# Contents

# Initial Information

The given data is the credit facility dataset that contained different features about the customers. We had to perform the different data preparation techniques to make our data ready for modelling. Once the preparation was done, the modelling was to be done using the scikit-learn linear regression model. There is a feature **B1** i.e., the customer's billable amount in $1^{st}$ month which will be predicted using the linear regression model.

# Data Dictionary

The list of features of the dataset is following:

| | |
|---|---|
| ID | Customer's Unique Identifier |
| LIMIT | Customer's Total Limit |
| BALANCE | Customer's current credit balance |
| INCOME | Customer's current income |
| GENDER | Customer's Gender |
| EDUCATION | Customer's Highest Education attained |
| MARITAL | Customer's Marital Status |
| AGE | Customer's Age in Years |
| S(n) | Customer's repayment reflected status in nth month |
| B(n) | Customer's Billable amount in nth month |
| R(n) | Customer's previous repayment amount, paid in nth month |
| RATING | Customer's rating |

# Initial Setup of Data

There is some initial setup which needed to be done for the data. This setup is almost same for all the data analysis projects.

## Including the necessary imports

```
# Importing required packages
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

# Import model functions from scikit-learn
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import normalize
from sklearn.model_selection import train_test_split
```

### Reading the Data in a DataFrame

```
# Reading the given data file in pandas dataframe
customers = pd.read_csv('../Data/customers.csv')
# Check the data
customers.head()
```

# Listing the Variables in the dataset

At first, we done listing the categorical and numerical variables in the dataset.

# Solution

There are different kinds of variables in the dataset. They can be either numeric or categorical. These two kinds are further divided into different parts. But if we talk about these types, they reflect the behavior of the variable. In our dataset, there are different categorical and the numerical variables.

From the Data Dictionary of the data provided above, we can see that there are some variables which have different classes in them. Numeric symbols are used to depict the values of those categories. So, we can call them as the categorical variables. We can display them separately. The variables which behave as the category are listed below:

```
# Defining the categorical variables
categorical_variables = ['GENDER', 'EDUCATION', 'MARITAL', 'S1', 'S2', 'S3',
'S4', 'S5', 'RATING']
# Defining the numerical variables
numeric_variables = [variable for variable in customers.columns if variable not
in categorical_variables]

print(f"Categorical Variables:\n{categorical_variables}\n")
print(f"Numeric Variables:\n{numeric_variables}")
```

### Code Result

```
Categorical Variables:
['GENDER', 'EDUCATION', 'MARITAL', 'S1', 'S2', 'S3', 'S4', 'S5', 'RATING']

Numeric Variables:
['ID', 'LIMIT', 'BALANCE', 'INCOME', 'AGE', 'B1', 'B2', 'B3', 'B4', 'B5', 'R1', 'R2', 'R3', 'R4', 'R5']
```

In this way, the categorical and the numerical variables were listed.

# Data Preprocessing Activities

Here we conducted four (4) data pre-processing tasks for the analysis of the data, explaining the results obtained.

# Solution

The data must be analyzed for checking the issues in the data. These issues are needed to be resolved before the modelling process. The four data pre-processing tasks that were performed in this solution are following:

1. Deal with Missing Values
2. Removing the Duplicated Records
3. Fixing Outliers
4. Datatype Mismatch Solution

## Preprocessing Task 1 – Deal with missing values

We must look for missing data fields or blank spaces (if any). This makes our data incomplete. Then, some necessary steps should be performed to deal with the missing values. The data was looked in a following way:

```
customers.isna().sum()
```

### Code Result

```
ID            0
LIMIT         0
BALANCE       0
INCOME        0
RATING        0
GENDER        0
EDUCATION    13
MARITAL      38
AGE           0
S1            0
S2            0
S3            0
S4            0
S5            0
B1            0
B2            0
B3            0
B4            0
B5            0
R1            0
R2            0
R3            0
R4            0
R5            0
dtype: int64
```

We saw that we had not excessively large number of samples in our data. So instead of dropping the samples with missing values, we deal those values by filling them with the values which occurred most of the times in a variable column.

```
# Filling the blank values with the most occured value in a column
customers['EDUCATION'].fillna(value = 2.0, inplace=True)
customers['MARITAL'].fillna(value = 2.0, inplace=True);

# Checking the updated length of concerned variables
len(customers.EDUCATION), len(customers.MARITAL)
```

As a result, the length of these columns was filled, and we had not any other missing value in our dataset remaining.

```
# Check whether there are still any missing values or not
customers.isna().sum()
```

## Observation

Our data frame did not contain any missing values by this time.

# Pre-processing task 2 – Removing the duplicated records

There were some of the records which had duplicated information. One of our goals while data preparation is that there should not be any duplicated data in the dataset. Appropriate code was written to check whether were any duplicated rows in a dataset. If any, where were they located?

```
# Check the duplicate record
is_duplicated = customers.duplicated(keep='first')

# Getting indices where the duplicated records are located
is_duplicated[is_duplicated == True]
```

## Code Result

```
132    True
379    True
422    True
dtype: bool
```

## Observation

We can see that records on these indices contained the repeated information. We didn't want our dataset to contain the duplicated records. So, removed the duplicate samples from the data.

```
# Keeping the first occurrence of the duplicate records to have unique
information
customers.drop_duplicates(keep='first', inplace=True)
```

Let's check are there still any duplicated records?

```
is_any_duplicate = [x for x in customers.duplicated(keep='first') if x == True]
is_any_duplicate
```

## Code Result

```
[]
```

## Observation

Our dataframe was cleaned from the duplicated records and one more preprocessing task had done by this time.

## Pre-processing task 3 – Fixing Outliers

We didn't want any unexpected values in our dataset. So, we made this sure that there were no unexpected values in any of the variables. I made a user-defined function to display all the possible values in each column.

```python
# User defined function to check the unique values in each column
def check_valid_values(df):
    for column in df.columns:
        print(f"{column} Column:")
        print(f"{df[column].unique()}\n")
# Calling the function on our own data
check_valid_values(customers)
```

