Car Insurance Claims Classification Report

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Contents

Introduction

This report is dedicated to project of a workshop of master of data science at University of Luxembourg, I built the `aiinsurance`. You can install this package by first installing the devtools package and then using the following syntax:

```
devtools::install_github("https://github.com/berserkhmdvhb/aiinsurance")
```

You can explore the documentation of package I provided with

```
help(package="aiinsurance")
```

Also, this report is accessible as vignette of the package, which can be accessed with

```
vignette(package = "aiinsurance")
```

(Note: I just made a meta-reference)

Note that all functions of the package are suffixed with `hmd`.

Load Dataset

To provide a test case on a dataset with discrete target variable, I used the the car insurance data.

The dataset is embedded in the package, therefore by simply running the following commands one can load and display the dataset. . It can be used by the following syntax:

```
data("car_insurance_data")
```

```
data(car_insurance_data)

dplyr::glimpse(car_insurance_data)
```

```
## Rows: 10,000
## Columns: 19
## $ ID                  <int> 569520, 750365, 199901, 478866, 731664, 877557, 93~
## $ AGE                 <chr> "65+", "16-25", "16-25", "16-25", "26-39", "40-64"~
## $ GENDER              <chr> "female", "male", "female", "male", "male", "femal~
## $ RACE                <chr> "majority", "majority", "majority", "majority", "m~
## $ DRIVING_EXPERIENCE  <chr> "0-9y", "0-9y", "0-9y", "0-9y", "10-19y", "20-29y"~
## $ EDUCATION           <chr> "high school", "none", "high school", "university"~
## $ INCOME              <chr> "upper class", "poverty", "working class", "workin~
## $ CREDIT_SCORE        <dbl> 0.6290273, 0.3577571, 0.4931458, 0.2060129, 0.3883~
## $ VEHICLE_OWNERSHIP   <int> 1, 0, 1, 1, 1, 1, 0, 0, 0, 1, 1, 1, 1, 1, 1, 0, 1,~
## $ VEHICLE_YEAR        <chr> "after 2015", "before 2015", "before 2015", "befor~
## $ MARRIED             <int> 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 1,~
## $ CHILDREN            <int> 1, 0, 0, 1, 0, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 0, 1,~
## $ POSTAL_CODE         <int> 10238, 10238, 10238, 32765, 32765, 10238, 10238, 1~
## $ ANNUAL_MILEAGE      <int> 12000, 16000, 11000, 11000, 12000, 13000, 13000, 1~
## $ VEHICLE_TYPE        <chr> "sedan", "sedan", "sedan", "sedan", "sedan", "seda~
## $ SPEEDING_VIOLATIONS <int> 0, 0, 0, 0, 2, 3, 7, 0, 0, 0, 6, 4, 4, 0, 0, 0, 10~
## $ DUIS                <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 2, 0, 1, 0, 2, 0, 2,~
## $ PAST_ACCIDENTS      <int> 0, 0, 0, 0, 1, 3, 3, 0, 0, 0, 7, 0, 2, 0, 1, 0, 1,~
## $ OUTCOME             <int> 0, 1, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0,~
```

Summary of statistical properties of columns are provided in the following:

```
summary(car_insurance_data)
```

```
##        ID              AGE                GENDER               RACE          
##  Min.   :   101   Length:10000       Length:10000       Length:10000      
##  1st Qu.:249638   Class :character   Class :character   Class :character  
##  Median :501777   Mode  :character   Mode  :character   Mode  :character  
##  Mean   :500522                                                           
##  3rd Qu.:753974                                                           
##  Max.   :999976                                                           
##                                                                           
##  DRIVING_EXPERIENCE  EDUCATION            INCOME           CREDIT_SCORE   
##  Length:10000       Length:10000       Length:10000       Min.   :0.0534  
##  Class :character   Class :character   Class :character   1st Qu.:0.4172  
##  Mode  :character   Mode  :character   Mode  :character   Median :0.5250  
##                                                           Mean   :0.5158  
##                                                           3rd Qu.:0.6183  
```

```
##                                                           Max.   :0.9608
##                                                           NA's   :982
##  VEHICLE_OWNERSHIP VEHICLE_YEAR          MARRIED          CHILDREN
##  Min.   :0.000     Length:10000       Min.   :0.0000   Min.   :0.0000
##  1st Qu.:0.000     Class :character   1st Qu.:0.0000   1st Qu.:0.0000
##  Median :1.000     Mode  :character   Median :0.0000   Median :1.0000
##  Mean   :0.697                        Mean   :0.4982   Mean   :0.6888
##  3rd Qu.:1.000                        3rd Qu.:1.0000   3rd Qu.:1.0000
##  Max.   :1.000                        Max.   :1.0000   Max.   :1.0000
##
##   POSTAL_CODE    ANNUAL_MILEAGE  VEHICLE_TYPE       SPEEDING_VIOLATIONS
##  Min.   :10238   Min.   : 2000   Length:10000       Min.   : 0.000
##  1st Qu.:10238   1st Qu.:10000   Class :character   1st Qu.: 0.000
##  Median :10238   Median :12000   Mode  :character   Median : 0.000
##  Mean   :19865   Mean   :11697                      Mean   : 1.483
##  3rd Qu.:32765   3rd Qu.:14000                      3rd Qu.: 2.000
##  Max.   :92101   Max.   :22000                      Max.   :22.000
##                  NA's   :957
##       DUIS        PAST_ACCIDENTS      OUTCOME
##  Min.   :0.0000   Min.   : 0.000   Min.   :0.0000
##  1st Qu.:0.0000   1st Qu.: 0.000   1st Qu.:0.0000
##  Median :0.0000   Median : 0.000   Median :0.0000
##  Mean   :0.2392   Mean   : 1.056   Mean   :0.3133
##  3rd Qu.:0.0000   3rd Qu.: 2.000   3rd Qu.:1.0000
##  Max.   :6.0000   Max.   :15.000   Max.   :1.0000
##
```

Preprocess

Before feeding data to the model, various preprocessing stages are performed in the following subsections:

Clean Column Names

```
df <- janitor::clean_names(car_insurance_data)

names(df)
```

```
##  [1] "id"                  "age"                 "gender"
##  [4] "race"                "driving_experience"  "education"
##  [7] "income"              "credit_score"        "vehicle_ownership"
## [10] "vehicle_year"        "married"             "children"
## [13] "postal_code"         "annual_mileage"      "vehicle_type"
## [16] "speeding_violations" "duis"                "past_accidents"
## [19] "outcome"
```

And the following is to make the codes reproducible, as random values might be involved in different stages:

```
set.seed(12345)
```

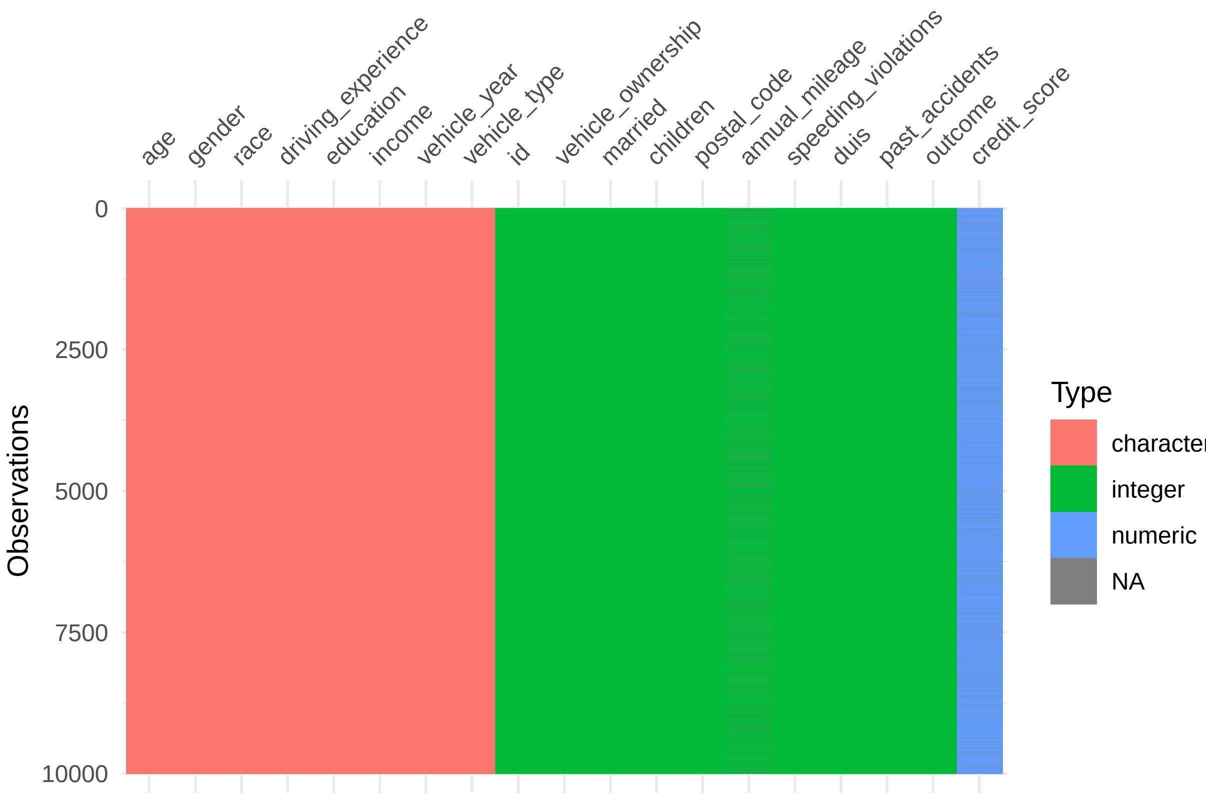
Categorical Columns

We need to factorise the categorical columns, which can be done by merely inputting columns intended to be converted in `cat_cols` in the `prepare_hmd` function. Before doing that, we report and visualise the nature of categorical data and their frequency in the dataset

```
categoricals_print_hmd(df)
```

```
## [1] "List of categorical columns containing characters: "
## [1] "age"                "gender"             "race"
## [4] "driving_experience" "education"          "income"
## [7] "vehicle_year"       "vehicle_type"
## [1] "List of categorical columns containing numbers: "
## [1] "vehicle_ownership" "married"           "children"
## [4] "postal_code"       "outcome"
```

```
vis_dat(df)
```

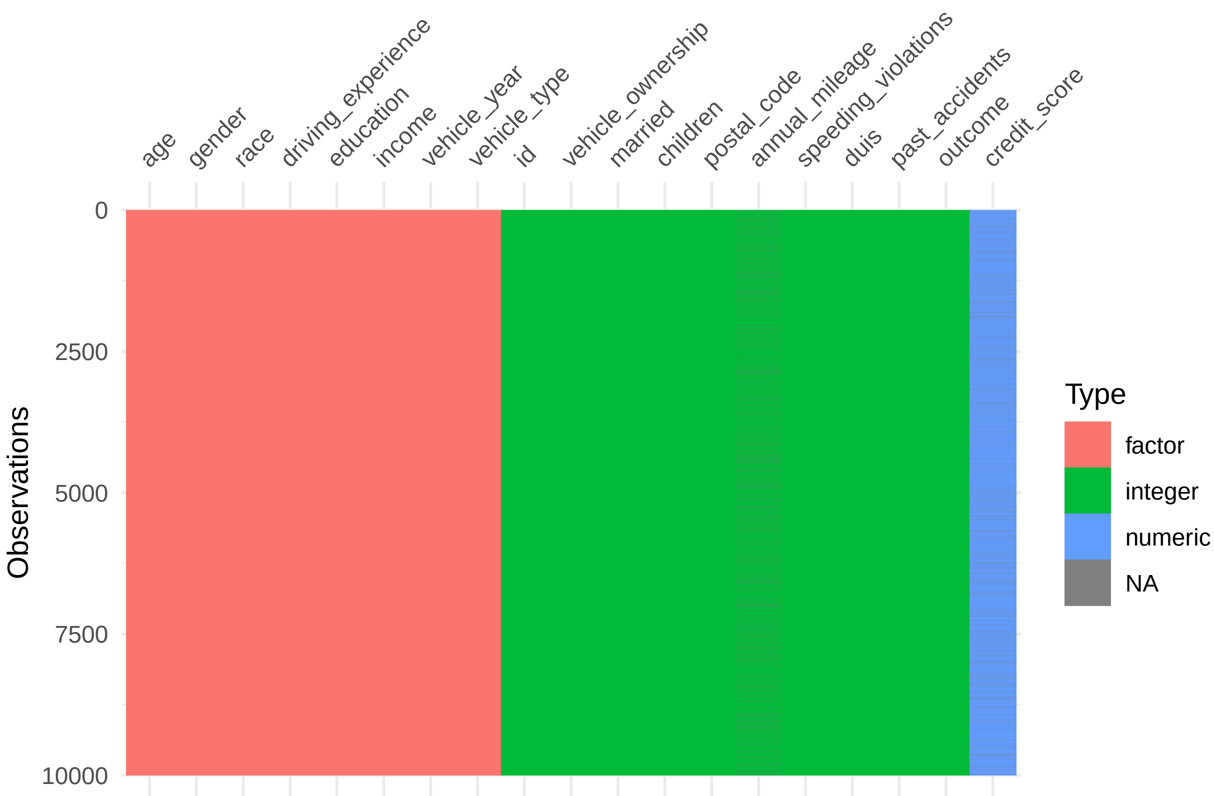



```
df <- categoricals_hmd(df)
dplyr::glimpse(df)
```

```
## Rows: 10,000
## Columns: 19
## $ id                  <int> 569520, 750365, 199901, 478866, 731664, 877557, 93~
## $ age                 <fct> 65+, 16-25, 16-25, 16-25, 26-39, 40-64, 65+, 26-39~
## $ gender              <fct> female, male, female, male, male, female, male, fe~
```

