Homework 04: Orange's Customer Relationships: Churn Prediction

Chicago Booth ML Team

***Note**: In order to illustrate the best practices, this script utilizes the popular **caret** package, which wraps around underlying algorithms such as randomForest and GBM with a consistent interface. We also illutrate the use of **multi-core parallel computation** to speed up computer run-time.*

***Note**: This script takes a **long time** to run completely.*

This KDD challenge as 3 predictive tasks, addressing **churn**, **appetency** and **upselling**. We'll tackle **churn** in this script. Doing **appetency** and **upselling** would be very similar.

Load Libraries & Modules; Set Randomizer Seed

```
library(caret)
library(data.table)
library(doParallel)

# load modules from the common HelpR repo
helpr_repo_raw_url <- 'https://raw.githubusercontent.com/ChicagoBoothML/HelpR/master'
source(file.path(helpr_repo_raw_url, 'EvaluationMetrics.R'))

# set randomizer's seed
set.seed(99)   # Gretzky was #99
```

Parallel Computation Setup

Let's set up a parallel computing infrastructure (thanks to the excellent **doParallel** package by Microsoft subsidiary **Revolution Analytics**) to allow more efficient computation in the rest of this exercise:

```
cl <- makeCluster(detectCores() - 2)   # create a compute cluster using all CPU cores but 2
clusterEvalQ(cl, library(foreach))
registerDoParallel(cl)   # register this cluster
```

We have set up a compute cluster with **6** worker nodes for computing.

Data Import & Cleaning

```
# download data and read data into data.table format

# ***************************************************************************************
# NOTE: the following path is specific to my computer
# You need to change it to a relevant folder on your computer containing the Orange data
```

```r
data_folder_path <- '/Cloud/Box Sync/Repos/DATA/DATA___KDDCup2009_OrangeCustomerRelationship'

# ***********************************************************************************

# Common NAs:
na_strings <- c(
  '',
  'na', 'n.a', 'n.a.',
  'nan', 'n.a.n', 'n.a.n.',
  'NA', 'N.A', 'N.A.',
  'NaN', 'N.a.N', 'N.a.N.',
  'NAN', 'N.A.N', 'N.A.N.',
  'nil', 'Nil', 'NIL',
  'null', 'Null', 'NULL')

X <- as.data.table(read.table(
  file.path(data_folder_path, 'orange_small_train.data.gz'),
  header=TRUE, sep='\t', stringsAsFactors=TRUE, na.strings=na_strings))

nb_input_features <- ncol(X)
input_feature_names <- names(X)
nb_samples <- nrow(X)

churn <- factor(
  read.table(
    file.path(data_folder_path, 'orange_small_train_churn.labels.txt'),
    header=FALSE, sep='\t')[[1]],
  levels=c(-1, 1),
  labels=c('no', 'yes'))
```

In total, there are **50,000** samples of **230** possible *anonymized* input features that can be used to predict the outcome of interest **churn**.

Let's split the data into a Training set and a Test set:

```r
train_proportion <- .4
train_indices <- createDataPartition(
  y=churn,
  p=train_proportion,
  list=FALSE)

X_train <- X[train_indices, ]
X_test <- X[-train_indices, ]
churn_train <- churn[train_indices]
churn_test <- churn[-train_indices]

nb_test_samples <- length(churn_test)
```

Let's also split out a Validation set for the purpose of estimating OOS performance of trained models before testing:

```r
valid_proportion <- .25
valid_indices <- createDataPartition(
  y=churn_train,
  p=valid_proportion,
  list=FALSE)

X_valid <- X_train[valid_indices, ]
X_train <- X_train[-valid_indices, ]
```

