

Can I Borrow Some Money?

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June 5, 2018

Introduction

There is a dataset from an expired Kaggle competition where it requires participants to improve on the state of the art in credit scoring, by predicting the probability that somebody will experience financial distress in the next two years.

Banks play a crucial role in market economies. They decide who can get finance and on what terms and can make or break investment decisions. For markets and society to function, individuals and companies need access to credit. Credit scoring algorithms, which make a guess at the probability of default, are the method banks use to determine whether or not a loan should be granted. The goal of this competition is to build a model that borrowers can use to help make the best financial decisions.

Data Preparation

First, we begin reading in the dataset. Then we need to look at the structure of our data to view the data types before performing exploratory analysis. The five number summary gives us an idea of the value range of the predictor variables and identifying the target variable or dependent variable.

```
credit = read.csv("cs-train.csv", header = TRUE) # reading in the dataset
str(credit) # View the structure of the data to see the data types
```

```
## 'data.frame': 150000 obs. of 12 variables:
## $ X : int 1 2 3 4 5 6 7 8 9 10 ...
## $ SeriousDlqin2yrs : int 1 0 0 0 0 0 0 0 0 0 ...
## $ RevolvingUtilizationOfUnsecuredLines: num 0.766 0.957 0.658 0.234 0.907 ...
## $ age : int 45 40 38 30 49 74 57 39 27 57 ...
## $ NumberOfTime30.59DaysPastDueNotWorse: int 2 0 1 0 1 0 0 0 0 0 ...
## $ DebtRatio : num 0.803 0.1219 0.0851 0.036 0.0249 ...
## $ MonthlyIncome : int 9120 2600 3042 3300 63588 3500 NA 3500 NA 23684 ...
## $ NumberOfOpenCreditLinesAndLoans : int 13 4 2 5 7 3 8 8 2 9 ...
## $ NumberOfTimes90DaysLate : int 0 0 1 0 0 0 0 0 0 0 ...
## $ NumberRealEstateLoansOrLines : int 6 0 0 0 1 1 3 0 0 4 ...
## $ NumberOfTime60.89DaysPastDueNotWorse: int 0 0 0 0 0 0 0 0 0 0 ...
## $ NumberOfDependents : int 2 1 0 0 0 1 0 0 NA 2 ...
```

```
summary(credit) # five number summary
```

```
##           X           SeriousDlqin2yrs  RevolvingUtilizationOfUnsecuredLines
## Min.      :    1      Min.      :0.00000      Min.      :    0.00
## 1st Qu.: 37501      1st Qu.:0.00000      1st Qu.:    0.03
## Median : 75001      Median :0.00000      Median :    0.15
## Mean   : 75001      Mean   :0.06684      Mean   :    6.05
## 3rd Qu.:112500      3rd Qu.:0.00000      3rd Qu.:    0.56
## Max.    :150000      Max.    :1.00000      Max.    :50708.00
##
##           age           NumberOfTime30.59DaysPastDueNotWorse      DebtRatio
## Min.      :    0.0      Min.      : 0.000      Min.      :    0.0
## 1st Qu.: 41.0      1st Qu.: 0.000      1st Qu.:    0.2
```

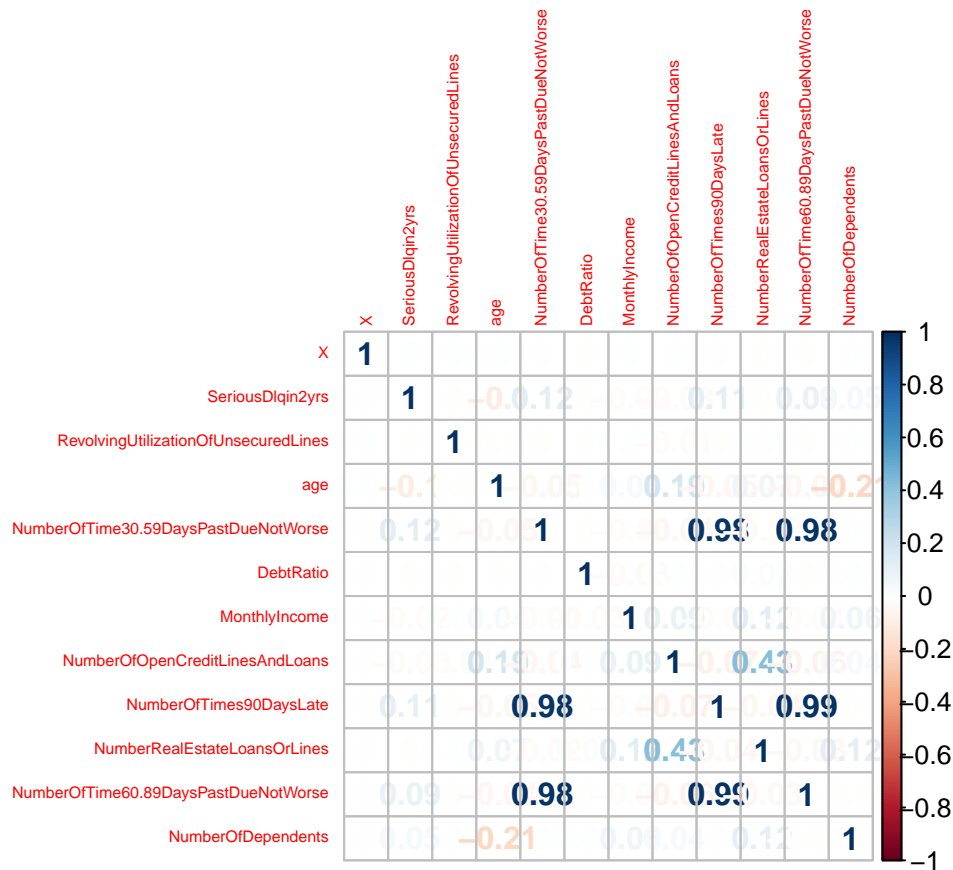
```
## Median : 52.0   Median : 0.000   Median : 0.4
## Mean   : 52.3   Mean   : 0.421   Mean   : 353.0
## 3rd Qu.: 63.0   3rd Qu.: 0.000   3rd Qu.: 0.9
## Max.   :109.0   Max.   :98.000   Max.   :329664.0
##
## MonthlyIncome   NumberOfOpenCreditLinesAndLoans   NumberOfTimes90DaysLate
## Min.   : 0   Min.   : 0.000   Min.   : 0.000
## 1st Qu.: 3400   1st Qu.: 5.000   1st Qu.: 0.000
## Median : 5400   Median : 8.000   Median : 0.000
## Mean   : 6670   Mean   : 8.453   Mean   : 0.266
## 3rd Qu.: 8249   3rd Qu.:11.000   3rd Qu.: 0.000
## Max.   :3008750   Max.   :58.000   Max.   :98.000
## NA's   :29731
## NumberRealEstateLoansOrLines   NumberOfTime60.89DaysPastDueNotWorse
## Min.   : 0.000   Min.   : 0.0000
## 1st Qu.: 0.000   1st Qu.: 0.0000
## Median : 1.000   Median : 0.0000
## Mean   : 1.018   Mean   : 0.2404
## 3rd Qu.: 2.000   3rd Qu.: 0.0000
## Max.   :54.000   Max.   :98.0000
##
## NumberOfDependents
## Min.   : 0.000
## 1st Qu.: 0.000
## Median : 0.000
## Mean   : 0.757
## 3rd Qu.: 1.000
## Max.   :20.000
## NA's   :3924
```

Here we look at the correlation matrix to measure the correlations between the predictors and the outcome variable. Noticed, there are cases of multi-collinearity between the NumberOfTime30.59DaysPastDueNotWorse, NumberOfTime60.89DaysPastDueNotWorse, and NumberOfTime60.89DaysPastDueNotWorse. This means we would have to drop two predictors and leave only one. Moreover, multicollinearity makes it tedious to assess the relative importance of the independent variables in explaining the variation caused by the dependent variable. Since they are closer to 1 on a scale to -1 to 1, we would keep the NumberOfTime30.59DaysPastDueNotWorse to avoid increases the standard errors of the coefficients.

```
library(corrplot)
```

```
## corrplot 0.84 loaded
```

```
credit_miss <- na.omit(credit) # temporarily remove NA's before correlation plot
corrplot(cor(credit_miss), method = "number", tl.cex = 0.5) # correlation matrix
```



```
credit_miss$SeriousDlqin2yrs[credit_miss$SeriousDlqin2yrs == 0] <- "No"
credit_miss$SeriousDlqin2yrs[credit_miss$SeriousDlqin2yrs == 1] <- "Yes"
credit_miss$SeriousDlqin2yrs <- as.factor(credit_miss$SeriousDlqin2yrs) #change the outcome variable to
```

We observed there are many missing values in the data and will deal those later. Next, we combined the three defaulted fields and removed two out of the three multi-collinearity predictor variables.

```
sum(is.na(credit_miss)) # count the number of NA's in the data

## [1] 0

credit_sub <- subset(credit_miss, select = -c(NumberOfTimes90DaysLate,NumberOfTime60.89DaysPastDueNotWor
str(credit_sub) # view to make sure both fields are removed

## 'data.frame': 120269 obs. of 10 variables:
## $ X : int 1 2 3 4 5 6 8 10 11 12 ...
## $ SeriousDlqin2yrs : Factor w/ 2 levels "No","Yes": 2 1 1 1 1 1 1 1 1 1 ...
## $ RevolvingUtilizationOfUnsecuredLines: num 0.766 0.957 0.658 0.234 0.907 ...
## $ age : int 45 40 38 30 49 74 39 57 30 51 ...
## $ NumberOfTime30.59DaysPastDueNotWorse: int 2 0 1 0 1 0 0 0 0 0 ...
## $ DebtRatio : num 0.803 0.1219 0.0851 0.036 0.0249 ...
## $ MonthlyIncome : int 9120 2600 3042 3300 63588 3500 3500 23684 2500 6501 ...
## $ NumberOfOpenCreditLinesAndLoans : int 13 4 2 5 7 3 8 9 5 7 ...
## $ NumberRealEstateLoansOrLines : int 6 0 0 0 1 1 0 4 0 2 ...
## $ NumberOfDependents : int 2 1 0 0 0 1 0 2 0 2 ...
```

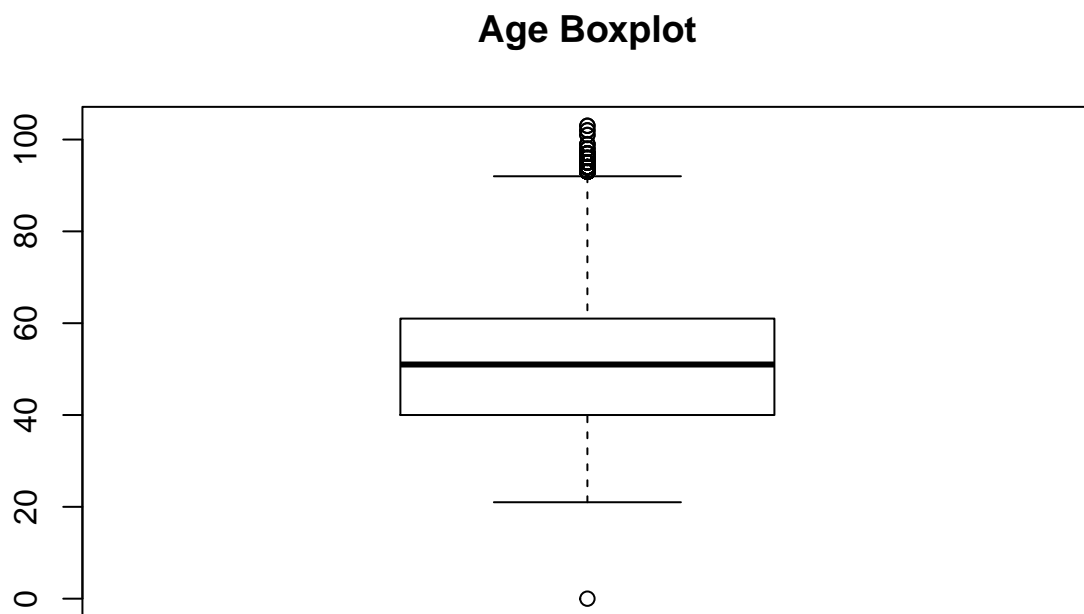
Data Cleaning/Exploratory Data Analysis

First, we noticed `RevolvingUtilizationOfUnsecuredLines` field had some individuals with higher credit utilization greater than 100 percent. These are cases we will need to remove because no one can go over their max usage of credit. So we will replace those values greater than 100 percent with NA's.

In the boxplot for Age, there are several outliers in the upper whisker and one in the lower whisker that needs to be removed. So we will replace those outliers with NA's as well.

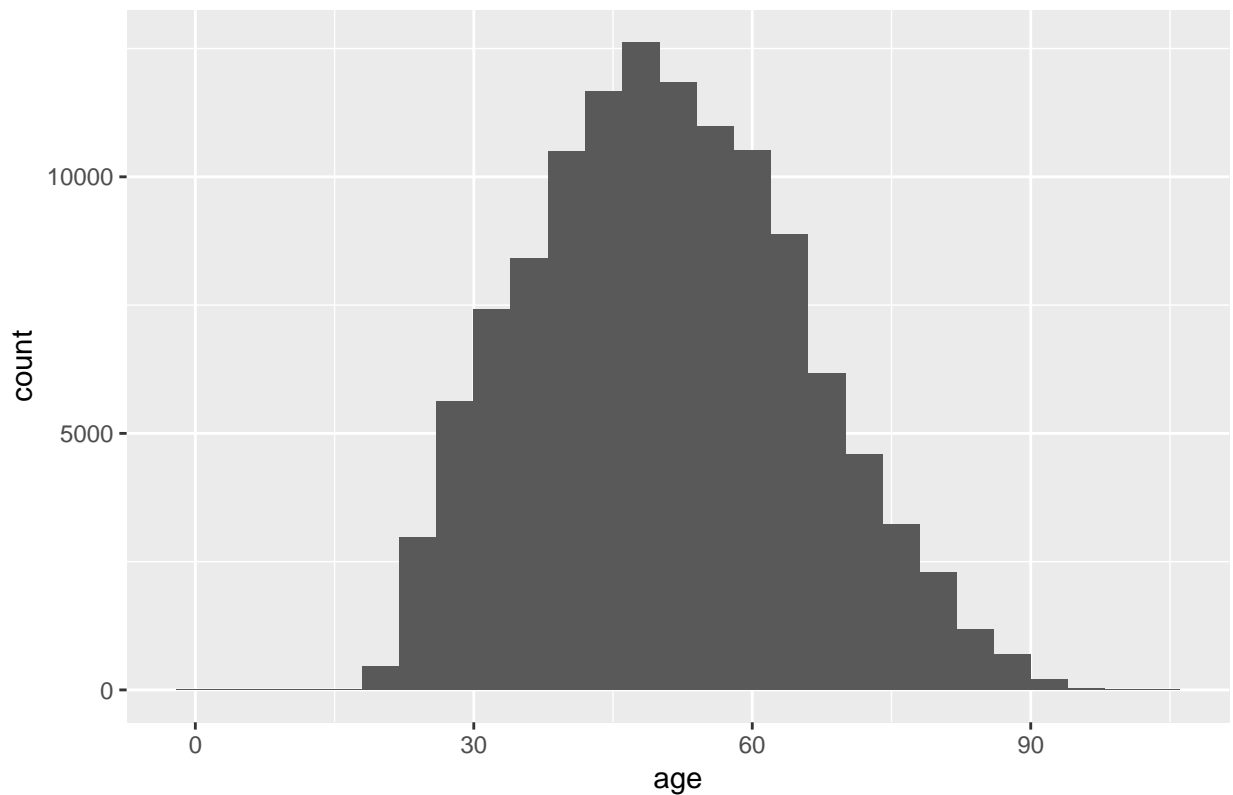
In the histogram, the skewness of Age, looks normally distributed.

```
library(ggplot2)
credit_sub$RevolvingUtilizationOfUnsecuredLines[credit_sub$RevolvingUtilizationOfUnsecuredLines > 1] <- NA
boxplot(credit_sub$age, main = "Age Boxplot")
```



```
ggplot(credit_sub, aes(age)) + geom_histogram(binwidth = 4) + labs(title="Age Histogram")
```

Age Histogram



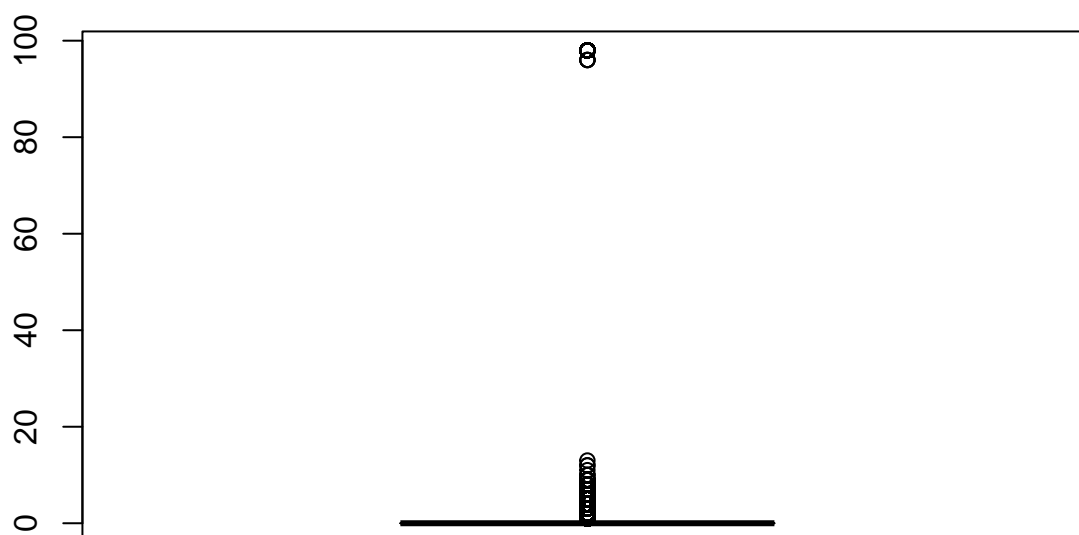
```
credit_sub$age[credit_sub$age < 21] <- NA
credit_sub$age[credit_sub$age > 90] <- NA
```

In the boxplot of `NumberOfTime30.59DaysPastDueNotWorse`, it's really difficult to find if there are cases of outliers, other than the two in the upper extreme, since there are no quartile boxes or whiskers to interpret. So, we will plot a histogram to see if we can get a better look at possible outliers. Noticed, the observations on the histogram displays values only less than approximately to 10. We can assume these values are outliers and replace them with NA.

The `DebtRatio` field had some individuals with credit usage greater than 100 percent. These are cases we will need to remove since no one can borrow money than their max credit given to them. So we will replace those values greater than 100 percent with NA's.

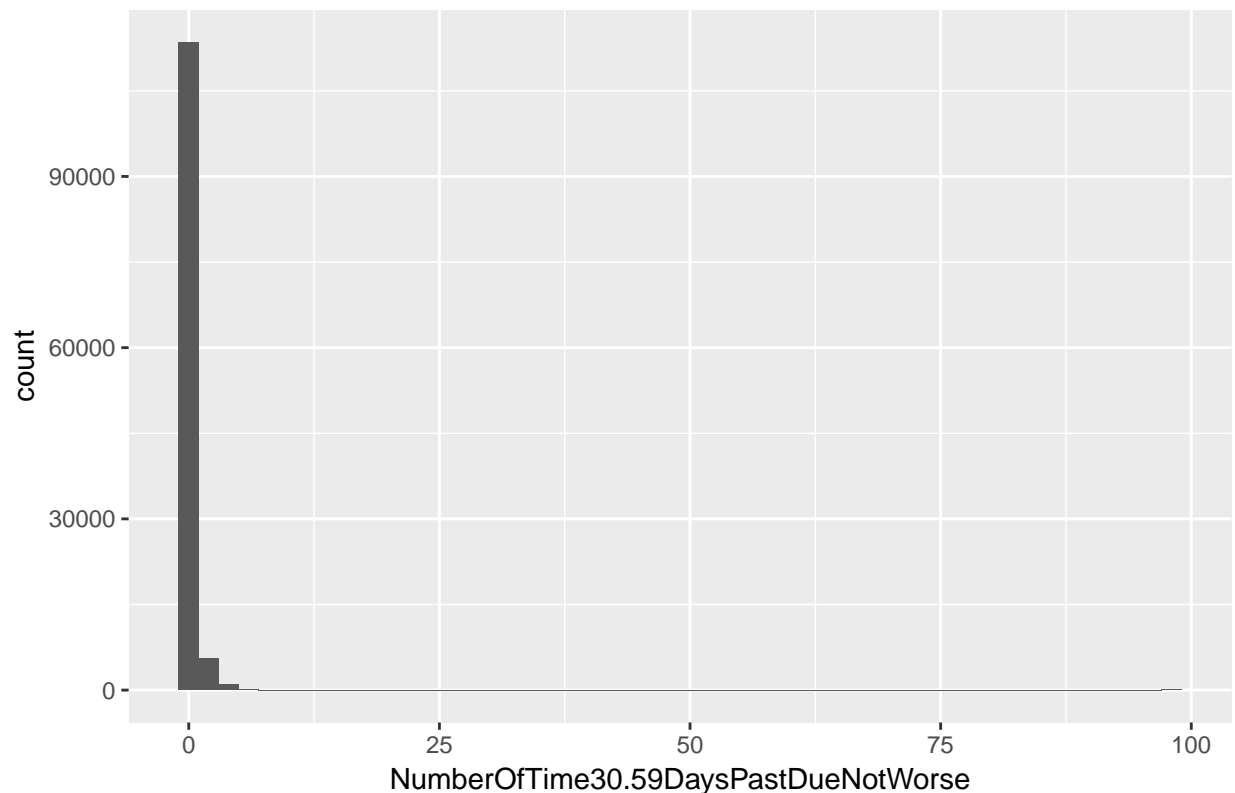
```
boxplot(credit_sub$NumberOfTime30.59DaysPastDueNotWorse, main = "Number Of Times 30 - 59 Days Past Due")
```

Number Of Times 30 – 59 Days Past Due Not Worse Boxplot



```
ggplot(credit_sub, aes(NumberOfTime30.59DaysPastDueNotWorse)) + geom_histogram(binwidth = 2) + labs(tit
```

Number Of Time 30 – 59 Days Past Due Not Worse



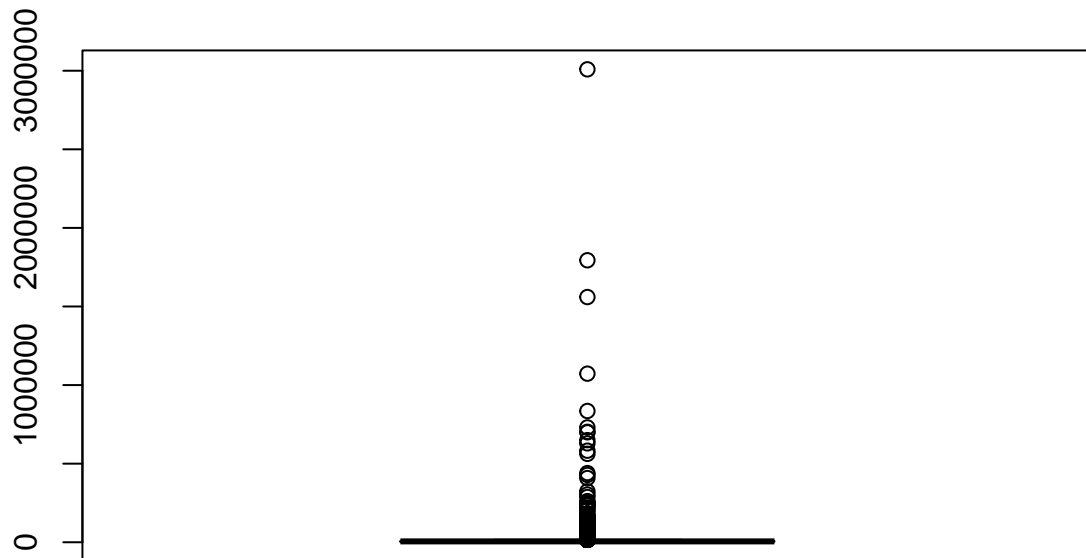
```
credit_sub$NumberOfTime30.59DaysPastDueNotWorse[credit_sub$NumberOfTime30.59DaysPastDueNotWorse > 10]
credit_sub$DebtRatio[credit_sub$DebtRatio > 1] <- NA
```

In the boxplot of `MonthlyIncome`, it's really difficult to find if there are cases of outliers, other than the one in the upper extreme, since there are no quartile boxes or whiskers to interpret. So, we will plot a histogram to see if we can get a better look of possible outliers. Noticed, the spread of the data is very skewed to the right and does not take shape of a normal distribution. Moreover, we are going to replace the `Monthly Income` greater 14000 to NA, so we can reduce inaccurate classifications errors before using several machine learning techniques later.

We plotted the `Monthly` Boxplot again to detect cases of outliers and they are no longer in our data.

