# MSD 2019 Final Project

A replication and extension of Comparing Random Forest with Logistic Regression for Predicting Class-Imbalanced Civil War Onset Data by David Muchlinski, David Siroky, et. al., October 22, 2015

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## Contents

# Introduction & Motivation

Prediction is at the heart of many machine learning and data science applications, and its importance is amplified in the context of political science. Especially for the case of civil war onset, robust models that can make correct predictions has the potential to save millions of lives and guide political agendas for the years to come.

Comparing Random Forest with Logistic Regression for Predicting Class-Imbalanced Civil War Onset Data by David Muchlinski, David Siroky, et. al. is an explaratory research paper that, among several other things, makes the argument that most well-known logistic models acquire relatively lower predictive powers for civil war onsets, and shows that a custom random forest model achieves much higer prediction accuracies.

This R Notebook begins with a data importing and processing section followed by a replication in the form of extracting code snippets from the original R code (found in `original_code/`), and rewriting them in an equivalent but more readable manner. After each section, you can find our notes where we question the reasonability, and the correctness of the methods and code semantics used. The main focus is naturally an effort if results can be completely replicated. Comments included with double hashcodes (`##`) corresponds to comments made by authors themselves.

We will then present our own implementations of the models and methods discussed in the paper, as well as several extensions for fairness of performance measures, usage of correct and standardized methodologies, and experimental ML methods like decision trees and boosting algorithms. This part will roughly go parallel to what authors have represented in the paper; we will have corrected variable importance graphs, seperation plots, and ROC curves, as well as additional metrics such as confusion matrices and F1 scores.

# Data Exploration

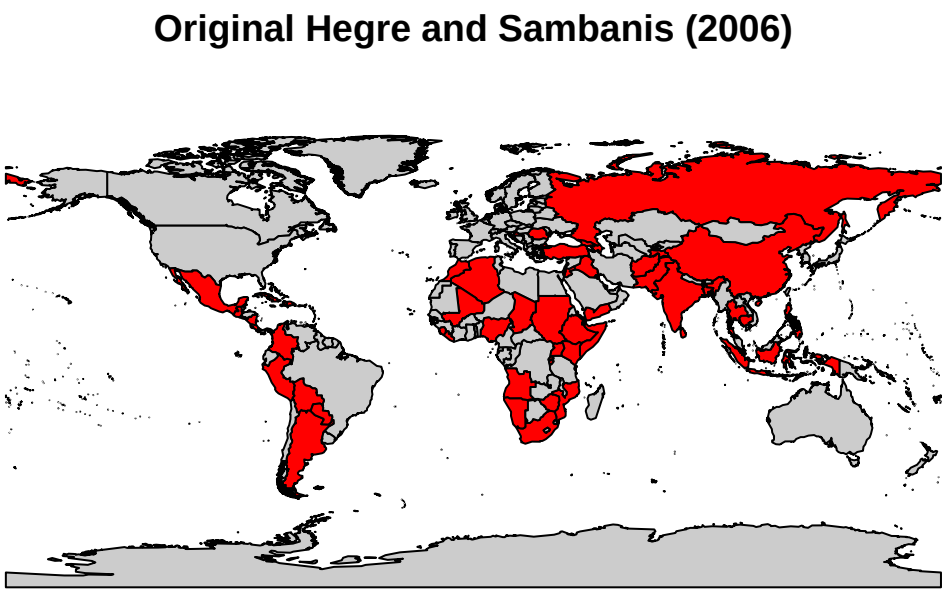
## Importing Datasets

```
# HS_original: Civil War Data by Hegre and Sambanis (2006), the original version
data_HS_original <- read.dta(file="data/Sambanis (Aug 06).dta")
# HS_cleaned: Civil War Data by Hegre and Sambanis (2006), NAs eliminated version
data_HS_cleaned <- na.omit(data_HS_original)
# HS_imputed: Civil War Data by Hegre and Sambanis (2006), imputed by authors
data_HS_imputed <- read.csv(file="data/SambnisImp.csv") ## data for prediction
# AM_imputed: Amelia dataset imputed by authors
data_AM_imputed <- read.csv(file="data/Amelia.Imp3.csv") ## data for causal machanisms
# AF_imputed: Africa dataset imputed by authors
data_AF_imputed <- read.csv(file="data/AfricaImp.csv")
```

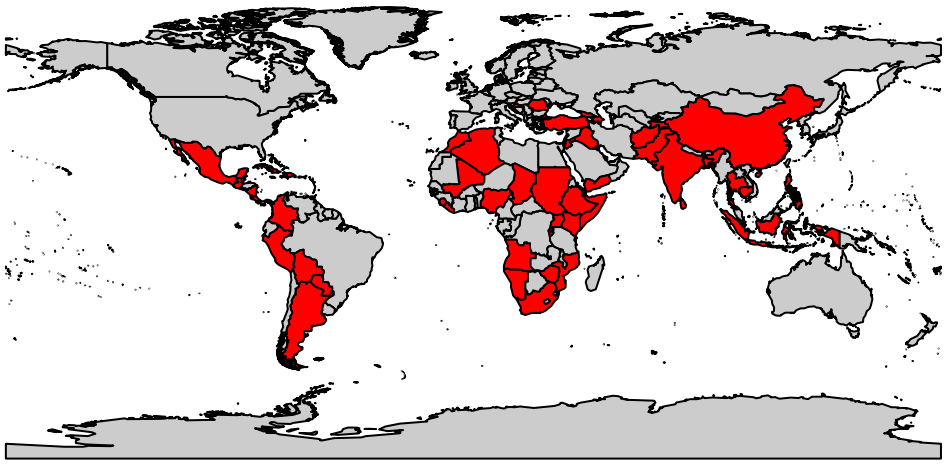
## Data Visualization

```
# Function for converting a specified dependent variable into factor levels
Y_factor <- function(dataset_column) {
  return(factor(dataset_column, levels=c(0,1), labels=c("peace", "war")))
}
```

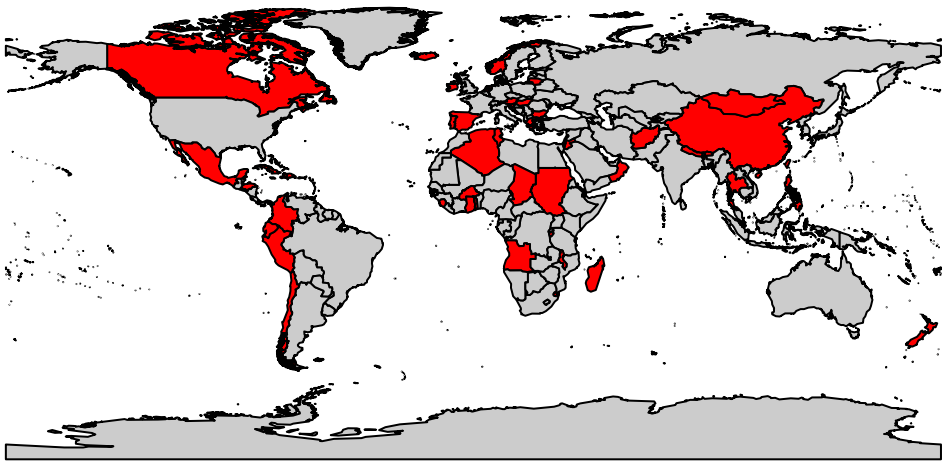
```r
# Function for getting dataset for correspondence between cid (Country ID) and country from original HS
# This is needed because some other datasets only include cid
country_correspondence <- data_HS_original[,c("cid", "country")]
get_countries <- function(country_ids) {
  countries <- c()
  for(id in country_ids) {
    countries <- c(countries, country_correspondence[country_correspondence$cid==id, ]$country[1])
  }
  return(countries)
}

# Convert 'warstds' column into 'peace' or 'war' (initially marked 0 or 1)
data_HS_original$warstds <- Y_factor(data_HS_original$warstds)
data_HS_imputed$warstds <- Y_factor(data_HS_imputed$warstds)
data_AM_imputed$warstds <- Y_factor(data_AM_imputed$warstds)
data_AF_imputed$warstds <- Y_factor(data_AF_imputed$warstds)

# Visualize countries with civil war for each dataset
data(wrld_simpl)
HS_original_countries <- wrld_simpl@data$NAME %in%
  data_HS_original[data_HS_original$warstds=='war',]$country
HS_imputed_countries <- wrld_simpl@data$NAME %in%
  get_countries(data_HS_imputed[data_HS_imputed$warstds=='war',]$cid)
AM_imputed_countries <- wrld_simpl@data$NAME %in%
  data_AM_imputed[data_AM_imputed$warstds=='war',]$country

plot(wrld_simpl, col=c(gray(.80),"red")[HS_original_countries+1],
    main='Original Hegre and Sambanis (2006)')
```




```r
plot(wrld_simpl, col=c(gray(.80),"red")[HS_imputed_countries+1],
    main='Imputed Hegre and Sambanis')
```




```
plot(wrld_simpl, col=c(gray(.80),"red")[AM_imputed_countries+1],
     main='Imputed Amelia Dataset')
```




### Dataset Exploration and Comparison

```
data_presentation <- matrix(c(ncol(data_HS_original), sum(is.na(data_HS_original)),
                              nrow(data_HS_original),
                              ncol(data_HS_cleaned), sum(is.na(data_HS_cleaned)),
                              nrow(data_HS_cleaned),
                              ncol(data_HS_imputed), sum(is.na(data_HS_imputed)),
                              nrow(data_HS_imputed),
                              ncol(data_AM_imputed), sum(is.na(data_AM_imputed)),
                              nrow(data_AM_imputed),
                              ncol(data_AF_imputed), sum(is.na(data_AF_imputed)),
                              nrow(data_AF_imputed)), ncol=5)
```

```r
colnames(data_presentation) <- c('HS_original', 'HS_cleaned',
                                 'HS_imputed', 'AM_imputed', 'AF_imputed')
rownames(data_presentation) <- c('No. features', 'No. empty cells', 'No. examples')
as.data.frame(data_presentation)
```

| | HS_original | HS_cleaned | HS_imputed | AM_imputed | AF_imputed |
|---|---|---|---|---|---|
| No. features | 284 | 284 | 286 | 53 | 11 |
| No. empty cells | 979981 | 0 | 0 | 778 | 0 |
| No. examples | 9691 | 0 | 7140 | 7141 | 737 |

## Data Insights and Moving Forward

There are a few questions left unanswered after replicating the data importing and processing done by authors. Below we represent the comparisons of various datasets mentioned in the paper and the original R code, and give insights about our reasoning.

- The reported comparison data frame highlights that the original Hegre and Sambanis (2006) dataset, denoted by `data_HS_original`, has 9691 examples, 284 features, and 979981 cells containing missing (NA) values.
- The dataset that is constructed by ourselves when these cells were omitted, `data_HS_cleaned`, shows that every single row of the original dataset contains some missing values. Naturally, this dataset is **dropped** from now on as it doesn't contain any entries.
- The dataset imputed by authors on the other hand, denoted `data_HS_imputed`, has 7140 examples, 286 features, and 0 cells containing missing (NA) values. It is unclear and unmentioned how and why the authors have imputed this dataset, filled all cells with missing values, and deleted ~2500 examples from the original dataset.
- The second dataset imputed by authors, denoted `data_AM_imputed`, has 7141 examples, 53 features, and 778 cells containing missing (NA) values.
- Lastly, the third dataset imputed by authors, denoted `data_AF_imputed`, has 737 examples, 11 features, and 0 cells containing missing (NA) values. This dataset is also **dropped**, because
  i) no country information exists whatsoever, and more importantly
  ii) none of the features (columns) in this dataset match with any of the other features in the other datasets (except the dependent variable).

It is also unclear why the paper needs three different imputed datasets. The `data_AM_imputed` dataset is supposed to be the smaller dataset where features theorized to be most relevant to the onset of civil war are imputed. Although the number of features decrease as claimed, 778 cells with missing (NA) values reappear in this dataset, and the number of examples increase by 1 without any explanation.

For comparison and metrics reporting purposes anyway, it is usually a better idea to select a singular dataset and train & test models on this same dataset through a reasonable splitting of data. We have decided the work with `data_HS_imputed`, and an explanation will be provided shortly. As we shall see, the authors have only reported in-sample metrics by using an unsplitted verions of `data_HS_imputed`; their models are never tested with unseen, **out-of-sample** data. Although this is neither the ideal nor correct way to assess the performance of a model, we will do so to see if we can **completely** replicate graphs and reported measures in the original paper. Other datasets explored above will also be utilized in parts where we try to replicate results from the paper.

Before generating the **out-of-sample** data through a train/test split, let's try to understand the difference between the datasets used by authors through an exploration of the respective numbers of binary classes in each dataset.

### Exploration of Class Imbalance in Datasets

```
# Explore class imbalance
class_imbalance_presentation <- matrix(
  c(table(data_HS_original$warstds)[1][[1]], table(data_HS_imputed$warstds)[1][[1]],
    table(data_AM_imputed$warstds)[1][[1]], table(data_AF_imputed$warstds)[1][[1]],
    table(data_HS_original$warstds)[2][[1]], table(data_HS_imputed$warstds)[2][[1]],
    table(data_AM_imputed$warstds)[2][[1]], table(data_AF_imputed$warstds)[2][[1]]),
  ncol=4, byrow=T)

colnames(class_imbalance_presentation) <- c('HS_original', 'HS_imputed', 'AM_imputed', 'AF_imputed')
rownames(class_imbalance_presentation) <- c('War', 'Peace')
as.data.frame(class_imbalance_presentation)
```

| | HS_original | HS_imputed | AM_imputed | AF_imputed |
|---|---|---|---|---|
| War | 6247 | 7024 | 7025 | 716 |
| Peace | 116 | 116 | 116 | 21 |

It can be inferred that authors have either deleted or modified examples from the `HS_original` dataset where the `warstds` variable was NA when they were preparing their imputed dataset `HS_imputed`. Hence, they increased examples of peace by 800 examples in their imputation. In such a class-imbalanced data (as displayed by tables above), one would imagine i) down-sampling from the majority class or ii) up-sampling from the minority class would be the reasonable action, rather than increasing the number of examples of the majority class.

We will shortly implement these two techniques, i) and ii), through a method called SMOTE and see if they yield better results.