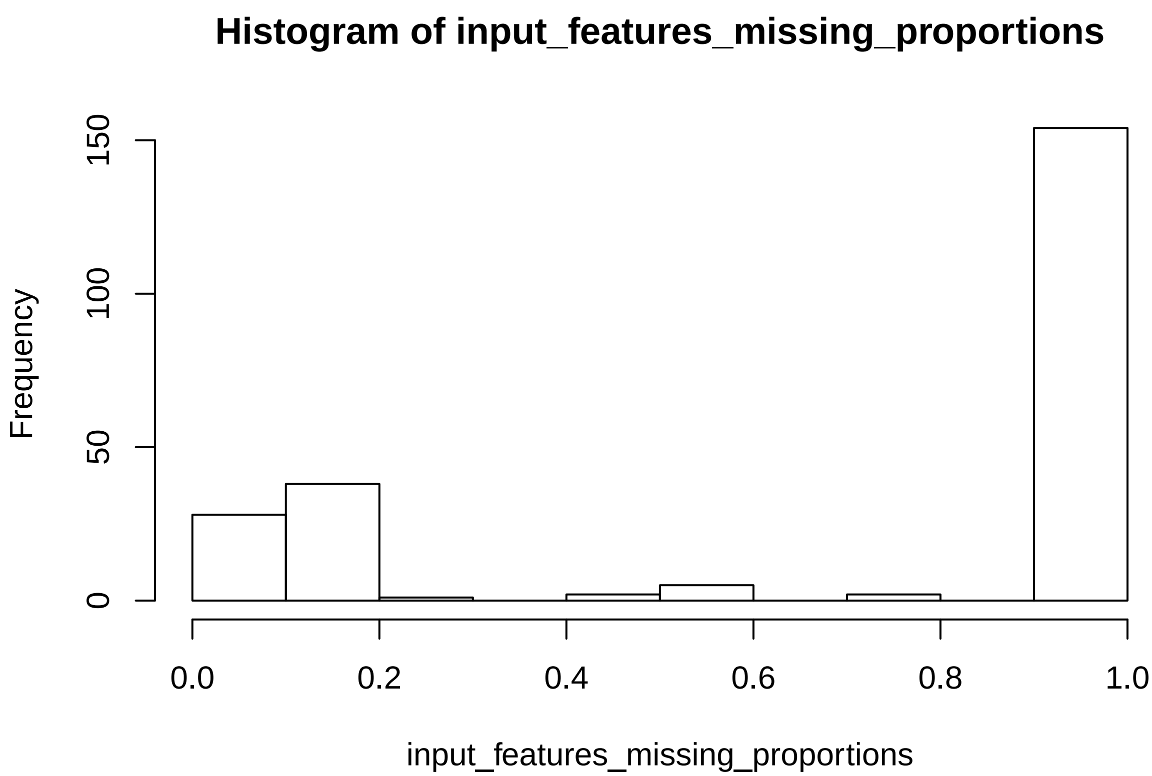
```
churn_valid <- churn_train[valid_indices]
churn_train <- churn_train[-valid_indices]

nb_train_samples <- length(churn_train)
nb_valid_samples <- length(churn_valid)
```

The numbers of samples in the Training, Validation and Test sets are **15000**, **5001** and **29999** respectively. Just to sanity-check that the data sets have been split representatively by **`caret`**: the **`churn`** incidences in the Training, Validation and Test sets are **7.34**, **7.36** and **7.34** respectively.

Getting Rid of Input Features x's with Too Many Missing Values

First of all, let's look at the proportions of missing values per input feature column x:

```
input_features_missing_proportions <-
  sapply(X_train, function(col) sum(is.na(col))) / nb_train_samples

hist(input_features_missing_proportions)
```



We can see that there are an awful lot of features with all missing data!! We'll kick them out, for sure. Also, there are a small handful of features that have over 20% missing data; since those are few and we are unlikely to miss out too many signals by removing them, let's not mess around with them either. In sum, we'll remove all features that have over 20% missing value:

```
input_feature_names <-
  input_feature_names[input_features_missing_proportions <= .2]

nb_input_features <- length(input_feature_names)

X_train <- X_train[ , input_feature_names, with=FALSE]
```

We're left with the following **66** input features x's:

```r
input_feature_names
```

```
##  [1] "Var6"   "Var7"   "Var13"  "Var21"  "Var22"  "Var24"  "Var25"
##  [8] "Var28"  "Var35"  "Var38"  "Var44"  "Var57"  "Var65"  "Var73"
## [15] "Var74"  "Var76"  "Var78"  "Var81"  "Var83"  "Var85"  "Var109"
## [22] "Var112" "Var113" "Var119" "Var123" "Var125" "Var132" "Var133"
## [29] "Var134" "Var140" "Var143" "Var144" "Var149" "Var153" "Var160"
## [36] "Var163" "Var173" "Var181" "Var192" "Var193" "Var195" "Var196"
## [43] "Var197" "Var198" "Var199" "Var202" "Var203" "Var204" "Var205"
## [50] "Var206" "Var207" "Var208" "Var210" "Var211" "Var212" "Var216"
## [57] "Var217" "Var218" "Var219" "Var220" "Var221" "Var222" "Var223"
## [64] "Var226" "Var227" "Var228"
```

