Report on Default of Credit Card Clients Dataset

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2021/6/26

Introduction

This is an R Markdown document. Markdown is a simple formatting syntax for authoring HTML, PDF, and MS Word documents. For more details on using R Markdown see http://rmarkdown.rstudio.com.

When you click the **Knit** button a document will be generated that includes both content as well as the output of any embedded R code chunks within the document. You can embed an R code chunk like this:

Data set and library

In this paper, we use libraries as follows: tidyverse, gridExtra, caret, rpart, pROC, DataExplorer, ranger.

Data is stored in my GitHub repository. We will use the direct link from my GitHub repository.

Data Exploration

First, we need to check the downloaded dataset.

```
## tibble [30,000 x 25] (S3: spec_tbl_df/tbl_df/tbl/data.frame)
##  $ ID                        : num [1:30000] 1 2 3 4 5 6 7 8 9 10 ...
##  $ LIMIT_BAL                 : num [1:30000] 20000 120000 90000 50000 50000 50000 500000 100000 1400
##  $ SEX                       : num [1:30000] 2 2 2 2 1 1 1 2 2 1 ...
##  $ EDUCATION                 : num [1:30000] 2 2 2 2 2 1 1 2 3 3 ...
##  $ MARRIAGE                  : num [1:30000] 1 2 2 1 1 2 2 2 1 2 ...
##  $ AGE                       : num [1:30000] 24 26 34 37 57 37 29 23 28 35 ...
##  $ PAY_0                     : num [1:30000] 2 -1 0 0 -1 0 0 0 0 -2 ...
##  $ PAY_2                     : num [1:30000] 2 2 0 0 0 0 0 -1 0 -2 ...
##  $ PAY_3                     : num [1:30000] -1 0 0 0 -1 0 0 -1 2 -2 ...
##  $ PAY_4                     : num [1:30000] -1 0 0 0 0 0 0 0 0 -2 ...
##  $ PAY_5                     : num [1:30000] -2 0 0 0 0 0 0 0 0 -1 ...
##  $ PAY_6                     : num [1:30000] -2 2 0 0 0 0 0 -1 0 -1 ...
##  $ BILL_AMT1                 : num [1:30000] 3913 2682 29239 46990 8617 ...
##  $ BILL_AMT2                 : num [1:30000] 3102 1725 14027 48233 5670 ...
##  $ BILL_AMT3                 : num [1:30000] 689 2682 13559 49291 35835 ...
##  $ BILL_AMT4                 : num [1:30000] 0 3272 14331 28314 20940 ...
##  $ BILL_AMT5                 : num [1:30000] 0 3455 14948 28959 19146 ...
##  $ BILL_AMT6                 : num [1:30000] 0 3261 15549 29547 19131 ...
##  $ PAY_AMT1                  : num [1:30000] 0 0 1518 2000 2000 ...
##  $ PAY_AMT2                  : num [1:30000] 689 1000 1500 2019 36681 ...
##  $ PAY_AMT3                  : num [1:30000] 0 1000 1000 1200 10000 657 38000 0 432 0 ...
##  $ PAY_AMT4                  : num [1:30000] 0 1000 1000 1100 9000 ...
```

```
##  $ PAY_AMT5                  : num [1:30000] 0 0 1000 1069 689 ...
##  $ PAY_AMT6                  : num [1:30000] 0 2000 5000 1000 679 ...
##  $ default.payment.next.month: num [1:30000] 1 1 0 0 0 0 0 0 0 0 ...
##  - attr(*, "spec")=
##   .. cols(
##   ..   ID = col_double(),
##   ..   LIMIT_BAL = col_double(),
##   ..   SEX = col_double(),
##   ..   EDUCATION = col_double(),
##   ..   MARRIAGE = col_double(),
##   ..   AGE = col_double(),
##   ..   PAY_0 = col_double(),
##   ..   PAY_2 = col_double(),
##   ..   PAY_3 = col_double(),
##   ..   PAY_4 = col_double(),
##   ..   PAY_5 = col_double(),
##   ..   PAY_6 = col_double(),
##   ..   BILL_AMT1 = col_double(),
##   ..   BILL_AMT2 = col_double(),
##   ..   BILL_AMT3 = col_double(),
##   ..   BILL_AMT4 = col_double(),
##   ..   BILL_AMT5 = col_double(),
##   ..   BILL_AMT6 = col_double(),
##   ..   PAY_AMT1 = col_double(),
##   ..   PAY_AMT2 = col_double(),
##   ..   PAY_AMT3 = col_double(),
##   ..   PAY_AMT4 = col_double(),
##   ..   PAY_AMT5 = col_double(),
##   ..   PAY_AMT6 = col_double(),
##   ..   default.payment.next.month = col_double()
##   .. )
```

```
summary(original_default)
```

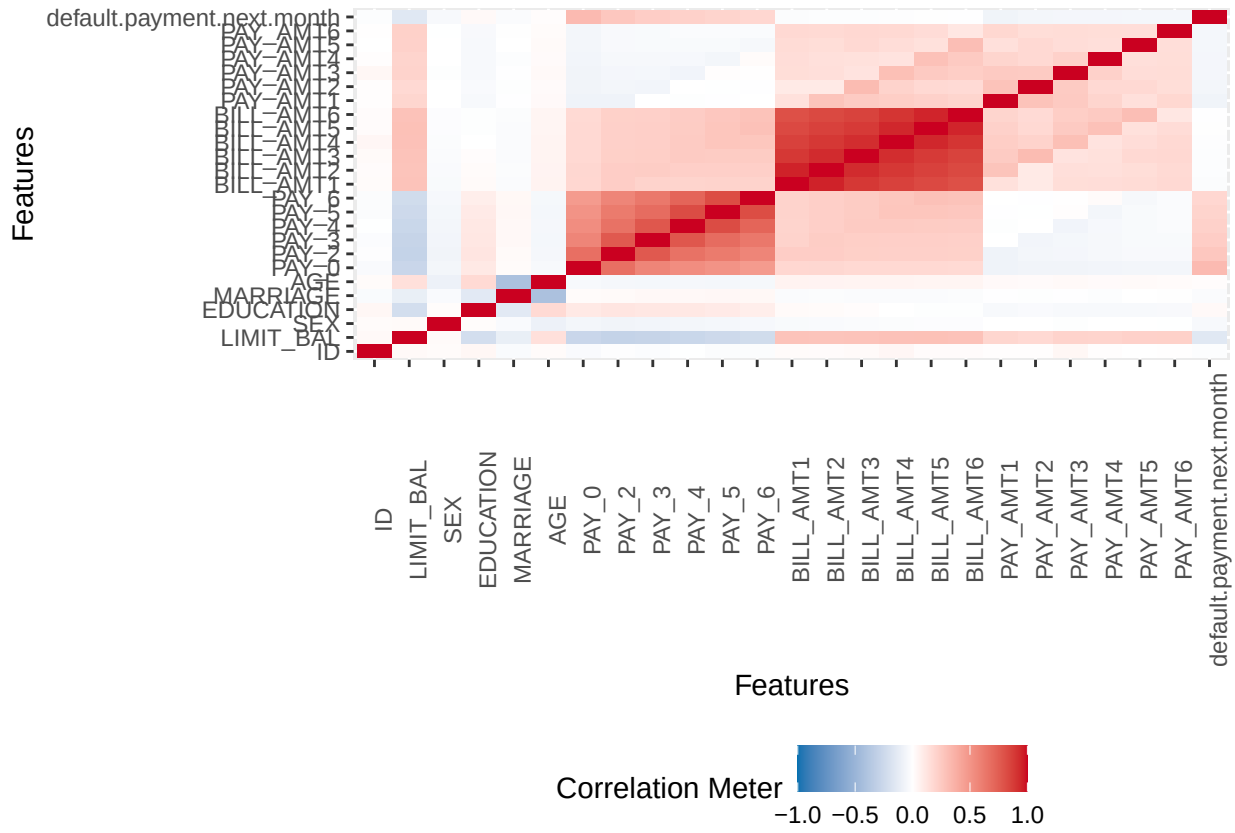
```
##        ID           LIMIT_BAL            SEX          EDUCATION
##  Min.   :    1   Min.   :  10000   Min.   :1.000   Min.   :0.000
##  1st Qu.: 7501   1st Qu.:  50000   1st Qu.:1.000   1st Qu.:1.000
##  Median :15000   Median : 140000   Median :2.000   Median :2.000
##  Mean   :15000   Mean   : 167484   Mean   :1.604   Mean   :1.853
##  3rd Qu.:22500   3rd Qu.: 240000   3rd Qu.:2.000   3rd Qu.:2.000
##  Max.   :30000   Max.   :1000000   Max.   :2.000   Max.   :6.000
##     MARRIAGE          AGE            PAY_0            PAY_2
##  Min.   :0.000   Min.   :21.00   Min.   :-2.0000   Min.   :-2.0000
##  1st Qu.:1.000   1st Qu.:28.00   1st Qu.:-1.0000   1st Qu.:-1.0000
##  Median :2.000   Median :34.00   Median : 0.0000   Median : 0.0000
##  Mean   :1.552   Mean   :35.49   Mean   :-0.0167   Mean   :-0.1338
##  3rd Qu.:2.000   3rd Qu.:41.00   3rd Qu.: 0.0000   3rd Qu.: 0.0000
##  Max.   :3.000   Max.   :79.00   Max.   : 8.0000   Max.   : 8.0000
##      PAY_3             PAY_4             PAY_5             PAY_6
##  Min.   :-2.0000   Min.   :-2.0000   Min.   :-2.0000   Min.   :-2.0000
##  1st Qu.:-1.0000   1st Qu.:-1.0000   1st Qu.:-1.0000   1st Qu.:-1.0000
##  Median : 0.0000   Median : 0.0000   Median : 0.0000   Median : 0.0000
##  Mean   :-0.1662   Mean   :-0.2207   Mean   :-0.2662   Mean   :-0.2911
##  3rd Qu.: 0.0000   3rd Qu.: 0.0000   3rd Qu.: 0.0000   3rd Qu.: 0.0000
```

```
##  Max.   : 8.0000   Max.   : 8.0000   Max.   : 8.0000   Max.   : 8.0000
##    BILL_AMT1         BILL_AMT2         BILL_AMT3         BILL_AMT4
##  Min.   :-165580   Min.   :-69777   Min.   :-157264   Min.   :-170000
##  1st Qu.:   3559   1st Qu.:  2985   1st Qu.:   2666   1st Qu.:   2327
##  Median :  22382   Median : 21200   Median :  20089   Median :  19052
##  Mean   :  51223   Mean   : 49179   Mean   :  47013   Mean   :  43263
##  3rd Qu.:  67091   3rd Qu.: 64006   3rd Qu.:  60165   3rd Qu.:  54506
##  Max.   : 964511   Max.   :983931   Max.   :1664089   Max.   : 891586
##    BILL_AMT5         BILL_AMT6          PAY_AMT1          PAY_AMT2
##  Min.   :-81334   Min.   :-339603   Min.   :     0   Min.   :      0
##  1st Qu.:  1763   1st Qu.:   1256   1st Qu.:  1000   1st Qu.:    833
##  Median : 18105   Median :  17071   Median :  2100   Median :   2009
##  Mean   : 40311   Mean   :  38872   Mean   :  5664   Mean   :   5921
##  3rd Qu.: 50191   3rd Qu.:  49198   3rd Qu.:  5006   3rd Qu.:   5000
##  Max.   :927171   Max.   : 961664   Max.   :873552   Max.   :1684259
##     PAY_AMT3          PAY_AMT4          PAY_AMT5           PAY_AMT6
##  Min.   :     0   Min.   :     0   Min.   :     0.0   Min.   :     0.0
##  1st Qu.:   390   1st Qu.:   296   1st Qu.:   252.5   1st Qu.:   117.8
##  Median :  1800   Median :  1500   Median :  1500.0   Median :  1500.0
##  Mean   :  5226   Mean   :  4826   Mean   :  4799.4   Mean   :  5215.5
##  3rd Qu.:  4505   3rd Qu.:  4013   3rd Qu.:  4031.5   3rd Qu.:  4000.0
##  Max.   :896040   Max.   :621000   Max.   :426529.0   Max.   :528666.0
##  default.payment.next.month
##  Min.   :0.0000
##  1st Qu.:0.0000
##  Median :0.0000
##  Mean   :0.2212
##  3rd Qu.:0.0000
##  Max.   :1.0000
```

No NAs.

Correlation.

```
plot_correlation(original_default)
```



1 Outcome

Kaggle's data explanation says

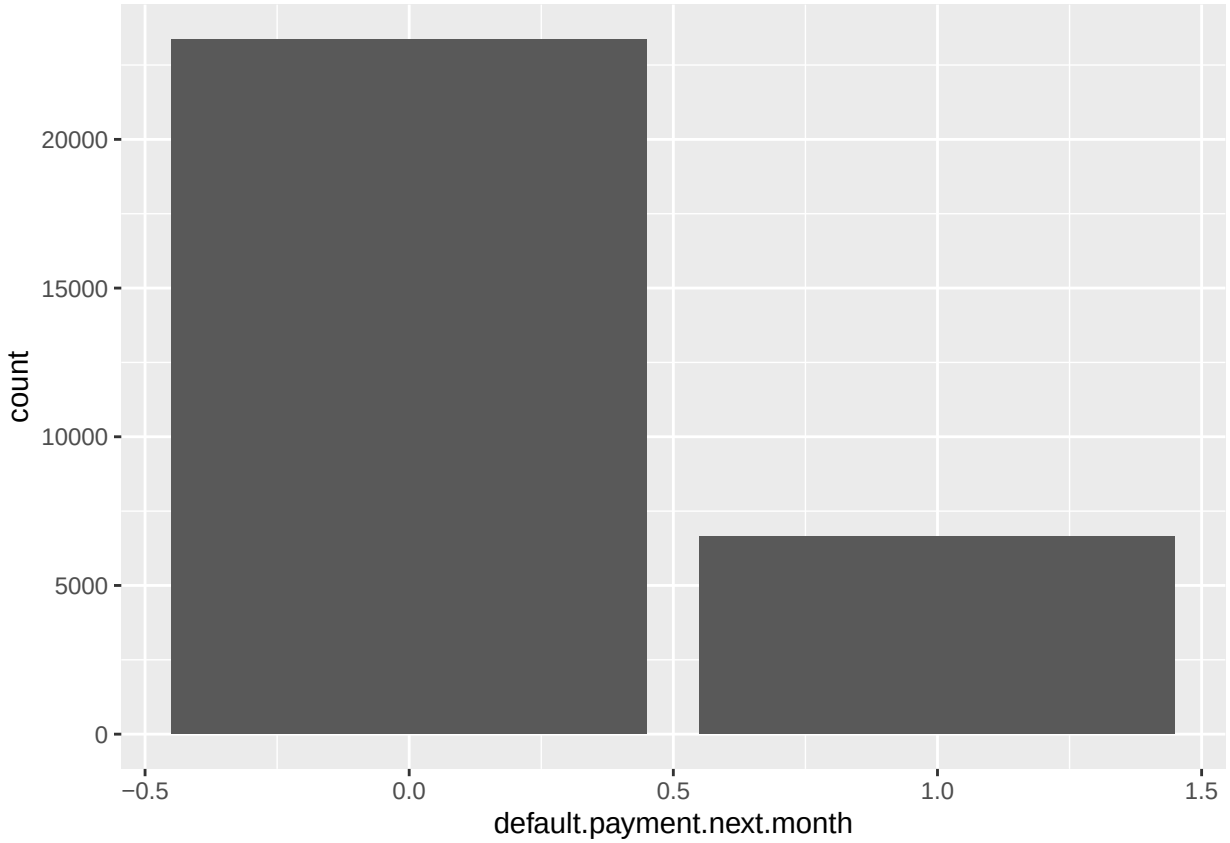
Default payment, 1=yes, 0=no

```
summary(original_default$default.payment.next.month)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.0000  0.0000  0.0000  0.2212  0.0000  1.0000
```

Show distribution graph.

```
ggplot(data=original_default, aes(default.payment.next.month)) +geom_bar()
```



Show proportion of 0,1

```
prop.table(table(original_default$default.payment.next.month))
```

```
##
##      0      1
## 0.7788 0.2212
```

Change name of "default.payment.next.month"

```
n <-which(names(original_default)=="default.payment.next.month")
names(original_default)[n] <- "DEFAULT"
```

Change outcome into factor

```
original_default$DEFAULT <- as.factor(original_default$DEFAULT)
```

2 "LIMIT_BAL"

