# Credit Card Default Payment in Taiwan

## Team Members


1. **Shreena Parekh - 18ucs179**
2. **Deepesh Kanodia - 18ucc002**
3. **Naman Maheshwari - 18ucc058**
4. **Manav Ladha - 18ucc160**


## About the Dataset:

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***.In recent years, the credit card issuers in Taiwan faced the cash and credit card debt crisis and the delinquency is expected to peak in the third quarter of 2006 (Chou,2006). In order to increase market share, card-issuing banks in Taiwan over-issued cash and credit cards to unqualified applicants. At the same time, most cardholders, irrespective of their repayment ability, overused credit cards for consumption and accumulated heavy credit and cash–card debts. The crisis caused the blow to consumer finance confidence and it is a big challenge for both banks and cardholders

## Data Description:

Our data set consisted of the following:

1. Data Set Characteristics: Multivariate
2. Number of Instances:30000
3. Area: Business
4. Attribute Characteristics:Integer,real
5. Number of Attributes:24
6. Associated Tasks:Classification
7. Missing Values:N/A

## Source of this dataset:

https://archive.ics.uci.edu/ml/datasets/default+of+credit+card+clients

## Link to the code :

https://drive.google.com/file/d/1wx6ZoK5NPydOQe3ALnuFTDM8LHSKUCt_/view?usp=sharing

# Dataset

We used the [Credit Card Default payment in Taiwan] to predict whether the credit card holders are defaulters or Non-defaulters. The Dataset and its attributes are described below

1. ID: ID of each client
2. LIMIT_BAL: Amount of given credit in NT dollars (includes individual and family/supplementary credit
3. SEX: Gender (1=male, 2=female)
4. EDUCATION: (1=graduate school, 2=university, 3=high school, 4=others, 5=unknown, 6=unknown)
5. MARRIAGE: Marital status (1=married, 2=single, 3=others)
6. AGE: Age in years
7. PAY_0: Repayment status in September, 2005 (-1=pay duly, 1=payment delay for one month, 2=payment delay for two months,8=payment delay for eight months, 9=payment delay for nine months and above)
8. PAY_2: Repayment status in August, 2005 (scale same as above)
9. PAY_3: Repayment status in July, 2005 (scale same as above)
10. PAY_4: Repayment status in June, 2005 (scale same as above)
11. PAY_5: Repayment status in May, 2005 (scale same as above)
12. PAY_6: Repayment status in April, 2005 (scale same as above)
13. BILL_AMT1: Amount of bill statement in September, 2005 (NT dollar)
14. BILL_AMT2: Amount of bill statement in August, 2005 (NT dollar)
15. BILL_AMT3: Amount of bill statement in July, 2005 (NT dollar)
16. BILL_AMT4: Amount of bill statement in June, 2005 (NT dollar)
17. BILL_AMT5: Amount of bill statement in May, 2005 (NT dollar)
18. BILL_AMT6: Amount of bill statement in April, 2005 (NT dollar)
19. PAY_AMT1: Amount of previous payment in September, 2005 (NT dollar)
20. PAY_AMT2: Amount of previous payment in August, 2005 (NT dollar)
21. PAY_AMT3: Amount of previous payment in July, 2005 (NT dollar)
22. PAY_AMT4: Amount of previous payment in June, 2005 (NT dollar)
23. PAY_AMT5: Amount of previous payment in May, 2005 (NT dollar)
24. PAY_AMT6: Amount of previous payment in April, 2005 (NT dollar)
25. default.payment.next.month: Default payment (1=yes, 0=no)

# 1. Importing

## 1.1 Importing Libraries for Data Structures and Visualization ¶

In [2]:
```
import pandas as pd        #for dataframe data structure
import numpy as np         # for numpy arrays and scientific computations
import matplotlib.pyplot as plt      #for data visualization
import seaborn as sns                #for visualization
import sys

%matplotlib inline
```

## 1.2 Importing Libraries for Data Preprocessing

In [3]:
```
#for Data Preprocessing
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
from sklearn import preprocessing
from sklearn.model_selection import cross_val_score
from sklearn import metrics
from sklearn.model_selection import GridSearchCV , cross_val_score
from sklearn.metrics import  accuracy_score, f1_score, precision_score, recall_score, roc_auc_score,roc_curve,auc
```

## 1.3 Importing Libraries for Classifiers

In [4]:
```
#for Classifiers
from sklearn.linear_model import LogisticRegression    #for LogisticRegression Model
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier       #for Random Forest Model
from sklearn.naive_bayes import BernoulliNB
```

## 1.4 Importing Dataset

In [5]:
```
card_df = pd.read_excel('default of credit card clients.xls',skiprows=[0],index_col="ID")
```

In [5]:
```
card_df.head(10).transpose()
```

Out[5]:

| ID | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| LIMIT_BAL | 20000 | 120000 | 90000 | 50000 | 50000 | 50000 | 500000 | 100000 | 140000 | 20000 |
| SEX | 2 | 2 | 2 | 2 | 1 | 1 | 1 | 2 | 2 | 1 |
| EDUCATION | 2 | 2 | 2 | 2 | 2 | 1 | 1 | 2 | 3 | 3 |
| MARRIAGE | 1 | 2 | 2 | 1 | 1 | 2 | 2 | 2 | 1 | 2 |
| AGE | 24 | 26 | 34 | 37 | 57 | 37 | 29 | 23 | 28 | 35 |
| PAY_0 | 2 | -1 | 0 | 0 | -1 | 0 | 0 | 0 | 0 | -2 |
| PAY_2 | 2 | 2 | 0 | 0 | 0 | 0 | 0 | -1 | 0 | -2 |
| PAY_3 | -1 | 0 | 0 | 0 | -1 | 0 | 0 | -1 | 2 | -2 |
| PAY_4 | -1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | -2 |
| PAY_5 | -2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | -1 |
| PAY_6 | -2 | 2 | 0 | 0 | 0 | 0 | 0 | -1 | 0 | -1 |
| BILL_AMT1 | 3913 | 2682 | 29239 | 46990 | 8617 | 64400 | 367965 | 11876 | 11285 | 0 |

## 2.1 Dataset Info

```
In [6]: card_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 30000 entries, 1 to 30000
Data columns (total 24 columns):
LIMIT_BAL                     30000 non-null int64
SEX                           30000 non-null int64
EDUCATION                     30000 non-null int64
MARRIAGE                      30000 non-null int64
AGE                           30000 non-null int64
PAY_0                         30000 non-null int64
PAY_2                         30000 non-null int64
PAY_3                         30000 non-null int64
PAY_4                         30000 non-null int64
PAY_5                         30000 non-null int64
PAY_6                         30000 non-null int64
BILL_AMT1                     30000 non-null int64
BILL_AMT2                     30000 non-null int64
BILL_AMT3                     30000 non-null int64
BILL_AMT4                     30000 non-null int64
BILL_AMT5                     30000 non-null int64
BILL_AMT6                     30000 non-null int64
PAY_AMT1                      30000 non-null int64
PAY_AMT2                      30000 non-null int64
PAY_AMT3                      30000 non-null int64
PAY_AMT4                      30000 non-null int64
PAY_AMT5                      30000 non-null int64
PAY_AMT6                      30000 non-null int64
default payment next month    30000 non-null int64
dtypes: int64(24)
memory usage: 5.7 MB
```

## 2.2 Check for Missing Values

```
In [7]: card_df.isnull().sum()                # no NA values present in the dataset
```

```
Out[7]: LIMIT_BAL                     0
SEX                           0
EDUCATION                     0
MARRIAGE                      0
AGE                           0
PAY_0                         0
PAY_2                         0
PAY_3                         0
PAY_4                         0
PAY_5                         0
PAY_6                         0
BILL_AMT1                     0
BILL_AMT2                     0
BILL_AMT3                     0
BILL_AMT4                     0
BILL_AMT5                     0
BILL_AMT6                     0
PAY_AMT1                      0
PAY_AMT2                      0
PAY_AMT3                      0
PAY_AMT4                      0
PAY_AMT5                      0
PAY_AMT6                      0
default payment next month    0
dtype: int64
```

No missing data, but a few anomalous things:

- EDUCATION has category 5 and 6 that are unlabelled, moreover the category 0 is undocumented.
- MARRIAGE has a label 0 that is undocumented

# 2.3 Descriptive Analysis

Descriptive statistics is the type of statistics which is used to summarize and describe the dataset. It is used to describe the characteristics of data.It is displayed through tables, charts, frequency distributions and is generally reported as a measure of central tendency.