The classes of these remaining x's are:

```r
input_feature_classes <- factor(sapply(X_train, class))

input_feature_classes
```

```
##    Var6    Var7   Var13   Var21   Var22   Var24   Var25   Var28   Var35
## integer integer integer integer integer integer integer numeric integer
##   Var38   Var44   Var57   Var65   Var73   Var74   Var76   Var78   Var81
## integer integer numeric integer integer integer integer integer numeric
##   Var83   Var85  Var109  Var112  Var113  Var119  Var123  Var125  Var132
## integer integer integer integer numeric integer integer integer integer
##  Var133  Var134  Var140  Var143  Var144  Var149  Var153  Var160  Var163
## integer integer integer integer integer integer integer integer integer
##  Var173  Var181  Var192  Var193  Var195  Var196  Var197  Var198  Var199
## integer integer  factor  factor  factor  factor  factor  factor  factor
##  Var202  Var203  Var204  Var205  Var206  Var207  Var208  Var210  Var211
##  factor  factor  factor  factor  factor  factor  factor  factor  factor
##  Var212  Var216  Var217  Var218  Var219  Var220  Var221  Var222  Var223
##  factor  factor  factor  factor  factor  factor  factor  factor  factor
##  Var226  Var227  Var228
##  factor  factor  factor
## Levels: factor integer numeric
```

Filling Missing Numeric x's with Means

The following x's are **integer** or **numeric**:

```r
numeric_input_feature_names <-
  input_feature_names[input_feature_classes != 'factor']

numeric_input_feature_names
```

```
##  [1] "Var6"   "Var7"   "Var13"  "Var21"  "Var22"  "Var24"  "Var25"
##  [8] "Var28"  "Var35"  "Var38"  "Var44"  "Var57"  "Var65"  "Var73"
## [15] "Var74"  "Var76"  "Var78"  "Var81"  "Var83"  "Var85"  "Var109"
## [22] "Var112" "Var113" "Var119" "Var123" "Var125" "Var132" "Var133"
## [29] "Var134" "Var140" "Var143" "Var144" "Var149" "Var153" "Var160"
## [36] "Var163" "Var173" "Var181"
```

It seems we don't have a problem with numeric columns made up of non-changing values:

```r
numeric_input_feature_standard_deviations <-
  sapply(X_train[ , numeric_input_feature_names, with=FALSE],
         function(col) sd(col, na.rm=TRUE))

numeric_input_feature_standard_deviations
```

```
##         Var6         Var7        Var13        Var21        Var22
## 2.843250e+03 6.413963e+00 2.699609e+03 5.867414e+02 7.330429e+02
##        Var24        Var25        Var28        Var35        Var38
## 1.096091e+01 2.107095e+02 9.637879e+01 2.860019e+00 3.000131e+06
##        Var44        Var57        Var65        Var73        Var74
## 1.424335e+00 2.028071e+00 1.030915e+01 5.338518e+01 4.038577e+02
##        Var76        Var78        Var81        Var83        Var85
## 1.830733e+06 2.130236e+00 1.055596e+05 1.002977e+02 2.377701e+01
##       Var109       Var112       Var113       Var119       Var123
## 1.634161e+02 1.645895e+02 7.729649e+05 2.291689e+03 2.391889e+02
##       Var125       Var132       Var133       Var134       Var140
## 1.056116e+05 9.773756e+00 2.451729e+06 5.988284e+05 3.036796e+03
##       Var143       Var144       Var149       Var153       Var160
## 6.530104e-01 1.180023e+01 6.573176e+05 4.357551e+06 9.910520e+01
##       Var163       Var173       Var181
## 8.376229e+05 1.252542e-01 2.431791e+00
```

Let's fill up the missing values with the means of the respective columns:

```r
numeric_input_feature_means <-
  sapply(X_train[ , numeric_input_feature_names, with=FALSE],
         function(col) mean(col, na.rm=TRUE))

for (numeric_col in numeric_input_feature_names) {
  x <- X_train[[numeric_col]]
  missing_value_row_yesno <- is.na(x)
  if (sum(missing_value_row_yesno) > 0) {
    X_train[ , numeric_col := as.numeric(x), with=FALSE]
    mu <- numeric_input_feature_means[numeric_col]
    X_train[missing_value_row_yesno, numeric_col := mu, with=FALSE]
  }
}
```

Let's double check to see that the numeric columns have all been filled and that their means stay the same as before the filling:

```r
all.equal(
  numeric_input_feature_means,
  sapply(X_train[ , numeric_input_feature_names, with=FALSE], mean))
```

```
## [1] TRUE
```

