# Click Traffic Fraud Detection in Mobile Application Advertisements

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```
setwd("C:/Projects")
set.seed(42)

# Import necessary libraries
library(e1071)
```

```
require(lubridate)
```

```
## Loading required package: lubridate
```

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

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

```
library(readr)
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
```

```
library(plyr)
```

```
##
## Attaching package: 'plyr'
```

```
## The following objects are masked from 'package:dplyr':
##
##     arrange, count, desc, failwith, id, mutate, rename, summarise,
##     summarize
```

```
library(caret)
```

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

```
## Loading required package: ggplot2
```

```
library(ROCR)
```

```
library(ggplot2)
library(gridExtra)
```

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

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

```
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
```

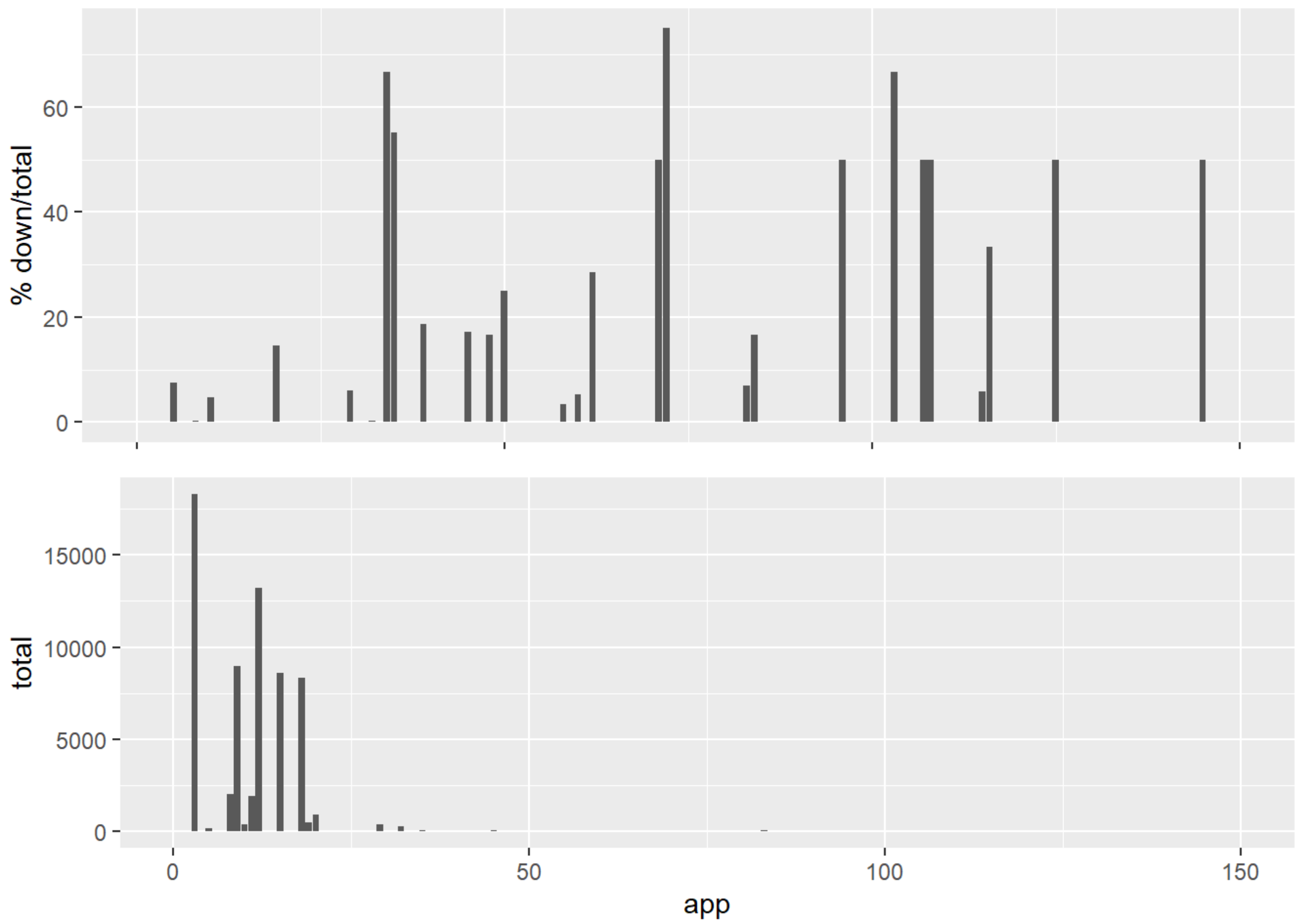
```r
library(e1071)