### Code Result

```
ID Column:
[     1      2      3 ... 18764 18765 18766]

LIMIT Column:
[210000 260000 400000  20000 180000  30000  50000 150000  60000 500000
 200000 190000 170000 280000 290000 240000 110000 140000 250000 100000
 120000 130000  10000  70000 360000 230000 340000 220000 300000  80000
 450000  40000 310000 160000  90000 330000 390000 380000 440000 410000
 320000 420000 610000 370000 480000 350000 430000 460000 490000 470000
 270000 620000 550000 510000 560000 327680 530000 660000 750000 520000
 740000 600000 700000 800000 590000 540000 570000 630000 680000 580000
 710000 640000 760000 690000 650000 780000 730000 720000 670000  16000]

BALANCE Column:
[    0.      10928.05  65397.85  ... 33065.9     294.525  8387.575]

INCOME Column:
[235822 278481 431993 ...  30327  94607  40267]

RATING Column:
[1 0]

GENDER Column:
[1 0]

EDUCATION Column:
[1. 2. 3. 0.]

MARITAL Column:
[2. 1. 0.]

AGE Column:
[ 30  31  51  58  42  26  44  34  23  24  40  37  35  48  25  29  43  27
  38  32  54  45  49  41  47  33  50  22  53  56  28  39  63  46  52  57
  36  59  21 199  68  55  62  -1  61  64  60  80  65  66  69  67  70  79
  72  75  71  73  74]
```

```
S1 Column:
[ 0 -1  2  4  3  1  7  5  6]

S2 Column:
[ 0  2  3 -1  4  1  6  7  5  8]

S3 Column:
[ 0  2 -1  3  1  4  5  6  7]

S4 Column:
[ 0 -1  2  3  4  5  7  6]

S5 Column:
[ 0 -1  2  3  5  4  7  6]

B1 Column:
[     0  54074 343591 ...   3356  78379  48905]

B2 Column:
[     0  46407 352484 ...   2758  76304  49764]

B3 Column:
[     0  38874 338823 ...  20878  52774  36535]

B4 Column:
[     0  31324 283288 ...   5190  11855  32428]

B5 Column:
[     0  24031 185288 ...  19357  48944  15313]

R1 Column:
[     0   2000  15000 ...   2977 111784   3526]

R2 Column:
[    0  2000 14000 ...  9011  4228  8998]

R3 Column:
['0' '2000' '11500' ... '8049' '129' '1926']

R4 Column:
[    0  2000  8000 ...  8040  3319 52964]

R5 Column:
[     0  72000   7000 ... 220076  16080   7022]
```

If we look at `age` column, can age be `199` or `-1`? These values are the clear outliers of the age column which can have a great impact on our results. To make sure that how many time these values occurred, the following code was written:

```
# Check how many times the unexpected values are occuring
len(customers[customers.AGE == -1]), len(customers[customers.AGE == 199])
```

## Code Result

```
(5, 5)
```

We will drop the samples with these values because they may result in false information about the data.

```
# Dropping the examples with unexpected value
customers = customers[(customers.AGE != -1) & (customers.AGE != 199)]
```

The selected samples were removed.

1st and 3rd quartiles were calculated to find the inter quartile range which helped us in analyzing the lower and upper bound of age column to detect the `outliers`.

```
first_quartile = customers.AGE.quantile(q=0.25)
third_quartile = customers.AGE.quantile(q=0.75)

iqr = third_quartile - first_quartile
```

```
lower_bound = first_quartile - 1.5 * iqr
upper_bound = third_quartile + 1.5 * iqr

print(f'First Quartile is: {first_quartile}\n'
      f'Third Quartile is: {third_quartile}\n'
      f'Interquartile range is: {iqr}\n'
      f'Lower Bound is: {lower_bound}\n'
      f'Upper Bound is: {upper_bound}')
```

### Code Result

```
First Quartile is: 28.0
Third Quartile is: 41.0
Interquartile range is: 13.0
Lower Bound is: 8.5
Upper Bound is: 60.5
```

```
customers[(customers['AGE'] < lower_bound) | (customers['AGE'] > upper_bound)]
```

### Code Result

| | ID | LIMIT | BALANCE | INCOME | RATING | GENDER | EDUCATION | MARITAL | AGE | S1 | ... | B1 | B2 | B3 | B4 | B5 | R1 | R2 | R3 | R4 | R5 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 135 | 135 | 180000 | 235.200 | 191600 | 1 | 1 | 3.0 | 1.0 | 63 | -1 | ... | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 277 | 277 | 20000 | 288.750 | 10948 | 0 | 0 | 2.0 | 2.0 | 63 | 2 | ... | 1650 | 1650 | 1650 | 1650 | 1650 | 0 | 0 | 0 | 0 | 0 |
| 575 | 573 | 180000 | 22388.275 | 210972 | 0 | 1 | 2.0 | 1.0 | 68 | 0 | ... | 133279 | 127636 | 138164 | 142921 | 153691 | 12000 | 20000 | 10000 | 20000 | 5000 |
| 585 | 583 | 50000 | 8986.250 | 39470 | 0 | 0 | 2.0 | 1.0 | 62 | -1 | ... | 50350 | 49289 | 49058 | 47512 | 48930 | 1800 | 1800 | 1800 | 2200 | 1774 |
| 743 | 741 | 330000 | 2606.975 | 370467 | 0 | 0 | 1.0 | 1.0 | 61 | 0 | ... | 19364 | 906 | 2342 | 1702 | 882 | 906 | 2342 | 1702 | 882 | 1940 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 17932 | 17930 | 360000 | 0.000 | 393590 | 1 | 1 | 3.0 | 1.0 | 73 | 0 | ... | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 17940 | 17938 | 510000 | 32737.250 | 537796 | 0 | 1 | 3.0 | 1.0 | 61 | 0 | ... | 181733 | 192903 | 181801 | 178179 | 223100 | 17000 | 0 | 6508 | 50000 | 7000 |
| 17942 | 17940 | 360000 | 0.000 | 376811 | 0 | 1 | 1.0 | 1.0 | 64 | 0 | ... | 4900 | 0 | 0 | 5640 | 0 | 0 | 0 | 5640 | 0 | 0 |
| 17944 | 17942 | 160000 | 13860.175 | 169109 | 0 | 1 | 3.0 | 1.0 | 74 | 0 | ... | 69376 | 66192 | 16905 | 0 | 19789 | 2268 | 16905 | 0 | 19789 | 26442 |
| 17948 | 17946 | 500000 | 0.000 | 588381 | 1 | 1 | 2.0 | 1.0 | 73 | 0 | ... | 2826 | 2652 | 2835 | 8896 | 3850 | 2652 | 2835 | 8896 | 3850 | 711 |

### Observation

When we were observing the outliers initially, we found that we cannot have any sample with the wrong values of any variable. But when observing these samples, we can see that they do not contain inaccurate values. So, we will keep these values in our dataset. So, the records with the `age = -1` and `age = 199` are removed.

We had now acceptable age values.

## Pre-processing task 4 – Datatype mismatch solution

From the data dictionary, we can see that `R(n)` is the `Customer previous repayment amount` which is paid in the nth month. We know that the amount paid should be in the `numeric` format. We have amount of 5 months. But the 3rd month has the values in the string format (object data type) and not all are numbers inside the strings. Now this issue is causing the data type mismatch issue.

