Report on Default of Credit Card Clients Dataset

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Introduction

Finance is one of fields where machine learning is commonly used. It deals with a huge amount of data and is surrounded by a lot of uncertainties. To predict future, ranging from stock market prices to individual repayment of a debt, using pre-existing data is a crucial part of finance. In this paper, we will deal with a problem many credit card companies are facing. Can we predict whether a credit client will pay their debt or fail to pay? Traditionally, finding a credible borrower have been a kind of know-how, or skill and experience nurtured by experts. Instead, we try to form machine learning models, using a dataset which is open to public.

The dataset we use, "Default of Credit Card Clients Dataset" is stored in Kaggle website. It was collected in Taiwan in 2005. It has 24 variables, such as age, education, and payment condition. Outcome has two results, "0" non-default, "1" default. Each data was anonymously collected and labeled with individual IDs.

Our goal is to form a classification model which predicts the most accurate outcome, default or not. But accuracy is not enough. We need to bear it in mind that its distribution of these outcomes is imbalanced. Namely, the number of default clients are small compared to non- default clients. To address the issue, we will use not only accuracy but also other metric, balanced accuracy.

We will use three machine learning models, logistic regression, decision tree, and random forest. If necessary, we will tune their parameters to find the best solution. Our process is as follows :

1. Data exploration and data preparation
2. Splitting the dataset into train_set, validation_set, and test_set
3. Applying models, logistic regression, decision tree, and random forest
4. Considering models performance, and evaluation

This paper is written as a final assignment in "HarvardX PH125.9x Data Science: Capstone."

Packages and Dataset

In this paper, we use following R packages, "tidyverse[1]", "DataExplorer[2]", "gridExtra[3]", "e1071[4]", "caret[5]", "rpart[6]", "rpart.plot[7]", and "ranger[8]".

[1]https://cran.r-project.org/web/packages/tidyverse/index.html
[2]https://cran.r-project.org/web/packages/DataExplorer/index.html
[3]https://cran.r-project.org/web/packages/gridExtra/index.html
[4]https://cran.r-project.org/web/packages/e1071/index.html
[5]https://cran.r-project.org/web/packages/caret/index.html
[6]https://cran.r-project.org/web/packages/rpart/index.html
[7]https://cran.r-project.org/web/packages/part.plot/index.html
[8]https://cran.r-project.org/web/packages/ranger/index.html

We use a dataset stored in Kaggle[9]website. Its description says, "This dataset contains information on default payments, demographic factors, credit data, history of payment, and bill statements of credit card clients in Taiwan from April 2005 to September 2005." It is CSV file.

Kaggle requires registration to download the dataset. For the sake of convenience, the file is stored in my GitHub repository[10].

Data Exploration

First, we look at the downloaded dataset. Here are variables and their data type. As we use "read_csv" function in tidyverse package, all variables are numeric.

```
## spec_tbl_df [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(),
```

[9]https://www.kaggle.com/uciml/default-of-credit-card-clients-dataset
[10]https://github.com/masa951125/Final_project/raw/main/UCI_Credit_Card.csv

```
##   ..   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()
##   .. )
```

It has 30000 rows and 25 columns. "Default.payment.next.month" is our target variable. Some variables' values are limited number of integers. Some are rather wide range of numbers. "SEX", "EDUCATION", "MARRIAGE", "PAY_0" -"PAY_6", and "default.payment.next.month" look like categorical data. Other features seem to be numerical.

We know there are no NAs, Nulls in the dataset.

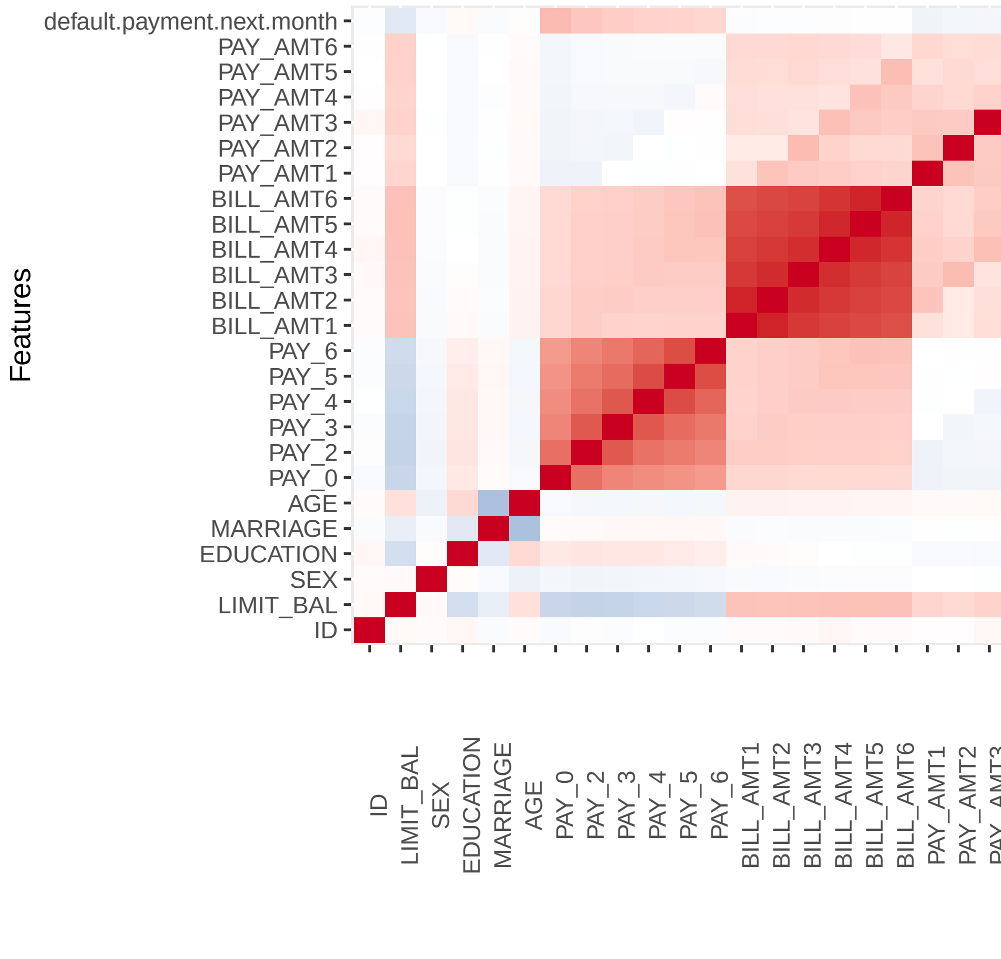
```
#Number of NAs
sum(is.na(original_default))
```

```
## [1] 0
```

```
#Number of Nulls
sum(is.null(original_default))
```

```
## [1] 0
```

How these predictors are correlated? We use "plot_correlation" function to investigate this.



Takeaways from this are;

1. Outcome (default.payment.next.month) has a positive correlation with PAY (positive), and PAY_AMT(negative), but a weak correlation with BILL_AMT.
2. Overall, LIMIT_BAL has a relatively strong correlation with other factors (except SEX).
3. EDUCATION, MARRIAGE, AGE have relatively strong correlation with one another.
4. EDUCATION and AGE have a relatively weak correlation with PAY and BILL_AMT respectively.
5. PAY and BILL_AMT, BILL_AMT and PAY_AMT have strong correlation.

We will look into individual features further.

1 Outcome

First, we look into the target variable, "default.payment.next.month". The data description says, "Default payment, 1=yes, 0=no.[11]" It is categorical data. We show the proportion of "0","1".

[11] https://www.kaggle.com/uciml/default-of-credit-card-clients-dataset

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

It is imbalanced. This means that if we predict all the outcome as “0”, we will get 77.9% accuracy. We should be aware of this fact considering model’s evaluation.

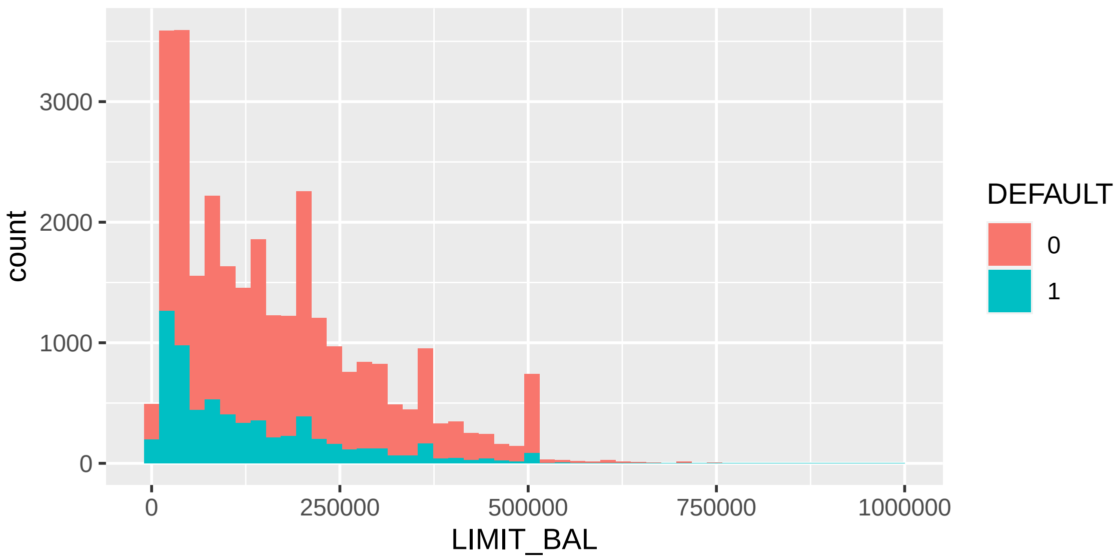
We change the name, “default.payment.next.month”, to“DEFAULT” for the sake of convenience. Also, we change this numeric variable into factor.

2 “LIMIT_BAL”

This is an “amount of given credit in NT dollars (includes individual and family/supplementary credit)[12]” NT stands for “New Taiwan”. It is numerical data.

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

We draw its distribution filling the bars with their proportion of default.



Distribution is skewed right. Default clients seem to be gathered around lower range of LIMIT_BAL values.

