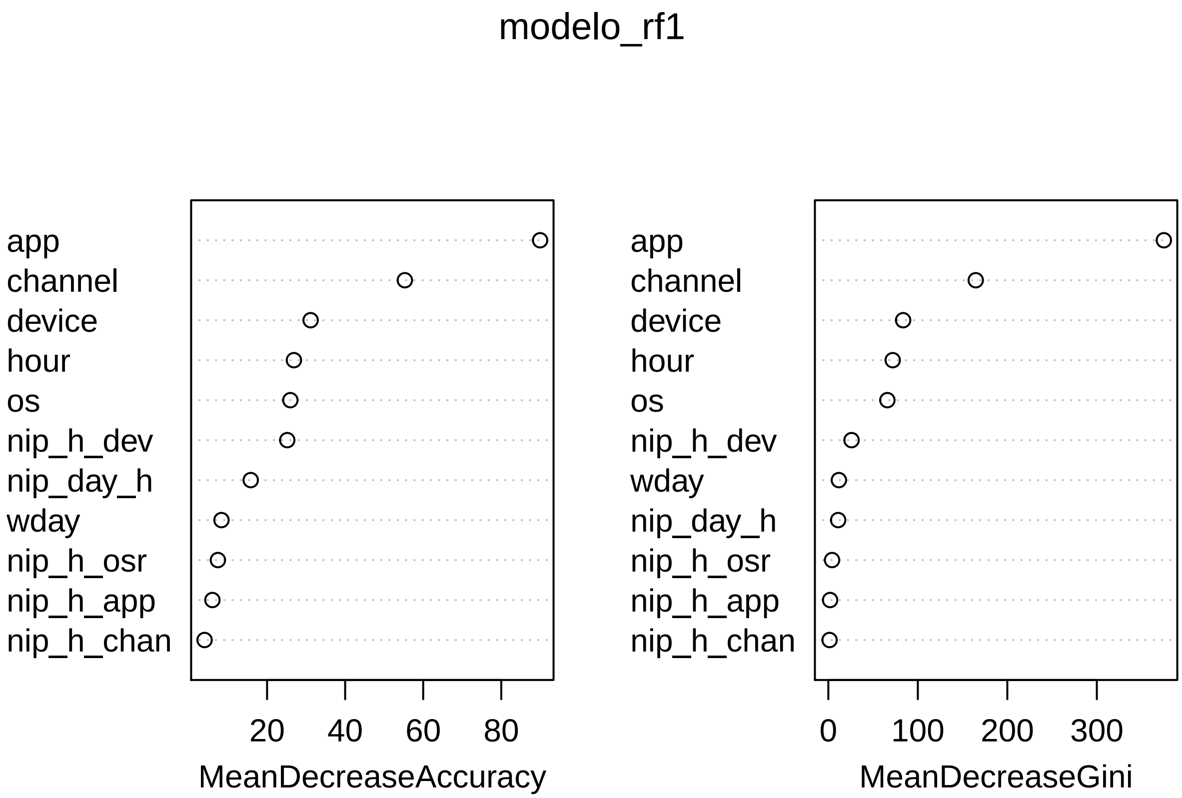
```
##
##    0    1
## 1362 1135
```

```r
# Podemos ver que o balanceamento funcionou
prop.table(table(balanced_train_sample$is_attributed))
```

```
##
##         0         1
## 0.5454545 0.4545455
```

Machine Learning

```r
# Dividino o dataset em dados de treino e dados e teste
set.seed(123)
smp_size <- floor(0.70 * nrow(balanced_train_sample))
train_ind <- sample(seq_len(nrow(balanced_train_sample)), size = smp_size)

train <- balanced_train_sample[train_ind, ]
test <- balanced_train_sample[-train_ind, ]

# Analisando relevância das variáveis para o modelo preditivo
# Aqui utilizo o algorítimo randomforest como ferramenta para averiguar a importância das variáveis
# para o modelo preditivo
modelo_rf1 <- randomForest(is_attributed ~ ., data=train, importance=TRUE)
varImpPlot(modelo_rf1)
```




```r
# Treinando novamente o modelo com as 7 variáveis de maior relevância
# Foi adotado o método Gini para a escolha das variáveis
modelo_rf1 <- randomForest(is_attributed ~ app +
                           channel +
                           hour +
                           device +
                           os +
                           nip_h_dev +
                           nip_day_h,
                           data=train)

# Análise da performance do modelo
# Criando dataframe com valores observados historicamente e com os valores previstos pelo
# modelo de machine learning
score_model <- data.frame(observado = test$is_attributed,
                          previsto = predictions <- predict(modelo_rf1, test[,-5]))

confusionMatrix(score_model$observado, score_model$previsto)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0 392   6
##          1  25 327
##
##                Accuracy : 0.9587
##                  95% CI : (0.9418, 0.9717)
##     No Information Rate : 0.556
```

```
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.9168
##
##  Mcnemar's Test P-Value : 0.001225
##
##             Sensitivity : 0.9400
##             Specificity : 0.9820
##          Pos Pred Value : 0.9849
##          Neg Pred Value : 0.9290
##              Prevalence : 0.5560
##          Detection Rate : 0.5227
##    Detection Prevalence : 0.5307
##       Balanced Accuracy : 0.9610
##
##        'Positive' Class : 0
##
```

