Project 5 - AdTracking Fraud Detection

Team 4

4/25/2017

Step 0: Load the packages, and get the directories

```
#
packages.used=c("lubridate","caret","dplyr","DMwR","ROSE","ggplot2","randomFo
rest","rpart","rpart.plot","data.table","e1071","gridExtra","xgboost","haven"
,"tidyverse","plyr","pROC","ROCR","data.table","DT","magrittr","corrplot","Rm
isc","ggalluvial","ModelMetrics","scales","irlba","forcats","forecast","TSA",
"zoo")
# packages.needed=setdiff(packages.used, intersect(installed.packages()[,1],
packages.used))
# if(length(packages.needed)>0){
#   install.packages(packages.needed, dependencies = TRUE)
# }
# # load packages
# library("lubridate")
# library("caret")
# library("dplyr")
# library("DMwR")
# library("ROSE")
# library("ggplot2")
# library("randomForest")
# library("rpart")
# library("rpart.plot")
# library("data.table")
# library("e1071")
# library("gridExtra")
# library("xgboost")
# library("haven")
# library("tidyverse")
# library("plyr")
# library("pROC")
# library("ROCR")
# library("data.table")
# library("DT")
# library("magrittr")
# library("corrplot")
# library("Rmisc")
# library("ggalluvial")
# library("ModelMetrics")
# require("scales")
# library("irlba")
# library("forcats")
```

```
# library("forecast")
# library("TSA")
# library("zoo")
# library("lightgbm")
```