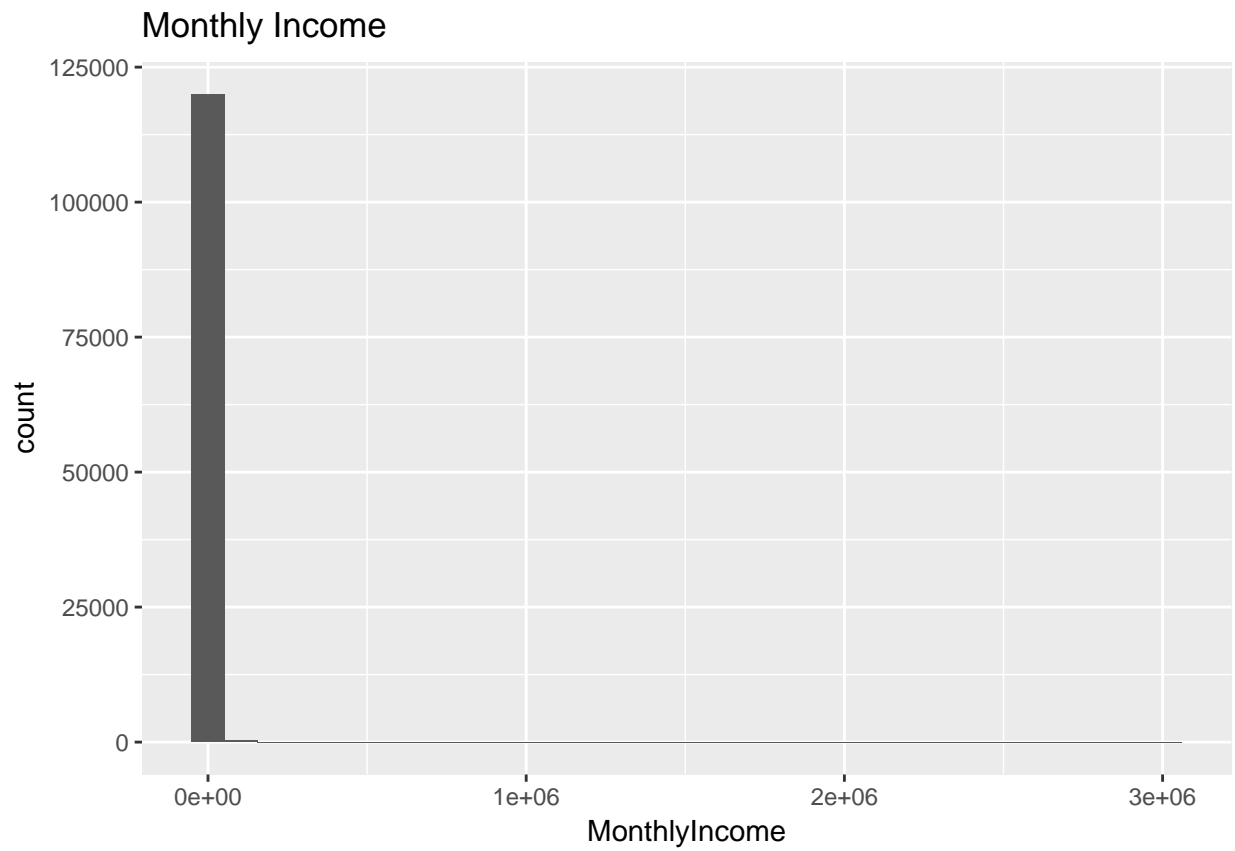
```
boxplot(credit_sub$MonthlyIncome, main = "Monthly Income Boxplot")
```

Monthly Income Boxplot



```
ggplot(credit_sub, aes(MonthlyIncome)) + geom_histogram() + labs(title="Monthly Income")
```

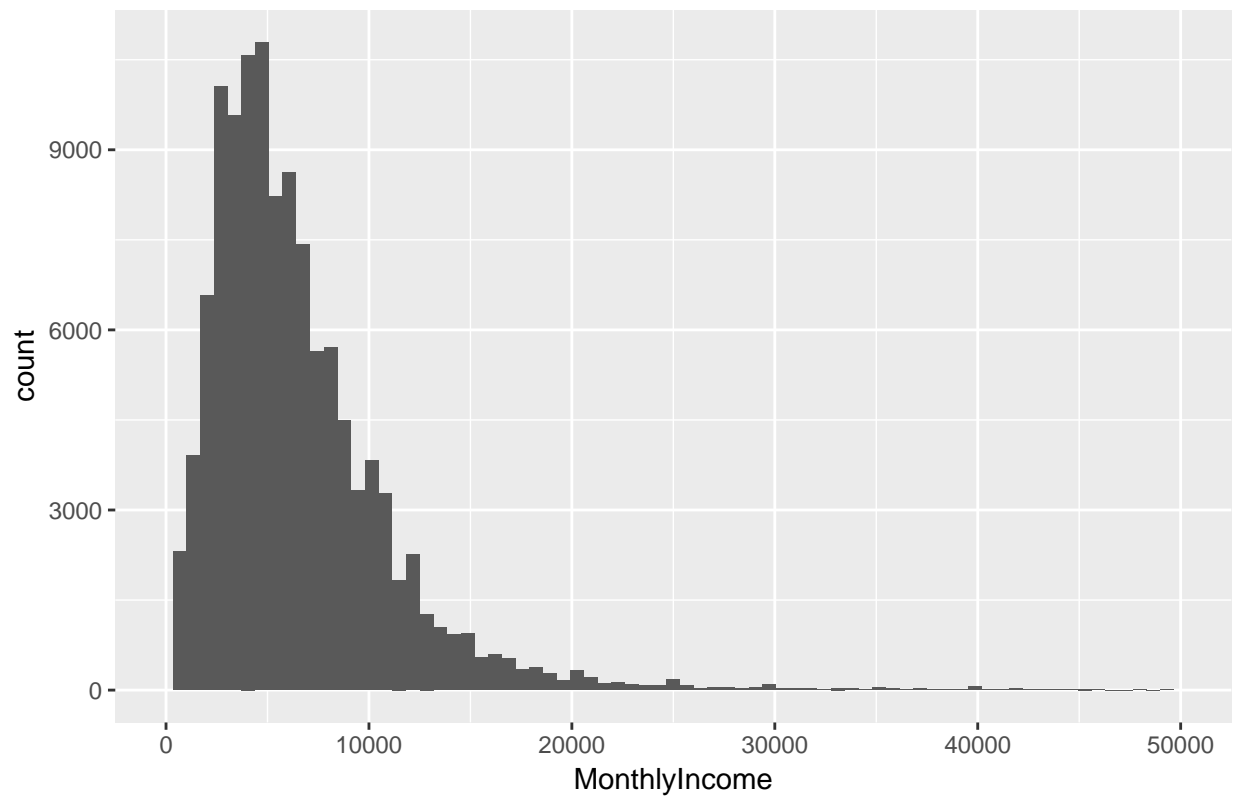
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

```
ggplot(credit_sub, aes(MonthlyIncome)) + geom_histogram(bins = 75) + labs(title="Monthly Income")+ xlim(0, 3500000)

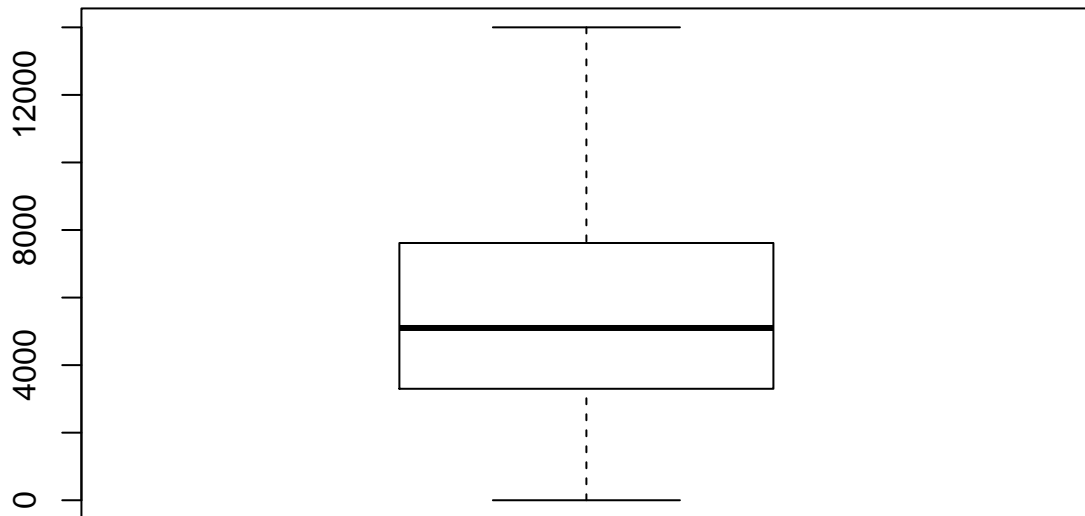
## Warning: Removed 301 rows containing non-finite values (stat_bin).
```

Monthly Income



```
credit_sub$MonthlyIncome[as.integer(credit_sub$MonthlyIncome) > 14000] <- NA  
boxplot(credit_sub$MonthlyIncome, main = "Monthly Income Boxplot")
```

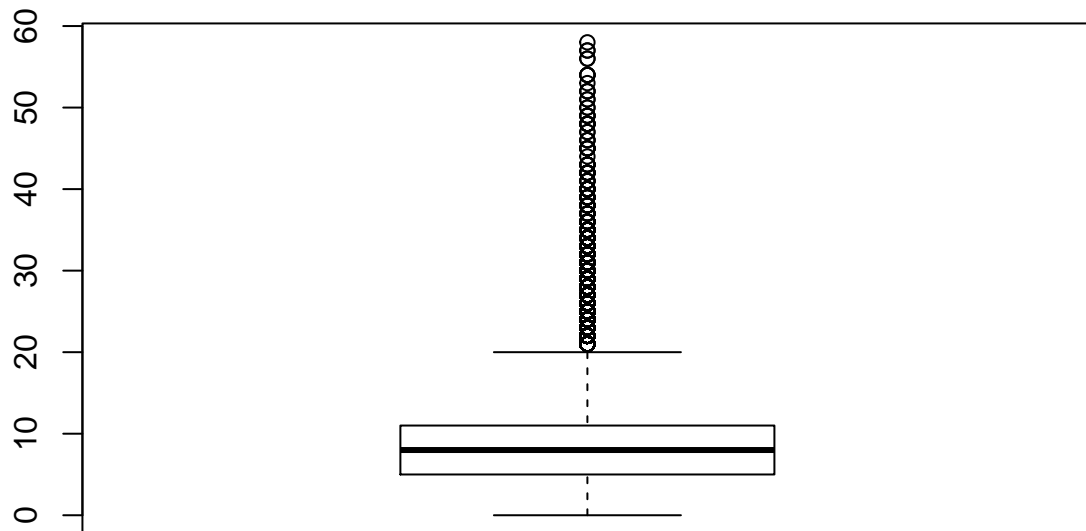
Monthly Income Boxplot



In the Number of Open Credit Lines And Loans boxplot, there are several outliers in the upper whisker and the data looks slightly skewed to the right. Let's take a look at the histogram to be sure they are outliers and data is slightly skewed to the right. The outliers in the boxplot could have caused it to not take the shape of a normal distribution, so let's remove them.

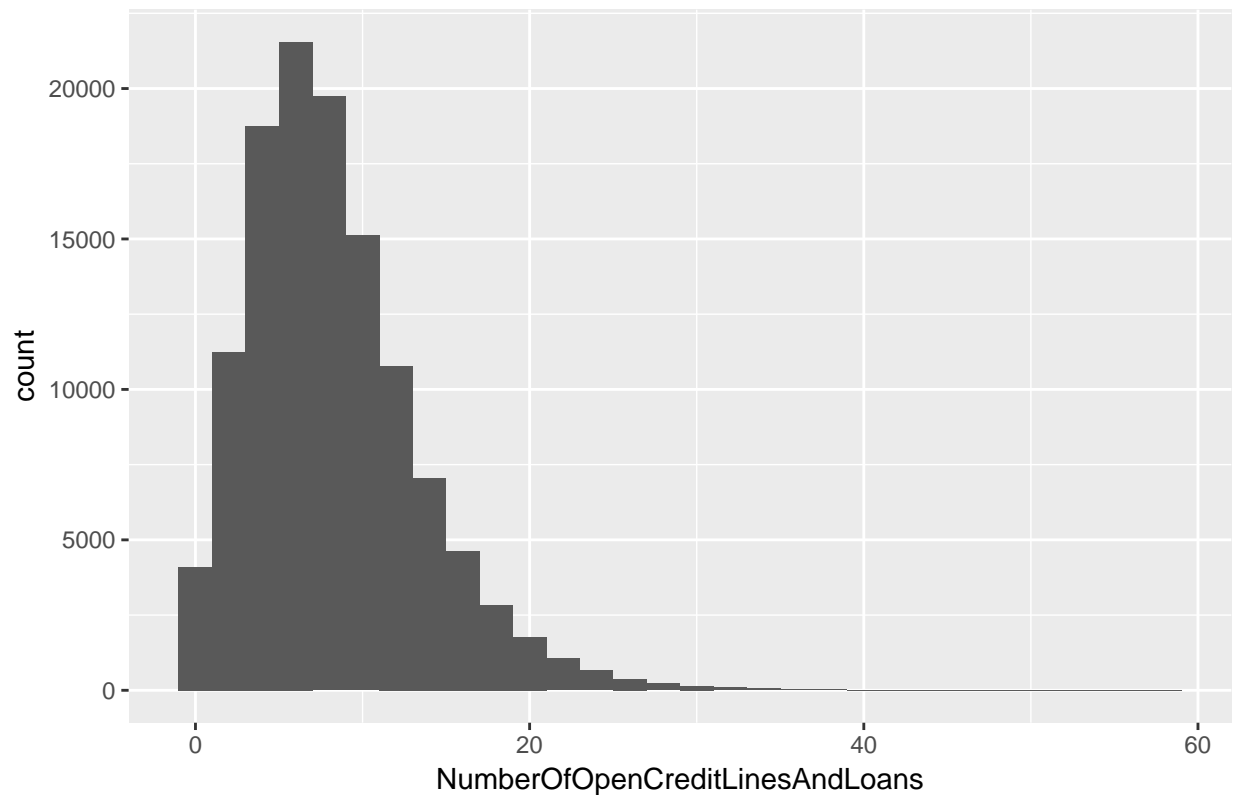
```
boxplot(credit_sub$NumberOfOpenCreditLinesAndLoans, main = "Number Of Open Credit Lines And Loans Boxplot")
```

Number Of Open Credit Lines And Loans Boxplot



```
ggplot(credit_sub, aes(NumberOfOpenCreditLinesAndLoans)) + geom_histogram(bins = 30) + labs(title="Number Of Open Credit Lines And Loans Histogram")
```

Number Of Open Credit Lines And Loans

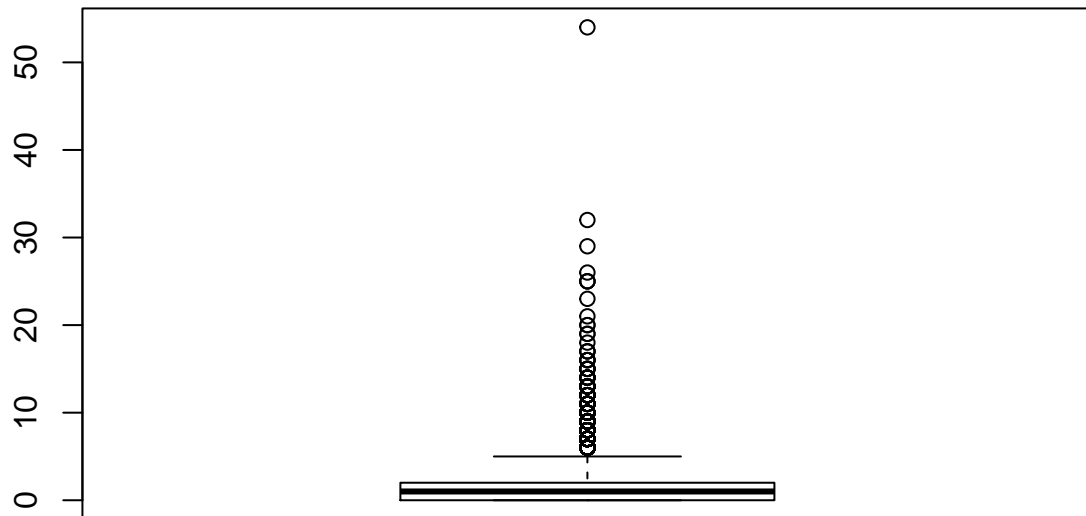


```
credit_sub$NumberOfOpenCreditLinesAndLoans[credit_sub$NumberOfOpenCreditLinesAndLoans > 20] <- NA
```

In the Number Real Estate Loans Or Lines boxplot, there are several outliers in the upper whisker and only one at the very top. Let's take a look at the histogram to be sure they are outliers. Noticed, the data is slightly skewed to the right and does not have a bell-shaped curve. Moreover, the outliers in the boxplot could have caused it to not take the shape of a normal distribution, so let's replace those values greater than 7 with NA.

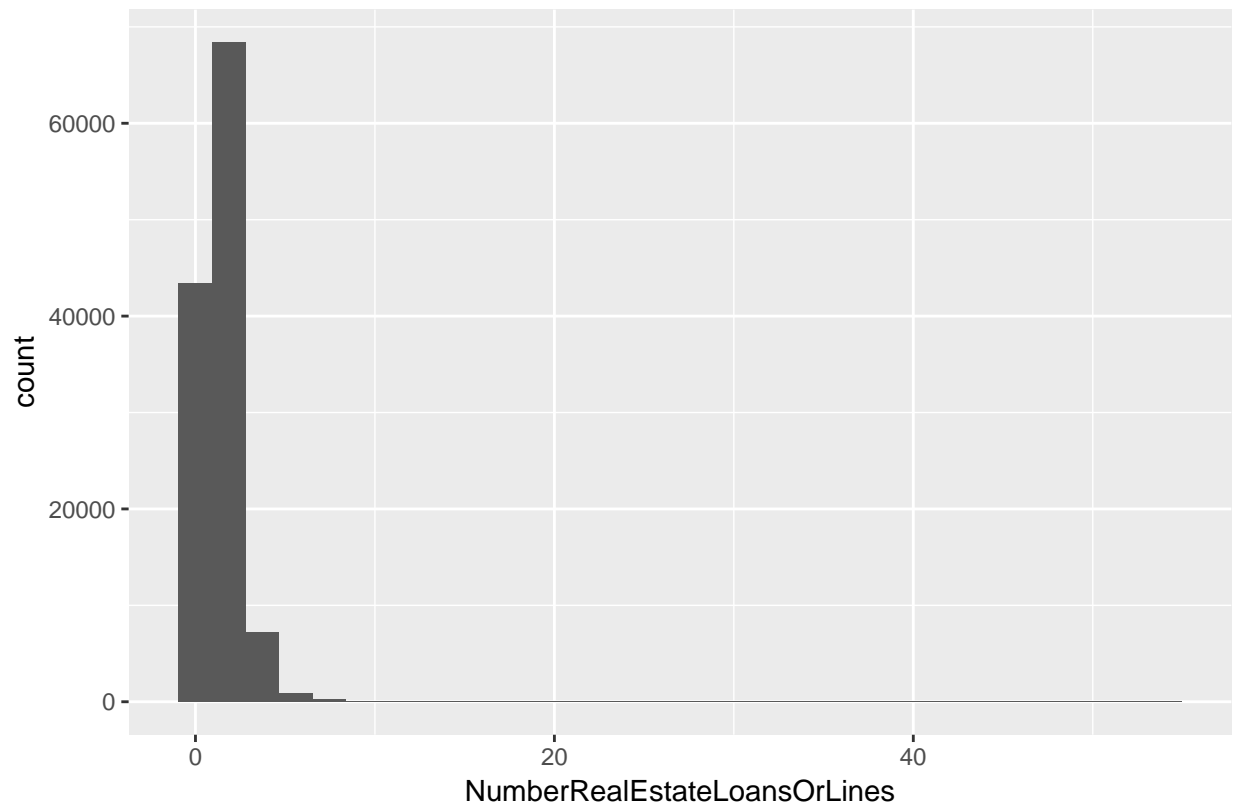
```
boxplot(credit_sub$NumberRealEstateLoansOrLines, main = "Number Real Estate Loan Or Lines Boxplot")
```

Number Real Estate Loan Or Lines Boxplot



```
ggplot(credit_sub, aes(NumberRealEstateLoansOrLines)) + geom_histogram(bins = 30) + labs(title="Number Real Estate Loan Or Lines")
```

Number Real Estate Loans Or Lines

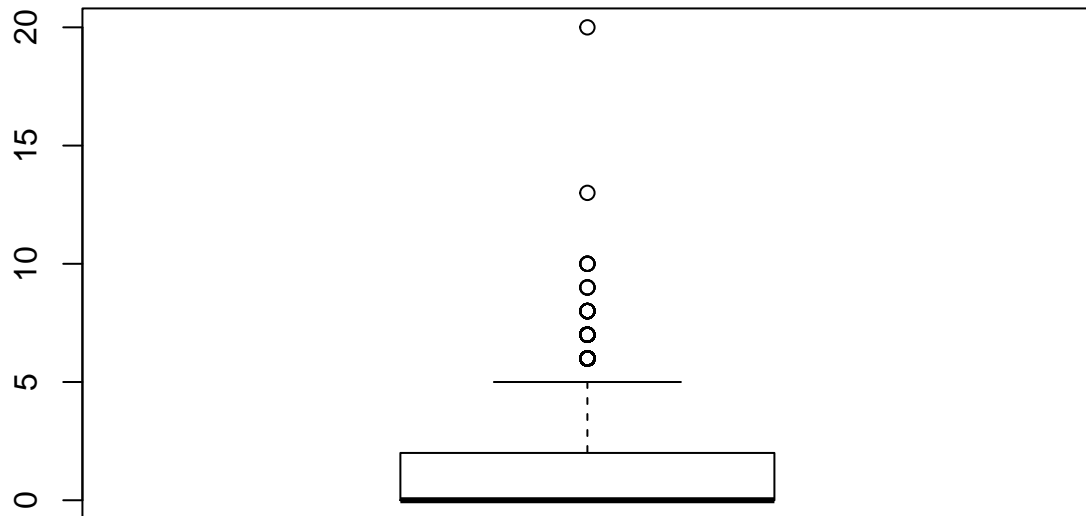


```
credit_sub$NumberRealEstateLoansOrLines[credit_sub$NumberRealEstateLoansOrLines > 7] <- NA
```

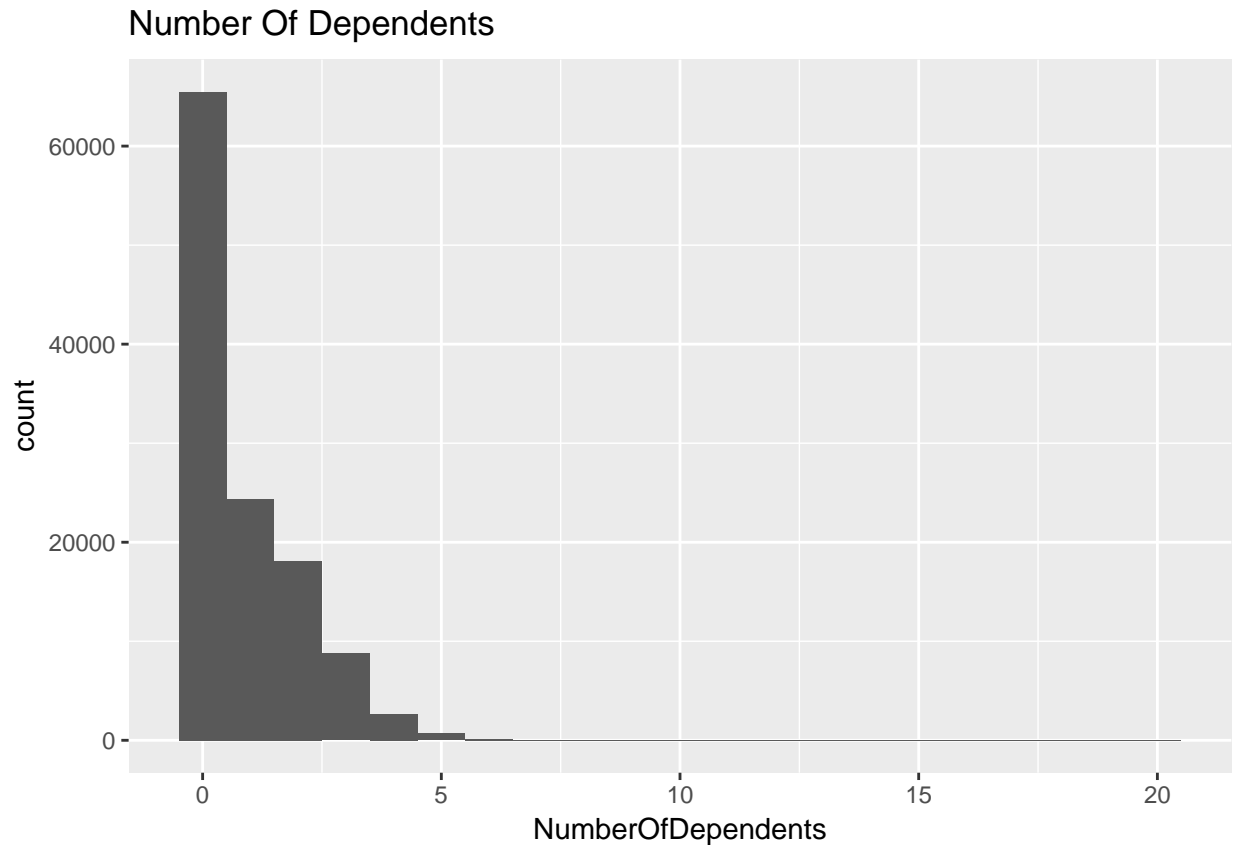
In the Number of Dependents boxplot, there are several outliers in the upper whisker. Let's take a look at the histogram to be sure they are outliers. Since it doesn't display the values greater than 5, let's assume these are outliers and replace them with NA.

```
boxplot(credit_sub$NumberOfDependents, main = "Number of Dependents")
```

Number of Dependents



```
ggplot(credit_sub, aes(NumberOfDependents)) + geom_histogram(binwidth = 1) + labs(title= "Number Of Dep
```

```
credit_sub$NumberOfDependents[credit_sub$NumberOfDependents > 5] <- NA
```

From the cleaning above, let's see how many NA's our data contain. There are quite a bit of NA's in our data, so let's remove them before performing EDA.

```
sum(is.na(credit_sub))
```

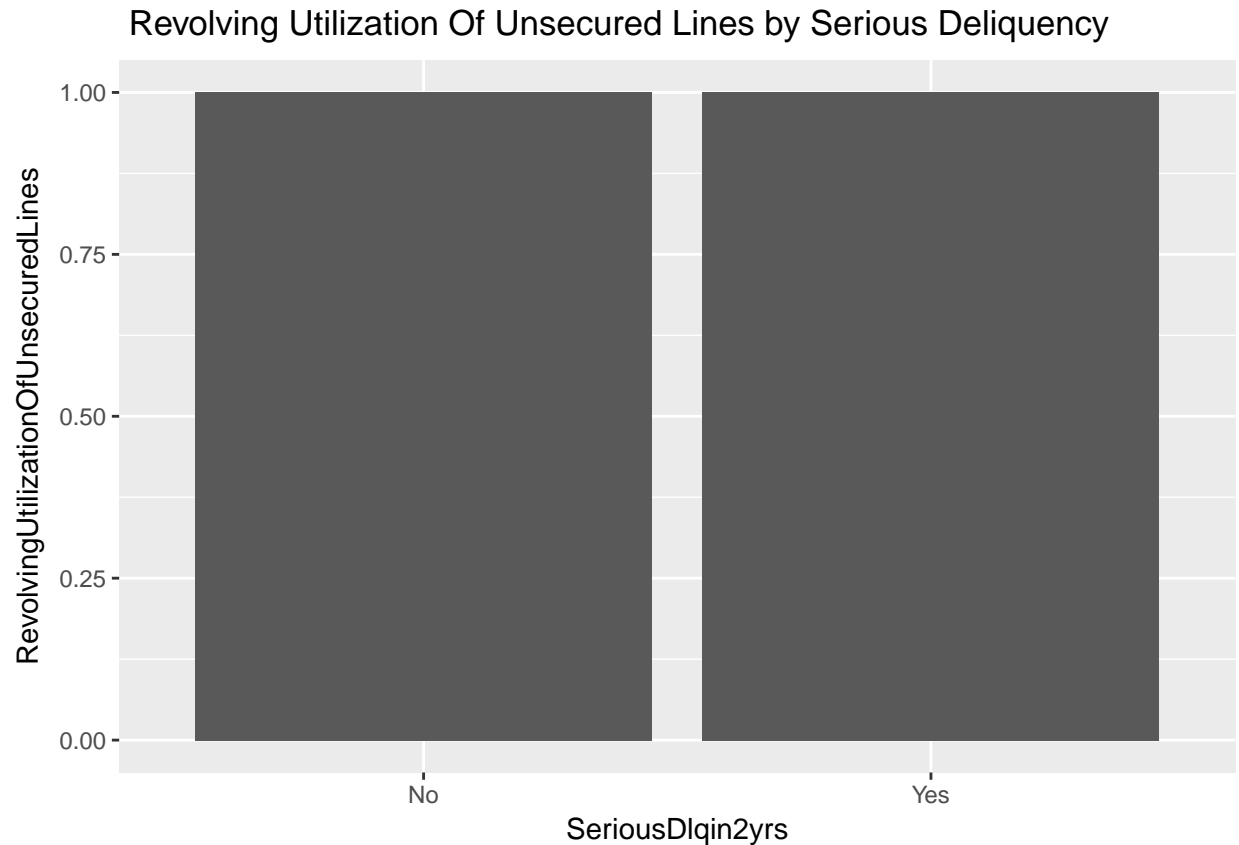
```
## [1] 21070
```

```
credit_clean <- na.omit(credit_sub)
attach(credit_clean)
```

From the barplot, there were an equivalent number of individuals who were seriously delinquent according to Revolving Utilization Of Unsecured Lines.