Kaggle's data explanation says

Amount of given credit in NT dollars (includes individual and family/supplementary credit

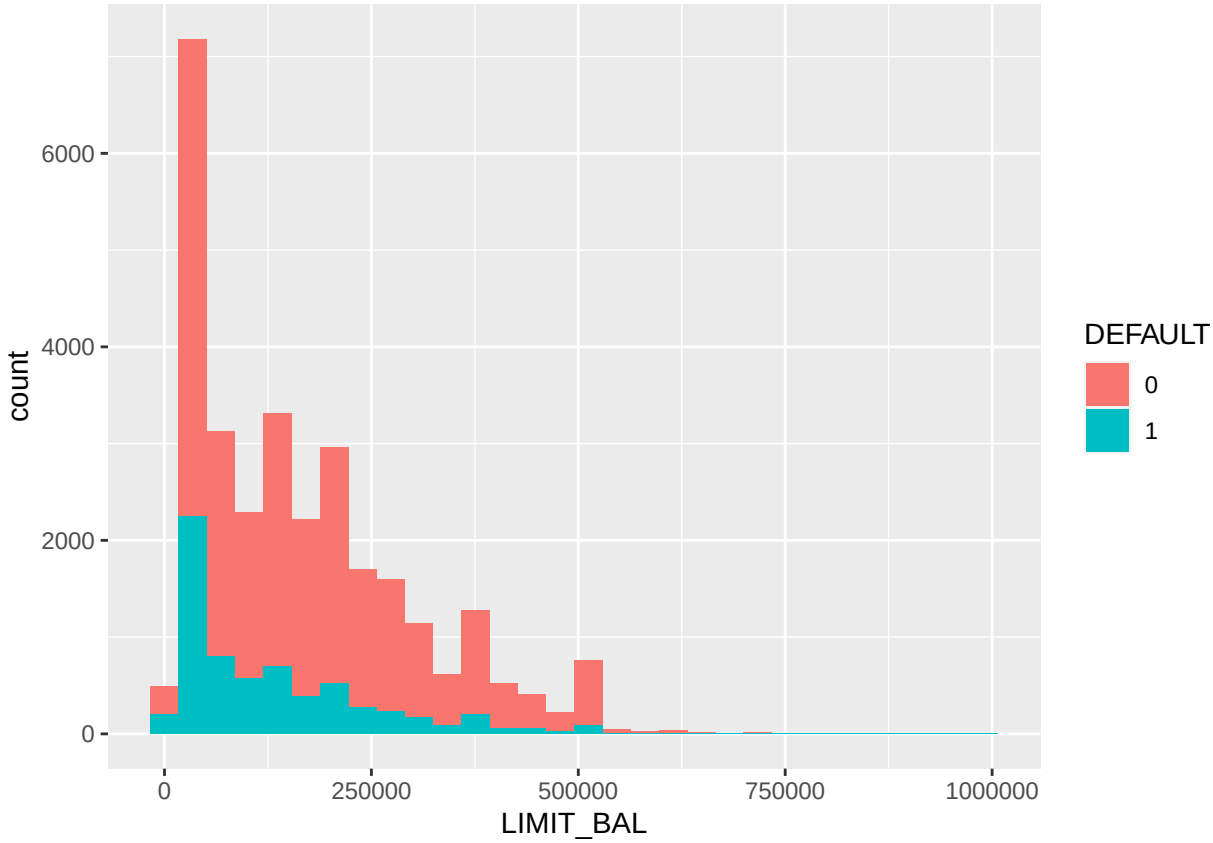
```
summary(original_default$LIMIT_BAL)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   10000   50000  140000  167484  240000 1000000
```

numeric data

```
ggplot(data=original_default, aes(LIMIT_BAL, fill=DEFAULT)) +geom_histogram()
```

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



Distribution is skewed right

3 "SEX"

Kaggle's data explanation says

1=male, 2=female

```
summary(original_default$SEX)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   1.000   2.000   1.604   2.000   2.000
```

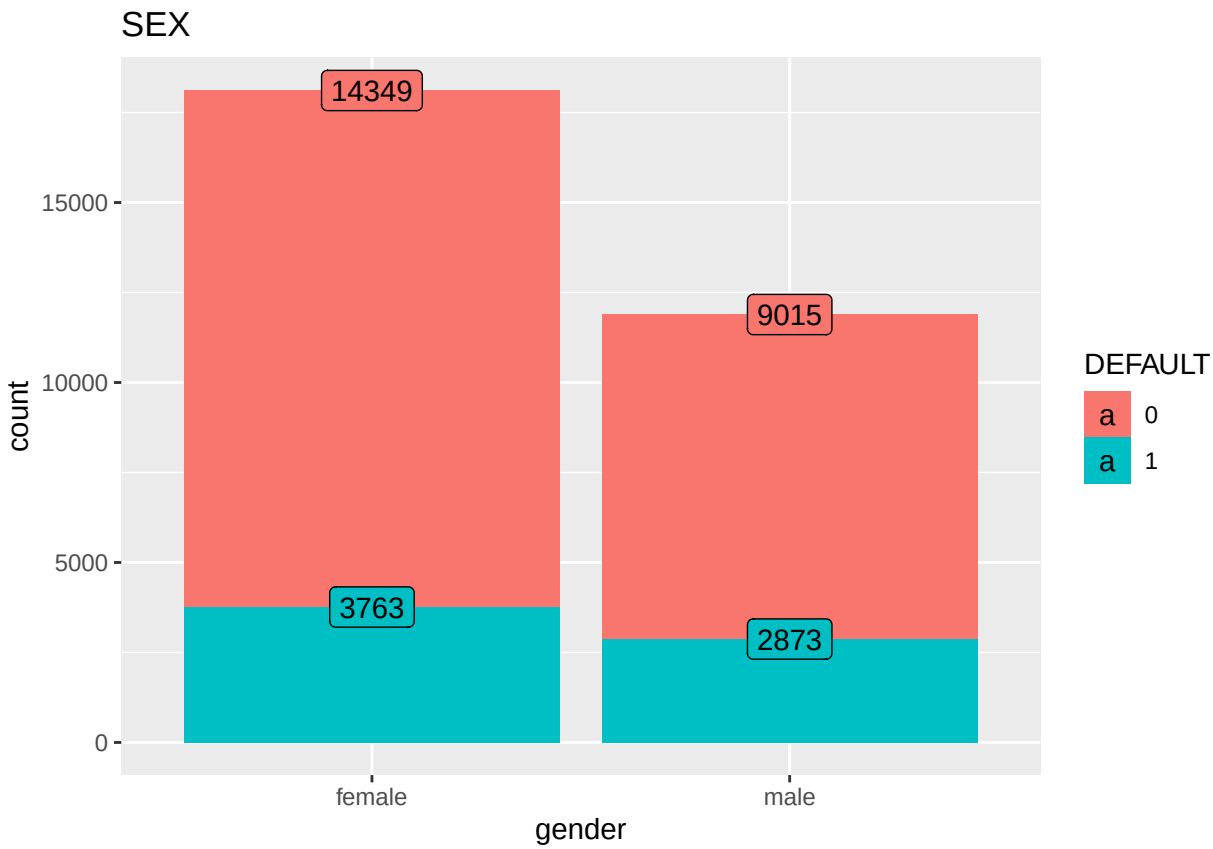
```
unique(original_default$SEX)
```

```
## [1] 2 1
```

categorical data. to make a plot, introducing new character vector.

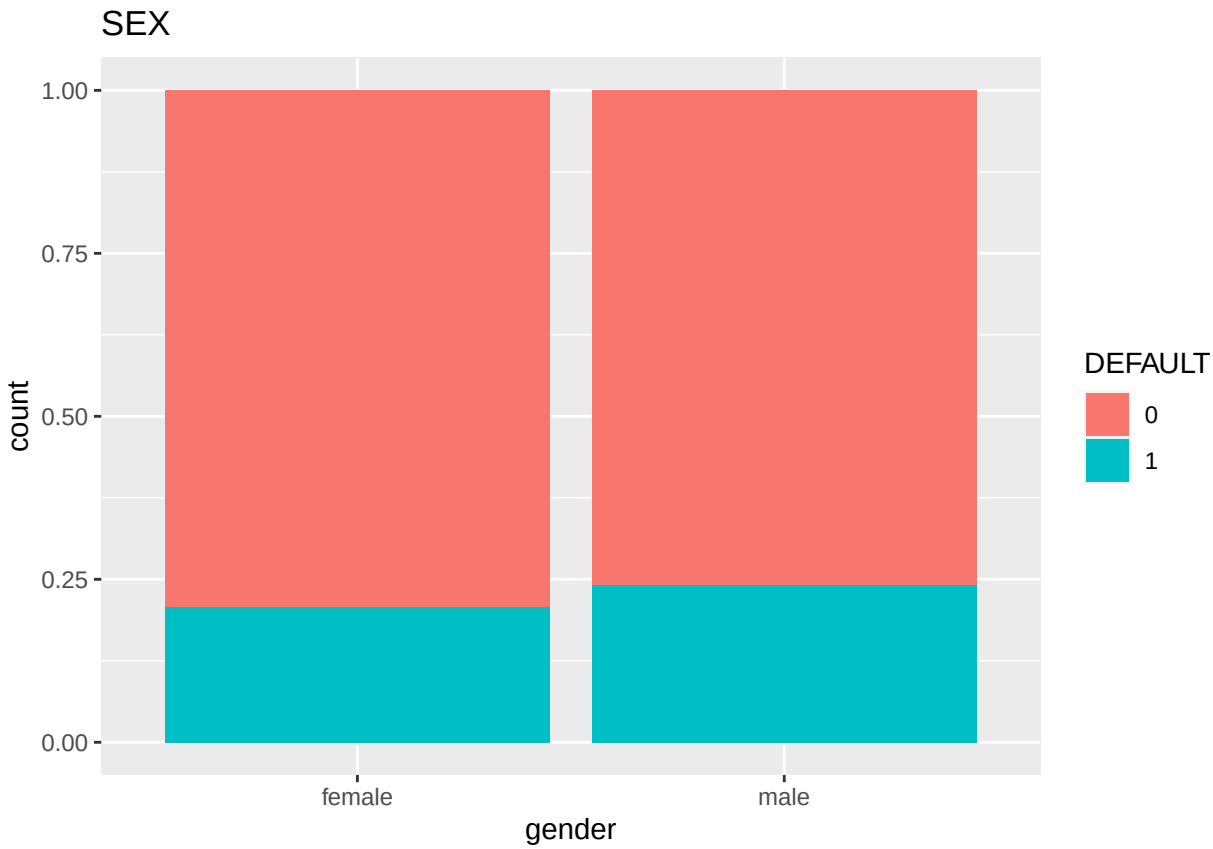
```
gender <- ifelse(original_default$SEX == 1, "male", "female")
```

```
original_default %>% ggplot(aes(x=gender, fill= DEFAULT)) +
  geom_bar() +
  ggtitle("SEX")+
  stat_count(aes(label = ..count..), geom = "label")# illustrate numbers
```



To make stacked bar graph.

```
original_default %>% ggplot(aes(x=gender, fill= DEFAULT)) +
  geom_bar(position="fill") +
  ggtitle("SEX")
```



There seemed to be little difference between genders.

4 "EDUCATION"

Kaggle's data explanation says;

1=graduate school, 2=university, 3=high school, 4=others, 5=unknown, 6=unknown

```
summary(original_default$EDUCATION)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.000   1.000   2.000   1.853   2.000   6.000
```

```
unique(original_default$EDUCATION)
```

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

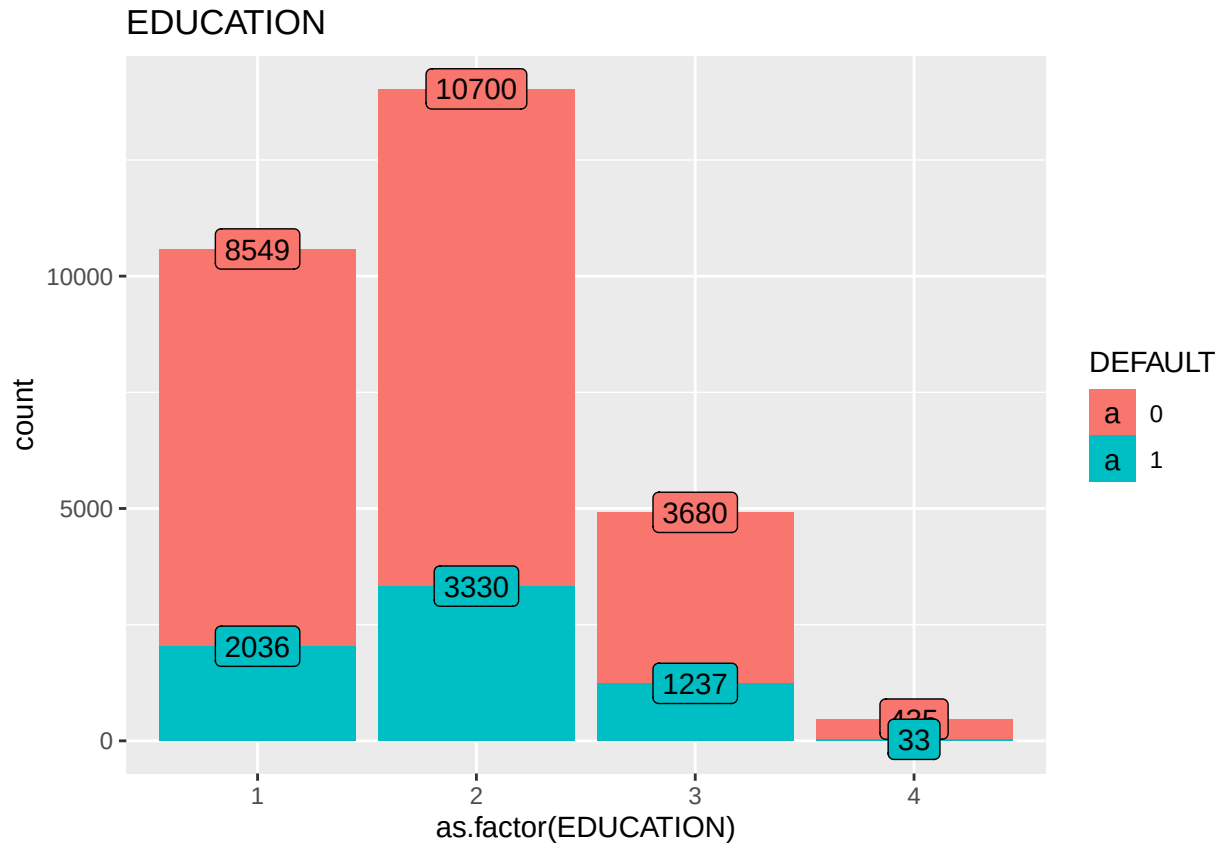
categorical data.

