Credit Card Default Research

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Abstract Credit card default might very well be a life altering event. It happens when a client have become severely delinquent on his/her credit card payment. It's a serious credit card status that not only affects person's standing with that credit card issuer, but also individual's credit standing in general and his/her ability to get approved for credit cards, loans, and other credit-based services. This research will make yet another attempt to predict if a client goint to default on the next payment. Employing verious machine learning technique we also will make an attemt to estime the amount a client would be able to pay when the bill comes. The authors of this study will try to discover who is more likely to default on the payment.

Background

Overdepandance on credit card debt has been an ongoing theme in many countries around the word. For example US consumers started 2018 owing more than $1 trillion in credit card debt (Ref: Comoreanu) It is projected that by the end of 2019 US consumers will increase their collective debt by another 60 billion dollars. Unfortunately many consumers overestimate their ability to pay the debt on time, or the unforeseen circumstances and luck of savings make people default on their payments. This is the least desirable outcome for all parties. Unpaid debt leads, in most cases, to default on the whole outstanding balance causing financial loss for the credit institutions. Majority of the clients go through tremendous emotional and financial stress, risking their credibility. The financial institution make significant efforts to evaluate the prospective client ability to sustain the debt and pay in time to avoid the credit default.

Objective

This study pursues a few goals. First of all employing the client personal characteristics and the last six month payment history we would like to predict ax accurate as possible if the client makes the next month payment or defaults. We will employ a few supervised learning models to attack the problem.

Another objective is to understand which features of the data set have the most impact on the next payment success/ failure.

We are also motivated to unearth, if possible, any trend that might shed light on what make people to default on the payment. And lastly the authors of this study will try to estimate how much a client could pay when the next bill comes

Data Analysis

This research employs the data set sourced from UCI Machine Learning Repository. This real-life data comprises 30000 observations of the credit card payment history of Taiwanese consumers.

Data Dictionary

Column Name	Column Description
ID	Customer ID
LIMIT_BAL	Amount of the given credit (NT dollar): it includes both the individual consumer credit and his/her family (supplementary) credit
SEX	Gender (1 = male; 2 = female).
EDUCATION	Education (1 = graduate school; 2 = university; 3 = high school; 4 = others)
MARRIAGE	Marital status (1 = married; 2 = single; 3 = divorced; 0 - other)
AGE	Age (year)

Column Name	Column Description
PAY_1	PAY_1 - PAY_6 are payment statuses over a course of the last six months, where -2: Balance paid in full and no transactions this period (we may refer to this credit card account as having been 'inactive' this period). -1: Balance paid in full, but account has a positive balance at end of period due to recent transactions for which payment has not yet come due; 0: Customer paid the minimum due amount, but not the entire balance. I.e., the customer paid enough for their account to remain in good standing, but did revolve a balance. Positive numbers denote payment delay in months. For example 1 = payment delay for one month; 2 = payment delay for two months; . . .; 9 = payment delay for nine months and above. PAY_1 - Payment status in September
PAY_2	Payment status in August
PAY_3	Payment status in July
PAY_4	Payment status in June
PAY_5	Payment status in May
PAY_6	Payment status in April
BILL_AMT1	BILL_AMT1 - BILL_AMT6 are bill amounts (NT dollar) from April till September. BILL_AMT1: September bill
BILL_AMT2	August bill
BILL_AMT3	July bill
BILL_AMT4	June bill
BILL_AMT5	May bill
BILL_AMT6	April bill
PAY_AMT1	Amount of previous payment (NT dollar). PAY_AMT1: paid in September (August bill)
PAY_AMT2	Amount paid in August (July bill)
PAY_AMT3	Amount paid in July (June bill)
PAY_AMT4	Amount paid in June (May bill)
PAY_AMT5	Amount paid in May (April bill)
PAY_AMT6	Amount paid in April (March bill)
DEFAULT	**Target label that denotes whether the client paid the next month bill (0) or did not (1)**

Data Exploration

Feature Analytics

We start our research with the feature exploration and understanding.

Table 2: Credit Card Payment Data Summary

No	Variable	Stats / Values	Freqs (% of Valid)	Missing
1	ID [integer]	Mean (sd) : 15000.5 (8660.4) min < med < max: 1 < 15000.5 < 30000 IQR (CV) : 14999.5 (0.6)	30000 distinct values (Integer sequence)	0 (0%)
2	LIMIT_BAL [integer]	Mean (sd) : 167484.3 (129747.7) min < med < max: 10000 < 140000 < 1e+06 IQR (CV) : 190000 (0.8)	81 distinct values	0 (0%)
3	SEX [integer]	Min : 1 Mean : 1.6 Max : 2	1 : 11888 (39.6%) 2 : 18112 (60.4%)	0 (0%)
4	EDUCATION [integer]	Mean (sd) : 1.9 (0.8) min < med < max: 0 < 2 < 6 IQR (CV) : 1 (0.4)	7 distinct values	0 (0%)
5	MARRIAGE [integer]	Mean (sd) : 1.6 (0.5) min < med < max: 0 < 2 < 3 IQR (CV) : 1 (0.3)	4 distinct values	0 (0%)