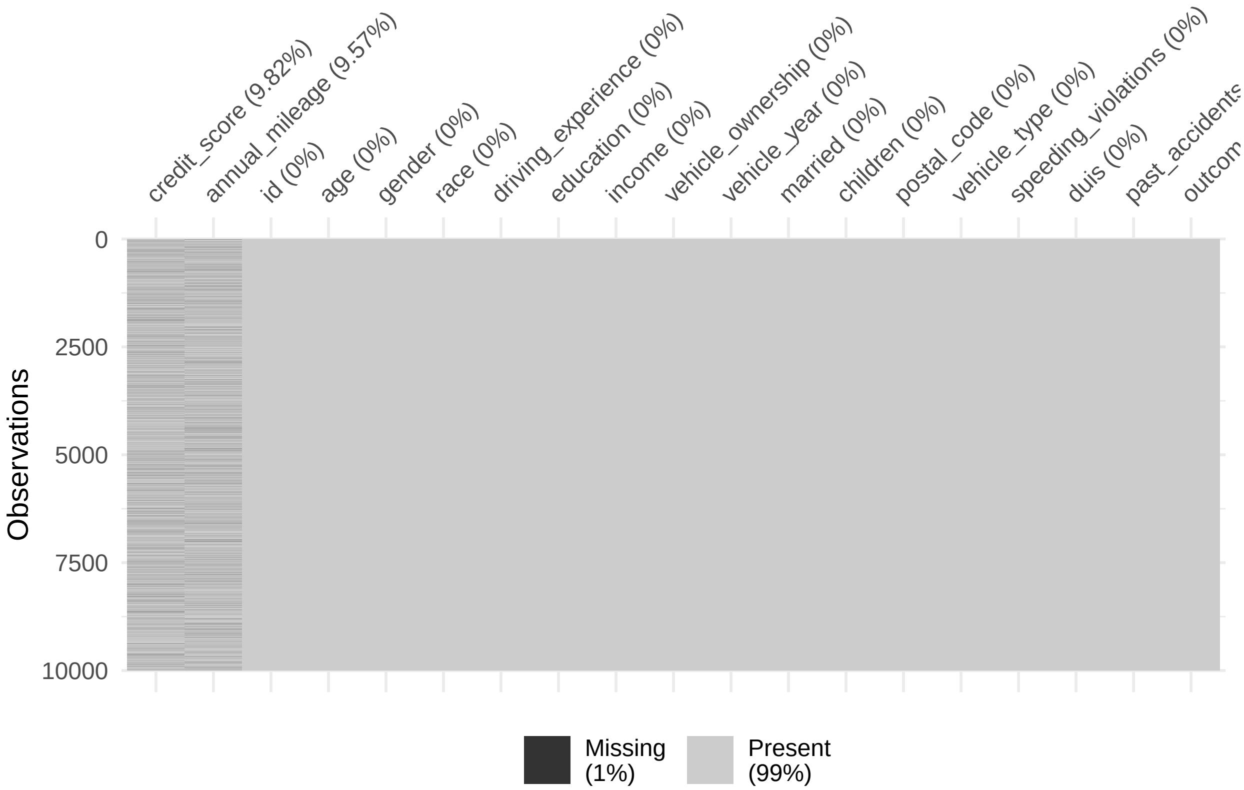
```
## $ race                <fct> majority, majority, majority, majority, majority, ~
## $ driving_experience  <fct> 0-9y, 0-9y, 0-9y, 0-9y, 10-19y, 20-29y, 30y+, 0-9y~
## $ education           <fct> high school, none, high school, university, none, ~
## $ income              <fct> upper class, poverty, working class, working class~
## $ credit_score        <dbl> 0.6290273, 0.3577571, 0.4931458, 0.2060129, 0.3883~
## $ vehicle_ownership   <int> 1, 0, 1, 1, 1, 1, 0, 0, 0, 1, 1, 1, 1, 1, 1, 0, 1,~
## $ vehicle_year        <fct> after 2015, before 2015, before 2015, before 2015,~
## $ married             <int> 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 1,~
## $ children            <int> 1, 0, 0, 1, 0, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 0, 1,~
## $ postal_code         <int> 10238, 10238, 10238, 32765, 32765, 10238, 10238, 1~
## $ annual_mileage      <int> 12000, 16000, 11000, 11000, 12000, 13000, 13000, 1~
## $ vehicle_type        <fct> sedan, sedan, sedan, sedan, sedan, sedan, sedan, s~
## $ speeding_violations <int> 0, 0, 0, 0, 2, 3, 7, 0, 0, 0, 6, 4, 4, 0, 0, 0, 10~
## $ duis                <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 2, 0, 1, 0, 2, 0, 2,~
## $ past_accidents      <int> 0, 0, 0, 0, 1, 3, 3, 0, 0, 0, 7, 0, 2, 0, 1, 0, 1,~
## $ outcome             <int> 0, 1, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0,~
```

```
vis_dat(df)
```



Missing Data

```
df[is.na(df) | df=="Inf"] = NA
vis_miss(df, sort_miss = TRUE)
```




```
is.na(df |> select("credit_score","annual_mileage")) |> colSums()
```

```
##   credit_score annual_mileage
##            982            957
```

```
## Classification Models
```

As only two numerical columns include NA values, the will be imputed with the median of their respective columns. For this `impute_median_hmd` function is used from the package:

```
df <- impute_median_hmd(df)
is.na(df) |> colSums()
```

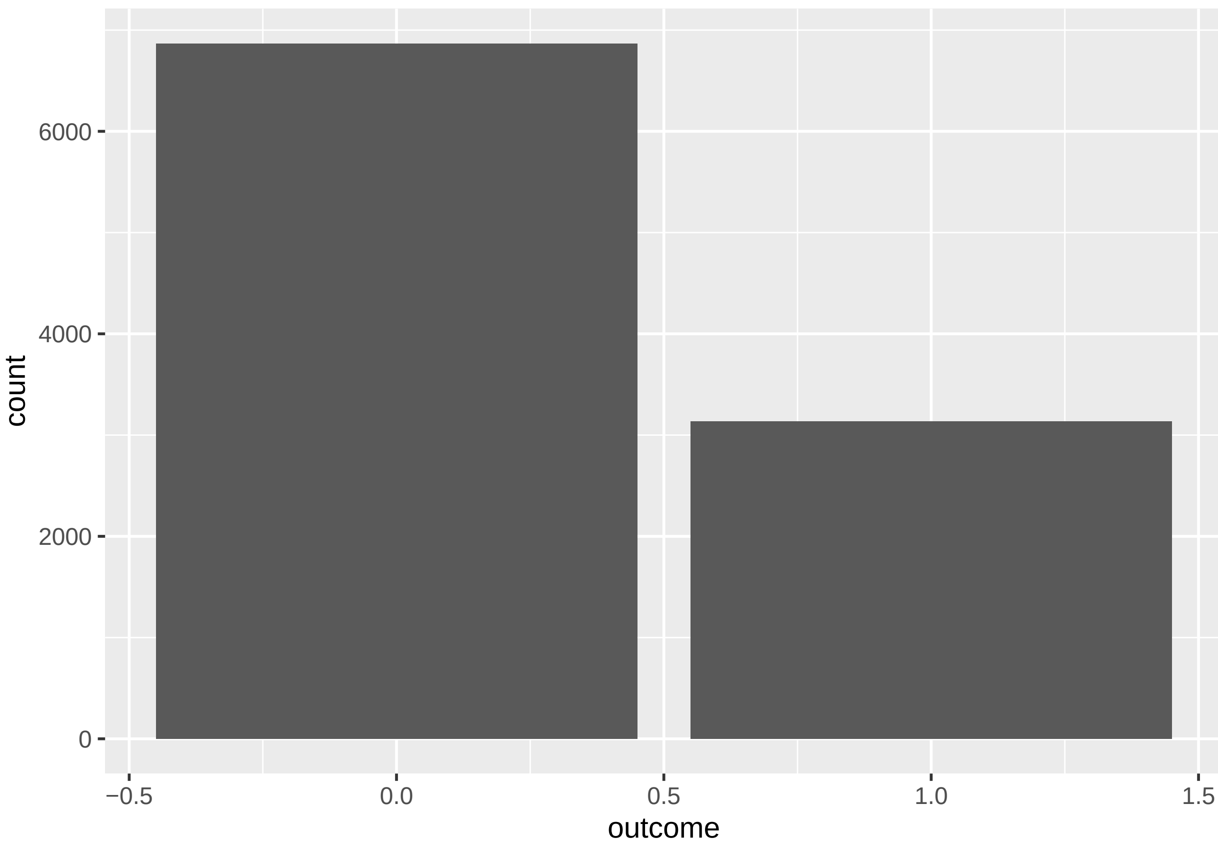
```
##                  id                 age              gender                race
##                   0                   0                   0                   0
##  driving_experience           education              income        credit_score
##                   0                   0                   0                   0
##   vehicle_ownership        vehicle_year             married            children
##                   0                   0                   0                   0
##         postal_code      annual_mileage        vehicle_type speeding_violations
##                   0                   0                   0                   0
##                duis      past_accidents             outcome
##                   0                   0                   0
```

As evident, there is no missing data anymore. ## Check Imbalance of Target

Visualize Balance

As imbalance of target classes affect predictions, the frequency of each class in the `outcome` column is visualized:

```
# Most basic bar chart
ggplot(df, aes(x = outcome)) +
    geom_bar()
```




```
table(df$outcome)
```

```
##
##    0    1
## 6867 3133
```

```
imbalance::imbalanceRatio(df, classAttr = "outcome")
```

```
## [1] 0.45624
```