Can we work with the amount in that column regardless of the data type? I tried visualize the result of this variable.

```
# try to plot the values of R3 column
try:
```

```
    customers.R3.plot()
# Print the error message if it fails to plot
except TypeError:
    print("No numeric data to plot")
```

### Code Result

```
No numeric data to plot
```

Oops! We got an exception error. This was because we cannot plot the data which is of non-numeric type. We also know that all the data in the dataset should be in the numeric format before any analysis. Let's identify the data type of the R3 column.

```
customers.R3.dtype
```

### Code Result

```
dtype('O')
```

We see that R3 has the `Object` datatype. To keep record, we will keep our old unique values and the number of unique values that are present in the R3 column.

```
old_values = customers['R3'].unique()
len(customers['R3'].unique())
```

We saw what type of values are in this column apart from numbers.

```
print([x for x in customers.R3 if not str(x).isdigit()])
```

### Code Result

```
['$0', '$2,620', '$6,000', '$2,200', '$390', '$2,688', '$13,069', '$7,000', '$5,000', '$2,089']
```

### Observation

The above result showed us that there were not only the numbers inside the quotes. But we had to deal with the strings that contained the special symbols along with the numbers. Then I applied some regex for the conversion of data type.

```
# Replace the `$` and `,` from the Price.
customers['R3'] = customers['R3'].str.replace('[\$\,]', '', regex=True)
# Check whether there is still any unexpected value
print([x for x in customers.R3 if not str(x).isdigit()])
```

### Code Result

```
[]
```

```
# keep record of new values and it's length
```

```
new_values = customers['R3'].unique()
len(customers['R3'].unique())
```

Check the difference between the old and new values

```
len(old_values) - len(new_values)
```

## Code Result

```
9
```

## Observation

There were 10 values in total which had different format than the numbers. But after the conversion, we are facing the difference of 9. Why is it? Is there any new value which is added to column?

```
set(new_values) - set(old_values)
```

## Code Result

```
{'13069'}
```

Ah! now it makes sense. This value was only in the string format before but not in numeric. So after conversion, this was added as a numeric value.

Converting the Column into Numeric format.

```
customers['R3'] = customers['R3'].astype('int64')
# Checking the information about the data again
customers.info()
```

## Code Result

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 18756 entries, 0 to 18768
Data columns (total 24 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   ID         18756 non-null  int64
 1   LIMIT      18756 non-null  int64
 2   BALANCE    18756 non-null  float64
 3   INCOME     18756 non-null  int64
 4   RATING     18756 non-null  int64
 5   GENDER     18756 non-null  int64
 6   EDUCATION  18756 non-null  float64
 7   MARITAL    18756 non-null  float64
 8   AGE        18756 non-null  int64
 9   S1         18756 non-null  int64
 10  S2         18756 non-null  int64
 11  S3         18756 non-null  int64
 12  S4         18756 non-null  int64
 13  S5         18756 non-null  int64
 14  B1         18756 non-null  int64
 15  B2         18756 non-null  int64
 16  B3         18756 non-null  int64
 17  B4         18756 non-null  int64
 18  B5         18756 non-null  int64
 19  R1         18756 non-null  int64
 20  R2         18756 non-null  int64
 21  R3         18756 non-null  int64
 22  R4         18756 non-null  int64
 23  R5         18756 non-null  int64
dtypes: float64(3), int64(21)
memory usage: 3.6 MB
```

## Observation

Our column now contained only numeric values without any inconsistent format.

# Visualize data to get Insights.

Here we articulated five (5) relevant insights of the data, with supporting visualization for each insight.

# Solution

Data visualization helps us getting the useful insights from our data. We can better understand the visual results rather than struggling on the raw data. Various charts are used to help us getting familiar about the data. We performed different analysis on the data to get the proper idea about it.

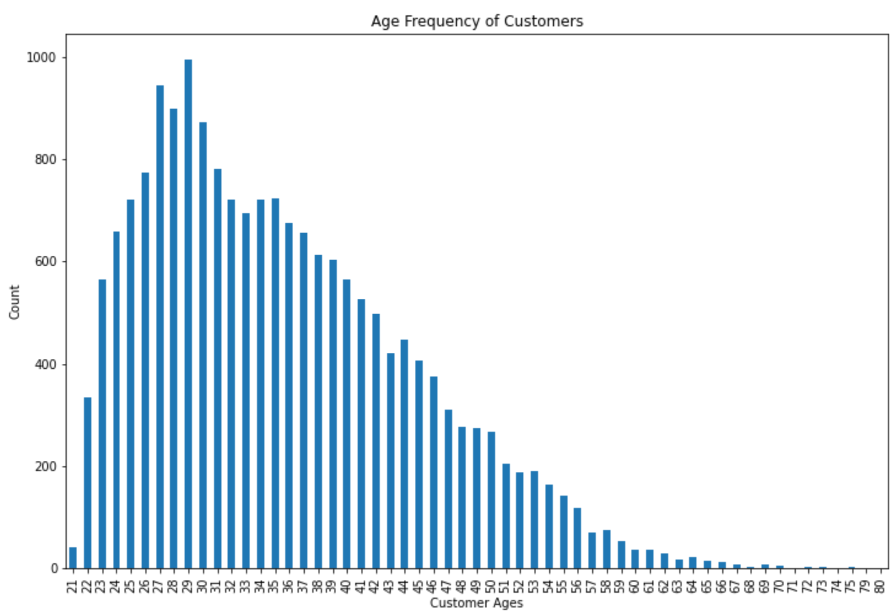
## Insight 1

```
# Check the ages of the customers
customers['AGE'].value_counts()
```

Visualizing to see the results in better way

```
customer_ages = customers['AGE'].value_counts().sort_index()
customer_ages.plot(kind='bar', figsize=(12, 8))

plt.title("Age Frequency of Customers")
plt.xlabel("Customer Ages")
plt.ylabel("Count");
```

## Code Plot



## Observation

Information about the ages of the customers can be seen. We can see that there are not more old-age customers. We have more customers in the age ranging from 25-40. The interesting fact is that more customers are females. We saw that by the following command:

```
customers['GENDER'].value_counts()
```

### Code Result

```
1    11598
0     7158
Name: GENDER, dtype: int64
```

We saw that we had a greater number of females in our dataset then the male customers. It means that the more samples were of female customers.

With the help of this information, we can decide what actions to take and what further facilities can be provided to the customers based on getting their age and gender dominancy.

## Insight 2

If there is a need to compare two columns, we can use the function `pd.crosstab(column1, column2)`. crosstab is used to compute the frequency table of factors by default.