# Read .csv data on a zipped folder
folder <- "C:/CursoDSA/BigDataAzure/Projetos/dataset_project1.zip"
con <- unz(folder,"dataset_project1/train_sample.csv")
train <- read_csv(con)
```

```
## 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()
## )
```

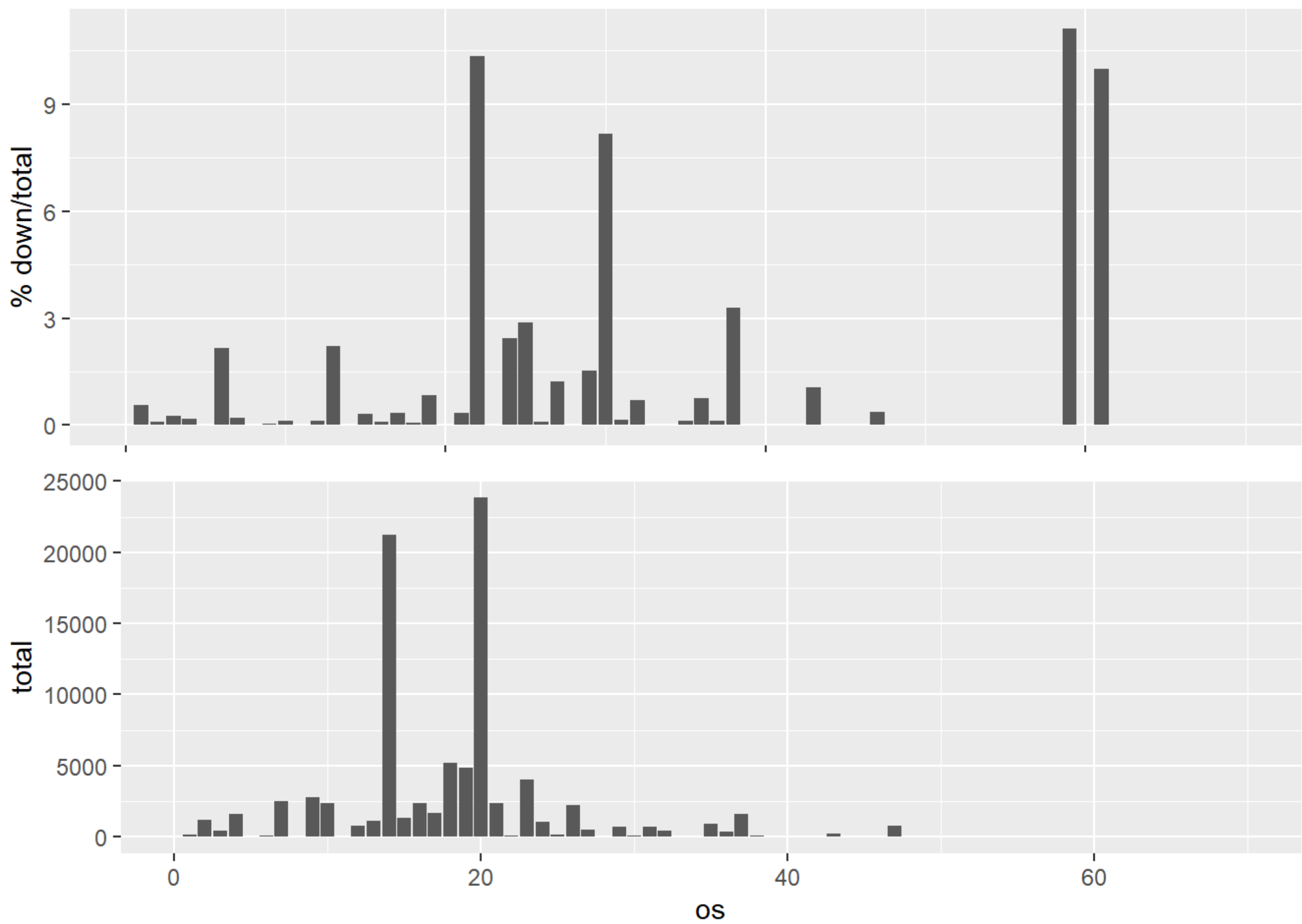
```r
View(head(train))