Encoding Categorical Columns

Since later it is realized that data is imbalanced and therefore it should be resampled, it is required that data would only contain numerical columns for the next part. For this reason, one-hot-encoding is applied in the following:

```
dummy <- dummyVars(" ~ .", data=df)
df_enc <- data.frame(predict(dummy, newdata = df))
dplyr::glimpse(df_enc)
```

```
## Rows: 10,000
## Columns: 34
## $ id                          <dbl> 569520, 750365, 199901, 478866, 731664, 8775~
## $ age.16.25                   <dbl> 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0,~
## $ age.26.39                   <dbl> 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1,~
## $ age.40.64                   <dbl> 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 1, 0, 0,~
## $ age.65.                     <dbl> 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0,~
## $ gender.female               <dbl> 1, 0, 1, 0, 0, 1, 0, 1, 1, 1, 0, 1, 0, 1, 0,~
## $ gender.male                 <dbl> 0, 1, 0, 1, 1, 0, 1, 0, 0, 0, 1, 0, 1, 0, 1,~
## $ race.majority               <dbl> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,~
## $ race.minority               <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,~
## $ driving_experience.0.9y     <dbl> 1, 1, 1, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0,~
## $ driving_experience.10.19y   <dbl> 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1,~
## $ driving_experience.20.29y   <dbl> 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0,~
## $ driving_experience.30y.     <dbl> 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0,~
## $ education.high.school       <dbl> 1, 0, 1, 0, 0, 1, 1, 0, 0, 1, 1, 1, 1, 0, 1,~
## $ education.none              <dbl> 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,~
## $ education.university        <dbl> 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0,~
## $ income.middle.class         <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1,~
## $ income.poverty              <dbl> 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,~
## $ income.upper.class          <dbl> 1, 0, 0, 0, 0, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0,~
## $ income.working.class        <dbl> 0, 0, 1, 1, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0,~
## $ credit_score                <dbl> 0.6290273, 0.3577571, 0.4931458, 0.2060129, ~
## $ vehicle_ownership           <dbl> 1, 0, 1, 1, 1, 1, 0, 0, 0, 1, 1, 1, 1, 1, 1,~
## $ vehicle_year.after.2015     <dbl> 1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 1, 1, 0, 0, 0,~
## $ vehicle_year.before.2015    <dbl> 0, 1, 1, 1, 1, 0, 0, 0, 1, 1, 0, 0, 1, 1, 1,~
## $ married                     <dbl> 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 1, 1, 0, 1,~
## $ children                    <dbl> 1, 0, 0, 1, 0, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1,~
## $ postal_code                 <dbl> 10238, 10238, 10238, 32765, 32765, 10238, 10~
## $ annual_mileage              <dbl> 12000, 16000, 11000, 11000, 12000, 13000, 13~
## $ vehicle_type.sedan          <dbl> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,~
## $ vehicle_type.sports.car     <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,~
## $ speeding_violations         <dbl> 0, 0, 0, 0, 2, 3, 7, 0, 0, 0, 6, 4, 4, 0, 0,~
## $ duis                        <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 2, 0, 1, 0, 2,~
## $ past_accidents              <dbl> 0, 0, 0, 0, 1, 3, 3, 0, 0, 0, 7, 0, 2, 0, 1,~
## $ outcome                     <dbl> 0, 1, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0,~
```

Ensuring the encoded dataframe didn't slip a NA value:

```
is.na(df_enc) |> colSums()
```

```
##                          id                 age.16.25                 age.26.39
##                           0                         0                         0
##                   age.40.64                   age.65.             gender.female
##                           0                         0                         0
##                 gender.male             race.majority             race.minority
##                           0                         0                         0
##     driving_experience.0.9y driving_experience.10.19y driving_experience.20.29y
```

```
##                         0                        0                        0
##   driving_experience.30y.     education.high.school           education.none
##                         0                        0                        0
##      education.university       income.middle.class          income.poverty
##                         0                        0                        0
##        income.upper.class      income.working.class            credit_score
##                         0                        0                        0
##         vehicle_ownership   vehicle_year.after.2015 vehicle_year.before.2015
##                         0                        0                        0
##                   married                  children             postal_code
##                         0                        0                        0
##            annual_mileage        vehicle_type.sedan   vehicle_type.sports.car
##                         0                        0                        0
##       speeding_violations                      duis           past_accidents
##                         0                        0                        0
##                   outcome
##                         0
```

Split to Train/Test

```r
df_dict <- train_test_splitter_hmd(df_enc,
                              proportion=0.8)
train <- df_dict$train
test <- df_dict$test
```

Normalize

```r
for (col in names(train)){
  if (col %in% c("annual_mileage", "postal_code", "credit_score"))
  {
    next
  }
  train[[col]] <- as.integer(train[[col]])
  test[[col]] <- as.integer(test[[col]])
}
```

```r
df_dict_norm <- normalizer_hmd(train,test)


train <- df_dict_norm$train_norm
test <- df_dict_norm$test_norm

train$id <- as.double(train$id)
test$id <- as.double(test$id)
```

```r
print(paste("train data has", nrow(train), "rows and", ncol(train), "columns"))
```

```
## [1] "train data has 8000 rows and 34 columns"
```

```r
print(paste("test data has", nrow(test), "rows and", ncol(test), "columns"))
```

```
## [1] "test data has 2000 rows and 34 columns"
```

Oversampling

```r
#train_racog <- racog(train,
#                      numInstances = 3000,
#                      burnin = 100,
#                      lag = 20,
#                      classAttr = "outcome")
```

Merge new sampled data with original train dataset

```r
#insurance_train <- rbind(train , train_racog)
```

Save the processed dataframe to memory:

```r
#path = "/home/hamed/Documents/R/aiinsurance/inst/"
#file_name = "insurance_train.csv"
#readr::write_csv(insurance_train,
#                 file = #paste(path,file_name,sep=""))
```

Load back the processed data

```r
#insurance_train <- #readr::read_csv(paste(path,file_name,sep=""))
```

Do the same for test data

```r
#insurance_test <- test
#path = "/home/hamed/Documents/R/aiinsurance/inst/"
#file_name = "insurance_test.csv"
#readr::write_csv(insurance_test,
#                 file = paste(path,file_name,sep=""))

#insurance_test <- #readr::read_csv(paste(path,file_name,sep=""))
```

we need to also remove the id of the beneficiaries as it will bias the learning towards this and may cause data leakage for test datasets with the same id

```r
#insurance_train <- within(insurance_train, rm("id"))
#insurance_test <- within(insurance_test, rm("id"))
```

```r
data("insurance_train")
data("insurance_test")
```

```r
glimpse(insurance_train)
```

```
## Rows: 11,000
## Columns: 33
## $ age.16.25                  <int> 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 0, 1, 1, 1,~
## $ age.26.39                  <int> 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0,~
## $ age.40.64                  <int> 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,~
## $ age.65.                    <int> 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0,~
## $ gender.female              <int> 0, 1, 0, 1, 1, 0, 0, 0, 0, 1, 0, 1, 1, 0, 1,~
## $ gender.male                <int> 1, 0, 1, 0, 0, 1, 1, 1, 1, 0, 1, 0, 0, 1, 0,~
## $ race.majority              <int> 1, 1, 1, 1, 0, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1,~
## $ race.minority              <int> 0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0,~
## $ driving_experience.0.9y    <int> 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 0, 1, 1, 1,~
## $ driving_experience.10.19y <int> 0, 1, 1, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0,~
## $ driving_experience.20.29y <int> 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,~
## $ driving_experience.30y.   <int> 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0,~
## $ education.high.school      <int> 0, 0, 1, 1, 1, 0, 1, 1, 1, 1, 0, 0, 1, 0, 0,~
## $ education.none             <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1,~
## $ education.university       <int> 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0,~
## $ income.middle.class        <int> 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 1, 1, 0, 0,~
## $ income.poverty             <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,~
## $ income.upper.class         <int> 1, 1, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0,~
## $ income.working.class       <int> 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 1,~
## $ credit_score               <dbl> 0.7172432, 0.7894224, 0.2496466, 0.3613210, ~
## $ vehicle_ownership          <int> 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 0, 1,~
## $ vehicle_year.after.2015    <int> 1, 1, 0, 1, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 0,~
## $ vehicle_year.before.2015   <int> 0, 0, 1, 0, 1, 1, 1, 1, 0, 0, 0, 0, 1, 1, 1,~
## $ married                    <int> 0, 1, 1, 1, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0,~
## $ children                   <int> 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 0, 1,~
## $ postal_code                <dbl> 0.0000000, 0.0000000, 0.0000000, 0.0000000, ~
## $ annual_mileage             <dbl> 0.60, 0.45, 0.50, 0.70, 0.50, 0.50, 0.45, 0.~
## $ vehicle_type.sedan         <int> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1,~
## $ vehicle_type.sports.car    <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0,~
## $ speeding_violations        <dbl> 0.22727273, 0.09090909, 0.04545455, 0.045454~
## $ duis                       <dbl> 0.0000000, 0.0000000, 0.0000000, 0.0000000, ~
## $ past_accidents             <dbl> 0.13333333, 0.00000000, 0.00000000, 0.000000~
## $ outcome                    <int> 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1,~
```

```r
glimpse(insurance_test)
```

```
## Rows: 2,000
## Columns: 33
## $ age.16.25                  <int> 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0,~
## $ age.26.39                  <int> 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0,~
## $ age.40.64                  <int> 1, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1,~
## $ age.65.                    <int> 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0,~
## $ gender.female              <int> 1, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1,~
## $ gender.male                <int> 0, 1, 0, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0,~
## $ race.majority              <int> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,~
## $ race.minority              <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,~
## $ driving_experience.0.9y    <int> 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0,~
## $ driving_experience.10.19y <int> 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0,~
```

```
## $ driving_experience.20.29y <int> 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1,~
## $ driving_experience.30y.   <int> 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0,~
## $ education.high.school     <int> 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 0, 1, 0, 0,~
## $ education.none            <int> 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0,~
## $ education.university      <int> 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1,~
## $ income.middle.class       <int> 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0,~
## $ income.poverty            <int> 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0,~
## $ income.upper.class        <int> 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 1, 1, 0, 1,~
## $ income.working.class      <int> 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0,~
## $ credit_score              <dbl> 0.6234644, 0.6248241, 0.7454570, 0.6432089, ~
## $ vehicle_ownership         <int> 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 0, 1, 0, 1,~
## $ vehicle_year.after.2015   <int> 1, 1, 1, 0, 1, 0, 0, 0, 0, 1, 0, 1, 0, 0, 1,~
## $ vehicle_year.before.2015  <int> 0, 0, 0, 1, 0, 1, 1, 1, 1, 0, 1, 0, 1, 1, 0,~
## $ married                   <int> 0, 1, 1, 1, 1, 1, 1, 0, 0, 1, 0, 0, 1, 0, 1,~
## $ children                  <int> 1, 1, 0, 1, 0, 1, 0, 1, 0, 1, 1, 1, 1, 0, 1,~
## $ postal_code               <dbl> 0.0000000, 0.0000000, 0.2751793, 0.0000000, ~
## $ annual_mileage            <dbl> 0.55, 0.40, 0.50, 0.30, 0.50, 0.50, 0.50, 0.~
## $ vehicle_type.sedan        <int> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1,~
## $ vehicle_type.sports.car   <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0,~
## $ speeding_violations       <dbl> 0.13636364, 0.27272727, 0.18181818, 0.181818~
## $ duis                      <dbl> 0.0000000, 0.3333333, 0.0000000, 0.1666667, ~
## $ past_accidents            <dbl> 0.20000000, 0.46666667, 0.00000000, 0.133333~
## $ outcome                   <int> 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0,~
```

```
table(insurance_train$outcome)
```

```
##
##    0    1
## 5484 5516
```

I added a `preprocess_hmd` function in package that is a wrapper around all the steps and functions from the preprocessing section section. Therefore, simply by writing the following syntax, the final `insurance_train` and `insurance_tetst` datasets can be obtained from the original `car_insurance_data`:

```
#h <- preprocess_hmd(car_insurance_data)
#insurance_train <- h$insurance_train
#insurance_test <- h$insurance_test
```

Data Visualisation

```
#insurance_train |> ggplot(aes(x = credit_score, y = #speeding_violations)) +
#  geom_point(color = outcome)
```

Classification Models

Generalized Linear Models

```
actual <- insurance_test$outcome
```

GLMNET

```
fit <- glmnet_fit_hmd(insurance_train, target="outcome", family="binomial")
h <- glmnet_predict_hmd(fit,
                        data = insurance_test,
                        target = "outcome",
                        type = "binomial")
```