No	Variable	Stats / Values	Freqs (% of Valid)	Missing
6	AGE [integer]	Mean (sd) : 35.5 (9.2) min < med < max: 21 < 34 < 79 IQR (CV) : 13 (0.3)	56 distinct values	0 (0%)
7	PAY_1 [integer]	Mean (sd) : 0 (1.1) min < med < max: -2 < 0 < 8 IQR (CV) : 1 (-67.3)	11 distinct values	0 (0%)
8	PAY_2 [integer]	Mean (sd) : -0.1 (1.2) min < med < max: -2 < 0 < 8 IQR (CV) : 1 (-8.9)	11 distinct values	0 (0%)
9	PAY_3 [integer]	Mean (sd) : -0.2 (1.2) min < med < max: -2 < 0 < 8 IQR (CV) : 1 (-7.2)	11 distinct values	0 (0%)
10	PAY_4 [integer]	Mean (sd) : -0.2 (1.2) min < med < max: -2 < 0 < 8 IQR (CV) : 1 (-5.3)	11 distinct values	0 (0%)
11	PAY_5 [integer]	Mean (sd) : -0.3 (1.1) min < med < max: -2 < 0 < 8 IQR (CV) : 1 (-4.3)	10 distinct values	0 (0%)
12	PAY_6 [integer]	Mean (sd) : -0.3 (1.1) min < med < max: -2 < 0 < 8 IQR (CV) : 1 (-4)	10 distinct values	0 (0%)
13	BILL_AMT1 [integer]	Mean (sd) : 51223.3 (73635.9) min < med < max: -165580 < 22381.5 < 964511 IQR (CV) : 63532.2 (1.4)	22723 distinct values	0 (0%)
14	BILL_AMT2 [integer]	Mean (sd) : 49179.1 (71173.8) min < med < max: -69777 < 21200 < 983931 IQR (CV) : 61021.5 (1.4)	22346 distinct values	0 (0%)
15	BILL_AMT3 [integer]	Mean (sd) : 47013.2 (69349.4) min < med < max: -157264 < 20088.5 < 1664089 IQR (CV) : 57498.5 (1.5)	22026 distinct values	0 (0%)
16	BILL_AMT4 [integer]	Mean (sd) : 43262.9 (64332.9) min < med < max: -170000 < 19052 < 891586 IQR (CV) : 52179.2 (1.5)	21548 distinct values	0 (0%)
17	BILL_AMT5 [integer]	Mean (sd) : 40311.4 (60797.2) min < med < max: -81334 < 18104.5 < 927171 IQR (CV) : 48427.5 (1.5)	21010 distinct values	0 (0%)
18	BILL_AMT6 [integer]	Mean (sd) : 38871.8 (59554.1) min < med < max: -339603 < 17071 < 961664 IQR (CV) : 47942.2 (1.5)	20604 distinct values	0 (0%)
19	PAY_AMT1 [integer]	Mean (sd) : 5663.6 (16563.3) min < med < max: 0 < 2100 < 873552 IQR (CV) : 4006 (2.9)	7943 distinct values	0 (0%)
20	PAY_AMT2 [integer]	Mean (sd) : 5921.2 (23040.9) min < med < max: 0 < 2009 < 1684259 IQR (CV) : 4167 (3.9)	7899 distinct values	0 (0%)

No	Variable	Stats / Values	Freqs (% of Valid)	Missing
21	PAY_AMT3 [integer]	Mean (sd) : 5225.7 (17607) min < med < max: 0 < 1800 < 896040 IQR (CV) : 4115 (3.4)	7518 distinct values	0 (0%)
22	PAY_AMT4 [integer]	Mean (sd) : 4826.1 (15666.2) min < med < max: 0 < 1500 < 621000 IQR (CV) : 3717.2 (3.2)	6937 distinct values	0 (0%)
23	PAY_AMT5 [integer]	Mean (sd) : 4799.4 (15278.3) min < med < max: 0 < 1500 < 426529 IQR (CV) : 3779 (3.2)	6897 distinct values	0 (0%)
24	PAY_AMT6 [integer]	Mean (sd) : 5215.5 (17777.5) min < med < max: 0 < 1500 < 528666 IQR (CV) : 3882.2 (3.4)	6939 distinct values	0 (0%)
25	DEFAULT [integer]	Min : 0 Mean : 0.2 Max : 1	0 : 23364 (77.9%) 1 : 6636 (22.1%)	0 (0%)

Table 2 describes main statistical parameters of each column. It also outputs the values of the binary features. The first thing that jumps at us is that the data set has no missing data! We shall note that our target feature is not balanced. Almost **80%** of the clients do pay on time. Secondly female customers make **60%** of the data set. **Customer ID** column, as usual, will be dropped since it presents no analytical value. Here is a look at the data sample.

ID	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_1	PAY_2	PAY_3	PAY_4	PAY_5	PAY_6	BILL_AMT1	BILL_AMT2	BILL_AMT3
1	20000	2	2	1	24	2	2	-1	-1	-2	-2	3913	3102	689
2	120000	2	2	2	26	-1	2	0	0	0	2	2682	1725	2682
3	90000	2	2	2	34	0	0	0	0	0	0	29239	14027	13559
4	50000	2	2	1	37	0	0	0	0	0	0	46990	48233	49291
5	50000	1	2	1	57	-1	0	-1	0	0	0	8617	5670	35835
6	50000	1	1	2	37	0	0	0	0	0	0	64400	57069	57608
7	500000	1	1	2	29	0	0	0	0	0	0	367965	412023	445007
8	100000	2	2	2	23	0	-1	-1	0	0	-1	11876	380	601
9	140000	2	3	1	28	0	0	2	0	0	0	11285	14096	12108
10	20000	1	3	2	35	-2	-2	-2	-2	-1	-1	0	0	0
11	200000	2	3	2	34	0	0	2	0	0	-1	11073	9787	5535
12	260000	2	1	2	51	-1	-1	-1	-1	-1	2	12261	21670	9966

BILL_AMT1	BILL_AMT2	BILL_AMT3	BILL_AMT4	BILL_AMT5	BILL_AMT6	PAY_AMT1	PAY_AMT2	PAY_AMT3	PAY_AMT4	PAY_AMT5
3913	3102	689	0	0	0	0	689	0	0	0
2682	1725	2682	3272	3455	3261	0	1000	1000	1000	0
29239	14027	13559	14331	14948	15549	1518	1500	1000	1000	1000
46990	48233	49291	28314	28959	29547	2000	2019	1200	1100	1069
8617	5670	35835	20940	19146	19131	2000	36681	10000	9000	689
64400	57069	57608	19394	19619	20024	2500	1815	657	1000	1000
367965	412023	445007	542653	483003	473944	55000	40000	38000	20239	13750
11876	380	601	221	-159	567	380	601	0	581	1687
11285	14096	12108	12211	11793	3719	3329	0	432	1000	1000
0	0	0	0	13007	13912	0	0	0	13007	1122
11073	9787	5535	2513	1828	3731	2306	12	50	300	3738
12261	21670	9966	8517	22287	13668	21818	9966	8583	22301	0