According to the t-test, there is a significant difference within the mean of the groups.

```
ggplot(data=credit_clean, aes(SeriousDlqin2yrs,RevolvingUtilizationOfUnsecuredLines)) +
  geom_bar(stat="identity", position=position_dodge()) + labs(title = "Revolving Utilization Of Unsecured Lines")
```



```
t.test(RevolvingUtilizationOfUnsecuredLines~SeriousDlqin2yrs, var.equal=FALSE) # testing the means of t
```

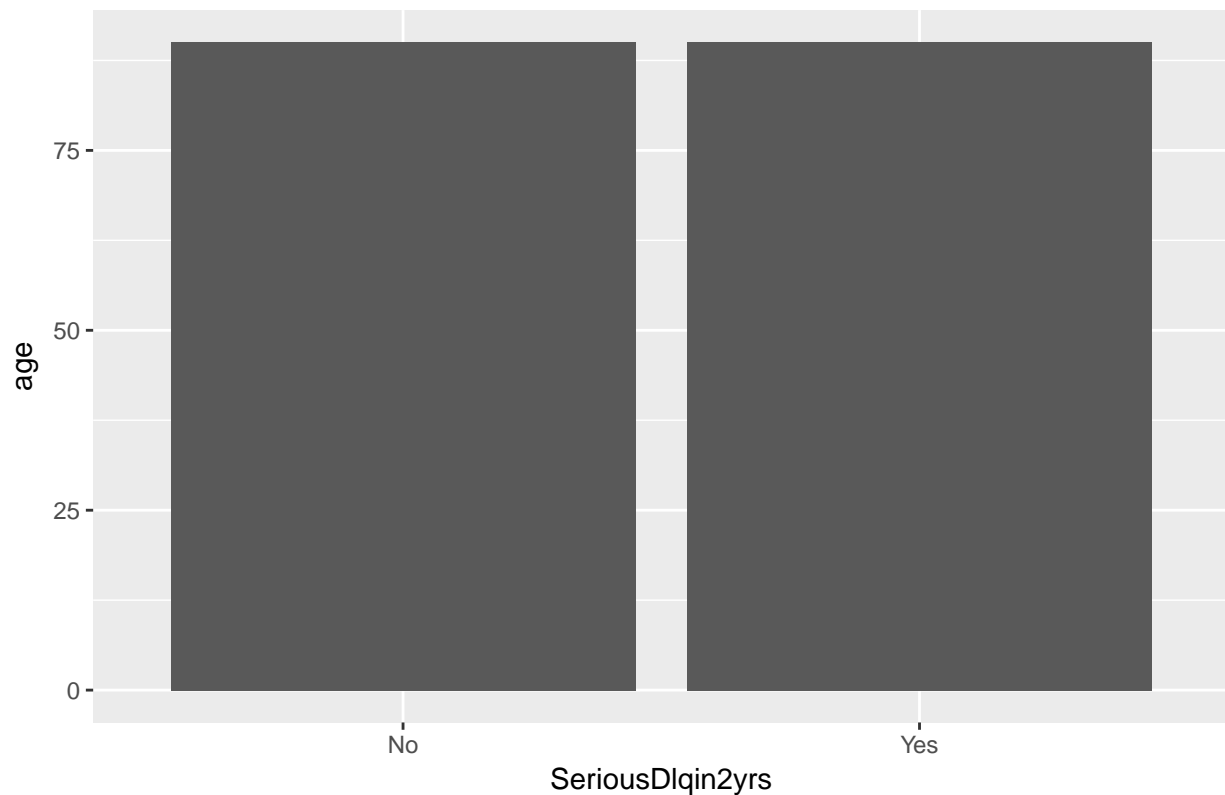
```
##
## Welch Two Sample t-test
##
## data: RevolvingUtilizationOfUnsecuredLines by SeriousDlqin2yrs
## t = -73.406, df = 6805.2, p-value < 2.2e-16
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
## -0.3493288 -0.3311565
## sample estimates:
## mean in group No mean in group Yes
## 0.2942551 0.6344977
```

From the barplot, there were an equivalent number of individuals who were seriously delinquent according to Age.

According to the t-test, there is a significant difference within the mean of the groups.

```
ggplot(credit_clean, aes(SeriousDlqin2yrs,age)) +
  geom_bar(stat="identity", position=position_dodge()) + labs(title = "Age by Serious Delinquency")
```

Age by Serious Delinquency



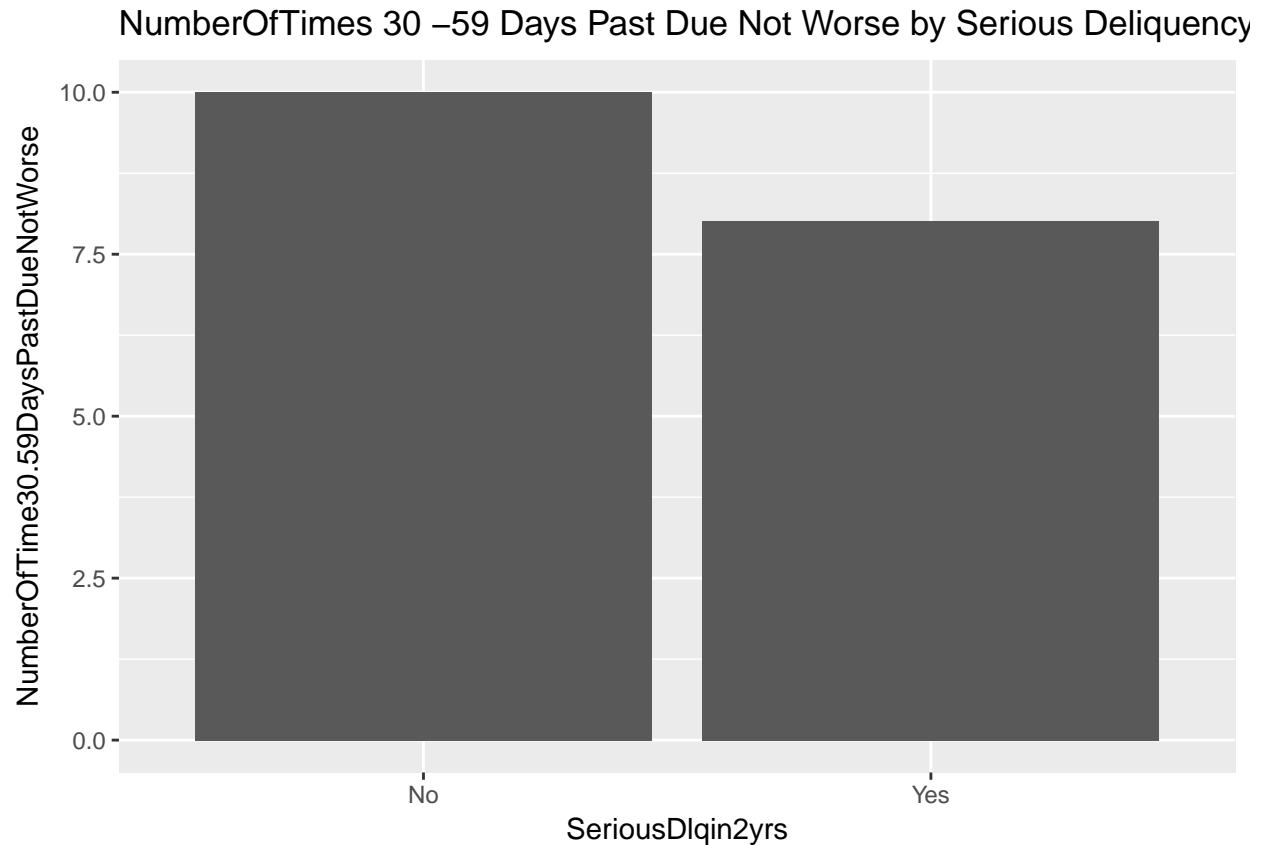
```
t.test(age~SeriousDlqin2yrs, var.equal=FALSE)
```

```
##
##  Welch Two Sample t-test
##
## data:  age by SeriousDlqin2yrs
## t = 33.805, df = 7173.7, p-value < 2.2e-16
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  5.444296 6.114582
## sample estimates:
##  mean in group No mean in group Yes
##           51.48477           45.70533
```

From the barplot, there were more number of individuals were Seriously Delinquent than were not delinquent according to NumberOfTimes 30 -59 Days Past Due Not Worse.

According to the t-test, there is a significant difference within the mean of the groups.

```
ggplot(credit_clean, aes(SeriousDlqin2yrs, NumberOfTime30.59DaysPastDueNotWorse)) +
  geom_bar(stat="identity", position=position_dodge()) + labs(title = "NumberOfTimes 30 -59 Days Past
```



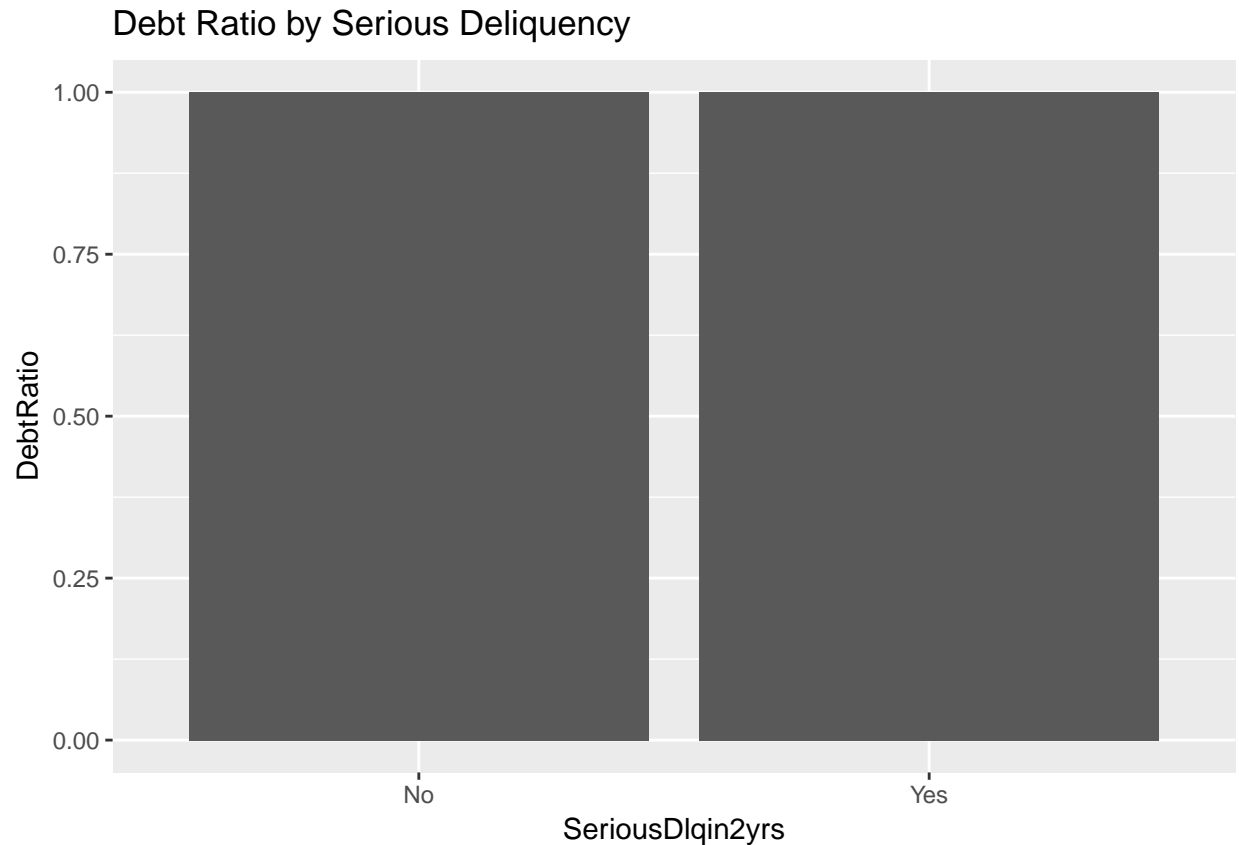
```
t.test(NumberOfTime30.59DaysPastDueNotWorse~SeriousDlqin2yrs, var.equal=FALSE)
```

```
##
## Welch Two Sample t-test
##
## data:  NumberOfTime30.59DaysPastDueNotWorse by SeriousDlqin2yrs
## t = -42.352, df = 6279, p-value < 2.2e-16
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -0.7218833 -0.6580127
## sample estimates:
##  mean in group No mean in group Yes
##      0.1940507      0.8839987
```

From the barplot, there were an equivalent number of individuals who were seriously delinquent according to Debt Ratio.

According to the t-test, there is a significant difference within the mean of the groups.

```
ggplot(credit_clean, aes(SeriousDlqin2yrs,DebtRatio)) +
  geom_bar(stat="identity", position=position_dodge()) + labs(title = "Debt Ratio by Serious Delinquency")
```



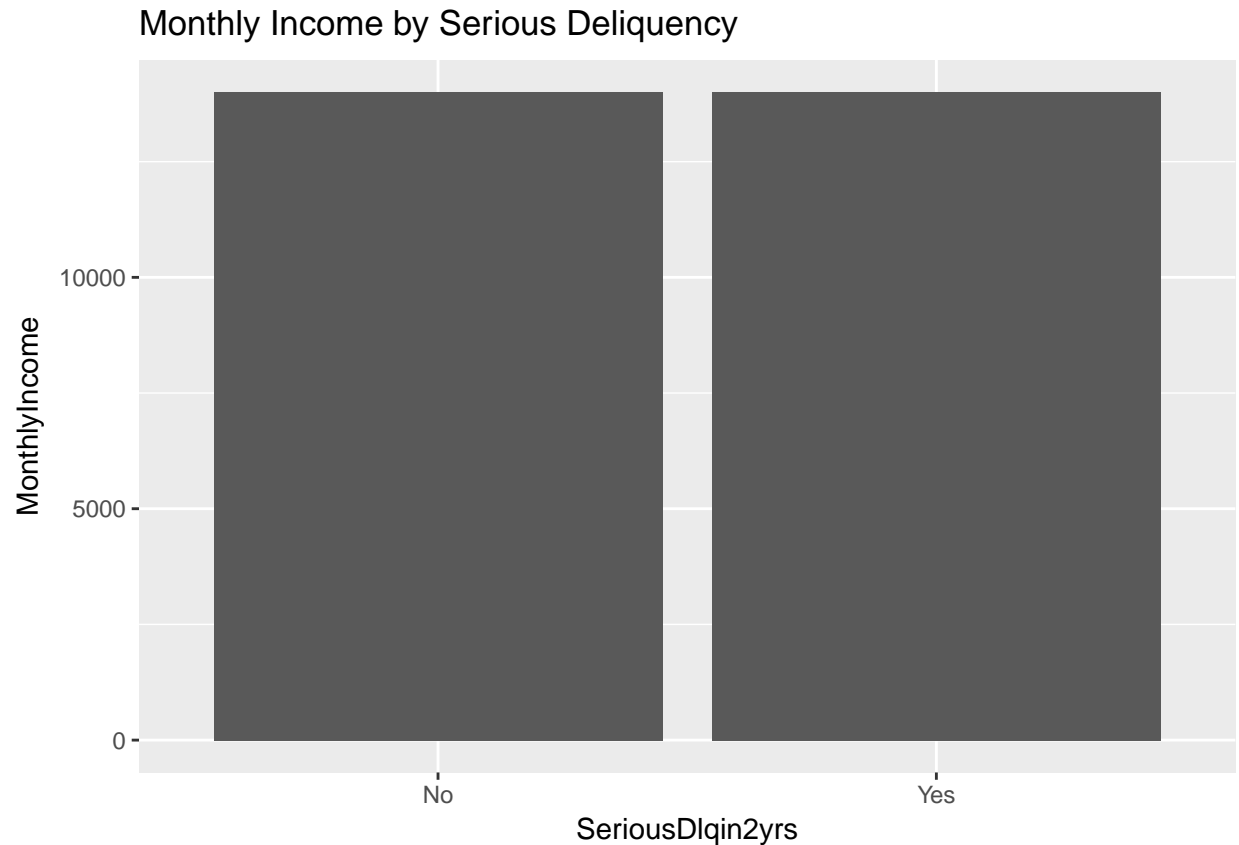
```
t.test(DebtRatio~SeriousDlqin2yrs, var.equal=FALSE)
```

```
##
## Welch Two Sample t-test
##
## data: DebtRatio by SeriousDlqin2yrs
## t = -16.357, df = 6766.1, p-value < 2.2e-16
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
## -0.05934597 -0.04664392
## sample estimates:
## mean in group No mean in group Yes
## 0.3037153 0.3567102
```

From the barplot, there were an equivalent number of individuals who were seriously delinquent according to Monthly Income.

According to the t-test, there is a significant difference within the mean of the groups.

```
ggplot(credit_clean, aes(SeriousDlqin2yrs,MonthlyIncome)) +
  geom_bar(stat="identity", position=position_dodge()) + labs(title = "Monthly Income by Serious Delinquency")
```



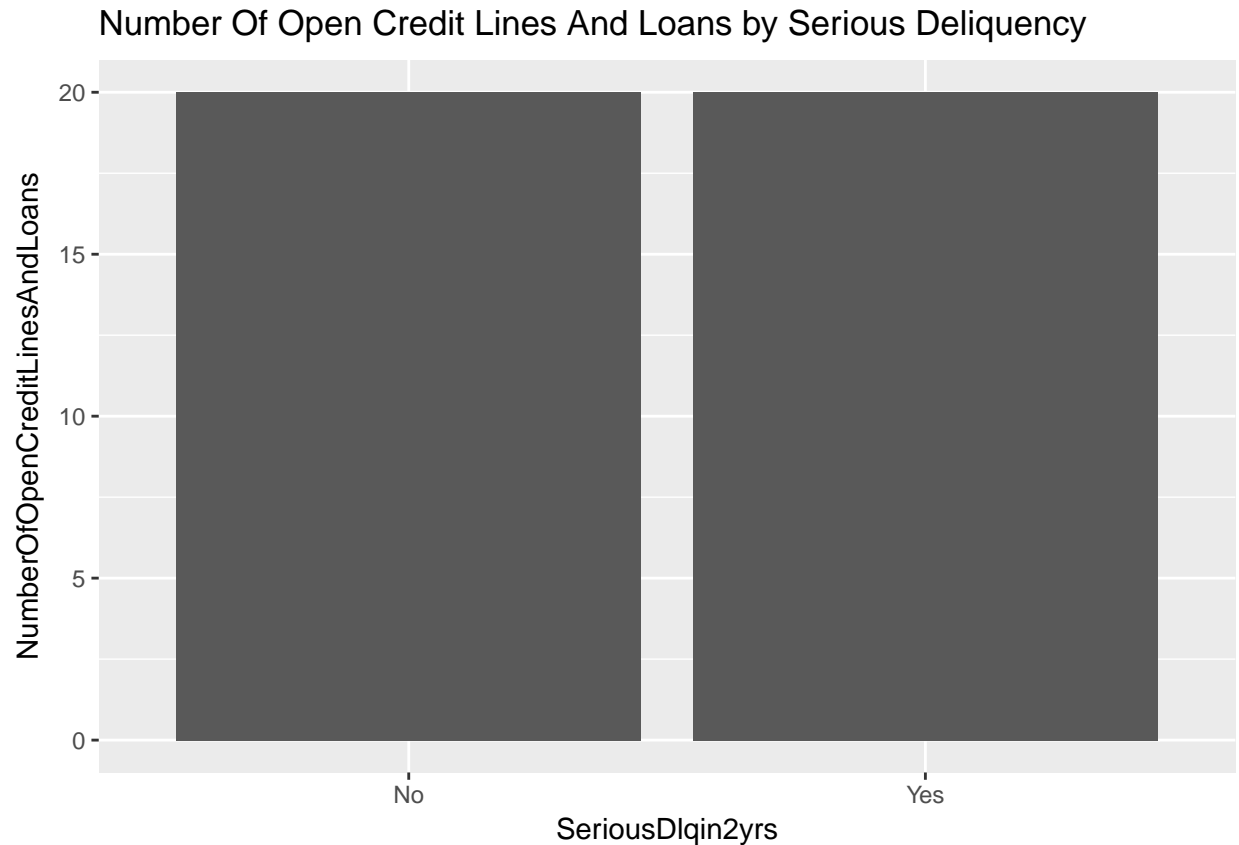
```
t.test(MonthlyIncome~SeriousDlqin2yrs, var.equal=FALSE)
```

```
##
##  Welch Two Sample t-test
##
## data:  MonthlyIncome by SeriousDlqin2yrs
## t = 20.66, df = 7083.6, p-value < 2.2e-16
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  684.1058 827.5337
## sample estimates:
##  mean in group No mean in group Yes
##      5886.675      5130.856
```

From the barplot, there were an equivalent number of individuals who were seriously delinquent according to Number Of Open Credit Lines And Loans.

According to the t-test, there is a significant difference within the mean of the groups.

```
ggplot(credit_clean, aes(SeriousDlqin2yrs,NumberOfOpenCreditLinesAndLoans)) +
  geom_bar(stat="identity", position=position_dodge()) + labs(title = "Number Of Open Credit Lines And
```



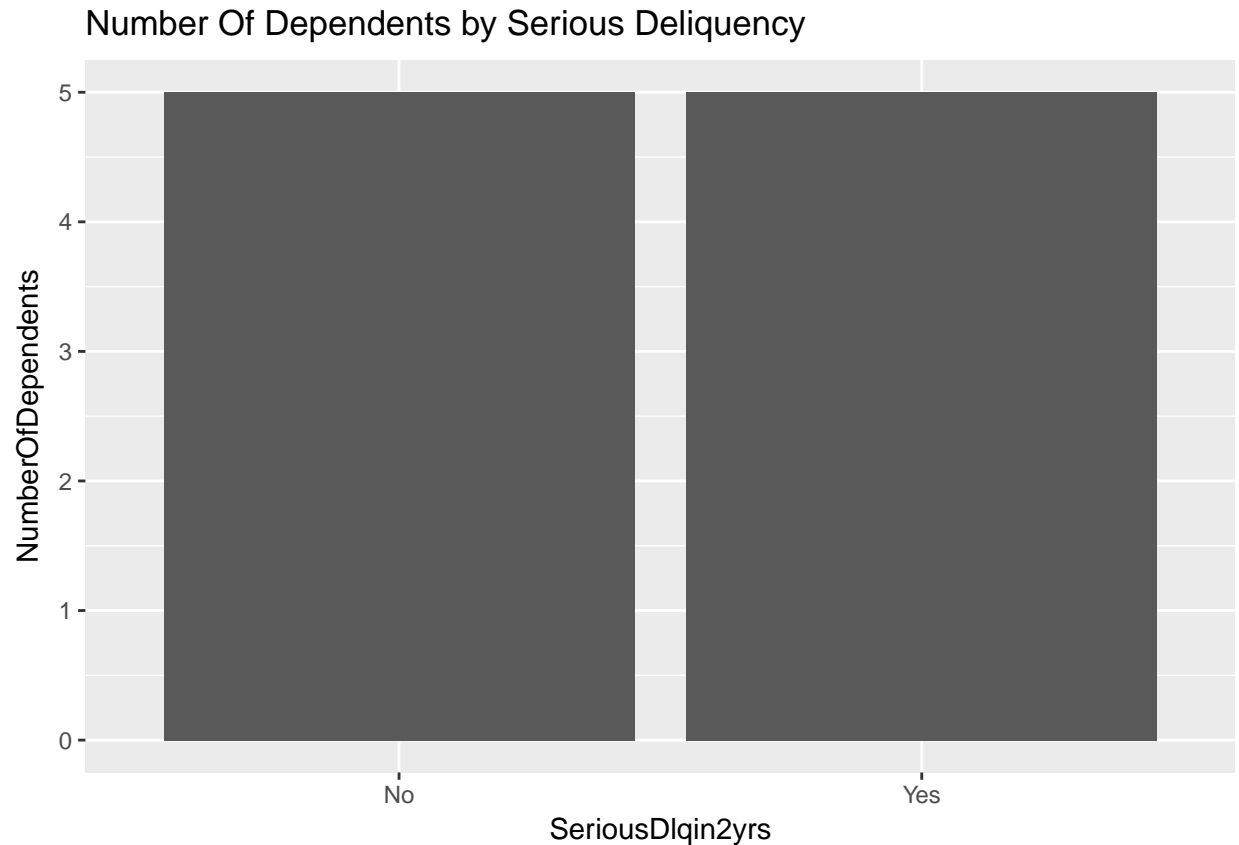
```
t.test(NumberOfOpenCreditLinesAndLoans~SeriousDlqin2yrs, var.equal=FALSE)
```

```
##
## Welch Two Sample t-test
##
## data:  NumberOfOpenCreditLinesAndLoans by SeriousDlqin2yrs
## t = 10.261, df = 6772.9, p-value < 2.2e-16
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  0.5156021 0.7591244
## sample estimates:
## mean in group No mean in group Yes
##      8.187920      7.550556
```

From the barplot, there were an equivalent number of individuals who were seriously delinquent in according to Number of Dependents.

According to the t-test, there is a significant difference within the mean of the groups.

```
ggplot(credit_clean, aes(SeriousDlqin2yrs,NumberOfDependents)) +
  geom_bar(stat="identity", position=position_dodge()) + labs(title = "Number Of Dependents by Serious")
```



```
t.test(NumberOfDependents~SeriousDlqin2yrs, var.equal=FALSE)
```

```
##
## Welch Two Sample t-test
##
## data:  NumberOfDependents by SeriousDlqin2yrs
## t = -13.737, df = 6790.6, p-value < 2.2e-16
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -0.2470072 -0.1853146
## sample estimates:
##  mean in group No mean in group Yes
##      0.8049451      1.0211060
```

Here, we checked the number of proportionate values for SeriousDlqin2yrs for unbalancing.

```
table(credit_clean$SeriousDlqin2yrs) # view the balance of the out
```

```
##
##    No    Yes
## 94599  6112
```

Modeling

Now we are going to begin introducing our cleaned and prepared data to different classification techniques to predict if an individual will experience financial distress in the next two years.