## Model Specifications

To keep track of model specifications which use different numbers and types of features based on either theory or computations, we propose that we explicitly define features and hence accompanying formulas to be used by models later in this next code block. The 4 specifications the paper have covered are:

1) Fearon and Laitin specification (2003) consisting of 11 variables
2) Collier and Hoeffler specification (2004) consisting of 12 variables
3) Hegre and Sambanis specification (2006) consisting of 20 variables
4) The authors' specifications consisting of 88 variables, selected from Sambanis (2006) index

### Feature Selection Based on Model Specifications

```
# Function to generate a formula given dependent variable label and features
# Ex: get_model_formula('height', c('age', 'weight')) : height ~ age + weight
get_model_formula <- function(label, feature_vector) {
  formula_string <- ""
  for (feature in feature_vector) {
    formula_string <- paste(formula_string, feature, "+")
  }
  formula_string <- substring(formula_string, 1, nchar(formula_string)-1)
  return(as.formula(paste(paste(label, "~"), formula_string)))
```

```
}

# Specify the dependent variable that will be predicted in all models
y_var <- "warstds"

# The 88 variables selected by authors from Sambanis (2006) Appendix as spec of their RF model
author_vars <- c("ager", "agexp", "anoc", "army85", "autch98", "auto4",
                 "autonomy", "avgnabo", "centpol3", "coldwar", "decade1", "decade2",
                 "decade3", "decade4", "dem", "dem4", "demch98", "dlang", "drel",
                 "durable", "ef", "ef2", "ehet", "elfo", "elfo2", "etdo4590",
                 "expgdp", "exrec", "fedpol3", "fuelexp", "gdpgrowth", "geo1", "geo2",
                 "geo34", "geo57", "geo69", "geo8", "illiteracy", "incumb", "infant",
                 "inst", "inst3", "life", "lmtnest", "ln_gdpen", "lpopns", "major", "manuexp",
                 "milper", "mirps0", "mirps1", "mirps2", "mirps3", "nat_war", "ncontig",
                 "nmgdp", "nmdp4_alt", "numlang", "nwstate", "oil", "p4mchg",
                 "parcomp", "parreg", "part", "partfree", "plural", "plurrel",
                 "pol4", "pol4m", "pol4sq", "polch98", "polcomp", "popdense",
                 "presi", "pri", "proxregc", "ptime", "reg", "regd4_alt", "relfrac",
                 "seceduc", "second", "semipol3", "sip2", "sxpnew", "sxpsq", "tnatwar",
                 "trade", "warhist", "xconst")
author_spec <- get_model_formula(y_var, author_vars)

# The 11 variables selected by Fearon and Laitin (2003) as spec of their LR model
FL_vars <- c("warhist", "ln_gdpen", "lpopns", "lmtnest", "ncontig",
             "oil", "nwstate", "inst3", "pol4", "ef", "relfrac")
FL_spec <- get_model_formula(y_var, FL_vars)

# The 12 variables selected by Collier and Hoeffler (2004) as spec of their LR model
CH_vars <- c("sxpnew", "sxpsq", "ln_gdpen", "gdpgrowth", "warhist", "lmtnest",
             "ef", "popdense", "lpopns", "coldwar", "seceduc", "ptime")
CH_spec <- get_model_formula(y_var, CH_vars)

# The 20 variables selected by Hegre and Sambanis (2006) as spec of their LR model
HS_vars <- c("lpopns", "ln_gdpen", "inst3", "parreg", "geo34", "proxregc", "gdpgrowth",
             "anoc", "partfree", "nat_war", "lmtnest", "decade1", "pol4sq", "nwstate",
             "regd4_alt", "etdo4590", "milper", "geo1", "tnatwar", "presi")
HS_spec <- get_model_formula(y_var, HS_vars)
```

## Data Processing

Based on our exploration, we will **drop** every dataset discussed up until now except `data_HS_imputed`, and do a split on this dataset. The original R code also **mostly** uses this same dataset for training and testing models. This is to prevent any ambiguity, and also to respect the research done by Muchlinski et. al. (2016). Although it is unmentioned how they removed examples and filled missing values, this dataset seems the most workable with when the missing values and variables in other datasets are considered. The specific splitting strategy is the one that was mentioned but not implemented by the authors: Examples spanning years *1945-1990* will construct the training set, whereas examples spanning years *1990-2000* will construct the testing set.

### Removing Unused Columns

```
# Specify extra variables to keep apart from specifications mentioned in the previous segment
extra_vars <- c(y_var, "year", "cid")
all_vars <- unique(c(author_vars, FL_vars, CH_vars, HS_vars, extra_vars))
# Remove unwanted columns and specify chosen dataset
data <- data_HS_imputed[,all_vars] # KEEP: corresponds to data.full in original author's code
ncol(data) # debugging
```

```
## [1] 93
```

### Training/Test Split for Accurate Assessment

```
# Perform the split
split_year <- 1990
data_train <- data[data$year <= split_year,]
data_test <- data[data$year > split_year,]

# Observe class-imbalance in training and testing sets
split_presentation <- matrix(
  c(table(data_train$warstds)[1][[1]], table(data_test$warstds)[1][[1]],
    table(data_train$warstds)[2][[1]], table(data_test$warstds)[2][[1]]),
  ncol=2, byrow=T)

colnames(split_presentation) <- c('Training Set', 'Test Set')
rownames(split_presentation) <- c('War', 'Peace')
as.data.frame(split_presentation)
```

| | Training Set | Test Set |
|---|---|---|
| War | 5357 | 1667 |
| Peace | 93 | 23 |

```
# Since we are done with visualizations and exploration, refactor the dependent variable
data_train$warstds <- as.factor(data_train$warstds)
data_test$warstds <- as.factor(data_test$warstds)
```

The ratios of war/peace in our training and test sets are respectively ~0.013 and ~0.017. Since these two ratios are comparable, we assume that the training and test set generated by our split year share similar characteristics. Hence, we stick to this train-test split suggested by the authors as we think the split year was chosen consciously.

## SMOTE

SMOTE (Synthetic Minority Over-sampling Technique) is designed for problems when one class dominates the other, which usually happens in rare-event occurrences. We can easily make the argument that it is thus appropraite for the civil war onset data at hand. The general idea of this method is to artificially generate new examples of the minority class using the nearest neighbors of these cases. Furthermore, the majority class examples are also under-sampled, leading to a more balanced dataset. (RDocumentation)

```
# SMOTE for artificially creating a more balanced training dataset
set.seed(666) ## the most metal seed for CV
```

```r
data_train_balanced <- SMOTE(warstds ~ ., data_train, perc.over=600, perc.under=125, k=5)
table(data_train_balanced$warstds)
```

```
##
## peace   war
##   697   651
```

## General Training Setup

Below is the general setup to be run before training. One thing to look for is that, we set the seed beforehand for each function call that includes some randomness in order to present results that are replicable. The original code by the authors only set the seed once, which in turn makes some their results unreplicable. Specifically, the random forest models are not replicable as downsampling is applied but no seed setting occurs beforehand. Moreover, the `tc_original` and `tc` training controls showcase the difference in indexing between author's approach and our approach. Setting the index argument makes our models replicable, whereas the lack of it causes author's models to be unreplicable.

```r
set.seed(666) ## the most metal seed for CV

# Specify number of folds (10 by default, suggested by authors)
num_folds <- 10

# Indexing that will be used with our models -> aimed to control randomness so all models are replicabl
cv_index <- createFolds(factor(data_train$warstds), num_folds, returnTrain=T)

# This is the original training control included in author's code that unfortunately makes models NOT r
# This will only be used with author's models (notice that the index argument is NOT set)
tc_original <- trainControl(method="cv",
                            number=num_folds, ## creates CV folds - 10 for this data
                            summaryFunction=twoClassSummary, ## provides ROC stats in call to model
                            classProb=T)

# This is the corrected training control with indexing for replicability
tc <- trainControl(method="cv",
                   index=cv_index,
                   number=num_folds, ## creates CV folds - 10 for this data
                   summaryFunction=twoClassSummary, ## provides ROC stats in call to model
                   classProb=T)
```

## Replications

### Authors' Training Processes

The authors trained all models on the full `data_HS_imputed` dataset. For each of the previously outlined specifications 1), 2), and 3), they trained uncorrected and penalized logistic regression models. For their own specification, 4), they trained a random forest model with n=1000 trees and applied downsampling to the data provided.

```r
# Fearon and Laitin LR Model (2003) Uncorrected
REP_model_FL_uncorrected <- train(FL_spec,
                                  metric="ROC", method="glm", family="binomial",
```

```
                                trControl=tc_original, data=data)

# Fearon and Laitin LR Model (2003) Penalized
REP_model_FL_penalized <- train(FL_spec,
                                metric="ROC", method="plr", # Firth's penalized LR
                                trControl=tc_original, data=data)

# Collier and Hoeffler LR Model (2004) Uncorrected
REP_model_CH_uncorrected <- train(CH_spec,
                                  metric="ROC", method="glm", family="binomial",
                                  trControl=tc_original, data=data)
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
# Collier and Hoeffler LR Model (2004) Penalized
REP_model_CH_penalized <- train(CH_spec,
                                metric="ROC", method="plr", # Firth's penalized LR
                                trControl=tc_original, data=data)
```

```
##
## Convergence warning in plr: 2
```

```
# Hegre and Sambanis LR Model (2006) Uncorrected
REP_model_HS_uncorrected <- train(HS_spec,
                                  metric="ROC", method="glm", family="binomial",
                                  trControl=tc_original, data=data)

# Hegre and Sambanis LR Model (2006) Penalized
REP_model_HS_penalized <- train(HS_spec,
                                metric="ROC", method="plr", # Firth's penalized LR
                                trControl=tc_original, data=data)
```

```
##
## Convergence warning in plr: 2
```

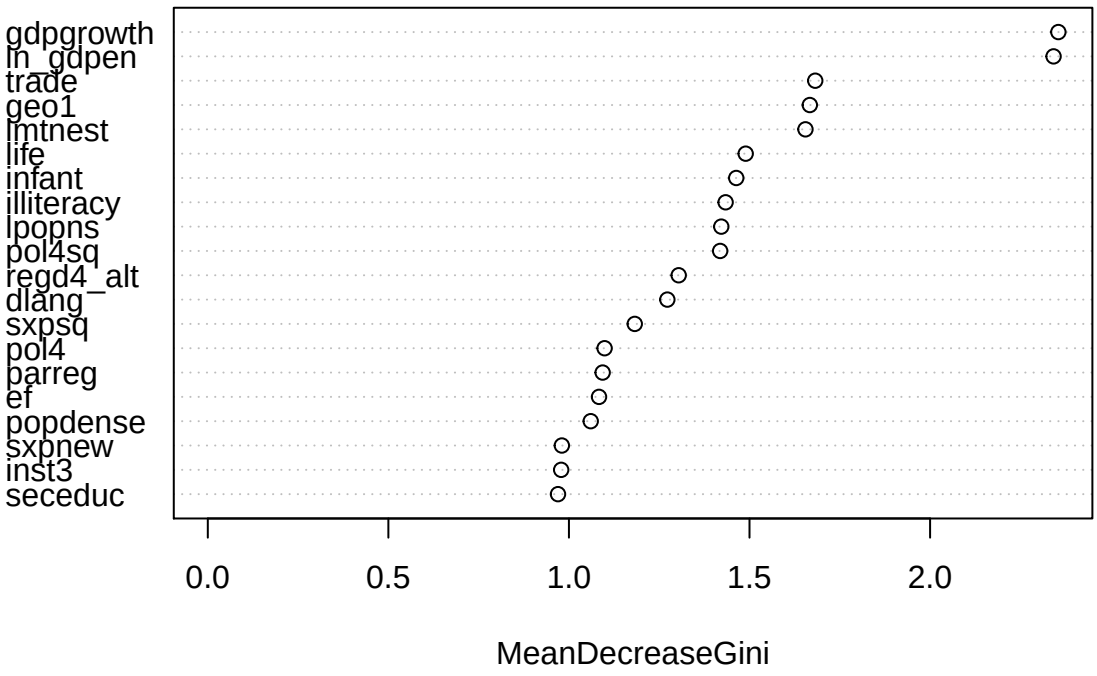
```
# Random Forest Model on author specification (2016)
REP_model_AS_RF <- train(author_spec,
                         metric="ROC", method="rf",
                         sampsize=c(30,90), ## Downsampling the class-imbalanced DV
                         importance=T, ## Variable importance measures retained
                         proximity=F, ntree=1000, ## number of trees grown
                         trControl=tc_original, data=data)
```

## Authors' Variable Importance Visualizations

The authors have trained a seperate a seperate random forest model on the `data_AM_imputed` dataset in order to visualize the importance of the variables in this dataset, measured by the Gini classification error.

```
## Random Forests on Amelia Imputed Data for Variable Importance Plot
## Data Imputed only for Theoretically Important Variables
## Done to analyze causal mechanisms

# Author removes unnecessary columns from the dataset
removed_vars <- names(data_AM_imputed) %in% c("X", "country", "year", "atwards")
data_AM_imputed <- data_AM_imputed[!removed_vars]
```

```
REP_model_AM_imputed <-randomForest(as.factor(warstds)~., # new spec: all columns in Amelia dataset
                                    sampsize=c(30, 90), # downsampling
                                    importance=T, proximity=F, ntree=1000,
                                    confusion=T, err.rate=T, data=data_AM_imputed)
# NOTE: The downsampling is random at each run due to incorrect seed setting (not replicable)

varImpPlot(REP_model_AM_imputed, sort=T, type=2,
           main="Variables Contributing Most to Predictive Accuracy of Random Forests",
           n.var=20)
```




One can check the full descriptions of the variables printed above on the y-axis of the Variable Importance table from the included `data/Sambanis Appendix (Aug 06).pdf` PDF file. When compared to the results from the paper, we see that roughly the same variables are included in the plot as the 20 most important variables. However, it could be easily observed that the order of these variables are different than those reported in the original paper. This is parallel to unreplicability issue mentioned previously.

### Authors' Prediction Processes

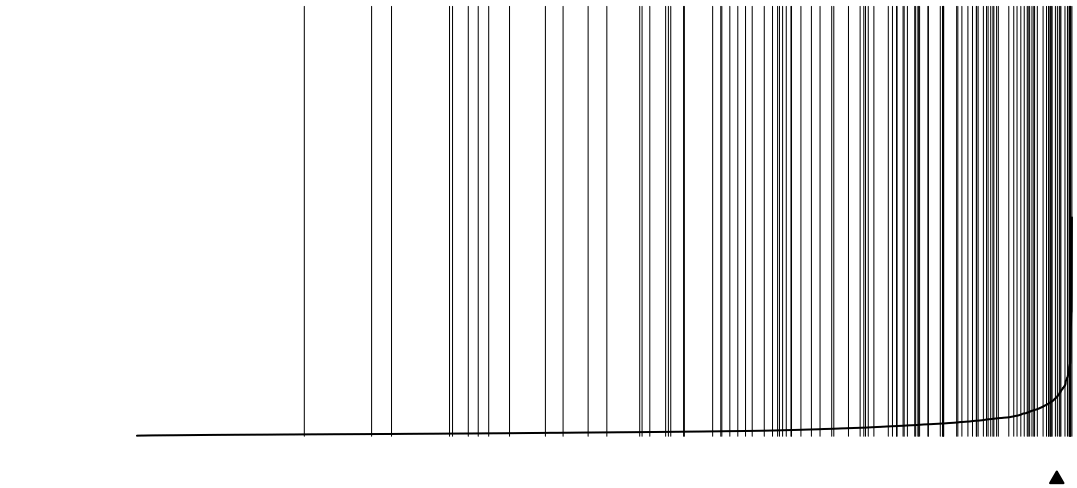
We have previously discussed that the author's replicated models are trained on the entire `HS_imputed` dataset, predicted/tested on the same, entire dataset as well, and how this hurts the reliability of the performance measures reported in the original paper. Below is the corresponding replication.

```
# Testing/predictions for Fearon and Laitin specification (2003)
REP_FL_uncorrected_pred_raw <- predict(REP_model_FL_uncorrected, newdata=data, type="raw")
REP_FL_uncorrected_pred_prob <- predict(REP_model_FL_uncorrected, newdata=data, type="prob")
REP_FL_penalized_pred_raw <- predict(REP_model_FL_penalized, newdata=data, type="raw")
REP_FL_penalized_pred_prob <- predict(REP_model_FL_penalized, newdata=data, type="prob")

# Testing/predictions for Collier and Hoeffler specification (2004)
```

```
REP_CH_uncorrected_pred_raw <- predict(REP_model_CH_uncorrected, newdata=data, type="raw")
REP_CH_uncorrected_pred_prob <- predict(REP_model_CH_uncorrected, newdata=data, type="prob")
REP_CH_penalized_pred_raw <- predict(REP_model_CH_penalized, newdata=data, type="raw")
REP_CH_penalized_pred_prob <- predict(REP_model_CH_penalized, newdata=data, type="prob")

# Testing/predictions for Hegre and Sambanis specification (2006)
REP_HS_uncorrected_pred_raw <- predict(REP_model_HS_uncorrected, newdata=data, type="raw")
REP_HS_uncorrected_pred_prob <- predict(REP_model_HS_uncorrected, newdata=data, type="prob")
REP_HS_penalized_pred_raw <- predict(REP_model_HS_penalized, newdata=data, type="raw")
REP_HS_penalized_pred_prob <- predict(REP_model_HS_penalized, newdata=data, type="prob")

# Testing/predictions for author specification (2016)
REP_AS_RF_pred_raw <- predict(REP_model_AS_RF, newdata=data, type="raw")
REP_AS_RF_pred_prob <- predict(REP_model_AS_RF, newdata=data, type="prob")
```