- **BILL_AMT 1 TO 6**

```
In [10]: # Bill Statement description
         card_df[['BILL_AMT1', 'BILL_AMT2', 'BILL_AMT3', 'BILL_AMT4', 'BILL_AMT5', 'BILL_AMT6']].describe()
```

Out[10]:

| | BILL_AMT1 | BILL_AMT2 | BILL_AMT3 | BILL_AMT4 | BILL_AMT5 | BILL_AMT6 |
|---|---|---|---|---|---|---|
| count | 30000.000000 | 30000.000000 | 3.000000e+04 | 30000.000000 | 30000.000000 | 30000.000000 |
| mean | 51223.330900 | 49179.075167 | 4.701315e+04 | 43262.948967 | 40311.400967 | 38871.760400 |
| std | 73635.860576 | 71173.768783 | 6.934939e+04 | 64332.856134 | 60797.155770 | 59554.107537 |
| min | -165580.000000 | -69777.000000 | -1.572640e+05 | -170000.000000 | -81334.000000 | -339603.000000 |
| 25% | 3558.750000 | 2984.750000 | 2.666250e+03 | 2326.750000 | 1763.000000 | 1256.000000 |
| 50% | 22381.500000 | 21200.000000 | 2.008850e+04 | 19052.000000 | 18104.500000 | 17071.000000 |
| 75% | 67091.000000 | 64006.250000 | 6.016475e+04 | 54506.000000 | 50190.500000 | 49198.250000 |
| max | 964511.000000 | 983931.000000 | 1.664089e+06 | 891586.000000 | 927171.000000 | 961664.000000 |

The count denotes the number of observations. The mean and standard deviation are the statistical features of the data. Min and Max denote the range of the attribute value. 25% , 50% and 75% denote the values of First, Second and Third Quartile respectively.

- **PAY_AMT 1 TO 6**

```
In [11]: #Previous Payment Description
         card_df[['PAY_AMT1', 'PAY_AMT2', 'PAY_AMT3', 'PAY_AMT4', 'PAY_AMT5', 'PAY_AMT6']].describe()
```

Out[11]:

| | PAY_AMT1 | PAY_AMT2 | PAY_AMT3 | PAY_AMT4 | PAY_AMT5 | PAY_AMT6 |
|---|---|---|---|---|---|---|
| count | 30000.000000 | 3.000000e+04 | 30000.00000 | 30000.000000 | 30000.000000 | 30000.000000 |
| mean | 5663.580500 | 5.921163e+03 | 5225.68150 | 4826.076867 | 4799.387633 | 5215.502567 |
| std | 16563.280354 | 2.304087e+04 | 17606.96147 | 15666.159744 | 15278.305679 | 17777.465775 |
| min | 0.000000 | 0.000000e+00 | 0.00000 | 0.000000 | 0.000000 | 0.000000 |
| 25% | 1000.000000 | 8.330000e+02 | 390.00000 | 296.000000 | 252.500000 | 117.750000 |
| 50% | 2100.000000 | 2.009000e+03 | 1800.00000 | 1500.000000 | 1500.000000 | 1500.000000 |
| 75% | 5006.000000 | 5.000000e+03 | 4505.00000 | 4013.250000 | 4031.500000 | 4000.000000 |
| max | 873552.000000 | 1.684259e+06 | 896040.00000 | 621000.000000 | 426529.000000 | 528666.000000 |

- **LIMIT_BAL**

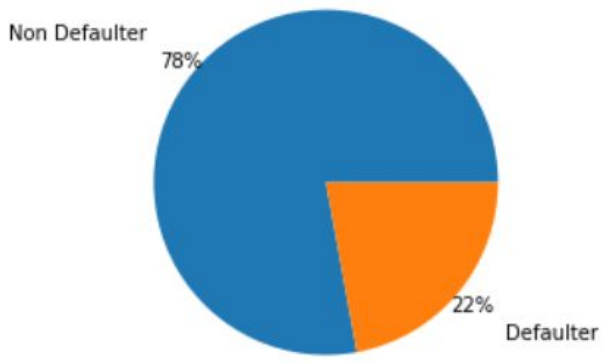
```
In [12]: card_df.LIMIT_BAL.describe()

Out[12]: count      30000.000000
         mean      167484.322667
         std       129747.661567
         min        10000.000000
         25%        50000.000000
         50%       140000.000000
         75%       240000.000000
         max      1000000.000000
         Name: LIMIT_BAL, dtype: float64
```

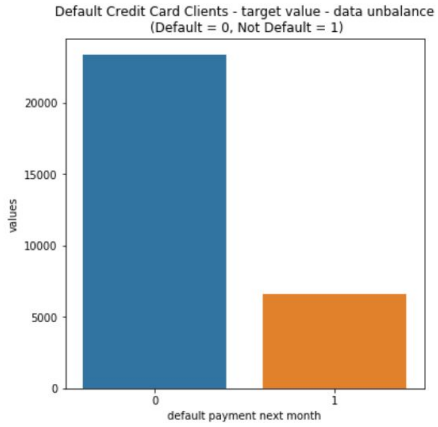
The average Limit Balance is around 1,67,484. The standard deviation is 129747.66. Similar are the definitions of other parameters described above.

## 2.4 Check Data Unbalancing

Here we try to find the ratio of each of the values in the target value. Our target column in the dataset i.e. default has only 2 values [ 0 and 1]

```
In [6]: def_type = card_df['default payment next month'].value_counts()
        def_label =['Non Defaulter','Defaulter']
        plt.pie(def_type,labels=def_label,autopct='%1.0f%%', pctdistance=1.1, labeldistance=1.35)
        plt.show()
```




```
In [13]: temp = card_df['default payment next month'].value_counts()
         df = pd.DataFrame({'default payment next month': temp.index,'values': temp.values})
         plt.figure(figsize = (6,6))
         plt.title('Default Credit Card Clients - target value - data unbalance\n (Default = 0, Not Default = 1)')
         sns.set_color_codes("pastel")
         sns.barplot(x = 'default payment next month', y="values", data=df)
         locs, labels = plt.xticks()
         plt.show()
```

A number of 6,636 out of 30,000 (or 22%) of clients will default next month. The data has not a large unbalance with respect to the target value (default.payment.next.month).

## 2.5 Renaming Columns : Output Column - Default

```
In [14]: card_df = card_df.rename(columns={'default payment next month': 'default'})
```

As the name output column is very large and it will be difficult to analyze with it. We rename it as default

```
In [15]: card_df
```

Out[15]:

| ID | LIMIT_BAL | SEX | EDUCATION | MARRIAGE | AGE | PAY_0 | PAY_2 | PAY_3 | PAY_4 | PAY_5 | ... | BILL_AMT4 | BILL_AMT5 | BILL_AMT6 | PAY_AMT1 | PAY_ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 20000 | 2 | 2 | 1 | 24 | 2 | 2 | -1 | -1 | -2 | ... | 0 | 0 | 0 | 0 | |
| 2 | 120000 | 2 | 2 | 2 | 26 | -1 | 2 | 0 | 0 | 0 | ... | 3272 | 3455 | 3261 | 0 | |
| 3 | 90000 | 2 | 2 | 2 | 34 | 0 | 0 | 0 | 0 | 0 | ... | 14331 | 14948 | 15549 | 1518 | |
| 4 | 50000 | 2 | 2 | 1 | 37 | 0 | 0 | 0 | 0 | 0 | ... | 28314 | 28959 | 29547 | 2000 | |
| 5 | 50000 | 1 | 2 | 1 | 57 | -1 | 0 | -1 | 0 | 0 | ... | 20940 | 19146 | 19131 | 2000 | |
| 6 | 50000 | 1 | 1 | 2 | 37 | 0 | 0 | 0 | 0 | 0 | ... | 19394 | 19619 | 20024 | 2500 | |
| 7 | 500000 | 1 | 1 | 2 | 29 | 0 | 0 | 0 | 0 | 0 | ... | 542653 | 483003 | 473944 | 55000 | |
| 8 | 100000 | 2 | 2 | 2 | 23 | 0 | -1 | -1 | 0 | 0 | ... | 221 | -159 | 567 | 380 | |
| 9 | 140000 | 2 | 3 | 1 | 28 | 0 | 0 | 2 | 0 | 0 | ... | 12211 | 11793 | 3719 | 3329 | |
| 10 | 20000 | 1 | 3 | 2 | 35 | -2 | -2 | -2 | -2 | -1 | ... | 0 | 13007 | 13912 | 0 | |
| 11 | 200000 | 2 | 3 | 2 | 34 | 0 | 0 | 2 | 0 | 0 | ... | 2513 | 1828 | 3731 | 2306 | |
| 12 | 260000 | 2 | 1 | 2 | 51 | -1 | -1 | -1 | -1 | -1 | ... | 8517 | 22287 | 13668 | 21818 | |
| 13 | 630000 | 2 | 2 | 2 | 41 | -1 | 0 | -1 | -1 | -1 | ... | 6500 | 6500 | 2870 | 1000 | |
| 14 | 70000 | 1 | 2 | 2 | 30 | 1 | 2 | 2 | 0 | 0 | ... | 66782 | 36137 | 36894 | 3200 | |
| 15 | 250000 | 1 | 1 | 2 | 29 | 0 | 0 | 0 | 0 | 0 | ... | 59696 | 56875 | 55512 | 3000 | |

```
In [16]: # Separating features and target
         y = card_df.default     # target default=1 or non-default=0
         features = card_df.drop('default', axis = 1, inplace = False)
```