First, we are going to split our data between 70/30 training and testing set.

```
library(caret)
attach(credit_clean)
sample_data <- createDataPartition(SeriousDlqin2yrs, p = 0.7, list = FALSE) # splitting 70/30 train and
train <- credit_clean[sample_data,] # training set
test <- credit_clean[-sample_data,] # testing set
```

```
table(train$SeriousDlqin2yrs) # viewing the train set proportionality of the outcome variable
```

```
##
##      No      Yes
## 66220  4279
```

```
table(test$SeriousDlqin2yrs) # viewing the test set proportionality of the outcome variable
```

```
##
##      No      Yes
## 28379  1833
```

After splitting the data, its good to make sure there are a equivalent amount of columns for the training and testing set.

```
dim(train)
```

```
## [1] 70499      10
```

```
dim(test)
```

```
## [1] 30212      10
```

Logistic Regression

First, we begin our modeling techniques with logistic regression. Since our outcome variable (SeriousDlqin2yrs) is dichotomous, we are going to use the non-linear approach because the its not a linear outcome. Also, note that we must specify family = “binomial” for a binary classification context.

```
library(ROCR)
library(ROSE)
logit_model <- glm(SeriousDlqin2yrs ~.-X, data = train, family = "binomial") # binomial for binary clas
summary(logit_model) # summary of the model
```

```
##
## Call:
## glm(formula = SeriousDlqin2yrs ~ . - X, family = "binomial",
##      data = train)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -2.7812  -0.3400  -0.2278  -0.1792   3.1080
##
## Coefficients:
##              Estimate Std. Error z value
## (Intercept)    -3.220e+00  8.293e-02 -38.825
## RevolvingUtilizationOfUnsecuredLines  2.110e+00  5.176e-02  40.765
## age            -1.289e-02  1.355e-03  -9.518
## NumberOfTime30.59DaysPastDueNotWorse  6.158e-01  1.607e-02  38.310
## DebtRatio       1.648e-01  9.983e-02   1.650
```

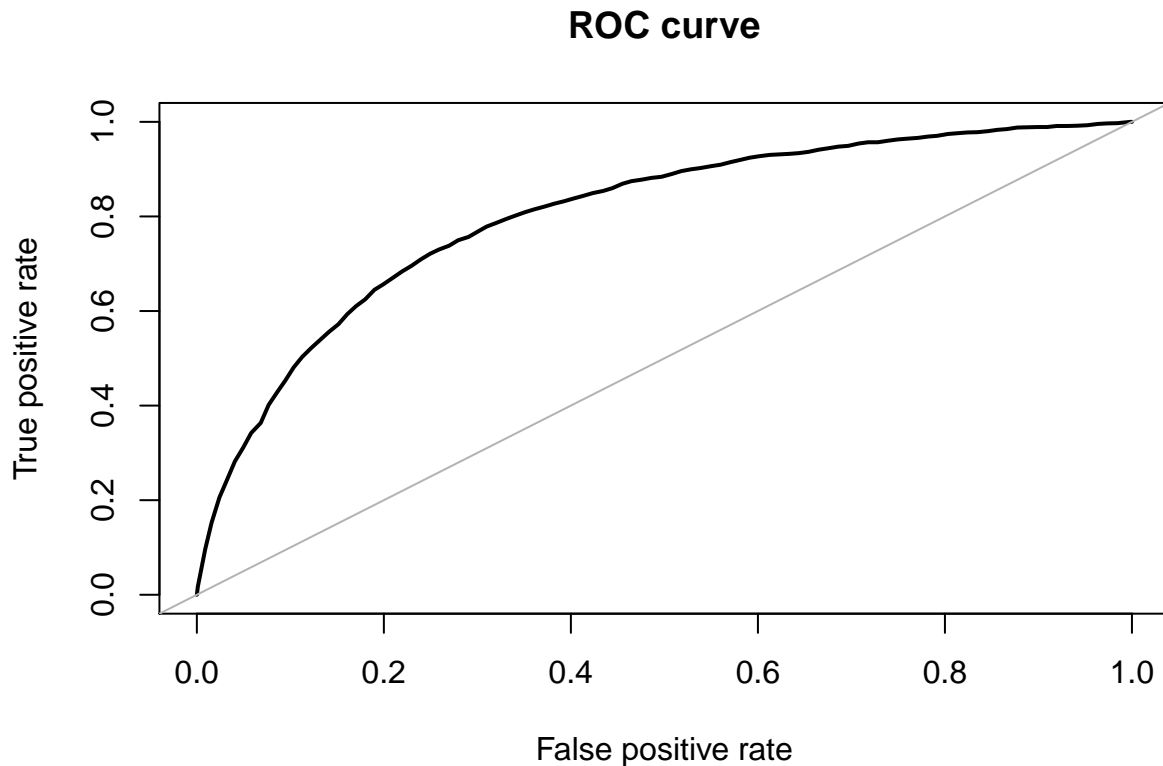
```

## MonthlyIncome -7.263e-05 7.772e-06 -9.345
## NumberOfOpenCreditLinesAndLoans 8.950e-03 4.999e-03 1.790
## NumberRealEstateLoansOrLines 4.398e-02 2.562e-02 1.717
## NumberOfDependents 1.047e-01 1.460e-02 7.173
## Pr(>|z|)
## (Intercept) < 2e-16 ***
## RevolvingUtilizationOfUnsecuredLines < 2e-16 ***
## age < 2e-16 ***
## NumberOfTime30.59DaysPastDueNotWorse < 2e-16 ***
## DebtRatio 0.0989 .
## MonthlyIncome < 2e-16 ***
## NumberOfOpenCreditLinesAndLoans 0.0734 .
## NumberRealEstateLoansOrLines 0.0860 .
## NumberOfDependents 7.34e-13 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
## Null deviance: 32271 on 70498 degrees of freedom
## Residual deviance: 26951 on 70490 degrees of freedom
## AIC: 26969
##
## Number of Fisher Scoring iterations: 6
logit_pred <- predict(logit_model,newdata = test, type = "response") # predicting the class on unseen d
logit_preds <- ifelse(logit_pred > 0.5, "Yes", "No") # threshold probabilities greater than 0.5
confusionMatrix(table(logit_preds,test$SeriousDlqin2yrs)) # confusion matrix and Kappa Statistic

## Confusion Matrix and Statistics
##
##
## logit_preds No Yes
## No 28269 1751
## Yes 110 82
##
## Accuracy : 0.9384
## 95% CI : (0.9356, 0.9411)
## No Information Rate : 0.9393
## P-Value [Acc > NIR] : 0.7545
##
## Kappa : 0.0703
## McNemar's Test P-Value : <2e-16
##
## Sensitivity : 0.99612
## Specificity : 0.04474
## Pos Pred Value : 0.94167
## Neg Pred Value : 0.42708
## Prevalence : 0.93933
## Detection Rate : 0.93569
## Detection Prevalence : 0.99364
## Balanced Accuracy : 0.52043
##
## 'Positive' Class : No
##

```

```
roc.curve(test$SeriousDlqin2yrs, logit_pred) #
```



```
## Area under the curve (AUC): 0.803
```

Noticed, in the summary table, there are a couple of variables that were not significant to our model, DebitRatio, NumberOfOpenCreditLinesAndLoans and NumberRealEstateLoansOrLines. They had p-values greater than 0.05, so we are going to remove both them to see if they will make difference in improving the accuracy of our next model.

How do we know that 0.5 value is the “optimal” value for accuracy. In reality, other cutoff values may be better (although 0.5 will tend to be the best value if all model assumptions are true and the sample size is reasonably large since we are dealing with a binary outcome).

From our current model, its classification accuracy of 94% is very good but it seems like the learning algorithm has some issues with overfitting. If you look at the Kappa statistic, it has a value of 0.08 or 8% on a 100% scale. This means our model has an agreement equivalent to chance which means guessing in other words. Before, implementing our second model, we are going to balance the data, to improve the Kappa statistic and possibly the overall accuracy of our model.

For the ROC plot, we would like the curve to “hug” the right and upper borders of the plot (indicating high sensitivity and specificity). Although it's not as close to the upper right boarders as I expected, we will evaluate it on our next model to see if it has improved.

Oversampling unbalanced data

As stated above in our previous model, there were some problems with overfitting and unproportioned outcome variable imbalances. So we performed an oversampling method that works with minority class. It

replicates the observations from minority class to balance the data. Since our training and testing data are severely unbalanced, we are going to perform this technique on both samples.

```
data_oversample_train <- ovun.sample(SeriousDlqin2yrs ~.,data = train, method = "over")$data
table(data_oversample_train$SeriousDlqin2yrs)
```

```
##
##      No      Yes
## 66220 66226
```

```
data_oversample_test <- ovun.sample(SeriousDlqin2yrs ~.,data = test, method = "over")$data
table(data_oversample_test$SeriousDlqin2yrs)
```

```
##
##      No      Yes
## 28379 28331
```

As you can see from the results above, they are now both balanced now.

Below, we have our second logistic regression model. We removed a few of the predictor variables that were not significant to our first model. Noticed, we also incorporated the oversampled samples for our training and testing data.

```
logit_model2 <- glm(SeriousDlqin2yrs ~ RevolvingUtilizationOfUnsecuredLines + age + NumberOfTime30.59DaysPastDueNotWorse, data = data_oversample_train)
summary(logit_model2)
```

```
##
## Call:
## glm(formula = SeriousDlqin2yrs ~ RevolvingUtilizationOfUnsecuredLines +
##      age + NumberOfTime30.59DaysPastDueNotWorse + MonthlyIncome +
##      NumberOfDependents, family = "binomial", data = data_oversample_train)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -4.0543  -0.8135   0.0369   0.8624   2.1223
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)    -4.416e-01  2.933e-02  -15.06   <2e-16 ***
## RevolvingUtilizationOfUnsecuredLines  2.134e+00  1.829e-02  116.71   <2e-16 ***
## age           -1.370e-02  4.922e-04  -27.84   <2e-16 ***
## NumberOfTime30.59DaysPastDueNotWorse  8.262e-01  9.356e-03   88.31   <2e-16 ***
## MonthlyIncome  -6.160e-05  2.349e-06  -26.22   <2e-16 ***
## NumberOfDependents  1.022e-01  5.796e-03   17.63   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 183609  on 132445  degrees of freedom
```

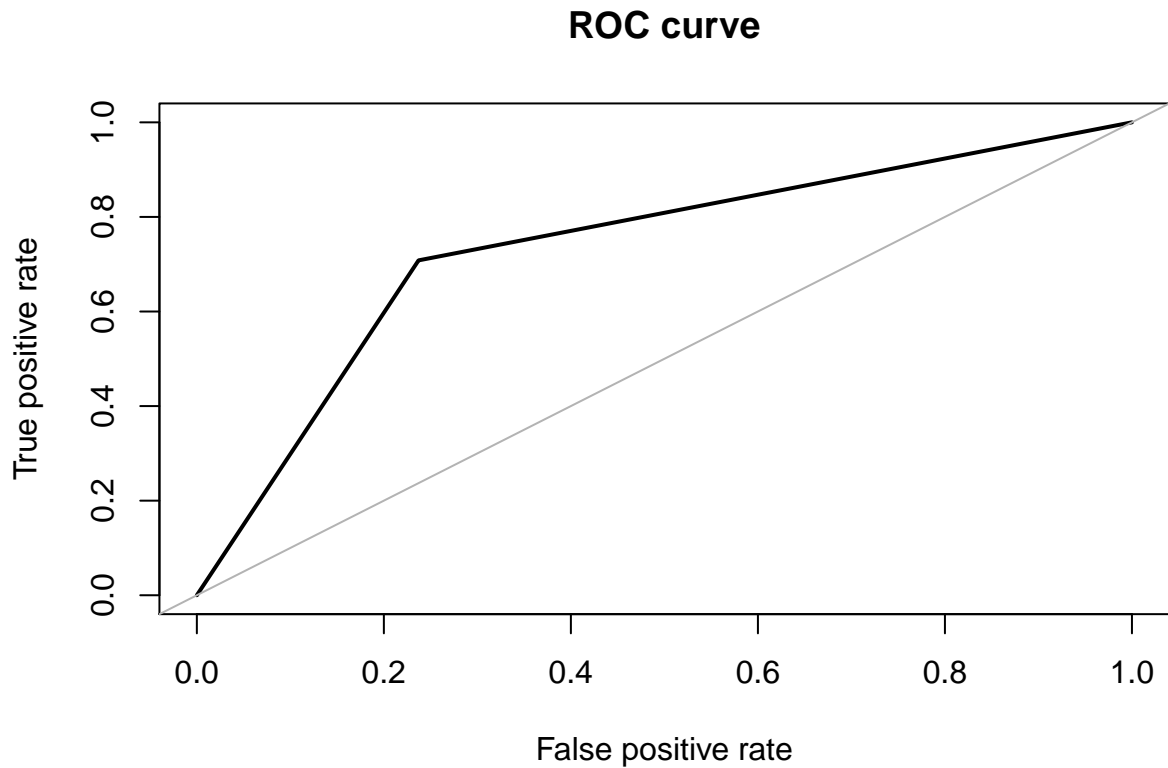
```

## Residual deviance: 142809  on 132440  degrees of freedom
## AIC: 142821
##
## Number of Fisher Scoring iterations: 5

os_pred <- predict(logit_model2, newdata = data_oversample_test, type = "response") # predicting the cl
os_preds <- ifelse(os_pred > 0.5, "Yes", "No") # threshold of probabilities greater than 0.5
confusionMatrix(table(data_oversample_test$SeriousDlqin2yrs, os_preds)) # confusion matrix

## Confusion Matrix and Statistics
##
##      os_preds
##      No  Yes
## No  21650  6729
## Yes   8269 20062
##
##              Accuracy : 0.7355
##              95% CI : (0.7319, 0.7392)
##      No Information Rate : 0.5276
##      P-Value [Acc > NIR] : < 2.2e-16
##
##              Kappa : 0.471
##  Mcnemar's Test P-Value : < 2.2e-16
##
##              Sensitivity : 0.7236
##              Specificity : 0.7488
##              Pos Pred Value : 0.7629
##              Neg Pred Value : 0.7081
##              Prevalence : 0.5276
##              Detection Rate : 0.3818
##      Detection Prevalence : 0.5004
##              Balanced Accuracy : 0.7362
##
##      'Positive' Class : No
##
roc.curve(data_oversample_test$SeriousDlqin2yrs, os_preds)

```



```
## Area under the curve (AUC): 0.736
```

From the results of our second model, it didn't performed as expected with a classification accuracy of 74%. Check out the Kappa statistic of a value of 49% has moderate agreement as oppose to no agreement in our first model.

The ROC value was very similar to our overall classification our model, which means our model is no longer overfitting.

ROSE Sampling

The ROSE sampling method generates data synthetically and provides a better estimate of original data. We wanted to try another balancing technique for our outcome variable to measure if we can improve or receive a better accuracy than using the oversampling method above.

Noticed, the training and testing sample data is clearly proportionate to both levels.

```
data_rose_train <- ROSE(SeriousDlqin2yrs ~., data = train)$data # synthetic training data generated enlarg
data_rose_test <- ROSE(SeriousDlqin2yrs ~., data = test)$data # synthetic testing data generated enlarg
table(data_rose_train$SeriousDlqin2yrs)
```

```
##
##      No      Yes
## 35381 35118
```

```
table(data_rose_test$SeriousDlqin2yrs)
```

```
##
```

```
##      No      Yes
## 15064 15148
```

From incorporating ROSE training and testing sample data, the model performed less than the oversampling method above. It had an accuracy of 73%. The Kappa statistic of a value of 45% has moderate agreement as oppose to no agreement.

```
logit_model3 <- glm(SeriousDlqin2yrs~.-X, data = data_rose_train, family = "binomial") # added the new
summary(logit_model3) # summary of the model
```

```
##
## Call:
## glm(formula = SeriousDlqin2yrs ~ . - X, family = "binomial",
##      data = data_rose_train)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -3.6231  -0.8729  -0.4280   0.9058   2.5942
##
## Coefficients:
##                                Estimate Std. Error z value
## (Intercept)                   -4.561e-01  3.785e-02 -12.051
## RevolvingUtilizationOfUnsecuredLines  1.956e+00  2.382e-02  82.107
## age                           -1.363e-02  6.035e-04 -22.578
## NumberOfTime30.59DaysPastDueNotWorse  6.202e-01  1.011e-02  61.365
## DebtRatio                       3.028e-01  4.130e-02   7.333
## MonthlyIncome                  -5.778e-05  3.172e-06 -18.217
## NumberOfOpenCreditLinesAndLoans     5.324e-03  2.078e-03   2.562
## NumberRealEstateLoansOrLines        1.317e-02  1.017e-02   1.295
## NumberOfDependents                9.647e-02  7.055e-03  13.674
##                                Pr(>|z|)
## (Intercept)                   < 2e-16 ***
## RevolvingUtilizationOfUnsecuredLines < 2e-16 ***
## age                           < 2e-16 ***
## NumberOfTime30.59DaysPastDueNotWorse < 2e-16 ***
## DebtRatio                     2.26e-13 ***
## MonthlyIncome                  < 2e-16 ***
## NumberOfOpenCreditLinesAndLoans    0.0104 *
## NumberRealEstateLoansOrLines        0.1952
## NumberOfDependents                < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 97731  on 70498  degrees of freedom
## Residual deviance: 78423  on 70490  degrees of freedom
## AIC: 78441
##
## Number of Fisher Scoring iterations: 4
```

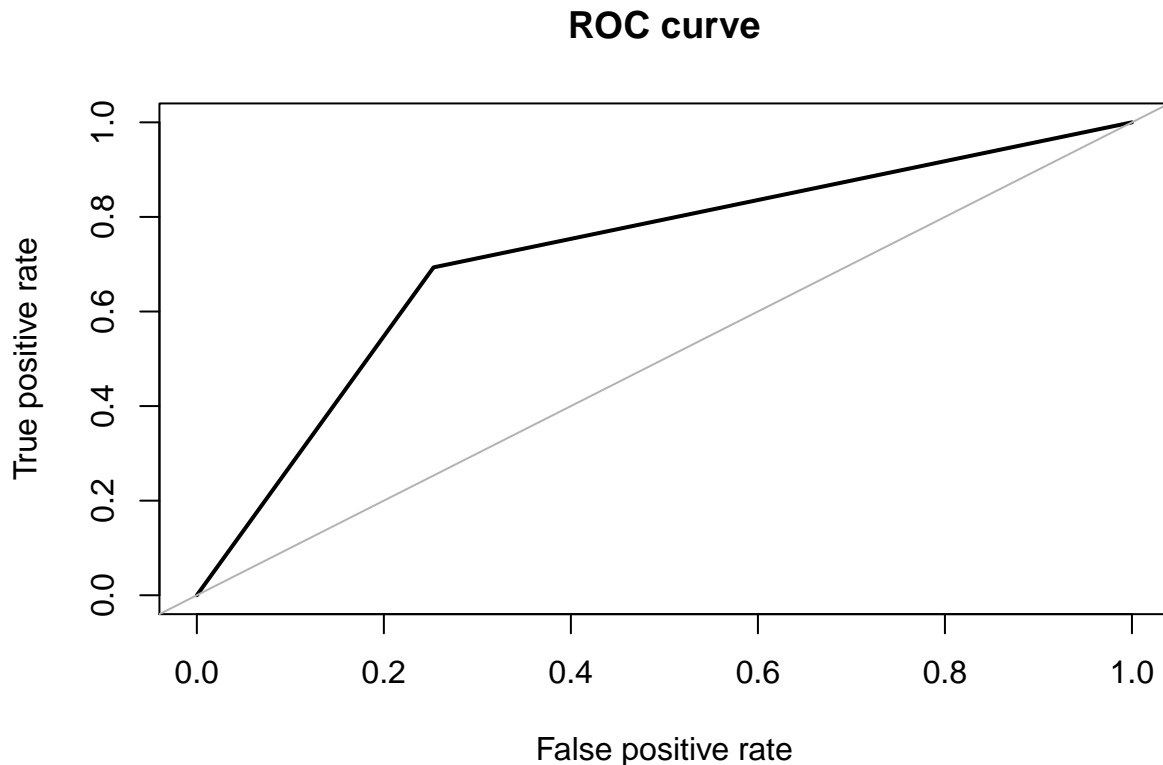
```
os_pred3 <- predict(logit_model3, newdata = data_rose_test, type = "response") # predicting the class u
os_preds3 <- ifelse(os_pred3 > 0.5, "Yes", "No") # threshold of probabilities greater than 0.5
confusionMatrix(table(data_rose_test$SeriousDlqin2yrs, os_preds3)) # confusion matrix
```

```
## Confusion Matrix and Statistics
```

```

##
##      os_preds3
##      No    Yes
## No  11251  3813
## Yes  4646 10502
##
##      Accuracy : 0.72
##      95% CI : (0.7149, 0.7251)
##      No Information Rate : 0.5262
##      P-Value [Acc > NIR] : < 2.2e-16
##
##      Kappa : 0.4401
## Mcnemar's Test P-Value : < 2.2e-16
##
##      Sensitivity : 0.7077
##      Specificity : 0.7336
##      Pos Pred Value : 0.7469
##      Neg Pred Value : 0.6933
##      Prevalence : 0.5262
##      Detection Rate : 0.3724
##      Detection Prevalence : 0.4986
##      Balanced Accuracy : 0.7207
##
##      'Positive' Class : No
##
roc.curve(data_rose_test$SeriousDlqin2yrs, os_preds3)

```

```
## Area under the curve (AUC): 0.720
```

As we can see there was little to no difference in the overall accuracy of model in comparison to oversampling technique above.

Decision Tree

Now we are going to fit a Tree to our data to predict if an individual is going to be seriously delinquent in two years. We are incorporating a cross-validation technique within the decision tree model to find the best optimal value for the complexity parameter for reducing the mean prediction error of our model.

Our Decision Tree tells us Revolving Utilization of Unsecured Lines and Number of Times 30 - 59 Days Past Due were the two most important variables in the model.

```
library(rpart)
rf_model <- train(SeriousDlqin2yrs ~.-X, data = data_oversample_train, method = "rpart", trControl = trControl)
print(rf_model) # Plot the trees
```

```
## CART
##
## 132446 samples
##      9 predictor
##      2 classes: 'No', 'Yes'
##
## No pre-processing
## Resampling: Cross-Validated (10 fold, repeated 1 times)
## Summary of sample sizes: 119202, 119201, 119201, 119201, 119201, 119202, ...
```

```
## Resampling results across tuning parameters:
```

```
##
```

```
##   cp          Accuracy   Kappa  
## 0.00576865 0.7322757 0.4645510  
## 0.04195107 0.7154006 0.4307979  
## 0.41643008 0.6020220 0.2040062
```

```
##
```

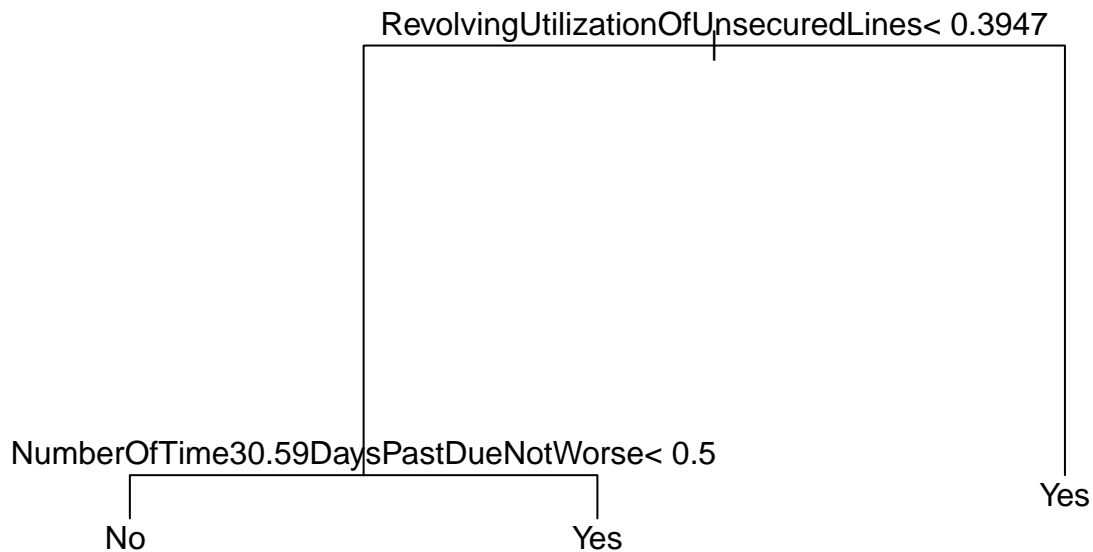
```
## Accuracy was used to select the optimal model using the largest value.
```

```
## The final value used for the model was cp = 0.00576865.
```

```
par(xpd = NA) # Avoid clipping the text in some device
```

```
plot(rf_model$finalModel)# Plot the final tree model
```

```
text(rf_model$finalModel, digits = 3) # adding the names of the relevant variable names to the trees
```



```
dt_y_hat <- predict(rf_model, data_oversample_test)
confusionMatrix(table(dt_y_hat, data_oversample_test$SeriousDlqin2yrs))
```

```
## Confusion Matrix and Statistics
```

```
##
```

```
##
```

```
## dt_y_hat    No    Yes
```

```
##      No 17979 4943
```

```
##      Yes 10400 23388
```

```
##
```

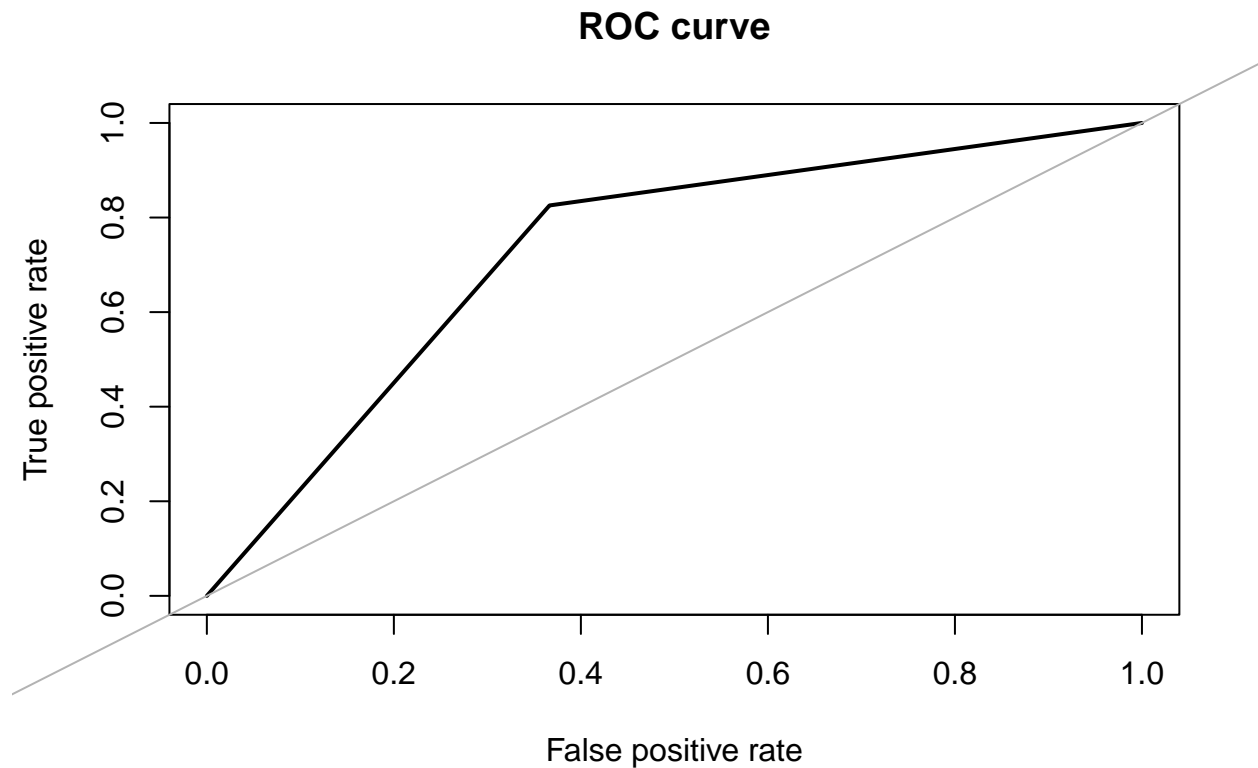
```
##              Accuracy : 0.7294
```

```
##              95% CI : (0.7258, 0.7331)
```

```
##      No Information Rate : 0.5004
```

```
##      P-Value [Acc > NIR] : < 2.2e-16
##
##              Kappa : 0.459
## Mcnemar's Test P-Value : < 2.2e-16
##
##      Sensitivity : 0.6335
##      Specificity : 0.8255
##      Pos Pred Value : 0.7844
##      Neg Pred Value : 0.6922
##      Prevalence : 0.5004
##      Detection Rate : 0.3170
##      Detection Prevalence : 0.4042
##      Balanced Accuracy : 0.7295
##
##      'Positive' Class : No
##
```

```
roc.curve(data_oversample_test$SeriousDlqin2yrs, dt_y_hat)
```



```
## Area under the curve (AUC): 0.730
```

By adding using the optimal value for the complexity paramter from our previous model for another model,there will be no improvement or changes in the overall classification accuracy nor the confusion matrix itself. The reason its going to be no change is due to the cp value being very small.