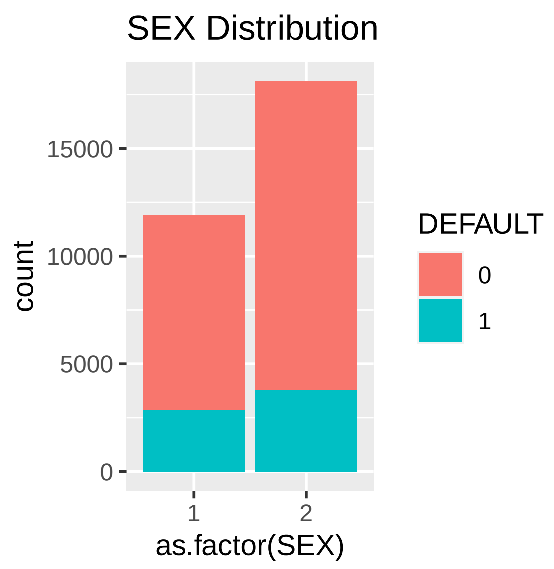
3 “SEX”

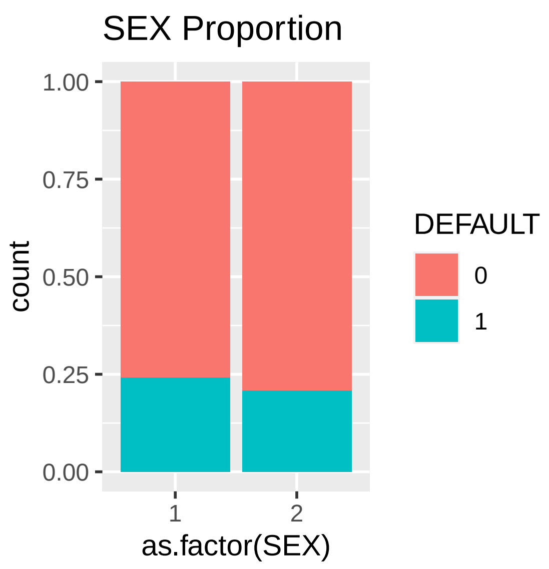
The values “1”, “2” correspond to male and female respectively[13]. It is categorical data. Male is approximately 40% and female is 60%.

```
##
##         1         2
## 0.3962667 0.6037333
```

[12]https://www.kaggle.com/uciml/default-of-credit-card-clients-dataset NT stands for “New Taiwan”.
[13]https://www.kaggle.com/uciml/default-of-credit-card-clients-dataset

We draw a distribution and a default rates proportion graph of this variable.

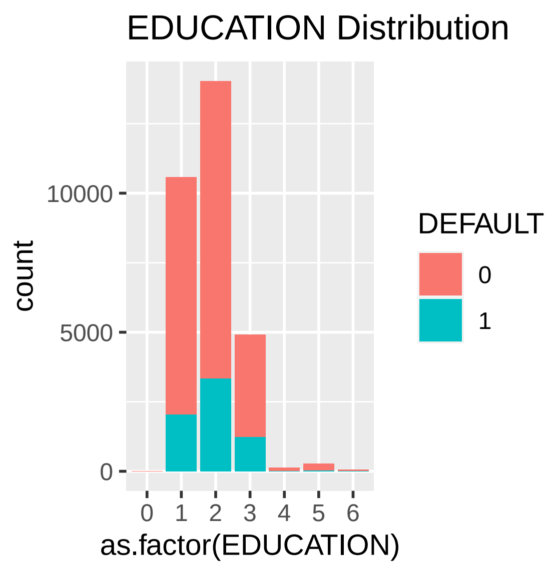


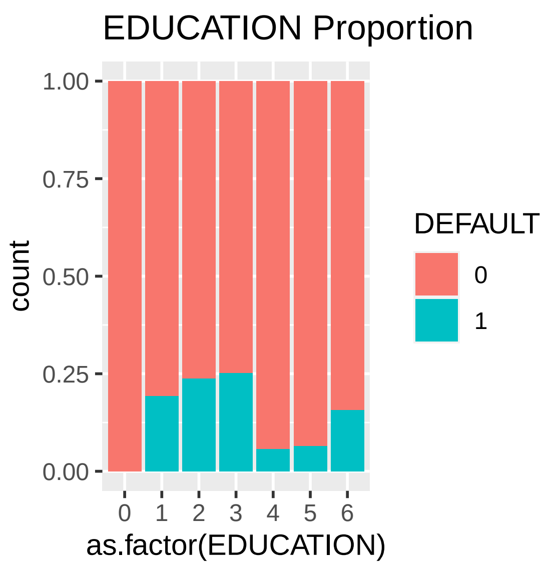


There seemed to be little difference between genders.

4 “EDUCATION”

In this variable, values are “1”, “2”, “3”, “4”, “5”, “6”. It is categorical variable. The numbers have meanings as follows ; 1=graduate school, 2=university, 3=high school, 4=others, 5=unknown, 6=unknown[14]. We draw a distribution and a default rates proportion graph of this variable.





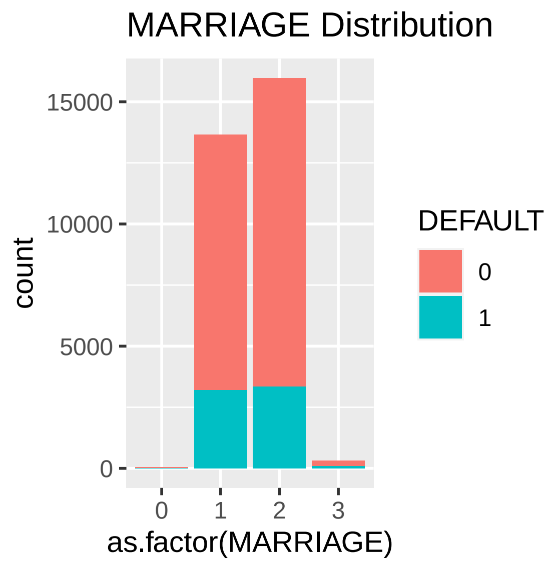
People whose final education is high school have relatively high default rate. On the other hand, people whose final education is graduate school have low default rate.

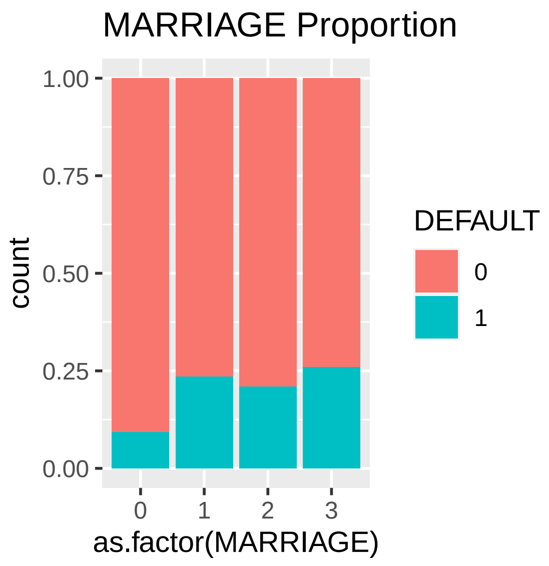
[14]https://www.kaggle.com/uciml/default-of-credit-card-clients-dataset

5 “MARRIAGE”

This is also categorical data. The value number means clients’ marital status[15]. 1=married, 2=single, 3=others. But this column includes undefined 0. It is also categorical variable. There are 54 individuals whose values are 0.

We draw a distribution and a default rates proportion graph of this variable.





Value 0 is negligible. Comparing married and single people, married people are a little more likely to default.

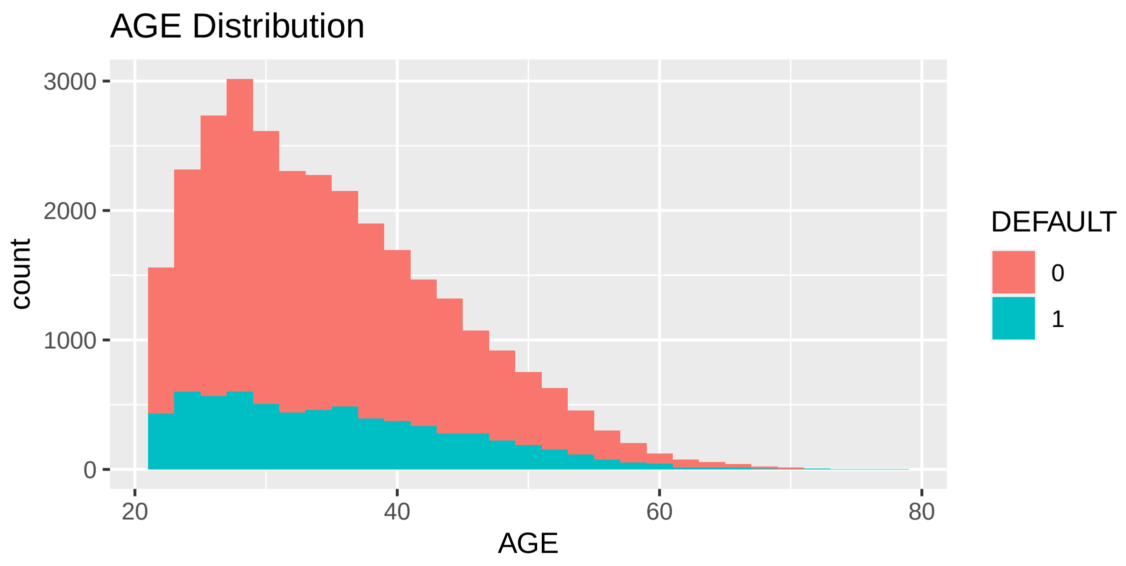
6 “AGE”

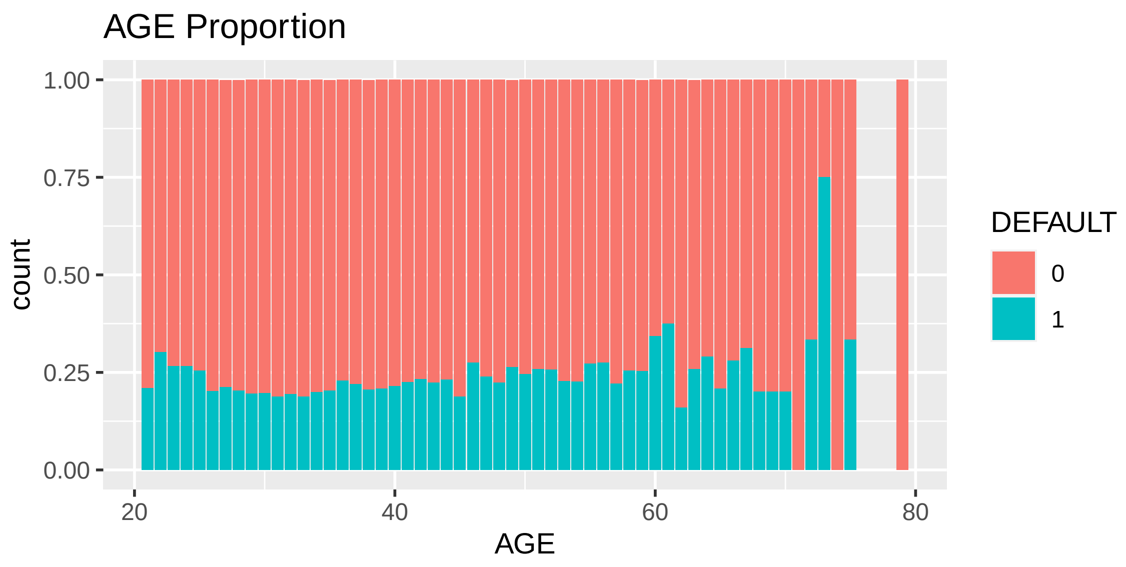
It is age in years[16]. As its name indicates, it is numerical data.