0 is not defined. 0,5 and 6 can be included into 4

```
original_default$EDUCATION <- ifelse( original_default$EDUCATION== 0|
                                      original_default$EDUCATION == 5|
                                      original_default$EDUCATION == 6, 4,
                                      original_default$EDUCATION)
```

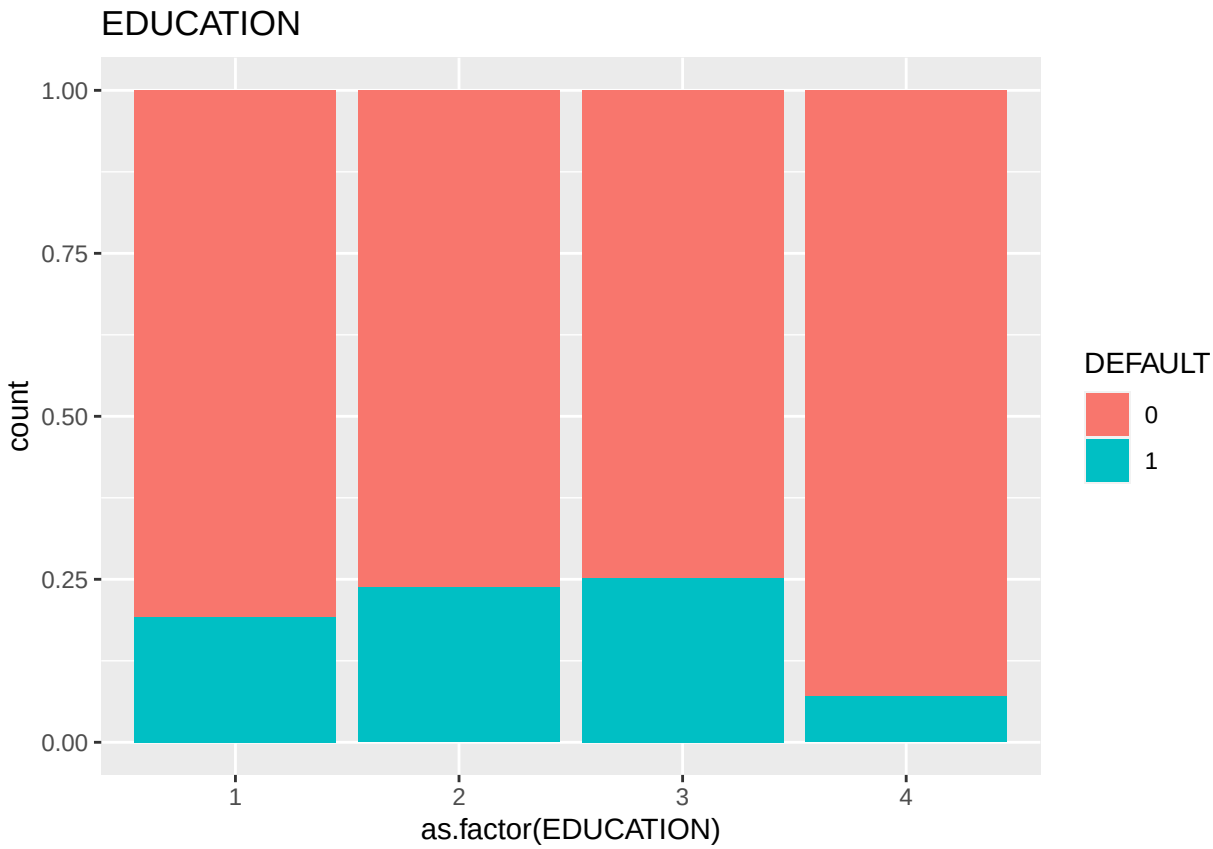
Plot.

```
original_default %>% ggplot(aes(x=as.factor(EDUCATION), fill= DEFAULT)) +
  geom_bar() +
  ggtitle("EDUCATION")+
  stat_count(aes(label = ..count..), geom = "label")# illustrate numbers
```



Stacked bar graph.

```
original_default %>% ggplot(aes(x=as.factor(EDUCATION), fill= DEFAULT)) +
  geom_bar(position="fill") +
  ggtitle("EDUCATION")
```



4 is the smallest in terms of default rate. but its numbers are very small.

5 "MARRIAGE"

Kaggle's data explanation says;

marital status. 1=married, 2=single, 3=others.

```
summary(original_default$ MARRIAGE)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.000   1.000   2.000   1.552   2.000   3.000
```

```
unique(original_default$ MARRIAGE)
```

```
## [1] 1 2 3 0
```

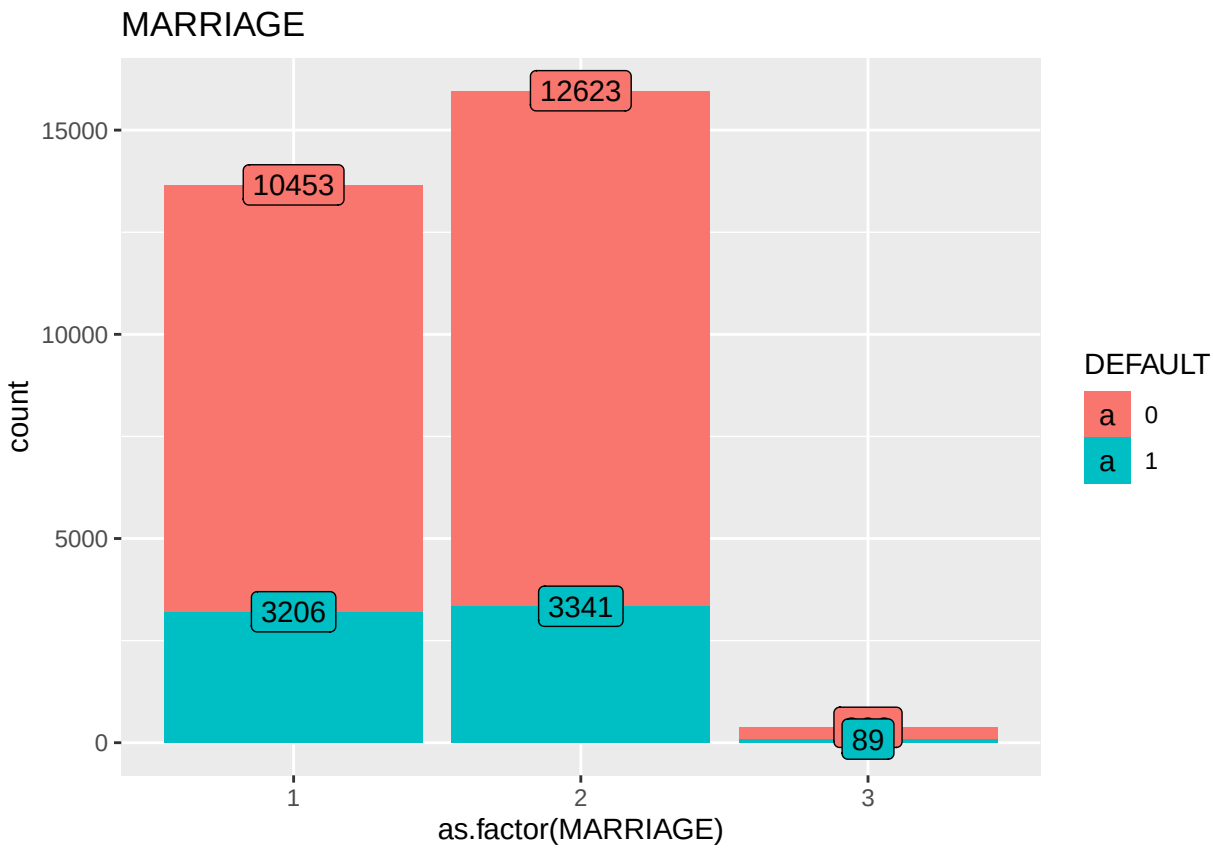
categorical data

0 is not defined. 0 can be included in 3.

```
original_default$MARRIAGE <- ifelse(original_default$MARRIAGE== 0, 3,
                                    original_default$MARRIAGE)
```

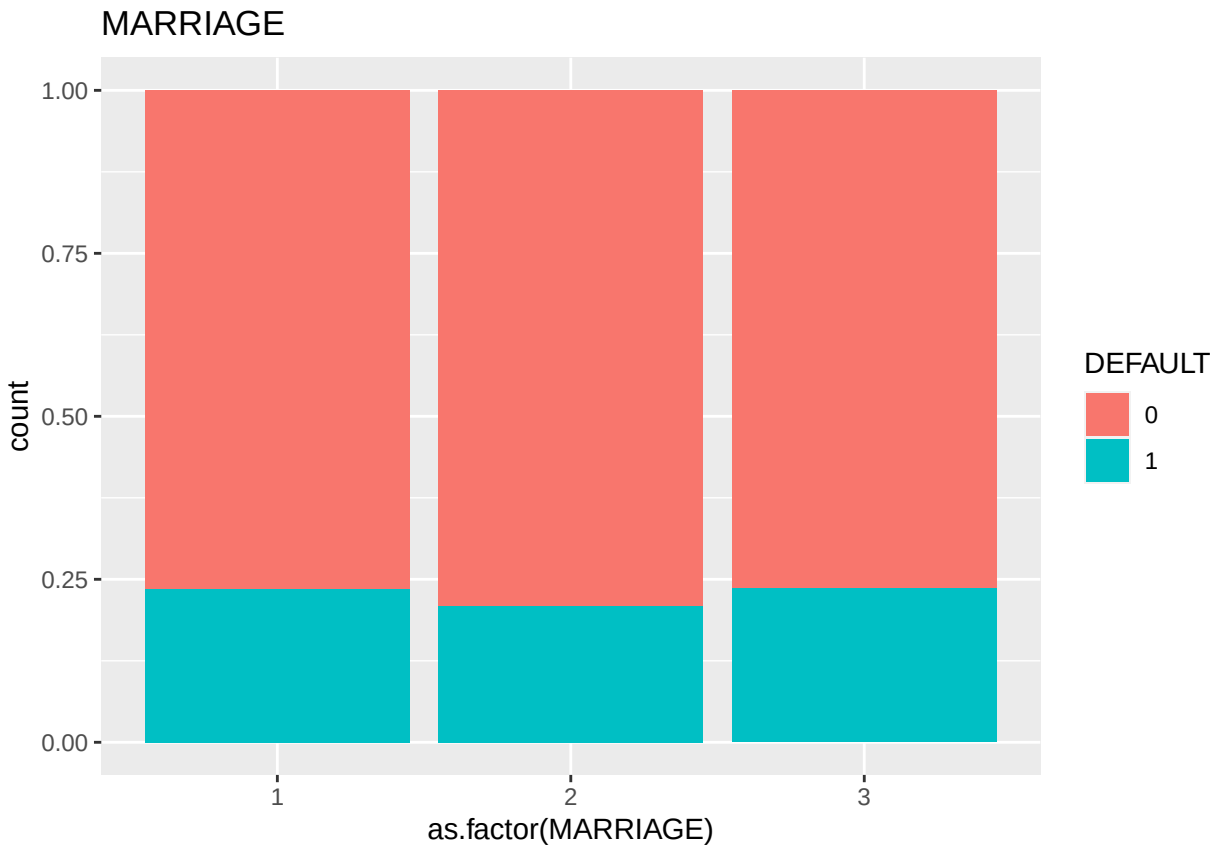
Plot.

```
original_default %>% ggplot(aes(x=as.factor(MARRIAGE), fill= DEFAULT)) +
  geom_bar() +
  ggtitle("MARRIAGE")+
  stat_count(aes(label = ..count..), geom = "label")# illustrate numbers
```



Stack bar graph

```
original_default %>% ggplot(aes(x=as.factor(MARRIAGE), fill= DEFAULT)) +
  geom_bar(position="fill") +
  ggtitle("MARRIAGE")
```



There seems to be little difference among the groups.

6 "AGE"

```
summary(original_default$AGE)
```

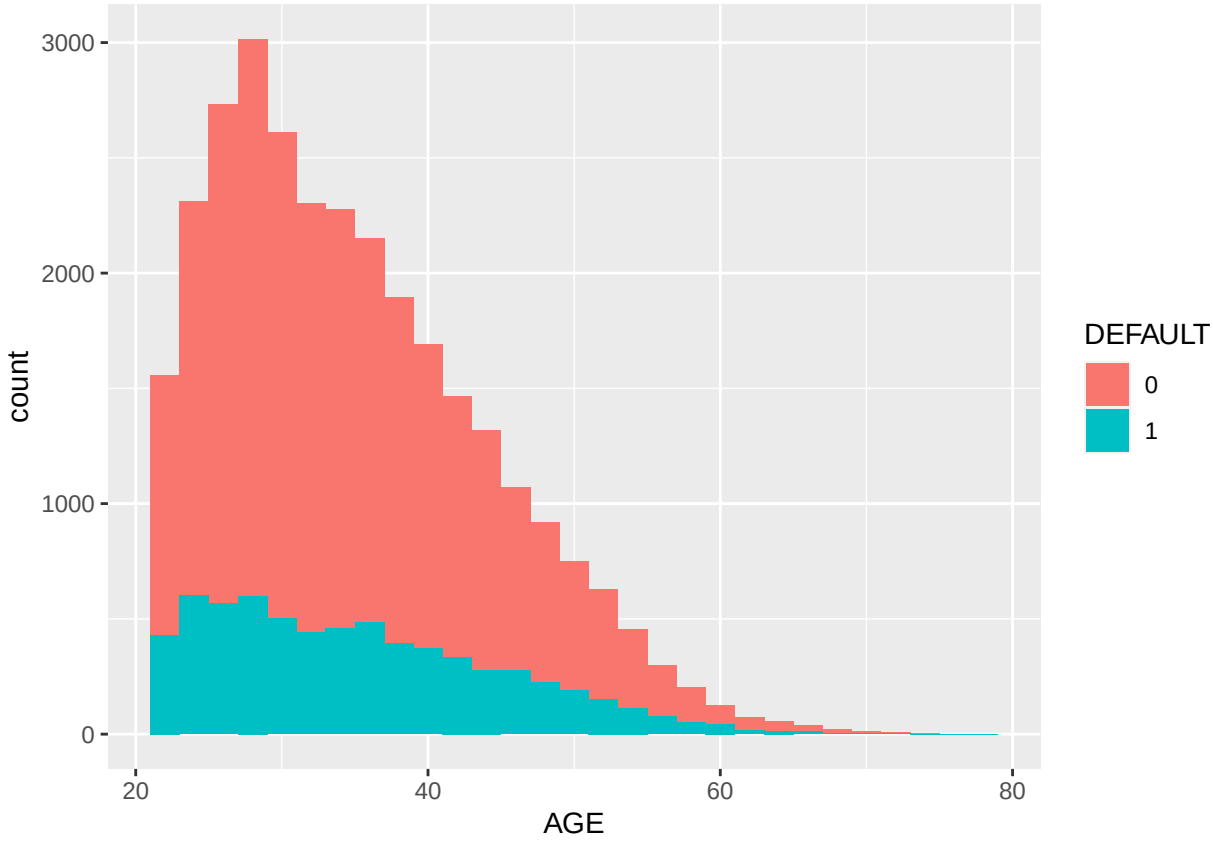
```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   21.00   28.00   34.00   35.49   41.00   79.00
```

numeric data

Plot.

```
ggplot(data=original_default, aes(AGE, fill=DEFAULT)) +geom_histogram()
```

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



7 "PAY"

Kaggle's data explanation says;

PAY_0 means repayment status in September, 2005.

-1=pay duly, 1=payment delay for one month, 2=payment delay for two months, ... 8=payment delay for eight months, 9=payment delay for nine months and above. Regarding values from PAY_2 to PAY_6, the scales are the same as PAY_0. As the number increases, the date of repayment status goes back in time by a month until April, 2005 which is PAY_6.