# Convert time to seconds
train$click_time <- as.numeric(train$click_time)

# Check if there is NA values on each colum
for(i in 1:length(train)){if(any(is.na(train[, i]))){print(i)}}
```

```
## [1] 7
```

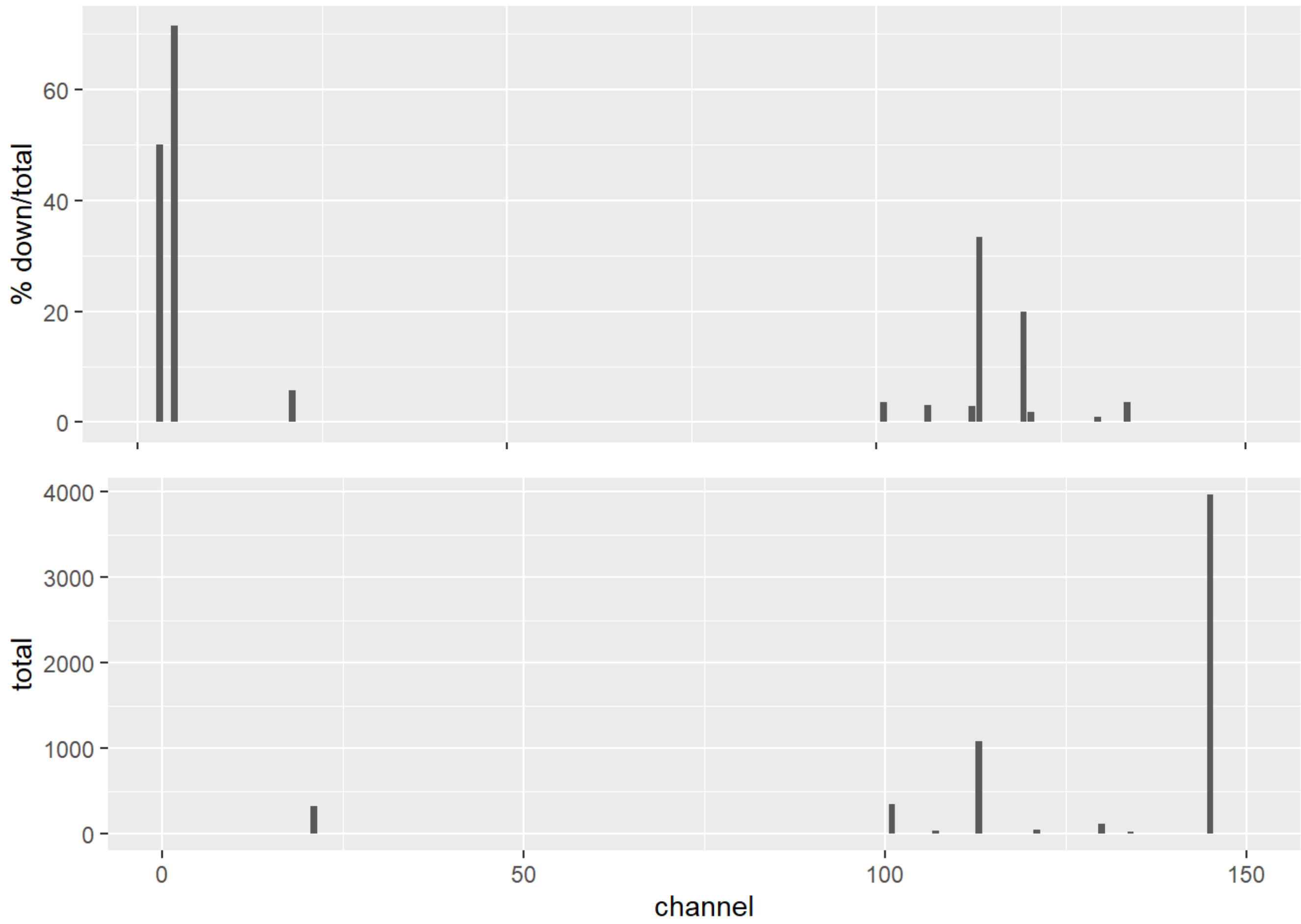
```
# Drop attributed time column as it is not going to be used
train <- train[,-7]