```
pd.crosstab(customers.GENDER, customers.RATING)
```

| RATING | 0 | 1 |
|---|---|---|
| GENDER | | |
| 0 | 5420 | 1738 |
| 1 | 9222 | 2376 |

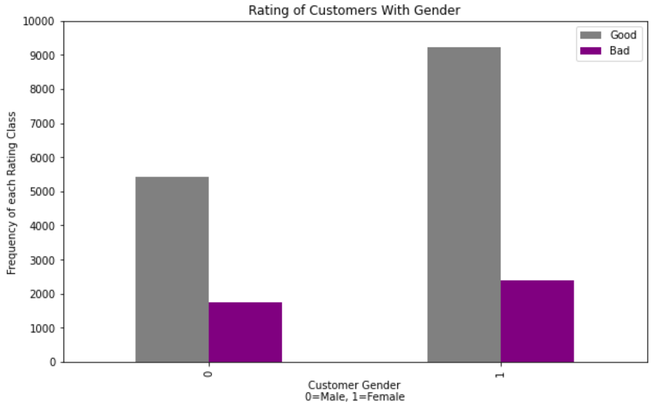
What can we infer from this?

Since there is the difference between the good and the bad rating ratio. We saw that there were more good ratings then the bad ratings. But the Males had almost 75-25 ratio of giving the positive and negative rating. Females have almost 80-20 ratio. It means there were more positive feedback than the negative ones.

To make our crosstab visual:

```
# Plotting the crosstab
pd.crosstab(customers.GENDER, customers.RATING).plot(kind="bar",
                                                      figsize=(10,6),
                                                      color=["grey", "purple"]);

plt.legend(['Good', 'Bad']);
plt.title("Rating of Customers With Gender")
plt.xlabel("Customer Gender\n0=Male, 1=Female")
plt.ylabel("Frequency of each Rating Class")
plt.yticks(np.arange(0, 11000, 1000));
```

## Code Plot



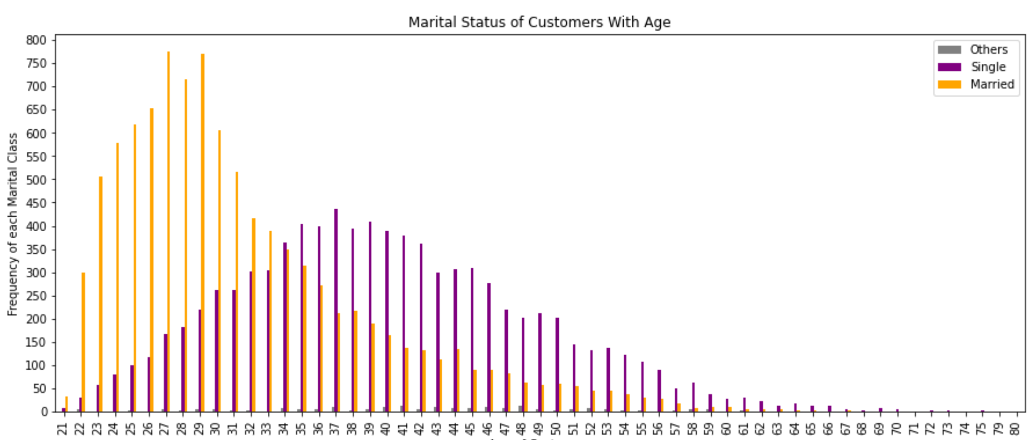

Oh, it means the customers were enjoying the facility. But the organization can also learn from this purple bar. It means that they should improve some of their terms to make this even lower. These types of visualizations would help the organization to analyze why there are negative ratings as well.

# Insight 3

Now, we can do the similar analysis by identifying the marital status of the customers. In what age the customer would be married? Are there any customers who are single even in their grown age?

```
pd.crosstab(customers.AGE, customers.MARITAL).plot(kind="bar",
                                                   figsize=(15,6),
                                                   color=["grey", "purple",
"orange"])

plt.legend(['Others', 'Single', 'Married']);
plt.title("Marital Status of Customers With Age")
plt.xlabel("Age of Customers")
plt.ylabel("Frequency of each Marital Class")
plt.yticks(np.arange(0, 850, 50));
```

## Code Plot



Now, what we infer from here?

We can clearly see that the customers up to age 33 have the dominancy of married status. But the graph has shown that the customers after age 33 are more single than the married ones. Also, there is some portion of other customers as well. But why is that?

The marital state dominancy is very much based on the age based on this graph.

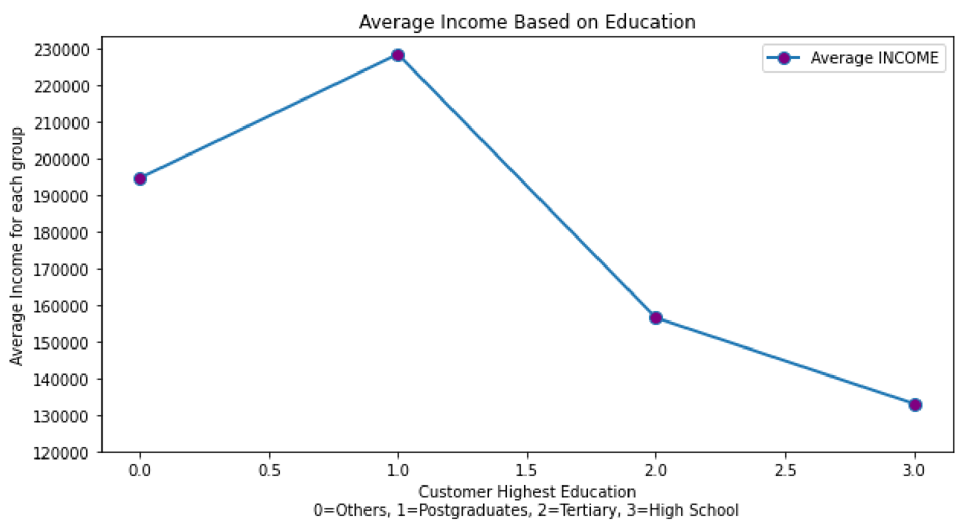
We can find and work based on the information we have from our visualization and do further processing if required.

## Insight 4

The average income of the customers based on their education was seen. Who earn more? This will also help us getting the knowledge about the income we can get based on the education level.

```
figure, axis = plt.subplots(figsize=(10, 5))

axis.plot(customers.groupby('EDUCATION')['INCOME'].mean(), marker='o', ms=8,
mfc='purple', linewidth=2, label='Average INCOME')