K-Nearest Neighbor

Now we are going to implement a K-Nearest Neighbor technique identifying the k most similar training observations to our new observation. Also, we incorporate cross-validation along with the K-NN algorithm to find the optimal k value to reduce the mean prediction error.

```
knn_model <- train(SeriousDlqin2yrs ~.-X, data = data_oversample_train, method = "knn", trControl = trainControl(method = "cv", number = 10))  
print(knn_model) # summary of our model
```

```
## k-Nearest Neighbors  
##  
## 132446 samples  
##      9 predictor  
##      2 classes: 'No', 'Yes'  
##  
## Pre-processing: centered (8), scaled (8)  
## Resampling: Cross-Validated (10 fold, repeated 1 times)  
## Summary of sample sizes: 119201, 119202, 119201, 119201, 119201, 119202, ...  
## Resampling results across tuning parameters:  
##  
##   k   Accuracy   Kappa  
##   5  0.8944400  0.7888780  
##   7  0.8678178  0.7356325  
##   9  0.8459674  0.6919306  
##  11  0.8281639  0.6563226  
##  13  0.8153587  0.6307114  
##  15  0.8055434  0.6110803  
##  17  0.7990728  0.5981390  
##  19  0.7942104  0.5884145  
##  21  0.7908732  0.5817404  
##  23  0.7877852  0.5755648  
##  
## Accuracy was used to select the optimal model using the largest value.  
## The final value used for the model was k = 5.
```

```
knn_model$bestTune # optimal value for k
```

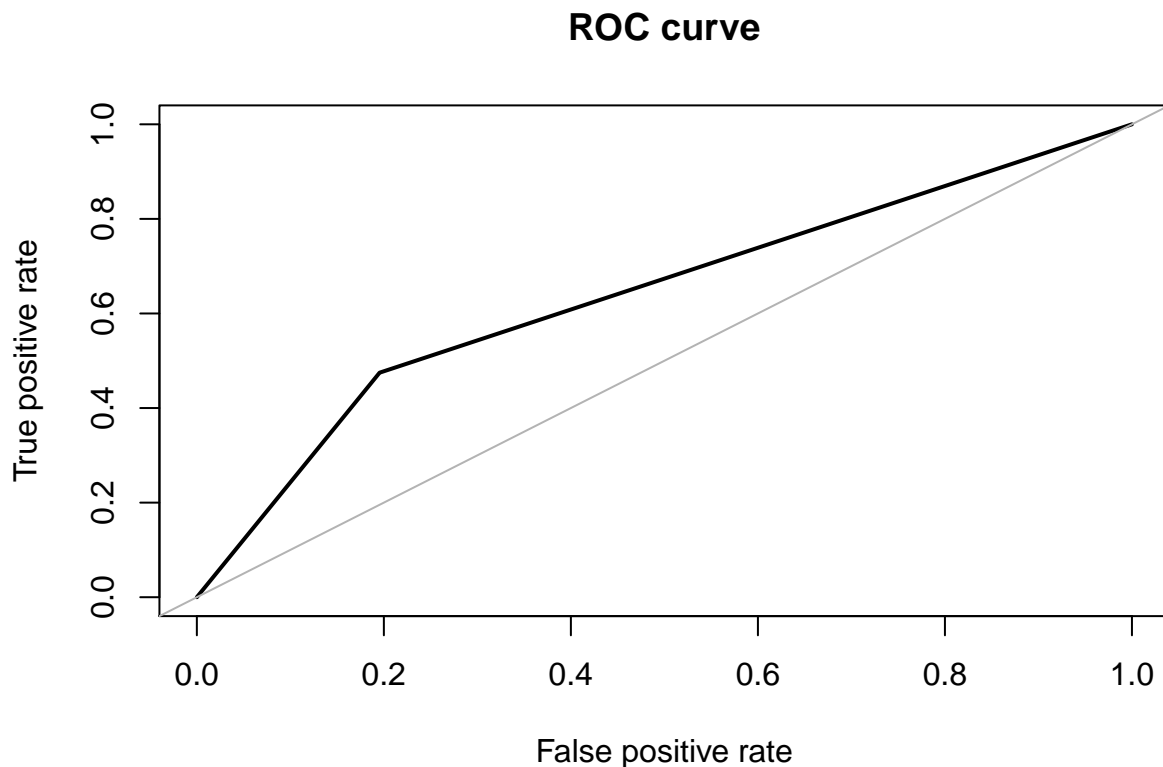
```
##   k  
## 1 5
```

```
knn_y_hat <- predict(knn_model, data_oversample_test) # predicting the class on unseen data  
confusionMatrix(table(knn_y_hat, data_oversample_test$SeriousDlqin2yrs)) # confusion matrix
```

```
## Confusion Matrix and Statistics  
##  
##  
##   knn_y_hat      No      Yes  
##      No  22833 14879  
##      Yes   5546 13452  
##  
##              Accuracy : 0.6398  
##              95% CI : (0.6359, 0.6438)  
##      No Information Rate : 0.5004  
##      P-Value [Acc > NIR] : < 2.2e-16  
##  
##              Kappa : 0.2795
```

```
## McNemar's Test P-Value : < 2.2e-16
##
##      Sensitivity : 0.8046
##      Specificity : 0.4748
##      Pos Pred Value : 0.6055
##      Neg Pred Value : 0.7081
##      Prevalence : 0.5004
##      Detection Rate : 0.4026
##      Detection Prevalence : 0.6650
##      Balanced Accuracy : 0.6397
##
##      'Positive' Class : No
##
```

```
roc.curve(data_oversample_test$SeriousDlqin2yrs, knn_y_hat)
```



```
## Area under the curve (AUC): 0.640
```

From the results from our K-NN model above, the optimal value for the best accuracy of our model is 5. We are going to use the optimal k value for our tuneLength to measure if our model accuracy will improve or not.

From the results of our model above, it had a classification accuracy of 65-%. Check out the Kappa statistic of a value of 30% has slight agreement as oppose to no agreement.

As you can see, we used 5 for our tuneLength for our second model.

```
ctrl <- trainControl(method="repeatedcv",repeats = 3,classProbs=TRUE,summaryFunction = twoClassSummary)
knn_model2 <- train(SeriousDlqin2yrs ~.-X, data = data_oversample_train, method = "knn",trControl = ctrl)
```

```
## Warning in train.default(x, y, weights = w, ...): The metric "Accuracy" was
## not in the result set. ROC will be used instead.
```

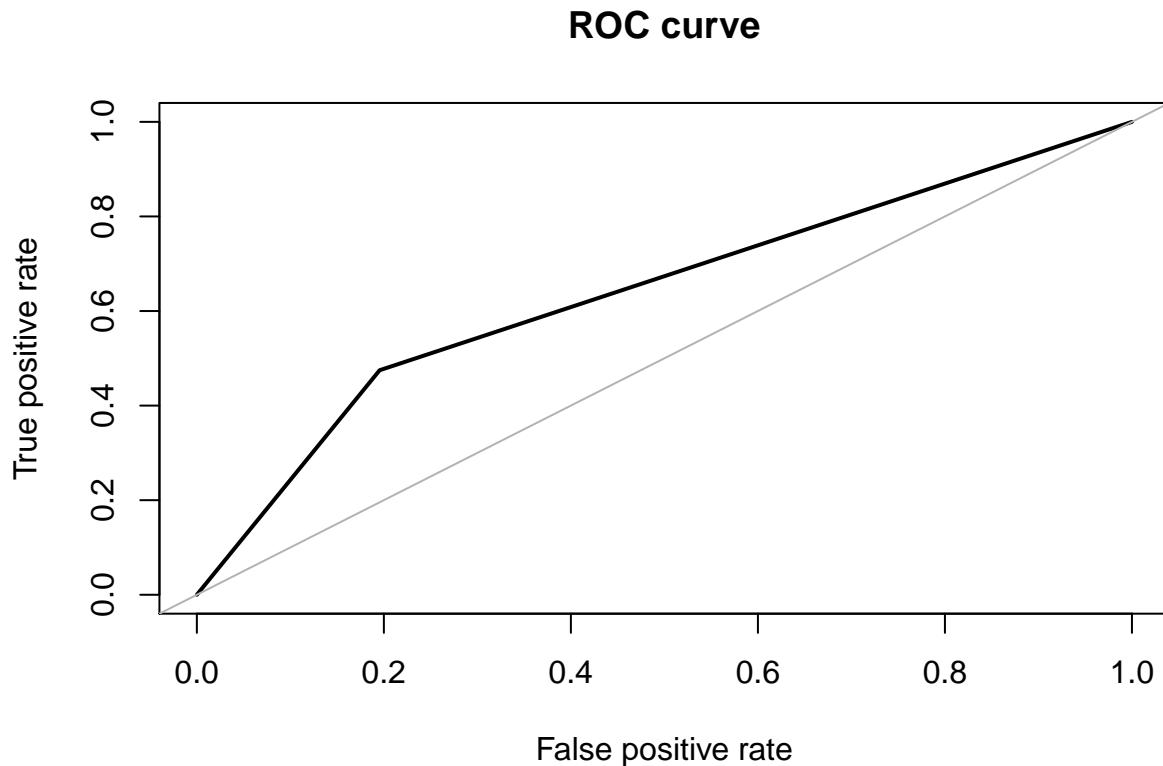
```
knn_model2
```

```
## k-Nearest Neighbors
##
## 132446 samples
##      9 predictor
##      2 classes: 'No', 'Yes'
##
## Pre-processing: centered (8), scaled (8)
## Resampling: Cross-Validated (10 fold, repeated 3 times)
## Summary of sample sizes: 119201, 119201, 119201, 119201, 119202, 119202, ...
## Resampling results across tuning parameters:
##
##  k   ROC          Sens          Spec
##   5  0.9710719  0.7885030  0.9999547
##   7  0.9699722  0.7361019  0.9997131
##   9  0.9662008  0.6929276  0.9991594
##  11  0.9576316  0.6591966  0.9977400
##  13  0.9440488  0.6358502  0.9940557
##
## ROC was used to select the optimal model using the largest value.
## The final value used for the model was k = 5.
```

```
knn_y_hat2 <- predict(knn_model2, data_oversample_test) # predicting the class on unseen data
confusionMatrix(knn_y_hat2, data_oversample_test$SeriousDlqin2yrs) # confusion matrix
```

```
## Confusion Matrix and Statistics
##
##              Reference
## Prediction    No  Yes
##      No  22832 14879
##      Yes   5547 13452
##
##              Accuracy : 0.6398
##              95% CI : (0.6358, 0.6438)
##      No Information Rate : 0.5004
##      P-Value [Acc > NIR] : < 2.2e-16
##
##              Kappa : 0.2794
##      McNemar's Test P-Value : < 2.2e-16
##
##              Sensitivity : 0.8045
##              Specificity : 0.4748
##              Pos Pred Value : 0.6054
##              Neg Pred Value : 0.7080
##              Prevalence : 0.5004
##              Detection Rate : 0.4026
##      Detection Prevalence : 0.6650
##              Balanced Accuracy : 0.6397
##
##      'Positive' Class : No
##
```

```
roc.curve(data_oversample_test$SeriousDlqin2yrs, knn_y_hat2) # ROC curve
```



```
## Area under the curve (AUC): 0.640
```

From the results from our K-NN model above, the optimal value for the best accuracy of our model is 65%. The model did not improve at all.

Ensemble Learning

Given a list of caret models, the `caretStack()` function can be used to specify a higher-order model to learn how to best combine the predictions of sub-models together.

Let's first look at creating 5 sub-models for to finish our analysis specifically:

```
Gradient Boosting (GBM)
Classification and Regression Trees (CART)
Logistic Regression (via Generalized Linear Model or GLM)
k-Nearest Neighbors (kNN)
Naive Bayes (NB)
```

Below is an example that creates these 5 sub-models. Note the new helpful `caretList()` function provided by the `caretEnsemble` package for creating a list of standard caret models.

```
library(caretEnsemble)
control <- trainControl(method="repeatedcv", number=10, repeats=3, savePredictions='final', classProbs=
algorithmList <- c('gbm', 'rpart', 'glm', 'knn', 'nb') # stacking 5 modeling techniques
ensemble_learning <- caretList(SeriousDlqin2yrs~.-X, data=data_oversample_train, trControl=control, met
```

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3534	nan	0.1000	0.0165
##	2	1.3263	nan	0.1000	0.0133
##	3	1.3038	nan	0.1000	0.0112
##	4	1.2824	nan	0.1000	0.0107
##	5	1.2649	nan	0.1000	0.0088
##	6	1.2484	nan	0.1000	0.0082
##	7	1.2344	nan	0.1000	0.0072
##	8	1.2214	nan	0.1000	0.0066
##	9	1.2099	nan	0.1000	0.0057
##	10	1.1996	nan	0.1000	0.0052
##	20	1.1356	nan	0.1000	0.0020
##	40	1.0935	nan	0.1000	0.0005
##	60	1.0780	nan	0.1000	0.0003
##	80	1.0703	nan	0.1000	0.0001
##	100	1.0649	nan	0.1000	0.0001
##	120	1.0606	nan	0.1000	0.0001
##	140	1.0575	nan	0.1000	0.0000
##	150	1.0562	nan	0.1000	0.0001
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3446	nan	0.1000	0.0210
##	2	1.3083	nan	0.1000	0.0180
##	3	1.2803	nan	0.1000	0.0140
##	4	1.2558	nan	0.1000	0.0123
##	5	1.2342	nan	0.1000	0.0108
##	6	1.2146	nan	0.1000	0.0098
##	7	1.1989	nan	0.1000	0.0078
##	8	1.1846	nan	0.1000	0.0071
##	9	1.1718	nan	0.1000	0.0064
##	10	1.1613	nan	0.1000	0.0052
##	20	1.1041	nan	0.1000	0.0015
##	40	1.0700	nan	0.1000	0.0003
##	60	1.0576	nan	0.1000	0.0002
##	80	1.0497	nan	0.1000	0.0002
##	100	1.0445	nan	0.1000	0.0001
##	120	1.0405	nan	0.1000	0.0001
##	140	1.0371	nan	0.1000	0.0001
##	150	1.0356	nan	0.1000	0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3391	nan	0.1000	0.0236
##	2	1.2998	nan	0.1000	0.0195
##	3	1.2681	nan	0.1000	0.0158
##	4	1.2413	nan	0.1000	0.0133
##	5	1.2196	nan	0.1000	0.0109
##	6	1.2011	nan	0.1000	0.0093
##	7	1.1854	nan	0.1000	0.0078
##	8	1.1715	nan	0.1000	0.0070
##	9	1.1598	nan	0.1000	0.0058
##	10	1.1494	nan	0.1000	0.0051
##	20	1.0919	nan	0.1000	0.0017
##	40	1.0592	nan	0.1000	0.0003
##	60	1.0461	nan	0.1000	0.0002

##	80	1.0379	nan	0.1000	0.0003
##	100	1.0318	nan	0.1000	0.0001
##	120	1.0274	nan	0.1000	0.0001
##	140	1.0235	nan	0.1000	0.0000
##	150	1.0217	nan	0.1000	0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3534	nan	0.1000	0.0165
##	2	1.3266	nan	0.1000	0.0135
##	3	1.3044	nan	0.1000	0.0111
##	4	1.2834	nan	0.1000	0.0106
##	5	1.2658	nan	0.1000	0.0088
##	6	1.2493	nan	0.1000	0.0083
##	7	1.2350	nan	0.1000	0.0071
##	8	1.2221	nan	0.1000	0.0065
##	9	1.2106	nan	0.1000	0.0057
##	10	1.2005	nan	0.1000	0.0050
##	20	1.1368	nan	0.1000	0.0020
##	40	1.0949	nan	0.1000	0.0005
##	60	1.0798	nan	0.1000	0.0002
##	80	1.0716	nan	0.1000	0.0002
##	100	1.0665	nan	0.1000	0.0001
##	120	1.0624	nan	0.1000	0.0001
##	140	1.0591	nan	0.1000	0.0001
##	150	1.0578	nan	0.1000	0.0001
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3444	nan	0.1000	0.0210
##	2	1.3095	nan	0.1000	0.0174
##	3	1.2800	nan	0.1000	0.0148
##	4	1.2558	nan	0.1000	0.0119
##	5	1.2342	nan	0.1000	0.0108
##	6	1.2143	nan	0.1000	0.0100
##	7	1.1997	nan	0.1000	0.0073
##	8	1.1855	nan	0.1000	0.0070
##	9	1.1734	nan	0.1000	0.0060
##	10	1.1618	nan	0.1000	0.0057
##	20	1.1050	nan	0.1000	0.0017
##	40	1.0714	nan	0.1000	0.0004
##	60	1.0579	nan	0.1000	0.0002
##	80	1.0509	nan	0.1000	0.0001
##	100	1.0455	nan	0.1000	0.0001
##	120	1.0410	nan	0.1000	0.0001
##	140	1.0377	nan	0.1000	0.0000
##	150	1.0363	nan	0.1000	0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3391	nan	0.1000	0.0235
##	2	1.3002	nan	0.1000	0.0194
##	3	1.2688	nan	0.1000	0.0158
##	4	1.2423	nan	0.1000	0.0132
##	5	1.2204	nan	0.1000	0.0109
##	6	1.2021	nan	0.1000	0.0092
##	7	1.1865	nan	0.1000	0.0078

##	8	1.1725	nan	0.1000	0.0069
##	9	1.1604	nan	0.1000	0.0061
##	10	1.1506	nan	0.1000	0.0049
##	20	1.0939	nan	0.1000	0.0013
##	40	1.0604	nan	0.1000	0.0004
##	60	1.0473	nan	0.1000	0.0002
##	80	1.0397	nan	0.1000	0.0001
##	100	1.0342	nan	0.1000	0.0001
##	120	1.0294	nan	0.1000	0.0001
##	140	1.0252	nan	0.1000	0.0001
##	150	1.0226	nan	0.1000	0.0000

##

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3534	nan	0.1000	0.0165
##	2	1.3265	nan	0.1000	0.0135
##	3	1.3042	nan	0.1000	0.0111
##	4	1.2824	nan	0.1000	0.0107
##	5	1.2648	nan	0.1000	0.0087
##	6	1.2480	nan	0.1000	0.0083
##	7	1.2338	nan	0.1000	0.0071
##	8	1.2206	nan	0.1000	0.0066
##	9	1.2090	nan	0.1000	0.0057
##	10	1.1987	nan	0.1000	0.0052
##	20	1.1353	nan	0.1000	0.0021
##	40	1.0938	nan	0.1000	0.0005
##	60	1.0780	nan	0.1000	0.0002
##	80	1.0699	nan	0.1000	0.0001
##	100	1.0647	nan	0.1000	0.0001
##	120	1.0606	nan	0.1000	0.0001
##	140	1.0575	nan	0.1000	0.0001
##	150	1.0562	nan	0.1000	0.0001

##

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3437	nan	0.1000	0.0210
##	2	1.3077	nan	0.1000	0.0179
##	3	1.2793	nan	0.1000	0.0140
##	4	1.2550	nan	0.1000	0.0124
##	5	1.2343	nan	0.1000	0.0104
##	6	1.2151	nan	0.1000	0.0096
##	7	1.1979	nan	0.1000	0.0086
##	8	1.1848	nan	0.1000	0.0066
##	9	1.1730	nan	0.1000	0.0059
##	10	1.1618	nan	0.1000	0.0055
##	20	1.1042	nan	0.1000	0.0015
##	40	1.0705	nan	0.1000	0.0005
##	60	1.0577	nan	0.1000	0.0002
##	80	1.0500	nan	0.1000	0.0001
##	100	1.0449	nan	0.1000	0.0000
##	120	1.0406	nan	0.1000	0.0001
##	140	1.0369	nan	0.1000	0.0001
##	150	1.0353	nan	0.1000	0.0000

##

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3389	nan	0.1000	0.0237

##	2	1.3001	nan	0.1000	0.0194
##	3	1.2687	nan	0.1000	0.0159
##	4	1.2420	nan	0.1000	0.0133
##	5	1.2199	nan	0.1000	0.0110
##	6	1.2012	nan	0.1000	0.0093
##	7	1.1842	nan	0.1000	0.0083
##	8	1.1708	nan	0.1000	0.0066
##	9	1.1582	nan	0.1000	0.0062
##	10	1.1474	nan	0.1000	0.0053
##	20	1.0920	nan	0.1000	0.0017
##	40	1.0590	nan	0.1000	0.0004
##	60	1.0457	nan	0.1000	0.0003
##	80	1.0383	nan	0.1000	0.0001
##	100	1.0327	nan	0.1000	0.0001
##	120	1.0277	nan	0.1000	0.0002
##	140	1.0236	nan	0.1000	0.0001
##	150	1.0217	nan	0.1000	0.0001
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3536	nan	0.1000	0.0165
##	2	1.3268	nan	0.1000	0.0135
##	3	1.3043	nan	0.1000	0.0112
##	4	1.2829	nan	0.1000	0.0108
##	5	1.2650	nan	0.1000	0.0089
##	6	1.2484	nan	0.1000	0.0084
##	7	1.2340	nan	0.1000	0.0070
##	8	1.2207	nan	0.1000	0.0065
##	9	1.2092	nan	0.1000	0.0057
##	10	1.1989	nan	0.1000	0.0052
##	20	1.1354	nan	0.1000	0.0020
##	40	1.0933	nan	0.1000	0.0005
##	60	1.0778	nan	0.1000	0.0003
##	80	1.0700	nan	0.1000	0.0001
##	100	1.0646	nan	0.1000	0.0001
##	120	1.0604	nan	0.1000	0.0001
##	140	1.0571	nan	0.1000	0.0001
##	150	1.0558	nan	0.1000	0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3443	nan	0.1000	0.0210
##	2	1.3097	nan	0.1000	0.0171
##	3	1.2797	nan	0.1000	0.0150
##	4	1.2550	nan	0.1000	0.0123
##	5	1.2318	nan	0.1000	0.0116
##	6	1.2137	nan	0.1000	0.0091
##	7	1.1987	nan	0.1000	0.0076
##	8	1.1854	nan	0.1000	0.0066
##	9	1.1735	nan	0.1000	0.0058
##	10	1.1623	nan	0.1000	0.0056
##	20	1.1033	nan	0.1000	0.0018
##	40	1.0699	nan	0.1000	0.0004
##	60	1.0571	nan	0.1000	0.0002
##	80	1.0495	nan	0.1000	0.0001
##	100	1.0440	nan	0.1000	0.0001

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##      120      1.0395      nan      0.1000      0.0000
##      140      1.0361      nan      0.1000      0.0000
##      150      1.0346      nan      0.1000      0.0000
##
## Iter   TrainDeviance   ValidDeviance   StepSize   Improve
##      1      1.3389      nan      0.1000      0.0237
##      2      1.2996      nan      0.1000      0.0195
##      3      1.2680      nan      0.1000      0.0159
##      4      1.2417      nan      0.1000      0.0131
##      5      1.2197      nan      0.1000      0.0110
##      6      1.1998      nan      0.1000      0.0100
##      7      1.1828      nan      0.1000      0.0084
##      8      1.1693      nan      0.1000      0.0068
##      9      1.1578      nan      0.1000      0.0057
##     10      1.1469      nan      0.1000      0.0054
##     20      1.0914      nan      0.1000      0.0013
##     40      1.0584      nan      0.1000      0.0004
##     60      1.0456      nan      0.1000      0.0002
##     80      1.0373      nan      0.1000      0.0002
##    100      1.0321      nan      0.1000      0.0001
##    120      1.0268      nan      0.1000      0.0002
##    140      1.0228      nan      0.1000      0.0001
##    150      1.0210      nan      0.1000      0.0000
##
## Iter   TrainDeviance   ValidDeviance   StepSize   Improve
##      1      1.3535      nan      0.1000      0.0165
##      2      1.3264      nan      0.1000      0.0133
##      3      1.3042      nan      0.1000      0.0110
##      4      1.2826      nan      0.1000      0.0107
##      5      1.2650      nan      0.1000      0.0087
##      6      1.2481      nan      0.1000      0.0084
##      7      1.2339      nan      0.1000      0.0071
##      8      1.2208      nan      0.1000      0.0066
##      9      1.2093      nan      0.1000      0.0057
##     10      1.1992      nan      0.1000      0.0051
##     20      1.1354      nan      0.1000      0.0019
##     40      1.0937      nan      0.1000      0.0005
##     60      1.0782      nan      0.1000      0.0002
##     80      1.0700      nan      0.1000      0.0001
##    100      1.0646      nan      0.1000      0.0001
##    120      1.0607      nan      0.1000      0.0001
##    140      1.0574      nan      0.1000      0.0001
##    150      1.0560      nan      0.1000      0.0000
##
## Iter   TrainDeviance   ValidDeviance   StepSize   Improve
##      1      1.3441      nan      0.1000      0.0210
##      2      1.3081      nan      0.1000      0.0179
##      3      1.2798      nan      0.1000      0.0140
##      4      1.2547      nan      0.1000      0.0125
##      5      1.2339      nan      0.1000      0.0102
##      6      1.2135      nan      0.1000      0.0101
##      7      1.1986      nan      0.1000      0.0074
##      8      1.1845      nan      0.1000      0.0070
##      9      1.1726      nan      0.1000      0.0059