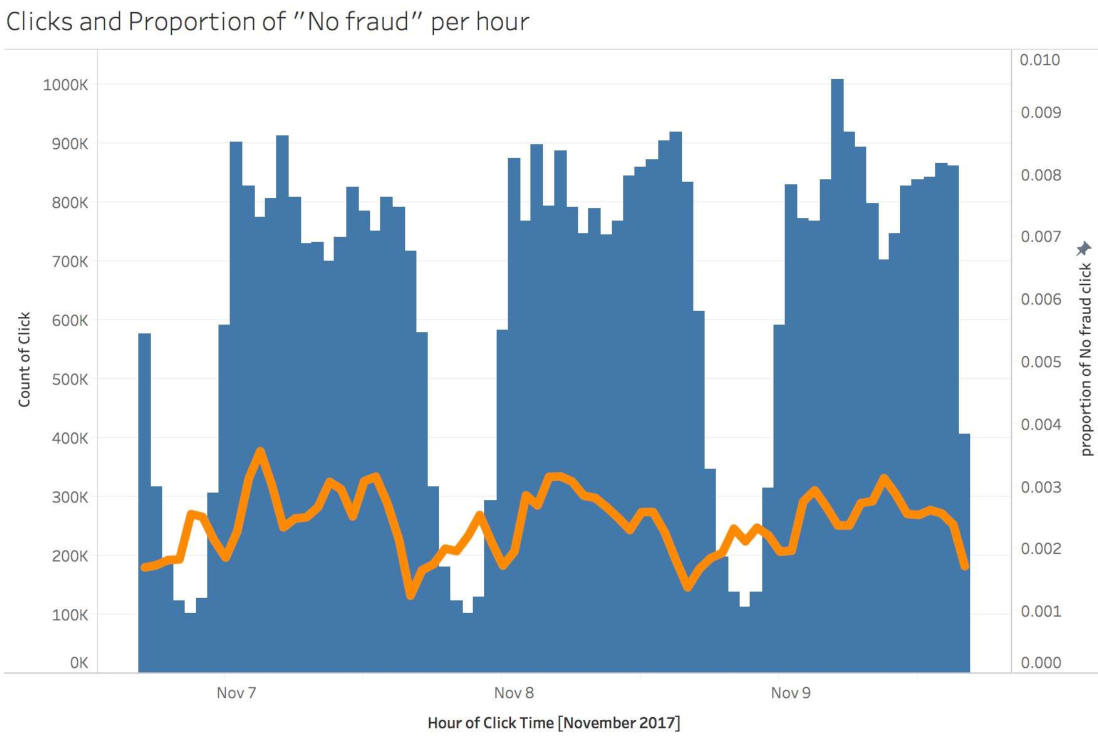
Step 1: Load and process the data

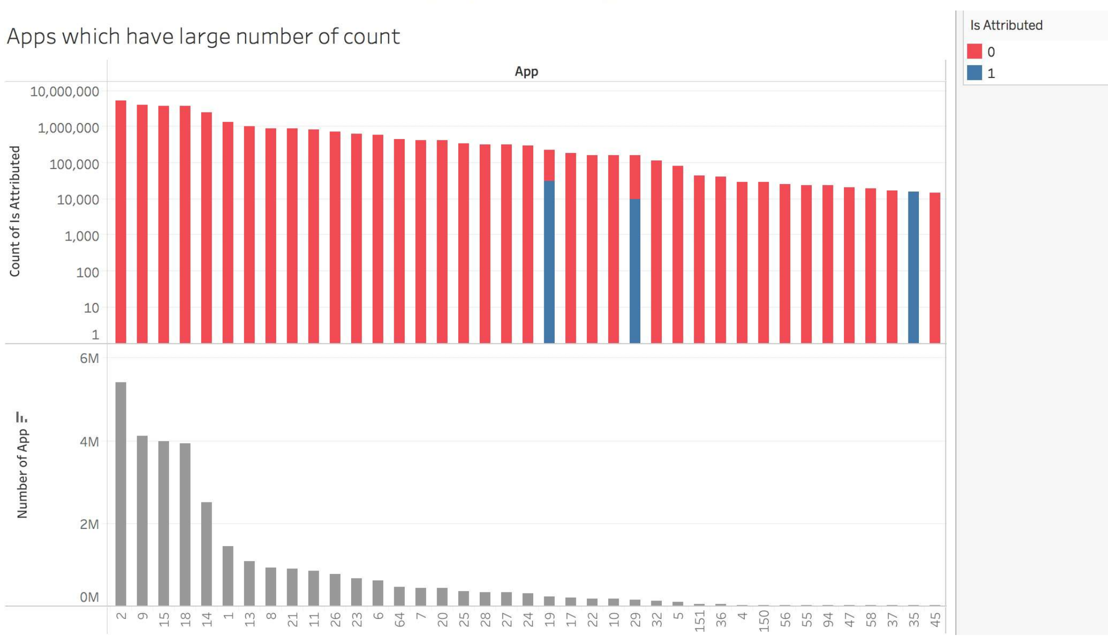
Here, we downloaded the data from kaggle competition for this project. Because the data is too big to upload to Github. Here we just uploaded the sample data of the trainset, which is processed by Kaggle. For the entire training set, we uploaded it to the Google Drive. You can download the data from here if you want:

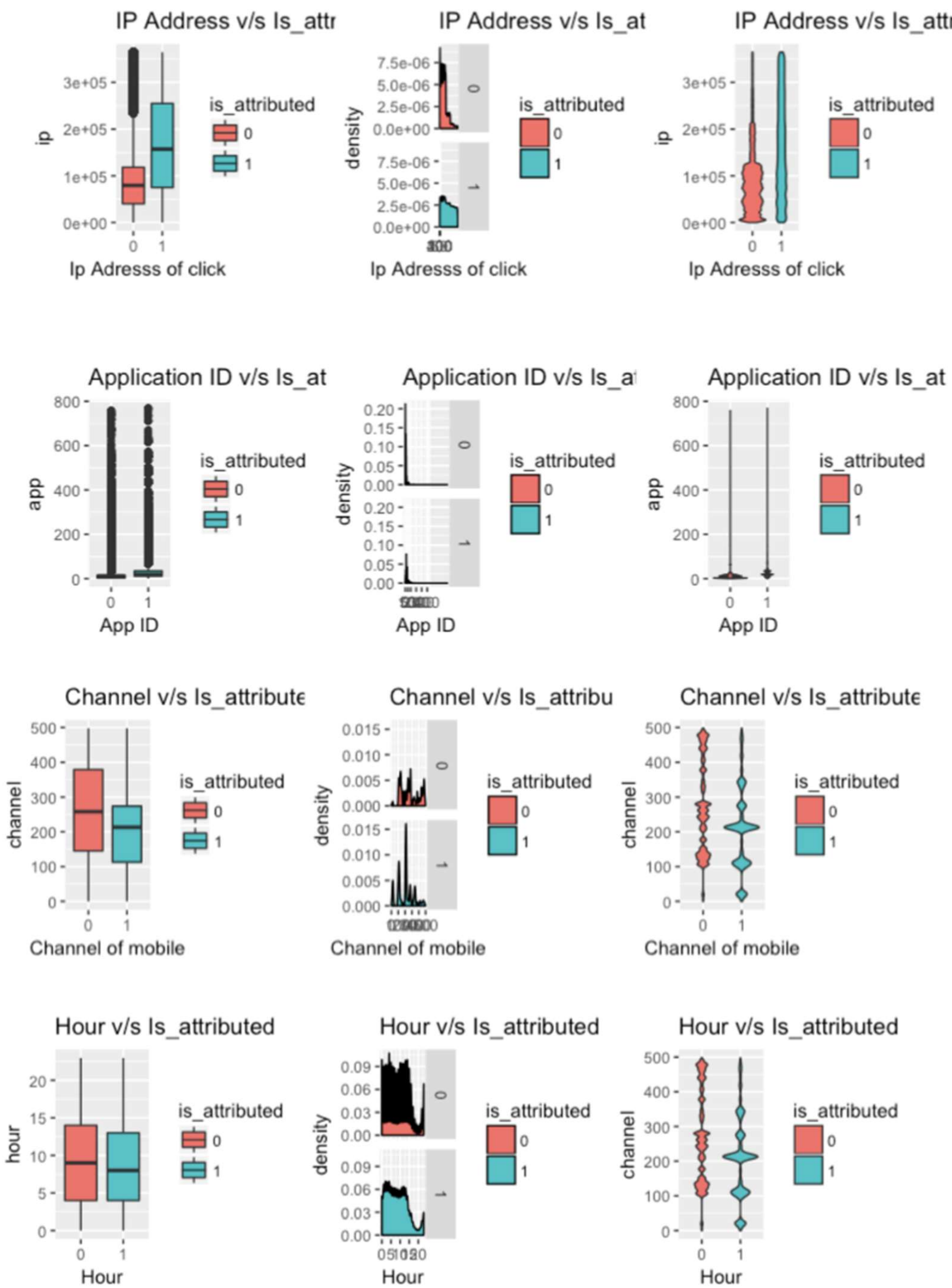
https://drive.google.com/drive/u/1/folders/1qDnsaZxyTxnPY89h2Gsh084l-QPqshav

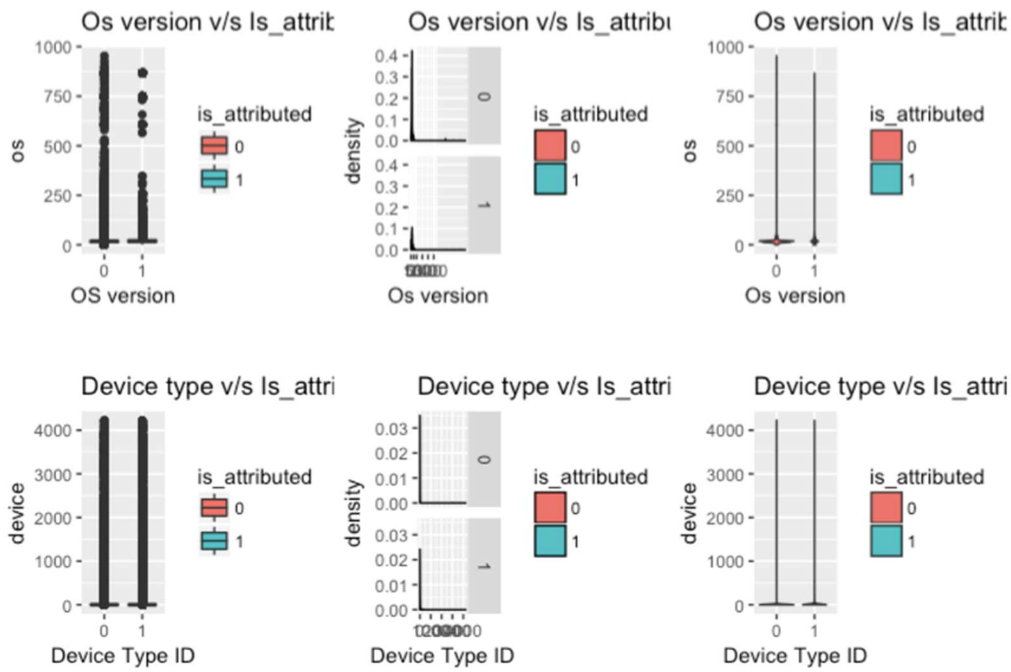
```
train.data <- read.csv("../data/train_sample.csv")
test.data <- read.csv("../data/test.csv")

# For the model using SMOTE data
set.seed(1234)
smote_train <- SMOTE(is_attributed ~ ., data  = train_val)
table(smote_train$is_attributed)
```