# Setting the title, xlabel, ylabel, values on y-axis, and legend for the plot
axis.set_title("Average Income Based on Education")
axis.set_xlabel("Customer Highest Education\n0=Others, 1=Postgraduates,
2=Tertiary, 3=High School")
axis.set_ylabel("Average Income for each group")
axis.set_yticks(np.arange(120000, 240000, 10000))
axis.legend();
```

### Code Plot




Now this clearly reminds us that we are not going to get the high incomes in High School. This information clarifies the importance of education as well.

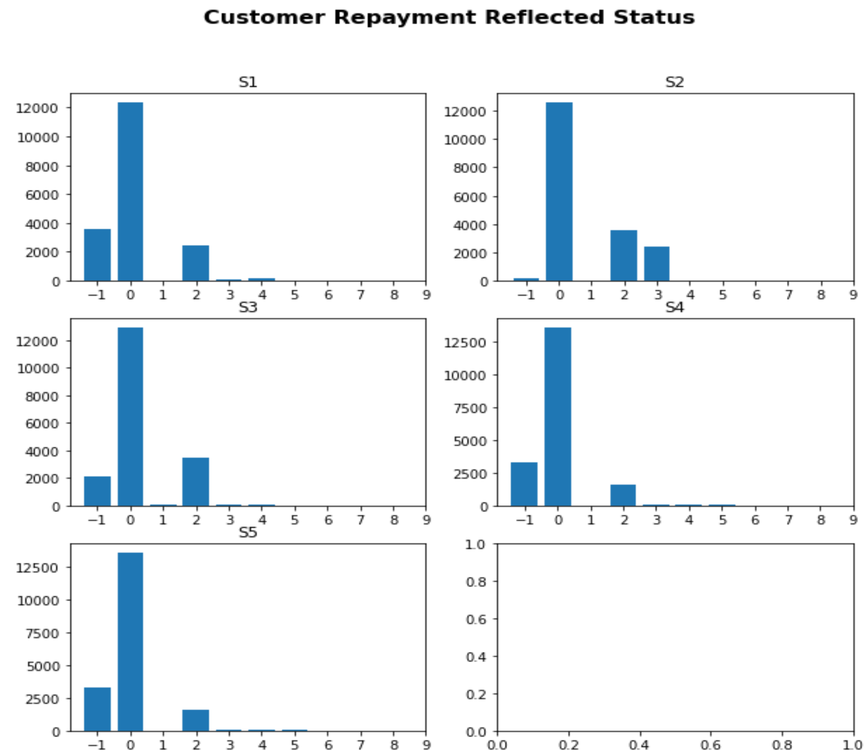
The graph told us that the highest income on average was of the customers who were `Postgraduates`. There is also `Other` as Education level of the customers. This plot clarifies that the other class lied between the Tertiary and the Postgraduates w.r.t. income.

## Insight 5

Next, the Customer repayment reflected status of each month was found.

```
# Opening the figure with 3 rows and 2 columns. Each cell contain a subplot
fig, ((ax_0, ax_1), (ax_2, ax_3), (ax_4, ax_5)) = plt.subplots(figsize=(10, 10),
nrows=3, ncols=2)

# Defining the axis to be used
axis = [ax_0, ax_1, ax_2, ax_3, ax_4]

# Using a for loop to perform the same plot on 5 different columns
for i in range(1, len(axis) + 1):
    # Making a bar plot which represent the frequency of each value
    axis[i-1].bar(customers['S'+str(i)].unique(),
customers['S'+str(i)].value_counts())

    # Adding the extra useful information in each subplot
    axis[i-1].set_title("S" + str(i))
    axis[i-1].set_xticks(np.arange(-1,10, 1))

# Setting the super title for the figure
fig.suptitle("Customer Repayment Reflected Status", fontsize=16,
fontweight='bold');
```

## Code Plot




# Observation

Each subplot is providing the information about the repayment reflected status of each month for the customers. The figure shows that all the customers have the `minimum sum payment` status in maximum. It means that most of the customers has the minimum payment due specified in the statement of Accounts that should be paid by them by the Payment due date.

In most of the months, the customers with prompt payment are also greater in number.

With the help of this graph, we can get knowledge about the customers that where they are lying.

# Correlation between independent variables

Finally, I compared all the independent variables in one hit.

Why?

Because this may give an idea of which independent variables may or may not have an impact on our label.

We did this using the function called df.corr() which created a **correlation matrix** for us, or we can say, a big table of numbers telling us how related each variable is the other.