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##	10	1.1624	nan	0.1000	0.0051
##	20	1.1032	nan	0.1000	0.0016
##	40	1.0695	nan	0.1000	0.0005
##	60	1.0570	nan	0.1000	0.0002
##	80	1.0491	nan	0.1000	0.0002
##	100	1.0433	nan	0.1000	0.0001
##	120	1.0390	nan	0.1000	0.0001
##	140	1.0359	nan	0.1000	0.0001
##	150	1.0344	nan	0.1000	0.0001
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3391	nan	0.1000	0.0237
##	2	1.3009	nan	0.1000	0.0193
##	3	1.2684	nan	0.1000	0.0161
##	4	1.2424	nan	0.1000	0.0131
##	5	1.2197	nan	0.1000	0.0114
##	6	1.2011	nan	0.1000	0.0092
##	7	1.1844	nan	0.1000	0.0083
##	8	1.1701	nan	0.1000	0.0071
##	9	1.1585	nan	0.1000	0.0058
##	10	1.1476	nan	0.1000	0.0055
##	20	1.0916	nan	0.1000	0.0015
##	40	1.0586	nan	0.1000	0.0005
##	60	1.0460	nan	0.1000	0.0002
##	80	1.0384	nan	0.1000	0.0001
##	100	1.0326	nan	0.1000	0.0001
##	120	1.0275	nan	0.1000	0.0001
##	140	1.0228	nan	0.1000	0.0001
##	150	1.0210	nan	0.1000	0.0001
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3528	nan	0.1000	0.0165
##	2	1.3259	nan	0.1000	0.0134
##	3	1.3034	nan	0.1000	0.0112
##	4	1.2824	nan	0.1000	0.0106
##	5	1.2650	nan	0.1000	0.0087
##	6	1.2487	nan	0.1000	0.0083
##	7	1.2347	nan	0.1000	0.0070
##	8	1.2217	nan	0.1000	0.0066
##	9	1.2105	nan	0.1000	0.0056
##	10	1.2003	nan	0.1000	0.0050
##	20	1.1359	nan	0.1000	0.0022
##	40	1.0943	nan	0.1000	0.0005
##	60	1.0792	nan	0.1000	0.0002
##	80	1.0715	nan	0.1000	0.0001
##	100	1.0661	nan	0.1000	0.0001
##	120	1.0622	nan	0.1000	0.0001
##	140	1.0591	nan	0.1000	0.0000
##	150	1.0578	nan	0.1000	0.0001
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3442	nan	0.1000	0.0210
##	2	1.3101	nan	0.1000	0.0171
##	3	1.2802	nan	0.1000	0.0149

##	4	1.2556	nan	0.1000	0.0122
##	5	1.2327	nan	0.1000	0.0115
##	6	1.2145	nan	0.1000	0.0091
##	7	1.1992	nan	0.1000	0.0076
##	8	1.1852	nan	0.1000	0.0070
##	9	1.1729	nan	0.1000	0.0062
##	10	1.1617	nan	0.1000	0.0057
##	20	1.1040	nan	0.1000	0.0017
##	40	1.0703	nan	0.1000	0.0004
##	60	1.0577	nan	0.1000	0.0001
##	80	1.0505	nan	0.1000	0.0002
##	100	1.0456	nan	0.1000	0.0001
##	120	1.0417	nan	0.1000	0.0001
##	140	1.0382	nan	0.1000	0.0001
##	150	1.0368	nan	0.1000	0.0001
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3386	nan	0.1000	0.0236
##	2	1.3000	nan	0.1000	0.0193
##	3	1.2684	nan	0.1000	0.0158
##	4	1.2421	nan	0.1000	0.0132
##	5	1.2200	nan	0.1000	0.0109
##	6	1.2015	nan	0.1000	0.0093
##	7	1.1840	nan	0.1000	0.0087
##	8	1.1705	nan	0.1000	0.0067
##	9	1.1581	nan	0.1000	0.0062
##	10	1.1482	nan	0.1000	0.0048
##	20	1.0929	nan	0.1000	0.0014
##	40	1.0596	nan	0.1000	0.0004
##	60	1.0473	nan	0.1000	0.0003
##	80	1.0395	nan	0.1000	0.0001
##	100	1.0336	nan	0.1000	0.0001
##	120	1.0290	nan	0.1000	0.0001
##	140	1.0250	nan	0.1000	0.0001
##	150	1.0234	nan	0.1000	0.0001
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3541	nan	0.1000	0.0164
##	2	1.3274	nan	0.1000	0.0134
##	3	1.3051	nan	0.1000	0.0112
##	4	1.2838	nan	0.1000	0.0106
##	5	1.2661	nan	0.1000	0.0087
##	6	1.2495	nan	0.1000	0.0083
##	7	1.2354	nan	0.1000	0.0070
##	8	1.2221	nan	0.1000	0.0066
##	9	1.2106	nan	0.1000	0.0057
##	10	1.2003	nan	0.1000	0.0052
##	20	1.1369	nan	0.1000	0.0022
##	40	1.0957	nan	0.1000	0.0005
##	60	1.0805	nan	0.1000	0.0002
##	80	1.0724	nan	0.1000	0.0001
##	100	1.0671	nan	0.1000	0.0001
##	120	1.0631	nan	0.1000	0.0001
##	140	1.0599	nan	0.1000	0.0000

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##      150      1.0586      nan      0.1000      0.0000
##
## Iter   TrainDeviance   ValidDeviance   StepSize   Improve
##      1      1.3443      nan      0.1000      0.0209
##      2      1.3088      nan      0.1000      0.0178
##      3      1.2809      nan      0.1000      0.0139
##      4      1.2570      nan      0.1000      0.0119
##      5      1.2348      nan      0.1000      0.0111
##      6      1.2147      nan      0.1000      0.0100
##      7      1.2002      nan      0.1000      0.0073
##      8      1.1869      nan      0.1000      0.0066
##      9      1.1742      nan      0.1000      0.0063
##     10      1.1627      nan      0.1000      0.0058
##     20      1.1060      nan      0.1000      0.0018
##     40      1.0723      nan      0.1000      0.0004
##     60      1.0594      nan      0.1000      0.0002
##     80      1.0519      nan      0.1000      0.0001
##    100      1.0464      nan      0.1000      0.0001
##    120      1.0423      nan      0.1000      0.0001
##    140      1.0390      nan      0.1000      0.0001
##    150      1.0376      nan      0.1000      0.0001
##
## Iter   TrainDeviance   ValidDeviance   StepSize   Improve
##      1      1.3390      nan      0.1000      0.0235
##      2      1.3004      nan      0.1000      0.0193
##      3      1.2689      nan      0.1000      0.0157
##      4      1.2427      nan      0.1000      0.0130
##      5      1.2209      nan      0.1000      0.0108
##      6      1.2022      nan      0.1000      0.0093
##      7      1.1860      nan      0.1000      0.0082
##      8      1.1726      nan      0.1000      0.0067
##      9      1.1602      nan      0.1000      0.0062
##     10      1.1497      nan      0.1000      0.0053
##     20      1.0943      nan      0.1000      0.0014
##     40      1.0619      nan      0.1000      0.0003
##     60      1.0491      nan      0.1000      0.0002
##     80      1.0413      nan      0.1000      0.0001
##    100      1.0353      nan      0.1000      0.0001
##    120      1.0306      nan      0.1000      0.0001
##    140      1.0264      nan      0.1000      0.0000
##    150      1.0243      nan      0.1000      0.0000
##
## Iter   TrainDeviance   ValidDeviance   StepSize   Improve
##      1      1.3531      nan      0.1000      0.0165
##      2      1.3260      nan      0.1000      0.0135
##      3      1.3034      nan      0.1000      0.0112
##      4      1.2822      nan      0.1000      0.0107
##      5      1.2645      nan      0.1000      0.0087
##      6      1.2480      nan      0.1000      0.0083
##      7      1.2337      nan      0.1000      0.0071
##      8      1.2207      nan      0.1000      0.0066
##      9      1.2093      nan      0.1000      0.0057
##     10      1.1992      nan      0.1000      0.0050
##     20      1.1356      nan      0.1000      0.0020

```

##	40	1.0942	nan	0.1000	0.0005
##	60	1.0791	nan	0.1000	0.0002
##	80	1.0708	nan	0.1000	0.0001
##	100	1.0654	nan	0.1000	0.0001
##	120	1.0614	nan	0.1000	0.0001
##	140	1.0583	nan	0.1000	0.0001
##	150	1.0570	nan	0.1000	0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3446	nan	0.1000	0.0211
##	2	1.3104	nan	0.1000	0.0172
##	3	1.2805	nan	0.1000	0.0151
##	4	1.2567	nan	0.1000	0.0119
##	5	1.2352	nan	0.1000	0.0108
##	6	1.2158	nan	0.1000	0.0097
##	7	1.1984	nan	0.1000	0.0085
##	8	1.1843	nan	0.1000	0.0071
##	9	1.1714	nan	0.1000	0.0064
##	10	1.1608	nan	0.1000	0.0053
##	20	1.1042	nan	0.1000	0.0017
##	40	1.0708	nan	0.1000	0.0005
##	60	1.0583	nan	0.1000	0.0002
##	80	1.0508	nan	0.1000	0.0001
##	100	1.0452	nan	0.1000	0.0001
##	120	1.0410	nan	0.1000	0.0000
##	140	1.0375	nan	0.1000	0.0001
##	150	1.0362	nan	0.1000	0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3390	nan	0.1000	0.0237
##	2	1.3000	nan	0.1000	0.0195
##	3	1.2679	nan	0.1000	0.0159
##	4	1.2415	nan	0.1000	0.0133
##	5	1.2197	nan	0.1000	0.0109
##	6	1.2011	nan	0.1000	0.0093
##	7	1.1839	nan	0.1000	0.0084
##	8	1.1691	nan	0.1000	0.0074
##	9	1.1571	nan	0.1000	0.0060
##	10	1.1473	nan	0.1000	0.0049
##	20	1.0924	nan	0.1000	0.0018
##	40	1.0601	nan	0.1000	0.0004
##	60	1.0476	nan	0.1000	0.0002
##	80	1.0395	nan	0.1000	0.0001
##	100	1.0342	nan	0.1000	0.0001
##	120	1.0289	nan	0.1000	0.0001
##	140	1.0249	nan	0.1000	0.0001
##	150	1.0232	nan	0.1000	0.0001
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3532	nan	0.1000	0.0165
##	2	1.3266	nan	0.1000	0.0134
##	3	1.3043	nan	0.1000	0.0112
##	4	1.2826	nan	0.1000	0.0108
##	5	1.2649	nan	0.1000	0.0087

##	6	1.2483	nan	0.1000	0.0084
##	7	1.2340	nan	0.1000	0.0071
##	8	1.2206	nan	0.1000	0.0067
##	9	1.2090	nan	0.1000	0.0057
##	10	1.1986	nan	0.1000	0.0052
##	20	1.1350	nan	0.1000	0.0020
##	40	1.0929	nan	0.1000	0.0005
##	60	1.0775	nan	0.1000	0.0002
##	80	1.0695	nan	0.1000	0.0002
##	100	1.0641	nan	0.1000	0.0001
##	120	1.0600	nan	0.1000	0.0001
##	140	1.0568	nan	0.1000	0.0000
##	150	1.0555	nan	0.1000	0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3440	nan	0.1000	0.0211
##	2	1.3097	nan	0.1000	0.0171
##	3	1.2798	nan	0.1000	0.0150
##	4	1.2554	nan	0.1000	0.0123
##	5	1.2345	nan	0.1000	0.0105
##	6	1.2141	nan	0.1000	0.0103
##	7	1.1984	nan	0.1000	0.0079
##	8	1.1835	nan	0.1000	0.0073
##	9	1.1713	nan	0.1000	0.0060
##	10	1.1611	nan	0.1000	0.0051
##	20	1.1029	nan	0.1000	0.0019
##	40	1.0690	nan	0.1000	0.0004
##	60	1.0569	nan	0.1000	0.0002
##	80	1.0494	nan	0.1000	0.0001
##	100	1.0441	nan	0.1000	0.0001
##	120	1.0398	nan	0.1000	0.0001
##	140	1.0366	nan	0.1000	0.0001
##	150	1.0350	nan	0.1000	0.0001
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3387	nan	0.1000	0.0237
##	2	1.2997	nan	0.1000	0.0194
##	3	1.2676	nan	0.1000	0.0160
##	4	1.2411	nan	0.1000	0.0131
##	5	1.2190	nan	0.1000	0.0110
##	6	1.2006	nan	0.1000	0.0093
##	7	1.1847	nan	0.1000	0.0080
##	8	1.1696	nan	0.1000	0.0075
##	9	1.1579	nan	0.1000	0.0058
##	10	1.1478	nan	0.1000	0.0050
##	20	1.0921	nan	0.1000	0.0013
##	40	1.0585	nan	0.1000	0.0004
##	60	1.0456	nan	0.1000	0.0002
##	80	1.0384	nan	0.1000	0.0002
##	100	1.0327	nan	0.1000	0.0001
##	120	1.0281	nan	0.1000	0.0001
##	140	1.0235	nan	0.1000	0.0001
##	150	1.0217	nan	0.1000	0.0001
##					

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3538	nan	0.1000	0.0164
##	2	1.3272	nan	0.1000	0.0135
##	3	1.3048	nan	0.1000	0.0111
##	4	1.2832	nan	0.1000	0.0108
##	5	1.2657	nan	0.1000	0.0087
##	6	1.2489	nan	0.1000	0.0084
##	7	1.2346	nan	0.1000	0.0071
##	8	1.2215	nan	0.1000	0.0066
##	9	1.2102	nan	0.1000	0.0057
##	10	1.1996	nan	0.1000	0.0053
##	20	1.1358	nan	0.1000	0.0020
##	40	1.0937	nan	0.1000	0.0005
##	60	1.0781	nan	0.1000	0.0003
##	80	1.0701	nan	0.1000	0.0001
##	100	1.0648	nan	0.1000	0.0001
##	120	1.0609	nan	0.1000	0.0001
##	140	1.0578	nan	0.1000	0.0000
##	150	1.0564	nan	0.1000	0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3447	nan	0.1000	0.0211
##	2	1.3102	nan	0.1000	0.0171
##	3	1.2804	nan	0.1000	0.0150
##	4	1.2559	nan	0.1000	0.0123
##	5	1.2326	nan	0.1000	0.0116
##	6	1.2144	nan	0.1000	0.0091
##	7	1.1992	nan	0.1000	0.0074
##	8	1.1840	nan	0.1000	0.0075
##	9	1.1722	nan	0.1000	0.0058
##	10	1.1606	nan	0.1000	0.0057
##	20	1.1037	nan	0.1000	0.0016
##	40	1.0704	nan	0.1000	0.0004
##	60	1.0574	nan	0.1000	0.0002
##	80	1.0496	nan	0.1000	0.0002
##	100	1.0445	nan	0.1000	0.0001
##	120	1.0403	nan	0.1000	0.0001
##	140	1.0370	nan	0.1000	0.0001
##	150	1.0355	nan	0.1000	0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3391	nan	0.1000	0.0236
##	2	1.2997	nan	0.1000	0.0195
##	3	1.2678	nan	0.1000	0.0159
##	4	1.2413	nan	0.1000	0.0132
##	5	1.2192	nan	0.1000	0.0109
##	6	1.2008	nan	0.1000	0.0093
##	7	1.1850	nan	0.1000	0.0079
##	8	1.1700	nan	0.1000	0.0075
##	9	1.1583	nan	0.1000	0.0058
##	10	1.1475	nan	0.1000	0.0054
##	20	1.0924	nan	0.1000	0.0014
##	40	1.0596	nan	0.1000	0.0004
##	60	1.0465	nan	0.1000	0.0002

##	80	1.0394	nan	0.1000	0.0001
##	100	1.0340	nan	0.1000	0.0001
##	120	1.0292	nan	0.1000	0.0001
##	140	1.0248	nan	0.1000	0.0001
##	150	1.0228	nan	0.1000	0.0001
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3532	nan	0.1000	0.0166
##	2	1.3259	nan	0.1000	0.0135
##	3	1.3037	nan	0.1000	0.0112
##	4	1.2825	nan	0.1000	0.0106
##	5	1.2649	nan	0.1000	0.0087
##	6	1.2483	nan	0.1000	0.0083
##	7	1.2340	nan	0.1000	0.0071
##	8	1.2210	nan	0.1000	0.0065
##	9	1.2094	nan	0.1000	0.0058
##	10	1.1990	nan	0.1000	0.0052
##	20	1.1352	nan	0.1000	0.0022
##	40	1.0935	nan	0.1000	0.0006
##	60	1.0783	nan	0.1000	0.0002
##	80	1.0704	nan	0.1000	0.0001
##	100	1.0650	nan	0.1000	0.0001
##	120	1.0610	nan	0.1000	0.0001
##	140	1.0577	nan	0.1000	0.0001
##	150	1.0563	nan	0.1000	0.0001
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3441	nan	0.1000	0.0211
##	2	1.3103	nan	0.1000	0.0171
##	3	1.2802	nan	0.1000	0.0150
##	4	1.2555	nan	0.1000	0.0123
##	5	1.2351	nan	0.1000	0.0101
##	6	1.2146	nan	0.1000	0.0103
##	7	1.1989	nan	0.1000	0.0079
##	8	1.1842	nan	0.1000	0.0073
##	9	1.1727	nan	0.1000	0.0058
##	10	1.1614	nan	0.1000	0.0055
##	20	1.1041	nan	0.1000	0.0018
##	40	1.0700	nan	0.1000	0.0005
##	60	1.0577	nan	0.1000	0.0002
##	80	1.0502	nan	0.1000	0.0001
##	100	1.0448	nan	0.1000	0.0001
##	120	1.0406	nan	0.1000	0.0001
##	140	1.0373	nan	0.1000	0.0001
##	150	1.0356	nan	0.1000	0.0001
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3390	nan	0.1000	0.0237
##	2	1.3002	nan	0.1000	0.0195
##	3	1.2683	nan	0.1000	0.0160
##	4	1.2416	nan	0.1000	0.0133
##	5	1.2200	nan	0.1000	0.0109
##	6	1.2014	nan	0.1000	0.0093
##	7	1.1842	nan	0.1000	0.0085

##	8	1.1702	nan	0.1000	0.0068
##	9	1.1582	nan	0.1000	0.0060
##	10	1.1474	nan	0.1000	0.0053
##	20	1.0918	nan	0.1000	0.0012
##	40	1.0592	nan	0.1000	0.0004
##	60	1.0462	nan	0.1000	0.0001
##	80	1.0390	nan	0.1000	0.0001
##	100	1.0338	nan	0.1000	0.0001
##	120	1.0291	nan	0.1000	0.0001
##	140	1.0246	nan	0.1000	0.0001
##	150	1.0227	nan	0.1000	0.0000

##

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3531	nan	0.1000	0.0164
##	2	1.3262	nan	0.1000	0.0135
##	3	1.3039	nan	0.1000	0.0112
##	4	1.2827	nan	0.1000	0.0106
##	5	1.2651	nan	0.1000	0.0086
##	6	1.2483	nan	0.1000	0.0083
##	7	1.2338	nan	0.1000	0.0071
##	8	1.2208	nan	0.1000	0.0065
##	9	1.2096	nan	0.1000	0.0057
##	10	1.1994	nan	0.1000	0.0051
##	20	1.1367	nan	0.1000	0.0019
##	40	1.0943	nan	0.1000	0.0005
##	60	1.0789	nan	0.1000	0.0002
##	80	1.0709	nan	0.1000	0.0001
##	100	1.0656	nan	0.1000	0.0001
##	120	1.0616	nan	0.1000	0.0001
##	140	1.0584	nan	0.1000	0.0000
##	150	1.0571	nan	0.1000	0.0000

##

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3443	nan	0.1000	0.0210
##	2	1.3083	nan	0.1000	0.0179
##	3	1.2791	nan	0.1000	0.0146
##	4	1.2556	nan	0.1000	0.0117
##	5	1.2357	nan	0.1000	0.0100
##	6	1.2148	nan	0.1000	0.0104
##	7	1.1990	nan	0.1000	0.0079
##	8	1.1854	nan	0.1000	0.0067
##	9	1.1724	nan	0.1000	0.0064
##	10	1.1625	nan	0.1000	0.0050
##	20	1.1050	nan	0.1000	0.0019
##	40	1.0713	nan	0.1000	0.0004
##	60	1.0587	nan	0.1000	0.0003
##	80	1.0511	nan	0.1000	0.0001
##	100	1.0459	nan	0.1000	0.0002
##	120	1.0421	nan	0.1000	0.0000
##	140	1.0382	nan	0.1000	0.0000
##	150	1.0367	nan	0.1000	0.0001

##

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3388	nan	0.1000	0.0235

##	2	1.2999	nan	0.1000	0.0195
##	3	1.2687	nan	0.1000	0.0159
##	4	1.2423	nan	0.1000	0.0132
##	5	1.2205	nan	0.1000	0.0109
##	6	1.2006	nan	0.1000	0.0099
##	7	1.1849	nan	0.1000	0.0077
##	8	1.1701	nan	0.1000	0.0073
##	9	1.1571	nan	0.1000	0.0063
##	10	1.1468	nan	0.1000	0.0050
##	20	1.0923	nan	0.1000	0.0016
##	40	1.0601	nan	0.1000	0.0005
##	60	1.0470	nan	0.1000	0.0003
##	80	1.0396	nan	0.1000	0.0001
##	100	1.0336	nan	0.1000	0.0001
##	120	1.0289	nan	0.1000	0.0001
##	140	1.0247	nan	0.1000	0.0001
##	150	1.0229	nan	0.1000	0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3535	nan	0.1000	0.0165
##	2	1.3268	nan	0.1000	0.0134
##	3	1.3042	nan	0.1000	0.0111
##	4	1.2828	nan	0.1000	0.0107
##	5	1.2654	nan	0.1000	0.0087
##	6	1.2484	nan	0.1000	0.0084
##	7	1.2343	nan	0.1000	0.0071
##	8	1.2214	nan	0.1000	0.0066
##	9	1.2100	nan	0.1000	0.0057
##	10	1.1997	nan	0.1000	0.0051
##	20	1.1357	nan	0.1000	0.0023
##	40	1.0939	nan	0.1000	0.0005
##	60	1.0783	nan	0.1000	0.0003
##	80	1.0706	nan	0.1000	0.0001
##	100	1.0652	nan	0.1000	0.0001
##	120	1.0612	nan	0.1000	0.0001
##	140	1.0578	nan	0.1000	0.0000
##	150	1.0564	nan	0.1000	0.0001
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3442	nan	0.1000	0.0210
##	2	1.3096	nan	0.1000	0.0174
##	3	1.2800	nan	0.1000	0.0149
##	4	1.2564	nan	0.1000	0.0117
##	5	1.2337	nan	0.1000	0.0113
##	6	1.2160	nan	0.1000	0.0087
##	7	1.1984	nan	0.1000	0.0088
##	8	1.1849	nan	0.1000	0.0067
##	9	1.1724	nan	0.1000	0.0062
##	10	1.1627	nan	0.1000	0.0048
##	20	1.1039	nan	0.1000	0.0016
##	40	1.0702	nan	0.1000	0.0004
##	60	1.0576	nan	0.1000	0.0002
##	80	1.0500	nan	0.1000	0.0001
##	100	1.0448	nan	0.1000	0.0001

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##      120      1.0406      nan      0.1000      0.0001
##      140      1.0375      nan      0.1000      0.0001
##      150      1.0358      nan      0.1000      0.0000
##
## Iter   TrainDeviance   ValidDeviance   StepSize   Improve
##      1      1.3389      nan      0.1000      0.0235
##      2      1.3001      nan      0.1000      0.0194
##      3      1.2682      nan      0.1000      0.0160
##      4      1.2413      nan      0.1000      0.0133
##      5      1.2195      nan      0.1000      0.0109
##      6      1.2008      nan      0.1000      0.0093
##      7      1.1838      nan      0.1000      0.0085
##      8      1.1702      nan      0.1000      0.0068
##      9      1.1579      nan      0.1000      0.0061
##     10      1.1470      nan      0.1000      0.0053
##     20      1.0924      nan      0.1000      0.0016
##     40      1.0595      nan      0.1000      0.0003
##     60      1.0458      nan      0.1000      0.0002
##     80      1.0381      nan      0.1000      0.0001
##    100      1.0326      nan      0.1000      0.0001
##    120      1.0276      nan      0.1000      0.0002
##    140      1.0241      nan      0.1000      0.0000
##    150      1.0219      nan      0.1000      0.0000
##
## Iter   TrainDeviance   ValidDeviance   StepSize   Improve
##      1      1.3535      nan      0.1000      0.0165
##      2      1.3267      nan      0.1000      0.0134
##      3      1.3043      nan      0.1000      0.0112
##      4      1.2834      nan      0.1000      0.0106
##      5      1.2656      nan      0.1000      0.0087
##      6      1.2488      nan      0.1000      0.0084
##      7      1.2346      nan      0.1000      0.0071
##      8      1.2215      nan      0.1000      0.0066
##      9      1.2098      nan      0.1000      0.0057
##     10      1.1993      nan      0.1000      0.0052
##     20      1.1360      nan      0.1000      0.0020
##     40      1.0935      nan      0.1000      0.0005
##     60      1.0779      nan      0.1000      0.0003
##     80      1.0702      nan      0.1000      0.0001
##    100      1.0648      nan      0.1000      0.0001
##    120      1.0607      nan      0.1000      0.0000
##    140      1.0575      nan      0.1000      0.0000
##    150      1.0561      nan      0.1000      0.0001
##
## Iter   TrainDeviance   ValidDeviance   StepSize   Improve
##      1      1.3444      nan      0.1000      0.0210
##      2      1.3104      nan      0.1000      0.0169
##      3      1.2802      nan      0.1000      0.0150
##      4      1.2555      nan      0.1000      0.0124
##      5      1.2351      nan      0.1000      0.0100
##      6      1.2169      nan      0.1000      0.0091
##      7      1.1992      nan      0.1000      0.0088
##      8      1.1851      nan      0.1000      0.0069
##      9      1.1726      nan      0.1000      0.0062

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##	10	1.1613	nan	0.1000	0.0056
##	20	1.1042	nan	0.1000	0.0019
##	40	1.0702	nan	0.1000	0.0005
##	60	1.0577	nan	0.1000	0.0002
##	80	1.0498	nan	0.1000	0.0001
##	100	1.0447	nan	0.1000	0.0001
##	120	1.0407	nan	0.1000	0.0001
##	140	1.0374	nan	0.1000	0.0000
##	150	1.0357	nan	0.1000	0.0001
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3387	nan	0.1000	0.0237
##	2	1.2996	nan	0.1000	0.0195
##	3	1.2679	nan	0.1000	0.0158
##	4	1.2418	nan	0.1000	0.0132
##	5	1.2199	nan	0.1000	0.0109
##	6	1.2014	nan	0.1000	0.0092
##	7	1.1842	nan	0.1000	0.0085
##	8	1.1703	nan	0.1000	0.0070
##	9	1.1584	nan	0.1000	0.0058
##	10	1.1478	nan	0.1000	0.0052
##	20	1.0922	nan	0.1000	0.0015
##	40	1.0591	nan	0.1000	0.0004
##	60	1.0465	nan	0.1000	0.0003
##	80	1.0389	nan	0.1000	0.0001
##	100	1.0334	nan	0.1000	0.0001
##	120	1.0288	nan	0.1000	0.0001
##	140	1.0249	nan	0.1000	0.0000
##	150	1.0229	nan	0.1000	0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3536	nan	0.1000	0.0165
##	2	1.3268	nan	0.1000	0.0135
##	3	1.3043	nan	0.1000	0.0113
##	4	1.2833	nan	0.1000	0.0106
##	5	1.2652	nan	0.1000	0.0088
##	6	1.2486	nan	0.1000	0.0084
##	7	1.2346	nan	0.1000	0.0070
##	8	1.2215	nan	0.1000	0.0066
##	9	1.2100	nan	0.1000	0.0058
##	10	1.1995	nan	0.1000	0.0052
##	20	1.1357	nan	0.1000	0.0022
##	40	1.0937	nan	0.1000	0.0006
##	60	1.0781	nan	0.1000	0.0003
##	80	1.0703	nan	0.1000	0.0001
##	100	1.0648	nan	0.1000	0.0001
##	120	1.0609	nan	0.1000	0.0000
##	140	1.0577	nan	0.1000	0.0001
##	150	1.0564	nan	0.1000	0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3441	nan	0.1000	0.0210
##	2	1.3086	nan	0.1000	0.0180
##	3	1.2803	nan	0.1000	0.0141

##	4	1.2550	nan	0.1000	0.0126
##	5	1.2347	nan	0.1000	0.0102
##	6	1.2171	nan	0.1000	0.0087
##	7	1.2000	nan	0.1000	0.0086
##	8	1.1846	nan	0.1000	0.0076
##	9	1.1727	nan	0.1000	0.0059
##	10	1.1611	nan	0.1000	0.0057
##	20	1.1029	nan	0.1000	0.0019
##	40	1.0699	nan	0.1000	0.0004
##	60	1.0572	nan	0.1000	0.0002
##	80	1.0496	nan	0.1000	0.0001
##	100	1.0444	nan	0.1000	0.0001
##	120	1.0404	nan	0.1000	0.0000
##	140	1.0368	nan	0.1000	0.0000
##	150	1.0353	nan	0.1000	0.0001
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3388	nan	0.1000	0.0237
##	2	1.3001	nan	0.1000	0.0194
##	3	1.2680	nan	0.1000	0.0159
##	4	1.2420	nan	0.1000	0.0130
##	5	1.2204	nan	0.1000	0.0108
##	6	1.2018	nan	0.1000	0.0093
##	7	1.1861	nan	0.1000	0.0079
##	8	1.1711	nan	0.1000	0.0074
##	9	1.1584	nan	0.1000	0.0062
##	10	1.1478	nan	0.1000	0.0052
##	20	1.0926	nan	0.1000	0.0014
##	40	1.0596	nan	0.1000	0.0005
##	60	1.0466	nan	0.1000	0.0002
##	80	1.0394	nan	0.1000	0.0001
##	100	1.0336	nan	0.1000	0.0001
##	120	1.0282	nan	0.1000	0.0001
##	140	1.0244	nan	0.1000	0.0001
##	150	1.0225	nan	0.1000	0.0001
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3531	nan	0.1000	0.0166
##	2	1.3259	nan	0.1000	0.0136
##	3	1.3034	nan	0.1000	0.0111
##	4	1.2818	nan	0.1000	0.0107
##	5	1.2639	nan	0.1000	0.0088
##	6	1.2471	nan	0.1000	0.0083
##	7	1.2329	nan	0.1000	0.0071
##	8	1.2198	nan	0.1000	0.0065
##	9	1.2082	nan	0.1000	0.0057
##	10	1.1980	nan	0.1000	0.0052
##	20	1.1345	nan	0.1000	0.0020
##	40	1.0926	nan	0.1000	0.0006
##	60	1.0773	nan	0.1000	0.0003
##	80	1.0694	nan	0.1000	0.0002
##	100	1.0640	nan	0.1000	0.0001
##	120	1.0599	nan	0.1000	0.0001
##	140	1.0566	nan	0.1000	0.0001