Table 3: Credit Card Payment Data Sample

Let's review demographic characteristics of the customer base, namely: *EDUCATION*, *MARITAL STATUS* and *AGE*. We immediately can observe some deficiencies in the data quality (Figure: 1). As we see the majority of the credit card holders have a university degree. There are three groups which are not supposed to be in the data set: **Unknown** - code **0**, **Unknown5** - code **5** and **Unkown6** - code **6**. We will assign these customers to the **Other** group, since the description for the aforementioned codes is not provided.

Number of single people is slightly higher than the number of the married ones.

Majority of the credit card holders are people between age of 25 and 50, which does not come as a surprise (Figure: 1)... Let's see if the *AGE* feature has outliers.

```
print(original %>% filter(AGE < 18 || AGE > 100) %>% summarise(COUNT = n()))
```

```
  COUNT
1     0
```

The *AGE* feature maintains perfect data.

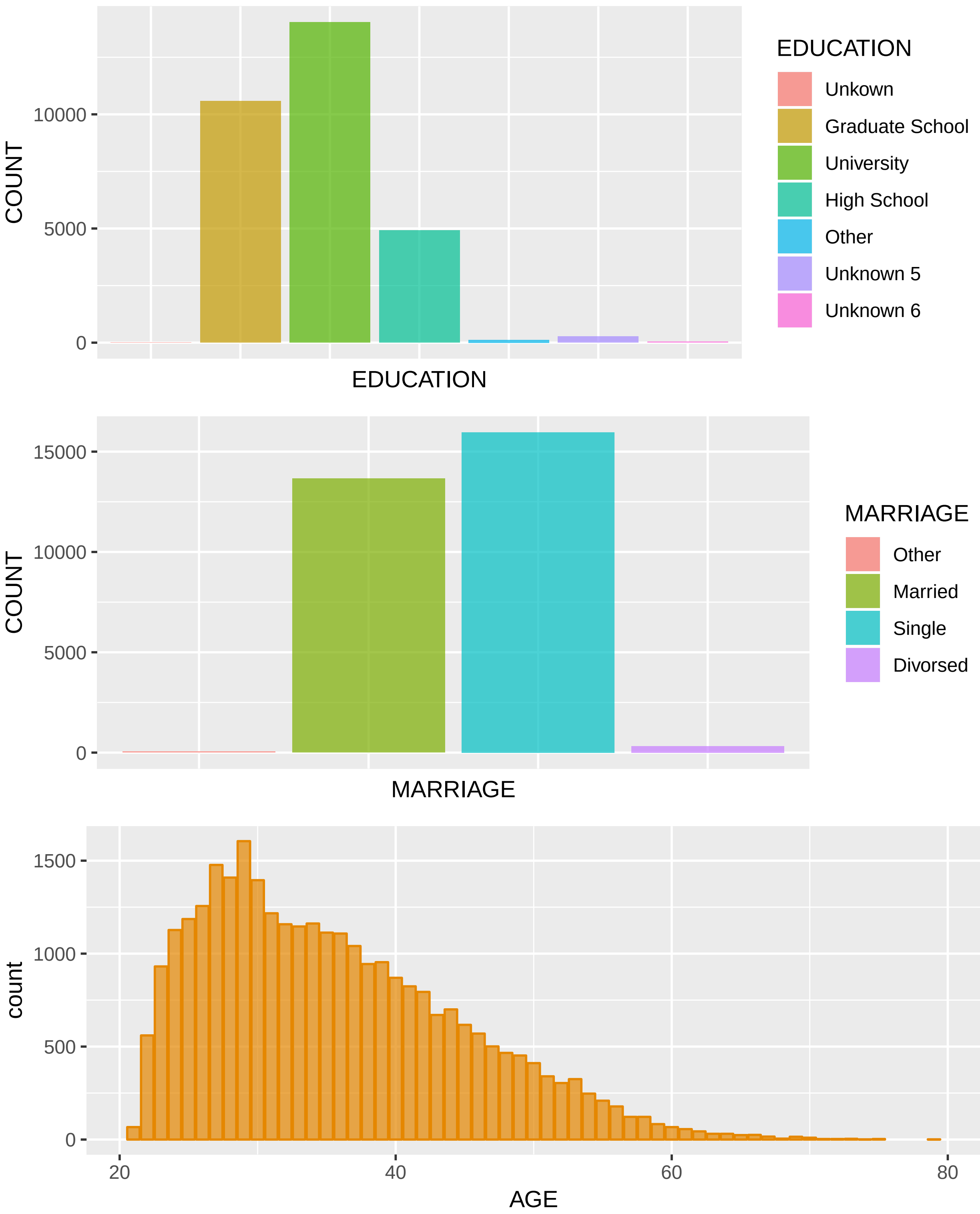


Figure 1: Customer Demographics

The next group of features we are going to explore is payment statuses. As per the data dictionary the payment statuses are supposed to have the status codes in the following range: **-2 : 9**. Let's verify the data integrity of the features.