Cleaning Categorical Variables

Below are categorical features and their number of categories:

```r
categorical_input_feature_names <-
  input_feature_names[input_feature_classes == 'factor']

categorical_input_feature_nb_levels <-
```

```
  sapply(X_train[ , categorical_input_feature_names, with=FALSE],
         function(col) length(levels(col)))

categorical_input_feature_nb_levels
```

```
## Var192 Var193 Var195 Var196 Var197 Var198 Var199 Var202 Var203 Var204
##    361     51     23      4    225   4291   5073   5713      5    100
## Var205 Var206 Var207 Var208 Var210 Var211 Var212 Var216 Var217 Var218
##      3     21     14      2      6      2     81   2016  13990      2
## Var219 Var220 Var221 Var222 Var223 Var226 Var227 Var228
##     22   4291      7   4291      4     23      7     30
```

Those variables having over 500 categories are likely to be just text / character data. Let's get rid of them:

```
categorical_input_feature_names <-
  categorical_input_feature_names[categorical_input_feature_nb_levels <= 500]

X_train <-
  X_train[ , c(numeric_input_feature_names, categorical_input_feature_names), with=FALSE]
```

For the remaining categorical variables, let's:

- Make their missing values another category ***zzzMISSING***; and
- Try to consolidate the categories, as having too many categories make modeling less meaningful and numerically more difficult; for each variable, we'll collapse all categories with prevalence of under 5% together into a ***zzzOTHER*** category;
- Drop categorical variables with only one category *(obviously)*; and
- Drop categorical variables with only one non-***zzzMISSING*** category.

```
collapsed_categories <- list()

for (cat_col in categorical_input_feature_names) {

  missing_value_row_yesno <- is.na(X_train[[cat_col]])
  if (sum(missing_value_row_yesno) > 0) {
    X_train[missing_value_row_yesno, cat_col := 'zzzMISSING', with=FALSE]
  }

  x <- X_train[[cat_col]]
  for (cat in levels(x)) {
    cat_rows_yesno <- x == cat
    if (sum(cat_rows_yesno) < .05 * nb_train_samples) {
      if (!(cat_col %in% names(collapsed_categories))) {
        collapsed_categories[[cat_col]] <- character()
      }
      collapsed_categories[[cat_col]] <- c(collapsed_categories[[cat_col]], cat)
      X_train[cat_rows_yesno, cat_col := 'zzzOTHER', with=FALSE]
      levels(X_train[[cat_col]])[levels(X_train[[cat_col]]) == cat] <- NA
    }
  }

  cats <- levels(X_train[[cat_col]])
  if ((length(cats) == 1) ||
    (length(cats[(cats != 'zzzMISSING') & (cats != 'zzzOTHER')]) < 2)) {
```

```r
    categorical_input_feature_names <- setdiff(categorical_input_feature_names, cat_col)
  }
}
```

Let's double-check by looking at the prevalence of the categories of the remaining categorical variables now:

```r
lapply(X_train[ , categorical_input_feature_names, with=FALSE],
      function(col) summary(col) / nb_train_samples)
```

```
## $Var193
##  2Knk1KF     RO12 zzzOTHER
##   0.1494   0.7202   0.1304
##
## $Var197
##       0Xwj       487l       JLbT       lK27       TyGl   zzzOTHER
## 0.09533333 0.07260000 0.06100000 0.08793333 0.08286667 0.60026667
##
## $Var203
##       9_Y1       HLqf   zzzOTHER
## 0.90200000 0.06466667 0.03333333
##
## $Var205
##       09_Q    sJzTlal       VpdQ   zzzOTHER
## 0.23313333 0.09040000 0.63880000 0.03766667
##
## $Var206
##       hAFG       haYg       IYzP       sYC_       zm5i zzzMISSING
##  0.0548000  0.0588000  0.3397333  0.0822000  0.1302667  0.1117333
##   zzzOTHER
##  0.2224667
##
## $Var207
##       7M47J5GA0pTYIFxg5uy DHn_WUyBhW_whjA88g9bvA64_
##                0.14260000                0.06893333
##                me75fM6ugJ                  zzzOTHER
##                0.70006667                0.08840000
##
## $Var208
##     kIsH     sBgB zzzOTHER
##   0.9200   0.0772   0.0028
##
## $Var211
##      L84s      Mtgm
## 0.8079333 0.1920667
##
## $Var212
##           CrNX       NhsEn4L XfqtO3UdzaXh_      zzzOTHER
##      0.0586000     0.5880667     0.1282000     0.2251333
##
## $Var218
##       cJvF       UYBR   zzzOTHER
## 0.50113333 0.48453333 0.01433333
##
## $Var221
##    d0EEeJi       oslk       zCkv   zzzOTHER
## 0.05973333 0.74280000 0.12426667 0.07320000
##
## $Var223
```

```
## jySVZNlOJy LM8l689qOp zzzMISSING   zzzOTHER
## 0.12140000 0.73073333 0.10540000 0.04246667
##
## $Var226
##       7P5s       Aoh3       FSa2       Qu4f       szEZ       WqMG
## 0.05433333 0.05286667 0.16473333 0.09546667 0.05953333 0.08566667
##   zzzOTHER
## 0.48740000
##
## $Var227
##       6fzt       RAYp       ZI9m   zzzOTHER
## 0.06826667 0.70226667 0.12726667 0.10220000
##
## $Var228
##       55YFVY9 F2FyR07IdsN7I ib5G6X1eUxUn6      zzzOTHER
##    0.08840000    0.65240000    0.05226667    0.20693333
```