```
correlation_matrix = customers.corr()
correlation_matrix
```

## Code Result

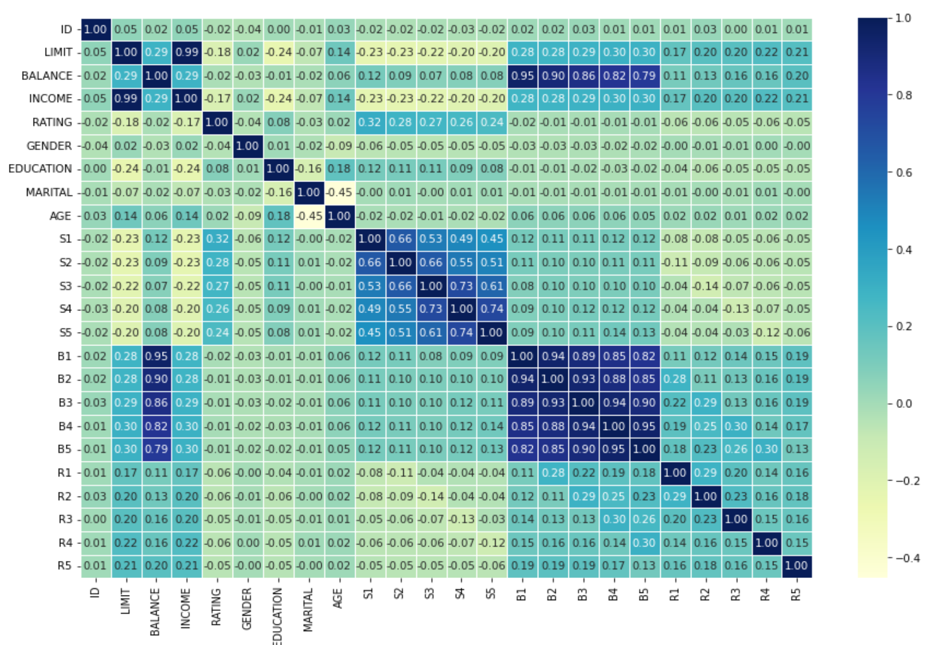
...

| | ID | LIMIT | BALANCE | INCOME | RATING | GENDER | EDUCATION | MARITAL | AGE | S1 | ... | B1 | B2 | B3 | B4 | B5 | R1 | R2 | R3 | R4 | R5 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ID | 1.000000 | 0.049053 | 0.019115 | 0.048510 | -0.024215 | -0.035078 | 0.002404 | -0.012450 | 0.029862 | -0.021156 | ... | 0.016897 | 0.018601 | 0.028841 | 0.010694 | 0.010086 | 0.007613 | 0.031518 | 0.002365 | 0.007603 | 0.011746 |
| LIMIT | 0.049053 | 1.000000 | 0.288451 | 0.993748 | -0.175631 | 0.024134 | -0.243592 | -0.071713 | 0.141387 | -0.234078 | ... | 0.279476 | 0.283542 | 0.293590 | 0.301587 | 0.297727 | 0.171917 | 0.203142 | 0.202466 | 0.222811 | 0.212134 |
| BALANCE | 0.019115 | 0.288451 | 1.000000 | 0.286335 | -0.022032 | -0.034711 | -0.010381 | -0.016615 | 0.057948 | 0.118599 | ... | 0.950885 | 0.901633 | 0.861524 | 0.823847 | 0.794155 | 0.110032 | 0.134365 | 0.162067 | 0.156033 | 0.202798 |
| INCOME | 0.048510 | 0.993748 | 0.286335 | 1.000000 | -0.173741 | 0.023471 | -0.241721 | -0.070837 | 0.140523 | -0.231589 | ... | 0.277372 | 0.281617 | 0.291626 | 0.299452 | 0.296145 | 0.169917 | 0.199446 | 0.200370 | 0.222412 | 0.210771 |
| RATING | -0.024215 | -0.175631 | -0.022032 | -0.173741 | 1.000000 | -0.044543 | 0.078907 | -0.032827 | 0.019423 | 0.323195 | ... | -0.015495 | -0.014766 | -0.012417 | -0.008279 | -0.006809 | -0.057883 | -0.059636 | -0.054990 | -0.061667 | -0.052689 |
| GENDER | -0.035078 | 0.024134 | -0.034711 | 0.023471 | -0.044543 | 1.000000 | 0.009876 | -0.024352 | -0.091329 | -0.057033 | ... | -0.033734 | -0.028966 | -0.026764 | -0.022252 | -0.020417 | -0.000971 | -0.010547 | -0.005313 | 0.004136 | -0.002080 |
| EDUCATION | 0.002404 | -0.243592 | -0.010381 | -0.241721 | 0.078907 | 0.009876 | 1.000000 | -0.163941 | 0.178314 | 0.115068 | ... | -0.011115 | -0.012805 | -0.020966 | -0.025325 | -0.019252 | -0.037796 | -0.061732 | -0.047183 | -0.054006 | -0.050473 |
| MARITAL | -0.012450 | -0.071713 | -0.016615 | -0.070837 | -0.032827 | -0.024352 | -0.163941 | 1.000000 | -0.453641 | -0.001380 | ... | -0.011988 | -0.013231 | -0.012207 | -0.012538 | -0.008205 | -0.010349 | -0.003364 | -0.012802 | 0.008214 | -0.004244 |
| AGE | 0.029862 | 0.141387 | 0.057948 | 0.140523 | 0.019423 | -0.091329 | 0.178314 | -0.453641 | 1.000000 | -0.015089 | ... | 0.057451 | 0.057922 | 0.058300 | 0.055342 | 0.050641 | 0.018293 | 0.024190 | 0.013670 | 0.018089 | 0.017475 |
| S1 | -0.021156 | -0.234078 | 0.118599 | -0.231589 | 0.323195 | -0.057033 | 0.115068 | -0.001380 | -0.015089 | 1.000000 | ... | 0.116328 | 0.111260 | 0.109025 | 0.115306 | 0.118311 | -0.075250 | -0.084888 | -0.052759 | -0.058790 | -0.048801 |
| S2 | -0.023941 | -0.229557 | 0.089513 | -0.228218 | 0.281169 | -0.052007 | 0.112082 | 0.006817 | -0.017270 | 0.664143 | ... | 0.111645 | 0.102260 | 0.102467 | 0.107768 | 0.110735 | -0.113694 | -0.089547 | -0.061251 | -0.060768 | -0.052832 |
| S3 | -0.017766 | -0.219808 | 0.069300 | -0.218470 | 0.268914 | -0.052352 | 0.108911 | -0.001000 | -0.014722 | 0.532689 | ... | 0.084994 | 0.099827 | 0.095880 | 0.101275 | 0.104121 | -0.041534 | -0.137692 | -0.073071 | -0.062283 | -0.050634 |
| S4 | -0.026344 | -0.202915 | 0.076478 | -0.200902 | 0.257891 | -0.048222 | 0.090867 | 0.005170 | -0.019065 | 0.494103 | ... | 0.090657 | 0.101831 | 0.119629 | 0.119569 | 0.119609 | -0.035460 | -0.041512 | -0.125974 | -0.068197 | -0.046712 |
| S5 | -0.021505 | -0.197564 | 0.075223 | -0.196620 | 0.243755 | -0.048291 | 0.082386 | 0.006819 | -0.023424 | 0.452293 | ... | 0.088766 | 0.096015 | 0.113171 | 0.136878 | 0.132128 | -0.041235 | -0.040474 | -0.029514 | -0.121710 | -0.056361 |
| B1 | 0.016897 | 0.279476 | 0.950885 | 0.277372 | -0.015495 | -0.033734 | -0.011115 | -0.011988 | 0.057451 | 0.116328 | ... | 1.000000 | 0.939005 | 0.894164 | 0.853458 | 0.824070 | 0.113953 | 0.124793 | 0.144877 | 0.145382 | 0.187239 |
| B2 | 0.018601 | 0.283542 | 0.901633 | 0.281617 | -0.014766 | -0.028966 | -0.012805 | -0.013231 | 0.057922 | 0.111260 | ... | 0.939005 | 1.000000 | 0.930093 | 0.882172 | 0.848708 | 0.284492 | 0.107934 | 0.134621 | 0.155812 | 0.194436 |
| B3 | 0.028841 | 0.293590 | 0.861524 | 0.291626 | -0.012417 | -0.026764 | -0.020966 | -0.012207 | 0.058300 | 0.109025 | ... | 0.894164 | 0.930093 | 1.000000 | 0.935690 | 0.896736 | 0.215477 | 0.293126 | 0.130852 | 0.156631 | 0.192041 |
| B4 | 0.010694 | 0.301587 | 0.823847 | 0.299452 | -0.008279 | -0.022252 | -0.025325 | -0.012538 | 0.055342 | 0.115306 | ... | 0.853458 | 0.882172 | 0.935690 | 1.000000 | 0.945010 | 0.193043 | 0.247081 | 0.296914 | 0.138950 | 0.174449 |
| B5 | 0.010086 | 0.297727 | 0.794155 | 0.296145 | -0.006809 | -0.020417 | -0.019252 | -0.008205 | 0.050641 | 0.118311 | ... | 0.824070 | 0.848708 | 0.896736 | 0.945010 | 1.000000 | 0.179671 | 0.225103 | 0.258631 | 0.304237 | 0.126834 |
| R1 | 0.007613 | 0.171917 | 0.110032 | 0.169917 | -0.057883 | -0.000971 | -0.037796 | -0.010349 | 0.018293 | -0.075250 | ... | 0.113953 | 0.284492 | 0.215477 | 0.193043 | 0.179671 | 1.000000 | 0.290046 | 0.198066 | 0.141830 | 0.160192 |
| R2 | 0.031518 | 0.203142 | 0.134365 | 0.199446 | -0.059636 | -0.010547 | -0.061732 | -0.003364 | 0.024190 | -0.084888 | ... | 0.124793 | 0.107934 | 0.293126 | 0.247081 | 0.225103 | 0.290046 | 1.000000 | 0.229128 | 0.163520 | 0.176206 |
| R3 | 0.002365 | 0.202466 | 0.162067 | 0.200370 | -0.054990 | -0.005313 | -0.047183 | -0.012802 | 0.013670 | -0.052759 | ... | 0.144877 | 0.134621 | 0.130852 | 0.296914 | 0.258631 | 0.198066 | 0.229128 | 1.000000 | 0.151691 | 0.163778 |
| R4 | 0.007603 | 0.222811 | 0.156033 | 0.222412 | -0.061667 | 0.004136 | -0.054006 | 0.008214 | 0.018089 | -0.058790 | ... | 0.145382 | 0.155812 | 0.156631 | 0.138950 | 0.304237 | 0.141830 | 0.163520 | 0.151691 | 1.000000 | 0.150216 |
| R5 | 0.011746 | 0.212134 | 0.202798 | 0.210771 | -0.052689 | -0.002080 | -0.050473 | -0.004244 | 0.017475 | -0.048801 | ... | 0.187239 | 0.194436 | 0.192041 | 0.174449 | 0.126834 | 0.160192 | 0.176206 | 0.163778 | 0.150216 | 1.000000 |

24 rows × 24 columns