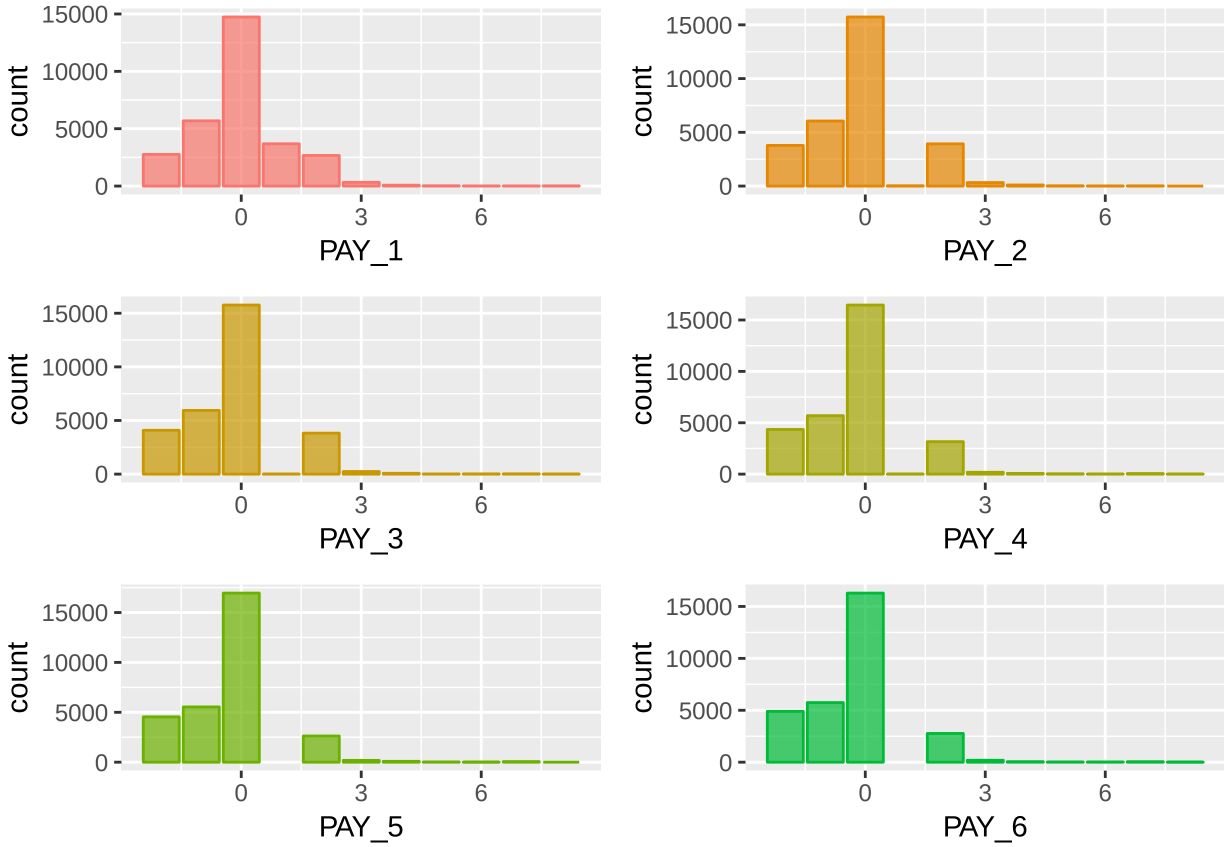


Figure 2: Customer Payment Statuses for the Last Six Months

As we have already noticed many of the credit card holders pay duly, codes: *-2 and -1* (see Figure: 2). Majority of the customers do maintain good standing. Noticeably though they **paid the required minimum or more but not the full balance** (code *0*). There is a rather significant group that falls behind with the payment by one or two months. The next group of features are the bill amounts for the last six months.