# 3. Feature Engineering

## 3.1 **SEX** Column

```
In [17]: features['SEX'].value_counts()

Out[17]: 2    18112
         1    11888
         Name: SEX, dtype: int64
```

## 3.2 **EDUCATION** Column

```
In [18]: features['EDUCATION'].unique()
Out[18]: array([2, 1, 3, 5, 4, 6, 0], dtype=int64)

In [19]: features['EDUCATION'].value_counts()
Out[19]: 2    14030
         1    10585
         3     4917
         5      280
         4      123
         6       51
         0       14
         Name: EDUCATION, dtype: int64
```

The categories 4:others, 5:unknown, and 6:unknown can be grouped into a single class '4'.

```
In [20]: features['EDUCATION'] = features['EDUCATION'].replace([0,5,6],4)

In [21]: features['EDUCATION'].value_counts()
         #(card_df['EDUCATION']==0 ).sum()
Out[21]: 2    14030
         1    10585
         3     4917
         4      468
         Name: EDUCATION, dtype: int64
```

## 3.3 **MARRIAGE** Column

```
In [22]: features["MARRIAGE"].value_counts()
Out[22]: 2    15964
         1    13659
         3      323
         0       54
         Name: MARRIAGE, dtype: int64
```

Similarly, the column 'marriage' should have three categories: 1 = married, 2 = single, 3 = others but it contains a category '0' which will be joined to the category '3'.

One might wonder what these labels might mean.

"Other" in education can be an education lower than the high school level. "Other" in marriage could be, for example, "divorced".

```
In [23]: features['MARRIAGE'] = features['MARRIAGE'].replace(0,3)

In [24]: features["MARRIAGE"].value_counts()

Out[24]: 2    15964
         1    13659
         3      377
         Name: MARRIAGE, dtype: int64
```

## 3.4 **PAY_n** Columns

```
In [25]: features = features.rename(columns={'PAY_0': 'PAY_1'})

In [26]: features['PAY_1'].value_counts()

Out[26]:  0    14737
         -1     5686
          1     3688
         -2     2759
          2     2667
          3      322
          4       76
          5       26
          8       19
          6       11
          7        9
         Name: PAY_1, dtype: int64
```

According to our documentation, the PAY_n variables indicate the number of months of delay and indicates "pay duly"with -1. Then what is -2? And what is 0? It seems to me the label has to be adjusted to 0 for pay duly.

```
In [27]: features['PAY_1'] = features['PAY_1'].replace([-1,-2],0)
         features['PAY_2'] = features['PAY_2'].replace([-1,-2],0)
         features['PAY_3'] = features['PAY_3'].replace([-1,-2],0)
         features['PAY_4'] = features['PAY_4'].replace([-1,-2],0)
         features['PAY_5'] = features['PAY_5'].replace([-1,-2],0)
         features['PAY_6'] = features['PAY_6'].replace([-1,-2],0)

In [28]: features['PAY_1'].value_counts()

Out[28]: 0    23182
         1     3688
         2     2667
         3      322
         4       76
         5       26
         8       19
         6       11
         7        9
         Name: PAY_1, dtype: int64
```

# 4. Data Visualization

In [29]:
```
card_df = pd.concat([features,y],axis=1)
```

We have merged the attributes that decide whether the person is defaulter or not (features) with the result for data visualization.

In [30]:
```
def draw_histograms(df, variables, n_rows, n_cols, n_bins):
    fig=plt.figure()
    for i, var_name in enumerate(variables):
        ax=fig.add_subplot(n_rows,n_cols,i+1)
        df[var_name].hist(bins=n_bins,ax=ax)
        ax.set_title(var_name)
    fig.tight_layout()  # Improves appearance a bit.
    plt.show()
```

The function draw_histogram is used to draw a histogram and this approach reduces the redundancy from the code notebook

In [31]:
```
# Bar Chart Visualization Function
def single_bar_chart(feature):
    default_1 = card_df[card_df['default']==1][feature].value_counts()
    default_0 = card_df[card_df['default']==0][feature].value_counts()
    df = pd.DataFrame([default_0,default_1])
    df.index = ['default=0','default=1']
    df.plot(kind='bar',stacked=True, figsize=(10,5))
```

Function single_bar_chart is used to draw bar chart and this approach reduces the redundancy from the code book

In [32]:
```
# Bar Chart Visualization Function
def draw_barcharts(df, variables, n_rows, n_cols):
    fig=plt.figure()
    for i, feature in enumerate(variables):
        ax=fig.add_subplot(n_rows,n_cols,i+1)

        default_1 = df[card_df['default']==1][feature].value_counts()
        default_0 = df[card_df['default']==0][feature].value_counts()
        df_temp = pd.DataFrame([default_0,default_1])
        df_temp.index = ['default=0','default=1']
        df_temp.plot(kind='bar',stacked=True, figsize=(10,5),ax=ax)
        ax.set_title(feature)
    plt.show()
```

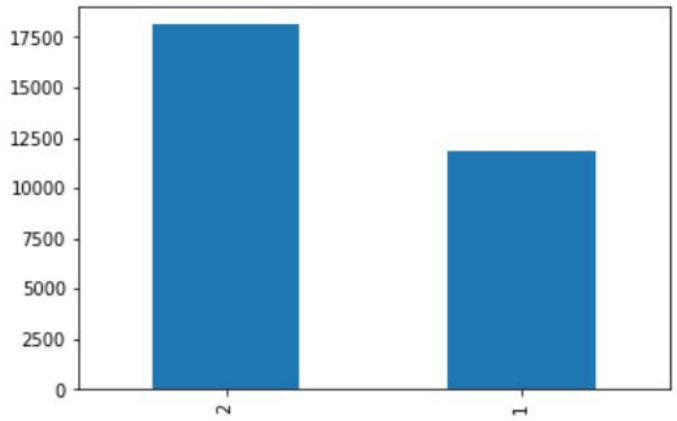
Function draw_bar_chart is used to draw a bar chart w.r.t the default variable.

