MATH154 Team Challenge

NAMES

November 08, 2020

Loading the packages:

```
library(e1071)
library(ggplot2)
library(plyr)
library(tidyverse)
```

EDA

We began our analysis by first loading the training data set and then examine the predicators.

```
data_train <- read.csv('data/cs-training.csv')
colnames(data_train)
```

```
##  [1] "X"
##  [2] "SeriousDlqin2yrs"
##  [3] "RevolvingUtilizationOfUnsecuredLines"
##  [4] "age"
##  [5] "NumberOfTime30.59DaysPastDueNotWorse"
##  [6] "DebtRatio"
##  [7] "MonthlyIncome"
##  [8] "NumberOfOpenCreditLinesAndLoans"
##  [9] "NumberOfTimes90DaysLate"
## [10] "NumberRealEstateLoansOrLines"
## [11] "NumberOfTime60.89DaysPastDueNotWorse"
## [12] "NumberOfDependents"
```

Portion of defaulted

```
mean(data_train$SeriousDlqin2yrs)
```

```
## [1] 0.06684
```

We then check each feature with **summary()** and see which of these features have null data and how many.

```
data_col <- colnames(data_train)
for(i in 2:12){
  print(data_col[i])
  print(summary(data_train[,i]))
}
```

```
## [1] "SeriousDlqin2yrs"
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 0.00000 0.00000 0.00000 0.06684 0.00000 1.00000
## [1] "RevolvingUtilizationOfUnsecuredLines"
##     Min.   1st Qu.    Median      Mean   3rd Qu.      Max.
##     0.00      0.03      0.15      6.05      0.56  50708.00
## [1] "age"
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##     0.0    41.0    52.0    52.3    63.0   109.0
```

```
## [1] "NumberOfTime30.59DaysPastDueNotWorse"
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.000   0.000   0.000   0.421   0.000  98.000
## [1] "DebtRatio"
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
##      0.0      0.2      0.4    353.0      0.9 329664.0
## [1] "MonthlyIncome"
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##       0    3400    5400    6670    8249 3008750   29731
## [1] "NumberOfOpenCreditLinesAndLoans"
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.000   5.000   8.000   8.453  11.000  58.000
## [1] "NumberOfTimes90DaysLate"
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.000   0.000   0.000   0.266   0.000  98.000
## [1] "NumberRealEstateLoansOrLines"
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.000   0.000   1.000   1.018   2.000  54.000
## [1] "NumberOfTime60.89DaysPastDueNotWorse"
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.0000  0.0000  0.0000  0.2404  0.0000 98.0000
## [1] "NumberOfDependents"
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##   0.000   0.000   0.000   0.757   1.000  20.000    3924
```

This suggests that only monthly income and number of dependents have missing data, which we would later either fill in or drop. We then examine each variable to check for the existence of outliers

```r
data_train$SeriousDlqin2yrs <- as.factor(data_train$SeriousDlqin2yrs)
```

Revolving-Utilization-Of-Unsecured-Lines

For the second variable **Revolving-Utilization-Of-Unsecured-Lines**, which measures the total balance on credit card divided by sum of credit limits (amounts owing divided by total available for borrowing), the max number is 50708, which is unlikely as we can't borrow beyond the limit by that much.