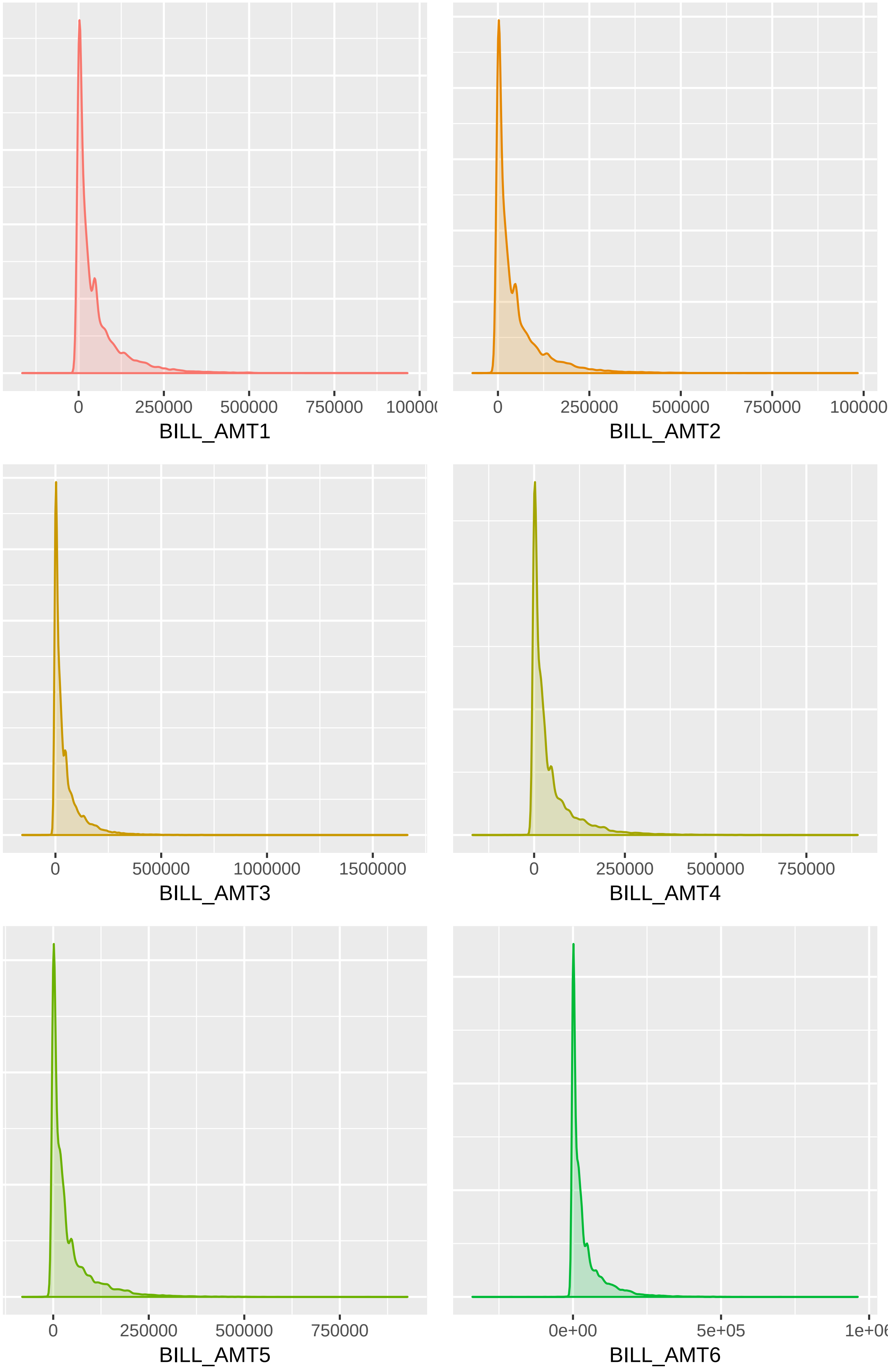


Figure 3: Customer Bill Amount Distribution for the Last Six Months

The bill payment amounts have negative values, significant amounts that reach at times **thens of thousands** of NT dollars! The negative amount on the credit card bill statements happen when a card holder overpaid his/her bill or were issued a credit after he/she already paid the bill.

Noticeably the bill amounts have very long tails. They average in tens of thousands of TN dollars, hovering around 50,000 dollars or so on average (see Table: 2). Thus it makes the negative bill amounts we previously observed more plausible.

The last group of the features is the client monthly payments. The data maintained in those columns appears to be integral (see Table: 2). Let's see how the customer payments are distributed. We employ normal and log-scaled visualization for better presentation.

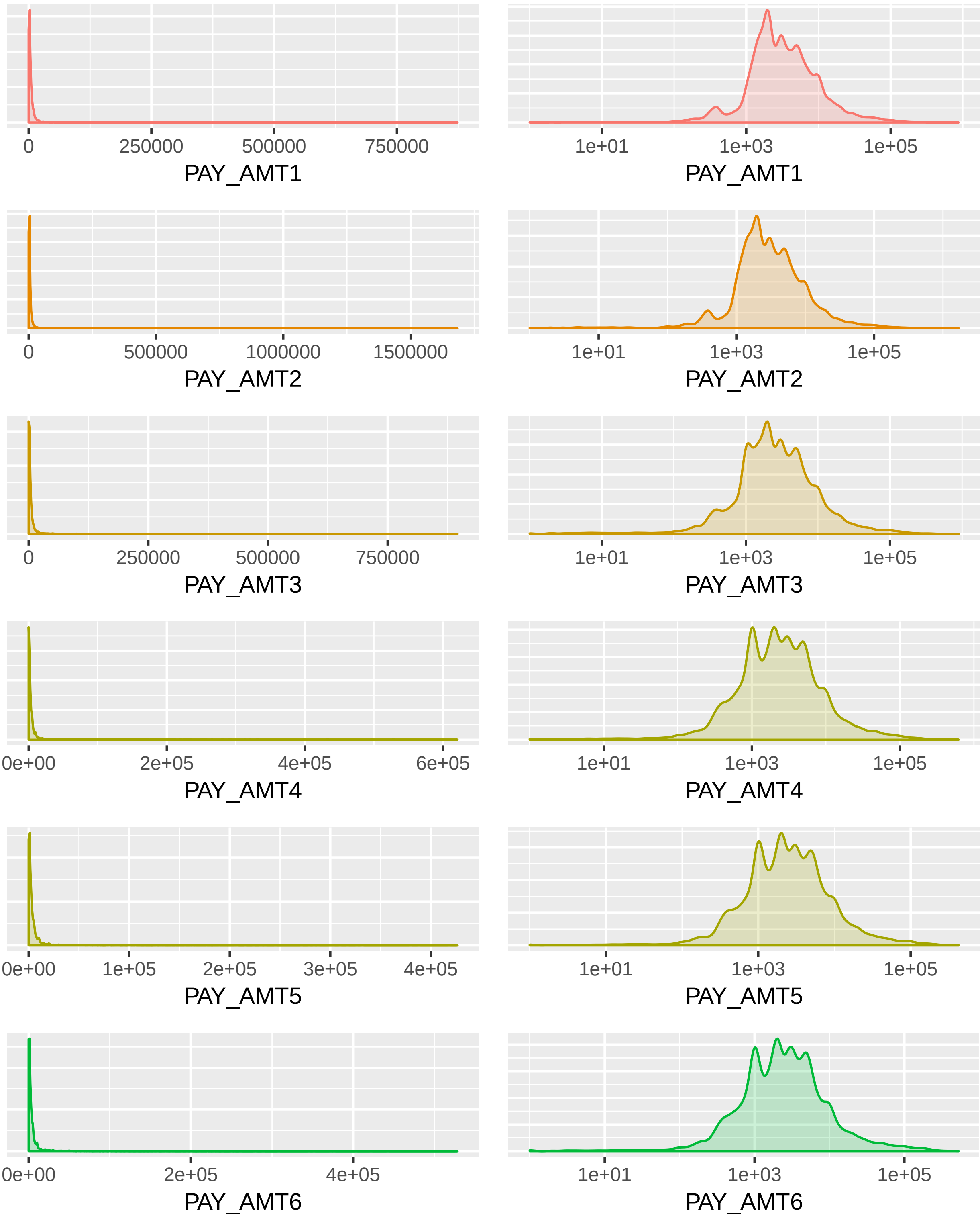


Figure 4: Customer Payment Amount Distribution for the Last Six Months

The pay amounts mirror in the distribution the bill amounts, which is expected. The charts have very long tails which imply that the amounts the card holdrs pay, very greatly. Most likely the payments that are way outside of the normal distribution curve are lump sum payments. More often than not the clients pay between 1000 and 10000 dollars monthly, which is still way below the average bill amount. This finding and the payment status statistics (see Figure: 2) make us believe that the majority of the credit card hodlders do have quite significant debt, despite the good standing. This hyposesys also explains the distribution of the payments. To keep the debt growth in check the customers pay lump sums whenever they accumulate some saving. Let's plot the delta between the bill amounts and the payment amounts to support our theory. Figure 5