```r
modelo_rf2 <- randomForest(is_attributed ~ app +
                           channel +
                           hour +
                           device +
                           os +
                           nip_h_dev +
                           nip_day_h,
                           data=train,
                           ntree = 300,
                           nodesize = 3)

score_model2 <- data.frame(observado = test$is_attributed,
                          previsto = predictions <- predict(modelo_rf2, test[,-5]))

confusionMatrix(score_model2$observado, score_model2$previsto)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0 390   8
##          1  23 329
##
##                Accuracy : 0.9587
##                  95% CI : (0.9418, 0.9717)
##     No Information Rate : 0.5507
##     P-Value [Acc > NIR] : < 2e-16
##
##                   Kappa : 0.9168
##
##  Mcnemar's Test P-Value : 0.01192
##
##             Sensitivity : 0.9443
##             Specificity : 0.9763
##          Pos Pred Value : 0.9799
##          Neg Pred Value : 0.9347
##              Prevalence : 0.5507
```

```
##          Detection Rate : 0.5200
##    Detection Prevalence : 0.5307
##       Balanced Accuracy : 0.9603
##
##        'Positive' Class : 0
##
```

```r
# Testando outro algorítimo de classificação SVM

# Utilizando kernel linear
modelo_svm_linear = tune.svm(is_attributed ~ app +
                             channel +
                             hour +
                             device +
                             os +
                             nip_h_dev +
                             nip_day_h,
                             data=train,
                             kernel="linear")

# Salvando a melhro versão do modelo
best.linear = modelo_svm_linear$best.model

## Analisando a performance do modelo

best.test=predict(best.linear,newdata=test,type="class")
confusionMatrix(best.test,test$is_attributed)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0 350 154
##          1  48 198
##
##                Accuracy : 0.7307
##                  95% CI : (0.6974, 0.7621)
##     No Information Rate : 0.5307
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.4497