Take a look at Observations with **Revolving-Utilization-Of-Unsecured-Lines** > 1 and > 100. There are 3338 obs with **Revolving-Utilization-Of-Unsecured-Lines** > 1 and 223 obs with **Revolving-Utilization-Of-Unsecured-Lines** > 100.

```r
g1 <- subset(data_train,RevolvingUtilizationOfUnsecuredLines>=1)
g2 <- subset(data_train,RevolvingUtilizationOfUnsecuredLines>=100)
summary(g1)
```

```
##        X          SeriousDlqin2yrs RevolvingUtilizationOfUnsecuredLines
##  Min.   :   163   0:2097           Min.   :    1.00
##  1st Qu.: 38548   1:1241           1st Qu.:    1.02
##  Median : 76612                    Median :    1.07
##  Mean   : 75818                    Mean   :  258.46
##  3rd Qu.:112457                    3rd Qu.:    1.30
##  Max.   :149974                    Max.   :50708.00
##
##       age        NumberOfTime30.59DaysPastDueNotWorse   DebtRatio
##  Min.   :21.00   Min.   : 0.000                       Min.   :    0.001
##  1st Qu.:34.00   1st Qu.: 0.000                       1st Qu.:    0.180
##  Median :43.00   Median : 1.000                       Median :    0.374
```

```
##  Mean   :44.05   Mean   : 1.013                      Mean   :  244.619
##  3rd Qu.:52.00   3rd Qu.: 2.000                      3rd Qu.:    0.806
##  Max.   :88.00   Max.   :10.000                      Max.   :21395.000
##
##  MonthlyIncome    NumberOfOpenCreditLinesAndLoans NumberOfTimes90DaysLate
##  Min.   :     0   Min.   : 0.000                  Min.   : 0.000
##  1st Qu.:  2700   1st Qu.: 3.000                  1st Qu.: 0.000
##  Median :  4182   Median : 6.000                  Median : 0.000
##  Mean   :  5282   Mean   : 6.365                  Mean   : 0.636
##  3rd Qu.:  6430   3rd Qu.: 8.000                  3rd Qu.: 1.000
##  Max.   :141500   Max.   :40.000                  Max.   :15.000
##  NA's   :550
##  NumberRealEstateLoansOrLines NumberOfTime60.89DaysPastDueNotWorse
##  Min.   : 0.0000              Min.   :0.0000
##  1st Qu.: 0.0000              1st Qu.:0.0000
##  Median : 0.0000              Median :0.0000
##  Mean   : 0.6812              Mean   :0.4308
##  3rd Qu.: 1.0000              3rd Qu.:1.0000
##  Max.   :10.0000              Max.   :7.0000
##
##  NumberOfDependents
##  Min.   :0.0000
##  1st Qu.:0.0000
##  Median :0.0000
##  Mean   :0.9204
##  3rd Qu.:2.0000
##  Max.   :8.0000
##  NA's   :61
```

```r
summary(g2)
```

```
##        X           SeriousDlqin2yrs RevolvingUtilizationOfUnsecuredLines
##  Min.   :   294   0:212            Min.   :  112
##  1st Qu.: 43785   1: 11            1st Qu.: 1082
##  Median : 80200                    Median : 2159
##  Mean   : 77440                    Mean   : 3848
##  3rd Qu.:110755                    3rd Qu.: 4318
##  Max.   :149280                    Max.   :50708
##
##       age        NumberOfTime30.59DaysPastDueNotWorse   DebtRatio
##  Min.   :24.00   Min.   :0.00                         Min.   :    0.001
##  1st Qu.:39.00   1st Qu.:0.00                         1st Qu.:    0.213
##  Median :48.00   Median :0.00                         Median :    0.381
##  Mean   :50.59   Mean   :0.13                         Mean   :  604.614
##  3rd Qu.:62.50   3rd Qu.:0.00                         3rd Qu.:   81.500
##  Max.   :87.00   Max.   :2.00                         Max.   :21395.000
##
##  MonthlyIncome   NumberOfOpenCreditLinesAndLoans NumberOfTimes90DaysLate
##  Min.   :    0   Min.   : 1.000                  Min.   :0.00000
##  1st Qu.: 4800   1st Qu.: 4.000                  1st Qu.:0.00000
##  Median : 7083   Median : 5.000                  Median :0.00000
##  Mean   : 8629   Mean   : 5.637                  Mean   :0.03139
##  3rd Qu.:10400   3rd Qu.: 7.000                  3rd Qu.:0.00000
##  Max.   :44472   Max.   :21.000                  Max.   :3.00000
##  NA's   :62
```