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

We plots its distribution filling the bar with each age bin’s default rate.

[15]https://www.kaggle.com/uciml/default-of-credit-card-clients-dataset
[16]https://www.kaggle.com/uciml/default-of-credit-card-clients-dataset





The number of clients are decreasing as they get older. Regarding the default clients, younger people in their early 20s and older age groups around 60s show higher proportions of default than other age groups.

7 "PAY"

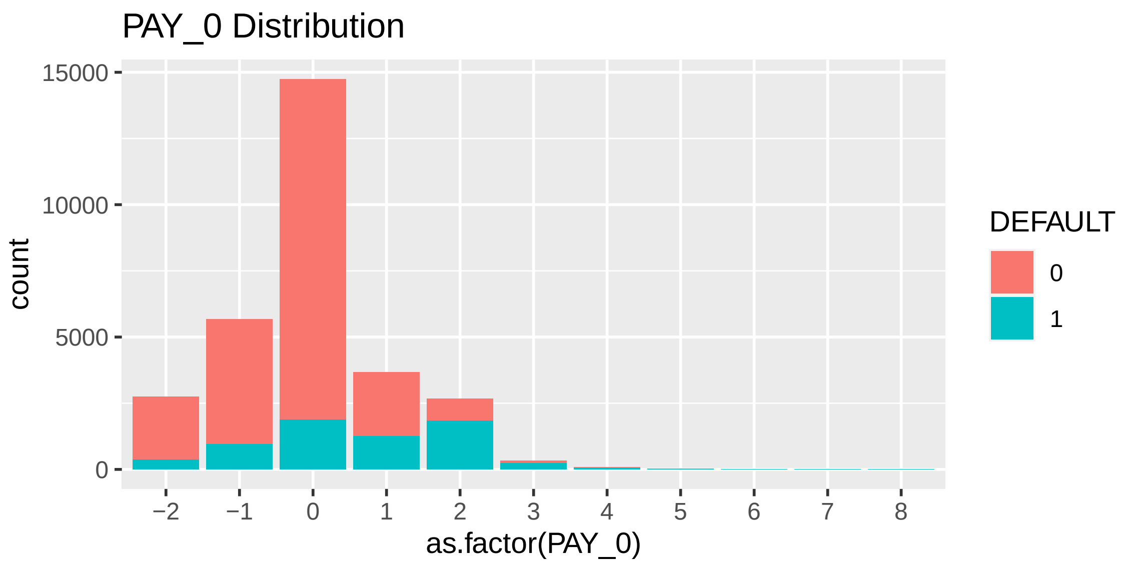
This group includes variable from PAY_0, PAY_2 ~PAY_6[17]. PAY_0 means repayment status in September, 2005. They go back in time by a month until April, 2005, PAY_6. They are categorical variables. Each column have values as follows;

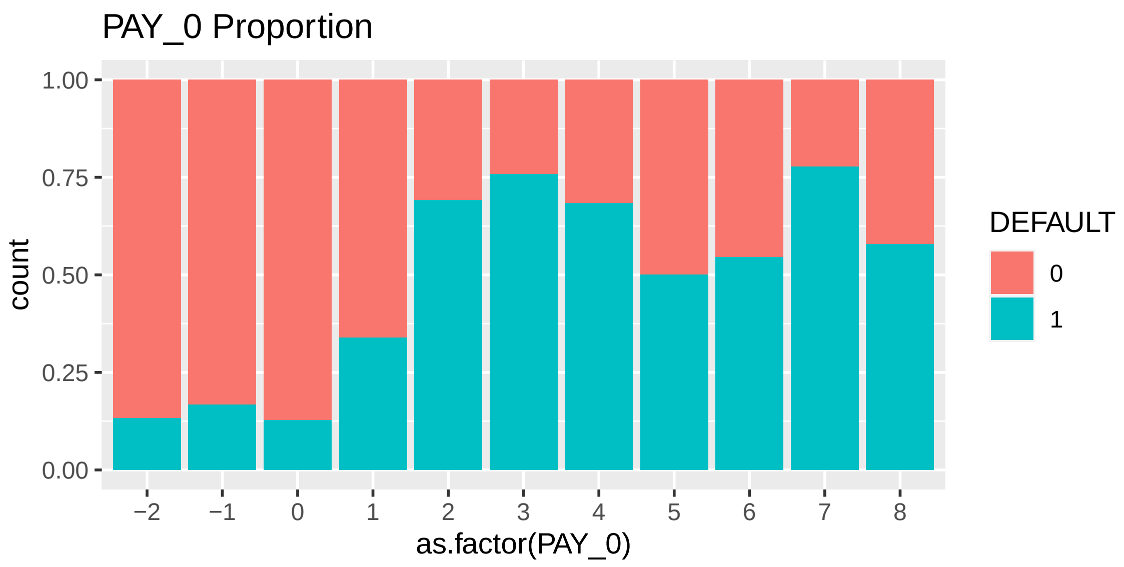
```
##  [1]  2 -1  0 -2  1  3  4  8  7  5  6
```

They mean; "-1"= pay duly, "1"= payment delay for 1 month, "2" = payment delay for 2 months, . . . 9 = payment delay for 9 months and above. "0" and "-2" are not defined.

We draw a distribution and a default rates proportion graph of PAY_0.

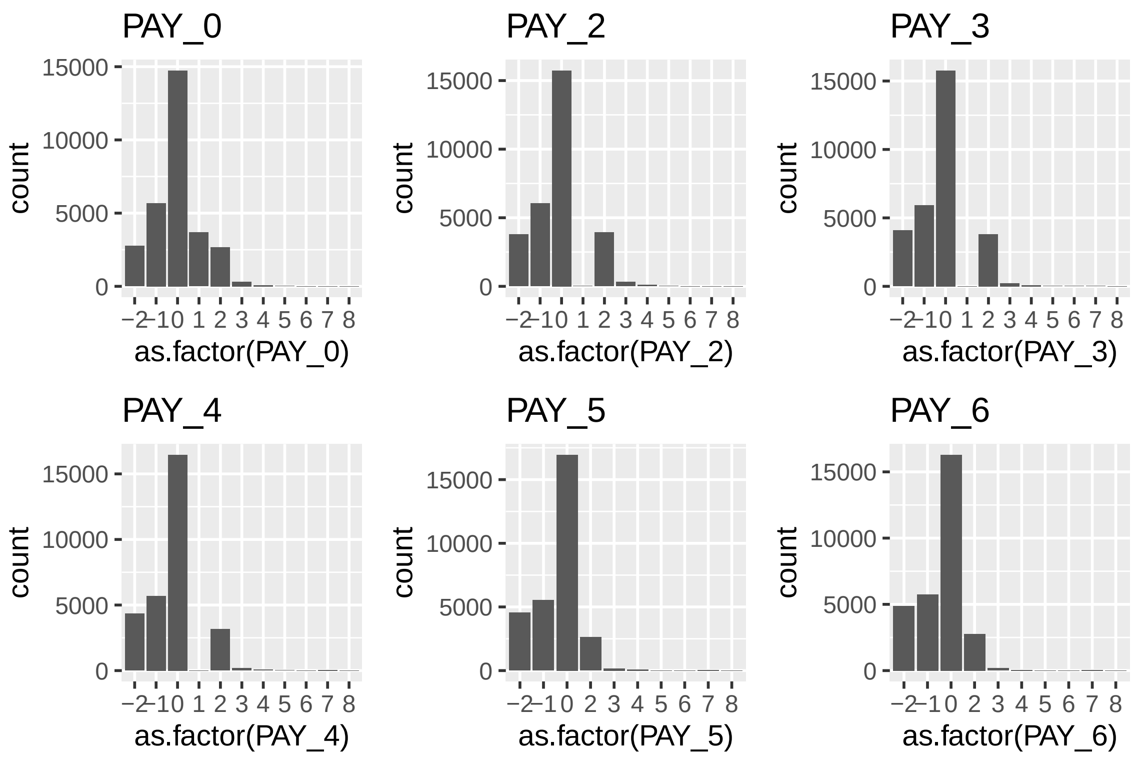
[17]https://www.kaggle.com/uciml/default-of-credit-card-clients-dataset





We are not sure what “-2” and “0” mean. Non-default clients distribution is centered around 0. The proportion of the default clients is left skewed. From these two graphs we understand that as payment delay becomes longer, clients are more likely to come to a default.

PAY_2 ~ PAY_6 ’s distributions are almost as the same as PAY_0. We show their distributions.



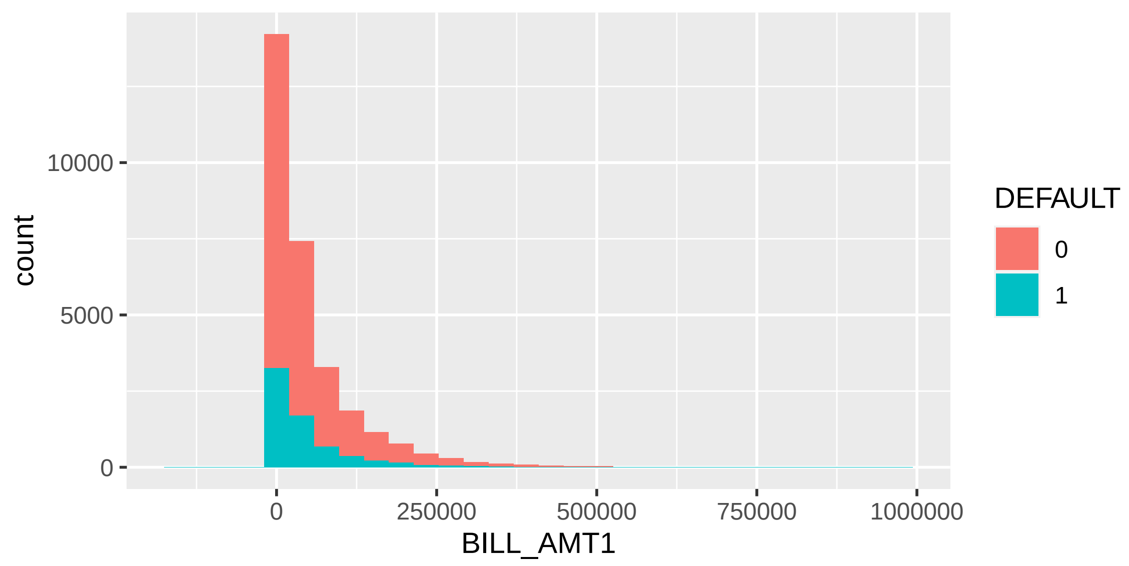
8 "BILL_AMT"

This group indicate an amount of bill statement. BILL_AMT1 is a record in September, 2005[18]. They go back in time by a month until April, 2005. They are numeric data.