Step 2: EDA of Train Dataset and Test Dataset






IP Address v/s Is_attr
IP Address v/s Is_at
IP Address v/s Is_attr
ip
density
is_attributed
0
1
Ip Adresss of click
Application ID v/s Is_at
app
App ID
Channel v/s Is_attribute
Channel v/s Is_attribu
channel
Channel of mobile
Hour v/s Is_attributed
hour
Hour



For detail, please see our eda.Rmd in the doc folder.

From the EDA, we got some insights about the train and test dataset. Following are some conclusion we made in the EDA:

1. Application ID is definitely going to be one of the important feature to differentiate user downloaded the application or not.
2. OS feature is not an important feature for prediction.
3. IP Address could play an important role in prediction as clear diffrenation exist between 2 groups.
4. Device is not an important variable for our analysis.
5. Channel got some predictive power, and we can use this for our feature analysis.
6. Hour plays a least important feature.

Conclusion: After EDA, we select ip, app, channel, hour as our predictors.

Step 3: Model

Here, we write out the models we used in this project. Models include Naive Bayesian, Decision Tree, Random Forest, LightGBM and XgBoost.

Here is all the procedure we have for this algorithm.

```
aiveBayes <- function(TRAIN = "traindata.csv", TEST = "testdata.csv",IP=1,
APP=1, OS=1, DV=1, CH=1, TM=0)
{
  TimeToNum <- function(x)
  {
```

```r
    Hour <- as.numeric(substr(x, start = 12, stop = 13)) * 2
    HourHalf <- as.numeric(substr(x, start = 15, stop = 15))
    if (HourHalf >= 3)
      Hour <- Hour + 1
    return(Hour)
  }
  CalcProb <- function(User, deno)
  {
    if (is.na(tmp[User]))
      return(lambda / deno)
    return((tmp[User] + lambda) / deno)
  }

  TrainData <- read.csv(file = TRAIN)
  TrainData$Hour <- mapply(TimeToNum, TrainData)
  #head(TrainData)
  #table(TrainData$is_attributed)

  IpCount <- table(TrainData$ip)
  AppCount <- table(TrainData$app)
  OsCount <- table(TrainData$os)
  DvCount <- table(TrainData$device)#TrainData$device: 0,1,2,3(Others)
  ChCount <- table(TrainData$channel)
  TmCount <- table(TrainData$Hour)

  TrainData$ip <- as.character(TrainData$ip)
  TrainData$app <- as.character(TrainData$app)
  TrainData$os <- as.character(TrainData$os)
  TrainData$device <- as.character(TrainData$device)
  TrainData$channel <- as.character(TrainData$channel)
  TrainData$is_attributed <- as.numeric(TrainData$is_attributed) + 1

  lambda <- 0.1
  Prior <- rep(NA, 2)
  Prior[1] <- (sum(1 - TrainData$is_attributed) + lambda) / (nrow(TrainData)
+ lambda * 2)
  Prior[2] <- (sum(TrainData$is_attributed) + lambda) / (nrow(TrainData) +
lambda * 2)

  #calc IP Prob
  if (IP==1){
    IpTest <-  names(table(TestData$ip))
    IpTestNew <- setdiff(IpTest, names(IpCount))
    IpIntersect <- intersect(IpTest, names(IpCount))
    #IpProbNew <- matrix(0, nrow = length(IpTestNew), ncol = 2)

    IpProb <- matrix(0, nrow = length(IpIntersect) + length(IpTestNew), ncol
= 2)
    row.names(IpProb) <- c(IpIntersect, IpTestNew)
```

```r