Not bad, *eh*?, not bad... It seems we can embark now on the next steps: variable selection.

Selecting Candidate Input Features x's

```
input_feature_names <-
  c(numeric_input_feature_names, categorical_input_feature_names)

nb_input_features <- length(input_feature_names)

X_train <- X_train[ , input_feature_names, with=FALSE]
```

After data cleaning, we have **53** numeric and categorical input features left:

```
sapply(X_train, class)
```

```
##      Var6      Var7     Var13     Var21     Var22     Var24     Var25
## "numeric" "numeric" "numeric" "numeric" "numeric" "numeric" "numeric"
##     Var28     Var35     Var38     Var44     Var57     Var65     Var73
## "numeric" "numeric" "numeric" "numeric" "numeric" "numeric" "integer"
##     Var74     Var76     Var78     Var81     Var83     Var85    Var109
## "numeric" "numeric" "numeric" "numeric" "numeric" "numeric" "numeric"
##    Var112    Var113    Var119    Var123    Var125    Var132    Var133
## "numeric" "numeric" "numeric" "numeric" "numeric" "numeric" "numeric"
##    Var134    Var140    Var143    Var144    Var149    Var153    Var160
## "numeric" "numeric" "numeric" "numeric" "numeric" "numeric" "numeric"
##    Var163    Var173    Var181    Var193    Var197    Var203    Var205
## "numeric" "numeric" "numeric"  "factor"  "factor"  "factor"  "factor"
##    Var206    Var207    Var208    Var211    Var212    Var218    Var221
##  "factor"  "factor"  "factor"  "factor"  "factor"  "factor"  "factor"
##    Var223    Var226    Var227    Var228
##  "factor"  "factor"  "factor"  "factor"
```

Building models with all of them will still be quite clunky. Let's try to select features containing good amounts of "signals" by:

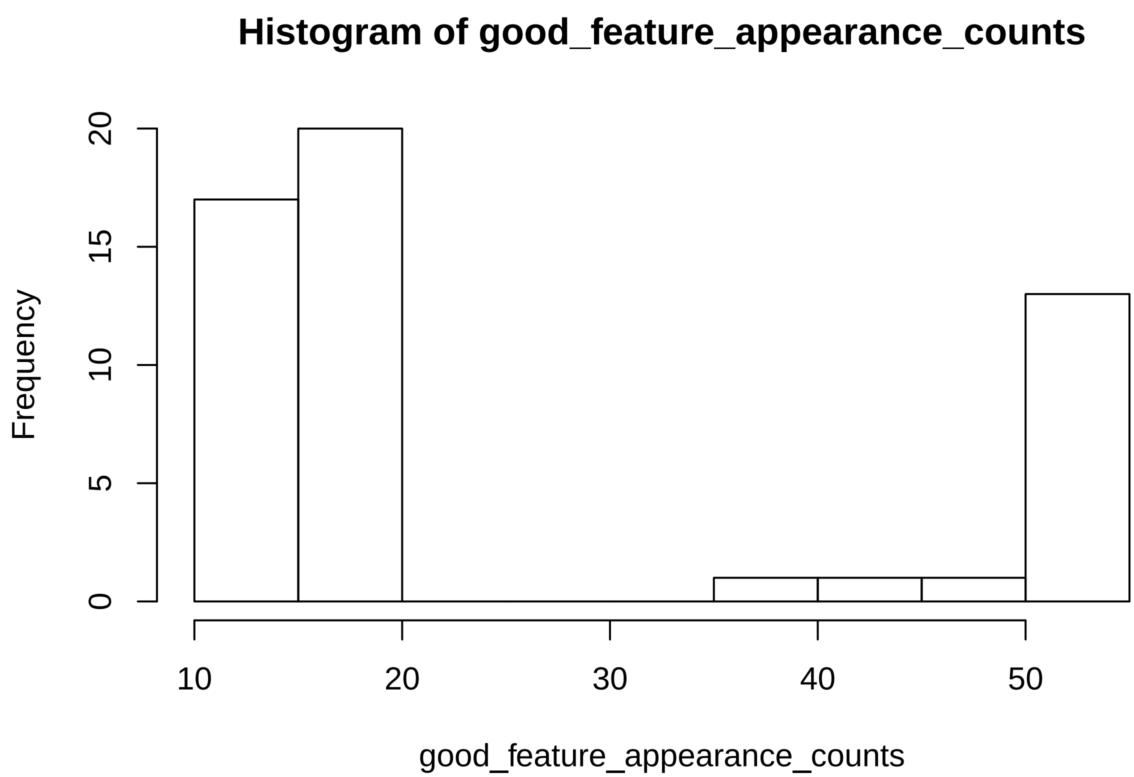
1. Fitting Random Forests on pairs of features and measuring the OOS performances of such Random Forests
2. Pick pairs of higher OOB performances