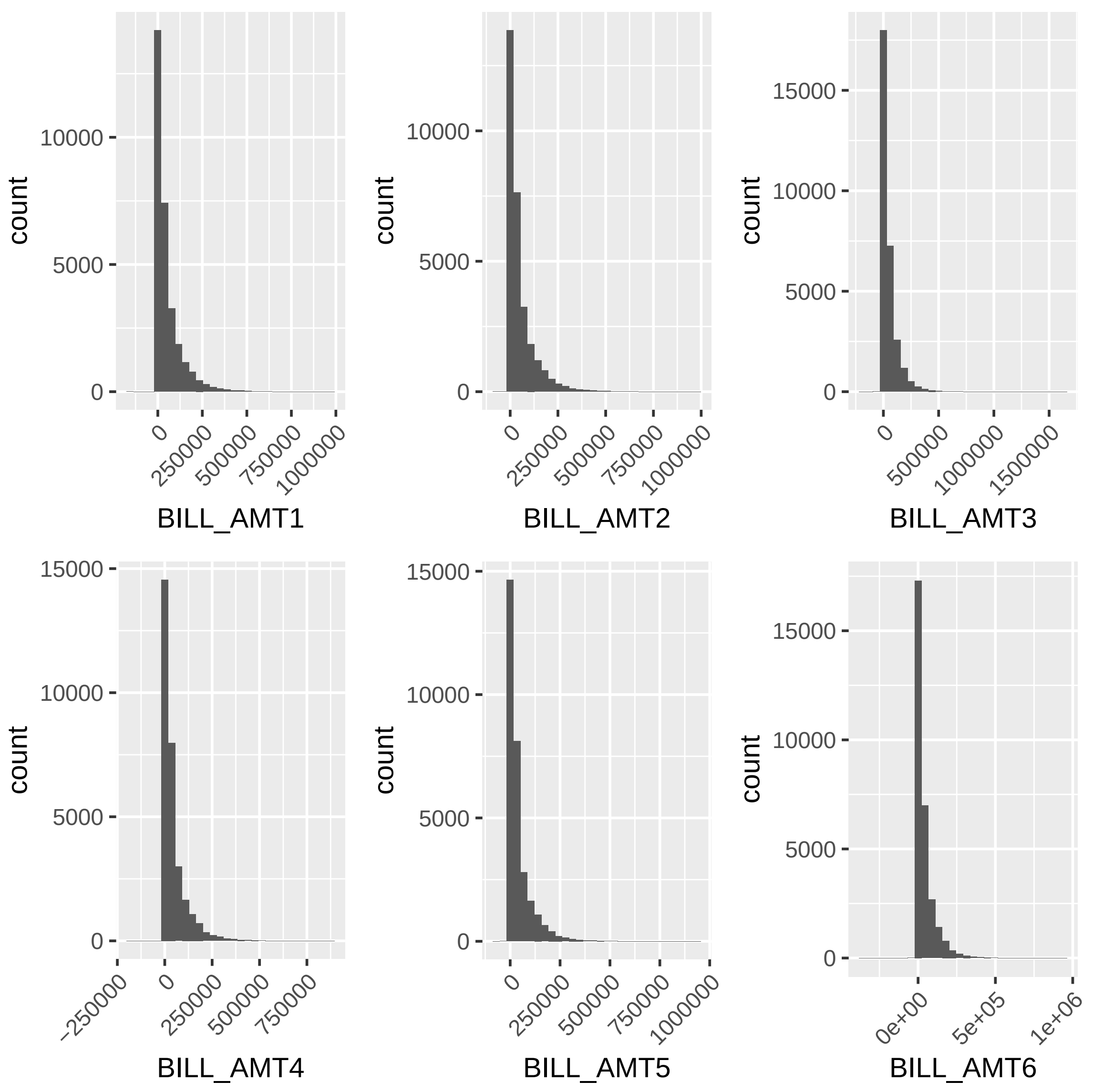
```
##    BILL_AMT1         BILL_AMT2        BILL_AMT3         BILL_AMT4
##  Min.   :-165580   Min.   :-69777   Min.   :-157264   Min.   :-170000
##  1st Qu.:   3559   1st Qu.:  2985   1st Qu.:   2666   1st Qu.:   2327
##  Median :  22382   Median : 21200   Median :  20089   Median :  19052
##  Mean   :  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
##  Min.   :-81334   Min.   :-339603
##  1st Qu.:  1763   1st Qu.:   1256
##  Median : 18105   Median :  17071
##  Mean   : 40311   Mean   :  38872
##  3rd Qu.: 50191   3rd Qu.:  49198
##  Max.   :927171   Max.   : 961664
```

Maximum values are approximately 900000, except BILL_AMT3. And medians and means are decreasing from BILL_AMT1 to BILL_AMT6. Likewise previous variables, we plot BILL_AMT distribution filling each bar with its default rate.

[18]https://www.kaggle.com/uciml/default-of-credit-card-clients-dataset



It is right skewed. From BILL_AMT1 to BILL_AMT6, their distributions are almost the same as are shown in following plots.



9 "PAY_AMT"

These variables mean an amount of previous payment. PAY_AMT1 is an amount of previous payment in September, 2005[19]. Likewise BILL_AMT, PAY_AMT goes back in time by a month from August to April, 2005 which is PAY_AMT6. They are also numeric variables.

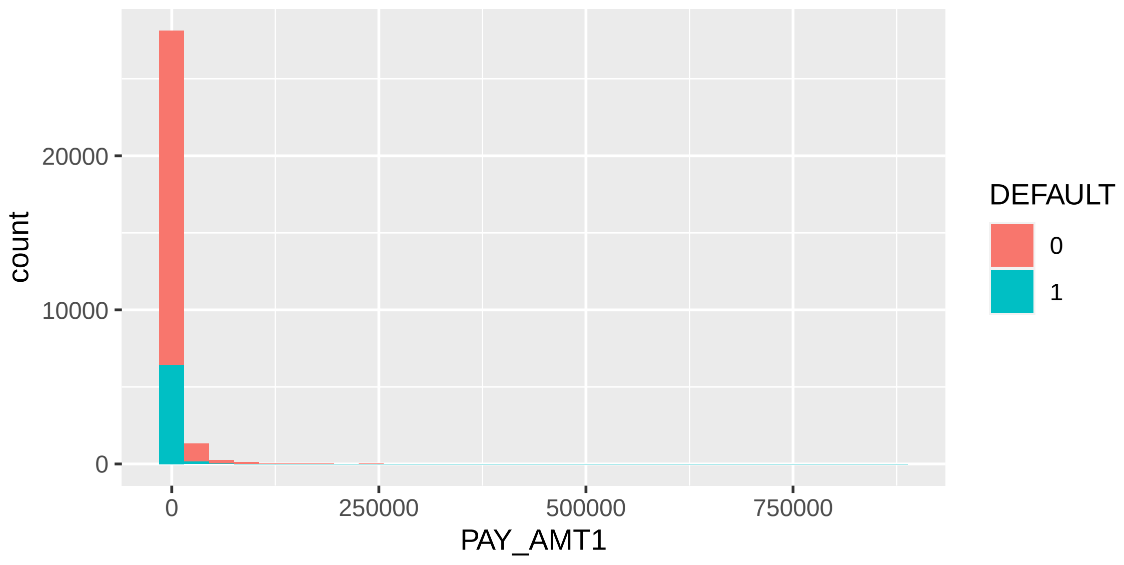
```
##     PAY_AMT1         PAY_AMT2          PAY_AMT3         PAY_AMT4     
##  Min.   :     0   Min.   :      0   Min.   :     0   Min.   :     0  
##  1st Qu.:  1000   1st Qu.:    833   1st Qu.:   390   1st Qu.:   296  
##  Median :  2100   Median :   2009   Median :  1800   Median :  1500  
##  Mean   :  5664   Mean   :   5921   Mean   :  5226   Mean   :  4826  
##  3rd Qu.:  5006   3rd Qu.:   5000   3rd Qu.:  4505   3rd Qu.:  4013  
##  Max.   :873552   Max.   :1684259   Max.   :896040   Max.   :621000  
##     PAY_AMT5           PAY_AMT6      
```

[19]https://www.kaggle.com/uciml/default-of-credit-card-clients-dataset

```
##   Min.   :     0.0   Min.   :     0.0  
##   1st Qu.:   252.5   1st Qu.:   117.8  
##   Median :  1500.0   Median :  1500.0  
##   Mean   :  4799.4   Mean   :  5215.5  
##   3rd Qu.:  4031.5   3rd Qu.:  4000.0  
##   Max.   :426529.0   Max.   :528666.0  
```

Their maximum values are fluctuating, but medians are gradually decreasing from PAY_AMT1 to PAY_AMT6.

We plot PAY_AMT1 distribution filling each bar with its default rate.