```

##      150      1.0553      nan      0.1000      0.0000
##
## Iter   TrainDeviance   ValidDeviance   StepSize   Improve
##      1      1.3441      nan      0.1000      0.0211
##      2      1.3098      nan      0.1000      0.0170
##      3      1.2793      nan      0.1000      0.0151
##      4      1.2545      nan      0.1000      0.0123
##      5      1.2312      nan      0.1000      0.0116
##      6      1.2132      nan      0.1000      0.0091
##      7      1.1971      nan      0.1000      0.0080
##      8      1.1833      nan      0.1000      0.0069
##      9      1.1718      nan      0.1000      0.0058
##     10      1.1606      nan      0.1000      0.0056
##     20      1.1021      nan      0.1000      0.0018
##     40      1.0692      nan      0.1000      0.0004
##     60      1.0563      nan      0.1000      0.0002
##     80      1.0487      nan      0.1000      0.0001
##    100      1.0433      nan      0.1000      0.0001
##    120      1.0392      nan      0.1000      0.0001
##    140      1.0356      nan      0.1000      0.0001
##    150      1.0339      nan      0.1000      0.0001
##
## Iter   TrainDeviance   ValidDeviance   StepSize   Improve
##      1      1.3390      nan      0.1000      0.0238
##      2      1.3006      nan      0.1000      0.0194
##      3      1.2677      nan      0.1000      0.0162
##      4      1.2416      nan      0.1000      0.0132
##      5      1.2198      nan      0.1000      0.0110
##      6      1.2006      nan      0.1000      0.0095
##      7      1.1846      nan      0.1000      0.0080
##      8      1.1708      nan      0.1000      0.0068
##      9      1.1576      nan      0.1000      0.0066
##     10      1.1467      nan      0.1000      0.0054
##     20      1.0910      nan      0.1000      0.0016
##     40      1.0580      nan      0.1000      0.0004
##     60      1.0451      nan      0.1000      0.0002
##     80      1.0379      nan      0.1000      0.0001
##    100      1.0324      nan      0.1000      0.0001
##    120      1.0272      nan      0.1000      0.0000
##    140      1.0230      nan      0.1000      0.0001
##    150      1.0211      nan      0.1000      0.0001
##
## Iter   TrainDeviance   ValidDeviance   StepSize   Improve
##      1      1.3534      nan      0.1000      0.0164
##      2      1.3266      nan      0.1000      0.0133
##      3      1.3045      nan      0.1000      0.0110
##      4      1.2832      nan      0.1000      0.0107
##      5      1.2657      nan      0.1000      0.0087
##      6      1.2490      nan      0.1000      0.0083
##      7      1.2346      nan      0.1000      0.0070
##      8      1.2212      nan      0.1000      0.0065
##      9      1.2099      nan      0.1000      0.0056
##     10      1.1995      nan      0.1000      0.0051
##     20      1.1370      nan      0.1000      0.0022

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##	40	1.0952	nan	0.1000	0.0005
##	60	1.0798	nan	0.1000	0.0003
##	80	1.0722	nan	0.1000	0.0001
##	100	1.0669	nan	0.1000	0.0001
##	120	1.0629	nan	0.1000	0.0001
##	140	1.0598	nan	0.1000	0.0000
##	150	1.0584	nan	0.1000	0.0001
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3442	nan	0.1000	0.0209
##	2	1.3084	nan	0.1000	0.0179
##	3	1.2802	nan	0.1000	0.0142
##	4	1.2565	nan	0.1000	0.0118
##	5	1.2352	nan	0.1000	0.0106
##	6	1.2150	nan	0.1000	0.0101
##	7	1.2004	nan	0.1000	0.0072
##	8	1.1866	nan	0.1000	0.0068
##	9	1.1739	nan	0.1000	0.0064
##	10	1.1628	nan	0.1000	0.0054
##	20	1.1053	nan	0.1000	0.0016
##	40	1.0718	nan	0.1000	0.0004
##	60	1.0592	nan	0.1000	0.0004
##	80	1.0519	nan	0.1000	0.0001
##	100	1.0465	nan	0.1000	0.0001
##	120	1.0425	nan	0.1000	0.0001
##	140	1.0392	nan	0.1000	0.0000
##	150	1.0377	nan	0.1000	0.0001
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3392	nan	0.1000	0.0235
##	2	1.3009	nan	0.1000	0.0191
##	3	1.2689	nan	0.1000	0.0161
##	4	1.2424	nan	0.1000	0.0132
##	5	1.2207	nan	0.1000	0.0109
##	6	1.2017	nan	0.1000	0.0095
##	7	1.1858	nan	0.1000	0.0079
##	8	1.1713	nan	0.1000	0.0073
##	9	1.1589	nan	0.1000	0.0061
##	10	1.1488	nan	0.1000	0.0050
##	20	1.0939	nan	0.1000	0.0016
##	40	1.0610	nan	0.1000	0.0004
##	60	1.0483	nan	0.1000	0.0003
##	80	1.0407	nan	0.1000	0.0002
##	100	1.0351	nan	0.1000	0.0001
##	120	1.0305	nan	0.1000	0.0001
##	140	1.0265	nan	0.1000	0.0001
##	150	1.0245	nan	0.1000	0.0001
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3534	nan	0.1000	0.0164
##	2	1.3267	nan	0.1000	0.0134
##	3	1.3044	nan	0.1000	0.0111
##	4	1.2830	nan	0.1000	0.0107
##	5	1.2653	nan	0.1000	0.0087

##	6	1.2489	nan	0.1000	0.0082
##	7	1.2345	nan	0.1000	0.0071
##	8	1.2215	nan	0.1000	0.0065
##	9	1.2100	nan	0.1000	0.0056
##	10	1.1997	nan	0.1000	0.0051
##	20	1.1365	nan	0.1000	0.0021
##	40	1.0950	nan	0.1000	0.0006
##	60	1.0798	nan	0.1000	0.0003
##	80	1.0719	nan	0.1000	0.0001
##	100	1.0665	nan	0.1000	0.0001
##	120	1.0624	nan	0.1000	0.0001
##	140	1.0591	nan	0.1000	0.0001
##	150	1.0577	nan	0.1000	0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3445	nan	0.1000	0.0210
##	2	1.3086	nan	0.1000	0.0179
##	3	1.2808	nan	0.1000	0.0140
##	4	1.2575	nan	0.1000	0.0116
##	5	1.2354	nan	0.1000	0.0109
##	6	1.2149	nan	0.1000	0.0101
##	7	1.1998	nan	0.1000	0.0075
##	8	1.1866	nan	0.1000	0.0066
##	9	1.1740	nan	0.1000	0.0064
##	10	1.1632	nan	0.1000	0.0054
##	20	1.1047	nan	0.1000	0.0015
##	40	1.0716	nan	0.1000	0.0005
##	60	1.0594	nan	0.1000	0.0002
##	80	1.0519	nan	0.1000	0.0002
##	100	1.0463	nan	0.1000	0.0001
##	120	1.0419	nan	0.1000	0.0001
##	140	1.0386	nan	0.1000	0.0000
##	150	1.0371	nan	0.1000	0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3390	nan	0.1000	0.0235
##	2	1.3006	nan	0.1000	0.0192
##	3	1.2684	nan	0.1000	0.0161
##	4	1.2422	nan	0.1000	0.0130
##	5	1.2205	nan	0.1000	0.0108
##	6	1.2017	nan	0.1000	0.0094
##	7	1.1843	nan	0.1000	0.0086
##	8	1.1708	nan	0.1000	0.0066
##	9	1.1593	nan	0.1000	0.0058
##	10	1.1486	nan	0.1000	0.0054
##	20	1.0943	nan	0.1000	0.0013
##	40	1.0616	nan	0.1000	0.0003
##	60	1.0487	nan	0.1000	0.0002
##	80	1.0411	nan	0.1000	0.0001
##	100	1.0353	nan	0.1000	0.0001
##	120	1.0304	nan	0.1000	0.0001
##	140	1.0266	nan	0.1000	0.0001
##	150	1.0247	nan	0.1000	0.0001
##					

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3533	nan	0.1000	0.0165
##	2	1.3264	nan	0.1000	0.0135
##	3	1.3039	nan	0.1000	0.0112
##	4	1.2824	nan	0.1000	0.0108
##	5	1.2650	nan	0.1000	0.0087
##	6	1.2482	nan	0.1000	0.0084
##	7	1.2338	nan	0.1000	0.0071
##	8	1.2205	nan	0.1000	0.0066
##	9	1.2093	nan	0.1000	0.0057
##	10	1.1989	nan	0.1000	0.0052
##	20	1.1353	nan	0.1000	0.0019
##	40	1.0933	nan	0.1000	0.0007
##	60	1.0781	nan	0.1000	0.0002
##	80	1.0700	nan	0.1000	0.0002
##	100	1.0646	nan	0.1000	0.0001
##	120	1.0607	nan	0.1000	0.0001
##	140	1.0575	nan	0.1000	0.0001
##	150	1.0561	nan	0.1000	0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3438	nan	0.1000	0.0211
##	2	1.3077	nan	0.1000	0.0180
##	3	1.2794	nan	0.1000	0.0141
##	4	1.2550	nan	0.1000	0.0122
##	5	1.2348	nan	0.1000	0.0100
##	6	1.2150	nan	0.1000	0.0098
##	7	1.1997	nan	0.1000	0.0076
##	8	1.1844	nan	0.1000	0.0075
##	9	1.1725	nan	0.1000	0.0059
##	10	1.1618	nan	0.1000	0.0053
##	20	1.1036	nan	0.1000	0.0016
##	40	1.0697	nan	0.1000	0.0005
##	60	1.0568	nan	0.1000	0.0002
##	80	1.0495	nan	0.1000	0.0001
##	100	1.0440	nan	0.1000	0.0001
##	120	1.0404	nan	0.1000	0.0000
##	140	1.0369	nan	0.1000	0.0000
##	150	1.0351	nan	0.1000	0.0001
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3389	nan	0.1000	0.0237
##	2	1.3002	nan	0.1000	0.0193
##	3	1.2680	nan	0.1000	0.0162
##	4	1.2412	nan	0.1000	0.0133
##	5	1.2193	nan	0.1000	0.0109
##	6	1.2008	nan	0.1000	0.0093
##	7	1.1837	nan	0.1000	0.0085
##	8	1.1690	nan	0.1000	0.0072
##	9	1.1573	nan	0.1000	0.0057
##	10	1.1469	nan	0.1000	0.0052
##	20	1.0922	nan	0.1000	0.0013
##	40	1.0586	nan	0.1000	0.0004
##	60	1.0461	nan	0.1000	0.0002

##	80	1.0381	nan	0.1000	0.0002
##	100	1.0322	nan	0.1000	0.0001
##	120	1.0270	nan	0.1000	0.0001
##	140	1.0230	nan	0.1000	0.0002
##	150	1.0212	nan	0.1000	0.0001
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3530	nan	0.1000	0.0164
##	2	1.3263	nan	0.1000	0.0134
##	3	1.3039	nan	0.1000	0.0112
##	4	1.2829	nan	0.1000	0.0105
##	5	1.2654	nan	0.1000	0.0088
##	6	1.2488	nan	0.1000	0.0083
##	7	1.2350	nan	0.1000	0.0071
##	8	1.2218	nan	0.1000	0.0066
##	9	1.2102	nan	0.1000	0.0058
##	10	1.1999	nan	0.1000	0.0050
##	20	1.1358	nan	0.1000	0.0022
##	40	1.0942	nan	0.1000	0.0005
##	60	1.0788	nan	0.1000	0.0002
##	80	1.0707	nan	0.1000	0.0001
##	100	1.0651	nan	0.1000	0.0001
##	120	1.0610	nan	0.1000	0.0001
##	140	1.0577	nan	0.1000	0.0001
##	150	1.0564	nan	0.1000	0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3442	nan	0.1000	0.0210
##	2	1.3084	nan	0.1000	0.0180
##	3	1.2790	nan	0.1000	0.0146
##	4	1.2556	nan	0.1000	0.0117
##	5	1.2351	nan	0.1000	0.0103
##	6	1.2155	nan	0.1000	0.0097
##	7	1.1985	nan	0.1000	0.0086
##	8	1.1849	nan	0.1000	0.0069
##	9	1.1726	nan	0.1000	0.0062
##	10	1.1612	nan	0.1000	0.0057
##	20	1.1047	nan	0.1000	0.0017
##	40	1.0705	nan	0.1000	0.0004
##	60	1.0574	nan	0.1000	0.0003
##	80	1.0499	nan	0.1000	0.0001
##	100	1.0448	nan	0.1000	0.0001
##	120	1.0410	nan	0.1000	0.0000
##	140	1.0374	nan	0.1000	0.0001
##	150	1.0358	nan	0.1000	0.0001
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3397	nan	0.1000	0.0236
##	2	1.3006	nan	0.1000	0.0195
##	3	1.2686	nan	0.1000	0.0159
##	4	1.2426	nan	0.1000	0.0131
##	5	1.2200	nan	0.1000	0.0111
##	6	1.2001	nan	0.1000	0.0099
##	7	1.1847	nan	0.1000	0.0077

##	8	1.1699	nan	0.1000	0.0073
##	9	1.1575	nan	0.1000	0.0061
##	10	1.1471	nan	0.1000	0.0052
##	20	1.0919	nan	0.1000	0.0014
##	40	1.0588	nan	0.1000	0.0004
##	60	1.0457	nan	0.1000	0.0002
##	80	1.0383	nan	0.1000	0.0002
##	100	1.0325	nan	0.1000	0.0002
##	120	1.0275	nan	0.1000	0.0001
##	140	1.0237	nan	0.1000	0.0001
##	150	1.0219	nan	0.1000	0.0001

##

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3536	nan	0.1000	0.0164
##	2	1.3267	nan	0.1000	0.0135
##	3	1.3044	nan	0.1000	0.0112
##	4	1.2832	nan	0.1000	0.0105
##	5	1.2657	nan	0.1000	0.0087
##	6	1.2488	nan	0.1000	0.0085
##	7	1.2346	nan	0.1000	0.0070
##	8	1.2215	nan	0.1000	0.0066
##	9	1.2099	nan	0.1000	0.0058
##	10	1.1994	nan	0.1000	0.0052
##	20	1.1362	nan	0.1000	0.0022
##	40	1.0941	nan	0.1000	0.0005
##	60	1.0785	nan	0.1000	0.0003
##	80	1.0704	nan	0.1000	0.0002
##	100	1.0652	nan	0.1000	0.0001
##	120	1.0611	nan	0.1000	0.0001
##	140	1.0579	nan	0.1000	0.0001
##	150	1.0566	nan	0.1000	0.0001

##

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3442	nan	0.1000	0.0210
##	2	1.3083	nan	0.1000	0.0179
##	3	1.2802	nan	0.1000	0.0141
##	4	1.2558	nan	0.1000	0.0122
##	5	1.2357	nan	0.1000	0.0100
##	6	1.2165	nan	0.1000	0.0096
##	7	1.1992	nan	0.1000	0.0086
##	8	1.1852	nan	0.1000	0.0070
##	9	1.1727	nan	0.1000	0.0062
##	10	1.1621	nan	0.1000	0.0053
##	20	1.1043	nan	0.1000	0.0016
##	40	1.0705	nan	0.1000	0.0005
##	60	1.0576	nan	0.1000	0.0002
##	80	1.0500	nan	0.1000	0.0001
##	100	1.0443	nan	0.1000	0.0001
##	120	1.0402	nan	0.1000	0.0000
##	140	1.0368	nan	0.1000	0.0000
##	150	1.0353	nan	0.1000	0.0000

##

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3388	nan	0.1000	0.0236

##	2	1.3007	nan	0.1000	0.0191
##	3	1.2683	nan	0.1000	0.0161
##	4	1.2418	nan	0.1000	0.0133
##	5	1.2197	nan	0.1000	0.0109
##	6	1.2010	nan	0.1000	0.0093
##	7	1.1856	nan	0.1000	0.0076
##	8	1.1707	nan	0.1000	0.0074
##	9	1.1580	nan	0.1000	0.0063
##	10	1.1472	nan	0.1000	0.0052
##	20	1.0920	nan	0.1000	0.0015
##	40	1.0599	nan	0.1000	0.0004
##	60	1.0465	nan	0.1000	0.0003
##	80	1.0392	nan	0.1000	0.0001
##	100	1.0332	nan	0.1000	0.0001
##	120	1.0284	nan	0.1000	0.0001
##	140	1.0242	nan	0.1000	0.0001
##	150	1.0222	nan	0.1000	0.0001
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3533	nan	0.1000	0.0165
##	2	1.3264	nan	0.1000	0.0135
##	3	1.3040	nan	0.1000	0.0112
##	4	1.2829	nan	0.1000	0.0106
##	5	1.2652	nan	0.1000	0.0087
##	6	1.2482	nan	0.1000	0.0084
##	7	1.2340	nan	0.1000	0.0071
##	8	1.2208	nan	0.1000	0.0065
##	9	1.2094	nan	0.1000	0.0056
##	10	1.1989	nan	0.1000	0.0052
##	20	1.1351	nan	0.1000	0.0022
##	40	1.0932	nan	0.1000	0.0005
##	60	1.0777	nan	0.1000	0.0002
##	80	1.0697	nan	0.1000	0.0001
##	100	1.0642	nan	0.1000	0.0001
##	120	1.0601	nan	0.1000	0.0001
##	140	1.0568	nan	0.1000	0.0001
##	150	1.0555	nan	0.1000	0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3439	nan	0.1000	0.0211
##	2	1.3080	nan	0.1000	0.0180
##	3	1.2802	nan	0.1000	0.0138
##	4	1.2555	nan	0.1000	0.0122
##	5	1.2329	nan	0.1000	0.0114
##	6	1.2145	nan	0.1000	0.0091
##	7	1.1971	nan	0.1000	0.0085
##	8	1.1836	nan	0.1000	0.0068
##	9	1.1709	nan	0.1000	0.0063
##	10	1.1603	nan	0.1000	0.0053
##	20	1.1040	nan	0.1000	0.0016
##	40	1.0701	nan	0.1000	0.0004
##	60	1.0573	nan	0.1000	0.0002
##	80	1.0497	nan	0.1000	0.0001
##	100	1.0445	nan	0.1000	0.0001

##	120	1.0403	nan	0.1000	0.0000
##	140	1.0367	nan	0.1000	0.0001
##	150	1.0353	nan	0.1000	0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3392	nan	0.1000	0.0237
##	2	1.3003	nan	0.1000	0.0195
##	3	1.2685	nan	0.1000	0.0159
##	4	1.2423	nan	0.1000	0.0132
##	5	1.2204	nan	0.1000	0.0111
##	6	1.2006	nan	0.1000	0.0099
##	7	1.1837	nan	0.1000	0.0085
##	8	1.1701	nan	0.1000	0.0067
##	9	1.1575	nan	0.1000	0.0063
##	10	1.1473	nan	0.1000	0.0051
##	20	1.0919	nan	0.1000	0.0014
##	40	1.0587	nan	0.1000	0.0004
##	60	1.0457	nan	0.1000	0.0002
##	80	1.0384	nan	0.1000	0.0001
##	100	1.0329	nan	0.1000	0.0001
##	120	1.0282	nan	0.1000	0.0001
##	140	1.0242	nan	0.1000	0.0001
##	150	1.0224	nan	0.1000	0.0001
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3533	nan	0.1000	0.0165
##	2	1.3265	nan	0.1000	0.0134
##	3	1.3040	nan	0.1000	0.0113
##	4	1.2827	nan	0.1000	0.0106
##	5	1.2653	nan	0.1000	0.0087
##	6	1.2487	nan	0.1000	0.0083
##	7	1.2345	nan	0.1000	0.0071
##	8	1.2212	nan	0.1000	0.0066
##	9	1.2099	nan	0.1000	0.0058
##	10	1.1995	nan	0.1000	0.0052
##	20	1.1358	nan	0.1000	0.0021
##	40	1.0937	nan	0.1000	0.0005
##	60	1.0783	nan	0.1000	0.0003
##	80	1.0705	nan	0.1000	0.0001
##	100	1.0652	nan	0.1000	0.0001
##	120	1.0613	nan	0.1000	0.0001
##	140	1.0580	nan	0.1000	0.0001
##	150	1.0567	nan	0.1000	0.0001
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3438	nan	0.1000	0.0211
##	2	1.3081	nan	0.1000	0.0179
##	3	1.2798	nan	0.1000	0.0141
##	4	1.2552	nan	0.1000	0.0122
##	5	1.2345	nan	0.1000	0.0104
##	6	1.2148	nan	0.1000	0.0098
##	7	1.1977	nan	0.1000	0.0086
##	8	1.1840	nan	0.1000	0.0069
##	9	1.1723	nan	0.1000	0.0058

##	10	1.1608	nan	0.1000	0.0057
##	20	1.1041	nan	0.1000	0.0013
##	40	1.0702	nan	0.1000	0.0004
##	60	1.0578	nan	0.1000	0.0002
##	80	1.0503	nan	0.1000	0.0001
##	100	1.0449	nan	0.1000	0.0001
##	120	1.0409	nan	0.1000	0.0000
##	140	1.0371	nan	0.1000	0.0001
##	150	1.0355	nan	0.1000	0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3392	nan	0.1000	0.0237
##	2	1.3007	nan	0.1000	0.0194
##	3	1.2681	nan	0.1000	0.0161
##	4	1.2417	nan	0.1000	0.0133
##	5	1.2199	nan	0.1000	0.0109
##	6	1.2012	nan	0.1000	0.0093
##	7	1.1855	nan	0.1000	0.0077
##	8	1.1706	nan	0.1000	0.0074
##	9	1.1579	nan	0.1000	0.0063
##	10	1.1473	nan	0.1000	0.0053
##	20	1.0916	nan	0.1000	0.0016
##	40	1.0600	nan	0.1000	0.0005
##	60	1.0474	nan	0.1000	0.0002
##	80	1.0397	nan	0.1000	0.0002
##	100	1.0339	nan	0.1000	0.0001
##	120	1.0291	nan	0.1000	0.0001
##	140	1.0249	nan	0.1000	0.0000
##	150	1.0231	nan	0.1000	0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3530	nan	0.1000	0.0165
##	2	1.3262	nan	0.1000	0.0135
##	3	1.3040	nan	0.1000	0.0111
##	4	1.2828	nan	0.1000	0.0107
##	5	1.2651	nan	0.1000	0.0088
##	6	1.2481	nan	0.1000	0.0083
##	7	1.2339	nan	0.1000	0.0070
##	8	1.2208	nan	0.1000	0.0066
##	9	1.2095	nan	0.1000	0.0057
##	10	1.1990	nan	0.1000	0.0052
##	20	1.1355	nan	0.1000	0.0020
##	40	1.0938	nan	0.1000	0.0005
##	60	1.0782	nan	0.1000	0.0002
##	80	1.0704	nan	0.1000	0.0001
##	100	1.0649	nan	0.1000	0.0001
##	120	1.0608	nan	0.1000	0.0001
##	140	1.0576	nan	0.1000	0.0001
##	150	1.0561	nan	0.1000	0.0001
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3439	nan	0.1000	0.0210
##	2	1.3080	nan	0.1000	0.0179
##	3	1.2798	nan	0.1000	0.0141