    tmp <- table(TrainData$ip[which(TrainData$is_attributed == 0)])
    deno <- (sum(1 - TrainData$is_attributed) + length(IpCount) * lambda)
    IpProb[,1] <- mapply(CalcProb, row.names(IpProb), deno = deno)

    tmp <- table(TrainData$ip[which(TrainData$is_attributed == 1)])
    deno <- (sum(TrainData$is_attributed) + length(IpCount) * lambda)
    IpProb[,2] <- mapply(CalcProb, row.names(IpProb), deno = deno)
  }
  #calc App prob
  if (APP==1){
    AppTest <-  names(table(TestData$app))
    AppTestNew <- setdiff(AppTest, names(AppCount))
    AppIntersect <- intersect(AppTest, names(AppCount))
    #AppProbNew <- matrix(0, nrow = length(AppTestNew), ncol = 2)
    AppProb <- matrix(0, nrow = length(AppCount) + length(AppTestNew), ncol =
2)
    row.names(AppProb) <- c(names(AppCount), AppTestNew)

    tmp <- table(TrainData$app[which(TrainData$is_attributed == 0)])
    deno <- (sum(1 - TrainData$is_attributed) + length(AppCount) * lambda)
    AppProb[,1] <- mapply(CalcProb, row.names(AppProb), deno = deno)
    tmp <- table(TrainData$app[which(TrainData$is_attributed == 1)])
    deno <- (sum(TrainData$is_attributed) + length(AppCount) * lambda)
    AppProb[,2] <- mapply(CalcProb, row.names(AppProb), deno = deno)
  }
  #calc Os prob
  if (OS==1){
    OsTest <-  names(table(TestData$os))
    OsTestNew <- setdiff(OsTest, names(OsCount))
    OsIntersect <- intersect(OsTest, names(OsCount))
    #AppProbNew <- matrix(0, nrow = length(AppTestNew), ncol = 2)
    OsProb <- matrix(0, nrow = length(OsCount) + length(OsTestNew), ncol = 2)
    row.names(OsProb) <- c(names(OsCount), OsTestNew)

    tmp <- table(TrainData$os[which(TrainData$is_attributed == 0)])
    deno <- (sum(1 - TrainData$is_attributed) + length(OsCount) * lambda)
    OsProb[,1] <- mapply(CalcProb, row.names(OsProb), deno = deno)
    tmp <- table(TrainData$os[which(TrainData$is_attributed == 1)])
    deno <- (sum(TrainData$is_attributed) + length(OsCount) * lambda)
    OsProb[,2] <- mapply(CalcProb, row.names(OsProb), deno = deno)
  }
  #calc Ch prob
  if (CH==1){
    ChTest <-  names(table(TestData$channel))
    ChTestNew <- setdiff(ChTest, names(ChCount))
    ChIntersect <- intersect(ChTest, names(ChCount))
    #ChProbNew <- matrix(0, nrow = length(ChTestNew), ncol = 2)
    ChProb <- matrix(0, nrow = length(ChCount) + length(ChTestNew), ncol = 2)
```

```
  row.names(ChProb) <- c(names(ChCount), ChTestNew)

  tmp <- table(TrainData$channel[which(TrainData$is_attributed == 0)])
  deno <- (sum(1 - TrainData$is_attributed) + length(ChCount) * lambda)
  ChProb[,1] <- mapply(CalcProb, row.names(ChProb), deno = deno)
  tmp <- table(TrainData$channel[which(TrainData$is_attributed == 1)])
  deno <- (sum(TrainData$is_attributed) + length(ChCount) * lambda)
  ChProb[,2] <- mapply(CalcProb, row.names(ChProb), deno = deno)
}
#calc device prob
if (DV==1){
  DvTest <-  names(table(TestData$device))
  DvTestNew <- setdiff(DvTest, names(DvCount))
  DvIntersect <- intersect(DvTest, names(DvCount))
  #AppProbNew <- matrix(0, nrow = length(AppTestNew), ncol = 2)
  DvProb <- matrix(0, nrow = length(DvCount) + length(DvTestNew), ncol = 2)