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

```
coef = h$coef
pred_glm <- h$predictions
pred_proba_glm <- h$predict_proba
```

```
summary(fit)
```

```
##
## Call:
## stats::glm(formula = glm_format, family = {
##     {
##         family
##     }
## }, data = df)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -3.2941  -0.5332   0.0968   0.5764   3.2898
##
## Coefficients: (4 not defined because of singularities)
##                           Estimate Std. Error z value Pr(>|z|)
## (Intercept)                0.17229    0.33125   0.520 0.602967
## age.16.25                  0.12188    0.11505   1.059 0.289454
## age.26.39                 -0.13679    0.09681  -1.413 0.157657
## age.40.64                 -0.27321    0.10319  -2.648 0.008105 **
## age.65.                   -0.12704    0.12689  -1.001 0.316755
## gender.female             -0.90848    0.05888 -15.430  < 2e-16 ***
## gender.male                     NA         NA      NA       NA
## race.majority              0.11025    0.09034   1.220 0.222292
## race.minority                   NA         NA      NA       NA
## driving_experience.0.9y    2.25425    0.18599  12.120  < 2e-16 ***
## driving_experience.10.19y  0.55940    0.17247   3.243 0.001181 **
## driving_experience.20.29y -1.04472    0.18714  -5.583 2.37e-08 ***
## driving_experience.30y.   -1.65633    0.26683  -6.207 5.39e-10 ***
## education.high.school      0.20773    0.11088   1.873 0.061006 .
## education.none             0.38751    0.10403   3.725 0.000195 ***
## education.university       0.16342    0.10899   1.499 0.133778
## income.middle.class        0.19168    0.09211   2.081 0.037448 *
## income.poverty             0.25226    0.11247   2.243 0.024908 *
## income.upper.class         0.17092    0.10740   1.591 0.111518
## income.working.class       0.40319    0.09166   4.399 1.09e-05 ***
## credit_score              -0.14892    0.26484  -0.562 0.573910
## vehicle_ownership         -1.55159    0.06183 -25.095  < 2e-16 ***
## vehicle_year.after.2015   -1.65975    0.07259 -22.865  < 2e-16 ***
```

```
## vehicle_year.before.2015        NA         NA      NA       NA    
## married                   -0.45440    0.06346  -7.161 8.03e-13 ***
## children                  -0.26748    0.06318  -4.233 2.30e-05 ***
## postal_code                1.73352    0.12759  13.586  < 2e-16 ***
## annual_mileage             1.19594    0.25215   4.743 2.11e-06 ***
## vehicle_type.sedan        -0.17842    0.12571  -1.419 0.155821    
## vehicle_type.sports.car         NA         NA      NA       NA    
## speeding_violations        1.49235    0.44509   3.353 0.000800 ***
## duis                      -0.16071    0.38786  -0.414 0.678611    
## past_accidents            -2.38947    0.45009  -5.309 1.10e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 15249.1  on 10999  degrees of freedom
## Residual deviance:  8434.7  on 10971  degrees of freedom
## AIC: 8492.7
##
## Number of Fisher Scoring iterations: 6
```

```
coef
```

```
##              (Intercept)                age.16.25                age.26.39 
##                0.1722946                0.1218785               -0.1367859 
##                age.40.64                  age.65.            gender.female 
##               -0.2732099               -0.1270374               -0.9084817 
##              gender.male            race.majority            race.minority 
##                       NA                0.1102514                       NA 
##   driving_experience.0.9y driving_experience.10.19y driving_experience.20.29y 
##                2.2542490                0.5593966               -1.0447194 
##   driving_experience.30y.    education.high.school           education.none 
##               -1.6563349                0.2077277                0.3875125 
##     education.university      income.middle.class           income.poverty 
##                0.1634237                0.1916752                0.2522558 
##       income.upper.class      income.working.class             credit_score 
##                0.1709167                0.4031949               -0.1489177 
##        vehicle_ownership   vehicle_year.after.2015  vehicle_year.before.2015 
##               -1.5515944               -1.6597537                       NA 
##                  married                 children              postal_code 
##               -0.4544041               -0.2674758                1.7335224 
##           annual_mileage       vehicle_type.sedan   vehicle_type.sports.car 
##                1.1959431               -0.1784208                       NA 
##      speeding_violations                     duis           past_accidents 
##                1.4923479               -0.1607137               -2.3894743 
```

```
head(pred_glm)
```

```
## 1 2 3 4 5 6 
## 0 0 0 0 0 0 
```

Extract AIC and BIC from the fit of glm

```r
fit$aic
```

```
## [1] 8492.693
```

avplot of results

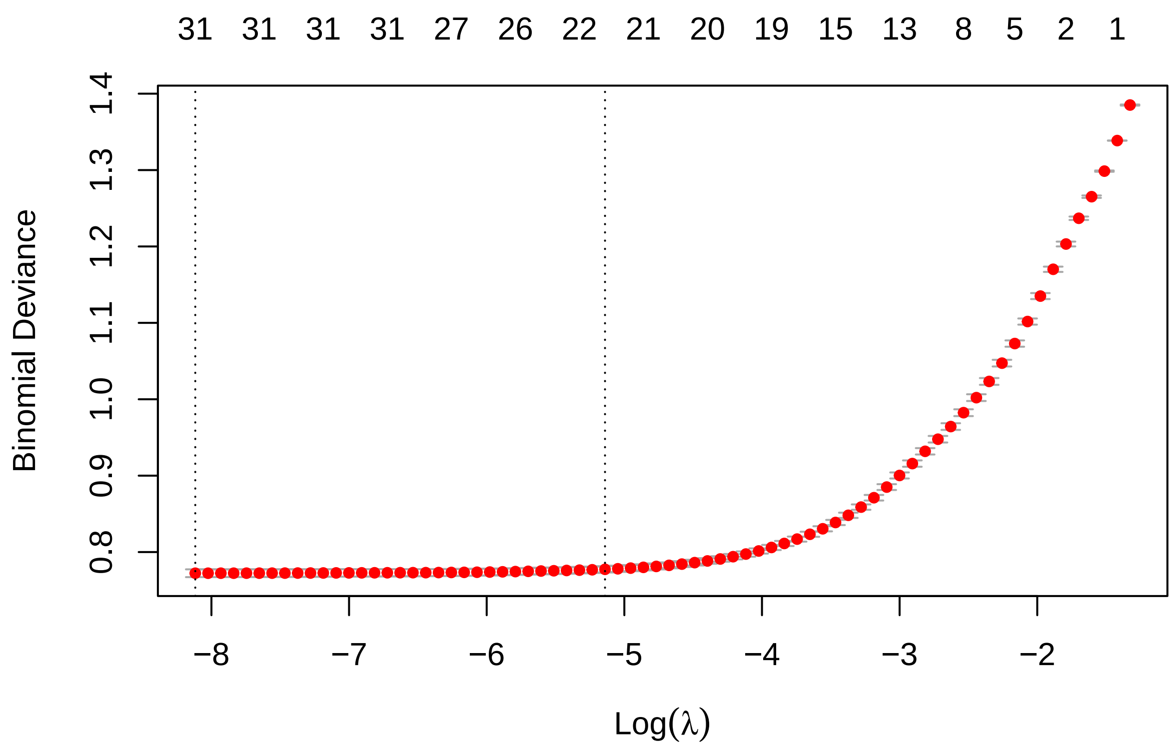
```r
#glmnet_plot_hmd(fit)
```

cross validated GLMNET

min

```r
fit <- glmnet_cv_fit_hmd(insurance_train, target="outcome", family="binomial")
h <- glmnet_cv_predict_hmd(fit,
                           data = insurance_test,
                           target = "outcome",
                           lchoice = "min",
                           type = "binomial")
coef = h$coef
pred_glm_cv_min <- h$predictions
pred_proba_glm_cv_min <- h$predict_proba
```

```r
glmnet_cv_plot_hmd(fit)
```




```r
summary(fit)
```

```
##            Length Class  Mode
```

```
## lambda     74     -none- numeric
## cvm        74     -none- numeric
## cvsd       74     -none- numeric
## cvup       74     -none- numeric
## cvlo       74     -none- numeric
## nzero      74     -none- numeric
## call        4     -none- call
## name        1     -none- character
## glmnet.fit 13     lognet list
## lambda.min  1     -none- numeric
## lambda.1se  1     -none- numeric
## index       2     -none- numeric
```

```
coef
```

```
## 33 x 1 sparse Matrix of class "dgCMatrix"
##                                        s1
## (Intercept)                  2.606699e-01
## age.16.25                    1.470227e-01
## age.26.39                   -1.053756e-01
## age.40.64                   -2.477387e-01
## age.65.                     -9.772754e-02
## gender.female               -9.024817e-01
## gender.male                  5.554381e-05
## race.majority                1.002116e-01
## race.minority                .
## driving_experience.0.9y      2.191045e+00
## driving_experience.10.19y  5.082683e-01
## driving_experience.20.29y -1.064324e+00
## driving_experience.30y.   -1.649878e+00
## education.high.school      1.627430e-01
## education.none             3.502781e-01
## education.university       1.262105e-01
## income.middle.class        1.579856e-01
## income.poverty             2.240788e-01
## income.upper.class         1.266337e-01
## income.working.class       3.765955e-01
## credit_score              -1.131380e-01
## vehicle_ownership         -1.540379e+00
## vehicle_year.after.2015   -1.644180e+00
## vehicle_year.before.2015   4.626151e-12
## married                   -4.489660e-01
## children                  -2.668132e-01
## postal_code                1.714963e+00
## annual_mileage             1.160143e+00
## vehicle_type.sedan        -1.672808e-01
## vehicle_type.sports.car    1.407297e-13
## speeding_violations        1.359474e+00
## duis                      -1.350778e-01
## past_accidents            -2.372703e+00
```

```
head(pred_glm_cv_min)
```

```
##      lambda.min
```

```
## [1,]          0
## [2,]          0
## [3,]          0
## [4,]          0
## [5,]          0
## [6,]          0
```

Extract AIC and BIC from the fit of glm

```
glmnet_cv_aic_hmd(fit, lchoice = "min")
```

```
## $AICc
## [1] -6751.432
##
## $BIC
## [1] -6525.138
```

1SE

```
fit <- glmnet_cv_fit_hmd(insurance_train, target="outcome", family="binomial")
h <- glmnet_cv_predict_hmd(fit,
                           data = insurance_test,
                           target = "outcome",
                           lchoice = "1se",
                           type = "binomial")
coef = h$coef
pred_glm_cv_1se <- h$predictions
pred_proba_glm_cv_1se <- h$predict_proba
```

```
summary(fit)
```

```
##            Length Class  Mode
## lambda     74     -none- numeric
## cvm        74     -none- numeric
## cvsd       74     -none- numeric
## cvup       74     -none- numeric
## cvlo       74     -none- numeric
## nzero      74     -none- numeric
## call        4     -none- call
## name        1     -none- character
## glmnet.fit 13     lognet list
## lambda.min  1     -none- numeric
## lambda.1se  1     -none- numeric
## index       2     -none- numeric
```

```
coef
```

```
## 33 x 1 sparse Matrix of class "dgCMatrix"
##                                     s1
## (Intercept)               1.018119e+00
## age.16.25                 2.181744e-01
```

```
## age.26.39                   .
## age.40.64                  -1.022830e-01
## age.65.                    -7.228297e-04
## gender.female              -7.039896e-01
## gender.male                 9.213086e-06
## race.majority               .
## race.minority               .
## driving_experience.0.9y     1.512906e+00
## driving_experience.10.19y  .
## driving_experience.20.29y -1.158297e+00
## driving_experience.30y.   -1.306864e+00
## education.high.school       .
## education.none              1.261959e-01
## education.university        .
## income.middle.class         .
## income.poverty              5.757163e-02
## income.upper.class         -4.045528e-02
## income.working.class        1.615831e-01
## credit_score               -1.235961e-01
## vehicle_ownership          -1.338798e+00
## vehicle_year.after.2015    -1.390326e+00
## vehicle_year.before.2015    4.251933e-12
## married                    -3.962552e-01
## children                   -2.364787e-01
## postal_code                 1.231771e+00
## annual_mileage              5.689875e-01
## vehicle_type.sedan          .
## vehicle_type.sports.car     .
## speeding_violations         .
## duis                        .
## past_accidents             -1.830717e+00
```

```
head(pred_glm_cv_1se)
```

```
##      lambda.1se
## [1,]          0
## [2,]          0
## [3,]          0
## [4,]          0
## [5,]          0
## [6,]          0
```

Extract AIC and BIC from the fit of glm

```
glmnet_cv_aic_hmd(fit, lchoice = "1se")
```

```
## $AICc
## [1] -6634.007
##
## $BIC
## [1] -6480.673
```