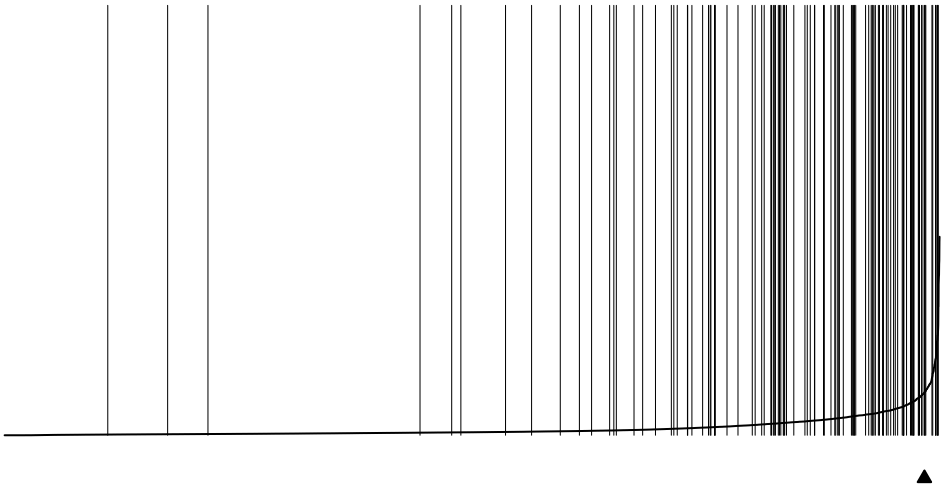
### Authors' Seperation Plots

```
# Seperation plot for prediction with Fearon and Laitin specification (2003) uncorrected LR
separationplot(REP_FL_uncorrected_pred_prob$war,
               as.numeric(data$warstds)-1, type="line",
               line=T, lwd2=1, show.expected=T,
               heading="REP: Fearon and Laitin Spec (2003) Uncorrected LR Seperation Plot",
               height=1.5, col0="white", col1="black", newplot=F)
```



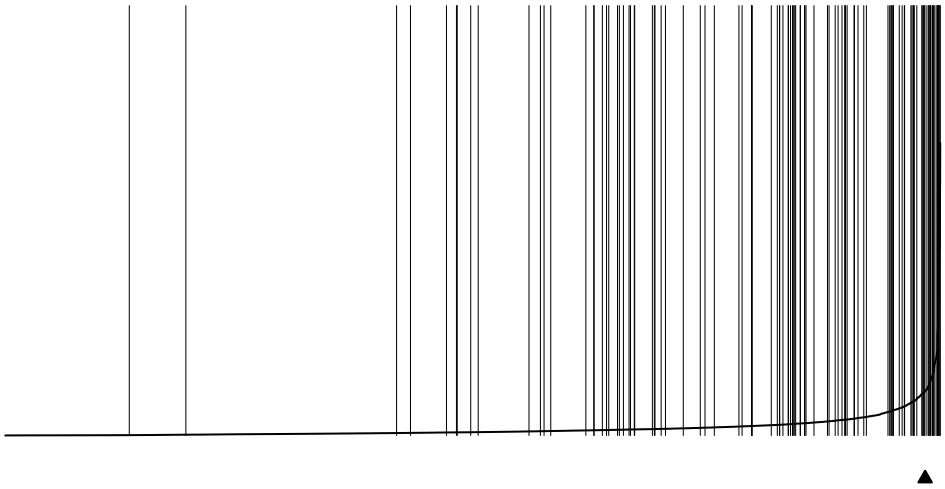

```
# Seperation plot for prediction with Collier and Hoeffler specification (2004) uncorrected LR
separationplot(REP_CH_uncorrected_pred_prob$war,
               as.numeric(data$warstds)-1, type="line",
               line=T, lwd2=1, show.expected=T,
               heading="REP: Collier and Hoeffler Spec (2004) Uncorrected LR Seperation Plot",
               height=1.5, col0="white", col1="black", newplot=F)
```

## REP: Collier and Hoeffler Spec (2004) Uncorrected LR Seperation Pl



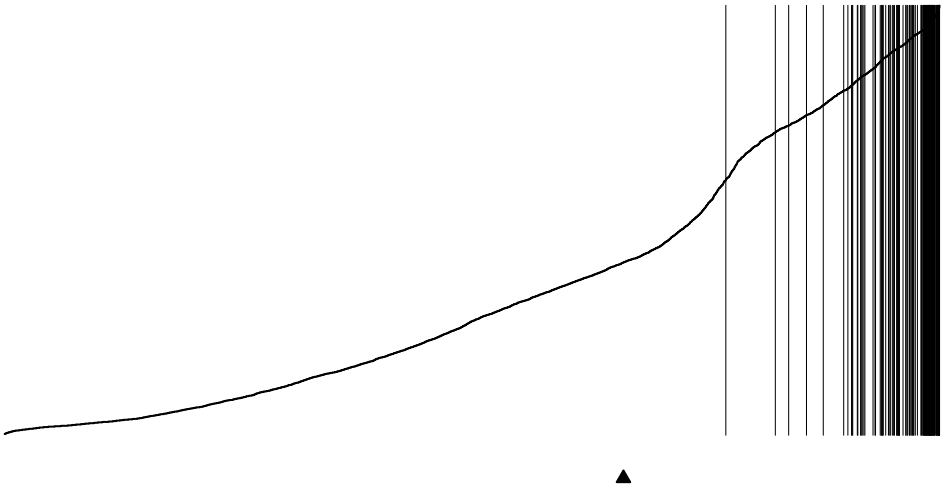
```
# Seperation plot for prediction with Hegre and Sambanis specification (2006) uncorrected LR
separationplot(REP_HS_uncorrected_pred_prob$war,
               as.numeric(data$warstds)-1, type="line",
               line=T, lwd2=1, show.expected=T,
               heading="REP: Hegre and Sambanis Spec (2006) Uncorrected LR Seperation Plot",
               height=1.5, col0="white", col1="black", newplot=F)
```

## REP: Hegre and Sambanis Spec (2006) Uncorrected LR Seperation P



```
# Seperation plot for prediction with Hegre and Sambanis specification (2006) uncorrected LR
separationplot(REP_AS_RF_pred_prob$war,
               as.numeric(data$warstds)-1, type="line",
               line=T, lwd2=1, show.expected=T,
               heading="REP: Author Spec (2016) Random Forests Seperation Plot",
               height=1.5, col0="white", col1="black", newplot=F)
```

## REP: Author Spec (2016) Random Forests Seperation Plot



Although we have argued that models are not replicable, the seperation plots we generated for author's replicated models and the ones presented in the original paper are somewhat similar for all of the three logistic regression models. The Random Forests model's seperation plot differs **occasionally**, and this is expected, as this is the model with the highest randomness (both downsampling and training control). Otherwise, the final represented seperation plot of random forest may look similar to the one represented in paper.

### Authors' F1 scores

The F1-Score is F1 = 2 x (Precision x Recall) / (Precision + Recall) where Precision = TP / (TP + FP) and Recall = TP / (TP + FN). Therefore, some of the reported scores here will be NaN as those models had 0 predicted true positive cases.

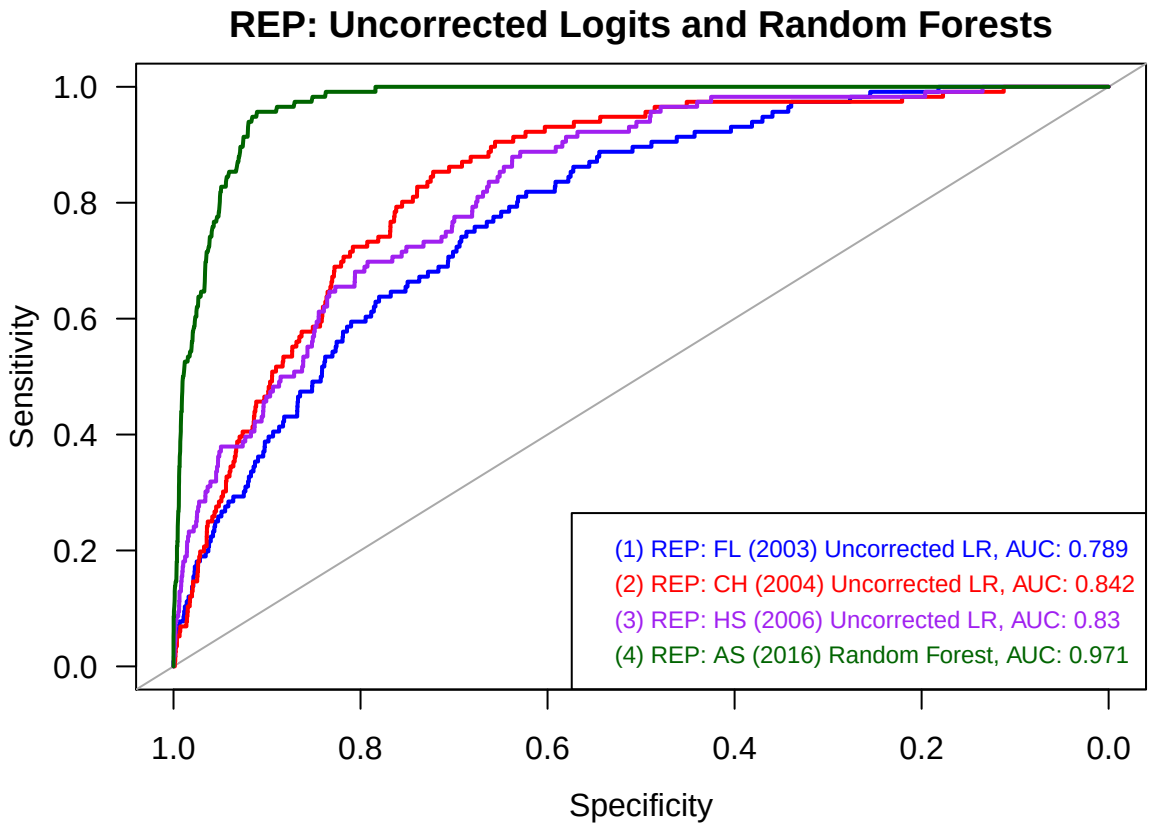
```
REP_f1_presentation <- matrix(
  c(F1_Score(data$warstds, REP_FL_uncorrected_pred_raw, positive = "war"),
    F1_Score(data$warstds, REP_FL_penalized_pred_raw, positive = "war"),
    F1_Score(data$warstds, REP_CH_uncorrected_pred_raw, positive = "war"),
    F1_Score(data$warstds, REP_CH_penalized_pred_raw, positive = "war"),
    F1_Score(data$warstds, REP_HS_uncorrected_pred_raw, positive = "war"),
    F1_Score(data$warstds, REP_HS_penalized_pred_raw, positive = "war"),
    F1_Score(data$warstds, REP_AS_RF_pred_raw, positive = "war")),
  ncol=1, byrow=T)

colnames(REP_f1_presentation) <- c('F1-Score')
rownames(REP_f1_presentation) <- c('REP FL (2003) Uncorrected LR', 'REP FL (2003) Penalized LR',
                                   'REP CH (2004) Uncorrected LR', 'REP CH (2004) Penalized LR',
                                   'REP HS (2006) Uncorrected LR', 'REP HS (2006) Penalized LR',
                                   'REP AS (2016) RF')
as.data.frame(REP_f1_presentation)
```

| | F1-Score |
|---|---|
| REP FL (2003) Uncorrected LR | 0.0170940 |
| REP FL (2003) Penalized LR | NaN |
| REP CH (2004) Uncorrected LR | NaN |
| REP CH (2004) Penalized LR | NaN |

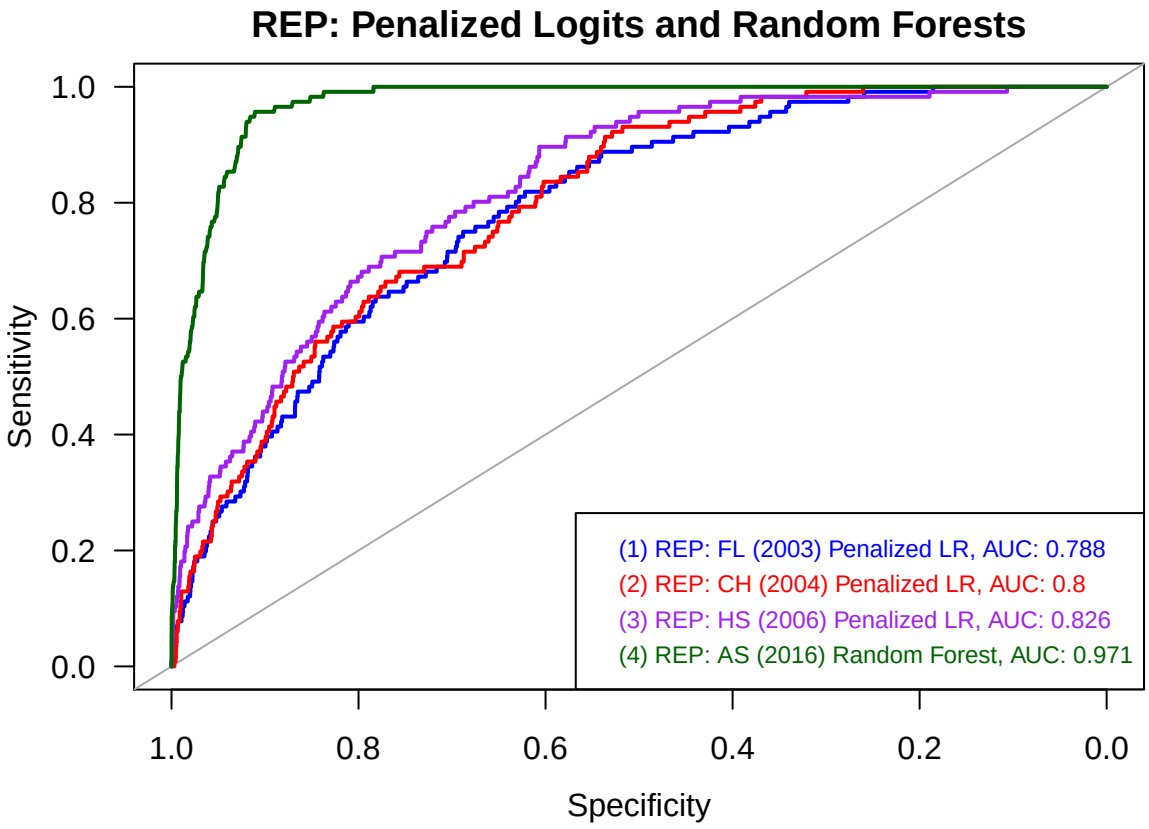
| | F1-Score |
|---|---|
| REP HS (2006) Uncorrected LR | 0.0168067 |
| REP HS (2006) Penalized LR | 0.0169492 |
| REP AS (2016) RF | 0.1158263 |