  row.names(DvProb) <- c(names(DvCount), DvTestNew)

  tmp <- table(TrainData$device[which(TrainData$is_attributed == 0)])
  deno <- (sum(1 - TrainData$is_attributed) + length(DvCount) * lambda)
  DvProb[,1] <- mapply(CalcProb, row.names(DvProb), deno = deno)
  tmp <- table(TrainData$device[which(TrainData$is_attributed == 1)])
  deno <- (sum(TrainData$is_attributed) + length(DvCount) * lambda)
  DvProb[,2] <- mapply(CalcProb, row.names(DvProb), deno = deno)
}
#calc Time prob
if (TM==1){
  TmTest <-  names(table(TestData$Hour))
  TmTestNew <- setdiff(TmTest, names(TmCount))
  TmIntersect <- intersect(TmTest, names(TmCount))
  #AppProbNew <- matrix(0, nrow = length(AppTestNew), ncol = 2)
  TmProb <- matrix(0, nrow = length(TmCount) + length(TmTestNew), ncol = 2)
  row.names(TmProb) <- c(names(TmCount), TmTestNew)

  tmp <- table(TrainData$Hour[which(TrainData$is_attributed == 0)])
  deno <- (sum(1 - TrainData$is_attributed) + length(TmCount) * lambda)
  TmProb[,1] <- mapply(CalcProb, row.names(TmProb), deno = deno)
  tmp <- table(TrainData$Hour[which(TrainData$is_attributed == 1)])
  deno <- (sum(TrainData$is_attributed) + length(TmCount) * lambda)
  TmProb[,2] <- mapply(CalcProb, row.names(TmProb), deno = deno)
}

TestData <- read.csv(TEST)

TestData$Prob0 <- rep(Prior[1], nrow(TestData))
TestData$Prob1 <- rep(Prior[2], nrow(TestData))
TestData$ip <- as.character(TestData$ip)
TestData$app <- as.character(TestData$app)
TestData$os <- as.character(TestData$os)
```

```
  TestData$device <- as.character(TestData$device)
  TestData$channel <- as.character(TestData$channel)
  TestData$Hour <- as.character(TestData$Hour)

  if (IP==1)
  {
    TestData$Prob0 <- TestData$Prob0 * IpProb[TestData$ip, 1]
    TestData$Prob1 <- TestData$Prob1 * IpProb[TestData$ip, 2]
  }
  if (APP==1)
  {
    TestData$Prob0 <- TestData$Prob0 * AppProb[TestData$app, 1]
    TestData$Prob1 <- TestData$Prob1 * AppProb[TestData$app, 2]
  }
  if (OS==1)
  {
    TestData$Prob0 <- TestData$Prob0 * OsProb[TestData$os, 1]
    TestData$Prob1 <- TestData$Prob1 * OsProb[TestData$os, 2]
  }
  if (DV==1)
  {
    TestData$Prob0 <- TestData$Prob0 * DvProb[TestData$device, 1]
    TestData$Prob1 <- TestData$Prob1 * DvProb[TestData$device, 2]
  }
  if (CH==1)
  {
    TestData$Prob0 <- TestData$Prob0 * ChProb[TestData$channel, 1]
    TestData$Prob1 <- TestData$Prob1 * ChProb[TestData$channel, 2]
  }
  if (TM==1)
  {
    TestData$Prob0 <- TestData$Prob0 * TmProb[TestData$Hour, 1]
    TestData$Prob1 <- TestData$Prob1 * TmProb[TestData$Hour, 2]
  }
  TestData$Ans <- round(TestData$Prob1 / (TestData$Prob0 + TestData$Prob1),
7)

  Ans <- TestData[,c("click_id", "Ans")]
  names(Ans)[2] <- "is_attributed"
  write.csv(Ans, file = "Ans.csv",row.names = FALSE)
}

train_decisiontree <- function(smote_train){
  set.seed(1234)
  # traindata has to be a matrix
  timestart <- Sys.time()
  # Cross Validation Preparation
  cv.3 <- createMultiFolds(smote_train$is_attributed, k = 3,
                           times = 3)
  # Control
```