Evaluate

GLMNET

```r
eval <- eval_hmd(actual, pred_glm)
```

```r
print("confusion matrix: ")
```

```
## [1] "confusion matrix: "
```

```r
print(eval$confusion_matrix)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 1186  139
##          1  197  478
##
##                Accuracy : 0.832
##                  95% CI : (0.8149, 0.8481)
##     No Information Rate : 0.6915
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.6162
##
##  Mcnemar's Test P-Value : 0.001873
##
##             Sensitivity : 0.8576
##             Specificity : 0.7747
##          Pos Pred Value : 0.8951
##          Neg Pred Value : 0.7081
##              Prevalence : 0.6915
##          Detection Rate : 0.5930
##    Detection Prevalence : 0.6625
##       Balanced Accuracy : 0.8161
##
##        'Positive' Class : 0
##
```

```r
print("accuracy: ")
```

```
## [1] "accuracy: "
```

```r
print(eval$accuracy)
```

```
## [1] 0.832
```

```r
print("precision: ")
```

```
## [1] "precision: "
```

```r
print(eval$precision)
```

```
## [1] 0.7747164
```

```r
print("recall: ")
```

```
## [1] "recall: "
```

```r
print(eval$recall)
```

```
## [1] 0.7081481
```

```r
print("f1_score")
```

```
## [1] "f1_score"
```

```r
print(eval$f1_score)
```

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

```r
print("fbeta_score")
```

```
## [1] "fbeta_score"
```

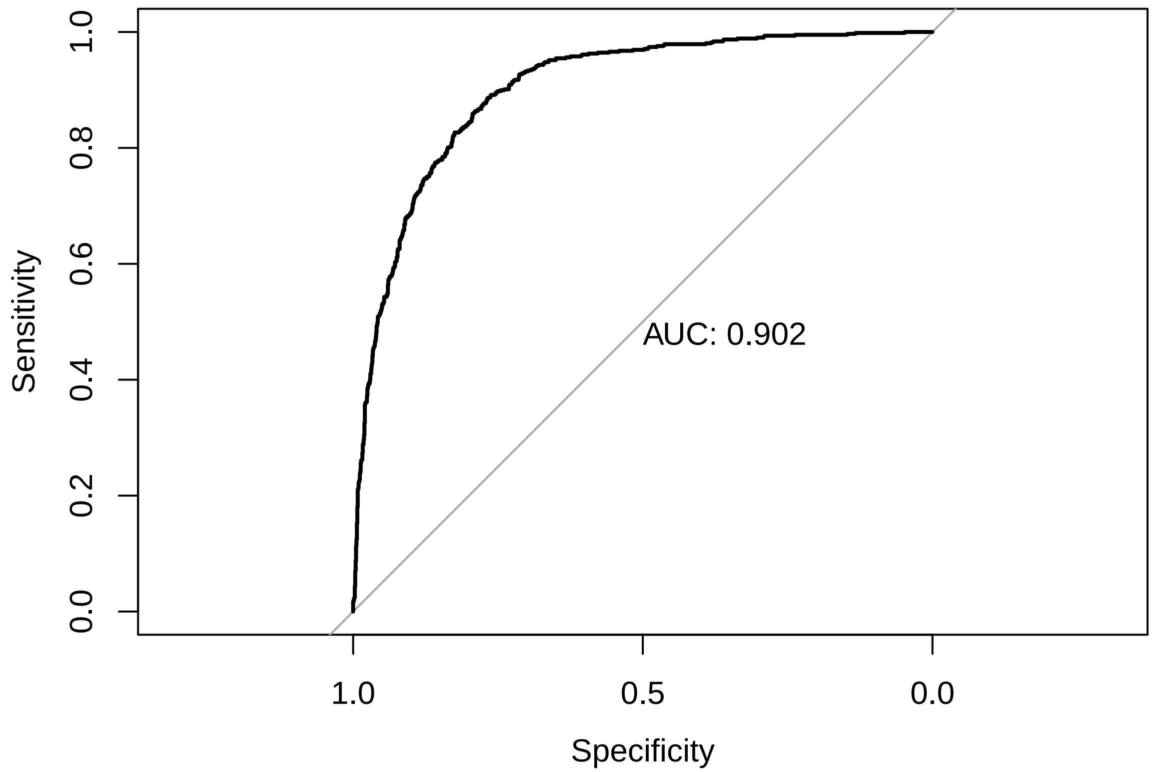
```r
print(eval$fbeta_score)
```

```
## [1] 0.7399381
```

```r
pROC::roc(actual ~ pred_proba_glm, plot = TRUE, print.auc = TRUE)
```

```
## Setting levels: control = 0, case = 1
```

```
## Setting direction: controls < cases
```




```
##
## Call:
## roc.formula(formula = actual ~ pred_proba_glm, plot = TRUE, print.auc = TRUE)
##
## Data: pred_proba_glm in 1383 controls (actual 0) < 617 cases (actual 1).
## Area under the curve: 0.9017
```

Plot Confusion Matrix

```
eval$confusion_matrix_plot
```

```
## Warning: Use of `plt$Prediction` is discouraged.
## i Use `Prediction` instead.
```

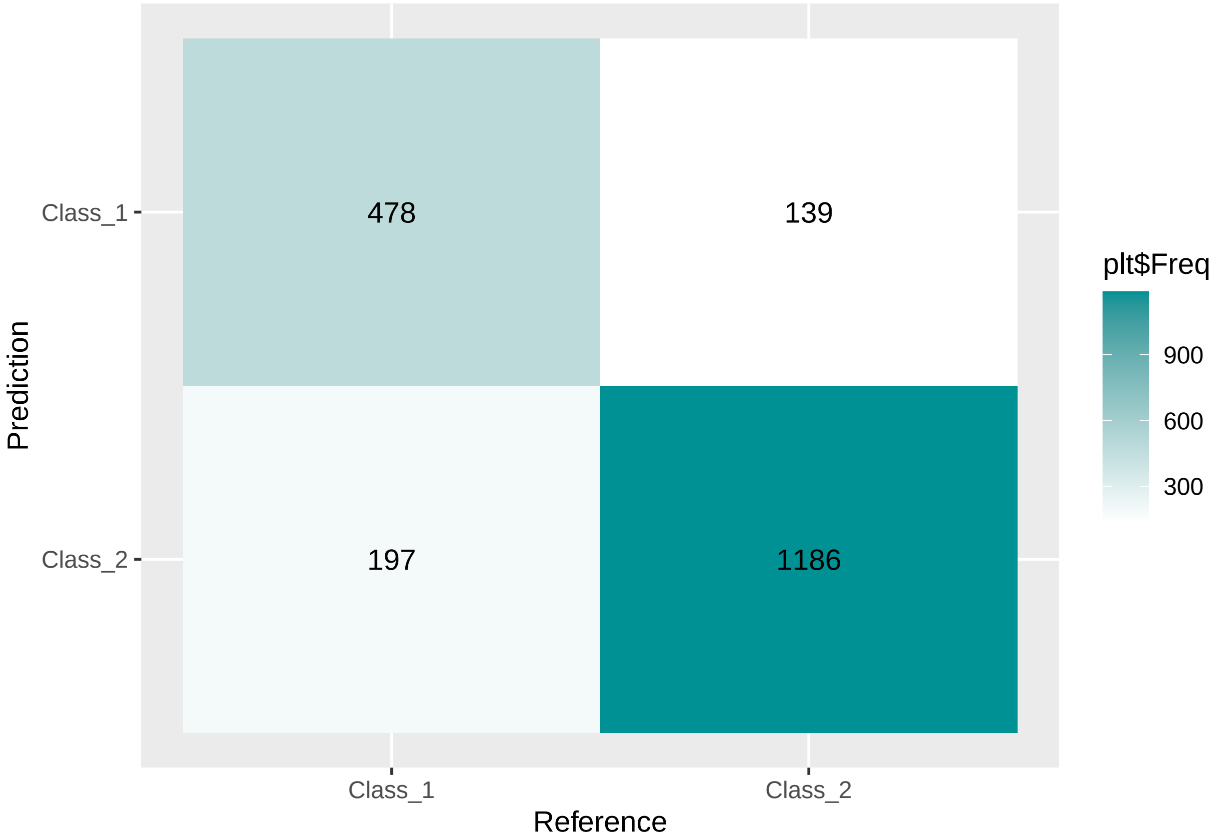
```
## Warning: Use of `plt$Reference` is discouraged.
## i Use `Reference` instead.
```

```
## Warning: Use of `plt$Freq` is discouraged.
## i Use `Freq` instead.
## Use of `plt$Freq` is discouraged.
## i Use `Freq` instead.
```

```
## Warning: Use of `plt$Prediction` is discouraged.
## i Use `Prediction` instead.
```

```
## Warning: Use of `plt$Reference` is discouraged.
## i Use `Reference` instead.
```

```
## Warning: Use of `plt$Freq` is discouraged.
## i Use `Freq` instead.
```



GLMNET CV

min

Confusion Matrix

```r
eval <- eval_hmd(actual, pred_glm_cv_min)
```

```r
print("confusion matrix: ")
```

```
## [1] "confusion matrix: "
```

```r
print(eval$confusion_matrix)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 1184  140
##          1  199  477
##
##                Accuracy : 0.8305
##                  95% CI : (0.8133, 0.8467)
```

```
##     No Information Rate : 0.6915
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.613
##
##  Mcnemar's Test P-Value : 0.001632
##
##             Sensitivity : 0.8561
##             Specificity : 0.7731
##          Pos Pred Value : 0.8943
##          Neg Pred Value : 0.7056
##              Prevalence : 0.6915
##          Detection Rate : 0.5920
##    Detection Prevalence : 0.6620
##       Balanced Accuracy : 0.8146
##
##        'Positive' Class : 0
##
```

```r
print("accuracy: ")
```

```
## [1] "accuracy: "
```

```r
print(eval$accuracy)
```

```
## [1] 0.8305
```

```r
print("precision: ")
```

```
## [1] "precision: "
```

```r
print(eval$precision)
```

```
## [1] 0.7730956
```

```r
print("recall: ")
```

```
## [1] "recall: "
```

```r
print(eval$recall)
```

```
## [1] 0.7056213
```

```r
print("f1_score")
```

```
## [1] "f1_score"
```

```r
print(eval$f1_score)
```

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

```r
print("fbeta_score")
```

```
## [1] "fbeta_score"
```

```r
print(eval$fbeta_score)
```

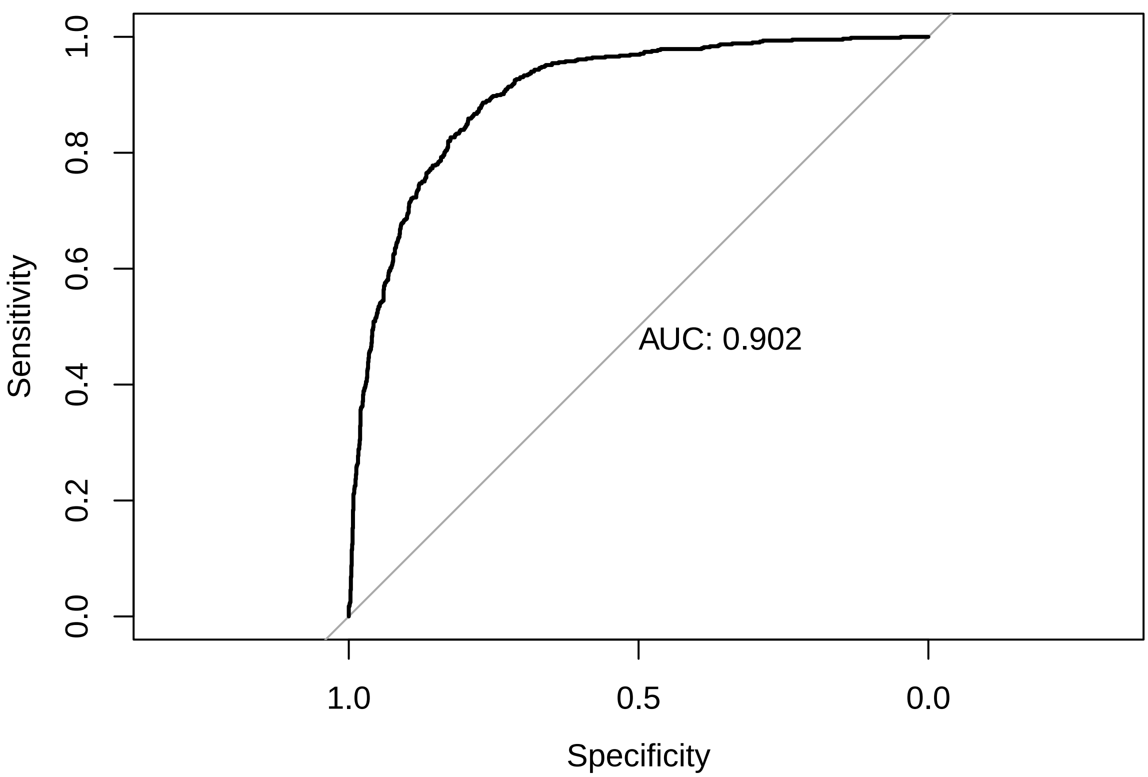
```
## [1] 0.737819
```

```r
pROC::roc(actual ~ pred_proba_glm_cv_min, plot = TRUE, print.auc = TRUE)
```

```
## Setting levels: control = 0, case = 1

## Warning in roc.default(response, predictors[, 1], ...): Deprecated use a matrix
## as predictor. Unexpected results may be produced, please pass a numeric vector.

## Setting direction: controls < cases
```




```
##
## Call:
## roc.formula(formula = actual ~ pred_proba_glm_cv_min, plot = TRUE,     print.auc = TRUE)
##
## Data: pred_proba_glm_cv_min in 1383 controls (actual 0) < 617 cases (actual 1).
## Area under the curve: 0.9017
```