```python
# Let's make it look a little prettier

correlation_matrix = customers.corr()
plt.figure(figsize=(16, 11))
sns.heatmap(correlation_matrix,
            annot=True,
            linewidths=0.5,
            fmt= ".2f",
            cmap="YlGnBu");
```

## Code Plot



The visual representation of heatmap is clearer. Here, a higher positive value shows a positive correlation (direct) and a higher negative value shows a negative correlation (opposite).

# Modelling

Performed linear regression modelling to predict the variable, B1, explaining the approach taken, including any further data pre-processing.

# Solution

Now, Linear regression modelling was to be done on the data to predict the B1 variable. But there was a need of some further preprocessing of data before the modelling process. The preprocessing steps are done to help the model in predicting the target variable easily.

We had some variables in the data which were needed to be transformed for the better performance of the model. **Normalization** is used when there are differently scaled features. The updated values are then scaled between the range of 0 and 1.

```
# Making a list of variables which have wide range of values
variable_list = ['LIMIT', 'BALANCE', 'INCOME', 'AGE', 'B1', 'B2', 'B3', 'B4',
'B5', 'R1', 'R2', 'R3', 'R4', 'R5']

# Extracting those variables from original dataframe to separate them
variables_to_normalize = customers[variable_list]
# Keep track of column names (can be used in future)
normalized_columns = list(variables_to_normalize.columns.values)
# Keep track of row numbers (can be used in future)
normalized_rows = list(variables_to_normalize.index)
# See the extracted columns
variables_to_normalize
```

## Code Result

| | LIMIT | BALANCE | INCOME | AGE | B1 | B2 | B3 | B4 | B5 | R1 | R2 | R3 | R4 | R5 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 210000 | 0.000 | 235822 | 30 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 260000 | 10928.050 | 278481 | 31 | 54074 | 46407 | 38874 | 31324 | 24031 | 2000 | 2000 | 2000 | 2000 | 72000 |
| 2 | 400000 | 65397.850 | 431993 | 51 | 343591 | 352484 | 338823 | 283288 | 185288 | 15000 | 14000 | 11500 | 8000 | 7000 |
| 3 | 20000 | 3695.300 | 22368 | 58 | 21470 | 200 | 0 | 28740 | 1295 | 0 | 0 | 28740 | 1565 | 0 |
| 4 | 180000 | 68.250 | 166900 | 42 | 1260 | 598 | 2056 | 4300 | 1802 | 598 | 2056 | 4300 | 1802 | 3691 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 18764 | 220000 | 33065.900 | 225862 | 39 | 192815 | 208365 | 88004 | 31237 | 15980 | 20000 | 5003 | 3047 | 5000 | 1000 |
| 18765 | 150000 | 294.525 | 149966 | 43 | 1828 | 3502 | 8979 | 5190 | 0 | 3526 | 8998 | 129 | 0 | 0 |
| 18766 | 30000 | 623.875 | 30327 | 37 | 3356 | 2758 | 20878 | 20582 | 19357 | 0 | 22000 | 4200 | 2000 | 3100 |
| 18767 | 80000 | 0.000 | 94607 | 41 | 78379 | 76304 | 52774 | 11855 | 48944 | 3409 | 1178 | 1926 | 52964 | 1804 |
| 18768 | 50000 | 8387.575 | 40267 | 46 | 48905 | 49764 | 36535 | 32428 | 15313 | 1800 | 1430 | 1000 | 1000 | 1000 |

18756 rows × 14 columns

Normalized the variables we selected from our dataset

```
# Perform normalization using sklearn.preprocessing.normalize on the selected
columns
normalized_array = normalize(variables_to_normalize)
```

```python
# The array returned after the normalization process can be stored as the dataframe with the rows and columns stored above
scaled_customers = pd.DataFrame(normalized_array, columns=normalized_columns, index = normalized_rows)
# Let's see the scaled customers
scaled_customers
```

## Code Result

| | LIMIT | BALANCE | INCOME | AGE | B1 | B2 | B3 | B4 | B5 | R1 | R2 | R3 | R4 | R5 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.665037 | 0.000000 | 0.746811 | 0.000095 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 |
| 1 | 0.652824 | 0.027439 | 0.699228 | 0.000078 | 0.135772 | 0.116522 | 0.097607 | 0.078650 | 0.060339 | 0.005022 | 0.005022 | 0.005022 | 0.005022 | 0.180782 |
| 2 | 0.440855 | 0.072077 | 0.476115 | 0.000056 | 0.378684 | 0.388485 | 0.373429 | 0.312222 | 0.204213 | 0.016532 | 0.015430 | 0.012675 | 0.008817 | 0.007715 |
| 3 | 0.363271 | 0.067120 | 0.406282 | 0.001053 | 0.389971 | 0.003633 | 0.000000 | 0.522020 | 0.023522 | 0.000000 | 0.000000 | 0.522020 | 0.028426 | 0.000000 |
| 4 | 0.732874 | 0.000278 | 0.679537 | 0.000171 | 0.005130 | 0.002435 | 0.008371 | 0.017508 | 0.007337 | 0.002435 | 0.008371 | 0.017508 | 0.007337 | 0.015028 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 18764 | 0.504003 | 0.075751 | 0.517433 | 0.000089 | 0.441724 | 0.477348 | 0.201610 | 0.071562 | 0.036609 | 0.045818 | 0.011461 | 0.006980 | 0.011455 | 0.002291 |
| 18765 | 0.705490 | 0.001385 | 0.705330 | 0.000202 | 0.008598 | 0.016471 | 0.042231 | 0.024410 | 0.000000 | 0.016584 | 0.042320 | 0.000607 | 0.000000 | 0.000000 |
| 18766 | 0.500805 | 0.010415 | 0.506263 | 0.000618 | 0.056023 | 0.046041 | 0.348527 | 0.343585 | 0.323136 | 0.000000 | 0.367257 | 0.070113 | 0.033387 | 0.051750 |
| 18767 | 0.424821 | 0.000000 | 0.502388 | 0.000218 | 0.416213 | 0.405194 | 0.280244 | 0.062953 | 0.259906 | 0.018103 | 0.006255 | 0.010228 | 0.281253 | 0.009580 |
| 18768 | 0.462466 | 0.077579 | 0.372442 | 0.000425 | 0.452338 | 0.460283 | 0.337924 | 0.299937 | 0.141635 | 0.016649 | 0.013227 | 0.009249 | 0.009249 | 0.009249 |

18756 rows × 14 columns

We kept the original (without transformation) and the normalized variables in our dataframe to predict the target variable `B1`. Concatenation of the scaled and the original customers dataset, the columns would be merged. So, we changed the name of the transformed variables to identify them.