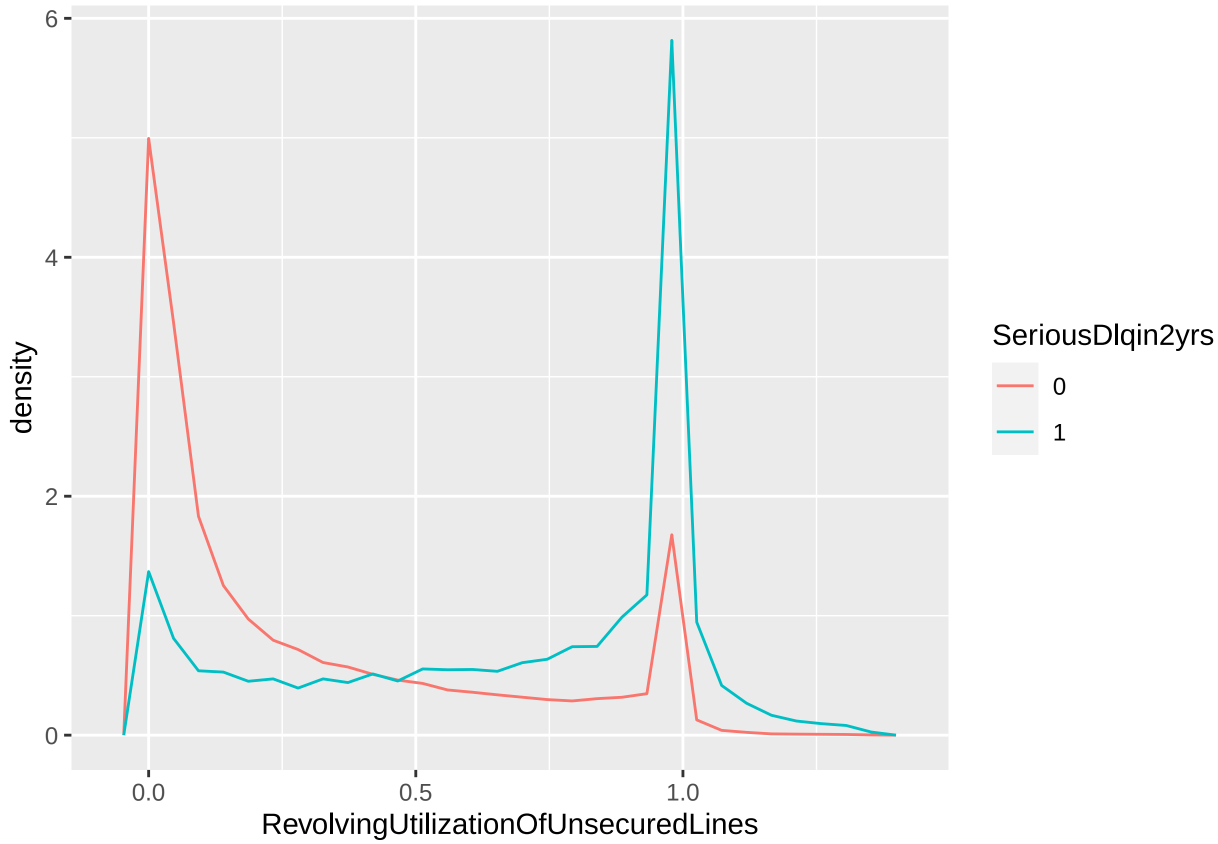
```
##  NumberRealEstateLoansOrLines NumberOfTime60.89DaysPastDueNotWorse
##  Min.   :0.000                Min.   :0.00000
##  1st Qu.:0.000                1st Qu.:0.00000
##  Median :1.000                Median :0.00000
##  Mean   :1.197                Mean   :0.02242
##  3rd Qu.:2.000                3rd Qu.:0.00000
##  Max.   :9.000                Max.   :1.00000
##
##  NumberOfDependents
##  Min.   :0.000
##  1st Qu.:0.000
##  Median :0.000
##  Mean   :0.684
##  3rd Qu.:1.000
##  Max.   :4.000
##  NA's   :11
```

If we remove the outliers using the 1.5IQR rule and plot the density plot grouped by whether there is a financial stress experienced, we observe an interesting shape. The group that has experienced financial stress is more likely to be concentrated on the higher end of the value of the **RevolvingUtilizationOfUnsecuredLines** variable.

```
Q <- quantile(data_train$RevolvingUtilizationOfUnsecuredLines, probs=c(.25, .75), na.rm = TRUE)
iqr <- IQR(data_train$RevolvingUtilizationOfUnsecuredLines, na.rm = TRUE)
data_revu <- subset(data_train,
                        data_train$RevolvingUtilizationOfUnsecuredLines > (Q[1] - 1.5*iqr) &
                          data_train$RevolvingUtilizationOfUnsecuredLines < (Q[2]+1.5*iqr))
```

```
ggplot(data = data_revu,
            mapping = aes(x = RevolvingUtilizationOfUnsecuredLines,
                          after_stat(density), colour = SeriousDlqin2yrs)) +
  geom_freqpoly()
```