Plot Confusion Matrix

```
eval$confusion_matrix_plot
```

```
## Warning: Use of `plt$Prediction` is discouraged.
## i Use `Prediction` instead.

## Warning: Use of `plt$Reference` is discouraged.
## i Use `Reference` instead.

## Warning: Use of `plt$Freq` is discouraged.
## i Use `Freq` instead.
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## i Use `Reference` instead.

## Warning: Use of `plt$Freq` is discouraged.
## i Use `Freq` instead.
```
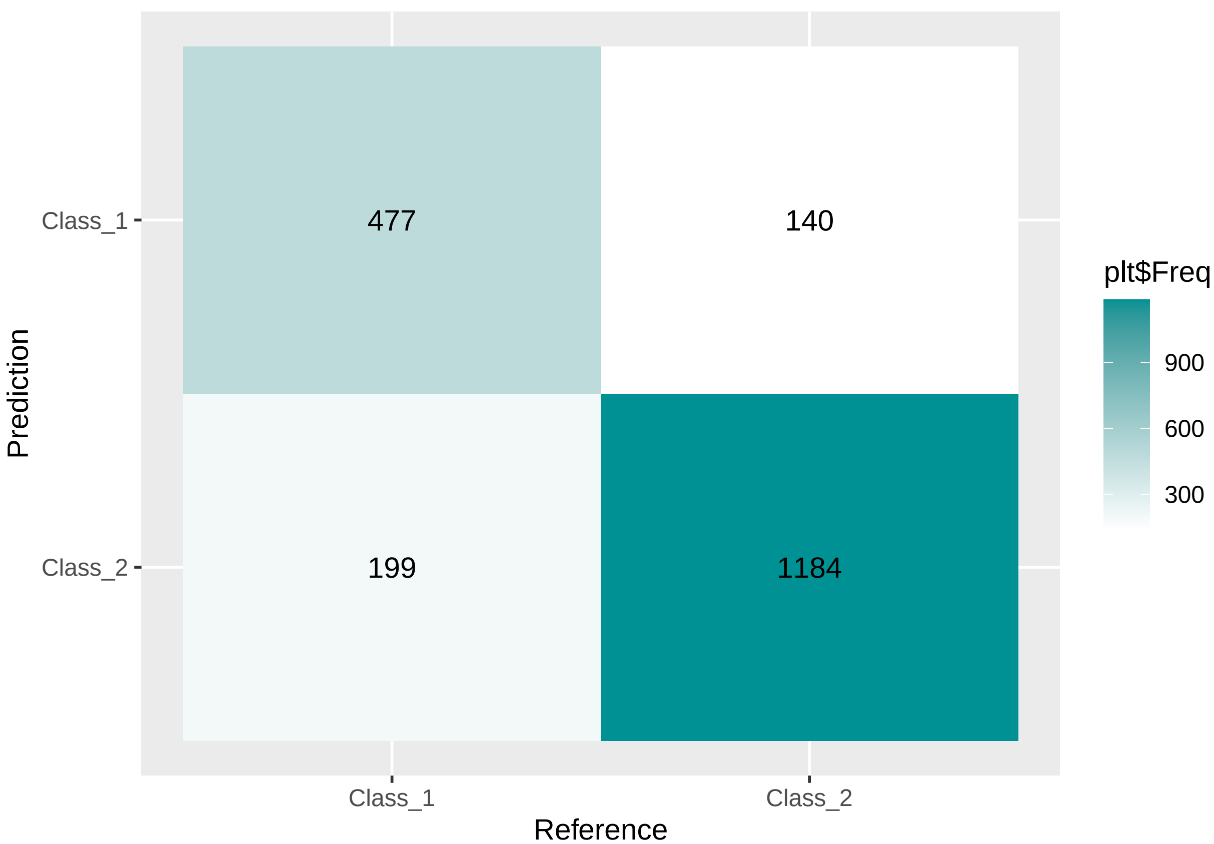



1se

```r
eval <- eval_hmd(actual, pred_glm_cv_1se)
```

```r
print("confusion matrix: ")
```

```
## [1] "confusion matrix: "
```

```r
print(eval$confusion_matrix)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 1193  145
##          1  190  472
##
##                Accuracy : 0.8325
##                  95% CI : (0.8154, 0.8486)
##     No Information Rate : 0.6915
##     P-Value [Acc > NIR] : < 2e-16
##
##                   Kappa : 0.6152
##
##  Mcnemar's Test P-Value : 0.01622
##
##             Sensitivity : 0.8626
##             Specificity : 0.7650
##          Pos Pred Value : 0.8916
##          Neg Pred Value : 0.7130
##              Prevalence : 0.6915
##          Detection Rate : 0.5965
##    Detection Prevalence : 0.6690
##       Balanced Accuracy : 0.8138
##
##        'Positive' Class : 0
##
```

```r
print("accuracy: ")
```

```
## [1] "accuracy: "
```

```r
print(eval$accuracy)
```

```
## [1] 0.8325
```

```r
print("precision: ")
```

```
## [1] "precision: "
```

```r
print(eval$precision)
```

```
## [1] 0.7649919
```

```r
print("recall: ")
```

```
## [1] "recall: "
```

```r
print(eval$recall)
```

```
## [1] 0.7129909
```

```r
print("f1_score")
```

```
## [1] "f1_score"
```

```r
print(eval$f1_score)
```

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

```r
print("fbeta_score")
```

```
## [1] "fbeta_score"
```

```r
print(eval$fbeta_score)
```

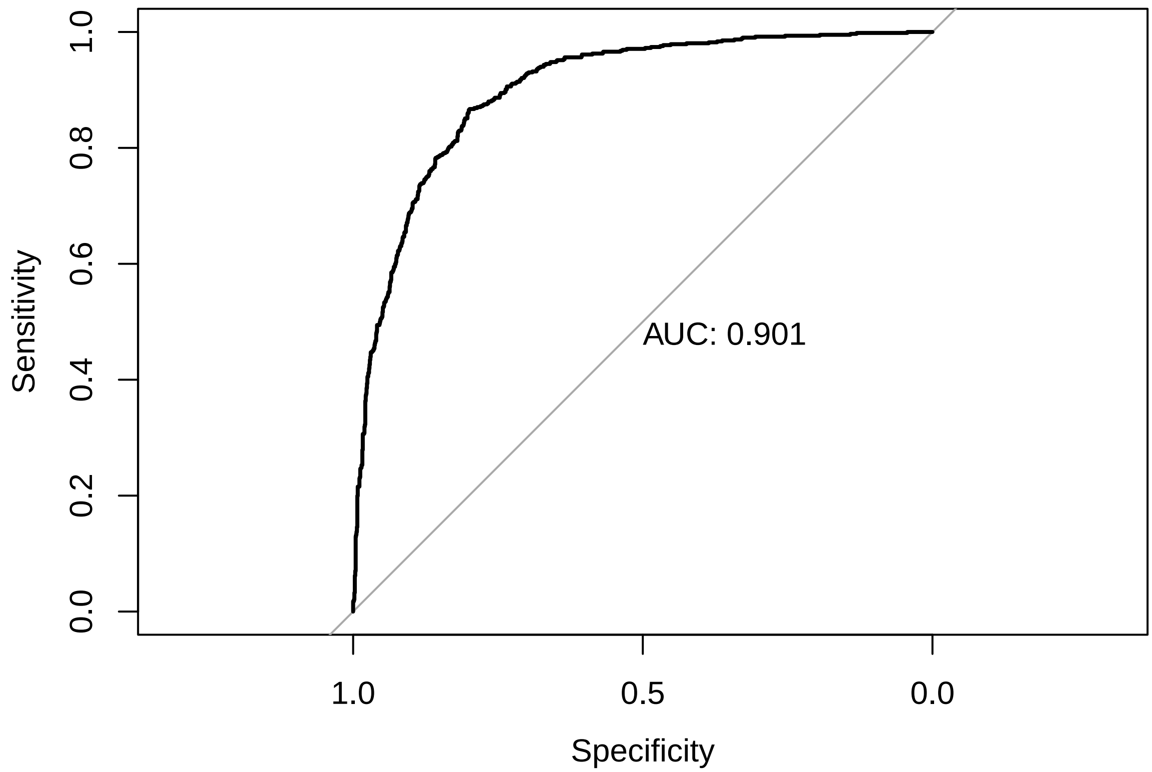
```
## [1] 0.7380766
```

```r
pROC::roc(actual ~ pred_proba_glm_cv_1se, plot = TRUE, print.auc = TRUE)
```

```
## Setting levels: control = 0, case = 1
```

```
## Warning in roc.default(response, predictors[, 1], ...): Deprecated use a matrix
## as predictor. Unexpected results may be produced, please pass a numeric vector.
```

```
## Setting direction: controls < cases
```




```
##
## Call:
## roc.formula(formula = actual ~ pred_proba_glm_cv_1se, plot = TRUE,     print.auc = TRUE)
##
## Data: pred_proba_glm_cv_1se in 1383 controls (actual 0) < 617 cases (actual 1).
## Area under the curve: 0.9012
```

Random Forest

```
actual <- aiinsurance::insurance_test$outcome
X_train <- aiinsurance::insurance_train[, colnames(aiinsurance::insurance_train)[colnames(aiinsurance::i
X_test <- aiinsurance::insurance_test[, colnames(aiinsurance::insurance_test)[colnames(aiinsurance::insu
y_train <- as.factor(aiinsurance::insurance_train[["outcome"]])
y_test <- as.factor(aiinsurance::insurance_test[["outcome"]])
```

```
rf <- rf_fit_hmd(insurance_train,
                 ntree = 300,
                 mtry = 10,
                 proximity = TRUE,
                 importance = TRUE)
```