# Transform column to factor data type
train$is_attributed <- as.factor(train$is_attributed)

#================================  DATA EXPLORATION ================================

# Function that plot 2 graphs: donwload rate by the total of clicks (upper graph), and total
 clicks (bellow graph)
plot_graph <- function(feature,limit_n){
  item <- train%>%filter(is_attributed==1)%>%group_by_at(feature)%>%group_keys()
  df1 <- data.frame(item=item[[1]] ,
                  downloads=train%>%filter(is_attributed==1)%>%group_by_at(feature)%>%group_s
ize())
  item <- train%>%filter(is_attributed==0)%>%group_by_at(feature)%>%group_keys()
  df2 <- data.frame(item=item[[1]],
                  no.downloads=train%>%filter(is_attributed==0)%>%group_by_at(feature)%>%grou
p_size())
  df <- merge.data.frame(df1, df2, by.y=0)
  df <- df%>%mutate(total=no.downloads+downloads)%>%mutate(rate=100*downloads/total)
  p1 <- ggplot(df,aes(x=item, y=rate)) + geom_bar(stat="identity") + xlim(0, limit_n) + ylab(
"% down/total") + theme(axis.title.x=element_blank(),

axis.text.x=element_blank())
  p2 <- ggplot(df,aes(x=item, y=total)) + geom_bar(stat="identity") + xlim(0, limit_n) + xlab
(feature)
  grid.arrange(p1, p2, ncol = 1)
}
# Plot function for app
plot_graph("app",150)
```




```
# Plot function for os
plot_graph("os",70)
```



```
# Plot function for channel
plot_graph("channel",150)
```




```
# Labels proportion
prop.table(table(train$is_attributed))
```

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

```
#================================  FEATURE ENGINEERING ================================

variables = c("ip","app","device","os","channel")

# create colums with the time since the previous click by groups
for(variable in variables){
  train <- arrange_at(train,c(variable,"click_time"))
  train[[paste("delay_last_",variable,sep="")]] <- c(0,sapply(seq(2,length(train$click_time)),
       function(i){ifelse(train$ip[i]==train$ip[i-1],train$click_time[i]-train$click_time[i-1],0)}))
}

# create colums with the runned time since the first and last click by groups
for(variable in variables){
  train <- train %>% group_by_at(variable) %>% mutate(time_first = min(click_time))
  train[[paste("delay_first_",variable,sep="")]] <- train$click_time - train$time_first
}

# Drop time_first colum
train <- train%>%subset(select=-time_first)

#================================  NORMALIZATION ================================

train[-7] <- sapply(train%>%select(-is_attributed), function(x){return ((x - min(x)) / (max(x) - min(x)))})
View(head(train))

#================================  FEATURE SELECTION ================================

train$is_attributed <- as.numeric(train$is_attributed)
control <- rfeControl(functions = rfFuncs, method = "cv",
                      verbose = FALSE, returnResamp = "all",
                      number = 6)
results.rfe <- rfe(x = train%>%subset(select=-is_attributed),
                   y = as.matrix(train%>%subset(select=is_attributed)),
                   sizes = 1:10,
                   rfeControl = control)
```