### Authors' ROC Curves with AUC Scores

```
# Plot ROC curves for prediction comparing uncorrected FL (2003), CH (2004),
# and HS (2006) specs, as well as the Random Forests models (author's versions)
plot.roc(data$warstds, REP_FL_uncorrected_pred_prob$war, col="blue",
         xlim=c(1,0), las=1, bty="n", asp=NA,
         main="REP: Uncorrected Logits and Random Forests")
plot.roc(data$warstds, add=T, REP_CH_uncorrected_pred_prob$war, col="red")
plot.roc(data$warstds, add=T, REP_HS_uncorrected_pred_prob$war, col="purple")
plot.roc(data$warstds, add=T, REP_AS_RF_pred_prob$war, col="darkgreen")
legend("bottomright", c(paste("(1) REP: FL (2003) Uncorrected LR, AUC:",
                              round(as.numeric(roc(data$warstds,
                                                   REP_FL_uncorrected_pred_prob$war)$auc),3)),
                        paste("(2) REP: CH (2004) Uncorrected LR, AUC:",
                              round(as.numeric(roc(data$warstds,
                                                   REP_CH_uncorrected_pred_prob$war)$auc),3)),
                        paste("(3) REP: HS (2006) Uncorrected LR, AUC:",
                              round(as.numeric(roc(data$warstds,
                                                   REP_HS_uncorrected_pred_prob$war)$auc),3)),
                        paste("(4) REP: AS (2016) Random Forest, AUC:",
                              round(as.numeric(roc(data$warstds,
                                                   REP_AS_RF_pred_prob$war)$auc),3))),
       text.col=c("blue","red","purple", "darkgreen"),
       cex = .75)
```




```
# Plot ROC curves for prediction comparing penalized FL (2003), CH (2004),
# and HS (2006) specs, as well as the Random Forests models (author's versions)
plot.roc(data$warstds, REP_FL_penalized_pred_prob$war, col="blue",
         xlim=c(1,0), las=1, bty="n", asp=NA,
         main="REP: Penalized Logits and Random Forests")
plot.roc(data$warstds, add=T, REP_CH_penalized_pred_prob$war, col="red")
plot.roc(data$warstds, add=T, REP_HS_penalized_pred_prob$war, col="purple")
plot.roc(data$warstds, add=T, REP_AS_RF_pred_prob$war, col="darkgreen")
legend("bottomright", c(paste("(1) REP: FL (2003) Penalized LR, AUC:",
                              round(as.numeric(roc(data$warstds,
                                                   REP_FL_penalized_pred_prob$war)$auc),3)),
                        paste("(2) REP: CH (2004) Penalized LR, AUC:",
                              round(as.numeric(roc(data$warstds,
                                                   REP_CH_penalized_pred_prob$war)$auc),3)),
                        paste("(3) REP: HS (2006) Penalized LR, AUC:",
                              round(as.numeric(roc(data$warstds,
                                                   REP_HS_penalized_pred_prob$war)$auc),3)),
                        paste("(4) REP: AS (2016) Random Forest, AUC:",
                              round(as.numeric(roc(data$warstds,
                                                   REP_AS_RF_pred_prob$war)$auc),3))),
       text.col=c("blue","red","purple", "darkgreen"),
       cex = .75)
```




The unreplicability of the results are justified most with the reported ROC curves and accompanying AUC curves as shown above. It should be remembered that the curves and measures presented above are NOT tested with **out-of-sample** data, rather they simply act as a training summary. This explains the rather high AUC score of the random forest model.

# Extensions & Improvements

## Training Insights from Replication

The initially commented out random forest training processes and the primary random forest model presented in paper includes an option for down-sampling, whereas the other logistic regression training processes don't have this option specified.This has the potential to yield unfair comparisons, so we decided to remove down-sampling option completely in our own implementations.

Perhaps the biggest problem is that the authors have only used an in-sample accuracy metric to report the performance of their models which couldn't be directly inferred from the paper otherwise. Hence, the reported performance measures on the paper don't really give us much insight into how these models might behave with unseen data. In order to assess the performance, we have to test our models for **out-of-sample data** `data_test` while training our models on the seperated `data_train`.

The already mentioned problem with index argument of the training controls and uncorrect seed setting unfortunately makes the results of the paper completely unreplicable. One can run `summary(<model_name>)` and `confusionMatrix(<model_name>)` functions below each model in the above code block to observe how ROC values changes (although in miniscule amounts) with every training instance. This could be confirmed by running the same corresponding lines from author's original code included in `data/Comparing+Random+Forest+with+Logistic+Regression+R+Code.R` and observing how ROC values changes (although in miniscule amounts) again. It seems that the authors were unaware of the unreplicability

of their results as they included hardcoded values for their AUC measures. In contrast, running the same functions below each model in the below code block should showcase how ROC values are preserved and hence prove the replicability of our implementation.

We will firstly train the 4 specifications mentioned in the paper with the `data_train` dataset, which was acquired by split (based on year) from the `data_HS_imputed` dataset provided by the authors. Then, finally, we will train a fifth instance with author specification (88 variables), but instead on the `data_train_balanced` dataset this time. As previously mentioned, this dataset was created with the SMOTE algorithm to deal with the class-imbalance in the dataset. For each of the 5 instances of training, we will include i) a logistic regression model (LR) with uncorrected logits, ii) a logistic regression model (LR) with penalized logits using Firth's method, and iii) a random forest model (RF).

For the author specification, 4), we will also include experimental models that we have implemented for performance comparison with Random Forest model.

All of the models use the corrected version of the cross-validation training control, `tc`. It should be noted that for author specification, 4), the penalized logistic regression and random forest models take long times for training (around ~30 minutes in our setup). This is partly because we removed downsampling from the original implementation.

## Training Processes

### Standard Models

1) Fearon and Laitin specification (2003) consisting of 11 variables

```
set.seed(666) ## the most metal seed for CV

# Fearon and Laitin LR Model (2003) Uncorrected
model_FL_uncorrected <- train(FL_spec,
                              metric="ROC", method="glm", family="binomial",
                              trControl=tc, data=data_train)

# Fearon and Laitin LR Model (2003) Penalized
model_FL_penalized <- train(FL_spec,
                            metric="ROC", method="plr", # Firth's penalized LR
                            trControl=tc, data=data_train)

# Random Forest Model on Fearon and Laitin (2003) specification
model_FL_RF <- train(FL_spec,
                     metric="ROC", method="rf",
                     trControl=tc, data=data_train)
```

2) Collier and Hoeffler specification (2004) consisting of 12 variables

```
set.seed(666) ## the most metal seed for CV

# Collier and Hoeffler LR Model (2004) Uncorrected
model_CH_uncorrected <- train(CH_spec,
                              metric="ROC", method="glm", family="binomial",
                              trControl=tc, data=data_train)
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
# Collier and Hoeffler LR Model (2004) Penalized
model_CH_penalized <- train(CH_spec,
```

```
                              metric="ROC", method="plr", # Firth's penalized LR
                              trControl=tc, data=data_train)
```

```
## Warning in nominalTrainWorkflow(x = x, y = y, wts = weights, info =
## trainInfo, : There were missing values in resampled performance measures.
```

```
##
## Convergence warning in plr: 2
```

```
# Random Forest Model on Collier and Hoeffler (2004) specification
model_CH_RF <- train(CH_spec,
                     metric="ROC", method="rf",
                     trControl=tc, data=data_train)
```

3) Hegre and Sambanis specification (2006) consisting of 20 variables

```
set.seed(666) ## the most metal seed for CV

# Hegre and Sambanis LR Model (2006) Uncorrected
model_HS_uncorrected <- train(HS_spec,
                              metric="ROC", method="glm", family="binomial",
                              trControl=tc, data=data_train)

# Hegre and Sambanis LR Model (2006) Penalized
model_HS_penalized <- train(HS_spec,
                            metric="ROC", method="plr", # Firth's penalized LR
                            trControl=tc, data=data_train)
```

```
##
## Convergence warning in plr: 2
```

```
# Random Forest Model on Hegre and Sambanis (2006) specification
model_HS_RF <- train(HS_spec,
                     metric="ROC", method="rf",
                     trControl=tc, data=data_train)
```

4) The authors' specifications consisting of 88 variables, selected from Sambanis (2006) index

```
set.seed(666) ## the most metal seed for CV

# Author specification (2016) LR Model Uncorrected
model_AS_uncorrected <- train(author_spec,
                              metric="ROC", method="glm", family="binomial",
                              trControl=tc, data=data_train)
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
# Author specification (2016) LR Model Penalized (CAUTION: estimated training time ~30 min)
model_AS_penalized <- train(author_spec,
                            metric="ROC", method="plr", # Firth's penalized LR
                            trControl=tc, data=data_train)
```

```
## Warning in nominalTrainWorkflow(x = x, y = y, wts = weights, info =
## trainInfo, : There were missing values in resampled performance measures.
```

```
##
## Convergence warning in plr: 2
```

```
# Random Forest Model on author specification (2016) (CAUTION: estimated training time ~30 min)
model_AS_RF <- train(author_spec,
                     metric="ROC", method="rf",
                     importance=T, ## Variable importance measures retained
                     trControl=tc, data=data_train)
```

5) The authors' specifications consisting of 88 variables, trained on `data_train_balanced`, which was artificially generated from `data_train` using the SMOTE algorithm discussed previously.

```
set.seed(666) ## the most metal seed for CV

# Author specification (2016) LR Model Uncorrected
model_AS_uncorrected_smoted <- train(author_spec,
                                     metric="ROC", method="glm", family="binomial",
                                     trControl=tc, data=data_train_balanced)
```

```
## Warning in nominalTrainWorkflow(x = x, y = y, wts = weights, info =
## trainInfo, : There were missing values in resampled performance measures.
```

```
## Warning: glm.fit: algorithm did not converge
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
# Author specification (2016) LR Model Penalized
model_AS_penalized_smoted <- train(author_spec,
                                   metric="ROC", method="plr", # Firth's penalized LR
                                   trControl=tc, data=data_train_balanced)
```

```
## Warning in nominalTrainWorkflow(x = x, y = y, wts = weights, info =
## trainInfo, : There were missing values in resampled performance measures.
```

```
##
## Convergence warning in plr: 2
```

```
# Random Forest Model on author specification (2016)
model_AS_RF_smoted <- train(author_spec,
                            metric="ROC", method="rf",
                            importance=T, ## Variable importance measures retained
                            trControl=tc, data=data_train_balanced)
```

```
## Warning in nominalTrainWorkflow(x = x, y = y, wts = weights, info =
## trainInfo, : There were missing values in resampled performance measures.
```

### Experimenting with Different Models

In order to assess whether Random Forest is the ideal model to capture the behavior of the data, we decided to experiment with some other Machine Learning models.

1) Decision Tree: The simpler Decision Tree model, which the Random Forest model is based on, builds a tree data structure. At every node of the tree, the data points are split based on one of three splits: Univariate split, linear combination split or categorical split. These splits are executed based on the predictor values of each data point during prediction. The decision tree model was not able to capture the nature of the dataset that well or achieve results comparable to Random Forest. Yet, the easy-to-visualize nature of decision trees allowed us to take a closer look at how predictors are being used during classification and what the cutoffs are for these predictors.

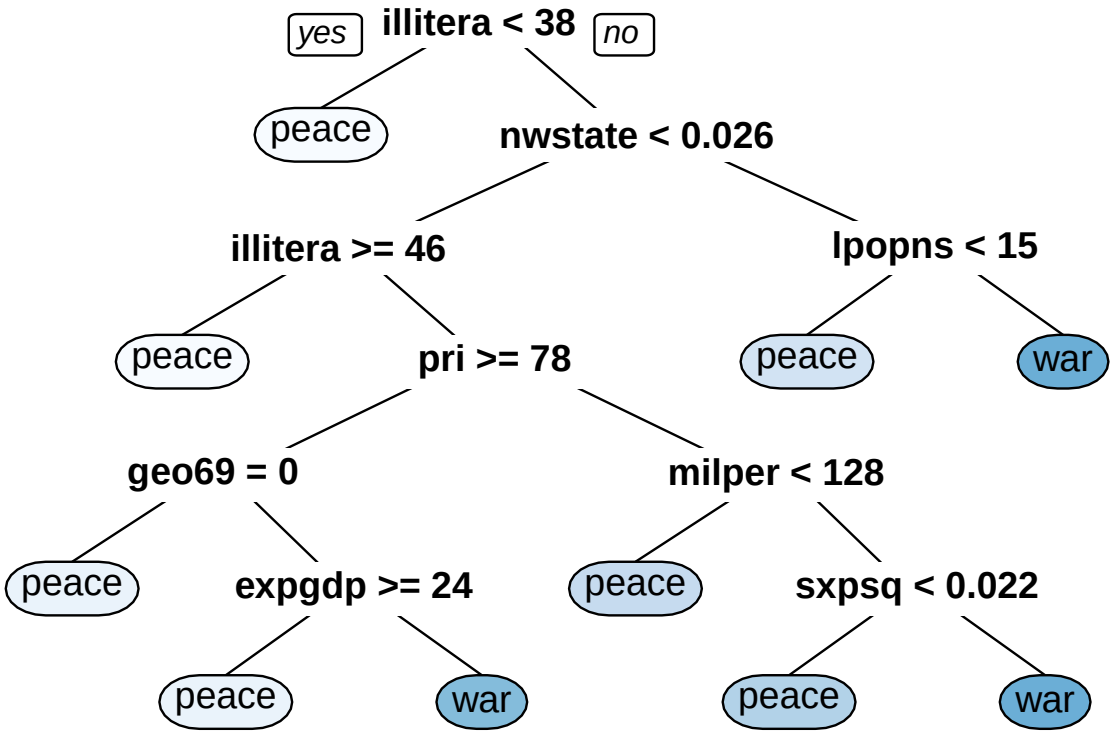
2) Boosted Classification Trees: After running some parameter grid searches, we noticed that the Boosted Classification Trees model with the parameters below can achieve an AUC score of 0.934 (will be

displayed later in the Notebook). The Boosted Classification Trees uses Adaptive Boosting which aims to combine a number of weak classifiers and predict based on a weighed voting procedure among these classifiers. Firstly, Adaptive Boosting trains a variety of weak classifiers. Those that have >50% accuracy receive positive weights whereas those that have <50% accuracy receive negative weights. The further the accuracy is from %50, more positive/more negative the weight of that weak classifier. Thus, even those classifiers that are unsuccessful at the task, in other words missclassify most of the time, can be incorporated and used as part of the ensemble.

Unlike Random Forests which is a bagging ensemble model, Boosted Classification Trees is a boosting model. While bagging models aim to decrease variance, boosting models aim to decrese bias. Random Forest trains $n$ Decision Trees on different random subsets of the dataset. Bagging ensemble models train their weak classifiers in parallel. Boosting on the other hand trains the weaker models in series. This sequential training method allows the model to determine which datapoints are misclassified and consequently assign/update the weights of datapoints such that on the next iteration, misclassified datapoints get high probabilities for classification. Thus, it iteratively corrects the mistakes of its classifiers. Moreover, it is not prone to overfitting.

```
# Decision Tree Model with Author Specification (2016)
model_AS_DT <- train(author_spec,
                     metric="ROC",
                     method="rpart",
                     trControl=tc,
                     data=data_train)

set.seed(666) ## the most metal seed for CV
# Boosted Classification Trees Model with Author Specification (2016)
model_AS_Boost <- train(author_spec,
                        metric="ROC",
                        method="ada", # Adaptive Boosting
                        trControl=tc,
                        tuneGrid=data.frame(.iter=150, .maxdepth=3, .nu=0.01),
                        data=data_train)
```

```
# Visualize the Decision Tree to assess which predictors were used and what the cut-offs were
prp(model_AS_DT$finalModel, box.palette = "Blues", tweak = 1.2)
```




## Variable Importance for Random Forest Models

One advantage of the Random Forests algorithm is that it is easy to interpret, robust to outliers and noise, and allows the analyst to infer causal mechanisms. Although the paper has serious methodological flaws, we think that its suggestion of Random Forests is well-grounded. The original R code by authors visualizes the variable importance for a Random Forest Model trained on the `data_AM_imputed` dataset, however we **dropped** that dataset as discussed before. It makes the most sense to us to visualize the variable importance on the 5 different random forest models we trained in the previous segment, 4 on `data_train` and 1 on `data_train_balanced` to be exact. By doing this, we can achieve: i) See if theories suggested by different parties on theoretical variables deciding a civil war onset agree with our findings or not, ii) Observe if any variables are deemed to be `unimportant` by the random forest algorithm, measured by mean decrease in Gini classification measure in the case that they are not considered in training, iii) Observe the difference of variable importance on random forests models trained on original training set and artifically created training set, and essentially see how the SMOTE algorithms affects this measure.