##	4	1.2551	nan	0.1000	0.0122
##	5	1.2343	nan	0.1000	0.0104
##	6	1.2142	nan	0.1000	0.0102
##	7	1.1994	nan	0.1000	0.0074
##	8	1.1847	nan	0.1000	0.0074
##	9	1.1728	nan	0.1000	0.0059
##	10	1.1617	nan	0.1000	0.0055
##	20	1.1037	nan	0.1000	0.0014
##	40	1.0696	nan	0.1000	0.0004
##	60	1.0570	nan	0.1000	0.0002
##	80	1.0494	nan	0.1000	0.0001
##	100	1.0440	nan	0.1000	0.0001
##	120	1.0397	nan	0.1000	0.0001
##	140	1.0360	nan	0.1000	0.0001
##	150	1.0343	nan	0.1000	0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3390	nan	0.1000	0.0237
##	2	1.3003	nan	0.1000	0.0194
##	3	1.2685	nan	0.1000	0.0159
##	4	1.2418	nan	0.1000	0.0133
##	5	1.2200	nan	0.1000	0.0109
##	6	1.2012	nan	0.1000	0.0093
##	7	1.1857	nan	0.1000	0.0077
##	8	1.1712	nan	0.1000	0.0072
##	9	1.1591	nan	0.1000	0.0060
##	10	1.1481	nan	0.1000	0.0055
##	20	1.0924	nan	0.1000	0.0014
##	40	1.0591	nan	0.1000	0.0006
##	60	1.0461	nan	0.1000	0.0003
##	80	1.0382	nan	0.1000	0.0001
##	100	1.0325	nan	0.1000	0.0001
##	120	1.0277	nan	0.1000	0.0001
##	140	1.0242	nan	0.1000	0.0001
##	150	1.0222	nan	0.1000	0.0001
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3535	nan	0.1000	0.0165
##	2	1.3266	nan	0.1000	0.0135
##	3	1.3042	nan	0.1000	0.0111
##	4	1.2827	nan	0.1000	0.0108
##	5	1.2650	nan	0.1000	0.0087
##	6	1.2483	nan	0.1000	0.0083
##	7	1.2341	nan	0.1000	0.0072
##	8	1.2208	nan	0.1000	0.0066
##	9	1.2094	nan	0.1000	0.0056
##	10	1.1990	nan	0.1000	0.0052
##	20	1.1356	nan	0.1000	0.0022
##	40	1.0938	nan	0.1000	0.0005
##	60	1.0783	nan	0.1000	0.0002
##	80	1.0704	nan	0.1000	0.0001
##	100	1.0649	nan	0.1000	0.0001
##	120	1.0608	nan	0.1000	0.0001
##	140	1.0576	nan	0.1000	0.0000

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##      150      1.0562      nan      0.1000      0.0000
##
## Iter   TrainDeviance   ValidDeviance   StepSize   Improve
##      1      1.3440      nan      0.1000      0.0210
##      2      1.3099      nan      0.1000      0.0170
##      3      1.2797      nan      0.1000      0.0150
##      4      1.2559      nan      0.1000      0.0120
##      5      1.2352      nan      0.1000      0.0103
##      6      1.2144      nan      0.1000      0.0104
##      7      1.1974      nan      0.1000      0.0085
##      8      1.1844      nan      0.1000      0.0066
##      9      1.1717      nan      0.1000      0.0063
##     10      1.1608      nan      0.1000      0.0054
##     20      1.1043      nan      0.1000      0.0015
##     40      1.0701      nan      0.1000      0.0005
##     60      1.0572      nan      0.1000      0.0002
##     80      1.0494      nan      0.1000      0.0002
##    100      1.0441      nan      0.1000      0.0001
##    120      1.0402      nan      0.1000      0.0000
##    140      1.0365      nan      0.1000      0.0001
##    150      1.0350      nan      0.1000      0.0000
##
## Iter   TrainDeviance   ValidDeviance   StepSize   Improve
##      1      1.3390      nan      0.1000      0.0236
##      2      1.3000      nan      0.1000      0.0195
##      3      1.2683      nan      0.1000      0.0160
##      4      1.2415      nan      0.1000      0.0133
##      5      1.2199      nan      0.1000      0.0108
##      6      1.2011      nan      0.1000      0.0093
##      7      1.1852      nan      0.1000      0.0079
##      8      1.1705      nan      0.1000      0.0075
##      9      1.1582      nan      0.1000      0.0062
##     10      1.1480      nan      0.1000      0.0051
##     20      1.0923      nan      0.1000      0.0016
##     40      1.0593      nan      0.1000      0.0004
##     60      1.0460      nan      0.1000      0.0003
##     80      1.0380      nan      0.1000      0.0002
##    100      1.0325      nan      0.1000      0.0000
##    120      1.0280      nan      0.1000      0.0001
##    140      1.0240      nan      0.1000      0.0001
##    150      1.0223      nan      0.1000      0.0001
##
## Iter   TrainDeviance   ValidDeviance   StepSize   Improve
##      1      1.3537      nan      0.1000      0.0165
##      2      1.3264      nan      0.1000      0.0135
##      3      1.3039      nan      0.1000      0.0111
##      4      1.2827      nan      0.1000      0.0106
##      5      1.2647      nan      0.1000      0.0088
##      6      1.2481      nan      0.1000      0.0082
##      7      1.2336      nan      0.1000      0.0071
##      8      1.2207      nan      0.1000      0.0065
##      9      1.2092      nan      0.1000      0.0057
##     10      1.1991      nan      0.1000      0.0050
##     20      1.1359      nan      0.1000      0.0021

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##	40	1.0938	nan	0.1000	0.0005
##	60	1.0784	nan	0.1000	0.0003
##	80	1.0703	nan	0.1000	0.0002
##	100	1.0648	nan	0.1000	0.0001
##	120	1.0610	nan	0.1000	0.0001
##	140	1.0578	nan	0.1000	0.0001
##	150	1.0565	nan	0.1000	0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3447	nan	0.1000	0.0209
##	2	1.3105	nan	0.1000	0.0171
##	3	1.2807	nan	0.1000	0.0150
##	4	1.2558	nan	0.1000	0.0125
##	5	1.2350	nan	0.1000	0.0104
##	6	1.2173	nan	0.1000	0.0088
##	7	1.2000	nan	0.1000	0.0087
##	8	1.1854	nan	0.1000	0.0072
##	9	1.1730	nan	0.1000	0.0061
##	10	1.1627	nan	0.1000	0.0051
##	20	1.1041	nan	0.1000	0.0016
##	40	1.0707	nan	0.1000	0.0004
##	60	1.0579	nan	0.1000	0.0002
##	80	1.0505	nan	0.1000	0.0001
##	100	1.0449	nan	0.1000	0.0001
##	120	1.0410	nan	0.1000	0.0001
##	140	1.0376	nan	0.1000	0.0000
##	150	1.0359	nan	0.1000	0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3390	nan	0.1000	0.0235
##	2	1.3004	nan	0.1000	0.0195
##	3	1.2687	nan	0.1000	0.0159
##	4	1.2425	nan	0.1000	0.0131
##	5	1.2204	nan	0.1000	0.0111
##	6	1.2012	nan	0.1000	0.0097
##	7	1.1855	nan	0.1000	0.0077
##	8	1.1717	nan	0.1000	0.0069
##	9	1.1599	nan	0.1000	0.0059
##	10	1.1488	nan	0.1000	0.0055
##	20	1.0928	nan	0.1000	0.0016
##	40	1.0609	nan	0.1000	0.0004
##	60	1.0478	nan	0.1000	0.0002
##	80	1.0395	nan	0.1000	0.0002
##	100	1.0336	nan	0.1000	0.0002
##	120	1.0286	nan	0.1000	0.0001
##	140	1.0246	nan	0.1000	0.0001
##	150	1.0226	nan	0.1000	0.0001
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3534	nan	0.1000	0.0165
##	2	1.3266	nan	0.1000	0.0133
##	3	1.3042	nan	0.1000	0.0112
##	4	1.2827	nan	0.1000	0.0107
##	5	1.2652	nan	0.1000	0.0086

##	6	1.2485	nan	0.1000	0.0084
##	7	1.2345	nan	0.1000	0.0071
##	8	1.2216	nan	0.1000	0.0065
##	9	1.2100	nan	0.1000	0.0057
##	10	1.2001	nan	0.1000	0.0050
##	20	1.1359	nan	0.1000	0.0021
##	40	1.0941	nan	0.1000	0.0006
##	60	1.0788	nan	0.1000	0.0003
##	80	1.0710	nan	0.1000	0.0001
##	100	1.0658	nan	0.1000	0.0001
##	120	1.0617	nan	0.1000	0.0001
##	140	1.0586	nan	0.1000	0.0001
##	150	1.0574	nan	0.1000	0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3442	nan	0.1000	0.0210
##	2	1.3093	nan	0.1000	0.0172
##	3	1.2797	nan	0.1000	0.0148
##	4	1.2564	nan	0.1000	0.0116
##	5	1.2340	nan	0.1000	0.0112
##	6	1.2167	nan	0.1000	0.0086
##	7	1.1989	nan	0.1000	0.0089
##	8	1.1856	nan	0.1000	0.0067
##	9	1.1729	nan	0.1000	0.0063
##	10	1.1613	nan	0.1000	0.0058
##	20	1.1052	nan	0.1000	0.0014
##	40	1.0706	nan	0.1000	0.0004
##	60	1.0585	nan	0.1000	0.0002
##	80	1.0509	nan	0.1000	0.0002
##	100	1.0457	nan	0.1000	0.0001
##	120	1.0413	nan	0.1000	0.0001
##	140	1.0381	nan	0.1000	0.0001
##	150	1.0366	nan	0.1000	0.0001
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3389	nan	0.1000	0.0235
##	2	1.3004	nan	0.1000	0.0192
##	3	1.2683	nan	0.1000	0.0160
##	4	1.2424	nan	0.1000	0.0130
##	5	1.2201	nan	0.1000	0.0111
##	6	1.1995	nan	0.1000	0.0101
##	7	1.1828	nan	0.1000	0.0083
##	8	1.1695	nan	0.1000	0.0066
##	9	1.1575	nan	0.1000	0.0061
##	10	1.1477	nan	0.1000	0.0049
##	20	1.0930	nan	0.1000	0.0016
##	40	1.0606	nan	0.1000	0.0004
##	60	1.0475	nan	0.1000	0.0002
##	80	1.0397	nan	0.1000	0.0002
##	100	1.0342	nan	0.1000	0.0001
##	120	1.0294	nan	0.1000	0.0001
##	140	1.0252	nan	0.1000	0.0001
##	150	1.0233	nan	0.1000	0.0001
##					

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3532	nan	0.1000	0.0165
##	2	1.3263	nan	0.1000	0.0134
##	3	1.3038	nan	0.1000	0.0112
##	4	1.2826	nan	0.1000	0.0106
##	5	1.2651	nan	0.1000	0.0088
##	6	1.2484	nan	0.1000	0.0083
##	7	1.2345	nan	0.1000	0.0070
##	8	1.2215	nan	0.1000	0.0066
##	9	1.2096	nan	0.1000	0.0057
##	10	1.1993	nan	0.1000	0.0051
##	20	1.1361	nan	0.1000	0.0021
##	40	1.0942	nan	0.1000	0.0005
##	60	1.0788	nan	0.1000	0.0003
##	80	1.0709	nan	0.1000	0.0001
##	100	1.0656	nan	0.1000	0.0001
##	120	1.0615	nan	0.1000	0.0001
##	140	1.0583	nan	0.1000	0.0001
##	150	1.0569	nan	0.1000	0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3445	nan	0.1000	0.0210
##	2	1.3088	nan	0.1000	0.0179
##	3	1.2807	nan	0.1000	0.0140
##	4	1.2558	nan	0.1000	0.0124
##	5	1.2348	nan	0.1000	0.0104
##	6	1.2151	nan	0.1000	0.0098
##	7	1.2000	nan	0.1000	0.0075
##	8	1.1849	nan	0.1000	0.0075
##	9	1.1733	nan	0.1000	0.0057
##	10	1.1620	nan	0.1000	0.0056
##	20	1.1053	nan	0.1000	0.0014
##	40	1.0712	nan	0.1000	0.0004
##	60	1.0582	nan	0.1000	0.0003
##	80	1.0502	nan	0.1000	0.0001
##	100	1.0453	nan	0.1000	0.0001
##	120	1.0415	nan	0.1000	0.0001
##	140	1.0383	nan	0.1000	0.0001
##	150	1.0365	nan	0.1000	0.0001
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3390	nan	0.1000	0.0235
##	2	1.3002	nan	0.1000	0.0193
##	3	1.2687	nan	0.1000	0.0159
##	4	1.2426	nan	0.1000	0.0130
##	5	1.2203	nan	0.1000	0.0111
##	6	1.2017	nan	0.1000	0.0092
##	7	1.1843	nan	0.1000	0.0087
##	8	1.1690	nan	0.1000	0.0074
##	9	1.1569	nan	0.1000	0.0059
##	10	1.1466	nan	0.1000	0.0052
##	20	1.0924	nan	0.1000	0.0018
##	40	1.0605	nan	0.1000	0.0005
##	60	1.0473	nan	0.1000	0.0002

##	80	1.0396	nan	0.1000	0.0001
##	100	1.0340	nan	0.1000	0.0001
##	120	1.0288	nan	0.1000	0.0001
##	140	1.0248	nan	0.1000	0.0000
##	150	1.0230	nan	0.1000	0.0001
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3535	nan	0.1000	0.0165
##	2	1.3267	nan	0.1000	0.0135
##	3	1.3044	nan	0.1000	0.0112
##	4	1.2830	nan	0.1000	0.0106
##	5	1.2655	nan	0.1000	0.0087
##	6	1.2490	nan	0.1000	0.0083
##	7	1.2346	nan	0.1000	0.0071
##	8	1.2215	nan	0.1000	0.0066
##	9	1.2101	nan	0.1000	0.0056
##	10	1.1997	nan	0.1000	0.0052
##	20	1.1363	nan	0.1000	0.0021
##	40	1.0949	nan	0.1000	0.0005
##	60	1.0797	nan	0.1000	0.0002
##	80	1.0719	nan	0.1000	0.0001
##	100	1.0666	nan	0.1000	0.0001
##	120	1.0626	nan	0.1000	0.0001
##	140	1.0593	nan	0.1000	0.0000
##	150	1.0580	nan	0.1000	0.0001
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3439	nan	0.1000	0.0210
##	2	1.3078	nan	0.1000	0.0179
##	3	1.2794	nan	0.1000	0.0141
##	4	1.2543	nan	0.1000	0.0124
##	5	1.2338	nan	0.1000	0.0103
##	6	1.2170	nan	0.1000	0.0084
##	7	1.1992	nan	0.1000	0.0090
##	8	1.1856	nan	0.1000	0.0066
##	9	1.1733	nan	0.1000	0.0064
##	10	1.1626	nan	0.1000	0.0053
##	20	1.1055	nan	0.1000	0.0014
##	40	1.0708	nan	0.1000	0.0004
##	60	1.0584	nan	0.1000	0.0002
##	80	1.0507	nan	0.1000	0.0001
##	100	1.0456	nan	0.1000	0.0001
##	120	1.0419	nan	0.1000	0.0001
##	140	1.0385	nan	0.1000	0.0000
##	150	1.0366	nan	0.1000	0.0001
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3392	nan	0.1000	0.0237
##	2	1.3003	nan	0.1000	0.0195
##	3	1.2684	nan	0.1000	0.0159
##	4	1.2422	nan	0.1000	0.0131
##	5	1.2202	nan	0.1000	0.0110
##	6	1.2000	nan	0.1000	0.0101
##	7	1.1834	nan	0.1000	0.0081

##	8	1.1699	nan	0.1000	0.0067
##	9	1.1586	nan	0.1000	0.0057
##	10	1.1488	nan	0.1000	0.0048
##	20	1.0945	nan	0.1000	0.0014
##	40	1.0599	nan	0.1000	0.0004
##	60	1.0474	nan	0.1000	0.0002
##	80	1.0395	nan	0.1000	0.0002
##	100	1.0340	nan	0.1000	0.0002
##	120	1.0291	nan	0.1000	0.0001
##	140	1.0251	nan	0.1000	0.0000
##	150	1.0234	nan	0.1000	0.0001

##

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3532	nan	0.1000	0.0164
##	2	1.3263	nan	0.1000	0.0134
##	3	1.3040	nan	0.1000	0.0112
##	4	1.2828	nan	0.1000	0.0105
##	5	1.2653	nan	0.1000	0.0087
##	6	1.2487	nan	0.1000	0.0083
##	7	1.2345	nan	0.1000	0.0071
##	8	1.2215	nan	0.1000	0.0066
##	9	1.2100	nan	0.1000	0.0057
##	10	1.1996	nan	0.1000	0.0052
##	20	1.1362	nan	0.1000	0.0020
##	40	1.0944	nan	0.1000	0.0005
##	60	1.0791	nan	0.1000	0.0003
##	80	1.0711	nan	0.1000	0.0001
##	100	1.0658	nan	0.1000	0.0001
##	120	1.0617	nan	0.1000	0.0001
##	140	1.0586	nan	0.1000	0.0000
##	150	1.0571	nan	0.1000	0.0000

##

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3446	nan	0.1000	0.0210
##	2	1.3083	nan	0.1000	0.0179
##	3	1.2797	nan	0.1000	0.0142
##	4	1.2558	nan	0.1000	0.0119
##	5	1.2362	nan	0.1000	0.0098
##	6	1.2162	nan	0.1000	0.0100
##	7	1.1984	nan	0.1000	0.0089
##	8	1.1843	nan	0.1000	0.0070
##	9	1.1728	nan	0.1000	0.0058
##	10	1.1621	nan	0.1000	0.0052
##	20	1.1047	nan	0.1000	0.0014
##	40	1.0705	nan	0.1000	0.0004
##	60	1.0584	nan	0.1000	0.0002
##	80	1.0507	nan	0.1000	0.0001
##	100	1.0455	nan	0.1000	0.0001
##	120	1.0415	nan	0.1000	0.0001
##	140	1.0378	nan	0.1000	0.0000
##	150	1.0364	nan	0.1000	0.0000

##

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3394	nan	0.1000	0.0236


```
##      2      1.3008      nan      0.1000      0.0195
##      3      1.2687      nan      0.1000      0.0160
##      4      1.2425      nan      0.1000      0.0131
##      5      1.2205      nan      0.1000      0.0111
##      6      1.2004      nan      0.1000      0.0100
##      7      1.1849      nan      0.1000      0.0079
##      8      1.1704      nan      0.1000      0.0073
##      9      1.1580      nan      0.1000      0.0061
##     10      1.1474      nan      0.1000      0.0054
##     20      1.0931      nan      0.1000      0.0014
##     40      1.0597      nan      0.1000      0.0004
##     60      1.0469      nan      0.1000      0.0001
##     80      1.0391      nan      0.1000      0.0001
##    100      1.0333      nan      0.1000      0.0001
##    120      1.0285      nan      0.1000      0.0001
##    140      1.0249      nan      0.1000      0.0000
##    150      1.0229      nan      0.1000      0.0001
```

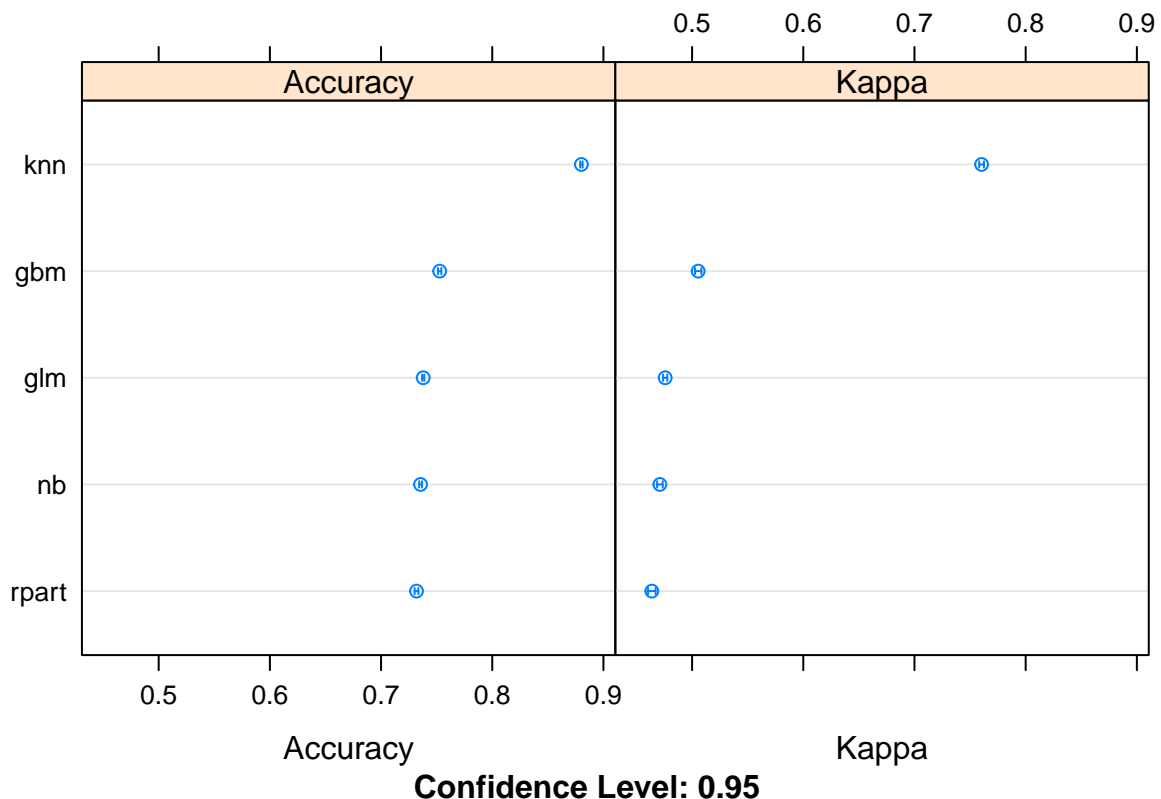
```
##
## Iter   TrainDeviance   ValidDeviance   StepSize   Improve
##      1      1.3389      nan      0.1000      0.0237
##      2      1.3007      nan      0.1000      0.0192
##      3      1.2686      nan      0.1000      0.0161
##      4      1.2419      nan      0.1000      0.0133
##      5      1.2201      nan      0.1000      0.0109
##      6      1.2014      nan      0.1000      0.0093
##      7      1.1855      nan      0.1000      0.0079
##      8      1.1715      nan      0.1000      0.0069
##      9      1.1588      nan      0.1000      0.0064
##     10      1.1489      nan      0.1000      0.0049
##     20      1.0932      nan      0.1000      0.0014
##     40      1.0605      nan      0.1000      0.0005
##     60      1.0474      nan      0.1000      0.0002
##     80      1.0396      nan      0.1000      0.0001
##    100      1.0341      nan      0.1000      0.0001
##    120      1.0298      nan      0.1000      0.0000
##    140      1.0257      nan      0.1000      0.0001
##    150      1.0235      nan      0.1000      0.0001
```

```
results <- resamples(ensemble_learning)
summary(results) # summary of all the combined models
```

```
##
## Call:
## summary.resamples(object = results)
##
## Models: gbm, rpart, glm, knn, nb
## Number of resamples: 30
##
## Accuracy
##      Min.    1st Qu.    Median      Mean    3rd Qu.      Max. NA's
## gbm  0.7468479 0.7497310 0.7522461 0.7527319 0.7556248 0.7629870    0
## rpart 0.7217818 0.7287038 0.7320498 0.7319008 0.7342004 0.7444881    0
## glm   0.7333333 0.7359947 0.7374283 0.7379033 0.7389343 0.7452431    0
## knn   0.8752737 0.8782371 0.8803700 0.8801826 0.8820098 0.8857682    0
## nb    0.7310683 0.7328942 0.7342948 0.7355224 0.7379200 0.7426004    0
```

```
##
## Kappa
##           Min.    1st Qu.    Median      Mean    3rd Qu.      Max. NA's
## gbm    0.4936953 0.4994613 0.5044913 0.5054633 0.5112486 0.5259740    0
## rpart  0.4435547 0.4574015 0.4640913 0.4637990 0.4684008 0.4889761    0
## glm    0.4666684 0.4719907 0.4748565 0.4758074 0.4778697 0.4904863    0
## knn    0.7505427 0.7564697 0.7607356 0.7603627 0.7640166 0.7715325    0
## nb     0.4621422 0.4657925 0.4685895 0.4710480 0.4758451 0.4852008    0
```

```
dotplot(results) # plot to check Kappa and Accuracy differences
```



We can see that the KNN creates the most accurate model with an accuracy of 89%.

```
stackControl <- trainControl(method="repeatedcv", number=10, repeats=3, savePredictions='final', classP
stack.glm <- caretStack(ensemble_learning, method="glm", metric="Accuracy", trControl=stackControl)
print(stack.glm)
```

```
## A glm ensemble of 2 base models: gbm, rpart, glm, knn, nb
##
## Ensemble results:
## Generalized Linear Model
##
## 397338 samples
##      5 predictor
##      2 classes: 'No', 'Yes'
##
## No pre-processing
## Resampling: Cross-Validated (10 fold, repeated 3 times)
```

```
## Summary of sample sizes: 357604, 357605, 357604, 357604, 357604, 357605, ...
## Resampling results:
##
## Accuracy Kappa
## 0.9706371 0.941274
```

From the model above, we combine the predictions of different models using stacking, it is desirable that the predictions made by the sub-models have low correlation. This would suggest that the models are skillful but in different ways, allowing a new classifier to figure out how to get the best from each model for an improved score.

Let's check these predictions from our training model on our testing set.

```
stacked_pred <- predict(stack.glm, data_oversample_test)
confusionMatrix(stacked_pred, data_oversample_test$SeriousDlqin2yrs)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    No   Yes
##           No 26907 25249
##           Yes  1472  3082
##
##           Accuracy : 0.5288
##           95% CI : (0.5247, 0.5329)
##           No Information Rate : 0.5004
##           P-Value [Acc > NIR] : < 2.2e-16
##
##           Kappa : 0.057
##           Mcnemar's Test P-Value : < 2.2e-16
##
##           Sensitivity : 0.9481
##           Specificity : 0.1088
##           Pos Pred Value : 0.5159
##           Neg Pred Value : 0.6768
##           Prevalence : 0.5004
##           Detection Rate : 0.4745
##           Detection Prevalence : 0.9197
##           Balanced Accuracy : 0.5285
##
##           'Positive' Class : No
##
```

The model didn't perform like I expected. From the combine predictions from the 5 classification models, the accuracy of 52% was lower than all the previous individual models shown above. We are going to use second model of logistic regression as our final model to submit to the kaggle competition.

Lastly, we write our results to a csv file for kaggle submission.

```
submission <- data.frame(ID = data_oversample_test$X, Serious_Delinquency = os_pred)
head(submission)
```

```
## ID Serious_Delinquency
## 1 3 0.7467114
## 2 4 0.3642371
## 3 21 0.2042830
## 4 23 0.7318677
```

```
## 5 30          0.7142131
## 6 34          0.2218167
```

```
write.csv(submission, file = "MySubmission.csv", row.names = F)
```