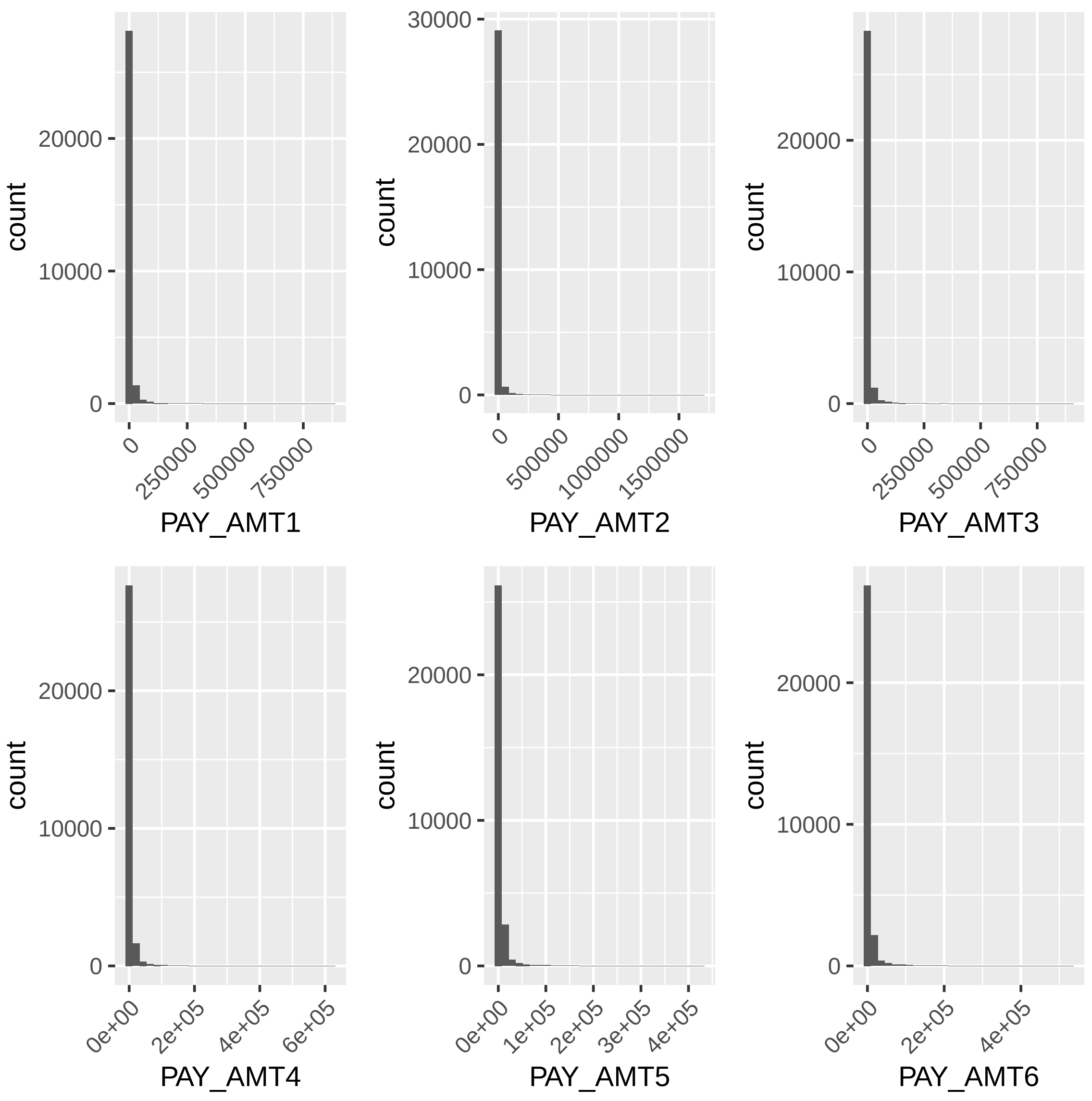


It is right skewed significantly. Maximum amount is more than 850,000 NT dollars, but its mean and median are 5664 and 2100 respectively. In addition to this, approximately 17% of clients' values are 0.

```
#proportion of clients whose PAY_AMT is 0
mean(original_default$PAY_AMT1==0)
```

```
## [1] 0.1749667
```

From PAY_AMT1 to PAY_AMT6, their distributions follow the same trend as PAY_AMT1.



Data Preparation

Before going further, we will arrange our dataset to make it easier to investigate. First, we remove ID column, as it is irrelevant to the outcome.

Currently our data is composed of numerical values. Categorical values need to be changed to a factor. As we saw in the data exploration section, SEX, EDUCATION, MARRIAGE, PAY_0~PAY_6 are categorical values.

Regarding numerical values, "LIMIT_BAL" ranges from 10000 to 1000000, but "AGE" from 21 to 79 as we saw in the previous section. When forming a regression model, these wide varieties of ranges of variables cause inaccuracy. Thus we standardize these variables, using following formula.

$$Transformed.Values = \frac{Values - Mean}{Standard.Deviation}$$

We get variables whose means are 0, and standard deviations are 1 using function "scale".

Then, we split the data into two. As we have relatively a large amount of data, 30000, the proportion we use is 80% and 20%. The smaller dataset will be used when evaluating a model at the final stage. We call it test_set.

We are going to use decision tree, and random forest algorithms later. They can be tuned to produce improved results by finding hyperparameters. If we tune the model using hyperparameters again and again, this might cause overfitting. To avoid this , we split the larger dataset again and produce two datasets, “train_set” and “validation_set”. Split proportion is the same as before, 80% and 20% respectively.

The three datasets have the almost same outcome ratio.

```
## # A tibble: 2 x 4
##   outcome train_set validation_set test_set
##     <dbl> <table>   <table>        <table>
## 1       0 0.7788311 0.7787961      0.7787035
## 2       1 0.2211689 0.2212039      0.2212965
```

Model Analysis

1 Evaluation Metrics

Overall accuracy is often used to evaluate a model. But this dataset has imbalanced proportion of outcomes as we explored. What consequences bring about? Guessing all responses are 0, we calculate its confusion matrix.

```
##           Reference
## Prediction    0    1
##          0 3739 1062
##          1    0    0
```

From this confusion matrix, we know even such a guess produces fairly good results.

- Accuracy (True positive + True Negative / Total) 0.7788
- Sensitivity (True Positive / True Positive+ False Negative) 1.0

In contrast,

- Specificity (True Negative / True Negative + False Positive) 0
- Balanced accuracy (arithmetic mean of sensitivity and specificity) 0.5

As such, the credit company would falsely give credit to a lot of clients who will fail to repay a debt. The loss for the company would be huge. Therefore, our goal is to pursue more accurate accuracy than guessing all responses are 0, taking account of improving specificity. We will use both *accuracy* and *balanced accuracy* to evaluate each model.

2 Logistic Regression

Firstly, we choose logistic regression. Logistic regression is commonly used in binary classification problems (outcome is 0 and 1, or True and False). As it uses logistic transformed odds, it produces outcome ranging from 0 to 1.

We have 24 features in the dataset. There are many ways to deal with such many predictors. First, we will form a logistic regression model with fewer variables. In the data exploration, we understand predictors from PAY_0 to PAY_6 seem to be important. But PAY variables, BILL_AMT variables and PAY_AMT variables have strong correlation. In addition to this, BILL_AMTs seem to have weak correlation with DEFAULT, target variable.

From these, we narrow down variables. We leave out BILL_AMT2 to BILL_AMT6, PAY_AMT2 to PAY_AMT6, PAY_2 to PAY_6 as well. Then we predict responses using glm function. The result;

```
##
## Call:
## glm(formula = DEFAULT ~ LIMIT_BAL + SEX + EDUCATION + MARRIAGE +
##     AGE + PAY_0 + PAY_AMT1 + BILL_AMT1, family = binomial(link = "logit"),
##     data = train_set)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.8600  -0.6012  -0.5244  -0.3403   3.2785
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -13.92484  105.25873  -0.132  0.89475
## LIMIT_BAL    -0.34333    0.02639 -13.008  < 2e-16 ***
## SEX2         -0.16184    0.03975  -4.071 4.68e-05 ***
## EDUCATION1   10.88972  105.25677   0.103  0.91760
## EDUCATION2   10.94220  105.25678   0.104  0.91720
## EDUCATION3   10.87972  105.25678   0.103  0.91767
## EDUCATION4   10.09138  105.25780   0.096  0.92362
## EDUCATION5    9.46368  105.25730   0.090  0.92836
## EDUCATION6   10.36704  105.25800   0.098  0.92154
## MARRIAGE1     1.57053    0.63924   2.457  0.01402 *
## MARRIAGE2     1.42360    0.63942   2.226  0.02599 *
## MARRIAGE3     1.62229    0.66105   2.454  0.01412 *
## AGE           0.01767    0.02247   0.787  0.43151
## PAY_0-1       0.18717    0.08471   2.210  0.02713 *
## PAY_00       -0.41514    0.08494  -4.887 1.02e-06 ***
## PAY_01        0.87807    0.08659  10.141  < 2e-16 ***
## PAY_02        2.21948    0.09468  23.441  < 2e-16 ***
## PAY_03        2.47682    0.17905  13.833  < 2e-16 ***
## PAY_04        1.99336    0.31677   6.293 3.12e-10 ***
## PAY_05        0.67991    0.63420   1.072  0.28369
## PAY_06        1.77298    0.73779   2.403  0.01626 *
## PAY_07        2.17427    0.84403   2.576  0.00999 **
## PAY_08        1.39957    0.56652   2.470  0.01349 *
## PAY_AMT1     -0.18223    0.03911  -4.659 3.17e-06 ***
## BILL_AMT1     0.13577    0.02525   5.378 7.54e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 20288  on 19197  degrees of freedom
## Residual deviance: 17045  on 19173  degrees of freedom
## AIC: 17095
##
## Number of Fisher Scoring iterations: 11
```

Note that due to factorization, some variables have been changed into dummy variables. For example, PAY_0 is changed to PAY_0-1 (minus 1), PAY_00, PAY_01, PAY_02, PAY_03, PAY_04, PAY_05, PAY_06, PAY_07, PAY_08. Right integer next to 0 means the level of the factor variables.

From this, we understand that;

- Important variables :

  LIMIT_BAL, SEX(whether a client is a female or not), PAY_0(whether its values are 0, 1, 2, 3, 4), BILL_AMT1,PAY_AMT1

Then fit the model to the validation set and show its confusion matrix.

```
##           Reference
## Prediction    0    1
##          0 3603  740
##          1  136  322
```

Statistic metrics are;

method	Accuracy	Sensitivity	Specificity	Balanced_Accuracy
glm fewer features	0.817538	0.9636266	0.3032015	0.6334141

Another option to deal with many variables is step-wise regression. This method is to repeatedly examine statistical significance of each variable in a regression model[20]. It includes three ways to conduct regression; forward selection, backward elimination, forward and backward elimination. Forward selection starts from no variable and add a variable step by step. Backward elimination starts from full model and subtract variables one by one. Forward and backward combines the two. One of the most convenient features of this method is we can get logistic regression results without knowing details of variables in the dataset.