### Retraining Random Forest Models

Firstly, we will retrain random forest models with the same specs and data mentioned above, but with `randomForests()` class this same in order to plot importance of variables. Note that these models will only be used to visualize variable importance, and will be dropped later in order to not cause any confusion.

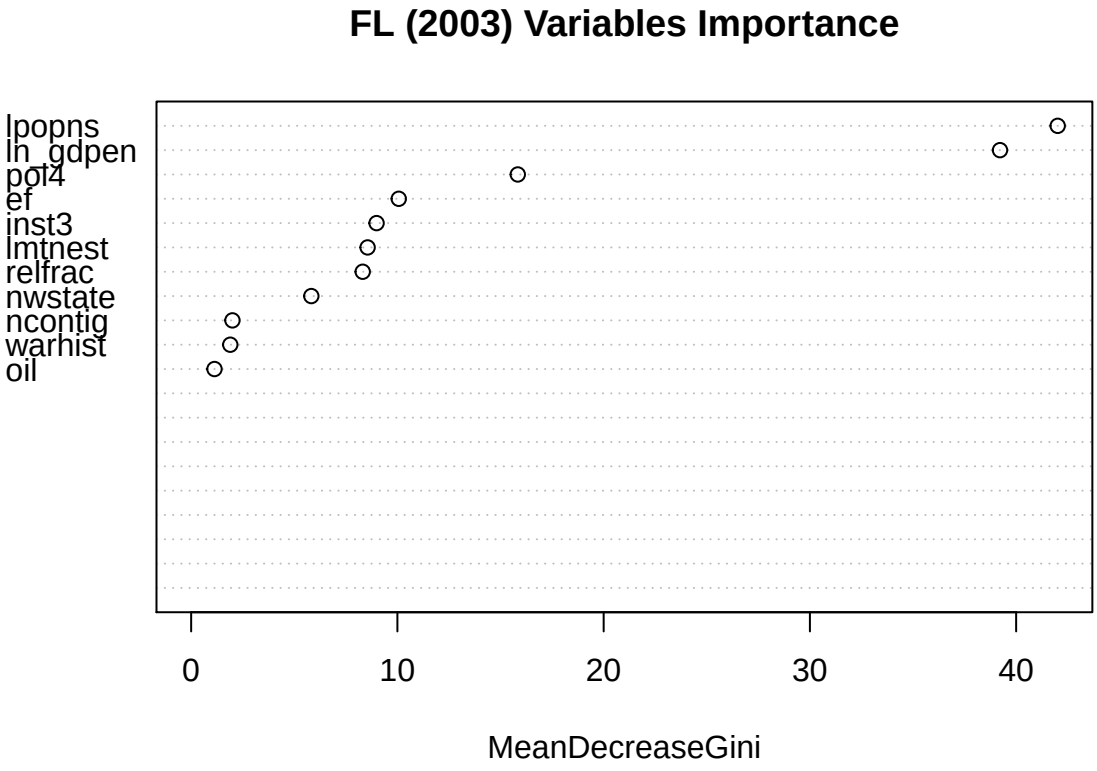
```
num_trees <- 1000
FL_RF <- randomForest(FL_spec, importance=T, proximity=F, ntree=num_trees,
                      confusion=T, err.rate=T, data=data_train)
CH_RF <- randomForest(CH_spec, importance=T, proximity=F, ntree=num_trees,
                      confusion=T, err.rate=T, data=data_train)
HS_RF <- randomForest(HS_spec, importance=T, proximity=F, ntree=num_trees,
                      confusion=T, err.rate=T, data=data_train)
AS_RF <- randomForest(author_spec, importance=T, proximity=F, ntree=num_trees,
```

```
                        confusion=T, err.rate=T, data=data_train)
AS_RF_smoted <- randomForest(author_spec, importance=T, proximity=F, ntree=num_trees,
                             confusion=T, err.rate=T, data=data_train_balanced)
```

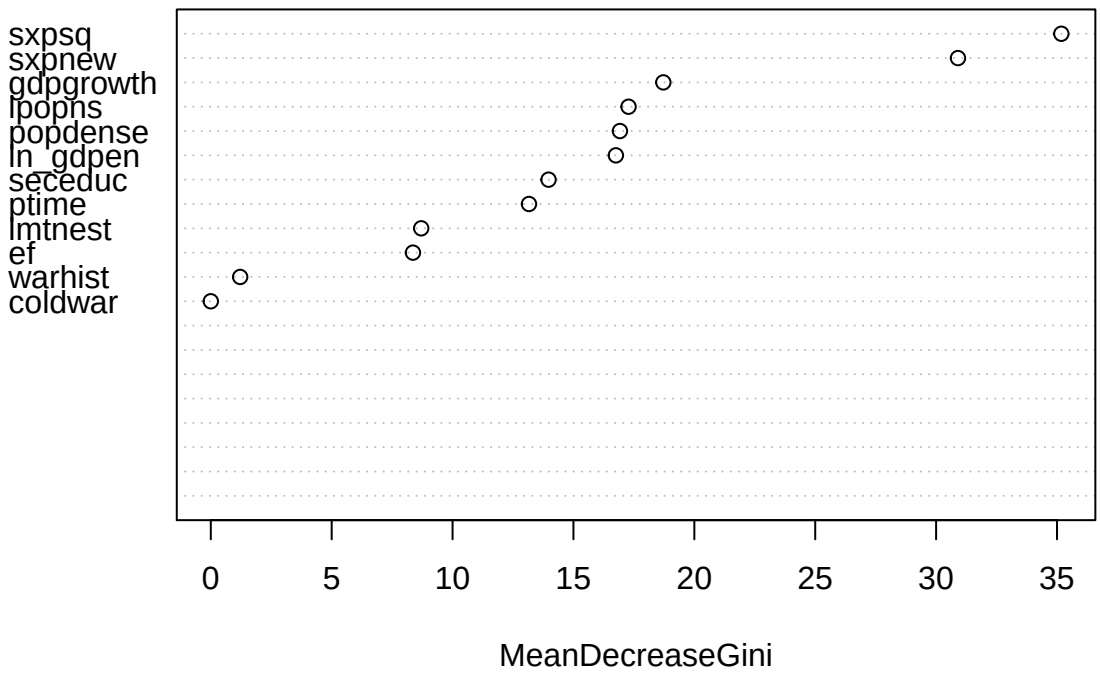
### Variable Importance Visualizations

Now, we can visualize the variable importances for each of the random forest models trained above.

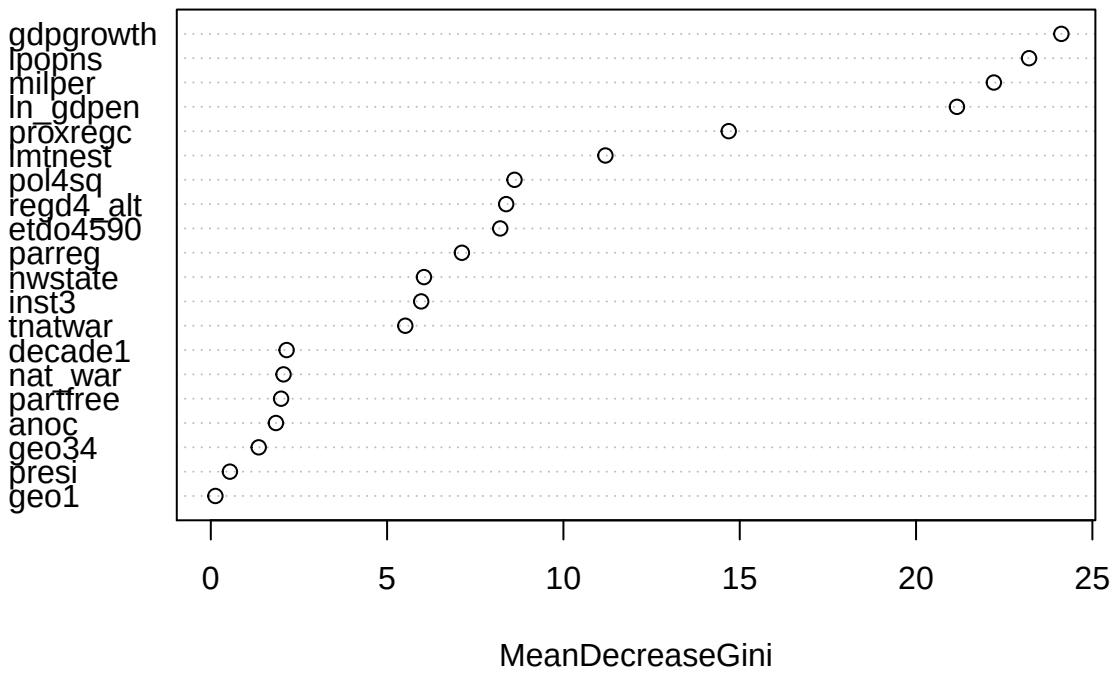
```
# Specify maximum number of variables (features) to be displayed
num_vars <- 20
varImpPlot(FL_RF, sort=T, type=2,
           main="FL (2003) Variables Importance",
           n.var=num_vars)
```




```
varImpPlot(CH_RF, sort=T, type=2,
           main="CH (2004) Variables Importance",
           n.var=num_vars)
```

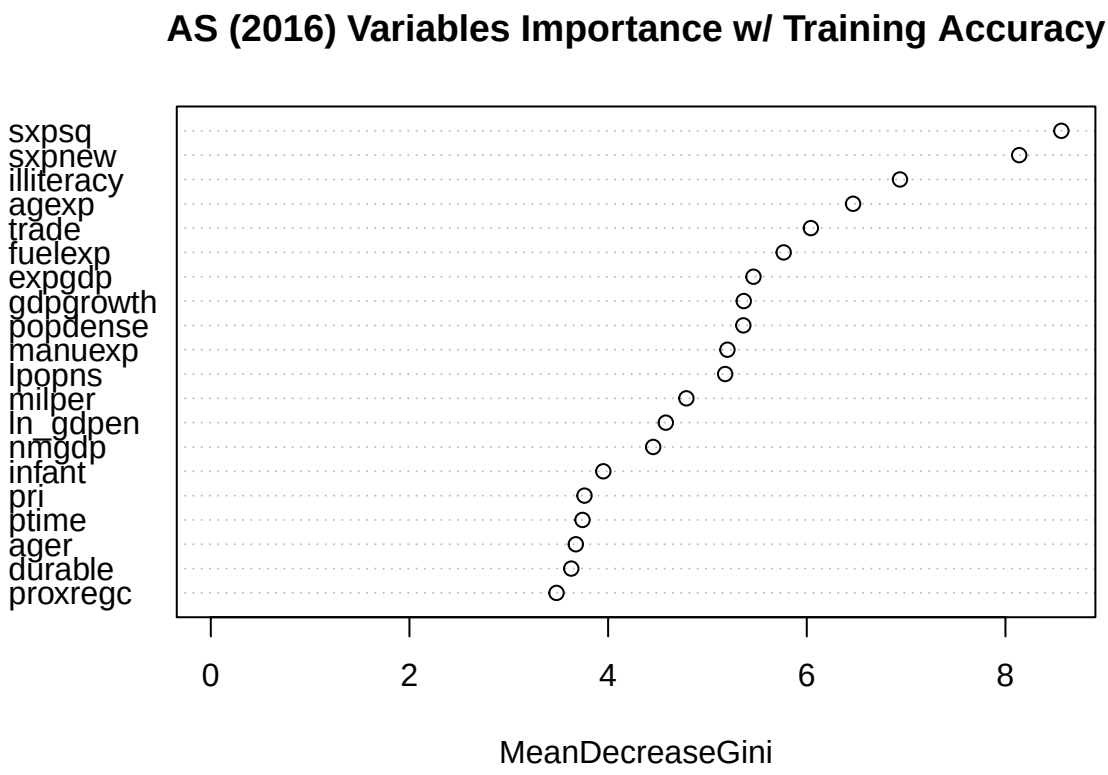



```
varImpPlot(HS_RF, sort=T, type=2,
           main="HS (2006) Variables Importance",
           n.var=num_vars)
```

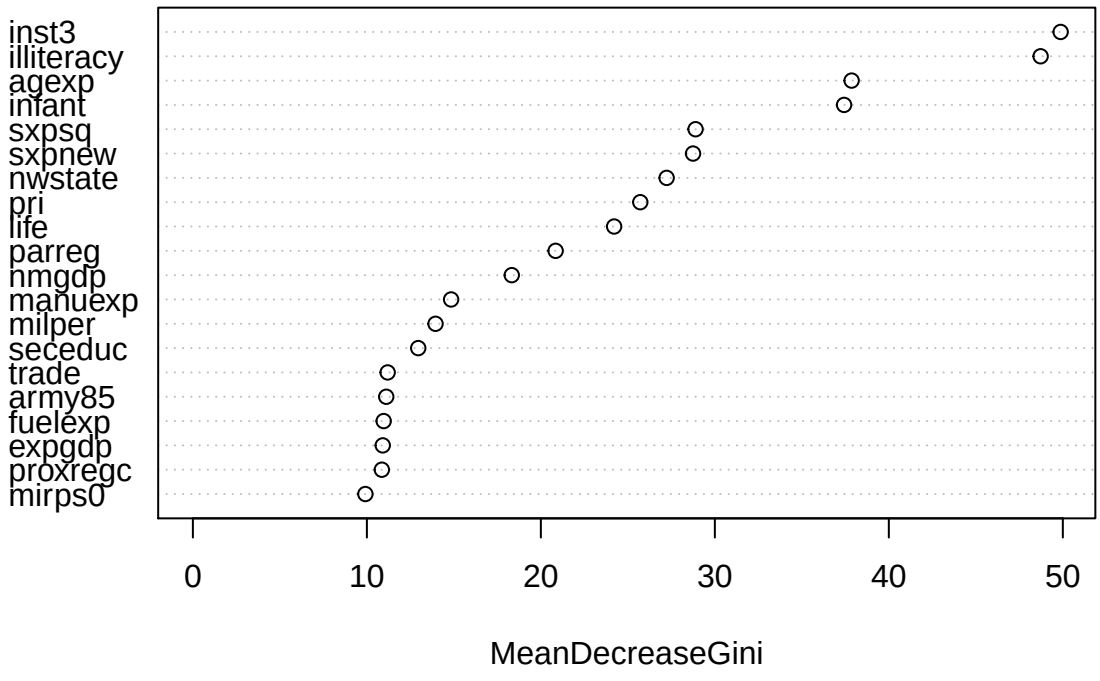



```
varImpPlot(AS_RF, sort=T, type=2,
           main="AS (2016) Variables Importance w/ Training Accuracy",
```

```
          n.var=num_vars)
```




```
varImpPlot(AS_RF_smoted, sort=T, type=2,
           main="AS (2016) Variables Importance w/ SMOTEd data",
           n.var=num_vars)
```




It should be

noted that some variables such as *oil*, *warhist*, and *ncontig* from Fearon and Laitin's (2003) and Collier and Hoeffler's (2004) theories gave near 0 mean decreases in Gini classification rate. In contrast to this, the author specification which has a lot more features don't have any values close to 0. Another thing to note would be that when SMOTE is applied, a lot of the variables change. An interesting thing to observe was that *illiteracy* seems to play an important role in classification regardless.