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



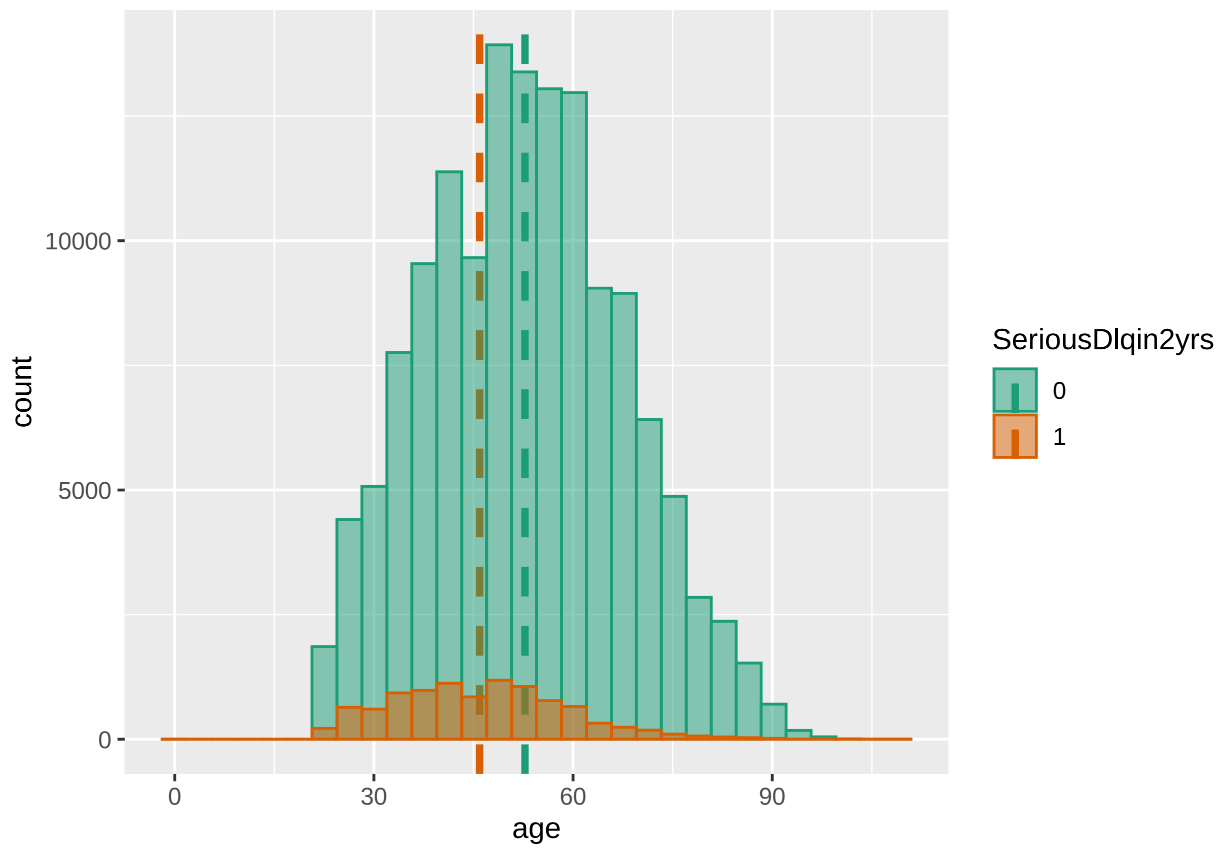
Age

An analysis of the third variable **age** shows that the group who have experienced financial distress in the next two years have an average of age lower than the other group who have not experienced such stress. This may suggest that young people are more likely to experience financial hardships relative to older people. Additionally, the histogram shows that there are far more people who have not experienced any financial distress than the other group.