. PAY_0.

```
summary(original_default$PAY_0)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -2.0000 -1.0000  0.0000 -0.0167  0.0000  8.0000
```

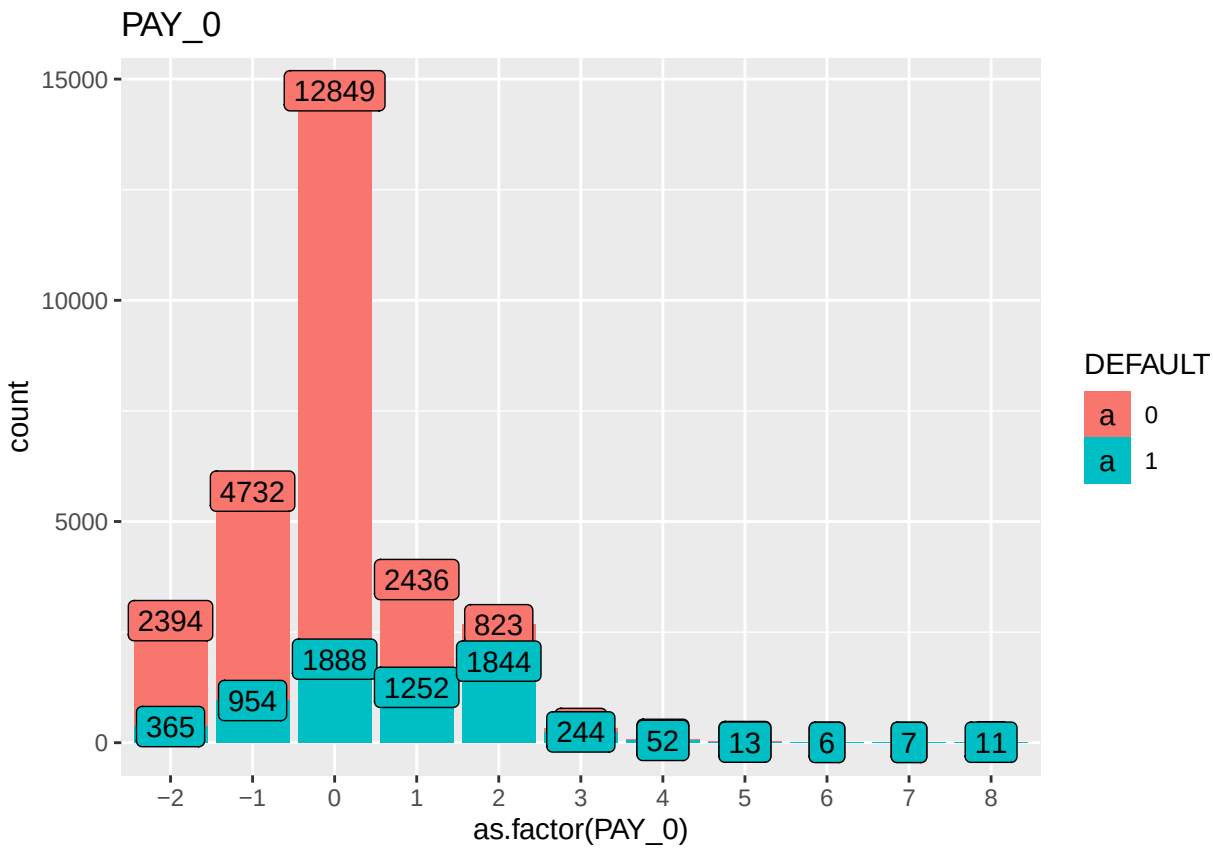
```
unique(original_default$PAY_0)
```

```
##  [1]  2 -1  0 -2  1  3  4  8  7  5  6
```

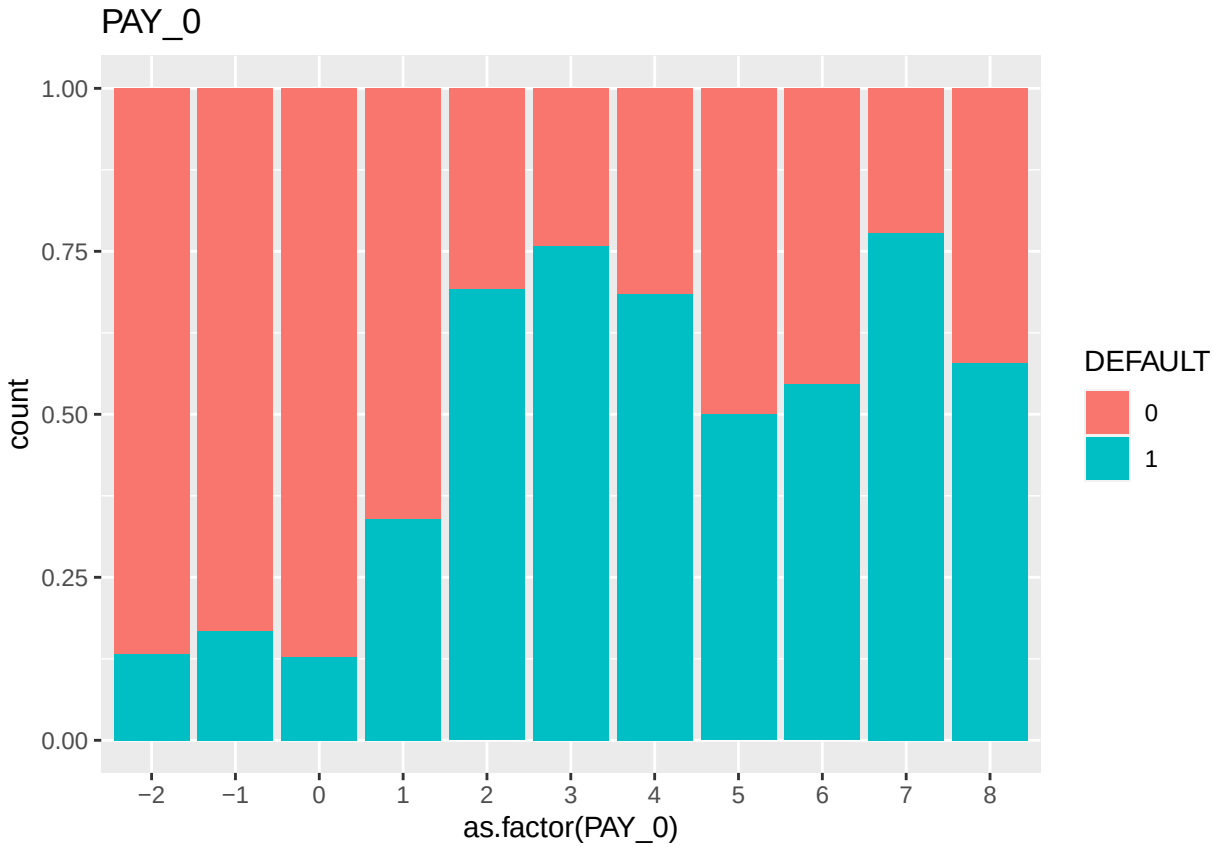
They are categorical data.

Plot.

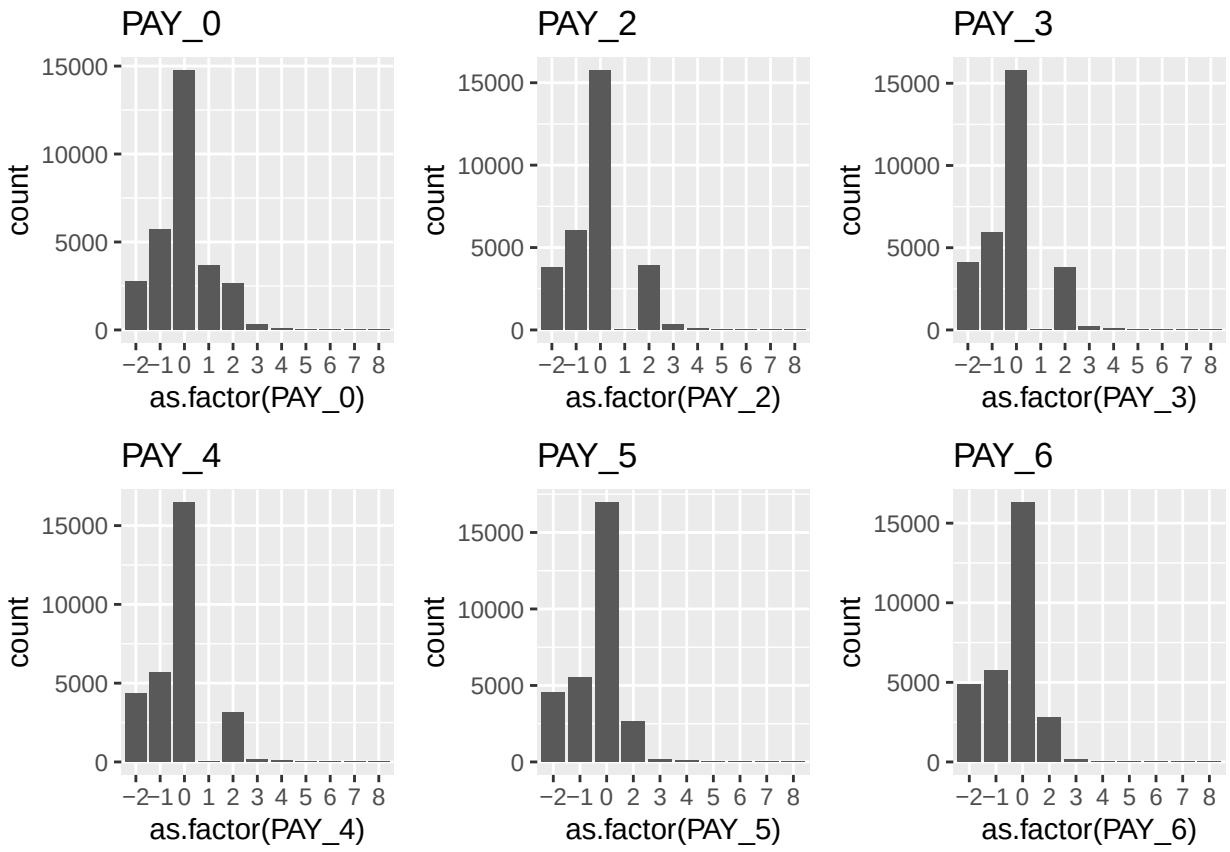
```
original_default %>% ggplot(aes(x=as.factor(PAY_0), fill= DEFAULT)) +
  geom_bar() +
  ggtitle("PAY_0")+
  stat_count(aes(label = ..count..), geom = "label")# illustrate numbers
```



Stack bar graph PAY_0.



PAY_2 ~ PAY_6 's structures are almost as same as PAY_0. Show distribution.



8 "BILL_AMT"

Kaggle's data explanation says;

BILL_AMT1 is an amount of bill statement in September, 2005 (NT dollar). Likewise PAY, BILL_AMT goes back in time by a month from August to April, 2005 which is BILL_AMT6.

```
summary(original_default$BILL_AMT1)
```

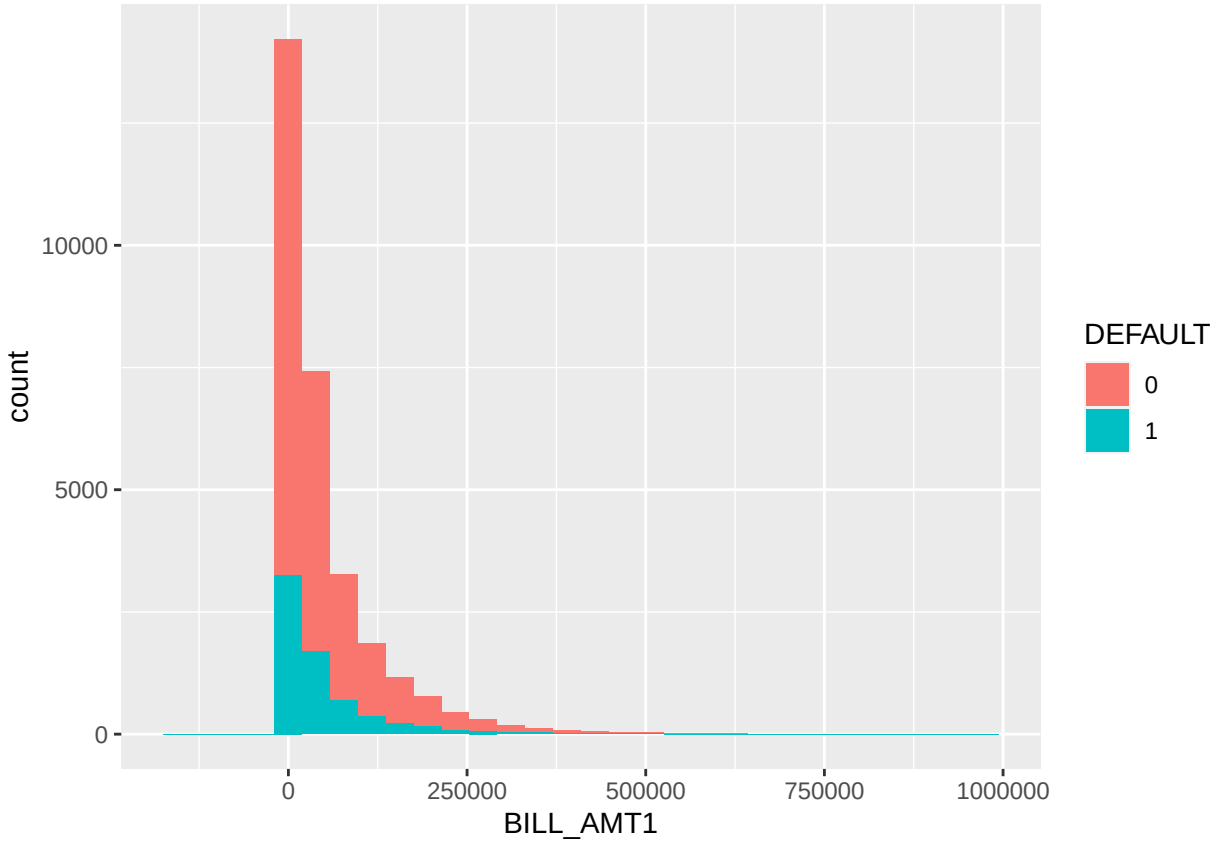
```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -165580    3559   22382   51223   67091  964511
```

These are numerical data.

Here is BILL_AMT1's plot.

```
ggplot(data=original_default, aes(BILL_AMT1,fill= DEFAULT)) +geom_histogram()
```

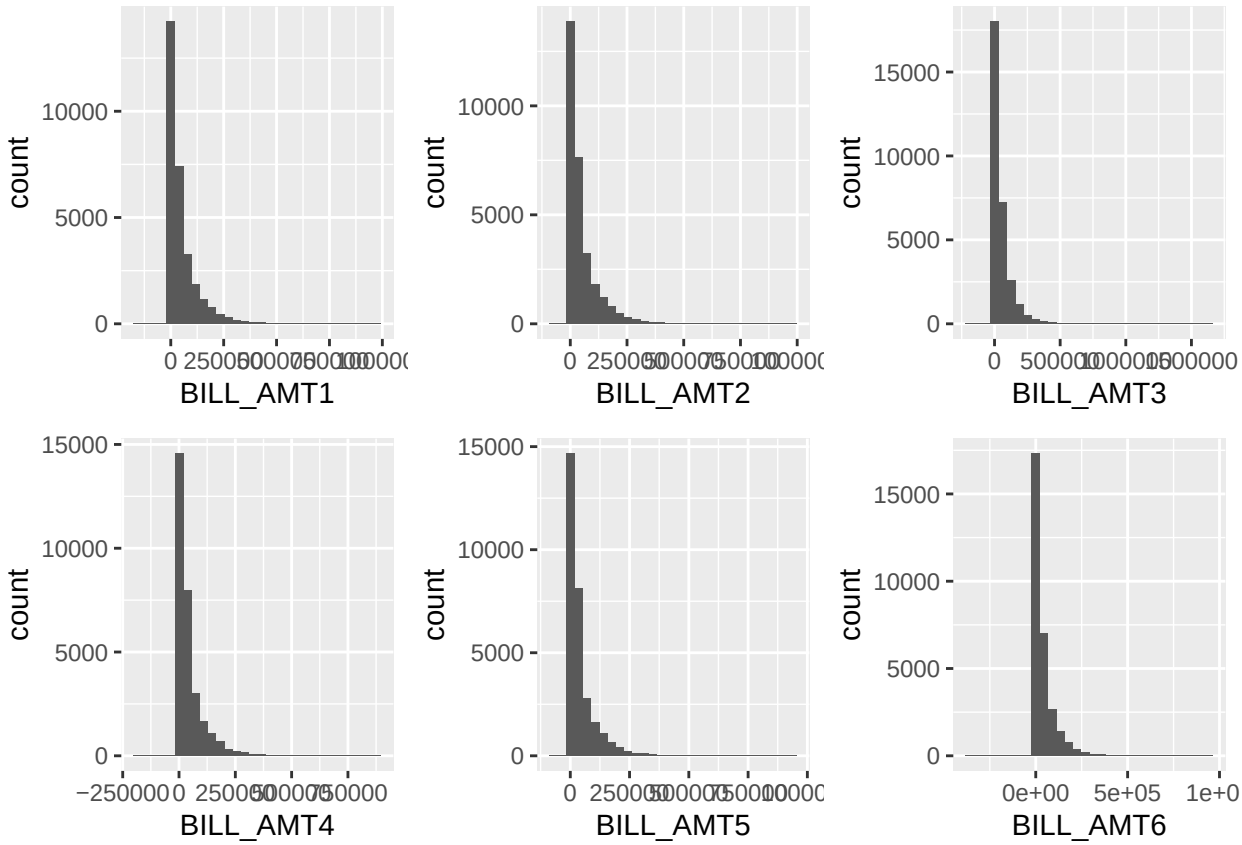
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



From BILL_AMT1 to BILL_AMT6, their structures are almost the same as are shown in following plots.

```
b1 <- ggplot(data=original_default, aes(BILL_AMT1)) +geom_histogram()
b2 <- ggplot(data=original_default, aes(BILL_AMT2)) +geom_histogram()
b3 <- ggplot(data=original_default, aes(BILL_AMT3)) +geom_histogram()
b4 <- ggplot(data=original_default, aes(BILL_AMT4)) +geom_histogram()
b5 <- ggplot(data=original_default, aes(BILL_AMT5)) +geom_histogram()
b6 <- ggplot(data=original_default, aes(BILL_AMT6)) +geom_histogram()
grid.arrange(b1,b2,b3,b4,b5,b6, nrow=2, ncol=3)
```

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



9 "PAY_AMT"

Kaggle's data explanation says;