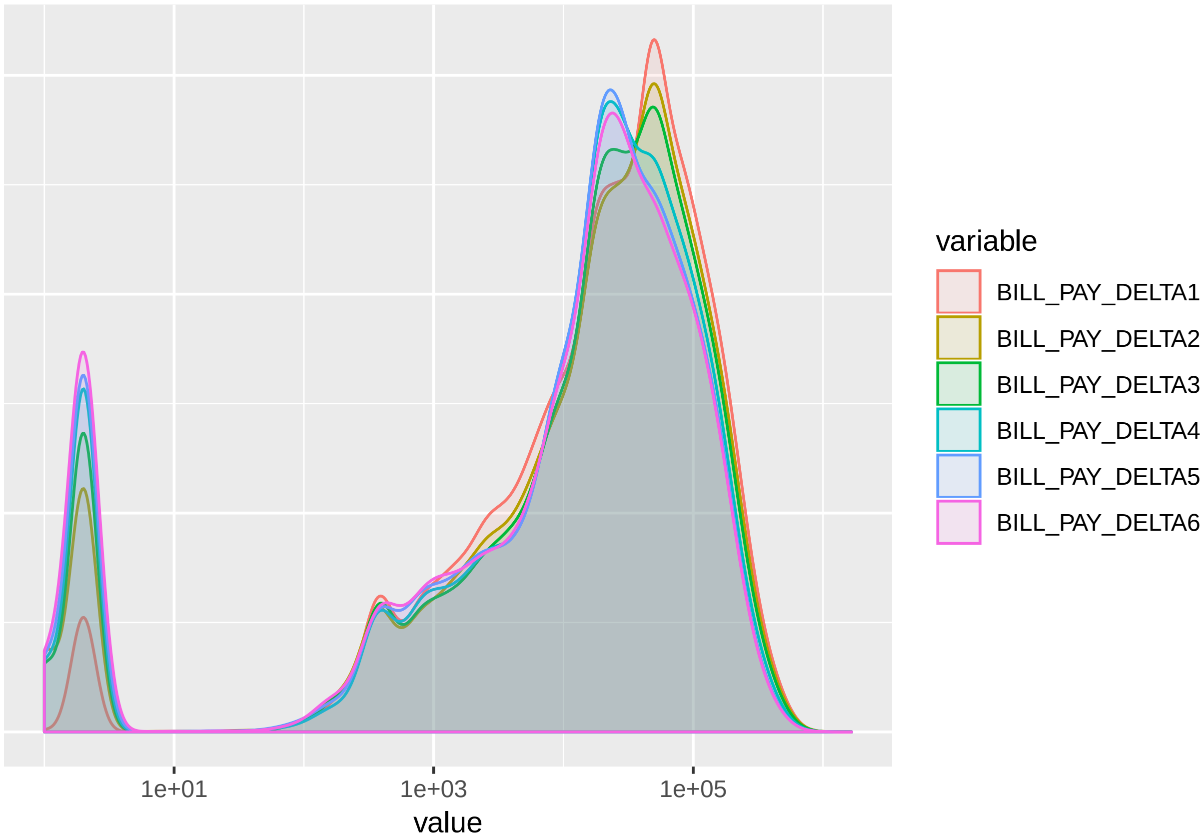


Figure 5: Customer Bill/Payment Amount Delta for Six Months

Data Transformation

Before we proceed further we are going to clean the data set as described in the previous paragraph, namely:

- We will remove *Customer ID* column
- We assign code **4 - Other** to the *EDUCATION* column values that fall out of the declared code range (1:4)

```
original$EDUCATION = with(original, ifelse(EDUCATION == 0 | EDUCATION == 5 | EDUCATION == 6 , 4, EDUCATION))
data = dplyr::select(original, -ID)
data %>% filter(EDUCATION == 0 | EDUCATION >4) %>% summarise(COUNT=n())
```

```
  COUNT
1     0
```

Data Correlation and Principal Component Analysis

In this section of our study we continue exploring the relations between various features of the data set. We put stress on finding the correlatated features, the coreelation between the features and the target label. We also are going to apply principal componenet analysis (PCA) to understand wich attributes of the data set exlain most variance of the original data. If our findings are fruitful we may design a model that requires smaller number of the input parameters without sacrificing the predictive power of the model.

Let's plot the correlation matrix first.