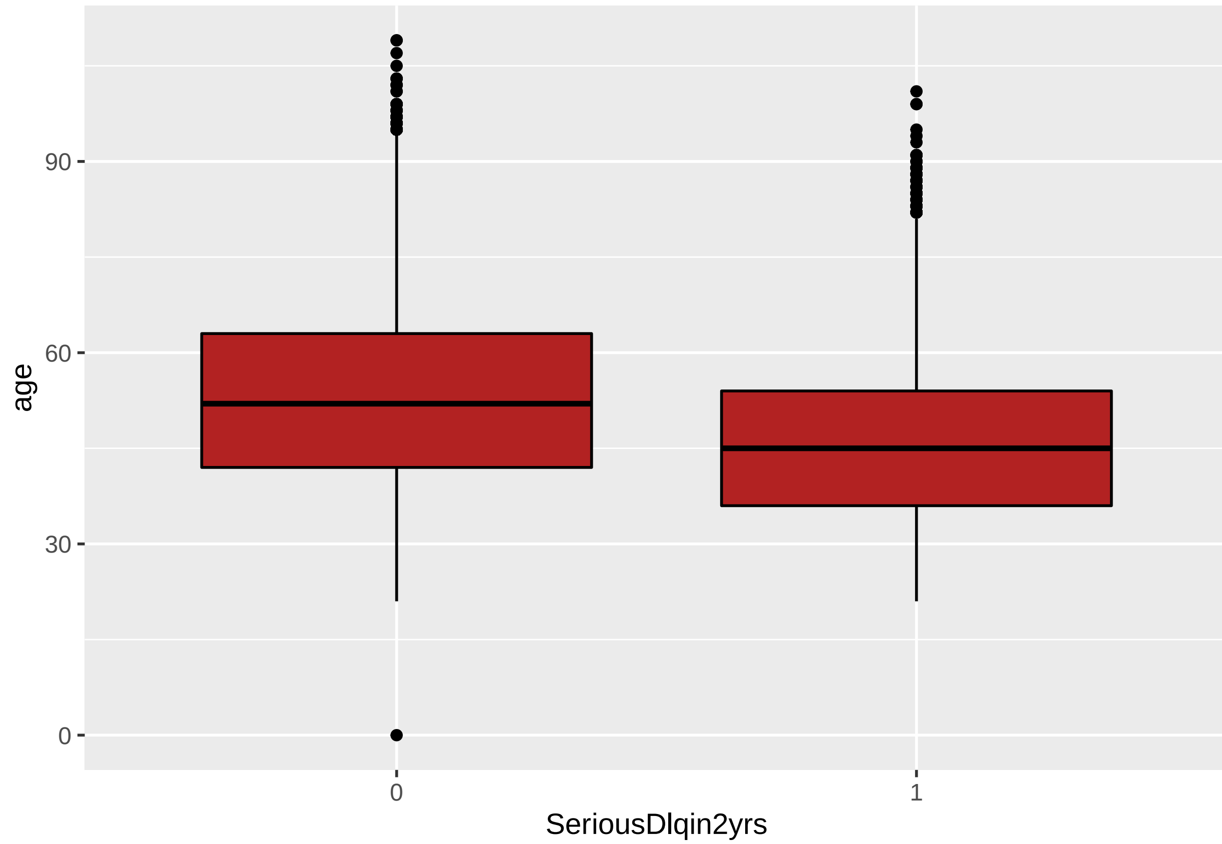
```r
mage <- ddply(data_train, "SeriousDlqin2yrs", summarise, grp.mean=mean(age))
head(mage)
```

```
##   SeriousDlqin2yrs grp.mean
## 1                0 52.75138
## 2                1 45.92659
```

```r
ggplot(data_train, aes(x=age, color=SeriousDlqin2yrs,
                       fill=SeriousDlqin2yrs)) +
  geom_vline(data=mage, aes(xintercept=grp.mean, color=SeriousDlqin2yrs),
                            linetype="dashed", size=1.3) +
  geom_histogram(alpha = 0.5, position = "identity") +
  scale_color_brewer(palette="Dark2") +
  scale_fill_brewer(palette="Dark2")
```




```r
data_train %>%
  ggplot(aes(x = SeriousDlqin2yrs, y = age)) +
  geom_boxplot(color = 'black', fill = 'firebrick') +
  labs(x = "SeriousDlqin2yrs", y = "age")
```




```
t.test(age ~ SeriousDlqin2yrs, data = data_train, var.equal = TRUE)
```

```
##
##  Two Sample t-test
##
## data:  age by SeriousDlqin2yrs
## t = 44.989, df = 149998, p-value < 2.2e-16
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  6.527456 7.122113
## sample estimates:
## mean in group 0 mean in group 1
##        52.75138        45.92659
```

Since p-value is much smaller than the conventional 0.05 threshold, we say that we have found statistical significance in comparing the average of age between the two groups.