3. Pick variables that appear in many well-performing pairs

```
feature_pair_performances <- data.table(
  feature_1=character(),
  feature_2=character(),
  deviance=numeric())

caret_optimized_metric <- 'logLoss'   # equivalent to 1 / 2 of Deviance

caret_train_control <- trainControl(
  classProbs=TRUE,              # compute class probabilities
  summaryFunction=mnLogLoss,    # equivalent to 1 / 2 of Deviance
  method='repeatedcv',          # repeated Cross Validation
  number=5,                     # number of folds
  repeats=1,                    # number of repeats
  allowParallel=TRUE)

B <- 30

for (i in 1 : (nb_input_features - 1)) {

  feature_1 <- input_feature_names[i]

  for (j in (i + 1) : nb_input_features) {

    cat('pair: ', i, ', ', j, '\n')

    feature_2 <- input_feature_names[j]

    rf_model <- train(
      x=X_train[, c(feature_1, feature_2), with=FALSE],
      y=churn_train,
      method='parRF',     # parallel Random Forest
      metric=caret_optimized_metric,
      ntree=B,            # number of trees in the Random Forest
      nodesize=300,       # minimum node size set small enough to allow for complex trees,
                          # but not so small as to require too large B to eliminate high variance
      importance=FALSE,   # skip evaluate importance of predictors
      keep.inbag=FALSE,   # not relevant as we're using Cross Validation
      trControl=caret_train_control,
      tuneGrid=NULL)

    feature_pair_performances <- rbind(
      feature_pair_performances,
     data.table(
        feature_1=feature_1,
        feature_2=feature_2,
        deviance=2 * rf_model$results$logLoss))
  }
}
```

```
feature_pair_performances_top_half <-
  feature_pair_performances[order(deviance), ][1 : round(nrow(feature_pair_performances) / 2), ]

good_feature_appearance_counts <- list()

for (i in 1: nrow(feature_pair_performances_top_half)) {

  feature_1 <- feature_pair_performances_top_half[i, feature_1]
```

```r
  if (!(feature_1 %in% names(good_feature_appearance_counts))) {
    good_feature_appearance_counts[[feature_1]] <- 1
  } else {
    good_feature_appearance_counts[[feature_1]] <-
      good_feature_appearance_counts[[feature_1]] + 1
  }

  feature_2 <- feature_pair_performances_top_half[i, feature_2]
  if (!(feature_2 %in% names(good_feature_appearance_counts))) {
    good_feature_appearance_counts[[feature_2]] <- 1
  } else {
    good_feature_appearance_counts[[feature_2]] <-
      good_feature_appearance_counts[[feature_2]] + 1
  }
}

good_feature_appearance_counts <-
   unlist(good_feature_appearance_counts)

hist(good_feature_appearance_counts)
```



We see that predictive power seems to concentrate in a much smaller number of features. Let's pick the features that appear over 30 times in the "good feature appearances".

```r
input_feature_names <-
  names(good_feature_appearance_counts)[good_feature_appearance_counts > 30]

input_feature_names
```

```
##  [1] "Var81"  "Var125" "Var134" "Var38"  "Var149" "Var153" "Var57"
##  [8] "Var133" "Var113" "Var163" "Var140" "Var76"  "Var13"  "Var119"
## [15] "Var6"   "Var28"
```

```r
nb_input_features <- length(input_feature_names)

X_train <- X_train[ , input_feature_names, with=FALSE]

input_feature_classes <- sapply(X_train, class)

input_feature_classes
```

```
##     Var81    Var125    Var134     Var38    Var149    Var153     Var57
## "numeric" "numeric" "numeric" "numeric" "numeric" "numeric" "numeric"
##    Var133    Var113    Var163    Var140     Var76     Var13    Var119
## "numeric" "numeric" "numeric" "numeric" "numeric" "numeric" "numeric"
##      Var6     Var28
## "numeric" "numeric"
```