```python
# Adding a prefix to mark the change in columns
scaled_customers = scaled_customers.add_prefix('normalized_')
# Concatenating the original and the scaled customers to predict the target variable
updated_customers = pd.concat([customers, scaled_customers], axis=1)
# Viewing the updated customers
updated_customers
```

## Code Result

| | ID | LIMIT | BALANCE | INCOME | RATING | GENDER | EDUCATION | MARITAL | AGE | S1 | ... | normalized_B1 | normalized_B2 | normalized_B3 | normalized_B4 | normalized_B5 | normalized_R1 | normalized_R2 | normalized_R3 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1 | 210000 | 0.000 | 235822 | 1 | 1 | 1.0 | 2.0 | 30 | 0 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 |
| 1 | 2 | 260000 | 10928.050 | 278481 | 0 | 0 | 2.0 | 2.0 | 31 | 0 | ... | 0.135772 | 0.116522 | 0.097607 | 0.078650 | 0.060339 | 0.005022 | 0.005022 | 0.005022 |
| 2 | 3 | 400000 | 65397.850 | 431993 | 0 | 0 | 3.0 | 1.0 | 51 | 0 | ... | 0.378684 | 0.388485 | 0.373429 | 0.312222 | 0.204213 | 0.016532 | 0.015430 | 0.012675 |
| 3 | 4 | 20000 | 3695.300 | 22368 | 0 | 0 | 2.0 | 1.0 | 58 | -1 | ... | 0.389971 | 0.003633 | 0.000000 | 0.522020 | 0.023522 | 0.000000 | 0.000000 | 0.522020 |
| 4 | 5 | 180000 | 68.250 | 166900 | 0 | 1 | 2.0 | 1.0 | 42 | 0 | ... | 0.005130 | 0.002435 | 0.008371 | 0.017508 | 0.007337 | 0.002435 | 0.008371 | 0.017508 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 18764 | 18762 | 220000 | 33065.900 | 225862 | 0 | 0 | 3.0 | 1.0 | 39 | 0 | ... | 0.441724 | 0.477348 | 0.201610 | 0.071562 | 0.036609 | 0.045818 | 0.011461 | 0.006980 |
| 18765 | 18763 | 150000 | 294.525 | 149966 | 0 | 0 | 3.0 | 2.0 | 43 | -1 | ... | 0.008598 | 0.016471 | 0.042231 | 0.024410 | 0.000000 | 0.016584 | 0.042320 | 0.000607 |
| 18766 | 18764 | 30000 | 623.875 | 30327 | 1 | 0 | 2.0 | 2.0 | 37 | 3 | ... | 0.056023 | 0.046041 | 0.348527 | 0.343585 | 0.323136 | 0.000000 | 0.367257 | 0.070113 |
| 18767 | 18765 | 80000 | 0.000 | 94607 | 1 | 0 | 3.0 | 1.0 | 41 | -1 | ... | 0.416213 | 0.405194 | 0.280244 | 0.062953 | 0.259906 | 0.018103 | 0.006255 | 0.010228 |
| 18768 | 18766 | 50000 | 8387.575 | 40267 | 1 | 0 | 2.0 | 1.0 | 46 | 0 | ... | 0.452338 | 0.460283 | 0.337924 | 0.299937 | 0.141635 | 0.016649 | 0.013227 | 0.009249 |

18756 rows × 38 columns

# Observation

Now we had a dataframe populated with the transformed and the original values of the columns. This preprocessing helped the model to predict the values in a better way then predicting the target variable with the large, ranged values.

After this, the modelling process was done on the updated data to predict the B1 variable. Appropriate code was written:

```
# Seperating the features and the label in X and y
X = updated_customers.drop('B1', axis=1)
y = updated_customers['B1']

# Using the train_test_split function to split data with specifying 30% size of test data
# Random state is specified for the reproducible results
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=6)

# Instantiating a model
model = LinearRegression()

# Training a model (on training portion)
model.fit(X_train, y_train)


# Make the predictions
y_preds = model.predict(X_test)
```

I compared the predicted and the true values of the data by comparing the output of y_preds and y_test. Since the model was built to predict a quantity, there was a slight difference between the model prediction and the actual values. But the model scored a good figure of **97.74%**.

```
print(f"The accuracy of the model is: {model.score(X_test, y_test)*100:.2f}%")
```

### Code Result

```
The accuracy of the model is: 97.74%
```

## Explaining the Approach Taken

The normalization is done on the variables with the large range of values. These type of variables causes difficulty in model to predict the target variable. When the preprocessing step is done on these variables, they are scaled into the shorter range. Hence, it becomes easy for a model to predict the target variables. So, we see the good efficiency of the model with this type of approach.

If we predict the model without scaling the large range variables, it will lag its performance. The demo was done using the code in jupyter notebook.

# State Linear Regression Equation

Stated the linear regression equation and explain key insights from the results obtained.

# Solution

In `linear regression`, we have X and Y (`dependent` and `independent` variables respectively). By using linear regression, we determine the behavior of dependent variable based on independent variable. There could be the positive, negative, or variable relationship between these variables.

Usually, there are many observations in the problem to be examined. Linear regression defines the line that best describes the observations. We can call that line, a regression line.

The `linear regression equation` is like the equation of line in the algebra. The equation of line is:

y = mx + c

Similarly, in linear regression we have equation:

$$\hat{y} = a_0 + a_1 x$$

Where, $a_0$ is the y-intercept and $a_1$ is the slope.

`y-intercept` is the point where a function line passes the y-axis. We can find it by using its formula.

We usually refer `slope` as **rise over run** formula. We can find the slope and the y-intercept to determine the dependent variable for linear regression equation.

## Key Insights from the results obtained

There are different observations that we can see from the result obtained from our modelling:

- Linear Regression model fits and evaluates the model to predict the quantity.
- There is a need of data transformation to scale the values with the large range of data.
- It is easy for the model to find patterns in the data with the small range, and normalization, and standardization helps in scaling the data in efficient way.
- Better results were obtained when there were variables in the dataset which had not large range values.
- There was 30% of the shuffled data on which the model was tested, and the linear model well suited on the current problem.
- When the linear regression model predicted the results, it predicted them by the linear approximation
- The linear regression model achieved more than 95% of accuracy while predicting the target variable.

# Conclusion

By the process of data analysis, we can analyze the data to find the key insights from it. Based on the information we take from our analysis; we can do different decision making. There are some quality issues that may have in a data because the data is gathered from different sources by using different means to collect them. Once the data is prepared, we can perform modelling on them using some machine learning algorithm by using which the machine learning model finds the pattern in data and then predict the results to generalize its knowledge. Python provides good libraries to handle the data and create and evaluate the models.