NumberOfTime30.59DaysPastDueNotWorse

In this variable, the max number is 98, which is not possible since $98 \times 30 = 2940$ days, which is equivalent to 8 years. However, the variable measures how many times the person has been 30-59 days past dues for the past 2 years, which makes the value 98 impossible. We should remove any value >24.33 as outliers.

Still, looking at the summary statistics stated below, we found that for the group who have experienced financial stress, their mean and standard deviation are both significantly higher than the group who have not.

```
data_train %>%
  group_by(SeriousDlqin2yrs) %>%
```

```r
  summarise(
          count = n(),
          mean_ntimes = mean(NumberOfTime30.59DaysPastDueNotWorse),
          sd_ntimes = sd(NumberOfTime30.59DaysPastDueNotWorse),
          min_ntimes = min(NumberOfTime30.59DaysPastDueNotWorse),
          max_ntimes = max(NumberOfTime30.59DaysPastDueNotWorse)
            )
```

```
## # A tibble: 2 x 6
##   SeriousDlqin2yrs  count mean_ntimes sd_ntimes min_ntimes max_ntimes
##   <fct>             <int>       <dbl>     <dbl>      <int>      <int>
## 1 0                139974       0.280      2.95          0         98
## 2 1                 10026       2.39      11.7           0         98
```

DebtRatio

There seem to be some abnormalities in the distribution of the debt ratio, which should be a percentage that is the Monthly debt payments, alimony, living costs divided by monthy gross income. It is possible for this number to be greater than one, but for some observations, the number is already over 1000, which seem to be quite impossible in real life.

```r
data_train %>%
  group_by(SeriousDlqin2yrs) %>%
  summarise(
          count = n(),
          mean = mean(DebtRatio),
          sd = sd(DebtRatio),
          min = min(DebtRatio),
          max = max(DebtRatio)
            )
```

```
## # A tibble: 2 x 6
##   SeriousDlqin2yrs  count  mean    sd   min    max
##   <fct>             <int> <dbl> <dbl> <dbl>  <dbl>
## 1 0                139974  357. 2083.     0 329664
## 2 1                 10026  295. 1238.     0  38793
```

```r
quantile(data_train$DebtRatio, probs=c(.25, .75), na.rm = TRUE)
```

```
##       25%       75% 
## 0.1750738 0.8682538
```