## Testing Insights from Replication

The paper includes a graph for comparing training AUC for uncorrected logistic regression models versus the random forest model, and a seperate graph for comparing the same metric for penalized logistic regression models versus the random forest model. The immediately noticable problem with this approach is that, each of these model have different specifications and hence different numbers of features they are trained on. As discussed before, the random forest model included downsampling which made the comparison even less reliable due to possible overfitting.

Here, we propose that we compare ROC curves and AUC scores for each of the specifications on **out-of-sample** data independently. With this methodology, we will be able to assess the performance of random forest algorithm in comparison to uncorrected & penalized logistic regression models in a more reliable way. We realize that the out-of-sample testing data contains a low number of examples, however this approach is still better than comparing plain training accuracies. Furthermore, this is due to the nature of this problem and the difficulty of data gathering associated with it.

For each of the 3 models used for each of the 5 specifications and, we will use the `predict()` function with: i) type="raw" for number/class of predictions to be used in confusion matrices, and ii) type="prob" for class probabilities to be used with ROC curves and computation of AUC metric.

## Prediction Processes

```
# Testing/predictions for Fearon and Laitin specification (2003)
FL_uncorrected_pred_raw <- predict(model_FL_uncorrected, newdata=data_test, type="raw")
FL_uncorrected_pred_prob <- predict(model_FL_uncorrected, newdata=data_test, type="prob")
FL_penalized_pred_raw <- predict(model_FL_penalized, newdata=data_test, type="raw")
FL_penalized_pred_prob <- predict(model_FL_penalized, newdata=data_test, type="prob")
FL_RF_pred_raw <- predict(model_FL_RF, newdata=data_test, type="raw")
FL_RF_pred_prob <- predict(model_FL_RF, newdata=data_test, type="prob")

# Testing/predictions for Collier and Hoeffler specification (2004)
CH_uncorrected_pred_raw <- predict(model_CH_uncorrected, newdata=data_test, type="raw")
```

```
## Warning in predict.lm(object, newdata, se.fit, scale = 1, type =
## ifelse(type == : prediction from a rank-deficient fit may be misleading
```

```
CH_uncorrected_pred_prob <- predict(model_CH_uncorrected, newdata=data_test, type="prob")
```

```
## Warning in predict.lm(object, newdata, se.fit, scale = 1, type =
## ifelse(type == : prediction from a rank-deficient fit may be misleading
```

```
CH_penalized_pred_raw <- predict(model_CH_penalized, newdata=data_test, type="raw")
CH_penalized_pred_prob <- predict(model_CH_penalized, newdata=data_test, type="prob")
CH_RF_pred_raw <- predict(model_CH_RF, newdata=data_test, type="raw")
CH_RF_pred_prob <- predict(model_CH_RF, newdata=data_test, type="prob")

# Testing/predictions for Hegre and Sambanis specification (2006)
HS_uncorrected_pred_raw <- predict(model_HS_uncorrected, newdata=data_test, type="raw")
```

```
HS_uncorrected_pred_prob <- predict(model_HS_uncorrected, newdata=data_test, type="prob")
HS_penalized_pred_raw <- predict(model_HS_penalized, newdata=data_test, type="raw")
HS_penalized_pred_prob <- predict(model_HS_penalized, newdata=data_test, type="prob")
HS_RF_pred_raw <- predict(model_HS_RF, newdata=data_test, type="raw")
HS_RF_pred_prob <- predict(model_HS_RF, newdata=data_test, type="prob")

#Testing/predictions for author specification (2016)
AS_uncorrected_pred_raw <- predict(model_AS_uncorrected, newdata=data_test, type="raw")
```

```
## Warning in predict.lm(object, newdata, se.fit, scale = 1, type =
## ifelse(type == : prediction from a rank-deficient fit may be misleading
```

```
AS_uncorrected_pred_prob <- predict(model_AS_uncorrected, newdata=data_test, type="prob")
```

```
## Warning in predict.lm(object, newdata, se.fit, scale = 1, type =
## ifelse(type == : prediction from a rank-deficient fit may be misleading
```

```
AS_penalized_pred_raw <- predict(model_AS_penalized, newdata=data_test, type="raw")
AS_penalized_pred_prob <- predict(model_AS_penalized, newdata=data_test, type="prob")
AS_RF_pred_raw <- predict(model_AS_RF, newdata=data_test, type="raw")
AS_RF_pred_prob <- predict(model_AS_RF, newdata=data_test, type="prob")

# Testing/prediction for author specification (2016) trained on SMOTEd dataset
AS_uncorrected_smoted_pred_raw <- predict(model_AS_uncorrected_smoted, newdata=data_test, type="raw")
```

```
## Warning in predict.lm(object, newdata, se.fit, scale = 1, type =
## ifelse(type == : prediction from a rank-deficient fit may be misleading
```

```
AS_uncorrected_smoted_pred_prob <- predict(model_AS_uncorrected_smoted, newdata=data_test, type="prob")
```

```
## Warning in predict.lm(object, newdata, se.fit, scale = 1, type =
## ifelse(type == : prediction from a rank-deficient fit may be misleading
```

```
AS_penalized_smoted_pred_raw <- predict(model_AS_penalized_smoted, newdata=data_test, type="raw")
AS_penalized_smoted_pred_prob <- predict(model_AS_penalized_smoted, newdata=data_test, type="prob")
AS_RF_smoted_pred_raw <- predict(model_AS_RF_smoted, newdata=data_test, type="raw")
AS_RF_smoted_pred_prob <- predict(model_AS_RF_smoted, newdata=data_test, type="prob")

# Testing/prediction for author specification (2016) with experimental ML models
AS_DT_pred_raw <- predict(model_AS_DT, newdata=data_test, type="raw")
AS_DT_pred_prob <- predict(model_AS_DT, newdata=data_test, type="prob")
AS_Boost_pred_raw <- predict(model_AS_Boost, newdata=data_test, type="raw")
AS_Boost_pred_prob <- predict(model_AS_Boost, newdata=data_test, type="prob")
```

## Confusion Matrices and F1 scores

As mentioned previously, it is natural that some F1 scores are Nan; some models won't be able to correct any civil war onsets correctly yielding a true positive count of 0. The confusion matrices are commented out to preserve space, and also because F1-scores are computed directly from them making them partially redundant. However, printing them can display the actual true positive, false positive, true negative, and false negative counts giving perhaps more intuition to the reader.

```
# Prediction with Fearon and Laitin specification (2003)
# table(pred=FL_uncorrected_pred_raw, obs=data_test$warstds)
# table(pred=FL_penalized_pred_raw, obs=data_test$warstds)
# table(pred=FL_RF_pred_raw, obs=data_test$warstds)
```

```r
# Present F1-scores
FL_f1_presentation <- matrix(
  c(F1_Score(data_test$warstds, FL_uncorrected_pred_raw, positive = "war"),
    F1_Score(data_test$warstds, FL_penalized_pred_raw, positive = "war"),
    F1_Score(data_test$warstds, FL_RF_pred_raw, positive = "war")),
  ncol=1, byrow=T)

colnames(FL_f1_presentation) <- c('F1-Score')
rownames(FL_f1_presentation) <- c('FL (2003) Uncorrected LR',
                                  'FL (2003) Penalized LR',
                                  'FL (2003) RF')
as.data.frame(FL_f1_presentation)
```

| | F1-Score |
|---|---|
| FL (2003) Uncorrected LR | NaN |
| FL (2003) Penalized LR | NaN |
| FL (2003) RF | 0.2068966 |

```r
# Prediction with Collier and Hoeffler specification (2004)
# table(pred=CH_uncorrected_pred_raw, obs=data_test$warstds)
# table(pred=CH_penalized_pred_raw, obs=data_test$warstds)
# table(pred=CH_RF_pred_raw, obs=data_test$warstds)
# Present F1-scores
CH_f1_presentation <- matrix(
  c(F1_Score(data_test$warstds, CH_uncorrected_pred_raw, positive = "war"),
    F1_Score(data_test$warstds, CH_penalized_pred_raw, positive = "war"),
    F1_Score(data_test$warstds, CH_RF_pred_raw, positive = "war")),
  ncol=1, byrow=T)

colnames(CH_f1_presentation) <- c('F1-Score')
rownames(CH_f1_presentation) <- c('CH (2004) Uncorrected LR',
                                  'CH (2004) Penalized LR',
                                  'CH (2004) RF')
as.data.frame(CH_f1_presentation)
```

| | F1-Score |
|---|---|
| CH (2004) Uncorrected LR | NaN |
| CH (2004) Penalized LR | 0.0985915 |
| CH (2004) RF | 0.4210526 |

```r
# Prediction with Hegre and Sambanis specification (2006)
# table(pred=HS_uncorrected_pred_raw, obs=data_test$warstds)
# table(pred=HS_penalized_pred_raw, obs=data_test$warstds)
# table(pred=HS_RF_pred_raw, obs=data_test$warstds)
# Present F1-scores
HS_f1_presentation <- matrix(
  c(F1_Score(data_test$warstds, HS_uncorrected_pred_raw, positive = "war"),
    F1_Score(data_test$warstds, HS_penalized_pred_raw, positive = "war"),
    F1_Score(data_test$warstds, HS_RF_pred_raw, positive = "war")),
  ncol=1, byrow=T)
```

```r
colnames(HS_f1_presentation) <- c('F1-Score')
rownames(HS_f1_presentation) <- c('HS (2006) Uncorrected LR',
                                  'HS (2006) Penalized LR',
                                  'HS (2006) RF')
as.data.frame(HS_f1_presentation)
```

| | F1-Score |
|---|---|
| HS (2006) Uncorrected LR | 0.0740741 |
| HS (2006) Penalized LR | 0.0833333 |
| HS (2006) RF | NaN |

```r
# Prediction with author specification (2016)
# table(pred=AS_uncorrected_pred_raw, obs=data_test$warstds)
# table(pred=AS_penalized_pred_raw, obs=data_test$warstds)
# table(pred=AS_RF_pred_raw, obs=data_test$warstds)
# Present F1-scores
AS_f1_presentation <- matrix(
  c(F1_Score(data_test$warstds, AS_uncorrected_pred_raw, positive = "war"),
    F1_Score(data_test$warstds, AS_penalized_pred_raw, positive = "war"),
    F1_Score(data_test$warstds, AS_RF_pred_raw, positive = "war")),
  ncol=1, byrow=T)

colnames(AS_f1_presentation) <- c('F1-Score')
rownames(AS_f1_presentation) <- c('AS (2016) Uncorrected LR',
                                  'AS (2016) Penalized LR',
                                  'AS (2016) RF')
as.data.frame(AS_f1_presentation)
```

| | F1-Score |
|---|---|
| AS (2016) Uncorrected LR | 0.09375 |
| AS (2016) Penalized LR | NaN |
| AS (2016) RF | NaN |

```r
# Prediction with author specification (2016) trained on SMOTEd dataset
# table(pred=AS_uncorrected_smoted_pred_raw, obs=data_test$warstds)
# table(pred=AS_penalized_smoted_pred_raw, obs=data_test$warstds)
# table(pred=AS_RF_smoted_pred_raw, obs=data_test$warstds)
# Present F1-scores
AS_smoted_f1_presentation <- matrix(
  c(F1_Score(data_test$warstds, AS_uncorrected_smoted_pred_raw, positive = "war"),
    F1_Score(data_test$warstds, AS_penalized_smoted_pred_raw, positive = "war"),
    F1_Score(data_test$warstds, AS_RF_smoted_pred_raw, positive = "war")),
  ncol=1, byrow=T)

colnames(AS_smoted_f1_presentation) <- c('F1-Score')
rownames(AS_smoted_f1_presentation) <- c('AS (2016) Uncorrected LR (SMOTEd)',
                                         'AS (2016) Penalized LR (SMOTEd)',
                                         'AS (2016) RF (SMOTEd)')
as.data.frame(AS_smoted_f1_presentation)
```

| | F1-Score |
|---|---|
| AS (2016) Uncorrected LR (SMOTEd) | 0.0861244 |
| AS (2016) Penalized LR (SMOTEd) | 0.0526316 |
| AS (2016) RF (SMOTEd) | 0.1894737 |

```
# Prediction with author specification (2016) using experimental ML models
# table(pred=AS_DT_pred_raw, obs=data_test$warstds)
# table(pred=AS_Boost_pred_raw, obs=data_test$warstds)
# Present F1-scores
AS_experimental_f1_presentation <- matrix(
  c(F1_Score(data_test$warstds, AS_DT_pred_raw, positive = "war"),
    F1_Score(data_test$warstds, AS_Boost_pred_raw, positive = "war")),
  ncol=1, byrow=T)

colnames(AS_experimental_f1_presentation) <- c('F1-Score')
rownames(AS_experimental_f1_presentation) <- c('AS (2016) Decision Trees',
                                               'AS (2016) Boosted Classification Trees')
as.data.frame(AS_experimental_f1_presentation)
```

| | F1-Score |
|---|---|
| AS (2016) Decision Trees | 0.1481481 |
| AS (2016) Boosted Classification Trees | 0.0800000 |

## ROC Curves with AUC Scores

Let's draw ROC Curves with AUC metric for each instance. There are two possible groupings that could be applied:

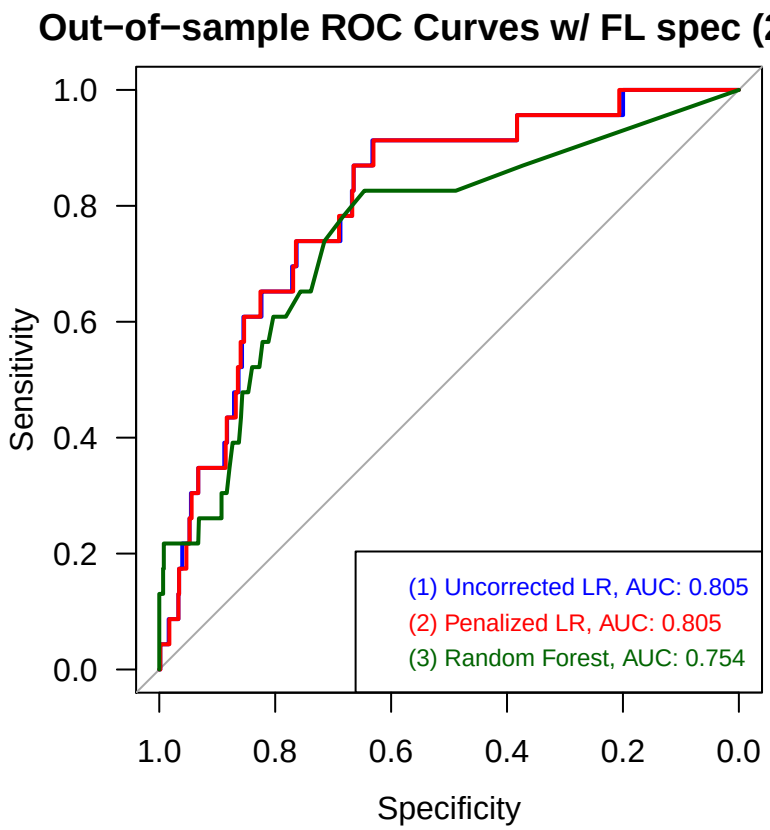
i) We can group by specifications and assess the performance difference between uncorrected logistic regression, penalized logistic regression, and random forest algorithm for each of the specifications, or
ii) We can group by type of model and assess the performance difference in same models when different specifications with different numbers of variables and circumstances (SMOTE) applied.