We use forward and backward step-wise regression, as it is commonly used. In the step-wise regression, we make two models, null model with no predictors and full model with all predictors at first. Then we use "step" function to conduct step-wise regression. The result;

```
##
## Call:
## glm(formula = DEFAULT ~ PAY_0 + PAY_4 + LIMIT_BAL + PAY_6 + PAY_AMT2 +
##     BILL_AMT3 + PAY_AMT1 + PAY_3 + MARRIAGE + EDUCATION + SEX +
##     PAY_AMT5 + PAY_5 + PAY_AMT3 + BILL_AMT5, family = binomial(link = "logit"),
##     data = train_set)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
```

[20] It uses Akaike information criterion (AIC) .https://en.wikipedia.org/wiki/Akaike_information_criterion

```
## -2.3707  -0.6010  -0.5041  -0.3009   3.4687
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -15.98503  286.37745  -0.056 0.955487
## PAY_0-1        0.39057    0.10989   3.554 0.000379 ***
## PAY_00        -0.24892    0.10957  -2.272 0.023098 *
## PAY_01         0.77280    0.10051   7.689 1.48e-14 ***
## PAY_02         1.99325    0.11628  17.142  < 2e-16 ***
## PAY_03         1.90918    0.20210   9.447  < 2e-16 ***
## PAY_04         1.60586    0.33553   4.786 1.70e-06 ***
## PAY_05         0.26727    0.67139   0.398 0.690564
## PAY_06         1.59286    0.84034   1.895 0.058027 .
## PAY_07         0.96314    1.25174   0.769 0.441634
## PAY_08       -12.20222  371.73655  -0.033 0.973814
## PAY_4-1       -0.21537    0.13474  -1.598 0.109960
## PAY_40        -0.14822    0.15003  -0.988 0.323175
## PAY_41         0.92374 1076.95006   0.001 0.999316
## PAY_42         0.12951    0.16021   0.808 0.418855
## PAY_43         0.13295    0.30917   0.430 0.667174
## PAY_44         0.50734    0.53958   0.940 0.347087
## PAY_45        -2.37446    1.04205  -2.279 0.022689 *
## PAY_46       -29.76168  497.36889  -0.060 0.952284
## PAY_47        -7.03294 6762.09451  -0.001 0.999170
## PAY_48       -35.13222 6819.44800  -0.005 0.995890
## LIMIT_BAL     -0.25510    0.02807  -9.088  < 2e-16 ***
## PAY_6-1       -0.21039    0.10068  -2.090 0.036646 *
## PAY_60        -0.42701    0.10790  -3.957 7.58e-05 ***
## PAY_62        -0.07930    0.12554  -0.632 0.527636
## PAY_63         0.77912    0.30280   2.573 0.010081 *
## PAY_64         0.06776    0.55390   0.122 0.902637
## PAY_65        -0.17413    0.90140  -0.193 0.846818
## PAY_66         0.50944    0.95489   0.534 0.593684
## PAY_67       -11.83717  348.38903  -0.034 0.972896
## PAY_68        24.98387 6829.59209   0.004 0.997081
## PAY_AMT2      -0.27007    0.06028  -4.480 7.47e-06 ***
## BILL_AMT3      0.28795    0.05843   4.928 8.29e-07 ***
## PAY_AMT1      -0.14662    0.03934  -3.727 0.000194 ***
## PAY_3-1        0.09293    0.11794   0.788 0.430741
## PAY_30         0.15585    0.12940   1.204 0.228411
## PAY_31       -13.48725  616.91616  -0.022 0.982558
## PAY_32         0.50002    0.13127   3.809 0.000140 ***
## PAY_33         0.27342    0.23206   1.178 0.238701
## PAY_34        -0.05606    0.46813  -0.120 0.904670
## PAY_35         0.49636    0.98075   0.506 0.612785
## PAY_36        15.31057  371.73748   0.041 0.967147
## PAY_37        -0.61752    1.30540  -0.473 0.636180
## PAY_38        -5.77319 6819.44810  -0.001 0.999325
## MARRIAGE1      1.75261    0.66165   2.649 0.008077 **
## MARRIAGE2      1.60347    0.66191   2.422 0.015415 *
## MARRIAGE3      1.89062    0.68302   2.768 0.005639 **
## EDUCATION1    12.78941  286.37668   0.045 0.964379
## EDUCATION2    12.83888  286.37668   0.045 0.964241
## EDUCATION3    12.79347  286.37668   0.045 0.964368
## EDUCATION4    12.08256  286.37706   0.042 0.966346
## EDUCATION5    11.54511  286.37687   0.040 0.967842
## EDUCATION6    12.45988  286.37710   0.044 0.965296
## SEX2          -0.14270    0.04010  -3.558 0.000373 ***
## PAY_AMT5      -0.08804    0.03253  -2.706 0.006809 **
## PAY_5-1       -0.03317    0.12973  -0.256 0.798219
## PAY_50         0.06647    0.14304   0.465 0.642155
## PAY_52         0.41577    0.15993   2.600 0.009329 **
## PAY_53         0.08700    0.30026   0.290 0.772008
## PAY_54        -0.26936    0.58798  -0.458 0.646874
## PAY_55         1.20656    1.07849   1.119 0.263249
## PAY_56        26.86203  655.12680   0.041 0.967294
## PAY_57        20.58158 6762.07341   0.003 0.997571
## PAY_58        29.61922 7061.38645   0.004 0.996653
## PAY_AMT3      -0.08144    0.04312  -1.889 0.058898 .
## BILL_AMT5     -0.09897    0.05642  -1.754 0.079381 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 20288  on 19197  degrees of freedom
## Residual deviance: 16612  on 19132  degrees of freedom
## AIC: 16744
##
## Number of Fisher Scoring iterations: 13
```

From this, we understand that;

- Used variables:

  LIMIT_BAL, MARRIAGE, EDUCATION, SEX, PAY_0, PAY_3, PAY_4, PAY_5, PAY_6, PAY_AMT1, PAY_AMT2, PAY_AMT3, PAY_AMT5, BILL_AMT3, BILL_AMT5

- Important variables :

  PAY_0(whether its values are -1, 1, 2, 3, 4), PAY_3(whether its values are 2), PAY_6(whether its values are 0), LIMIT_BAL, BILL_AMT3, PAY_AMT1, PAY_AMT2, SEX(whether a client is a female or not)

Then fit the model to the validation set and make a confusion matrix.

```
##           Reference
## Prediction    0    1
##          0 3567  714
##          1  172  348
```

Statistic metrics are;

method	Accuracy	Sensitivity	Specificity	Balanced_Accuracy
glm step wise	0.8154551	0.9539984	0.3276836	0.640841

Comparing the two models;

method	Accuracy	Sensitivity	Specificity	Balanced_Accuracy
glm fewer features	0.8175380	0.9636266	0.3032015	0.6334141
glm step wise	0.8154551	0.9539984	0.3276836	0.6408410

The model with fewer features shows better accuracy than the step-wise model. But its specificity is worse then the step-wise model, in consequence produces worse balanced accuracy. We understand from these regression the selection of variables are crucial in determining the result. We look into other models.

3 Decision Tree

A decision tree is a familiar and intuitive method. For example, if you feel sick, a physician may ask you questions following a tree chart. You are asked whether it is yes or no at each node of the chart. After following the nodes, the doctor gets your health outcome.

Decision tree algorithm recursively divides the dataset into partitions with similar values for the outcome. A metric is used to choose the partitions. One of decision tree R functions "rpart" uses Gini index.

$$\text{Gini}(j) = \sum_{k=1}^{K} \hat{p}_{j,k}(1 - \hat{p}_{j,k})$$

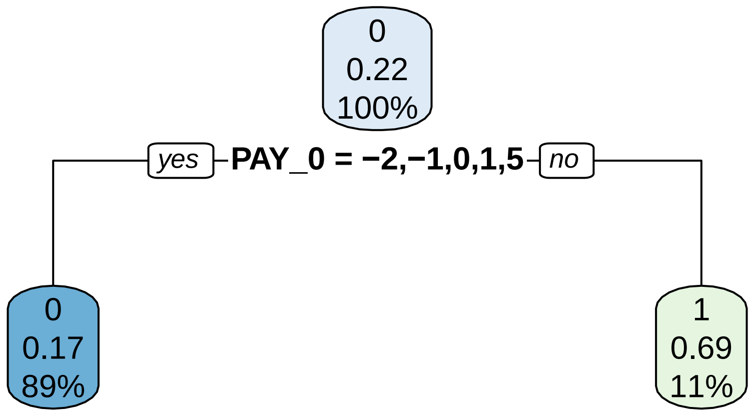
$\hat{p}_{j,k}$ as the proportion of observations in partition j that are of class k.[21] If there are lots of classes in the partition, Gini index, also called Gini impurity, increases up to 1. On the other hand, if there are few classes in the partition it decreases down to 0. If you predict perfectly, the index is 0.

We use "rpart" function to form a model, then predict the outcome.

```
## n= 19198
##
## node), split, n, loss, yval, (yprob)
##       * denotes terminal node
##
## 1) root 19198 4246 0 (0.7788311 0.2211689)
##   2) PAY_0=-2,-1,0,1,5 17180 2849 0 (0.8341676 0.1658324) *
##   3) PAY_0=2,3,4,6,7,8 2018  621 1 (0.3077304 0.6922696) *
```

We draw a decision tree based on this model.

[21] Irizarry, Rafael A, "Introduction to Data Science: Data Analysis and Prediction Algorithms with R, 31.10.4 Classification (decision) trees". *Internet archive*, https://rafalab.github.io/dsbook/examples-of-algorithms.html#classification-decision-trees



This model uses only PAY_O to make partitions. This means the credit company need to check a client's PAY_0. If the value is -2, -1, 0, 1, 5, they are likely to repay, otherwise, they are likely to default on the debt.

Then fit the model to the validation set, and show its confusion matrix.

```
##           Reference
## Prediction    0    1
##          0 3597  736
##          1  142  326
```

Statistic metrics;

method	Accuracy	Sensitivity	Specificity	Balanced_Accuracy
rpart	0.8171214	0.9620219	0.306968	0.634495

Compared with the step-wise logistic regression models, its accuracy has improved but its balanced accuracy got worse. Its balanced accuracy returned to the level of the regression with fewer variables.

method	Accuracy	Sensitivity	Specificity	Balanced_Accuracy
rpart	0.8171214	0.9620219	0.3069680	0.6344950
glm step wise	0.8154551	0.9539984	0.3276836	0.6408410
glm fewer features	0.8175380	0.9636266	0.3032015	0.6334141

We try to improve this result using other function "train" in caret package. When we use "train" , it conducts "cross validation" and finds optimal parameters in the decision tree algorithm.

One of the cross validation methods is k-fold cross validation. It splits the dataset into k "folds" randomly. For each group, it takes the group as a test dataset, and takes other groups as a training dataset. Then it fits a model on the training set and evaluates it on the test set. This procedure is repeated until every K-fold serve as the test set. Finally it summarizes the performance of the model as the average of these procedures.

"ModelLookup" function in caret package tells us what parameters in rpart we can tune.