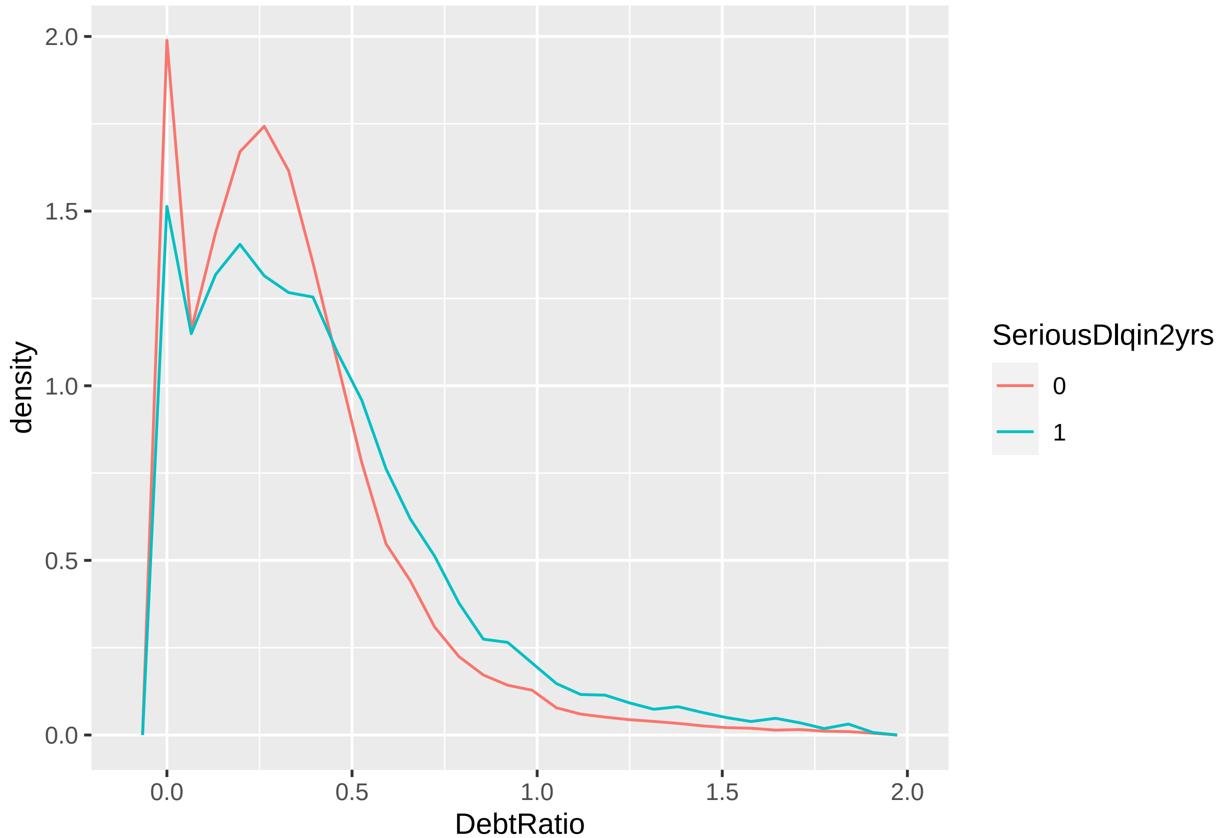
In the following steps, we first remove the outliers contained in the training data based on the **DebtRatio** variable, and instead of plotting the counts, we choose to plot the density plot and observe how the curves changes as the **DebtRatio** variable increases on the horizontal axis.

```r
Q <- quantile(data_train$DebtRatio, probs=c(.25, .75), na.rm = TRUE)
iqr <- IQR(data_train$DebtRatio, na.rm = TRUE)
data_dbtratio <- subset(data_train,
                        data_train$DebtRatio > (Q[1] - 1.5*iqr) &
                          data_train$DebtRatio < (Q[2]+1.5*iqr))
```

We observe that for the group without experiencing any financial stress, it has a distribution that is higher than the other gorup on the lower end of the debt ratio. As the raio increases, we observe that the density curve for the group with experience of financial stress becomes higher.

```r
ggplot(data = data_dbtratio,
            mapping = aes(x = DebtRatio, after_stat(density), colour = SeriousDlqin2yrs)) +
  geom_freqpoly()
```

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



MonthlyIncome

The summary statistics show that the group without financial stress has a higher mean/median monthly income than the group with financial stress, but we also observe that some people have a monthly income of 3008750, which is unusually high.

```r
data_train %>%
  group_by(SeriousDlqin2yrs) %>%
  summarise(
          count = n(),
          mean = mean(MonthlyIncome, na.rm = TRUE),
          median = median(MonthlyIncome, na.rm = TRUE),
          sd = sd(MonthlyIncome, na.rm = TRUE),
          min = min(MonthlyIncome, na.rm = TRUE),
          max = max(MonthlyIncome, na.rm = TRUE)
            )
```

```
## # A tibble: 2 x 7
##   SeriousDlqin2yrs  count  mean median     sd   min     max
##   <fct>             <int> <dbl>  <dbl>  <dbl> <int>   <int>
## 1 0                139974 6748.   5466 14814.     0 3008750
```

```
## 2 1                  10026 5631.   4500  6172.     0  250000
```