Here, we will represent both.

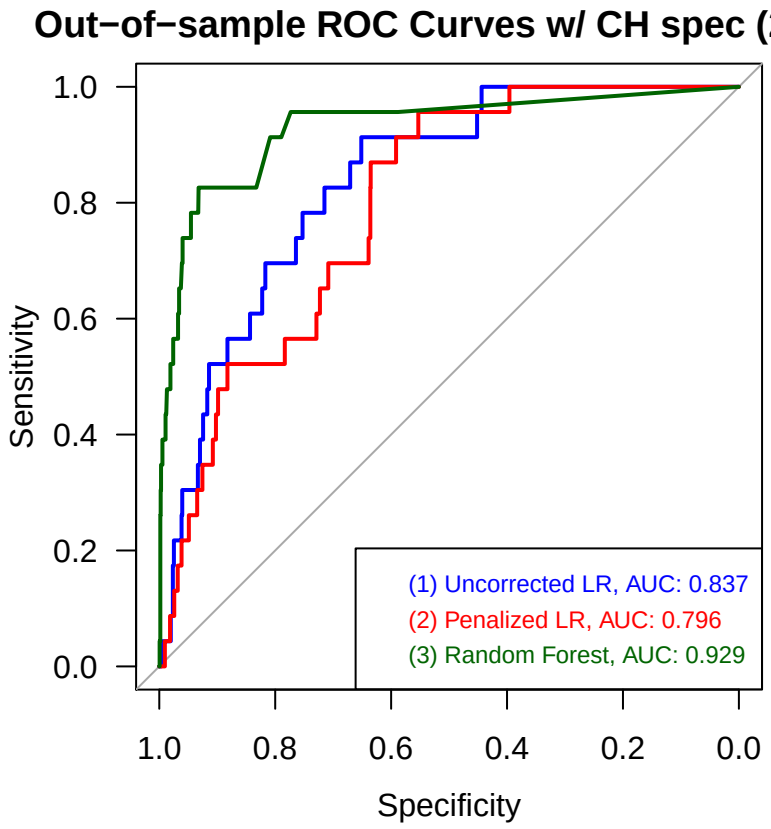
### Grouped By Specifications

```
# Set for square-grid ROC plots
par(pty = "s")

# Plot ROC curves for prediction with Fearon and Laitin specification (2003)
plot.roc(data_test$warstds, FL_uncorrected_pred_prob$war, col="blue",
         xlim=c(1,0), las=1, bty="n", asp=NA,
         main="Out-of-sample ROC Curves w/ FL spec (2003)")
plot.roc(data_test$warstds, add=T, FL_penalized_pred_prob$war, col="red")
plot.roc(data_test$warstds, add=T, FL_RF_pred_prob$war, col="darkgreen")
legend("bottomright", c(paste("(1) Uncorrected LR, AUC:",
                              round(as.numeric(roc(data_test$warstds,
                                                   FL_uncorrected_pred_prob$war)$auc),3)),
                        paste("(2) Penalized LR, AUC:",
```

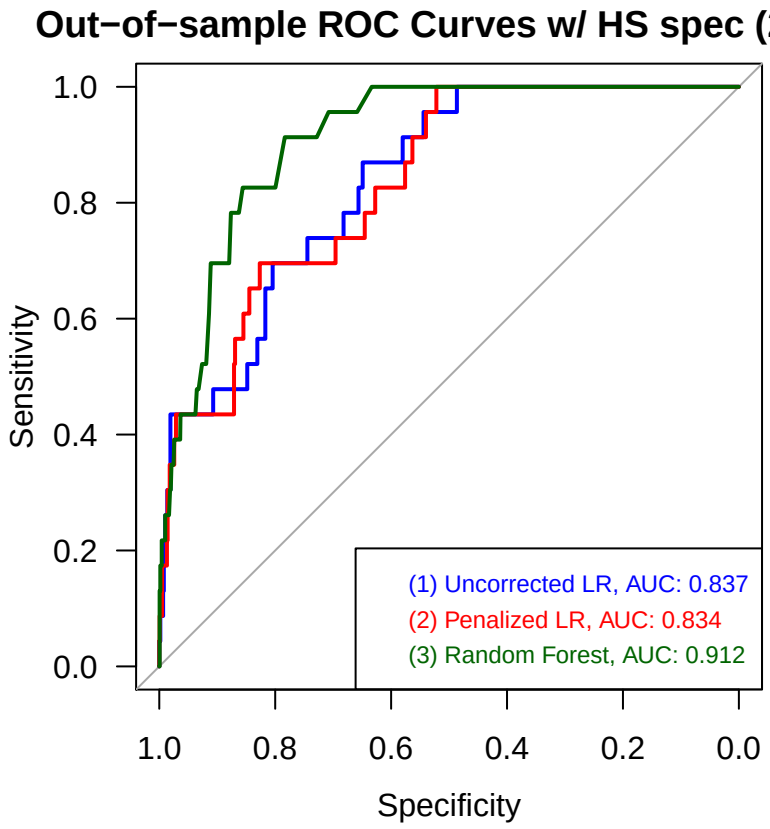
```
                              round(as.numeric(roc(data_test$warstds,
                                                   FL_penalized_pred_prob$war)$auc),3)),
                        paste("(3) Random Forest, AUC:",
                              round(as.numeric(roc(data_test$warstds,
                                                   FL_RF_pred_prob$war)$auc),3))),
       text.col=c("blue","red","darkgreen"),
       cex = .75)
```



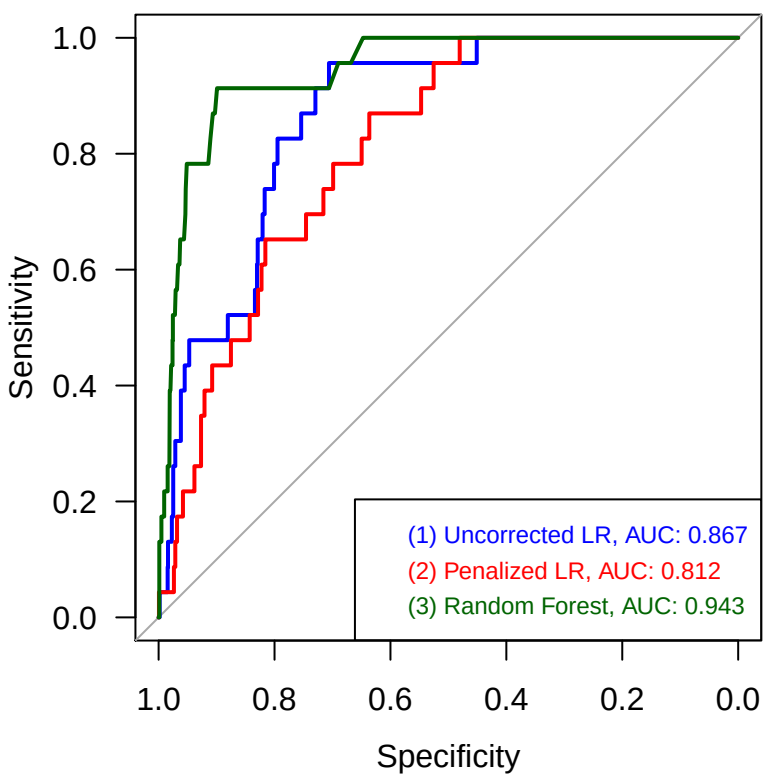

```
# Plot ROC curves for prediction with Collier and Hoeffler specification (2004)
plot.roc(data_test$warstds, CH_uncorrected_pred_prob$war, col="blue",
         xlim=c(1,0), las=1, bty="n", asp=NA,
         main="Out-of-sample ROC Curves w/ CH spec (2004)")
plot.roc(data_test$warstds, add=T, CH_penalized_pred_prob$war, col="red")
plot.roc(data_test$warstds, add=T, CH_RF_pred_prob$war, col="darkgreen")
legend("bottomright", c(paste("(1) Uncorrected LR, AUC:",
                              round(as.numeric(roc(data_test$warstds,
                                                   CH_uncorrected_pred_prob$war)$auc),3)),
                        paste("(2) Penalized LR, AUC:",
                              round(as.numeric(roc(data_test$warstds,
                                                   CH_penalized_pred_prob$war)$auc),3)),
                        paste("(3) Random Forest, AUC:",
                              round(as.numeric(roc(data_test$warstds,
                                                   CH_RF_pred_prob$war)$auc),3))),
       text.col=c("blue","red","darkgreen"),
       cex = .75)
```




```
# Plot ROC curves for prediction with Hegre and Sambanis specification (2006)
plot.roc(data_test$warstds, HS_uncorrected_pred_prob$war, col="blue",
         xlim=c(1,0), las=1, bty="n", asp=NA,
         main="Out-of-sample ROC Curves w/ HS spec (2006)")
plot.roc(data_test$warstds, add=T, HS_penalized_pred_prob$war, col="red")
plot.roc(data_test$warstds, add=T, HS_RF_pred_prob$war, col="darkgreen")
legend("bottomright", c(paste("(1) Uncorrected LR, AUC:",
                              round(as.numeric(roc(data_test$warstds,
                                                   HS_uncorrected_pred_prob$war)$auc),3)),
                        paste("(2) Penalized LR, AUC:",
                              round(as.numeric(roc(data_test$warstds,
                                                   HS_penalized_pred_prob$war)$auc),3)),
                        paste("(3) Random Forest, AUC:",
                              round(as.numeric(roc(data_test$warstds,
                                                   HS_RF_pred_prob$war)$auc),3))),
       text.col=c("blue","red","darkgreen"),
       cex = .75)
```



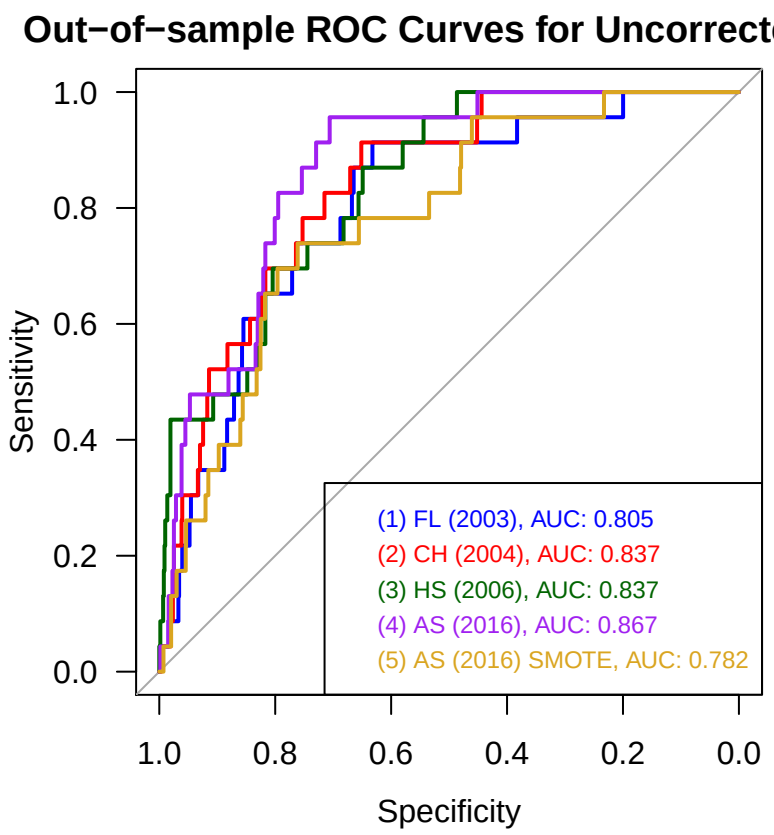

```
# Plot ROC curves for prediction with author specification (2016)
plot.roc(data_test$warstds, AS_uncorrected_pred_prob$war, col="blue",
         xlim=c(1,0), las=1, bty="n", asp=NA,
         main="Out-of-sample ROC Curves w/ author spec (2016)")
plot.roc(data_test$warstds, add=T, AS_penalized_pred_prob$war, col="red")
plot.roc(data_test$warstds, add=T, AS_RF_pred_prob$war, col="darkgreen")
legend("bottomright", c(paste("(1) Uncorrected LR, AUC:",
                              round(as.numeric(roc(data_test$warstds,
                                                   AS_uncorrected_pred_prob$war)$auc),3)),
                        paste("(2) Penalized LR, AUC:",
                              round(as.numeric(roc(data_test$warstds,
                                                   AS_penalized_pred_prob$war)$auc),3)),
                        paste("(3) Random Forest, AUC:",
                              round(as.numeric(roc(data_test$warstds,
                                                   AS_RF_pred_prob$war)$auc),3))),
       text.col=c("blue","red","darkgreen"),
       cex = .75)
```




**Grouped By Model Types**

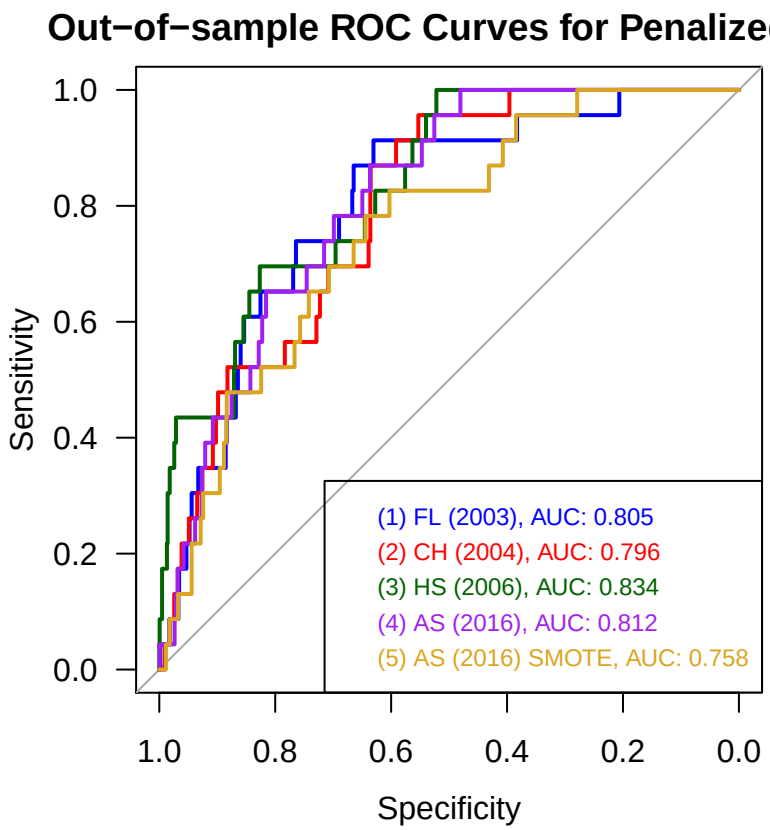
```
# Set for square-grid ROC plots
par(pty = "s")

# Plot ROC curves for prediction with uncorrected logistic regression model
plot.roc(data_test$warstds, FL_uncorrected_pred_prob$war, col="blue",
         xlim=c(1,0), las=1, bty="n", asp=NA,
         main="Out-of-sample ROC Curves for Uncorrected LR")
plot.roc(data_test$warstds, add=T, CH_uncorrected_pred_prob$war, col="red")
plot.roc(data_test$warstds, add=T, HS_uncorrected_pred_prob$war, col="darkgreen")
plot.roc(data_test$warstds, add=T, AS_uncorrected_pred_prob$war, col="purple")
plot.roc(data_test$warstds, add=T, AS_uncorrected_smoted_pred_prob$war, col="goldenrod")

legend("bottomright", c(paste("(1) FL (2003), AUC:",
                              round(as.numeric(roc(data_test$warstds,
                                                   FL_uncorrected_pred_prob$war)$auc),3)),
                        paste("(2) CH (2004), AUC:",
                              round(as.numeric(roc(data_test$warstds,
                                                   CH_uncorrected_pred_prob$war)$auc),3)),
                        paste("(3) HS (2006), AUC:",
                              round(as.numeric(roc(data_test$warstds,
                                                   HS_uncorrected_pred_prob$war)$auc),3)),
                        paste("(4) AS (2016), AUC:",
                              round(as.numeric(roc(data_test$warstds,
                                                   AS_uncorrected_pred_prob$war)$auc),3)),
```

```
                        paste("(5) AS (2016) SMOTE, AUC:",
                              round(as.numeric(roc(data_test$warstds,
                                                   AS_uncorrected_smoted_pred_prob$war)$auc),3))),

       text.col=c("blue","red","darkgreen", "purple", "goldenrod"),
       cex = .75)
```