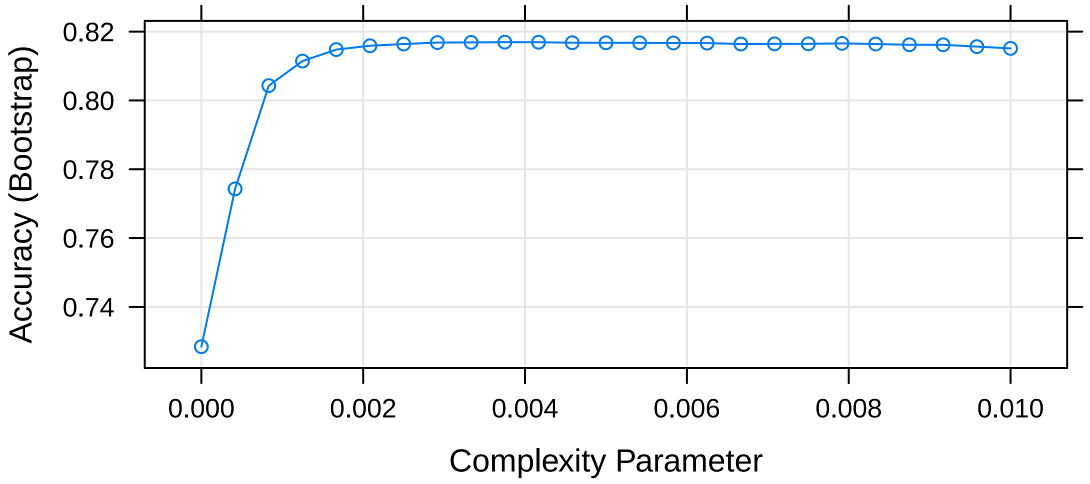
```
##   model parameter                label forReg forClass probModel
## 1 rpart        cp Complexity Parameter   TRUE     TRUE      TRUE
```

Cp stands for complexity parameter. It determines the complexity of the model. As its value gets smaller, the algorithm produces more trees. In the previous decision tree model we fit, cp is 0.01. We want to know whether cp values less than 0.01 will improve the performance.

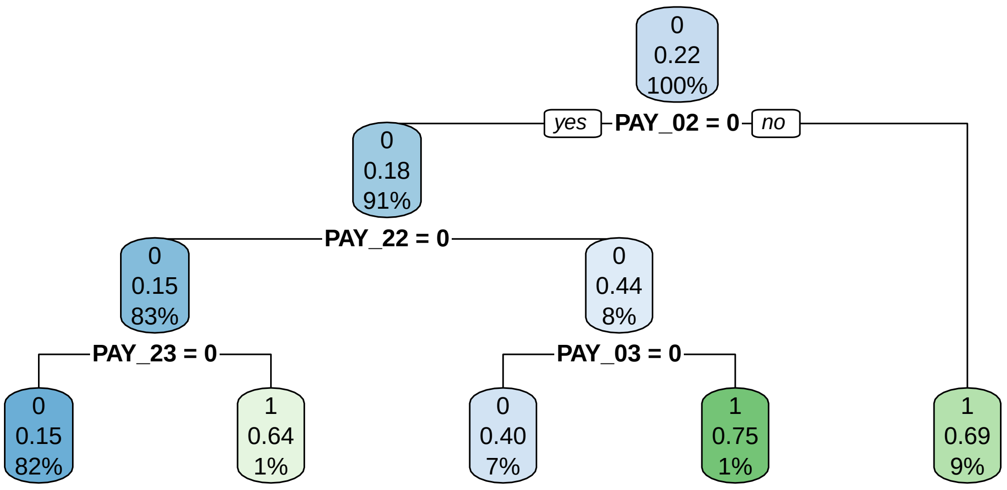
We train the dataset using "train" function. This function conducts 10 folds cross validation as a default. As we do not specify the number, it will conduct 10 folds cross validation.

```
## CART
##
## 19198 samples
##    23 predictor
##     2 classes: '0', '1'
##
## No pre-processing
## Resampling: Bootstrapped (25 reps)
## Summary of sample sizes: 19198, 19198, 19198, 19198, 19198, 19198, ...
## Resampling results across tuning parameters:
##
##   cp            Accuracy   Kappa
##   0.0000000000  0.7284228  0.2235331
##   0.0004166667  0.7742936  0.2859917
##   0.0008333333  0.8043130  0.3325194
##   0.0012500000  0.8114391  0.3445758
##   0.0016666667  0.8147804  0.3520765
##   0.0020833333  0.8158908  0.3523277
##   0.0025000000  0.8163979  0.3484179
##   0.0029166667  0.8168234  0.3458840
##   0.0033333333  0.8168740  0.3431768
##   0.0037500000  0.8169363  0.3425090
##   0.0041666667  0.8169238  0.3412075
##   0.0045833333  0.8167714  0.3405336
##   0.0050000000  0.8167598  0.3402173
##   0.0054166667  0.8167432  0.3408068
##   0.0058333333  0.8166985  0.3413150
##   0.0062500000  0.8166645  0.3414413
##   0.0066666667  0.8163935  0.3386679
##   0.0070833333  0.8164501  0.3381807
##   0.0075000000  0.8164443  0.3386962
##   0.0079166667  0.8165811  0.3373467
##   0.0083333333  0.8163949  0.3357974
##   0.0087500000  0.8161803  0.3344378
##   0.0091666667  0.8161803  0.3344378
##   0.0095833333  0.8156400  0.3303031
##   0.0100000000  0.8151237  0.3273365
##
## Accuracy was used to select the optimal model using the largest value.
## The final value used for the model was cp = 0.00375.
```

The cp which produces the highest accuracy is 0.00375. Plot cp.



Then draw a decision tree.



As mentioned before, PAY variables are factored and turned into a dummy variable.

Fit the model to the validation set and show its confusion matrix.

```
##             Reference
## Prediction    0    1
##            0 3587  730
##            1  152  332
```

Statistic metrics;

method	Accuracy	Sensitivity	Specificity	Balanced_Accuracy
rpart tuned	0.8162883	0.9593474	0.3126177	0.6359826

Comparing two decision models, the tuned model has improved in terms of specificity and balanced accuracy. But accuracy has got worse. Both performed worse than the step-wise logistic regression in terms of balanced accuracy.

method	Accuracy	Sensitivity	Specificity	Balanced_Accuracy
rpart tuned	0.8162883	0.9593474	0.3126177	0.6359826
rpart	0.8171214	0.9620219	0.3069680	0.6344950
glm step wise	0.8154551	0.9539984	0.3276836	0.6408410
glm fewer features	0.8175380	0.9636266	0.3032015	0.6334141

4 Random Forest

Decision tree algorithm is easy to understand as it follow human decision making process. However, it "can easily over-train" and "is not very flexible."[22] To improve this, we introduce random forest algorithm.

Random forest is one of the most popular machine learning algorithms. As its name implies, it makes multiple trees "**randomly** different" from a dataset, then produce a final prediction based on the average prediction of "combination of trees", namely "**forest**".[23]

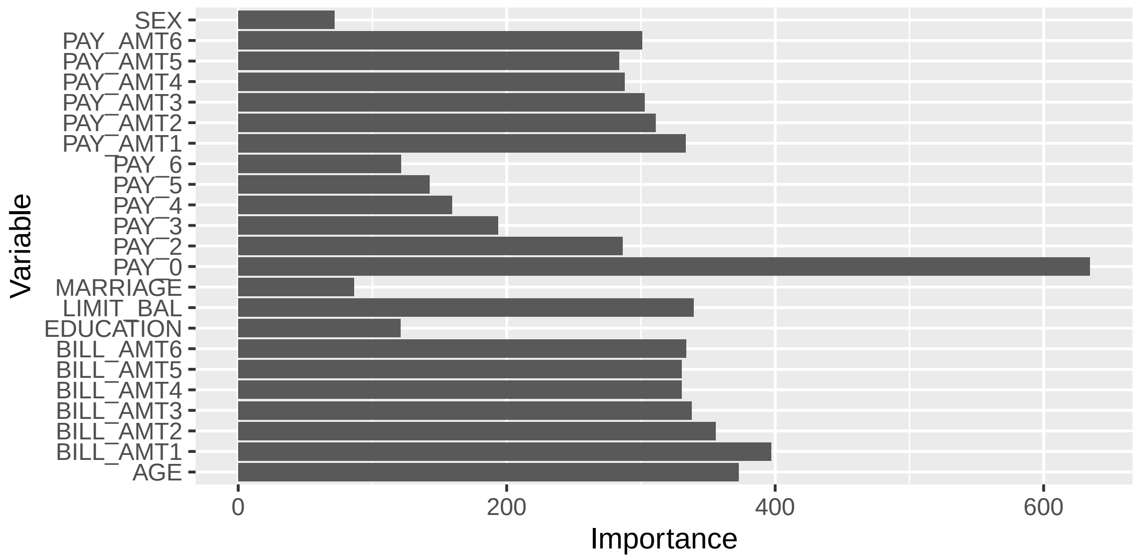
In this paper, we use "ranger" function. And show the model details;

```
## Ranger result
##
## Call:
##  ranger(formula = DEFAULT ~ ., data = train_set, importance = "impurity",      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:         impurity
## Splitrule:                        gini
## OOB prediction error:             18.30 %
```

What kind of variables are important to from this model? Plot the variables' importance;

[22] Irizarry, Rafael A, "Introduction to Data Science: Data Analysis and Prediction Algorithms with R, 31.10.4 Classification (decision) trees". *Internet archive*, https://rafalab.github.io/dsbook/examples-of-algorithms.html#classification-decision-trees

[23] Irizarry, Rafael A, "Introduction to Data Science: Data Analysis and Prediction Algorithms with R, 31.11 Random forests". *Internet archive*, https://rafalab.github.io/dsbook/examples-of-algorithms.html#random-forests



As we saw in the decision tree model, PAY_0 is considerably important compared with other features. As for other features, BILL_AMT1, PAY_AMT1, and LIMIT_BAL, and AGE are important.

Then fit the model to the validation set and show its confusion matrix.

```
##           Reference
## Prediction    0    1
##          0 3564  698
##          1  175  364
```

Statistic metrics;.

method	Accuracy	Sensitivity	Specificity	Balanced_Accuracy
random forest	0.8181629	0.953196	0.3427495	0.6479728

The results has been much improved, especially specificity, compared to other models.

method	Accuracy	Sensitivity	Specificity	Balanced_Accuracy
random forest	0.8181629	0.9531960	0.3427495	0.6479728
rpart tuned	0.8162883	0.9593474	0.3126177	0.6359826
rpart	0.8171214	0.9620219	0.3069680	0.6344950
glm step wise	0.8154551	0.9539984	0.3276836	0.6408410
glm fewer features	0.8175380	0.9636266	0.3032015	0.6334141

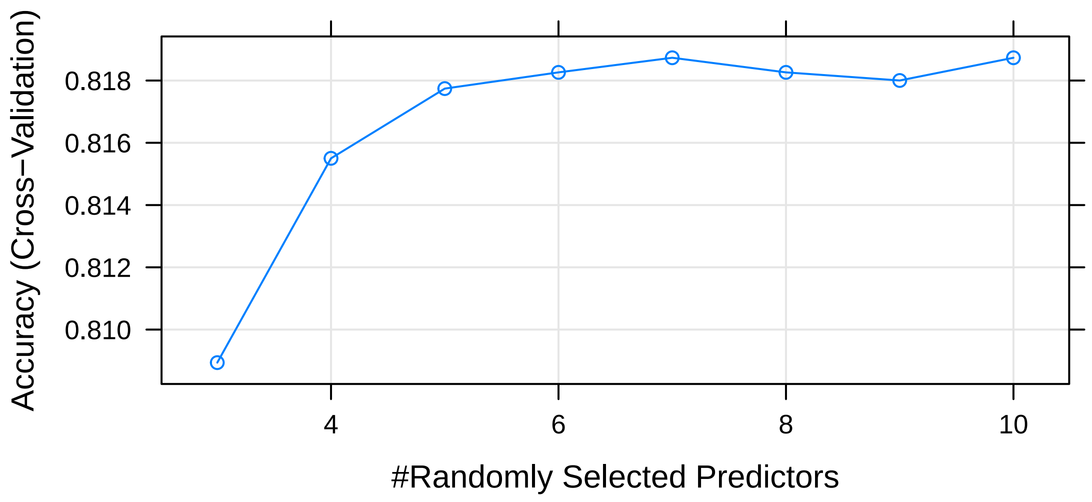
Can we improve the result further? Using “modelLookup”, we can see parameters which can be tuned.

```
##    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
```