# 4.1 Categorical

## 4.1.1 SEX

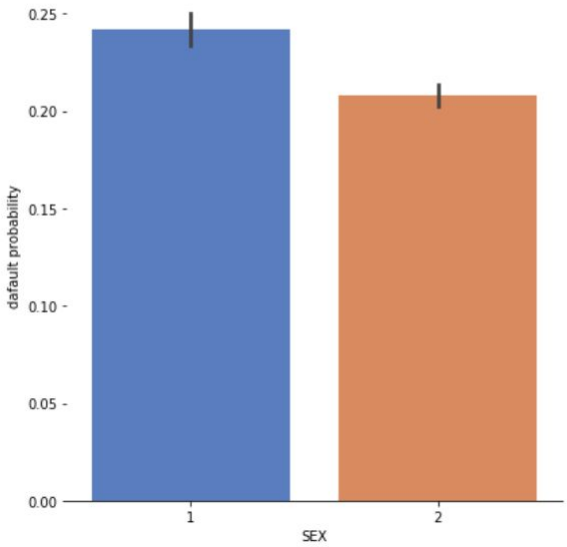
```
In [38]: card_df.SEX.value_counts().plot(kind = 'bar')
```

```
Out[38]: <matplotlib.axes._subplots.AxesSubplot at 0x257fb134b48>
```



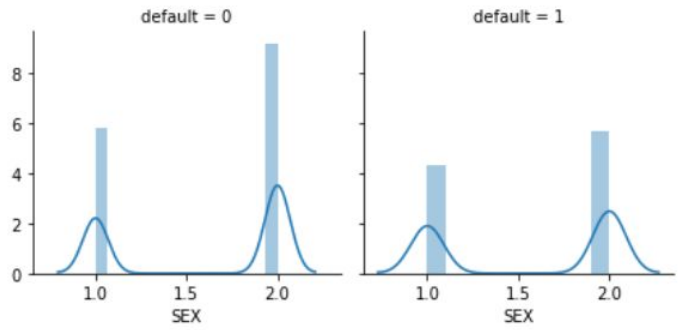

The dataset has more female cardholders than males cardholders. The number of female holders are above 17500 whereas the number of male holders only range from 10000 to 12500.

```
In [39]: # Explore SEX feature vs default
g = sns.catplot(x="SEX",y="default",data=card_df, kind="bar" , height = 6, palette = "muted")
g.despine(left=True)
g = g.set_ylabels("dafault probability")
```

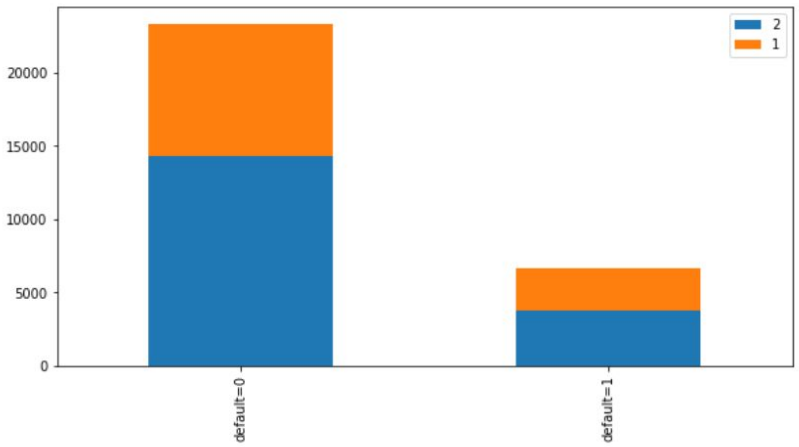



This figure shows that the probability of being defaulter is more in males than females.

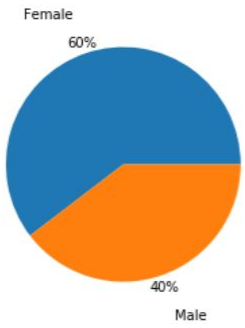
In [40]:
```
g = sns.FacetGrid(card_df, col='default')
g = g.map(sns.distplot, "SEX")
```




In [41]:
```
single_bar_chart('SEX')
```



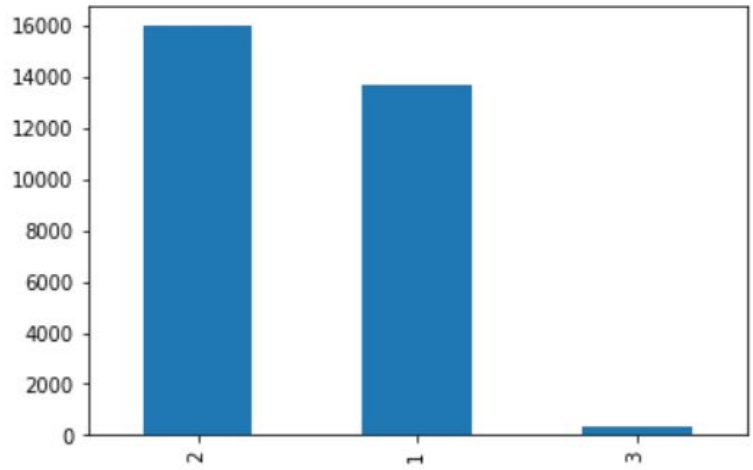

In [42]:
```
sex_type = card_df['SEX'].value_counts()
sex_label =['Female','Male']
plt.pie(sex_type,labels=sex_label,autopct='%1.0f%%', pctdistance=1.1, labeldistance=1.35)
plt.show()
```



### 4.1.2 MARRIAGE

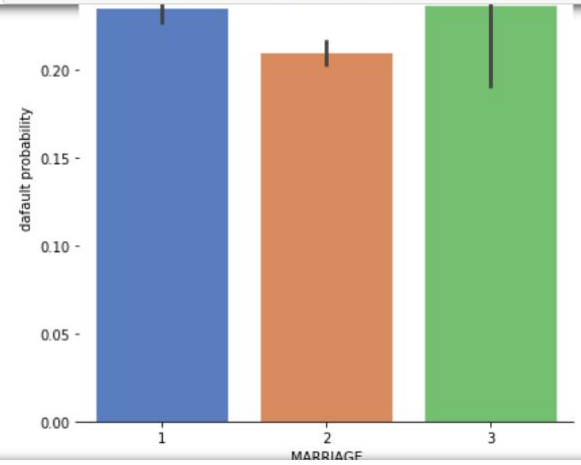
```
In [43]: card_df.MARRIAGE.value_counts().plot(kind = 'bar')
```

```
Out[43]: <matplotlib.axes._subplots.AxesSubplot at 0x257801ac888>
```



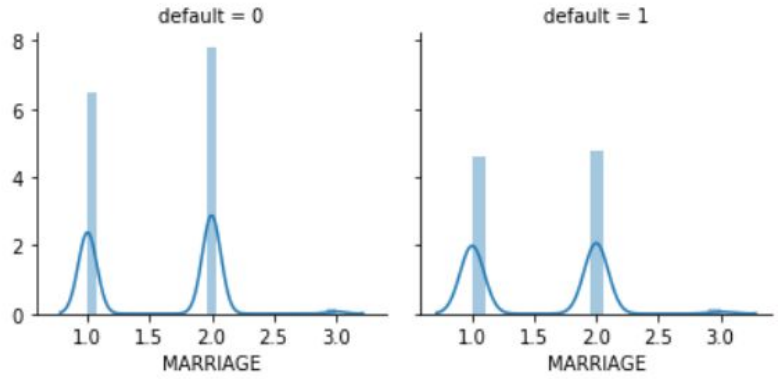

There are more unmarried in the dataset in comparison to the married.

```
In [35]: # Explore MARRIAGE feature vs default
g = sns.catplot(x="MARRIAGE",y="default",data=card_df, kind="bar" , height = 6, palette = "muted")
g.despine(left=True)
g = g.set_ylabels("dafault probability")
```

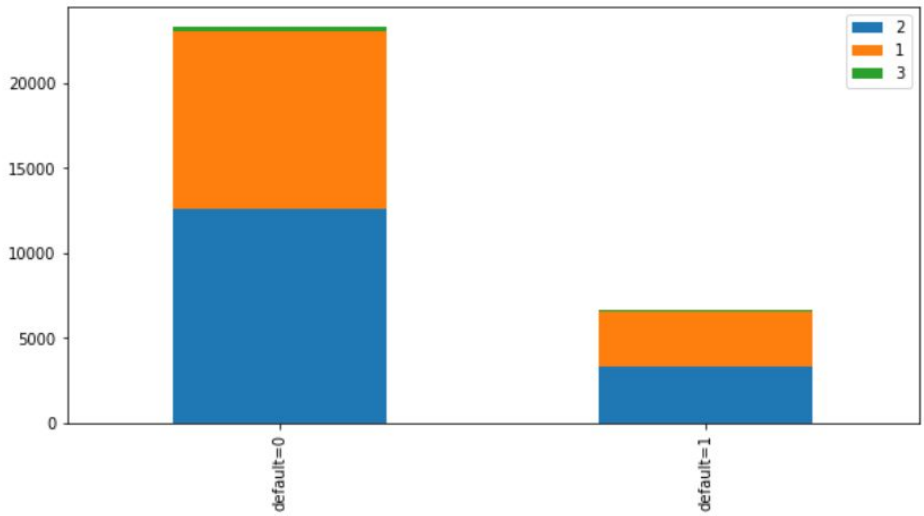



The probability of being defaulter is more for married than single.