PAY_AMT1 is an amount of previous payment in September, 2005 (NT dollar). Likewise BILL_AMT, PAY_AMT goes back in time by a month from August to April, 2005 which is PAY_AMT6.

```
summary(original_default$PAY_AMT1)
```

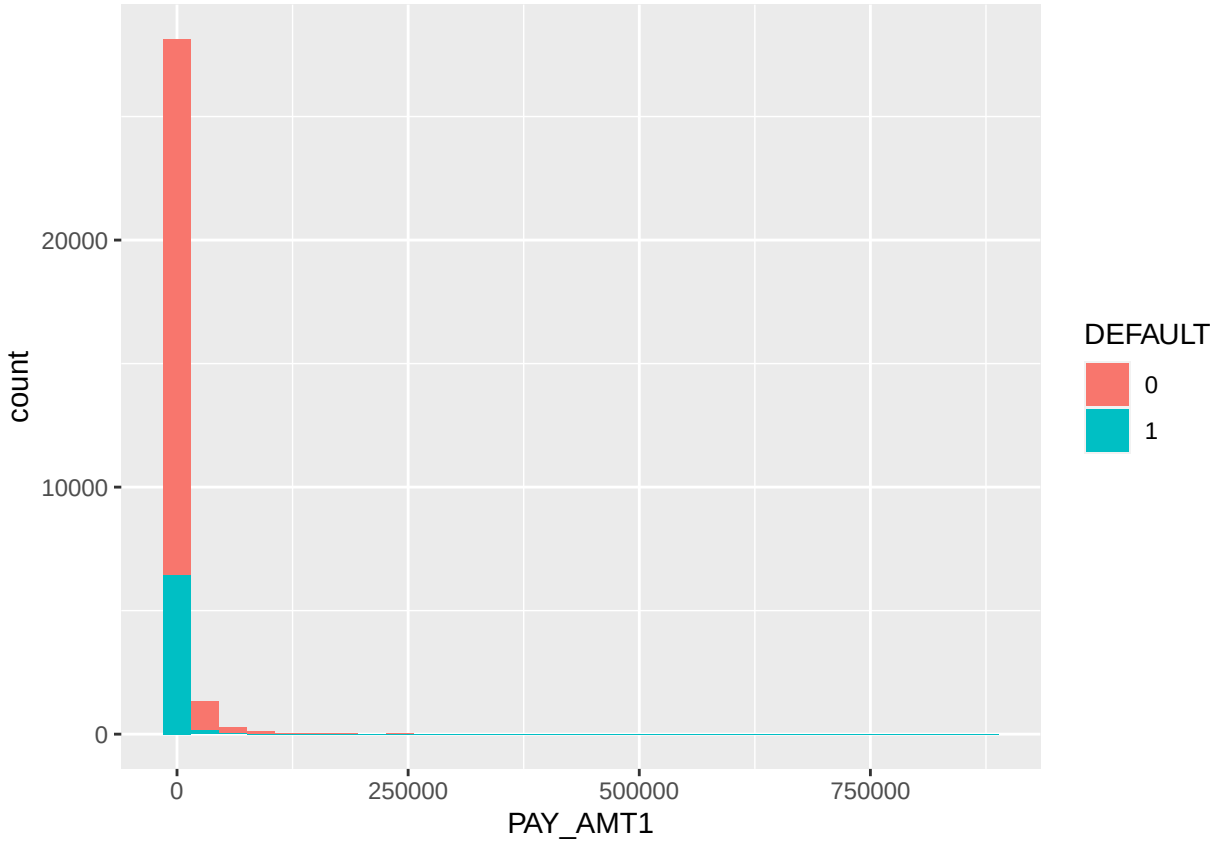
```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##       0    1000    2100    5664    5006  873552
```

They are numerical data.

Here is PAY_AMT1's plot.

```
ggplot(data=original_default, aes(PAY_AMT1,fill= DEFAULT)) +geom_histogram()
```

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



From PAY_AMT1 to PAY_AMT6, their structures are almost the same as are shown in following plots.

```
p1 <- ggplot(data=original_default, aes(PAY_AMT1)) +geom_histogram()
p2 <- ggplot(data=original_default, aes(PAY_AMT2)) +geom_histogram()
p3 <- ggplot(data=original_default, aes(PAY_AMT3)) +geom_histogram()
p4 <- ggplot(data=original_default, aes(PAY_AMT4)) +geom_histogram()
p5 <- ggplot(data=original_default, aes(PAY_AMT5)) +geom_histogram()
p6 <- ggplot(data=original_default, aes(PAY_AMT6)) +geom_histogram()

grid.arrange(p1,p2,p3,p4,p5,p6, nrow=2, ncol=3)
```

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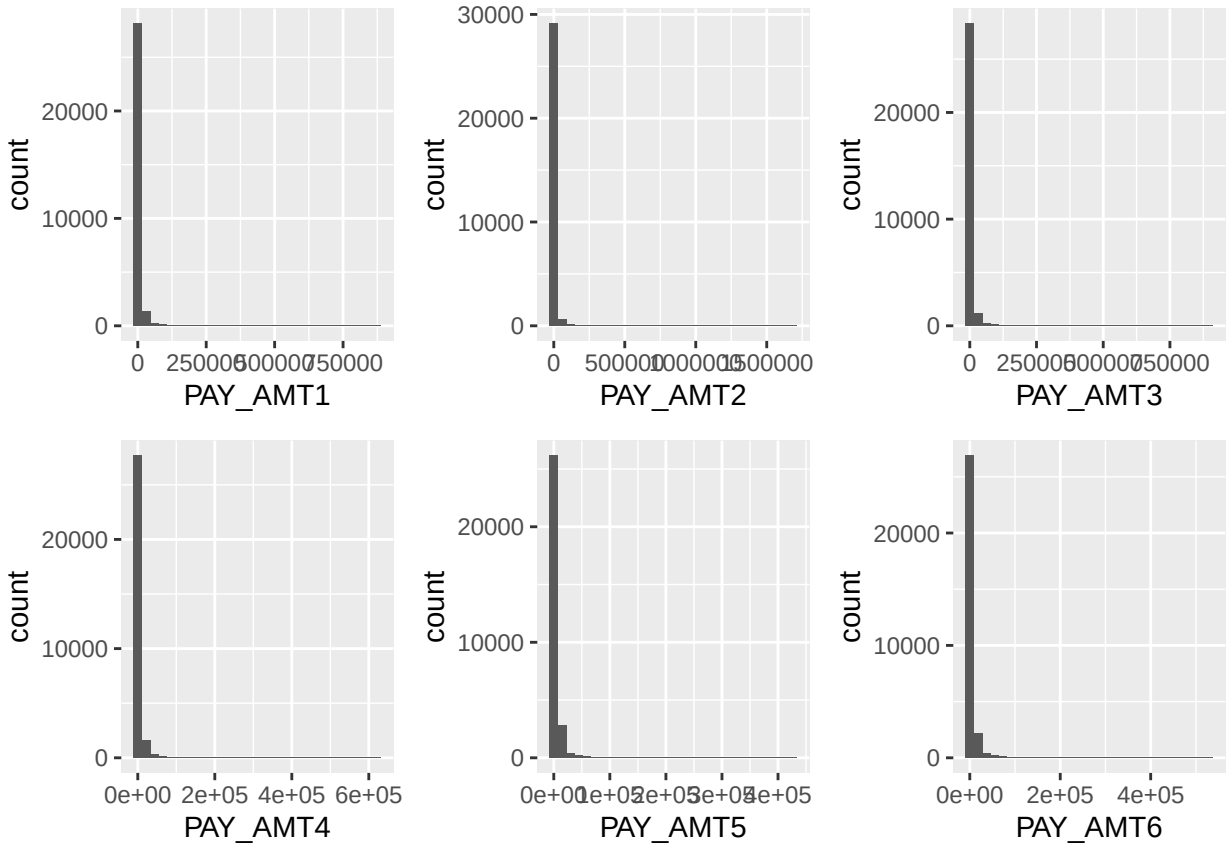



Data Preparation

Remove ID

```
original_default <- original_default %>% select(-ID)
```

Categorical data, change numeric to factor. SEX,EDUCATION,MARRIAGE, PAY_0~PAY_6 are categorical data

```
original_default <- original_default %>%
  mutate(SEX = as.factor(SEX),
         EDUCATION = as.factor(EDUCATION),
         MARRIAGE = as.factor(MARRIAGE),
         PAY_0 = as.factor(PAY_0),
         PAY_2 = as.factor(PAY_2),
         PAY_3 = as.factor(PAY_3),
         PAY_4 = as.factor(PAY_4),
         PAY_5 = as.factor(PAY_5),
         PAY_6 = as.factor(PAY_6) )
```

Scaling. We use "scale" function to standardize predictors. Categorical data columns. we assume these can be defined as factors.

```
cat_col <- c("SEX", "EDUCATION", "MARRIAGE",
             "PAY_0", "PAY_2", "PAY_3", "PAY_4", "PAY_5", "PAY_6", "DEFAULT")

#all columns
all_col <- names(original_default)

#numerical data columns
num_col <- all_col[-which(all_col %in% cat_col)]

#scaling numerical data
original_default[num_col] <-original_default %>% select(-all_of(cat_col)) %>% scale()
```

Check the dataset.

```
str(original_default)
```

```
## tibble [30,000 x 24] (S3: tbl_df/tbl/data.frame)
##  $ LIMIT_BAL: num [1:30000] -1.137 -0.366 -0.597 -0.905 -0.905 ...
##  $ SEX      : Factor w/ 2 levels "1","2": 2 2 2 2 1 1 1 2 2 1 ...
##  $ EDUCATION: Factor w/ 4 levels "1","2","3","4": 2 2 2 2 2 1 1 2 3 3 ...
##  $ MARRIAGE : Factor w/ 3 levels "1","2","3": 1 2 2 1 1 2 2 2 1 2 ...
##  $ AGE      : num [1:30000] -1.246 -1.029 -0.161 0.164 2.334 ...
##  $ PAY_0    : Factor w/ 11 levels "-2","-1","0",..: 5 2 3 3 2 3 3 3 3 1 ...
##  $ PAY_2    : Factor w/ 11 levels "-2","-1","0",..: 5 5 3 3 3 3 3 2 3 1 ...
##  $ PAY_3    : Factor w/ 11 levels "-2","-1","0",..: 2 3 3 3 2 3 3 2 5 1 ...
##  $ PAY_4    : Factor w/ 11 levels "-2","-1","0",..: 2 3 3 3 3 3 3 3 3 1 ...
##  $ PAY_5    : Factor w/ 10 levels "-2","-1","0",..: 1 3 3 3 3 3 3 3 3 2 ...
##  $ PAY_6    : Factor w/ 10 levels "-2","-1","0",..: 1 4 3 3 3 3 3 2 3 2 ...
##  $ BILL_AMT1: num [1:30000] -0.6425 -0.6592 -0.2986 -0.0575 -0.5786 ...
##  $ BILL_AMT2: num [1:30000] -0.6474 -0.6667 -0.4939 -0.0133 -0.6113 ...
##  $ BILL_AMT3: num [1:30000] -0.668 -0.6392 -0.4824 0.0328 -0.1612 ...
##  $ BILL_AMT4: num [1:30000] -0.672 -0.622 -0.45 -0.232 -0.347 ...
##  $ BILL_AMT5: num [1:30000] -0.663 -0.606 -0.417 -0.187 -0.348 ...
##  $ BILL_AMT6: num [1:30000] -0.653 -0.598 -0.392 -0.157 -0.331 ...
##  $ PAY_AMT1 : num [1:30000] -0.342 -0.342 -0.25 -0.221 -0.221 ...
##  $ PAY_AMT2 : num [1:30000] -0.227 -0.214 -0.192 -0.169 1.335 ...
##  $ PAY_AMT3 : num [1:30000] -0.297 -0.24 -0.24 -0.229 0.271 ...
##  $ PAY_AMT4 : num [1:30000] -0.308 -0.244 -0.244 -0.238 0.266 ...
##  $ PAY_AMT5 : num [1:30000] -0.314 -0.314 -0.249 -0.244 -0.269 ...
##  $ PAY_AMT6 : num [1:30000] -0.2934 -0.1809 -0.0121 -0.2371 -0.2552 ...
##  $ DEFAULT  : Factor w/ 2 levels "0","1": 2 2 1 1 1 1 1 1 1 1 ...
```

```
summary(original_default)
```

```
##    LIMIT_BAL       SEX       EDUCATION MARRIAGE       AGE        
##  Min.   :-1.2138   1:11888   1:10585   1:13659   Min.   :-1.5715  
##  1st Qu.:-0.9055   2:18112   2:14030   2:15964   1st Qu.:-0.8121  
##  Median :-0.2118             3: 4917   3:  377   Median :-0.1612  
##  Mean   : 0.0000             4:  468             Mean   : 0.0000  
##  3rd Qu.: 0.5589                                 3rd Qu.: 0.5982  
##  Max.   : 6.4164                                 Max.   : 4.7207  
##
```

```
##      PAY_0           PAY_2           PAY_3           PAY_4
##  0      :14737   0      :15730   0      :15764   0      :16455
##  -1     : 5686   -1     : 6050   -1     : 5938   -1     : 5687
##  1      : 3688   2      : 3927   -2     : 4085   -2     : 4348
##  -2     : 2759   -2     : 3782   2      : 3819   2      : 3159
##  2      : 2667   3      :  326   3      :  240   3      :  180
##  3      :  322   4      :   99   4      :   76   4      :   69
##  (Other):  141   (Other):   86   (Other):   78   (Other):  102
##      PAY_5           PAY_6         BILL_AMT1         BILL_AMT2
##  0      :16947   0      :16286   Min.   :-2.9443   Min.   :-1.6713
##  -1     : 5539   -1     : 5740   1st Qu.:-0.6473   1st Qu.:-0.6490
##  -2     : 4546   -2     : 4895   Median :-0.3917   Median :-0.3931
##  2      : 2626   2      : 2766   Mean   : 0.0000   Mean   : 0.0000
##  3      :  178   3      :  184   3rd Qu.: 0.2155   3rd Qu.: 0.2083
##  4      :   84   4      :   49   Max.   :12.4028   Max.   :13.1334
##  (Other):   80   (Other):   80
##    BILL_AMT3         BILL_AMT4         BILL_AMT5         BILL_AMT6
##  Min.   :-2.9456   Min.   :-3.3150   Min.   :-2.0008   Min.   :-6.3551
##  1st Qu.:-0.6395   1st Qu.:-0.6363   1st Qu.:-0.6340   1st Qu.:-0.6316
##  Median :-0.3882   Median :-0.3763   Median :-0.3653   Median :-0.3661
##  Mean   : 0.0000   Mean   : 0.0000   Mean   : 0.0000   Mean   : 0.0000
##  3rd Qu.: 0.1896   3rd Qu.: 0.1748   3rd Qu.: 0.1625   3rd Qu.: 0.1734
##  Max.   :23.3178   Max.   :13.1865   Max.   :14.5872   Max.   :15.4950
##
##     PAY_AMT1          PAY_AMT2          PAY_AMT3          PAY_AMT4
##  Min.   :-0.3419   Min.   :-0.25699   Min.   :-0.29680   Min.   :-0.30806
##  1st Qu.:-0.2816   1st Qu.:-0.22083   1st Qu.:-0.27465   1st Qu.:-0.28916
##  Median :-0.2152   Median :-0.16979   Median :-0.19456   Median :-0.21231
##  Mean   : 0.0000   Mean   : 0.00000   Mean   : 0.00000   Mean   : 0.00000
##  3rd Qu.:-0.0397   3rd Qu.:-0.03998   3rd Qu.:-0.04093   3rd Qu.:-0.05188
##  Max.   :52.3983   Max.   :72.84177   Max.   :50.59444   Max.   :39.33152
##
##     PAY_AMT5          PAY_AMT6        DEFAULT
##  Min.   :-0.31413   Min.   :-0.29338   0:23364
##  1st Qu.:-0.29760   1st Qu.:-0.28675   1: 6636
##  Median :-0.21595   Median :-0.20900
##  Mean   : 0.00000   Mean   : 0.00000
##  3rd Qu.:-0.05026   3rd Qu.:-0.06837
##  Max.   :27.60317   Max.   :29.44461
##
```

Spliting into train_set,validation_set, test_set.