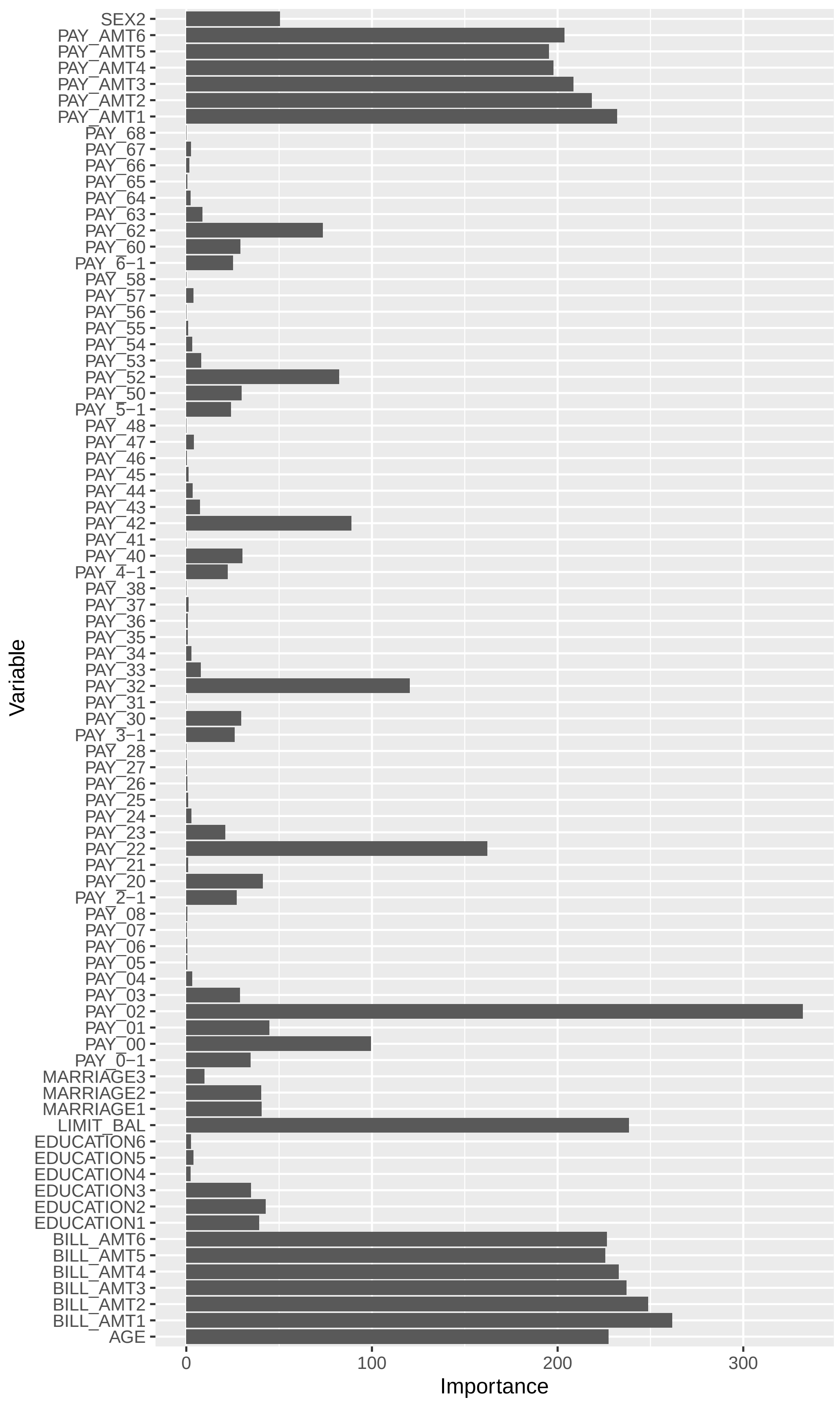
Mtry is a number of variables to possibly split at in each node. Splitrule is a splitting rule. Min.node.size is a minimal node size. In the previous random forest model, its mtry is 4, we used Gini index as a splitting rule, and minimal node size is 1. In the following model, we compare mtry ranging from 3 to 10 in terms of accuracy.

```
## Random Forest
##
## 19198 samples
##    23 predictor
##     2 classes: '0', '1'
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 17278, 17279, 17278, 17278, 17279, 17278, ...
## Resampling results across tuning parameters:
##
##   mtry  Accuracy   Kappa
##    3    0.8089386  0.2799217
##    4    0.8155016  0.3355440
##    5    0.8177415  0.3582670
##    6    0.8182623  0.3620446
##    7    0.8187315  0.3660563
##    8    0.8182623  0.3655969
##    9    0.8180020  0.3658315
##   10    0.8187312  0.3700717
##
## Tuning parameter 'splitrule' was held constant at a value of gini
##
## Tuning parameter 'min.node.size' was held constant at a value of 1
## Accuracy was used to select the optimal model using the largest value.
## The final values used for the model were mtry = 7, splitrule = gini
##  and min.node.size = 1.
```

The mtry which produces the highest accuracy is 7. Plot mtry and accuracy.



Likewise the simple random forest mode, plot the variables' importance;


SEX2
PAY_AMT6
PAY_AMT5
PAY_AMT4
PAY_AMT3
PAY_AMT2
PAY_AMT1
PAY_68
PAY_67
PAY_66
PAY_65
PAY_64
PAY_63
PAY_62
PAY_60
PAY_6−1
PAY_58
PAY_57
PAY_56
PAY_55
PAY_54
PAY_53
PAY_52
PAY_50
PAY_5−1
PAY_48
PAY_47
PAY_46
PAY_45
PAY_44
PAY_43
PAY_42
PAY_41
PAY_40
PAY_4−1
PAY_38
PAY_37
PAY_36
PAY_35
PAY_34
PAY_33
PAY_32
PAY_31
PAY_30
PAY_3−1
PAY_28
PAY_27
PAY_26
PAY_25
PAY_24
PAY_23
PAY_22
PAY_21
PAY_20
PAY_2−1
PAY_08
PAY_07
PAY_06
PAY_05
PAY_04
PAY_03
PAY_02
PAY_01
PAY_00
PAY_0−1
MARRIAGE3
MARRIAGE2
MARRIAGE1
LIMIT_BAL
EDUCATION6
EDUCATION5
EDUCATION4
EDUCATION3
EDUCATION2
EDUCATION1
BILL_AMT6
BILL_AMT5
BILL_AMT4
BILL_AMT3
BILL_AMT2
BILL_AMT1
AGE
Variable
0
100
200
300
Importance

Overall, the same trend as the previous random forest model is observed in the tuned random forest model.

Then fit the model to the validation set and show its confusion matrix;

```
##           Reference
## Prediction    0    1
##          0 3578  725
##          1  161  337
```

Statistic metrics;

method	Accuracy	Sensitivity	Specificity	Balanced_Accuracy
random forest tuned	0.8154551	0.9569404	0.3173258	0.6371331

Comparing these two random forest models, the results of the tuned model gets worse than the default model in terms of both accuracy and balanced accuracy. Over fitting seems to be occurring in the tuned model.

method	Accuracy	Sensitivity	Specificity	Balanced_Accuracy
random forest tuned	0.8154551	0.9569404	0.3173258	0.6371331
random forest	0.8181629	0.9531960	0.3427495	0.6479728

Evaluation

We look at the table in which the results of our 6 models are shown.

method	Accuracy	Sensitivity	Specificity	Balanced_Accuracy
glm step wise	0.8154551	0.9539984	0.3276836	0.6408410
glm fewer features	0.8175380	0.9636266	0.3032015	0.6334141
rpart	0.8171214	0.9620219	0.3069680	0.6344950
rpart tuned	0.8162883	0.9593474	0.3126177	0.6359826
random forest	0.8181629	0.9531960	0.3427495	0.6479728
random forest tuned	0.8154551	0.9569404	0.3173258	0.6371331

Among them, the best performance in terms of both accuracy and balanced accuracy is produced by "**random forest model**". As we mentioned before, **PAY_0** is the most important variables compared with others. Then follows **BILL_AMT1**, **PAY_AMT1**, and **LIMIT_BAL**, and **AGE.**

We fit this model to the test set and extract final results.

Final statistic metrics are as follows;

method	Accuracy	Sensitivity	Specificity	Balanced_Accuracy
final random forest	0.8226962	0.9621228	0.3320783	0.6471006

Fitting the model to the test set, we get **accuracy 0.8226962** and **balanced accuracy 0.6471006**. This results outperformed considerably our first guess (guessing all outcomes are 0), accuracy 0.7788 and balanced accuracy 0.5.

Conclusion

Summary of Our Research

In this paper, we used an open data, “Default of Credit Card Clients Dataset” and explored its information seeking for insights which contributed to the model making. We used three methods, logistic regression, decision tree, and random forest. In each method, we tried to improve the results by changing variables and tuning hyperparameters.

Random forest algorithm showed the best performance. Fitting it to the test set, we got accuracy 0.8226962 and balanced accuracy 0.6471006. But when tuned, the model showed over-fitted results.

Future Study

As we use rather simple methods in the paper, we recognized our limitations in terms of dealing with the variables. Basically, we formed logistic regression model assuming that independent variables are not highly correlated with each other. We eliminated some of the variables according to some insights from our exploration. But we need to use more rigorous methods regarding the variables. Tweaking the variables or regularization should be taken into consideration. Moreover, the variables, PAY, PAY_AMT,and BILL_AMT, are a kind of historical data over a half year. If we can look into these historical changes further, we might be able to acquire more accurate results.

From a business point of view, overall economic condition may play a very important role in predicting people’s financial behavior. A case in point, many people could not afford to pay their loan in the late 2000s due to the financial crisis at that time. On the other hand, when economy is booming, people repay the debt easily. Our dataset does not have such information, but if we want to make a more credible and practical model, we need to consider what kind of variables are offered and take into account of factors showing overall economic condition.