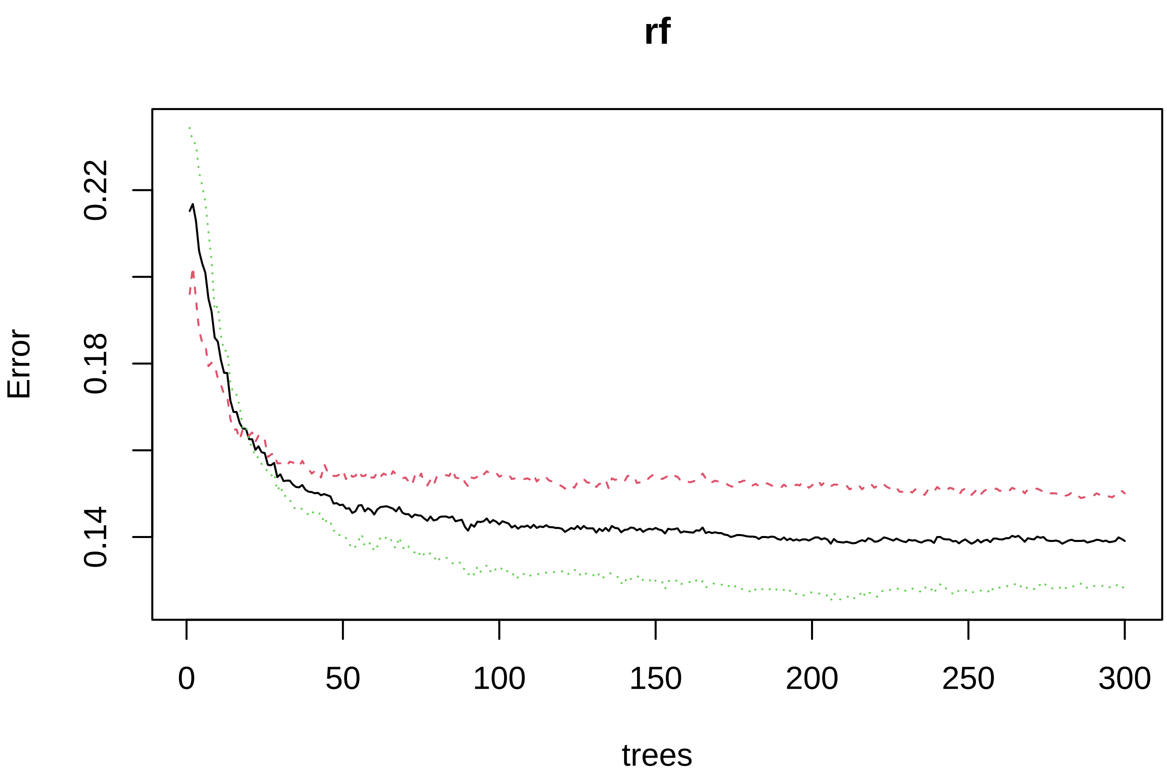
```
print(rf)
```

```
##
## Call:
```

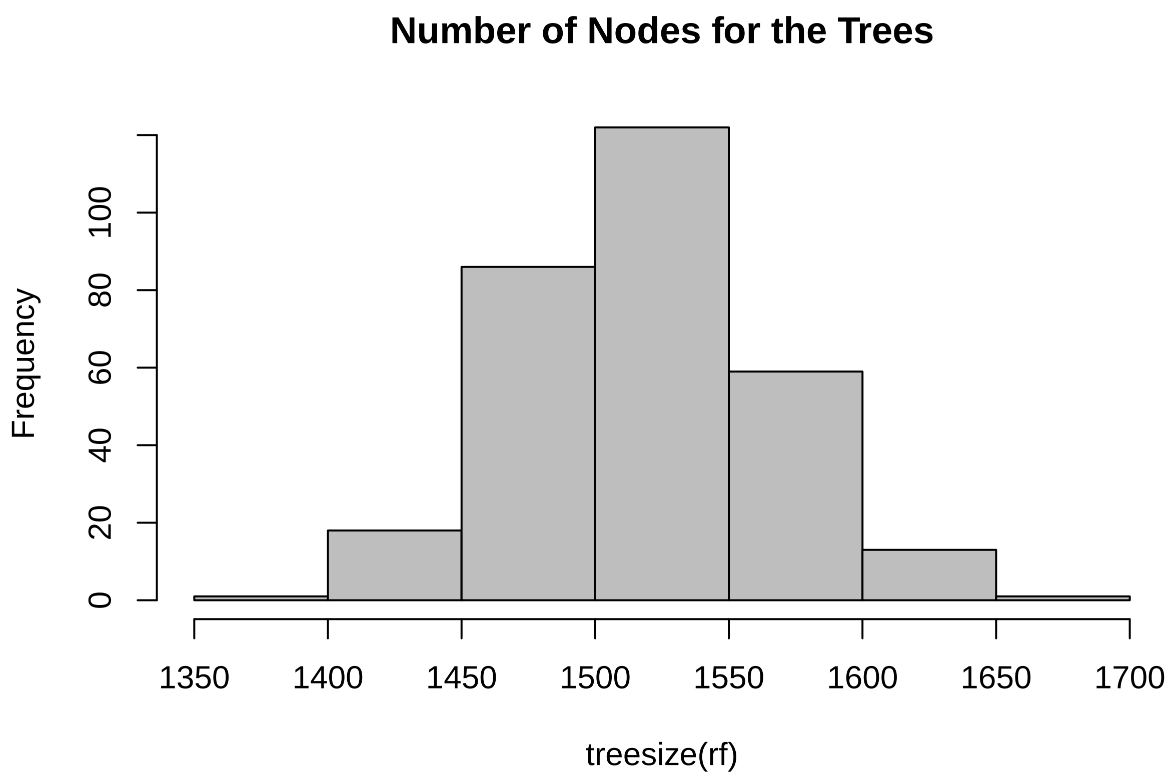
```
##  randomForest(x = X_train, y = y_train, ntree = {     {          ntree     } }, mtry = {     {
##                Type of random forest: classification
##                      Number of trees: 300
## No. of variables tried at each split: 10
##
##         OOB estimate of  error rate: 13.91%
## Confusion matrix:
##      0    1 class.error
## 0 4661  823   0.1500729
## 1  707 4809   0.1281726
```

```
predict_rf <- rf_predict_hmd(data=insurance_test, fit=rf)
```

```
plot(rf)
```

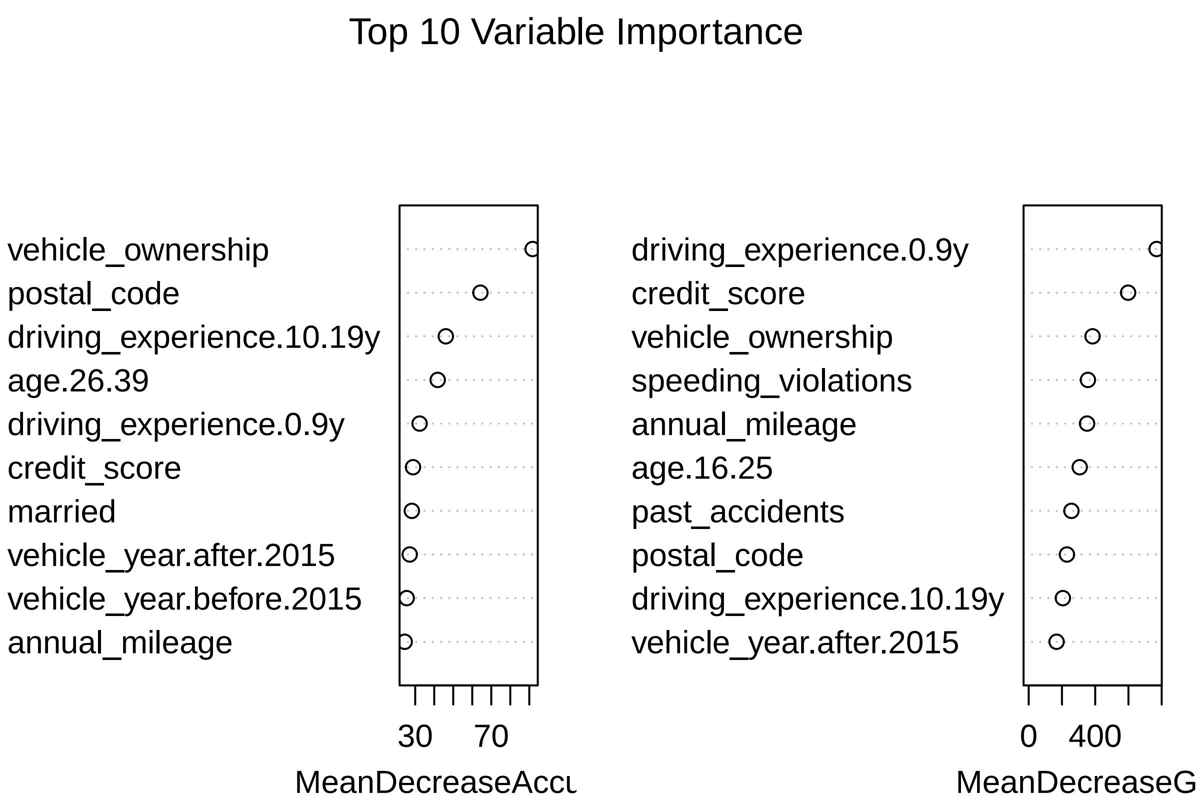



```
# Number of nodes for the trees
hist(treesize(rf),                          # give us the number of trees in term of number of nodes
     main = "Number of Nodes for the Trees",
     col = "grey")
```



Variable Importance

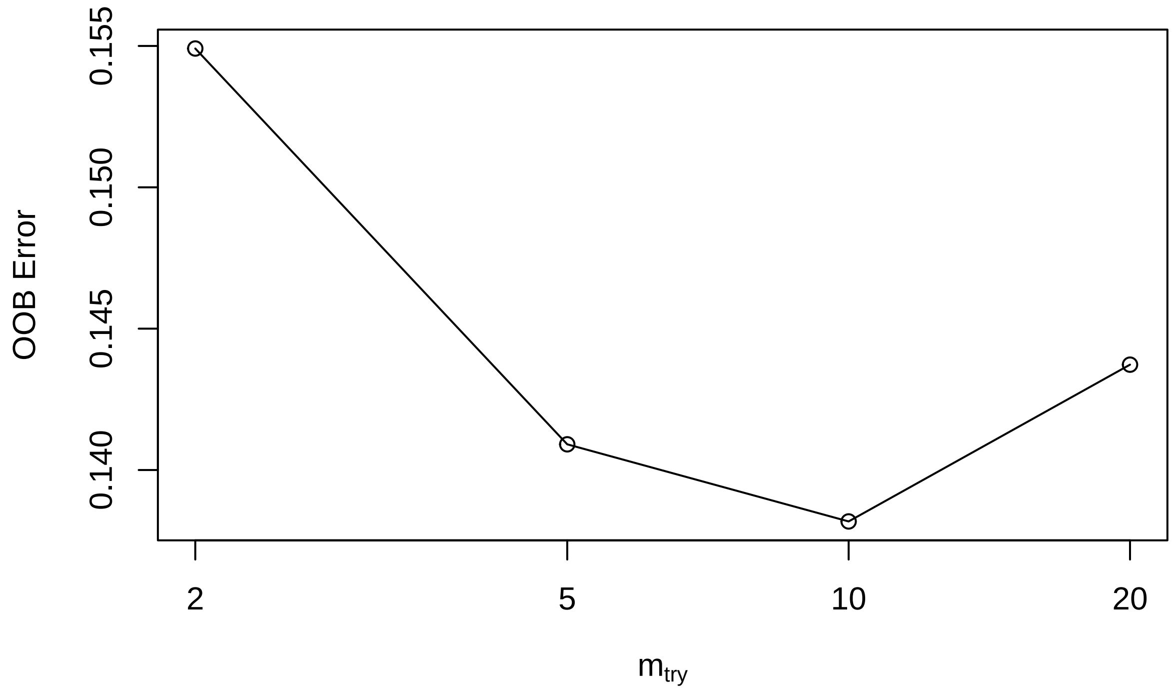
```
varImpPlot(rf,
           sort = T,
           n.var = 10,
           main = "Top 10 Variable Importance")
```



Hyperparameter Tuning

```
t <- tuneRF(X_train,
            y_train,
            stepFactor = 0.5,
            plot = TRUE,
            ntreeTry = 300,
            trace = TRUE,
            improve = 0.01)
```

```
## mtry = 5  OOB error = 14.09%
## Searching left ...
## mtry = 10     OOB error = 13.82%
## 0.01935484 0.01
## mtry = 20     OOB error = 14.37%
## -0.04013158 0.01
## Searching right ...
## mtry = 2      OOB error = 15.49%
## -0.1210526 0.01
```




```
print(t)
```

```
##        mtry  OOBError
## 2.OOB     2 0.1549091
## 5.OOB     5 0.1409091
## 10.OOB   10 0.1381818
## 20.OOB   20 0.1437273
```