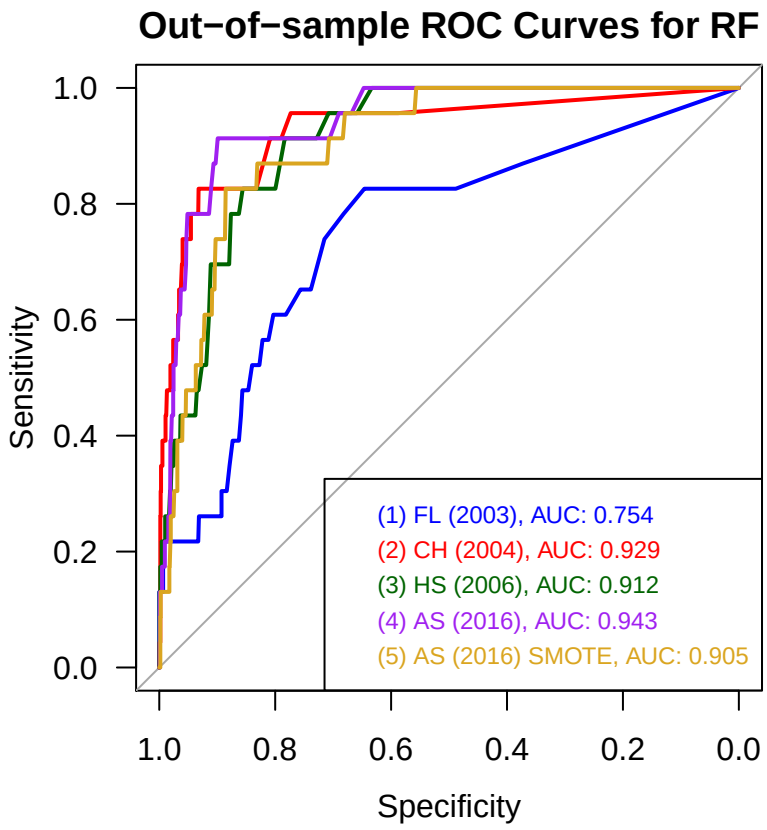

```
# Plot ROC curves for prediction with penalized logistic regression model
plot.roc(data_test$warstds, FL_penalized_pred_prob$war, col="blue",
         xlim=c(1,0), las=1, bty="n", asp=NA,
         main="Out-of-sample ROC Curves for Penalized LR")
plot.roc(data_test$warstds, add=T, CH_penalized_pred_prob$war, col="red")
plot.roc(data_test$warstds, add=T, HS_penalized_pred_prob$war, col="darkgreen")
plot.roc(data_test$warstds, add=T, AS_penalized_pred_prob$war, col="purple")
plot.roc(data_test$warstds, add=T, AS_penalized_smoted_pred_prob$war, col="goldenrod")

legend("bottomright", c(paste("(1) FL (2003), AUC:",
                              round(as.numeric(roc(data_test$warstds,
                                                   FL_penalized_pred_prob$war)$auc),3)),
                        paste("(2) CH (2004), AUC:",
                              round(as.numeric(roc(data_test$warstds,
                                                   CH_penalized_pred_prob$war)$auc),3)),
                        paste("(3) HS (2006), AUC:",
                              round(as.numeric(roc(data_test$warstds,
                                                   HS_penalized_pred_prob$war)$auc),3)),
                        paste("(4) AS (2016), AUC:",
                              round(as.numeric(roc(data_test$warstds,
```

```
                                                AS_penalized_pred_prob$war)$auc),3)),
                        paste("(5) AS (2016) SMOTE, AUC:",
                              round(as.numeric(roc(data_test$warstds,
                                                AS_penalized_smoted_pred_prob$war)$auc),3))),

       text.col=c("blue","red","darkgreen", "purple", "goldenrod"),
       cex = .75)
```




```
# Plot ROC curves for prediction with random forest model
plot.roc(data_test$warstds, FL_RF_pred_prob$war, col="blue",
         xlim=c(1,0), las=1, bty="n", asp=NA,
         main="Out-of-sample ROC Curves for RF")
plot.roc(data_test$warstds, add=T, CH_RF_pred_prob$war, col="red")
plot.roc(data_test$warstds, add=T, HS_RF_pred_prob$war, col="darkgreen")
plot.roc(data_test$warstds, add=T, AS_RF_pred_prob$war, col="purple")
plot.roc(data_test$warstds, add=T, AS_RF_smoted_pred_prob$war, col="goldenrod")

legend("bottomright", c(paste("(1) FL (2003), AUC:",
                              round(as.numeric(roc(data_test$warstds,
                                                FL_RF_pred_prob$war)$auc),3)),
                        paste("(2) CH (2004), AUC:",
                              round(as.numeric(roc(data_test$warstds,
                                                CH_RF_pred_prob$war)$auc),3)),
                        paste("(3) HS (2006), AUC:",
                              round(as.numeric(roc(data_test$warstds,
                                                HS_RF_pred_prob$war)$auc),3)),
                        paste("(4) AS (2016), AUC:",
```

```
                              round(as.numeric(roc(data_test$warstds,
                                                   AS_RF_pred_prob$war)$auc),3)),
                        paste("(5) AS (2016) SMOTE, AUC:",
                              round(as.numeric(roc(data_test$warstds,
                                                   AS_RF_smoted_pred_prob$war)$auc),3))),
       text.col=c("blue","red","darkgreen", "purple", "goldenrod"),
       cex = .75)
```

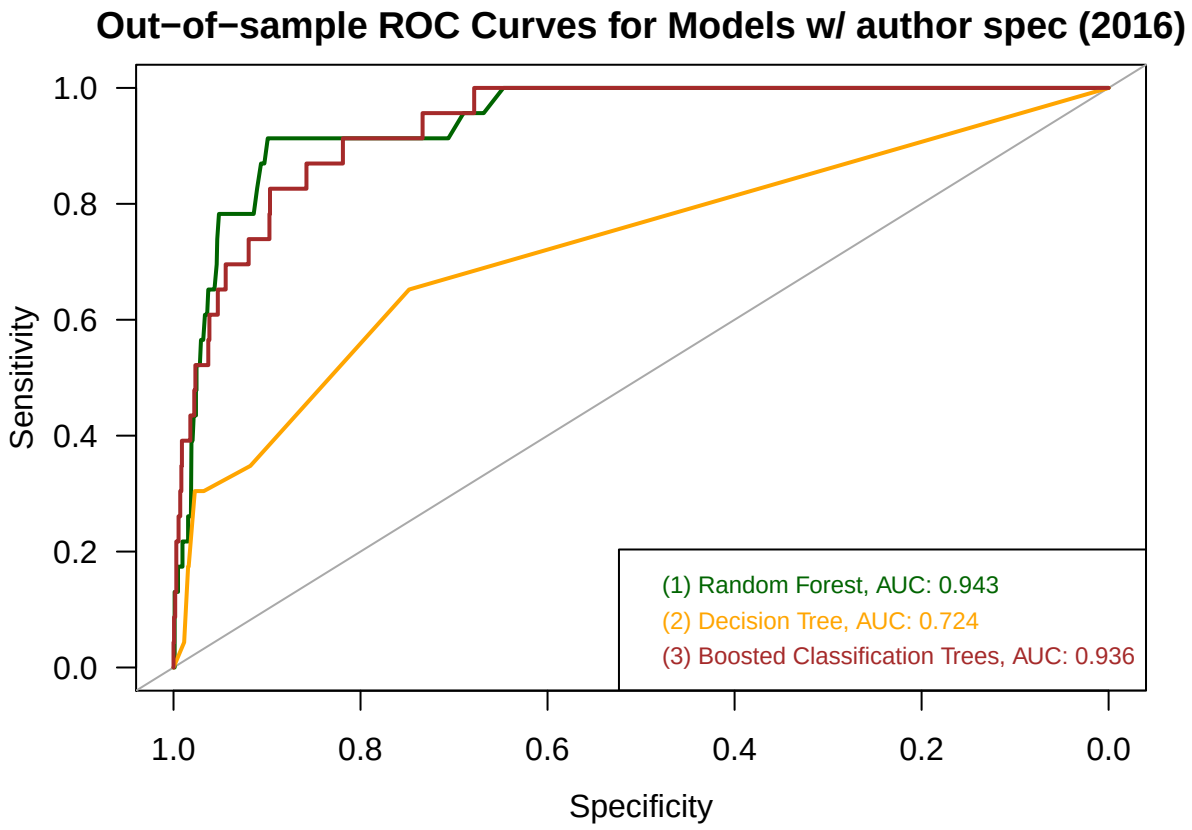



**Comparing experimental ML models vs. Random Forest Model**

We have seen how Random Forest models have performed againts the other well-known LR models with all specifications mentioned in the paper. We have even seen how the performance of Random Forest models varies when we played with parameters of the SMOTE algorithm. Finally, we can evaluate how the two models we proposed alongside the Random Forest model, i) Decision Tree and ii) Boosted Classification Trees, perform compared to the Random Forest model. It should be noted all of these models are trained with the same author specification (2016) and on the splitted `data_train` dataset.

```
# Plot ROC curves for prediction with author specification (2016)
plot.roc(data_test$warstds, AS_RF_pred_prob$war, col="darkgreen",
         xlim=c(1,0), las=1, bty="n", asp=NA,
         main="Out-of-sample ROC Curves for Models w/ author spec (2016)")
plot.roc(data_test$warstds, add=T, AS_DT_pred_prob$war, col="orange")
plot.roc(data_test$warstds, add=T, AS_Boost_pred_prob$war, col="brown")
legend("bottomright", c(paste("(1) Random Forest, AUC:",
                              round(as.numeric(roc(data_test$warstds,
                                                   AS_RF_pred_prob$war)$auc),3)),
                        paste("(2) Decision Tree, AUC:",
```

```
                        round(as.numeric(roc(data_test$warstds,
                                             AS_DT_pred_prob$war)$auc),3)),
                  paste("(3) Boosted Classification Trees, AUC:",
                        round(as.numeric(roc(data_test$warstds,
                                             AS_Boost_pred_prob$war)$auc),3))),
       text.col=c("darkgreen","orange","brown"),
       cex = .75)
```




## Summary

i) The original paper used different feature variables for each of the four models. To make the comparison fair, we have tested the performance of the four models across all set of features specified in the paper.
ii) Instead of measuring the performance only on the training data set, we do a train - test split to test performance on out of sample data
iii) Since we are working with an imbalanced dataset, we have used SMOTE to generate a more balanced version of the data. We have trained our models on this data and monitored their performance.
iv) We have also trained and checked the performance of new models on the original data - namely, Decision trees and Boosted Classification Trees.

More details regarding replications and our implementations, and the accuracy measures accompanying them are added in the `03_analysis_and_comparison.pdf`. We essentially did this to avoid running this final report for every small change in our summary.

## Dependencies Summary

The following is a list of all packages used to generate these results.

```
sessionInfo()
```

```
## R version 3.5.0 (2018-04-23)
## Platform: x86_64-apple-darwin15.6.0 (64-bit)
## Running under: macOS  10.14.4
##
## Matrix products: default
## BLAS: /Library/Frameworks/R.framework/Versions/3.5/Resources/lib/libRblas.0.dylib
## LAPACK: /Library/Frameworks/R.framework/Versions/3.5/Resources/lib/libRlapack.dylib
##
## locale:
## [1] en_US.UTF-8/en_US.UTF-8/en_US.UTF-8/C/en_US.UTF-8/en_US.UTF-8
##
## attached base packages:
## [1] grid      parallel  stats     graphics  grDevices utils     datasets
## [8] methods   base
##
## other attached packages:
##  [1] MLmetrics_1.1.1     separationplot_1.1  DMwR_0.4.1
##  [4] maptools_0.9-5      sp_1.3-1            foreign_0.8-71
##  [7] forcats_0.3.0       stringr_1.3.1       dplyr_0.7.5
## [10] purrr_0.2.5         readr_1.1.1         tidyr_0.8.1
## [13] tibble_1.4.2        tidyverse_1.2.1     doMC_1.3.5
## [16] iterators_1.0.10    foreach_1.4.4       stepPlr_0.93
## [19] pROC_1.14.0         ROCR_1.0-7          gplots_3.0.1.1
## [22] caret_6.0-84        ggplot2_2.2.1       lattice_0.20-35
## [25] rpart.plot_3.0.7    ada_2.0-5           rpart_4.1-13
## [28] randomForest_4.6-14
##
## loaded via a namespace (and not attached):
##  [1] nlme_3.1-137       bitops_1.0-6       xts_0.11-2
##  [4] lubridate_1.7.4    httr_1.3.1         rprojroot_1.3-2
##  [7] tools_3.5.0        backports_1.1.2    R6_2.2.2
## [10] KernSmooth_2.23-15 lazyeval_0.2.1     colorspace_1.3-2
## [13] nnet_7.3-12        withr_2.1.2        tidyselect_0.2.4
## [16] mnormt_1.5-5       curl_3.2           compiler_3.5.0
## [19] cli_1.0.0          rvest_0.3.2        xml2_1.2.0
## [22] caTools_1.17.1     scales_1.0.0       psych_1.8.4
## [25] digest_0.6.15      rmarkdown_1.10     pkgconfig_2.0.1
## [28] htmltools_0.3.6    highr_0.7          TTR_0.23-4
## [31] rlang_0.3.4        readxl_1.1.0       quantmod_0.4-14
## [34] rstudioapi_0.7     bindr_0.1.1        generics_0.0.2
## [37] zoo_1.8-5          jsonlite_1.5       gtools_3.8.1
## [40] ModelMetrics_1.2.2 magrittr_1.5       Matrix_1.2-14
## [43] Rcpp_0.12.17       munsell_0.5.0      abind_1.4-5
## [46] stringi_1.2.3      yaml_2.1.19        MASS_7.3-49
## [49] plyr_1.8.4         recipes_0.1.5      gdata_2.18.0
## [52] crayon_1.3.4       haven_1.1.1        splines_3.5.0
## [55] hms_0.4.2          knitr_1.20         pillar_1.2.3
## [58] reshape2_1.4.3     codetools_0.2-15   stats4_3.5.0
```

```
## [61] glue_1.2.0         evaluate_0.10.1    data.table_1.12.2
## [64] modelr_0.1.2       cellranger_1.1.0   gtable_0.2.0
## [67] assertthat_0.2.0   gower_0.2.0        prodlim_2018.04.18
## [70] broom_0.4.4        class_7.3-14       survival_2.41-3
## [73] timeDate_3043.102  bindrcpp_0.2.2     lava_1.6.5
## [76] ipred_0.9-9
```