First we split data into test_set, and default.Test_set will be only used as evaluation. We use "createDataPartition" function in "caret" package. Set seed 2021.

```
set.seed(2021, sample.kind = "Rounding")
```

```
## Warning in set.seed(2021, sample.kind = "Rounding"): non-uniform 'Rounding'
## sampler used
```

```
index_1 <- createDataPartition(original_default$DEFAULT, p=0.2, list=F, times=1)
test_set <- original_default[index_1,]
default <- original_default[-index_1,]
```

As we tune hyperparameters, we split default into train_set and validation_set. Validation set will be used when tuning models.

```
set.seed(2021, sample.kind = "Rounding")
```

```
## Warning in set.seed(2021, sample.kind = "Rounding"): non-uniform 'Rounding'
## sampler used
```

```
index_2 <- createDataPartition(default$DEFAULT, p=0.2, list=F, times=1)
validation_set <-default[index_2,]
train_set <- default[-index_2,]
```

Check default ratio.

```
#train_set
prop.table(table(train_set$DEFAULT))
```

```
##
##         0         1
## 0.7788311 0.2211689
```

```
#validation_set
prop.table(table(validation_set$DEFAULT))
```

```
##
##         0         1
## 0.7787961 0.2212039
```

```
#test_set
prop.table(table(test_set$DEFAULT))
```

```
##
##         0         1
## 0.7787035 0.2212965
```

Almost similar ratio.

Model analysis

1 Baseline prediction

All predicted as non_default make factor vectors.

```
base_pred <-factor(numeric(length(test_set$DEFAULT)),levels=c("0","1"))
```

Confusion matrix.

```
confusionMatrix(base_pred, test_set$DEFAULT)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 4673 1328
##          1    0    0
##
##                Accuracy : 0.7787
##                  95% CI : (0.768, 0.7892)
##     No Information Rate : 0.7787
##     P-Value [Acc > NIR] : 0.5074
##
##                   Kappa : 0
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 1.0000
##             Specificity : 0.0000
##          Pos Pred Value : 0.7787
##          Neg Pred Value :    NaN
##              Prevalence : 0.7787
##          Detection Rate : 0.7787
##    Detection Prevalence : 1.0000
##       Balanced Accuracy : 0.5000
##
##        'Positive' Class : 0
##
```

We need to find models which exceed these values(except sensitivity). In this model, sensitivity is 1, but specificity is 0. This means the credit company falsely give credit to a person who fail to repay a debt. The loss for the company would be huge.

evaluation method

as this is a classification problem, we calculate accuracy using confusion matrix. However, as is shown in this baseline prediction, default rate is imbalanced. As well as accuracy, we will pay attention to specificity and balanced accuracy.

2 Logistic regression

As this is a classification, we use logistic regression. we use "glm" function. There are 24 predictors in the train_set. We use "step regression" to find the best logistic regression model.

Stepwise regression explanation. First we make null-model and full-model.

```
#a null model with no predictors
null_model <- glm(DEFAULT~1, data = train_set, family = binomial(link = "logit"))

#a full model using all of the potential predictors
full_model <- glm(DEFAULT~., data = train_set, family = binomial(link = "logit"))
```

Forward and backward stepwise algorithm.

```r
step_mdl   <- step(null_model,
                   scope = list(lower = null_model, upper = full_model),
                   direction = "both")
```

```
## Start:  AIC=20289.81
## DEFAULT ~ 1
```

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

```
##             Df Deviance   AIC
## + PAY_0     10    17383 17405
## + PAY_2     10    18439 18461
## + PAY_3     10    18834 18856
## + PAY_4     10    18980 19002
## + PAY_5      9    19077 19097
## + PAY_6      9    19232 19252
## + LIMIT_BAL  1    19768 19772
## + PAY_AMT2   1    20063 20067
## + PAY_AMT1   1    20085 20089
## + PAY_AMT3   1    20112 20116
## + PAY_AMT5   1    20164 20168
## + PAY_AMT4   1    20177 20181
## + EDUCATION  3    20174 20182
## + PAY_AMT6   1    20220 20224
## + SEX        1    20257 20261
## + MARRIAGE   2    20277 20283
## + BILL_AMT1  1    20279 20283
## + BILL_AMT3  1    20284 20288
## + BILL_AMT2  1    20284 20288
## + BILL_AMT4  1    20285 20289
## <none>             20288 20290
## + BILL_AMT5  1    20286 20290
## + BILL_AMT6  1    20286 20290
## + AGE        1    20288 20292
##
## Step:  AIC=17404.59
## DEFAULT ~ PAY_0
```

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

```
##             Df Deviance   AIC
## + PAY_4     10    17107 17149
## + PAY_5      9    17114 17154
## + PAY_3     10    17128 17170
## + PAY_6      9    17137 17177
## + LIMIT_BAL  1    17178 17202
## + PAY_2      9    17243 17283
## + PAY_AMT2   1    17294 17318
## + PAY_AMT3   1    17312 17336
## + PAY_AMT1   1    17321 17345
## + EDUCATION  3    17324 17352
## + PAY_AMT5   1    17329 17353
```

```
## + PAY_AMT4   1    17338 17362
## + PAY_AMT6   1    17352 17376
## + SEX        1    17364 17388
## + BILL_AMT5  1    17377 17401
## + BILL_AMT6  1    17377 17401
## + MARRIAGE   2    17375 17401
## + BILL_AMT4  1    17379 17403
## + BILL_AMT3  1    17379 17403
## + BILL_AMT1  1    17380 17404
## <none>             17383 17405
## + BILL_AMT2  1    17381 17405
## + AGE        1    17381 17405
## - PAY_0     10    20288 20290
##
## Step:  AIC=17148.59
## DEFAULT ~ PAY_0 + PAY_4

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

##             Df Deviance   AIC
## + LIMIT_BAL  1    16957 17001
## + PAY_6      9    16990 17050
## + PAY_AMT2   1    17019 17063
## + PAY_5      9    17027 17087
## + PAY_3     10    17027 17089
## + PAY_AMT1   1    17051 17095
## + PAY_AMT5   1    17062 17106
## + EDUCATION  3    17062 17110
## + PAY_AMT3   1    17067 17111
## + PAY_2      9    17052 17112
## + PAY_AMT4   1    17075 17119
## + PAY_AMT6   1    17082 17126
## + SEX        1    17091 17135
## + BILL_AMT6  1    17095 17139
## + BILL_AMT5  1    17096 17140
## + BILL_AMT4  1    17099 17143
## + MARRIAGE   2    17099 17145
## + BILL_AMT3  1    17101 17145
## + BILL_AMT1  1    17104 17148
## + BILL_AMT2  1    17105 17149
## <none>             17107 17149
## + AGE        1    17105 17149
## - PAY_4     10    17383 17405
## - PAY_0     10    18980 19002
##
## Step:  AIC=17001.21
## DEFAULT ~ PAY_0 + PAY_4 + LIMIT_BAL
##
##             Df Deviance   AIC
## + PAY_6      9    16855 16917
## + PAY_5      9    16884 16946
## + PAY_3     10    16895 16959
## + PAY_AMT2   1    16916 16962
## + EDUCATION  3    16929 16979
```

```
## + PAY_AMT1   1    16934 16980
## + PAY_2      9    16919 16981
## + BILL_AMT2  1    16936 16982
## + BILL_AMT1  1    16937 16983
## + PAY_AMT5   1    16941 16987
## + SEX        1    16943 16989
## + MARRIAGE   2    16941 16989
## + BILL_AMT3  1    16943 16989
## + PAY_AMT3   1    16944 16990
## + BILL_AMT4  1    16946 16992
## + PAY_AMT4   1    16947 16993
## + AGE        1    16950 16996
## + BILL_AMT5  1    16950 16996
## + BILL_AMT6  1    16952 16998
## + PAY_AMT6   1    16952 16998
## <none>            16957 17001
## - LIMIT_BAL  1    17107 17149
## - PAY_4     10    17178 17202
## - PAY_0     10    18714 18738
##
## Step:  AIC=16916.88
## DEFAULT ~ PAY_0 + PAY_4 + LIMIT_BAL + PAY_6
##
##             Df Deviance   AIC
## + PAY_AMT2   1    16818 16882
## + PAY_3     10    16803 16885
## + BILL_AMT2  1    16828 16892
## + BILL_AMT1  1    16830 16894
## + EDUCATION  3    16827 16895
## + PAY_AMT1   1    16834 16898
## + BILL_AMT3  1    16837 16901
## + PAY_2      9    16823 16903
## + BILL_AMT4  1    16840 16904
## + MARRIAGE   2    16839 16905
## + SEX        1    16842 16906
## + PAY_AMT3   1    16843 16907
## + PAY_AMT5   1    16844 16908
## + BILL_AMT5  1    16845 16909
## + PAY_AMT4   1    16847 16911
## + AGE        1    16847 16911
## + PAY_5      9    16831 16911
## + BILL_AMT6  1    16848 16912
## + PAY_AMT6   1    16851 16915
## <none>            16855 16917
## - PAY_6      9    16957 17001
## - PAY_4     10    16975 17017
## - LIMIT_BAL  1    16990 17050
## - PAY_0     10    18464 18506
##
## Step:  AIC=16881.94
## DEFAULT ~ PAY_0 + PAY_4 + LIMIT_BAL + PAY_6 + PAY_AMT2

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

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

##             Df Deviance   AIC
## + BILL_AMT3  1    16780 16846
## + BILL_AMT2  1    16785 16851
## + BILL_AMT1  1    16787 16853
## + BILL_AMT4  1    16792 16858
## + PAY_3     10    16777 16861
## + EDUCATION  3    16792 16862
## + BILL_AMT5  1    16800 16866
## + BILL_AMT6  1    16805 16871
## + MARRIAGE   2    16803 16871
## + SEX        1    16805 16871
## + PAY_AMT1   1    16806 16872
## + PAY_2      9    16790 16872
## + AGE        1    16810 16876
## + PAY_5      9    16794 16876
## + PAY_AMT5   1    16811 16877
## + PAY_AMT3   1    16812 16878
## + PAY_AMT4   1    16813 16879
## <none>             16818 16882
## + PAY_AMT6   1    16816 16882
## - PAY_AMT2   1    16855 16917
## - PAY_6      9    16916 16962
## - LIMIT_BAL  1    16912 16974
## - PAY_4     10    16943 16987
## - PAY_0     10    18402 18446
##
## Step:  AIC=16845.65
## DEFAULT ~ PAY_0 + PAY_4 + LIMIT_BAL + PAY_6 + PAY_AMT2 + BILL_AMT3

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

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

##             Df Deviance   AIC
## + EDUCATION  3    16753 16825
## + PAY_AMT1   1    16758 16826
## + PAY_3     10    16744 16830
## + SEX        1    16767 16835
## + MARRIAGE   2    16765 16835
## + PAY_AMT5   1    16768 16836
## + PAY_AMT3   1    16770 16838
## + PAY_AMT4   1    16773 16841
## + AGE        1    16773 16841
## + PAY_5      9    16757 16841
## + PAY_2      9    16758 16842
## + BILL_AMT6  1    16774 16842
## + BILL_AMT5  1    16774 16842
## + PAY_AMT6   1    16776 16844
## <none>             16780 16846
## + BILL_AMT4  1    16778 16846
## + BILL_AMT2  1    16780 16848
```

```
## + BILL_AMT1  1    16780 16848
## - BILL_AMT3  1    16818 16882
## - PAY_AMT2   1    16837 16901
## - PAY_6      9    16882 16930
## - PAY_4     10    16895 16941
## - LIMIT_BAL  1    16909 16973
## - PAY_0     10    18342 18388
##
## Step:  AIC=16824.78
## DEFAULT ~ PAY_0 + PAY_4 + LIMIT_BAL + PAY_6 + PAY_AMT2 + BILL_AMT3 +
##     EDUCATION

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

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

##             Df Deviance   AIC
## + PAY_AMT1   1    16732 16806
## + PAY_3     10    16718 16810
## + SEX        1    16740 16814
## + PAY_AMT5   1    16741 16815
## + MARRIAGE   2    16739 16815
## + PAY_AMT3   1    16744 16818
## + PAY_AMT4   1    16745 16819
## + AGE        1    16746 16820
## + PAY_5      9    16730 16820
## + BILL_AMT6  1    16747 16821
## + PAY_2      9    16731 16821
## + BILL_AMT5  1    16748 16822
## + PAY_AMT6   1    16749 16823
## <none>             16753 16825
## + BILL_AMT4  1    16751 16825
## + BILL_AMT2  1    16753 16827
## + BILL_AMT1  1    16753 16827
## - EDUCATION  3    16780 16846
## - BILL_AMT3  1    16792 16862
## - PAY_AMT2   1    16809 16879
## - PAY_6      9    16855 16909
## - PAY_4     10    16866 16918
## - LIMIT_BAL  1    16872 16942
## - PAY_0     10    18314 18366
##
## Step:  AIC=16806.31
## DEFAULT ~ PAY_0 + PAY_4 + LIMIT_BAL + PAY_6 + PAY_AMT2 + BILL_AMT3 +
##     EDUCATION + PAY_AMT1

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

##             Df Deviance   AIC
## + PAY_3     10    16694 16788
## + SEX        1    16719 16795
## + MARRIAGE   2    16719 16797
## + PAY_AMT5   1    16723 16799
```

```
## + AGE        1    16726 16802
## + BILL_AMT6  1    16726 16802
## + PAY_5      9    16710 16802
## + PAY_AMT3   1    16726 16802
## + BILL_AMT5  1    16727 16803
## + PAY_AMT4   1    16727 16803
## + PAY_AMT6   1    16730 16806
## <none>            16732 16806
## + BILL_AMT4  1    16731 16807
## + PAY_2      9    16716 16808
## + BILL_AMT1  1    16732 16808
## + BILL_AMT2  1    16732 16808
## - PAY_AMT1   1    16753 16825
## - EDUCATION  3    16758 16826
## - PAY_AMT2   1    16780 16852
## - BILL_AMT3  1    16781 16853
## - PAY_6      9    16833 16889
## - PAY_4     10    16844 16898
## - LIMIT_BAL  1    16843 16915
## - PAY_0     10    18268 18322
##
## Step:  AIC=16788.3
## DEFAULT ~ PAY_0 + PAY_4 + LIMIT_BAL + PAY_6 + PAY_AMT2 + BILL_AMT3 +
##     EDUCATION + PAY_AMT1 + PAY_3
##
##             Df Deviance   AIC
## + SEX        1    16682 16778
## + MARRIAGE   2    16681 16779
## + PAY_AMT5   1    16685 16781
## + AGE        1    16687 16783
## + BILL_AMT6  1    16688 16784
## + PAY_5      9    16672 16784
## + PAY_AMT3   1    16688 16784
## + BILL_AMT5  1    16689 16785
## + PAY_AMT4   1    16689 16785
## + PAY_AMT6   1    16691 16787
## <none>            16694 16788
## + BILL_AMT4  1    16693 16789
## + BILL_AMT1  1    16694 16790
## + BILL_AMT2  1    16694 16790
## + PAY_2      9    16686 16798
## - PAY_3     10    16732 16806
## - EDUCATION  3    16720 16808
## - PAY_AMT1   1    16718 16810
## - PAY_AMT2   1    16730 16822
## - PAY_4     10    16752 16826
## - BILL_AMT3  1    16737 16829
## - PAY_6      9    16787 16863
## - LIMIT_BAL  1    16796 16888
## - PAY_0     10    18019 18093
##
## Step:  AIC=16777.92
## DEFAULT ~ PAY_0 + PAY_4 + LIMIT_BAL + PAY_6 + PAY_AMT2 + BILL_AMT3 +
##     EDUCATION + PAY_AMT1 + PAY_3 + SEX
```

```
##
##             Df Deviance   AIC
## + MARRIAGE   2    16668 16768
## + PAY_AMT5   1    16672 16770
## + PAY_AMT3   1    16675 16773
## + PAY_5      9    16660 16774
## + BILL_AMT6  1    16676 16774
## + PAY_AMT4   1    16676 16774
## + BILL_AMT5  1    16677 16775
## + AGE        1    16677 16775
## + PAY_AMT6   1    16679 16777
## <none>            16682 16778
## + BILL_AMT4  1    16680 16778
## + BILL_AMT1  1    16681 16779
## + BILL_AMT2  1    16682 16780
## + PAY_2      9    16674 16788
## - SEX        1    16694 16788
## - PAY_3     10    16719 16795
## - EDUCATION  3    16707 16797
## - PAY_AMT1   1    16706 16800
## - PAY_AMT2   1    16718 16812
## - PAY_4     10    16740 16816
## - BILL_AMT3  1    16725 16819
## - PAY_6      9    16773 16851
## - LIMIT_BAL  1    16782 16876
## - PAY_0     10    18007 18083
##
## Step:  AIC=16768.08
## DEFAULT ~ PAY_0 + PAY_4 + LIMIT_BAL + PAY_6 + PAY_AMT2 + BILL_AMT3 +
##     EDUCATION + PAY_AMT1 + PAY_3 + SEX + MARRIAGE
##
##             Df Deviance   AIC
## + PAY_AMT5   1    16659 16761
## + PAY_5      9    16645 16763
## + PAY_AMT3   1    16662 16764
## + BILL_AMT6  1    16662 16764
## + BILL_AMT5  1    16663 16765
## + PAY_AMT4   1    16663 16765
## + PAY_AMT6   1    16665 16767
## <none>            16668 16768
## + BILL_AMT4  1    16666 16768
## + BILL_AMT1  1    16667 16769
## + AGE        1    16668 16770
## + BILL_AMT2  1    16668 16770
## + PAY_2      9    16660 16778
## - MARRIAGE   2    16682 16778
## - SEX        1    16681 16779
## - PAY_3     10    16705 16785
## - EDUCATION  3    16693 16787
## - PAY_AMT1   1    16692 16790
## - PAY_AMT2   1    16704 16802
## - PAY_4     10    16725 16805
## - BILL_AMT3  1    16710 16808
## - PAY_6      9    16759 16841
```

```
## - LIMIT_BAL  1    16776 16874
## - PAY_0     10    17988 18068
##
## Step:  AIC=16760.67
## DEFAULT ~ PAY_0 + PAY_4 + LIMIT_BAL + PAY_6 + PAY_AMT2 + BILL_AMT3 +
##     EDUCATION + PAY_AMT1 + PAY_3 + SEX + MARRIAGE + PAY_AMT5
##
##             Df Deviance   AIC
## + PAY_5      9    16636 16756
## + BILL_AMT5  1    16654 16758
## + PAY_AMT3   1    16654 16758
## + PAY_AMT4   1    16655 16759
## + BILL_AMT6  1    16656 16760
## + PAY_AMT6   1    16657 16761
## <none>            16659 16761
## + BILL_AMT4  1    16657 16761
## + AGE        1    16658 16762
## + BILL_AMT1  1    16658 16762
## + BILL_AMT2  1    16658 16762
## - PAY_AMT5   1    16668 16768
## + PAY_2      9    16650 16770
## - MARRIAGE   2    16672 16770
## - SEX        1    16672 16772
## - PAY_3     10    16696 16778
## - EDUCATION  3    16683 16779
## - PAY_AMT1   1    16680 16780
## - PAY_AMT2   1    16690 16790
## - PAY_4     10    16717 16799
## - BILL_AMT3  1    16704 16804
## - PAY_6      9    16747 16831
## - LIMIT_BAL  1    16759 16859
## - PAY_0     10    17978 18060
##
## Step:  AIC=16755.58
## DEFAULT ~ PAY_0 + PAY_4 + LIMIT_BAL + PAY_6 + PAY_AMT2 + BILL_AMT3 +
##     EDUCATION + PAY_AMT1 + PAY_3 + SEX + MARRIAGE + PAY_AMT5 +
##     PAY_5

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

##             Df Deviance   AIC
## + PAY_AMT3   1    16629 16751
## + BILL_AMT5  1    16630 16752
## + BILL_AMT6  1    16633 16755
## + PAY_AMT4   1    16633 16755
## + PAY_AMT6   1    16633 16755
## + BILL_AMT4  1    16634 16756
## <none>            16636 16756
## + AGE        1    16635 16757
## + BILL_AMT1  1    16635 16757
## + BILL_AMT2  1    16635 16757
## - PAY_5      9    16659 16761
## - PAY_AMT5   1    16645 16763
## + PAY_2      9    16627 16765
```

```
## - MARRIAGE   2    16649 16765
## - SEX        1    16649 16767
## - PAY_4     10    16673 16773
## - PAY_3     10    16673 16773
## - PAY_AMT1   1    16656 16774
## - EDUCATION  3    16660 16774
## - PAY_6      9    16682 16784
## - PAY_AMT2   1    16667 16785
## - BILL_AMT3  1    16680 16798
## - LIMIT_BAL  1    16734 16852
## - PAY_0     10    17929 18029
##
## Step:  AIC=16751.29
## DEFAULT ~ PAY_0 + PAY_4 + LIMIT_BAL + PAY_6 + PAY_AMT2 + BILL_AMT3 +
##     EDUCATION + PAY_AMT1 + PAY_3 + SEX + MARRIAGE + PAY_AMT5 +
##     PAY_5 + PAY_AMT3

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

##             Df Deviance   AIC
## + BILL_AMT5  1    16626 16750
## + PAY_AMT4   1    16627 16751
## <none>            16629 16751
## + PAY_AMT6   1    16628 16752
## + BILL_AMT6  1    16628 16752
## + BILL_AMT2  1    16629 16753
## + AGE        1    16629 16753
## + BILL_AMT1  1    16629 16753
## + BILL_AMT4  1    16629 16753
## - PAY_AMT3   1    16636 16756
## - PAY_5      9    16654 16758
## - PAY_AMT5   1    16638 16758
## - MARRIAGE   2    16643 16761
## + PAY_2      9    16621 16761
## - SEX        1    16643 16763
## - PAY_4     10    16663 16765
## - PAY_AMT1   1    16647 16767
## - EDUCATION  3    16653 16769
## - PAY_3     10    16667 16769
## - PAY_AMT2   1    16657 16777
## - PAY_6      9    16675 16779
## - BILL_AMT3  1    16675 16795
## - LIMIT_BAL  1    16721 16841
## - PAY_0     10    17920 18022
##
## Step:  AIC=16750.12
## DEFAULT ~ PAY_0 + PAY_4 + LIMIT_BAL + PAY_6 + PAY_AMT2 + BILL_AMT3 +
##     EDUCATION + PAY_AMT1 + PAY_3 + SEX + MARRIAGE + PAY_AMT5 +
##     PAY_5 + PAY_AMT3 + BILL_AMT5

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

##             Df Deviance   AIC
```

```
## <none>            16626 16750
## + PAY_AMT6   1    16624 16750
## + BILL_AMT2  1    16625 16751
## + BILL_AMT4  1    16625 16751
## - BILL_AMT5  1    16629 16751
## + PAY_AMT4   1    16625 16751
## + AGE        1    16626 16752
## + BILL_AMT1  1    16626 16752
## + BILL_AMT6  1    16626 16752
## - PAY_AMT3   1    16630 16752
## - PAY_AMT5   1    16635 16757
## - PAY_5      9    16651 16757
## - MARRIAGE   2    16640 16760
## + PAY_2      9    16618 16760
## - SEX        1    16639 16761
## - PAY_4     10    16661 16765
## - PAY_AMT1   1    16644 16766
## - PAY_3     10    16664 16768
## - EDUCATION  3    16650 16768
## - BILL_AMT3  1    16650 16772
## - PAY_6      9    16671 16777
## - PAY_AMT2   1    16657 16779
## - LIMIT_BAL  1    16714 16836
## - PAY_0     10    17919 18023
```