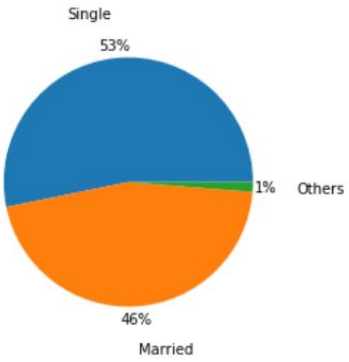
In [34]:
```
g = sns.FacetGrid(card_df, col='default')
g = g.map(sns.distplot, "MARRIAGE")
```



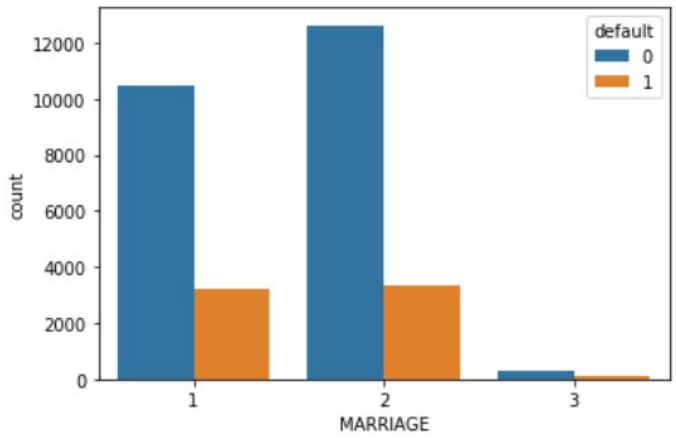

In [46]:
```
single_bar_chart("MARRIAGE")
```




In [47]:
```
mari_type = card_df['MARRIAGE'].value_counts()
mari_label =['Single','Married','Others']
plt.pie(mari_type,labels=mari_label,autopct='%1.0f%%', pctdistance=1.1, labeldistance=1.35)
plt.show()
```



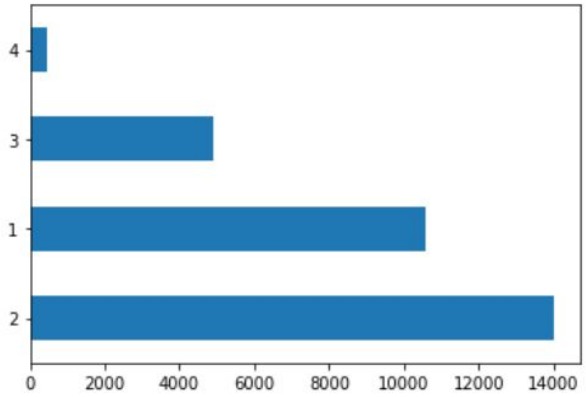
```
In [48]: sns.countplot(x='MARRIAGE', data=card_df,hue="default")
         plt.show()
```




The number of defaulters is almost same for unmarried and married even though the number of unmarried is more in the dataset.

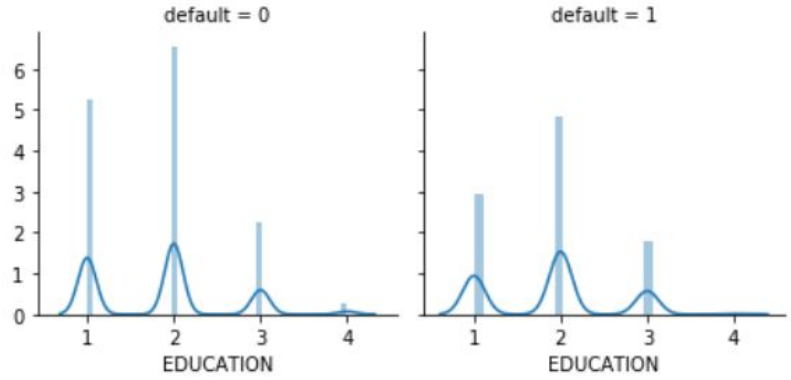
### 4.1.3 EDUCATION

```
In [49]: card_df.EDUCATION.value_counts().plot(kind = "barh")
Out[49]: <matplotlib.axes._subplots.AxesSubplot at 0x2578002e608>
```

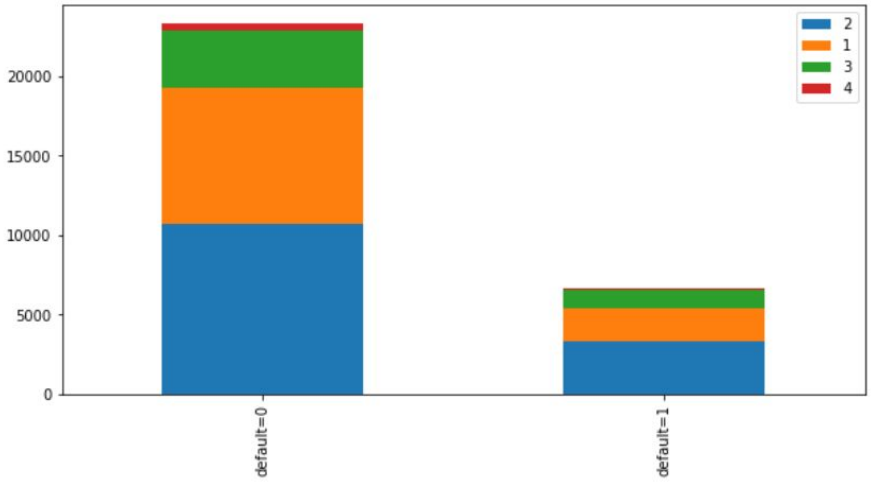



Most of the people in the dataset have an education of university level followed by graduate

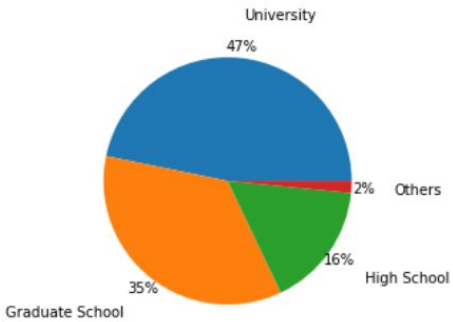
In [51]:
```
g = sns.FacetGrid(card_df, col='default')
g = g.map(sns.distplot, "EDUCATION")
```



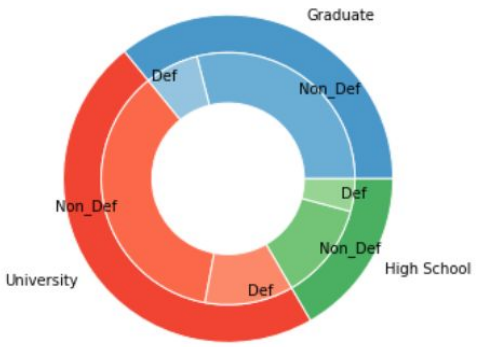

In [52]:
```
single_bar_chart("EDUCATION")
```




In [53]:
```
edu_type = card_df['EDUCATION'].value_counts()
edu_label =['University','Graduate School','High School','Others']
plt.pie(edu_type,labels=edu_label,autopct='%1.0f%%', pctdistance=1.1, labeldistance=1.35)
plt.show()
```