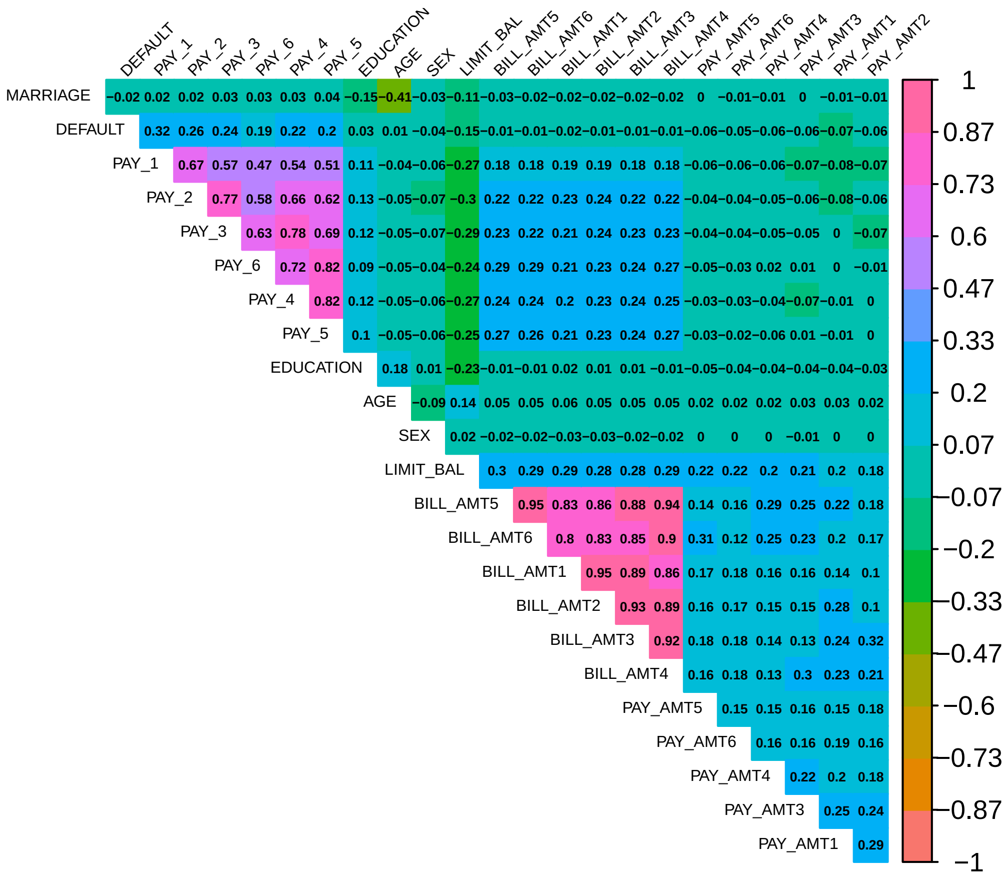


Figure 6: Data Correlation

The correlation matrix does not yield any surprises (see Figure: 6)). Bill payment amounts exhsibit higher correltation as well as the payment status gorup. This does not give us much. The target label has no correlation with any other feature. We proceed with the PCA analysis now. We scale and center the data to achieve meaningful result. We also remove the target feature from the PCA computation. We are going to retain the 15 top components.

```
       eigenvalue variance.percent cumulative.variance.percent
Dim.1  6.54287678       28.4472904                    28.44729
Dim.2  4.10332133       17.8405275                    46.28782
Dim.3  1.55513542        6.7614583                    53.04928
Dim.4  1.47549730        6.4152057                    59.46448
Dim.5  1.02455764        4.4545984                    63.91908
Dim.6  0.95545872        4.1541683                    68.07325
Dim.7  0.90407409        3.9307569                    72.00401
Dim.8  0.88793791        3.8605996                    75.86461
Dim.9  0.87030881        3.7839514                    79.64856
Dim.10 0.78268998        3.4029999                    83.05156
Dim.11 0.73278811        3.1860353                    86.23759
Dim.12 0.68195482        2.9650210                    89.20261
Dim.13 0.57091319        2.4822313                    91.68484
Dim.14 0.51977719        2.2599008                    93.94474
Dim.15 0.40359547        1.7547629                    95.69951
Dim.16 0.25988392        1.1299301                    96.82944
Dim.17 0.24930179        1.0839208                    97.91336
Dim.18 0.18869146        0.8203976                    98.73376
Dim.19 0.13178740        0.5729887                    99.30674
Dim.20 0.07015088        0.3050038                    99.61175
Dim.21 0.04078476        0.1773250                    99.78907
Dim.22 0.02529347        0.1099716                    99.89905
Dim.23 0.02321955        0.1009546                   100.00000
```

Good news! The top 10 components explain 83% of the data variance. Let's review what the top four components are made of.