Evaluate

```
eval <- eval_hmd(actual, predict_rf$predictions_num)
```

```
print("confusion matrix: ")
```

```
## [1] "confusion matrix: "
```

```
print(eval$confusion_matrix)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 1172  123
##          1  211  494
##
##                Accuracy : 0.833
##                  95% CI : (0.8159, 0.8491)
```

```
##     No Information Rate : 0.6915
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.6235
##
##  Mcnemar's Test P-Value : 1.932e-06
##
##             Sensitivity : 0.8474
##             Specificity : 0.8006
##          Pos Pred Value : 0.9050
##          Neg Pred Value : 0.7007
##              Prevalence : 0.6915
##          Detection Rate : 0.5860
##    Detection Prevalence : 0.6475
##       Balanced Accuracy : 0.8240
##
##        'Positive' Class : 0
##
```

```r
print("accuracy: ")
```

```
## [1] "accuracy: "
```

```r
print(eval$accuracy)
```

```
## [1] 0.833
```

```r
print("precision: ")
```

```
## [1] "precision: "
```

```r
print(eval$precision)
```

```
## [1] 0.8006483
```

```r
print("recall: ")
```

```
## [1] "recall: "
```

```r
print(eval$recall)
```

```
## [1] 0.7007092
```

```r
print("f1_score")
```

```
## [1] "f1_score"
```

```r
print(eval$f1_score)
```

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

```r
print("fbeta_score")
```

```
## [1] "fbeta_score"
```

```r
print(eval$fbeta_score)
```

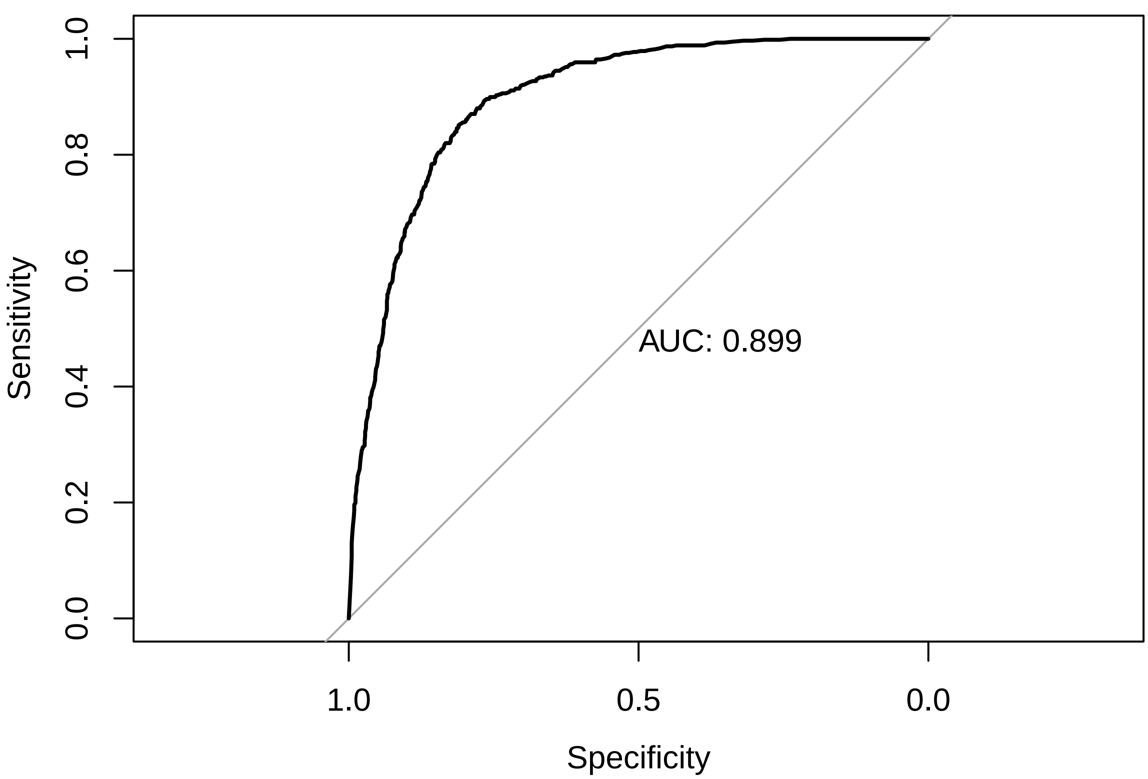
```
## [1] 0.7473525
```

```r
pred_proba_rf <- predict_rf$predict_proba
```

```r
pROC::roc(actual ~ pred_proba_rf, plot = TRUE, print.auc = TRUE)
```

```
## Setting levels: control = 0, case = 1
```

```
## Setting direction: controls < cases
```




```
##
## Call:
## roc.formula(formula = actual ~ pred_proba_rf, plot = TRUE, print.auc = TRUE)
##
## Data: pred_proba_rf in 1383 controls (actual 0) < 617 cases (actual 1).
## Area under the curve: 0.8992
```

Plot Confusion Matrix

```
eval$confusion_matrix_plot
```

```
## Warning: Use of `plt$Prediction` is discouraged.
## i Use `Prediction` instead.

## Warning: Use of `plt$Reference` is discouraged.
## i Use `Reference` instead.

## Warning: Use of `plt$Freq` is discouraged.
## i Use `Freq` instead.
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## i Use `Freq` instead.

## Warning: Use of `plt$Prediction` is discouraged.
## i Use `Prediction` instead.

## Warning: Use of `plt$Reference` is discouraged.
## i Use `Reference` instead.

## Warning: Use of `plt$Freq` is discouraged.
## i Use `Freq` instead.
```

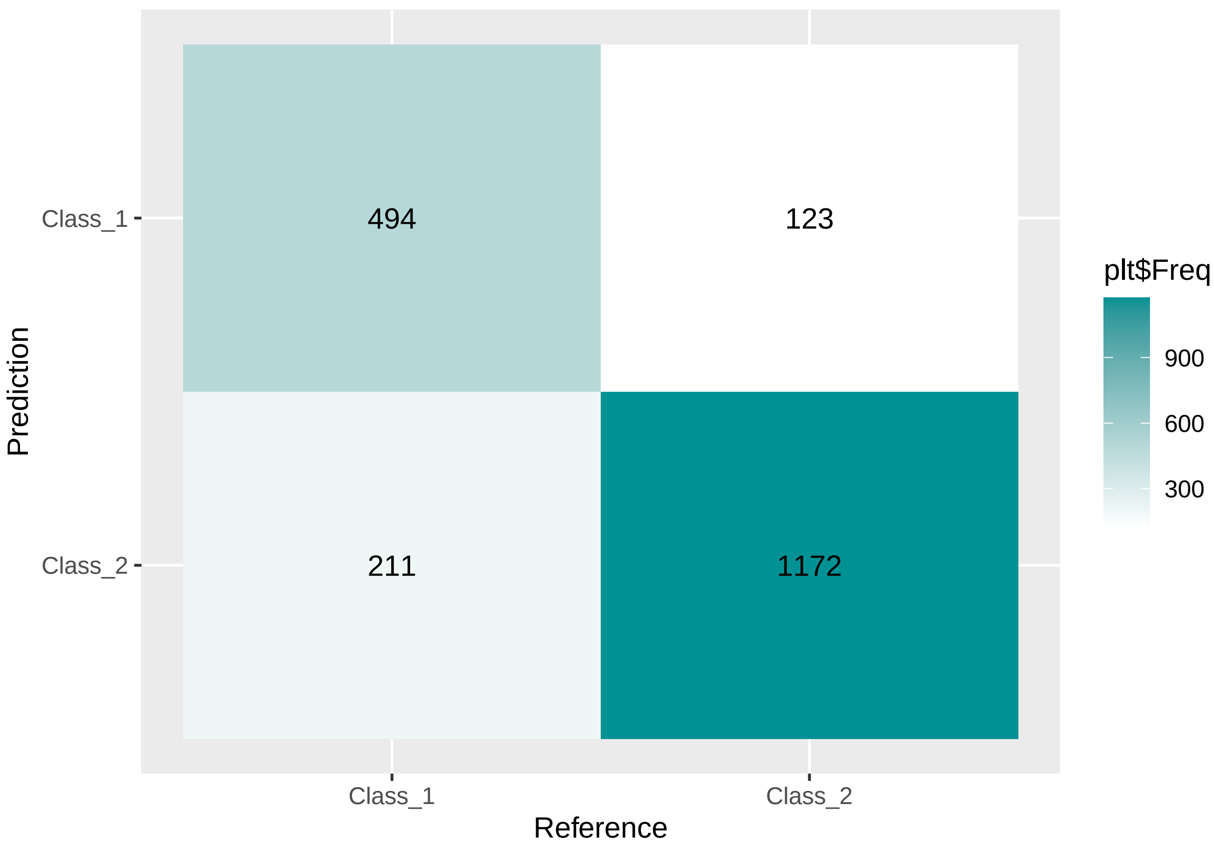

Extra Material: Decoding One-Hot-Encoding

```
col_list <- names(insurance_test)

cols_list_enc <- grep("\\.", col_list, value = TRUE, perl = TRUE)



pattern <- "([a-zA-Z0-9_-]*)(.)"
common_names <- list()
for (col in cols_list_enc)
{
  common_names <- append(common_names, str_match(col, pattern)[2])
}
common_names <- common_names |> unique()

insurance_test_revert <-
insurance_test[, !(colnames(insurance_test) %in% cols_list_enc)]

for (name in common_names){
  cols_revert <- lapply(cols_list_enc,
                      function(x) x[grepl(name, x)])
  cols_revert <- cols_revert[lengths(cols_revert)!=0]
  #cols_revert <- lapply(cols_list_enc,
  #                      function(x) str_match(x,"([\\.])(.*)")[3])

  cols_revert <- cols_revert |> unlist()


  w <- which(insurance_test[cols_revert]==1, arr.ind = T)

  insurance_test_revert_name <- names(insurance_test[cols_revert])[w[order(w[,1]),2]]

  insurance_test_revert[name] <- insurance_test_revert_name

}
```

```
insurance_test[,0:4] |> tidyr::pivot_longer(col=starts_with("age"), names_to = "age",  names_prefix="age
```

```
## # A tibble: 8,000 x 1
##    age
##    <chr>
##  1 16.25
##  2 26.39
##  3 40.64
##  4 65.
##  5 16.25
##  6 26.39
##  7 40.64
##  8 65.
##  9 16.25
## 10 26.39
```

```
## # ... with 7,990 more rows
```

```
insurance_test_revert |> dplyr::glimpse()
```

```
## Rows: 2,000
## Columns: 18
## $ credit_score        <dbl> 0.6234644, 0.6248241, 0.7454570, 0.6432089, 0.7817~
## $ vehicle_ownership   <int> 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 0, 1, 0, 1, 0, 1,~
## $ married             <int> 0, 1, 1, 1, 1, 1, 1, 0, 0, 1, 0, 0, 1, 0, 1, 0, 1,~
## $ children            <int> 1, 1, 0, 1, 0, 1, 0, 1, 0, 1, 1, 1, 1, 0, 1, 0, 1,~
## $ postal_code         <dbl> 0.0000000, 0.0000000, 0.2751793, 0.0000000, 0.0000~
## $ annual_mileage      <dbl> 0.55, 0.40, 0.50, 0.30, 0.50, 0.50, 0.50, 0.80, 0.~
## $ speeding_violations <dbl> 0.13636364, 0.27272727, 0.18181818, 0.18181818, 0.~
## $ duis                <dbl> 0.0000000, 0.3333333, 0.0000000, 0.1666667, 0.0000~
## $ past_accidents      <dbl> 0.20000000, 0.46666667, 0.00000000, 0.13333333, 0.~
## $ outcome             <int> 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 1, 1,~
## $ age                 <chr> "age.40.64", "age.65.", "age.65.", "age.40.64", "a~
## $ gender              <chr> "gender.female", "gender.male", "gender.female", "~
## $ race                <chr> "race.majority", "race.majority", "race.majority",~
## $ driving_experience  <chr> "driving_experience.20.29y", "driving_experience.3~
## $ education           <chr> "education.high.school", "education.high.school", ~
## $ income              <chr> "income.upper.class", "income.upper.class", "incom~
## $ vehicle_year        <chr> "vehicle_year.after.2015", "vehicle_year.after.201~
## $ vehicle_type        <chr> "vehicle_type.sedan", "vehicle_type.sedan", "vehic~
```