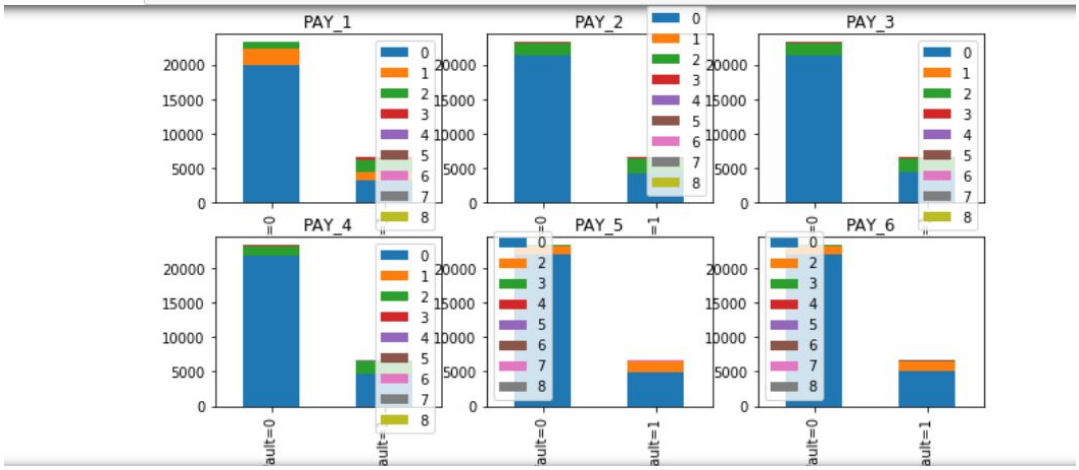


In [54]:
```
graduate_count= (card_df['EDUCATION']==1).sum()
graduate_df = card_df[card_df['EDUCATION']==1]
graduate_non_defauter = (graduate_df['default']==0).sum()

univerity_count= (card_df['EDUCATION']==2).sum()
uni_df = card_df[card_df['EDUCATION']==2]
university_non_defauter = (uni_df['default']==0).sum()

high_school_count= (card_df['EDUCATION']==3).sum()
high_df = card_df[card_df['EDUCATION']==3]
high_school_non_defauter = (high_df['default']==0).sum()

#1=graduate school, 2=university, 3=high school, 4=others
group_names=['Graduate', 'University', 'High School']
group_size=[graduate_count,univerity_count,high_school_count]
subgroup_names=['Non_Def', 'Def', 'Non_Def', 'Def', 'Non_Def', 'Def']
subgroup_size=[graduate_non_defauter,graduate_count-graduate_non_defauter,university_non_defauter,univerity_count-university_

# Create colors
a, b, c=[plt.cm.Blues, plt.cm.Reds, plt.cm.Greens]
# First Ring (outside)
fig, ax = plt.subplots()
ax.axis('equal')
mypie, _ = ax.pie(group_size, radius=1.3, labels=group_names, colors=[a(0.6), b(0.6), c(0.6)] )
plt.setp( mypie, width=0.3, edgecolor='white')

# Second Ring (Inside)
mypie2, _ = ax.pie(subgroup_size, radius=1.3-0.3, labels=subgroup_names, labeldistance=0.9, colors=[a(0.5),a(0.4),b(0.5),b(0.
plt.setp( mypie2, width=0.4, edgecolor='white')
plt.margins(0,0)
# show it
plt.show()
```



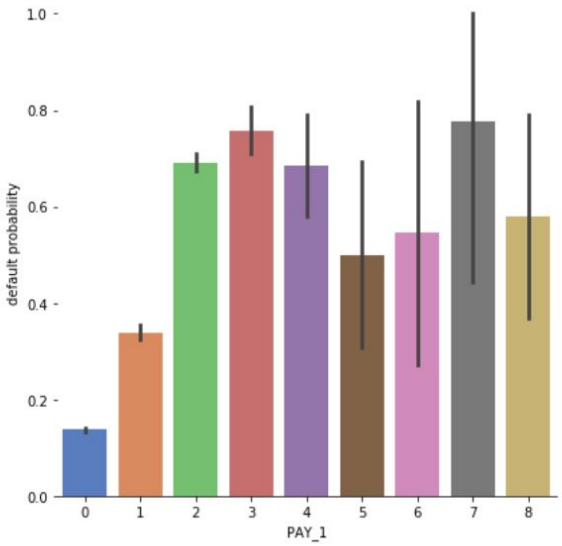

## 4.1.4 PAY_n

In [45]:
```
late = card_df[['PAY_1','PAY_2', 'PAY_3', 'PAY_4', 'PAY_5', 'PAY_6']]
draw_barcharts(late, late.columns, 2, 3)
```



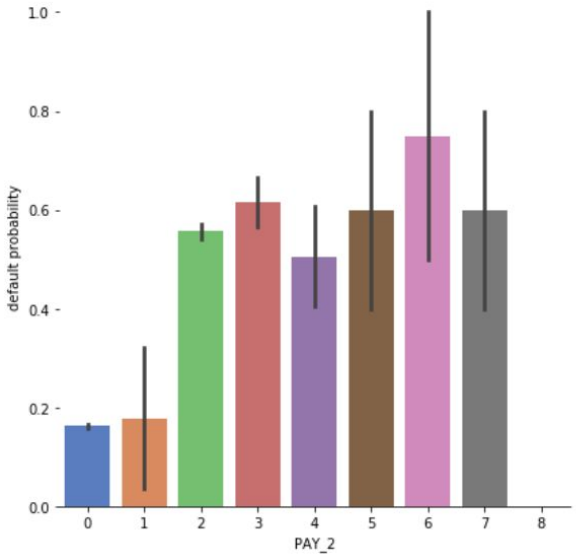
## PAY_1

In [47]:
```
# Explore PAY_1 feature vs default
g = sns.catplot(x="PAY_1",y="default",data=card_df,kind="bar" , height = 6, palette = "muted")
g.despine(left=True)
g = g.set_ylabels("default probability")
```



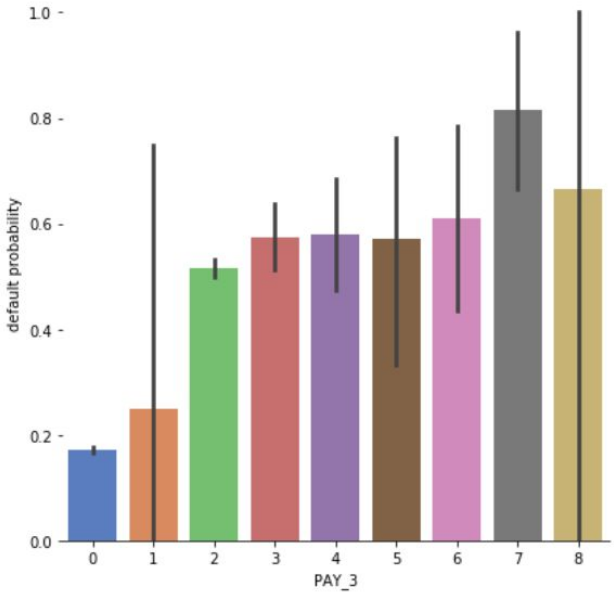

## PAY_2

In [48]:
```
# Explore PAY_2 feature vs default
g = sns.catplot(x="PAY_2",y="default",data=card_df,kind="bar" , height = 6, palette = "muted")
g.despine(left=True)
g = g.set_ylabels("default probability")
```



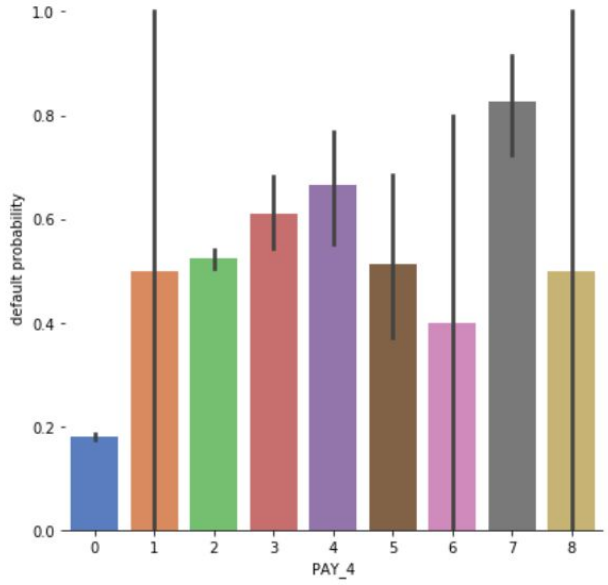
## PAY_3

In [49]:
```
# Explore PAY_3 feature vs default
g = sns.catplot(x="PAY_3",y="default",data=card_df,kind="bar" , height = 6, palette = "muted")
g.despine(left=True)
g = g.set_ylabels("default probability")
```