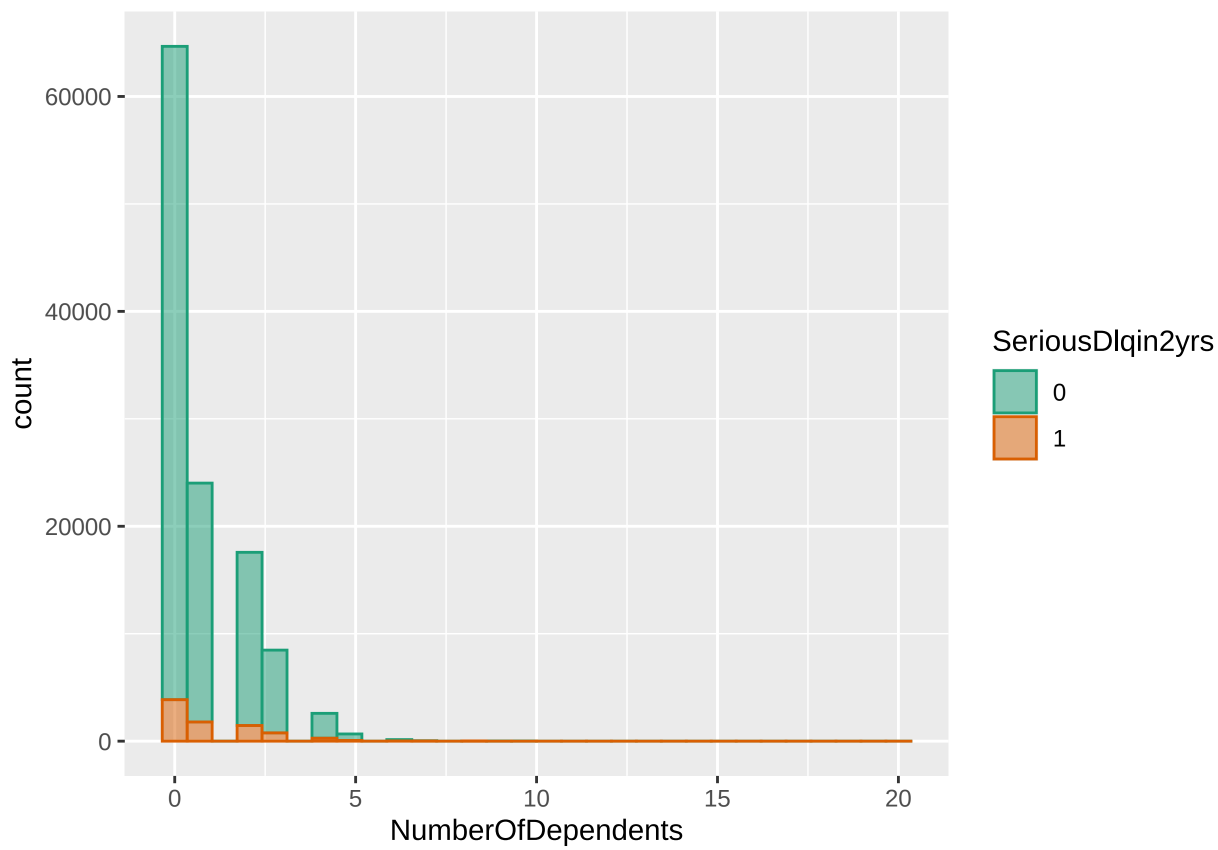
Number of Dependents

```
data_train %>%
  group_by(SeriousDlqin2yrs) %>%
  summarise(
          count = n(),
          mean = mean(NumberOfDependents, na.rm = TRUE),
          median = median(NumberOfDependents, na.rm = TRUE),
          sd = sd(MonthlyIncome, na.rm = TRUE),
          min = min(NumberOfDependents, na.rm = TRUE),
          max = max(NumberOfDependents, na.rm = TRUE)
            )
```

```
## # A tibble: 2 x 7
##   SeriousDlqin2yrs  count  mean median     sd   min   max
##   <fct>             <int> <dbl>  <int>  <dbl> <int> <int>
## 1 0                139974 0.743      0 14814.     0    20
## 2 1                 10026 0.948      0  6172.     0     8
```

```
ggplot(data_dbtratio, aes(x=NumberOfDependents, color=SeriousDlqin2yrs,
                       fill=SeriousDlqin2yrs)) +
  geom_histogram(alpha = 0.5) +
  scale_color_brewer(palette="Dark2") +
  scale_fill_brewer(palette="Dark2")
```

```
## Warning: Removed 476 rows containing non-finite values (stat_bin).
```



Data Cleaning

We thought about dropping the missing values, replacing missing values with medians, and using regressions to replace missing values

These code above give us the dataframe with incompleted observations dropped

```
train_complete <- complete.cases(data_train)
data_drop <- cbind(data_train,train_complete)
data_drop <- subset(data_drop,data_drop$train_complete == TRUE)
```

These code gave us data_median which uses the respective medians to fill in NAs in MonthlyIncome and NumberOfDependents