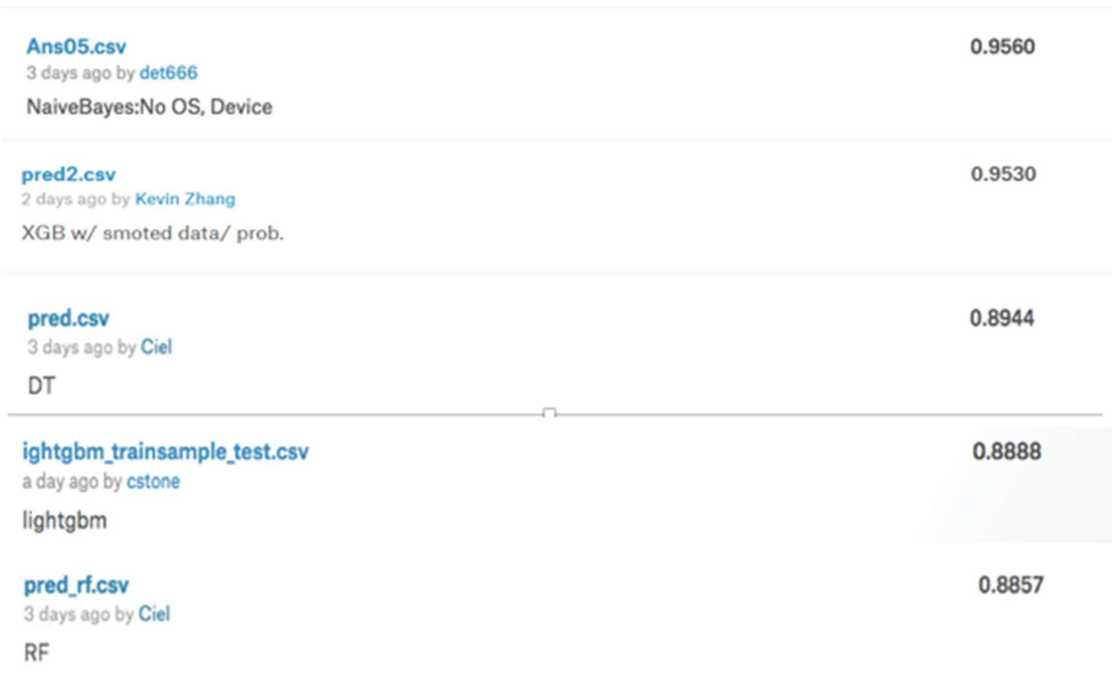
```
  ctrl <- trainControl(method = "repeatedcv", number = 3,
                       repeats = 3,
                       index = cv.3)
  # Train the data
  Model_fit <- train(x = smote_train[, -4], y = smote_train[, 4],
                     method = "rpart", tuneLength = 30,
                     trControl = ctrl)
  rpart.plot(Model_CDT$finalModel, extra = 3, fallen.leaves = T)
  PRE_VDTS <- predict(Model_CDT$finalModel,
                      newdata = test_val, type ="class")
  result <- confusionMatrix(PRE_VDTS, test_val$is_attributed)
  timeend <- Sys.time()
  runningtime <- timeend - timestart
  return(list(fit = Model_fit, evaluation = result, time = runningtime))
}

train_randomforest <- function(smote_train){
  set.seed(1234)
  ind <- createDataPartition(train$is_attributed, times = 1, p = 0.8, list =
FALSE)
  train_val <- train[ind, ]
  test_val <- train[-ind, ]
  # traindata has to be a matrix
  timestart <- Sys.time()
  # Train the data
  rf_fit <- train(x = smote_train[, -4], y = smote_train[, 4],
          method = "rf", tuneLength = 3,
           ntree = 100, trControl = ctrl)
  pr.rf <- predict(rf_fit, newdata = test_val)
  result <- confusionMatrix(pr.rf, test_val$is_attributed)
  timeend <- Sys.time()
  runningtime <- timeend - timestart
  return(list(fit = rf_fit, evaluation = result, time = runningtime))
}

train_xgboost <- function(traindata,nround,cv.nfold){
  # traindata has to be a matrix
  timestart <- Sys.time()
  # Data Preparation
  xgb.train.data <- xgb.DMatrix(data = traindata[,-1],label = traindata[,1] -
1)
  # Default Parameter
  xgb_params <- list("objective" = "binary:logistic",
                     "eval_metric" = "auc",
                     "silent"="0",
                     "booster" = "gbtree")
  # Nrounds in the XgBoost
  cv_model <- xgb.cv(params      = xgb_params,
                     data        = xgb.train.data,
                     nrounds     = nround,
```

```r
                     nfold       = cv.nfold,
                     verbose     = TRUE,
                     prediction  = TRUE,
                     tree_method = 'exact')

  max_auc = max(cv_model[["evaluation_log"]][, 4])
  max_auc_index = max((1:nround)[cv_model[["evaluation_log"]][, 4] ==
max_auc])

  xgb_fit <- xgb.train(data = xgb.train.data,
                       nround = max_auc_index,
                       params = xgb_params,
                       tree_method = 'exact')

  timeend <- Sys.time()
  runningtime <- timeend - timestart
  return(list(fit = xgb_fit, time = runningtime))
}


light_gbm<-function(train){
timestart <- Sys.time()
#train set and validation set
tr_index <- nrow(train)
dtrain <- train %>% head(0.95 * tr_index) # 95% data for training
valid <- train %>% tail(0.05 * tr_index) # 5% data for validation
categorical_features = c("app", "device", "os", "channel", "wday", "hour")
dtrain <- lgb.Dataset(data = as.matrix(dtrain[,colnames(dtrain) !=
"is_attributed"]),label = dtrain$is_attributed,categorical_feature =
categorical_features)
dvalid <- lgb.Dataset(data = as.matrix(valid[, colnames(valid) !=
"is_attributed"]),label = valid$is_attributed,categorical_feature =
categorical_features)
#parameter
params <- list(objective = "binary",
              metric = "auc",
              learning_rate= 0.1,
              num_leaves= 7,
              max_depth= 3,
              min_child_samples= 100,
              max_bin= 100,
              subsample= 0.7,
              subsample_freq= 1,
              colsample_bytree= 0.7,
              min_child_weight= 0,
              min_split_gain= 0,
              scale_pos_weight=99.76)
#model
model <- lgb.train(params, dtrain, valids = list(validation = dvalid),
```

```
nthread = 4,nrounds = 1000, verbose= 1, early_stopping_rounds = 50, eval_freq
= 50)
#prediction
preds <- predict(model, data = as.matrix(dvalid[, colnames(dvalid)], n =
model$best_iter))
result <- confusionMatrix(preds, dvalid$is_attributed)
timeend <- Sys.time()
#time
runningtime <- timeend - timestart
return(list(evaluation = result, time = runningtime))
}
```