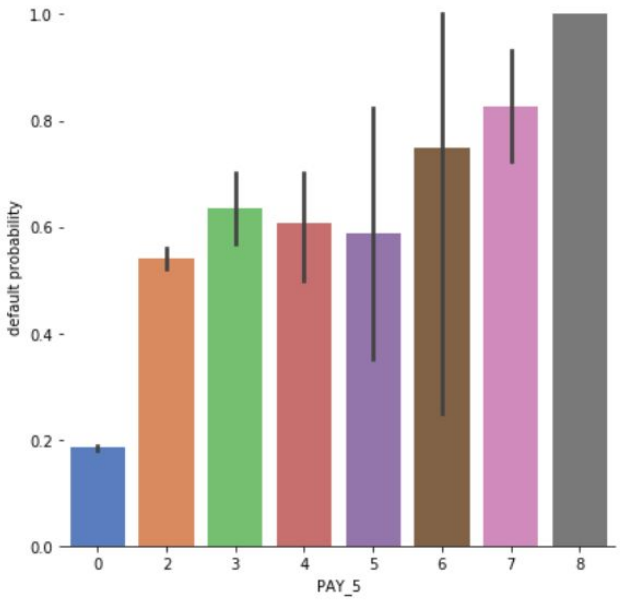

## PAY_4

In [50]:
```
# Explore PAY_4 feature vs default
g = sns.catplot(x="PAY_4",y="default",data=card_df,kind="bar" , height = 6, palette = "muted")
g.despine(left=True)
g = g.set_ylabels("default probability")
```



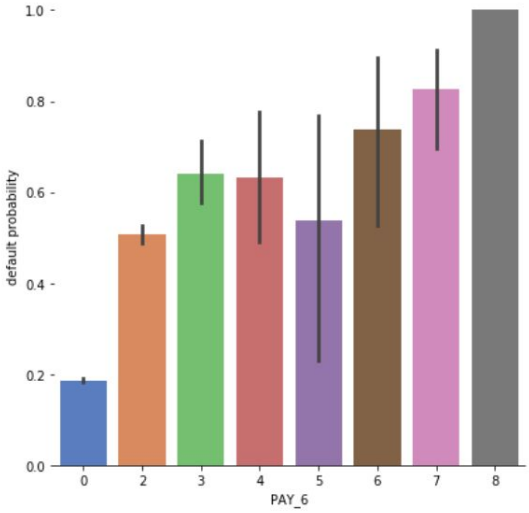
## PAY_5

In [51]:
```
# Explore PAY_5 feature vs default
g = sns.catplot(x="PAY_5",y="default",data=card_df,kind="bar" , height = 6, palette = "muted")
g.despine(left=True)
g = g.set_ylabels("default probability")
```




## PAY_6

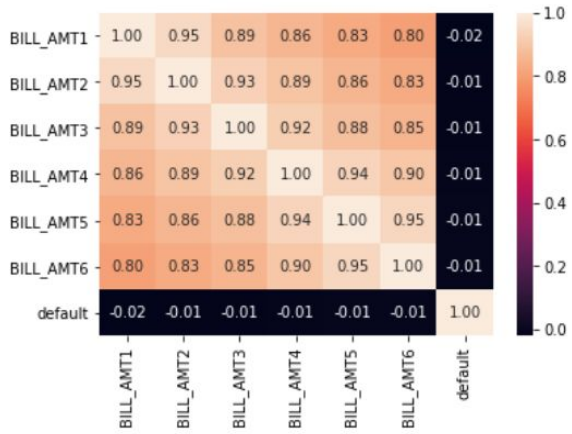
In [52]:
```
# Explore PAY_6 feature vs default
g = sns.catplot(x="PAY_6",y="default",data=card_df,kind="bar" , height = 6, palette = "muted")
g.despine(left=True)
g = g.set_ylabels("default probability")
```



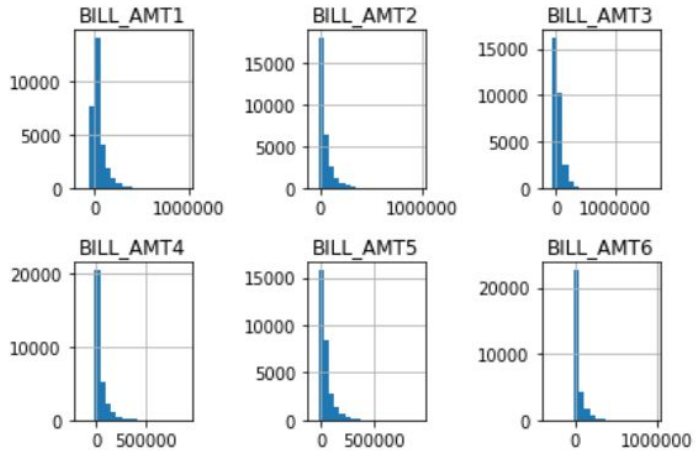
## 4.2 Numerical

### 4.2.1 BILL_AMTn

In [53]:
```
# Correlation matrix between numerical values (SibSp Parch Age and Fare values) and Survived
g = sns.heatmap(card_df[['BILL_AMT1','BILL_AMT2', 'BILL_AMT3', 'BILL_AMT4', 'BILL_AMT5', 'BILL_AMT6','default']]
                .corr(),annot=True,fmt = ".2f")
```

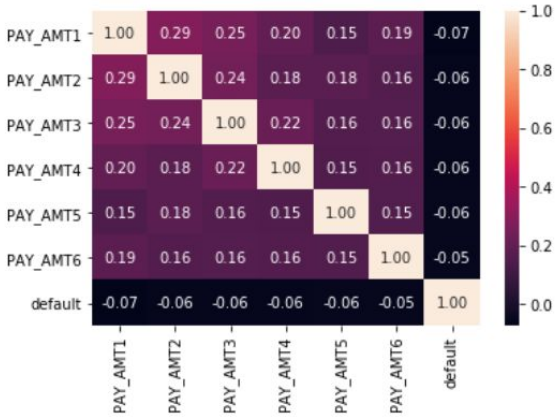



In [54]:
```
bills = card_df[['BILL_AMT1','BILL_AMT2', 'BILL_AMT3', 'BILL_AMT4', 'BILL_AMT5', 'BILL_AMT6',]]
draw_histograms(bills, bills.columns, 2, 3, 20)
```

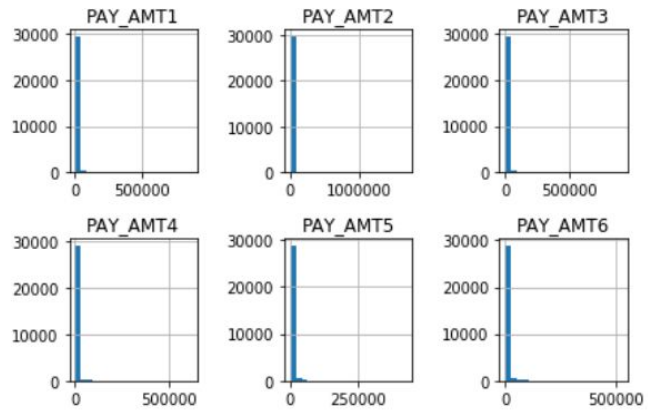


### 4.2.2 PAY_AMTn

In [56]:
```
# Correlation matrix between numerical values (SibSp Parch Age and Fare values) and Survived
g = sns.heatmap(card_df[['PAY_AMT1','PAY_AMT2', 'PAY_AMT3', 'PAY_AMT4', 'PAY_AMT5', 'PAY_AMT6','default']]
                .corr(),annot=True,fmt = ".2f")
```

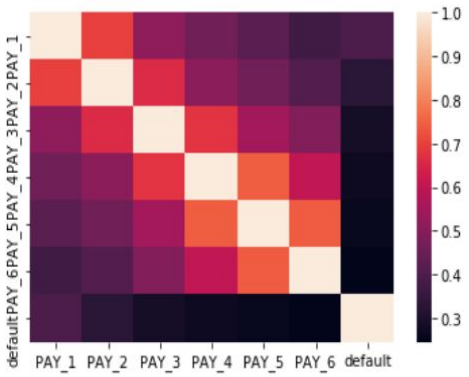



In [57]:
```
pay = card_df[['PAY_AMT1','PAY_AMT2', 'PAY_AMT3', 'PAY_AMT4', 'PAY_AMT5', 'PAY_AMT6']]
draw_histograms(pay, pay.columns, 2, 3, 20)
```