##
##  Mcnemar's Test P-Value : 1.493e-13
##
##             Sensitivity : 0.8794
##             Specificity : 0.5625
##          Pos Pred Value : 0.6944
##          Neg Pred Value : 0.8049
##              Prevalence : 0.5307
##          Detection Rate : 0.4667
##    Detection Prevalence : 0.6720
##       Balanced Accuracy : 0.7209
##
##        'Positive' Class : 0
##
```

```r
# Utilizando kernel radial
modelo_svm_radial = tune.svm(is_attributed ~ app +
                              channel +
                              hour +
                              device +
                              os +
                              nip_h_dev +
                              nip_day_h,
                              data=train,
                              kernel="radial")

best.radial=modelo_svm_radial$best.model
best.test=predict(best.radial,newdata=test,type="class")
confusionMatrix(best.test,test$is_attributed)
```

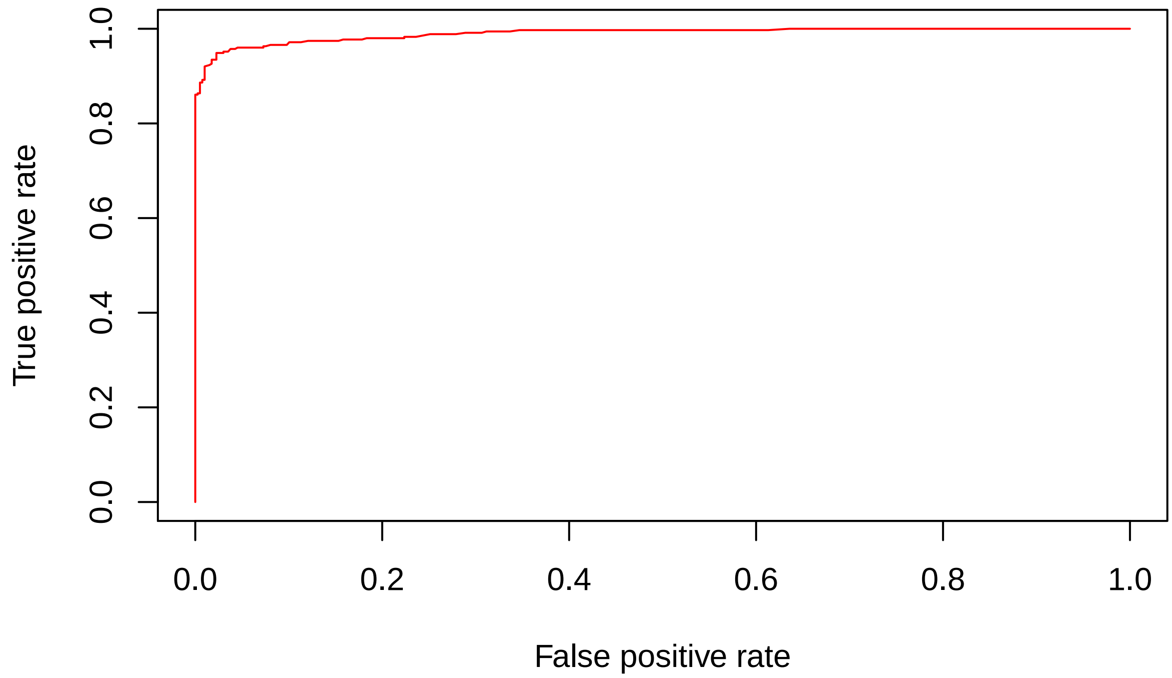
```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0 352 152
##          1  46 200
##
##                Accuracy : 0.736
##                  95% CI : (0.7029, 0.7672)
##     No Information Rate : 0.5307
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.4606
##
##  Mcnemar's Test P-Value : 8.52e-14
##
##             Sensitivity : 0.8844
##             Specificity : 0.5682
##          Pos Pred Value : 0.6984
##          Neg Pred Value : 0.8130
##              Prevalence : 0.5307
##          Detection Rate : 0.4693
##    Detection Prevalence : 0.6720
##       Balanced Accuracy : 0.7263
##
##        'Positive' Class : 0
##
```

```r
# Chamando a Função para executar o registrar todos os resultados do modelo
mult_rf <- nb_multiple_runs(train, 20)

# Média de acurácia do modelo
summary(mult_rf)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.9493  0.9560  0.9567  0.9573  0.9590  0.9667
```

Curva ROC

```r
# Criando curvas ROC
# Gerando as classes de dados
class1 <- predict(modelo_rf2, newdata = test, type = 'prob')
class2 <- test$is_attributed

# Gerando a curva ROC
pred <- prediction(class1[,2], class2)
perf <- performance(pred, "tpr","fpr")
plot(perf, col = rainbow(10))
```



Fim! Obrigado.