Predict by using validation_set. First we predict probabilities and then classify them using cut-off 0.5.

```
step_prob <- predict(step_mdl, validation_set,type="response")
step_pred <- ifelse(step_prob >0.5,1,0)
```

To show accuracy we use confusionMatrix function in caret library.

```
confusionMatrix(as.factor(step_pred), validation_set$DEFAULT)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 3568  715
##          1  171  347
##
##                Accuracy : 0.8155
##                  95% CI : (0.8042, 0.8263)
##     No Information Rate : 0.7788
##     P-Value [Acc > NIR] : 2.329e-10
##
##                   Kappa : 0.3441
##
##  Mcnemar's Test P-Value : < 2.2e-16
##
##             Sensitivity : 0.9543
##             Specificity : 0.3267
##          Pos Pred Value : 0.8331
```

```
##          Neg Pred Value : 0.6699
##              Prevalence : 0.7788
##          Detection Rate : 0.7432
##    Detection Prevalence : 0.8921
##       Balanced Accuracy : 0.6405
##
##        'Positive' Class : 0
##
```

Make a table.

```
results <- tibble(method = "logistic regresion",
                  Accuracy =confusionMatrix(as.factor(step_pred), validation_set$DEFAULT)$overall[1],
                  Sensitivity =confusionMatrix(as.factor(step_pred), validation_set$DEFAULT)$byClass[1]
                  Specificity =confusionMatrix(as.factor(step_pred), validation_set$DEFAULT)$byClass[2]
                  Balanced_Accuracy =confusionMatrix(as.factor(step_pred), validation_set$DEFAULT)$byCl

results %>% knitr::kable()
```

method	Accuracy	Sensitivity	Specificity	Balanced_Accuracy
logistic regresion	0.8154551	0.9542658	0.326742	0.6405039

3 Decision tree default model

Use CART classification and regression tree. Rpart ~ using default minsplit=20, cp=0.01.

```
set.seed(2021, sample.kind = "Rounding")
```

```
## Warning in set.seed(2021, sample.kind = "Rounding"): non-uniform 'Rounding'
## sampler used
```

```
rpart_mdl <-rpart(DEFAULT ~ .,data = train_set)
```

Predict.

```
rpart_pred <- predict(rpart_mdl, validation_set, type="class")
```

Confusion Matrix.

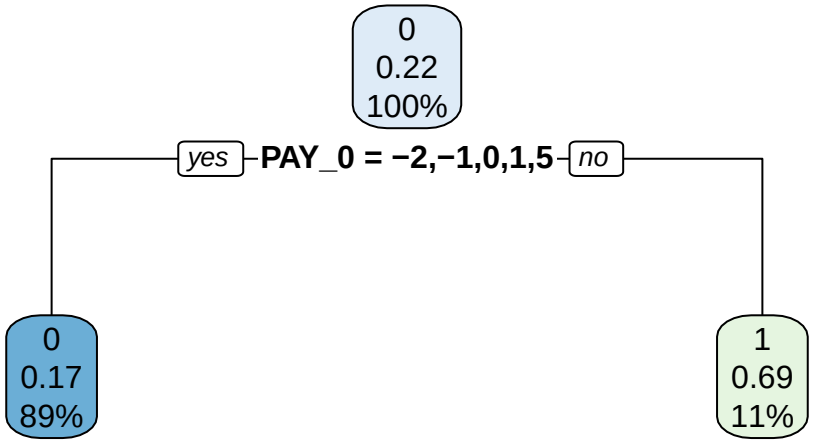
```
confusionMatrix(rpart_pred, validation_set$DEFAULT)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 3597  736
##          1  142  326
##
##                Accuracy : 0.8171
```

```
##                  95% CI : (0.8059, 0.828)
##     No Information Rate : 0.7788
##     P-Value [Acc > NIR] : 3.487e-11
##
##                   Kappa : 0.3363
##
##  Mcnemar's Test P-Value : < 2.2e-16
##
##             Sensitivity : 0.9620
##             Specificity : 0.3070
##          Pos Pred Value : 0.8301
##          Neg Pred Value : 0.6966
##              Prevalence : 0.7788
##          Detection Rate : 0.7492
##    Detection Prevalence : 0.9025
##       Balanced Accuracy : 0.6345
##
##        'Positive' Class : 0
##
```

Draw decision tree rpart.plot is good function to show decision tree clearly.

```
rpart.plot(rpart_mdl)
```



Find used features.

```
rpart_mdl$variable.importance
```

```
##      PAY_0      PAY_4      PAY_5      PAY_6      PAY_3      PAY_2
## 1000.94794   38.19276   36.20872   26.78453   25.29650   21.82443
```

This model illustrates that PAY_0 is overwhelmingly important.

Make a table

```
results <- bind_rows(
  results,
  tibble(method="CART default",
         Accuracy = confusionMatrix(rpart_pred,
                                    validation_set$DEFAULT)$overall[1],
         Sensitivity = confusionMatrix(rpart_pred,
                                       validation_set$DEFAULT)$byClass[1],
         Specificity = confusionMatrix(rpart_pred,
                                       validation_set$DEFAULT)$byClass[2],
         Balanced_Accuracy = confusionMatrix(rpart_pred,
                                             validation_set$DEFAULT)$byClass[11]))

results %>% knitr::kable()
```

method	Accuracy	Sensitivity	Specificity	Balanced_Accuracy
logistic regresion	0.8154551	0.9542658	0.326742	0.6405039
CART default	0.8171214	0.9620219	0.306968	0.6344950

4 Decision tree further tuning

We use "train" function in "caret" package. and tune cp. Cross validation

rpart ~tuning using smaller cp, less than 0.01

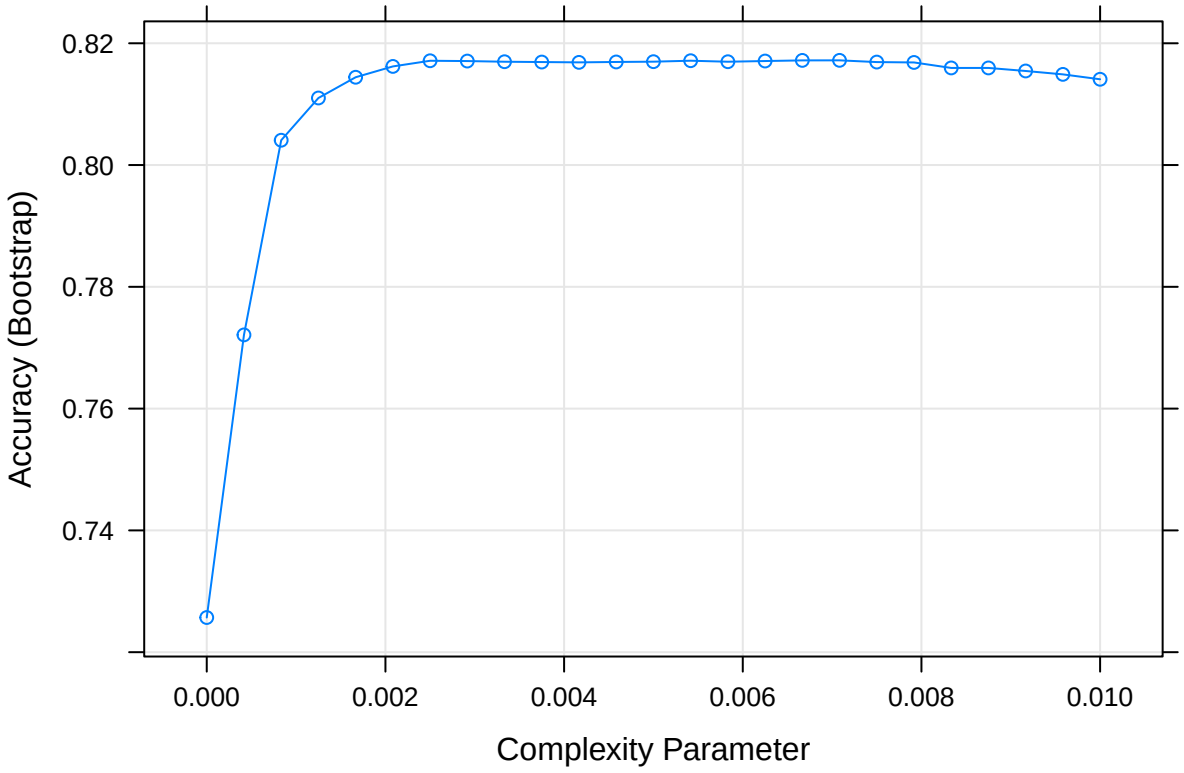
```
set.seed(2021, sample.kind = "Rounding")
```

```
## Warning in set.seed(2021, sample.kind = "Rounding"): non-uniform 'Rounding'
## sampler used
```

```
rpart_tuned_mdl <- train(DEFAULT ~ .,
                      method = "rpart",
                      tuneGrid = data.frame(cp = seq(0, 0.01, len = 25)),
                      control = rpart.control(minsplit = 0),
                      data = train_set)
```

Plot cp.