```
results.rfe
```

```
##
## Recursive feature selection
##
## Outer resampling method: Cross-Validated (6 fold)
##
## Resampling performance over subset size:
##
##  Variables    RMSE Rsquared      MAE   RMSESD RsquaredSD     MAESD Selected
##          1 0.04373   0.1570 0.003737 0.004039    0.04153 0.0003279
##          2 0.04192   0.2234 0.003490 0.003962    0.02788 0.0003433
##          3 0.04254   0.2049 0.003727 0.003858    0.02056 0.0003100
##          4 0.04277   0.1988 0.003772 0.003629    0.04046 0.0003018
##          5 0.04338   0.1737 0.003828 0.003542    0.04143 0.0003077
##          6 0.04400   0.1569 0.003621 0.003355    0.04460 0.0003309
##          7 0.04440   0.1412 0.003708 0.003579    0.04833 0.0003266
##          8 0.04474   0.1266 0.003780 0.003506    0.04326 0.0003133
##          9 0.04469   0.1377 0.003685 0.003401    0.04211 0.0003163
##         10 0.04410   0.1474 0.003709 0.003289    0.02759 0.0002954
##         16 0.04172   0.2296 0.003578 0.002230    0.05287 0.0002060        *
##
## The top 5 variables (out of 16):
##    app, channel, device, delay_first_app, delay_first_os
```

```
varImp((results.rfe))
```

```
##                       Overall
## app                 40.860564
## channel             37.992701
## device              23.532686
## delay_first_ip      20.769616
## delay_first_app     20.693777
## delay_first_os      20.588133
## delay_first_channel 20.470971
## delay_first_device  20.467030
## click_time          20.121574
## os                  18.732756
## delay_last_ip       13.277632
## ip                   8.814067
## delay_last_os        6.913896
## delay_last_app       0.000000
## delay_last_channel   0.000000
## delay_last_device    0.000000
```

```
# Select 10 top features
train_sel <- train%>%ungroup()%>%select(-c(delay_last_device,delay_last_channel,delay_last_ap
p,
                                   delay_last_os,ip,delay_last_ip))
View(head(train_sel))

#==================================  TRAINING ==================================

train_sel$is_attributed <- as.factor(train_sel$is_attributed)

# Split data
index <- createDataPartition(train_sel$is_attributed,p=0.7,list=FALSE)
train_data <- train_sel[c(index),]
test_data <- data.frame(train_sel)[-index,]

## Train models with up sampling method for data balance
# Random Forest model:
ctrl <- trainControl(method = "repeatedcv",
                     number = 5,
                     repeats = 5,
                     verboseIter = FALSE,
                     sampling = "up")
model_rf <- caret::train(is_attributed ~ .,
                      data = train_data,
                      method = "rf",
                      trControl = ctrl)
final_rf <- data.frame(actual = test_data$is_attributed,
                    predict(model_rf, newdata = test_data))

cm_rf_test <- confusionMatrix(final_rf$predict, test_data$is_attributed)
cm_rf_test
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction     1     2
##          1 29907    60
##          2    24     8
##
##                Accuracy : 0.9972
##                  95% CI : (0.9965, 0.9978)
##     No Information Rate : 0.9977
##     P-Value [Acc > NIR] : 0.9743531
##
##                   Kappa : 0.1588
##
##  Mcnemar's Test P-Value : 0.0001341
##
##             Sensitivity : 0.9992
##             Specificity : 0.1176
##          Pos Pred Value : 0.9980
##          Neg Pred Value : 0.2500
##              Prevalence : 0.9977
##          Detection Rate : 0.9969
##    Detection Prevalence : 0.9989
##       Balanced Accuracy : 0.5584
##
##        'Positive' Class : 1
##
```

```
# Knn model:
model_knn <- caret::train(is_attributed ~ .,
                         data = train_data,
                         method = "knn",
                         trControl = ctrl)
final_knn <- data.frame(actual = test_data$is_attributed,
                       predict(model_knn, newdata = test_data))

cm_knn_test <- confusionMatrix(final_knn$predict, test_data$is_attributed)
cm_knn_test
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction     1     2
##          1 29751    51
##          2   180    17
##
##                Accuracy : 0.9923
##                  95% CI : (0.9912, 0.9933)
##     No Information Rate : 0.9977
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.1254
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.99399
##             Specificity : 0.25000
##          Pos Pred Value : 0.99829
##          Neg Pred Value : 0.08629
##              Prevalence : 0.99773
##          Detection Rate : 0.99173
##    Detection Prevalence : 0.99343
##       Balanced Accuracy : 0.62199
##
##        'Positive' Class : 1
##
```