It turns out that **all of the remaining 16 strong features** are **numeric**! *(meaning the effort we spent on cleaning the categoricals has come to naught... but we couldn't have known that without trying)*

Classification Models

Let's train 2 types of classification models: a Random Forest and a Boosted Trees model:

```r
caret_optimized_metric <- 'logLoss'   # equivalent to 1 / 2 of Deviance

caret_train_control <- trainControl(
  classProbs=TRUE,             # compute class probabilities
  summaryFunction=mnLogLoss,   # equivalent to 1 / 2 of Deviance
  method='repeatedcv',         # repeated Cross Validation
  number=5,                    # 5 folds
  repeats=3,                   # 2 repeats
  allowParallel=TRUE)
```

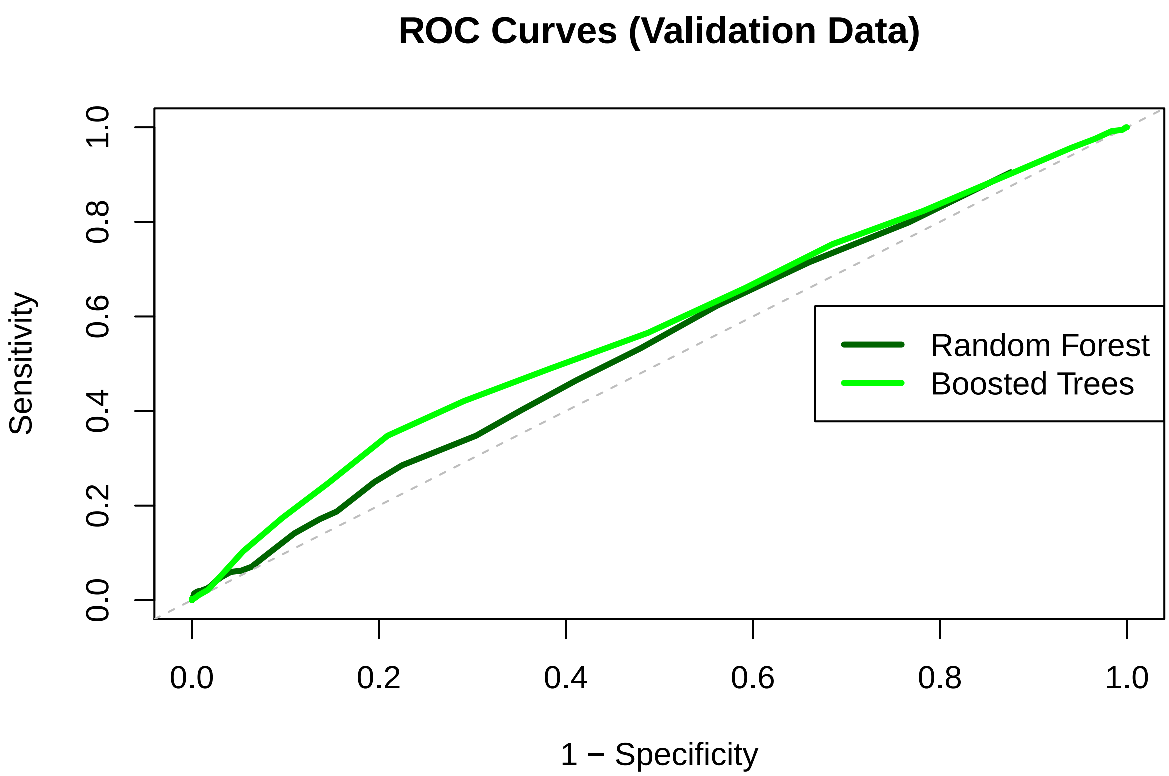
```r
B <- 600

rf_model <- train(
  x=X_train,
  y=churn_train,
  method='parRF',     # parallel Random Forest
  metric=caret_optimized_metric,
  ntree=B,            # number of trees in the Random Forest
  nodesize=100,       # minimum node size set small enough to allow for complex trees,
                      # but not so small as to require too large B to eliminate high variance
  importance=TRUE,    # evaluate importance of predictors
  keep.inbag=TRUE,
  trControl=caret_train_control,
  tuneGrid=NULL)
```

```r
B <- 1200

boost_model <- train(
  x=X_train,
  y=churn_train,
  method='gbm',       # Generalized Boosted Models
  metric=caret_optimized_metric,
  verbose=FALSE,
```

```
  trControl=caret_train_control,
  tuneGrid=expand.grid(
    n.trees=B,              # number of trees
    interaction.depth=10,   # max tree depth,
    n.minobsinnode=100,     # minimum node size
    shrinkage=0.01))        # shrinkage parameter, a.k.a. "learning rate"
```