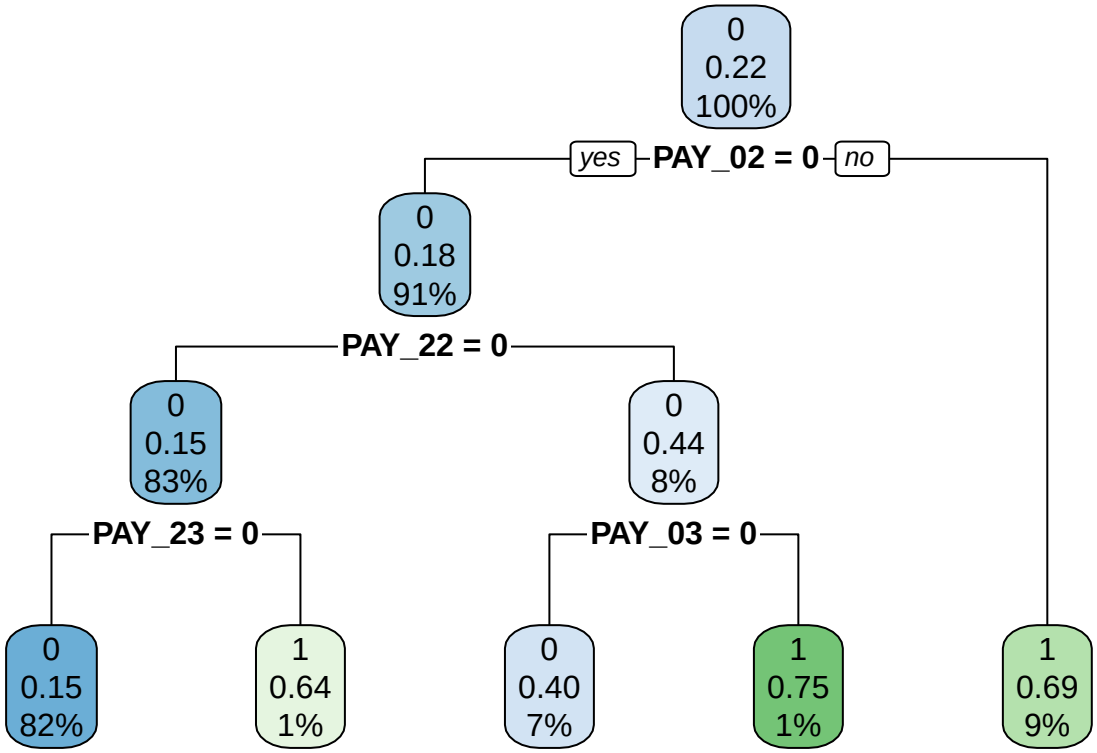
```
plot(rpart_tuned_mdl)
```




```
opt_cp <-rpart_tuned_mdl$bestTune
```

Draw decision tree. using rpart.plot.

```
rpart.plot(rpart_tuned_mdl$finalModel)
```



Note: numeric values are scaled

Prediction.

```
rpart_tuned_pred <- predict(rpart_tuned_mdl, validation_set)
```

Confusion matrix

```
confusionMatrix(rpart_tuned_pred, validation_set$DEFAULT)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 3587  730
##          1  152  332
##
##                Accuracy : 0.8163
##                  95% CI : (0.805, 0.8272)
##     No Information Rate : 0.7788
##     P-Value [Acc > NIR] : 9.111e-11
##
##                   Kappa : 0.3378
##
##  Mcnemar's Test P-Value : < 2.2e-16
##
```

```
##             Sensitivity : 0.9593
##             Specificity : 0.3126
##          Pos Pred Value : 0.8309
##          Neg Pred Value : 0.6860
##              Prevalence : 0.7788
##          Detection Rate : 0.7471
##    Detection Prevalence : 0.8992
##       Balanced Accuracy : 0.6360
##
##        'Positive' Class : 0
##
```

Make a table.

```
results <- bind_rows(
  results,
  tibble(method="CART tuned cp",
         Accuracy = confusionMatrix(rpart_tuned_pred, validation_set$DEFAULT)$overall[1],
         Sensitivity = confusionMatrix(rpart_tuned_pred, validation_set$DEFAULT)$byClass[1],
         Specificity = confusionMatrix(rpart_tuned_pred, validation_set$DEFAULT)$byClass[2],
         Balanced_Accuracy = confusionMatrix(rpart_tuned_pred, validation_set$DEFAULT)$byClass[11]) )

results %>% knitr::kable()
```

method	Accuracy	Sensitivity	Specificity	Balanced_Accuracy
logistic regresion	0.8154551	0.9542658	0.3267420	0.6405039
CART default	0.8171214	0.9620219	0.3069680	0.6344950
CART tuned cp	0.8162883	0.9593474	0.3126177	0.6359826

5 Random forest default

Using "ranger".

```
set.seed(2021, sample.kind = "Rounding")
```

```
## Warning in set.seed(2021, sample.kind = "Rounding"): non-uniform 'Rounding'
## sampler used
```

```
rf_mdl <- ranger(
  formula = DEFAULT ~ .,
  data = train_set,
  probability = F)
```

Model details.

```
rf_mdl
```

```
## Ranger result
##
```

```
## Call:
##  ranger(formula = DEFAULT ~ ., data = train_set, probability = F)
##
## Type:                             Classification
## Number of trees:                  500
## Sample size:                      19198
## Number of independent variables:  23
## Mtry:                             4
## Target node size:                 1
## Variable importance mode:         none
## Splitrule:                        gini
## OOB prediction error:             18.27 %
```

Prediction.

```
rf_pred <- predict(rf_mdl, validation_set)$predictions
```

Confusion matrix

```
confusionMatrix(rf_pred, validation_set$DEFAULT)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 3556  700
##          1  183  362
##
##                Accuracy : 0.8161
##                  95% CI : (0.8048, 0.8269)
##     No Information Rate : 0.7788
##     P-Value [Acc > NIR] : 1.154e-10
##
##                   Kappa : 0.3535
##
##  Mcnemar's Test P-Value : < 2.2e-16
##
##             Sensitivity : 0.9511
##             Specificity : 0.3409
##          Pos Pred Value : 0.8355
##          Neg Pred Value : 0.6642
##              Prevalence : 0.7788
##          Detection Rate : 0.7407
##    Detection Prevalence : 0.8865
##       Balanced Accuracy : 0.6460
##
##        'Positive' Class : 0
##
```

Make a table.

```
results <- bind_rows(
  results,
  tibble(method="random forest default",
         Accuracy = confusionMatrix(rf_pred, validation_set$DEFAULT)$overall[1],
         Sensitivity = confusionMatrix(rf_pred, validation_set$DEFAULT)$byClass[1],
         Specificity = confusionMatrix(rf_pred, validation_set$DEFAULT)$byClass[2],
         Balanced_Accuracy = confusionMatrix(rf_pred, validation_set$DEFAULT)$byClass[11]) )

results %>% knitr::kable()
```

method	Accuracy	Sensitivity	Specificity	Balanced_Accuracy
logistic regresion	0.8154551	0.9542658	0.3267420	0.6405039
CART default	0.8171214	0.9620219	0.3069680	0.6344950
CART tuned cp	0.8162883	0.9593474	0.3126177	0.6359826
random forest default	0.8160800	0.9510564	0.3408663	0.6459614

6 Random forest cross validation

Grid search

```
modelLookup("ranger")
```

```
##    model     parameter                          label forReg forClass probModel
## 1 ranger          mtry #Randomly Selected Predictors   TRUE     TRUE      TRUE
## 2 ranger     splitrule                Splitting Rule   TRUE     TRUE      TRUE
## 3 ranger min.node.size            Minimal Node Size   TRUE     TRUE      TRUE
```

Make a model.

```
set.seed(2021, sample.kind = "Rounding")
```

```
## Warning in set.seed(2021, sample.kind = "Rounding"): non-uniform 'Rounding'
## sampler used
```

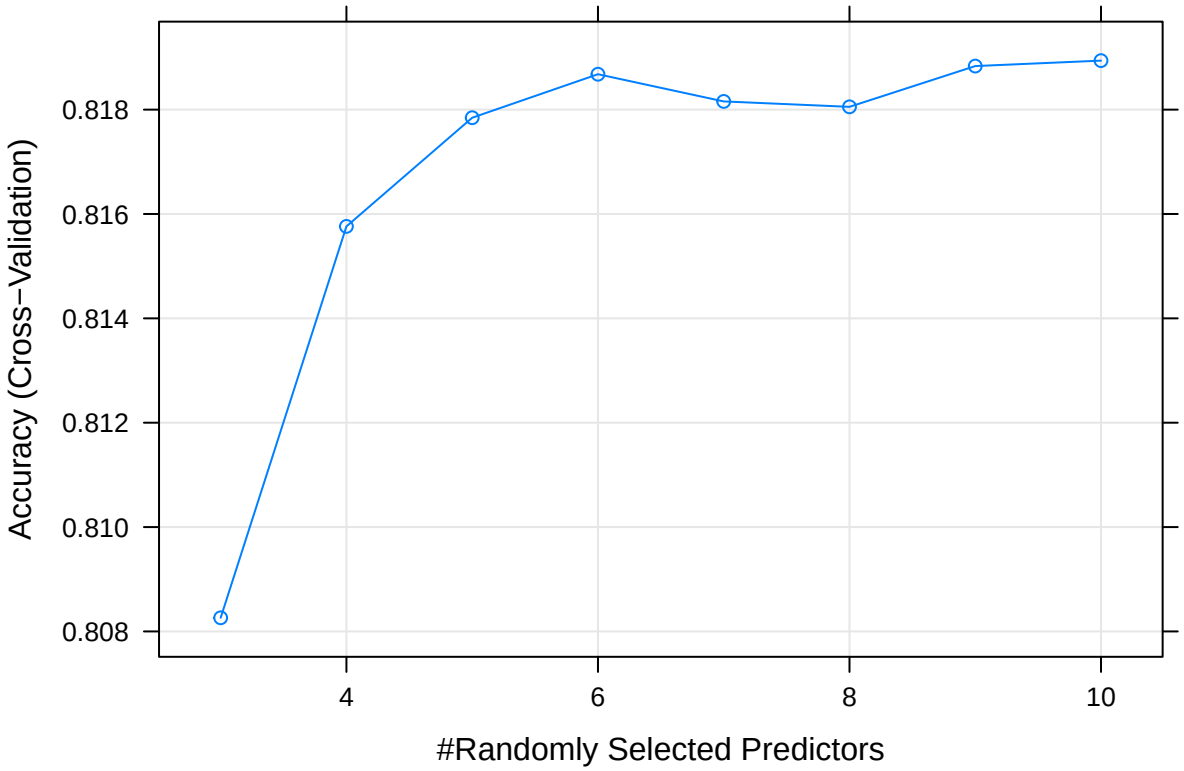
```
rf_cv_mdl <- train( DEFAULT~ .,
                    data = train_set,
                    method = 'ranger',
                    metric = 'Accuracy',
                    num.trees = 1000,
                    tuneGrid = expand.grid(
                      mtry = 3:10, splitrule = 'gini', min.node.size = 1),
                    trControl = trainControl(method = 'cv', number = 5))
```

```
## Growing trees.. Progress: 89%. Estimated remaining time: 3 seconds.
## Growing trees.. Progress: 81%. Estimated remaining time: 7 seconds.
## Growing trees.. Progress: 87%. Estimated remaining time: 4 seconds.
## Growing trees.. Progress: 76%. Estimated remaining time: 9 seconds.
## Growing trees.. Progress: 100%. Estimated remaining time: 0 seconds.
## Growing trees.. Progress: 88%. Estimated remaining time: 4 seconds.
```

```
## Growing trees.. Progress: 79%. Estimated remaining time: 8 seconds.
## Growing trees.. Progress: 90%. Estimated remaining time: 3 seconds.
## Growing trees.. Progress: 80%. Estimated remaining time: 7 seconds.
## Growing trees.. Progress: 99%. Estimated remaining time: 0 seconds.
## Growing trees.. Progress: 88%. Estimated remaining time: 4 seconds.
## Growing trees.. Progress: 81%. Estimated remaining time: 7 seconds.
## Growing trees.. Progress: 61%. Estimated remaining time: 19 seconds.
```

Plot.

```
plot(rf_cv_mdl)
```



Prediction.

```
rf_cv_pred <- predict(rf_cv_mdl, validation_set)
```

Confusion Matrix

```
confusionMatrix(rf_cv_pred, validation_set$DEFAULT)
```

```
## Confusion Matrix and Statistics
##
##            Reference
## Prediction    0    1
##          0 3570  710
```

```
##          1  169  352
##
##                Accuracy : 0.8169
##                  95% CI : (0.8057, 0.8278)
##     No Information Rate : 0.7788
##     P-Value [Acc > NIR] : 4.443e-11
##
##                   Kappa : 0.3501
##
##  Mcnemar's Test P-Value : < 2.2e-16
##
##             Sensitivity : 0.9548
##             Specificity : 0.3315
##          Pos Pred Value : 0.8341
##          Neg Pred Value : 0.6756
##              Prevalence : 0.7788
##          Detection Rate : 0.7436
##    Detection Prevalence : 0.8915
##       Balanced Accuracy : 0.6431
##
##        'Positive' Class : 0
##
```

Make a table.

```
results <- bind_rows( results,
                      tibble(
                        method="random forest tuned ",
Accuracy = confusionMatrix(rf_cv_pred, validation_set$DEFAULT)$overall[1],
Sensitivity = confusionMatrix(rf_cv_pred, validation_set$DEFAULT)$byClass[1],
Specificity = confusionMatrix(rf_cv_pred, validation_set$DEFAULT)$byClass[2],
Balanced_Accuracy= confusionMatrix(rf_cv_pred, validation_set$DEFAULT)$byClass[11]) )

results %>% knitr::kable()
```

method	Accuracy	Sensitivity	Specificity	Balanced_Accuracy
logistic regresion	0.8154551	0.9542658	0.3267420	0.6405039
CART default	0.8171214	0.9620219	0.3069680	0.6344950
CART tuned cp	0.8162883	0.9593474	0.3126177	0.6359826
random forest default	0.8160800	0.9510564	0.3408663	0.6459614
random forest tuned	0.8169131	0.9548007	0.3314501	0.6431254

Evaluation

Best performance in terms of balanced accuracy is "random forest default model" Best performance in terms of accuracy is "CART default model" Then evaluate by using test_set.

```
final_pred_rpart <- predict(rpart_mdl, test_set,type="class")
confusionMatrix(final_pred_rpart, test_set$DEFAULT)
```

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

```
##
##           Reference
## Prediction    0    1
##          0 4496  887
##          1  177  441
##
##                Accuracy : 0.8227
##                  95% CI : (0.8128, 0.8323)
##     No Information Rate : 0.7787
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.3638
##
##  Mcnemar's Test P-Value : < 2.2e-16
##
##             Sensitivity : 0.9621
##             Specificity : 0.3321
##          Pos Pred Value : 0.8352
##          Neg Pred Value : 0.7136
##              Prevalence : 0.7787
##          Detection Rate : 0.7492
##    Detection Prevalence : 0.8970
##       Balanced Accuracy : 0.6471
##
##        'Positive' Class : 0
##
```

```
final_pred_rf <-predict(rf_mdl, test_set)$predictions
confusionMatrix(final_pred_rf, test_set$DEFAULT)$byClass
```

```
##          Sensitivity          Specificity       Pos Pred Value
##            0.9505671            0.3576807            0.8389046
##       Neg Pred Value            Precision               Recall
##            0.6728045            0.8389046            0.9505671
##                   F1           Prevalence       Detection Rate
##            0.8912520            0.7787035            0.7402100
## Detection Prevalence    Balanced Accuracy
##            0.8823529            0.6541239
```

Make a table.

```
final_results <- tibble( method ="CART default",
                         Accuracy =confusionMatrix(final_pred_rpart, test_set$DEFAULT)$overall[1],
                         Sensitivity =confusionMatrix(final_pred_rpart, test_set$DEFAULT)$byClass[1],
                         Specificity =confusionMatrix(final_pred_rpart, test_set$DEFAULT)$byClass[2],
                         Balanced_Accuracy = confusionMatrix(final_pred_rpart, test_set$DEFAULT)$byClass

final_results <-  bind_rows( final_results,
                             tibble( method ="Random forest default",
                             Accuracy =confusionMatrix(final_pred_rf, test_set$DEFAULT)$overall[1],
                             Sensitivity =confusionMatrix(final_pred_rf, test_set$DEFAULT)$byClass[1],
                             Specificity =confusionMatrix(final_pred_rf, test_set$DEFAULT)$byClass[2],
                             Balanced_Accuracy = confusionMatrix(final_pred_rf, test_set$DEFAULT)$byCla
```

```
final_results %>% knitr::kable()
```

method	Accuracy	Sensitivity	Specificity	Balanced_Accuracy
CART default	0.8226962	0.9621228	0.3320783	0.6471006
Random forest default	0.8193634	0.9505671	0.3576807	0.6541239

Conclusion

###