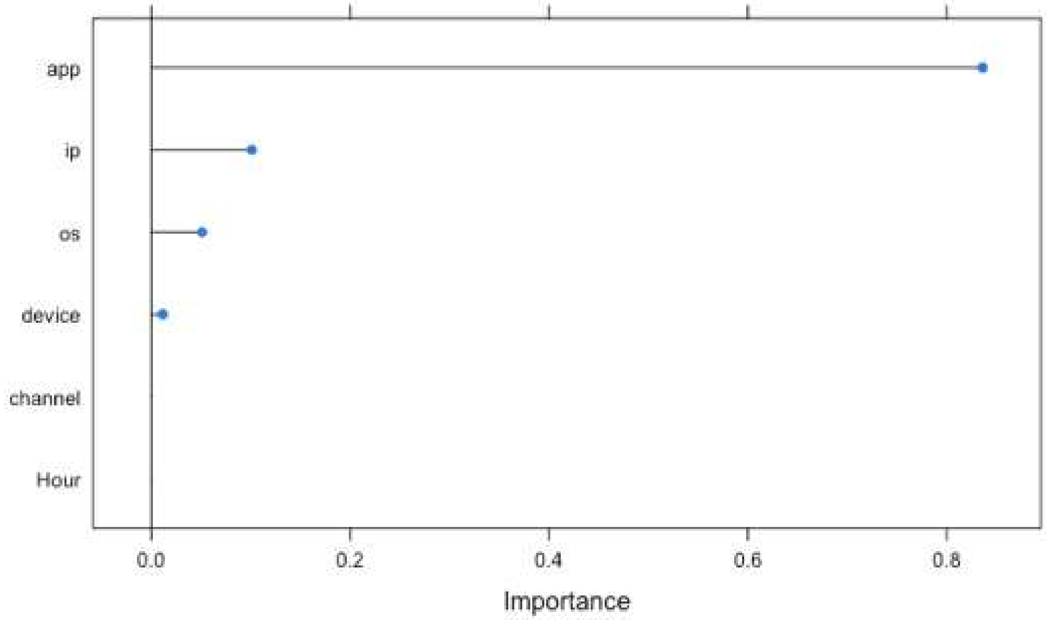
Step 4: Evaluation and Model Results

We used ROC to measure the performance all the models. And Kaggle provides evaluation for the prediction of models. Here is the screenshot from Kaggle.



Screenshot from Kaggle

Here is feature importance generated by XgBoost Model.



Features' Importance

Step 5: Discussion

Base on our results, we conclude that naive bayesian and XGBoost are appropriate models for our prediction, due to these two models can weaken the influence of imbalanced data in this topic. Also, in further study, we can tune the parameters in XGBoost model to fit the model better.

In our analysis, we find app, ip address, os version and device are important variables that impact click fraud heavily, which means these factors need to be paid more attention in the real world analysis.

We would like to implement these two models in the real world, to help app developers detecting and avoiding click fraud. We hope through this project, app developers could save advertising cost and obtain an accurate market feedback.