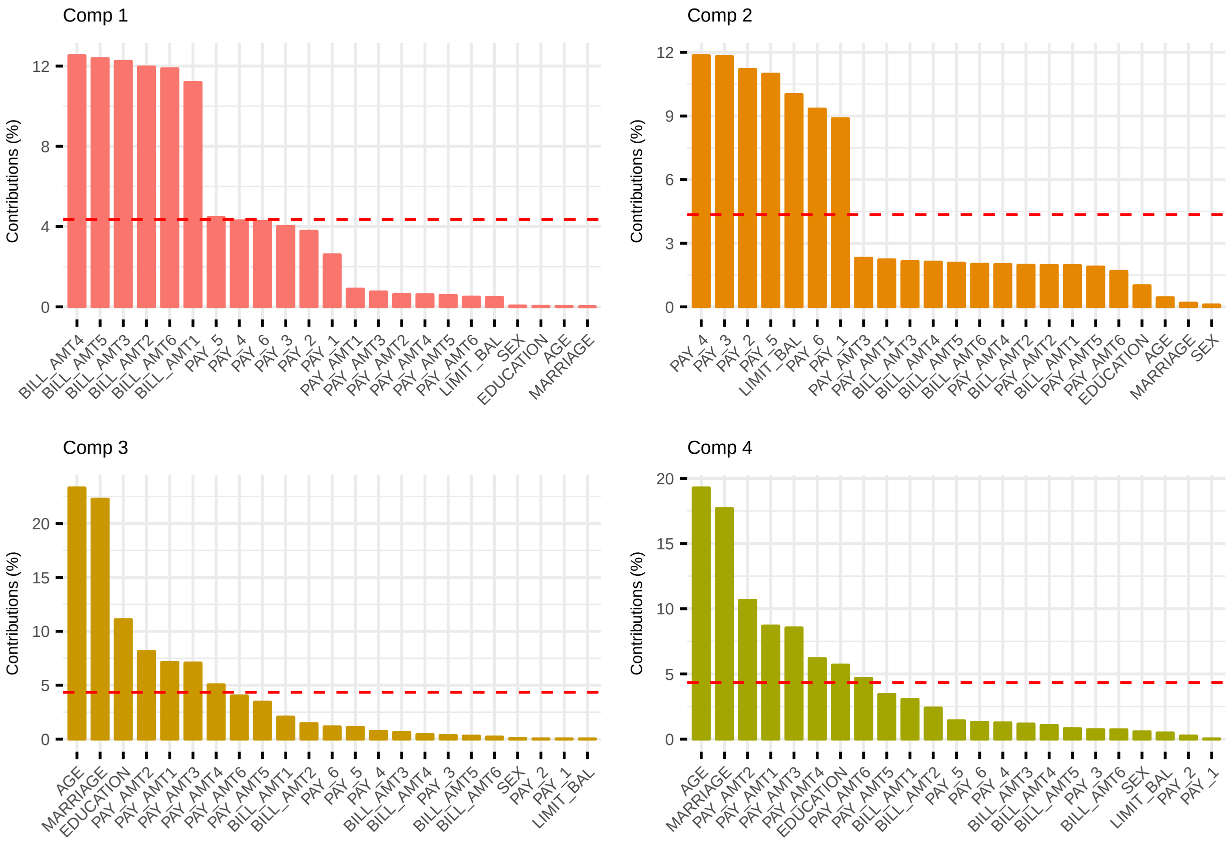
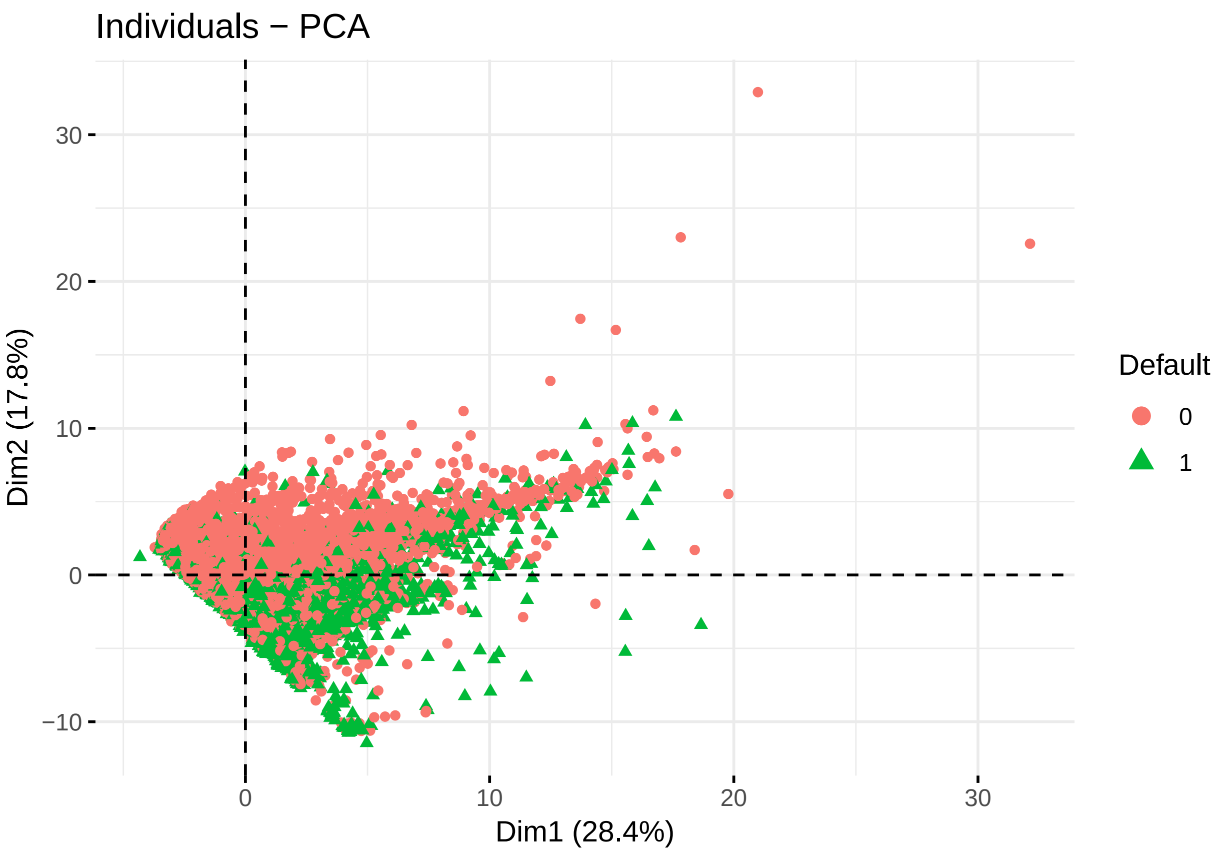


Figure 7: Feature Contribution to the Top Four Components

The red dashed line on the graph (see Figure: 7) indicates the expected average contribution. If the contribution of the variables were uniform, the expected value would about 4.3%. For a given component, a variable with a contribution larger than this cutoff could be considered as important in contributing to the component. The PCA analysis supports the correlation matrix (Figure: 6) in a sense that the bill amounts and the pay statuses are highly correlated and are subject to the dimentionality reduction due to the redundancy.

```
fviz_pca_ind(dataNOL.pca,geom.ind = "point", col.ind = as.factor(data$DEFAULT),
             palette = c(mainPalette[1],mainPalette[6]), addEllipses = F,
             legend.title = "Default")
```



Takeaways from Data Exploration Excersize

Data Preparation

Data Imputing

Modeling and Evalutation

Feature Selection

Data Upsampling

Decision Tree Model

Naive Bayes Model

Random Forest Model

Logistic Regression Model

Model Comparison

AUC - ROC perfomance

Model interpretibility

Data Preparation

Verdict Despite sensitivity to data quality Logistic Regression outperforms other models in all other major categories. This is our choice!

Model Deployment

Conclusion

Bibliography

A. Comoreanu. Credit card debt study. trends and insights. URL https://wallethub.com/edu/credit-card-debt-study/24400/. [p1]

Note from the Authors

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