We'll now evaluate the OOS performances of these 2 models on the Validation set to select the better one:

```
low_prob <- 1e-6
high_prob <- 1 - low_prob
log_low_prob <- log(low_prob)
log_high_prob <- log(high_prob)
log_prob_thresholds <- seq(from=log_low_prob, to=log_high_prob, length.out=100)
prob_thresholds <- exp(log_prob_thresholds)

# Prepare Validation Data for evaluation
prepare_oos_input_features <- function(X_OOS) {
  X_OOS <- X_OOS[ , input_feature_names, with=FALSE]
  for (numeric_col in input_feature_names) {
    x <- X_OOS[[numeric_col]]
    X_OOS[, numeric_col := as.numeric(x), with=FALSE]
    X_OOS[is.na(x), numeric_col := numeric_input_feature_means[numeric_col], with=FALSE]
  }
  X_OOS
}

X_valid <- prepare_oos_input_features(X_valid)

# *** NOTE: **
# the below "bin_classif_eval" function is from the "EvaluationMetrics.R" helper script
# in the "HelpR" GitHub repo

rf_pred_probs <- predict(
  rf_model, newdata=X_valid, type='prob')
rf_oos_performance <- bin_classif_eval(
  rf_pred_probs$yes, churn_valid, thresholds=prob_thresholds)

boost_pred_probs <- predict(
  boost_model, newdata=X_valid, type='prob')
boost_oos_performance <- bin_classif_eval(
  boost_pred_probs$yes, churn_valid, thresholds=prob_thresholds)


plot(x=1 - rf_oos_performance$specificity,
     y=rf_oos_performance$sensitivity,
     type = "l", col='darkgreen', lwd=3,
     xlim = c(0., 1.), ylim = c(0., 1.),
     main = "ROC Curves (Validation Data)",
     xlab = "1 - Specificity", ylab = "Sensitivity")
abline(a=0,b=1,lty=2,col=8)
lines(x=1 - boost_oos_performance$specificity,
      y=boost_oos_performance$sensitivity,
      col='green', lwd=3)
legend('right', c('Random Forest', 'Boosted Trees'),
   lty=1, col=c('darkgreen', 'green'), lwd=3, cex=1.)
```



It seems that although neither model seems super impressive – customer churn is probably a hard thing to predict very well – the Boosted Trees model offers a much better classification performance than the Random Forest. We now need to pick a decision threshold for the Boosted Trees model. If we are to be really rigorous, we'll need balance the costs of lost business and the costs of extra incentives to retain customers. Here, to make life simple, we'll pick a subjective threshold that enables us to anticipate **25%** of the churn cases:

```
sensitivity_threshold <- .25
i <- min(which(boost_oos_performance$sensitivity < sensitivity_threshold)) - 1
selected_prob_threshold <- prob_thresholds[i]
```

The selected decision threshold is **0.093** – meaning when we use the Boosted Tree model to predict on new data, we'll predict a customer churn when the predicted probability exceeds that threshold. The expected performance of the model at that threshold is as follows:

```
boost_oos_performance[i, ]
```

```
##     threshold  accuracy sensitivity specificity precision  f1_score
## 1: 0.09326026 0.7580484   0.3478261   0.7906324 0.1165756 0.1746248
##     deviance
## 1: 0.5268408
```

Note that the precision of the model at this sensitivity threshold is rather low, meaning that there'll be many false positives. We'll probably need business insights to decide whether to contact certain customers over other, and what incentives to offer them.

Test Performance of Selected Model

Let's then evaluate the performance of the selected Boosted Trees model, with a decision threshold at **0.093**:

```
X_test <- prepare_oos_input_features(X_test)
```

```r
boost_test_pred_probs <- predict(
  boost_model, newdata=X_test, type='prob')

boost_test_performance <- bin_classif_eval(
  boost_test_pred_probs$yes, churn_test, thresholds=selected_prob_threshold)

boost_test_performance
```

```
##    accuracy sensitivity specificity   precision    f1_score    deviance
##   0.7555252   0.3413527   0.7883508   0.1133384   0.1701742   0.5164742
```

We can see that the Test performance is similar to what we've estimated from the Validation set.

```r
stopCluster(cl)   # shut down the parallel computing cluster
```