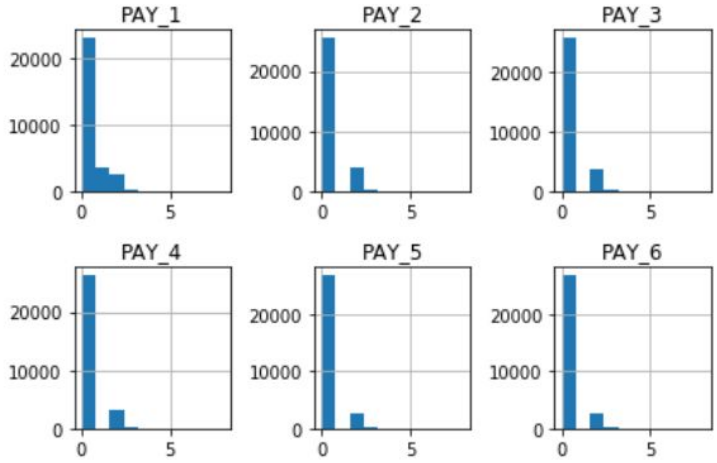



### 4.2.3 PAY_n

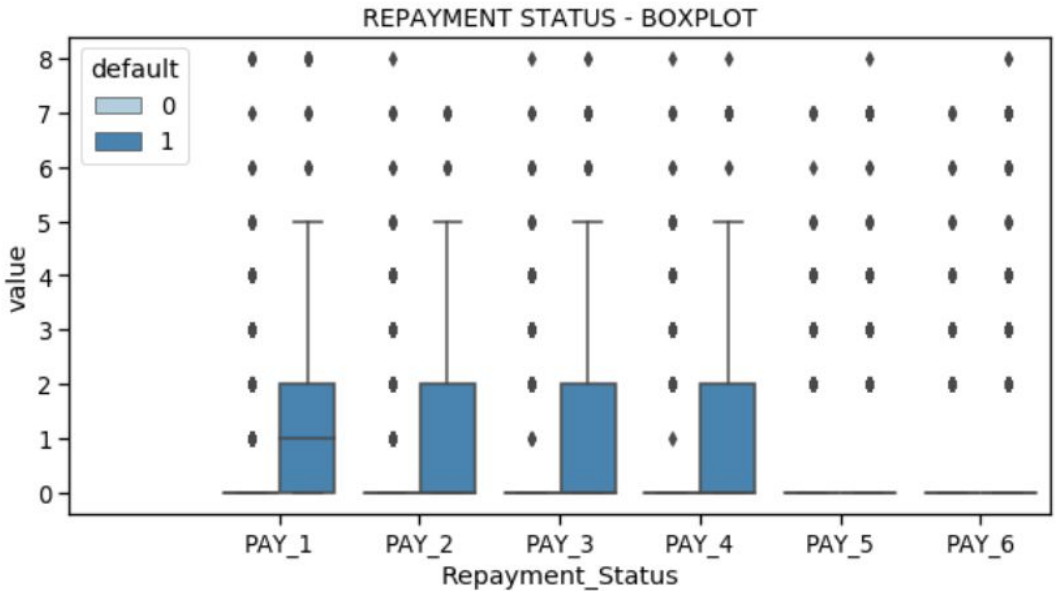
In [58]:
```
# Correlation matrix between numerical values (SibSp Parch Age and Fare values) and Survived
g = sns.heatmap(card_df[[ 'PAY_1','PAY_2','PAY_3','PAY_4','PAY_5','PAY_6','default']].corr(),annot=False,fmt = ".2f")
```



In [59]:
```
late = card_df[['PAY_1','PAY_2', 'PAY_3', 'PAY_4', 'PAY_5', 'PAY_6']]
draw_histograms(late, late.columns, 2, 3, 10)
```



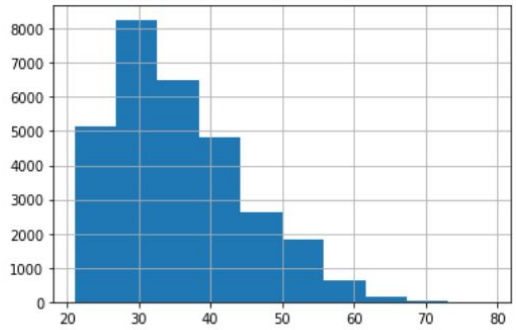

In [118]:
```
Repayment = card_df[['PAY_1', 'PAY_2', 'PAY_3', 'PAY_4', 'PAY_5', 'PAY_6']]

Repayment = pd.concat([y,Repayment],axis=1)
Repayment = pd.melt(Repayment,id_vars="default",
                    var_name="Repayment_Status",
                    value_name='value')

plt.figure(figsize=(10,5))
sns.set_context('notebook', font_scale=1.2)
sns.boxplot(y="value", x="Repayment_Status", hue="default", data=Repayment, palette='Blues')
plt.legend(loc='best', title= 'default', facecolor='white')
plt.xlim([-1.5,5.5])
plt.title('REPAYMENT STATUS - BOXPLOT', size=14)
plt.savefig('ImageName', format='png', dpi=200);
```



### 4.2.4 Age

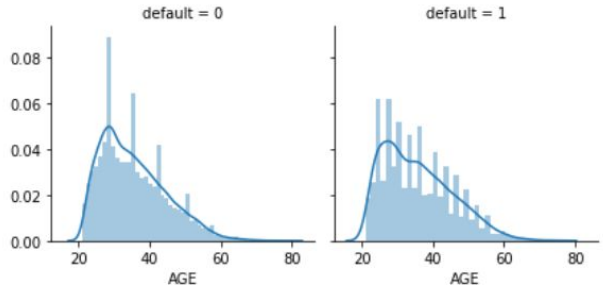
```
In [60]: card_df.AGE.hist()
```

```
Out[60]: <matplotlib.axes._subplots.AxesSubplot at 0x1ab7771acc8>
```

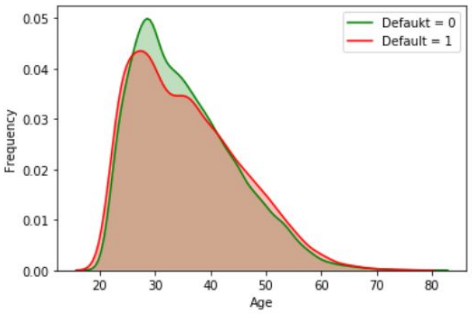



Majority of the people is in the age group of 20-50 with dominating subset 20-35

```
In [61]: # Explore Age feature vs default
g = sns.FacetGrid(card_df, col='default')
g = g.map(sns.distplot, "AGE")
```

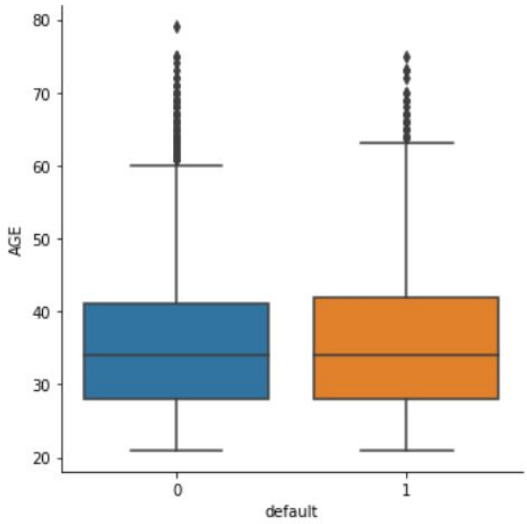



```
In [62]: # Explore Age distibution
g = sns.kdeplot(card_df["AGE"][(card_df["default"] == 0) &
                               (card_df["AGE"].notnull())], color="Green", shade = True)
g = sns.kdeplot(card_df["AGE"][(card_df["default"] == 1) &
                               (card_df["AGE"].notnull())], ax =g, color="Red", shade= True)
g.set_xlabel("Age")
g.set_ylabel("Frequency")
g = g.legend(["Defaukt = 0","Default = 1"])
```




The Age distribution of Defaulter is quite similar to the Non Defaulter but Non defaulter has higher peak.

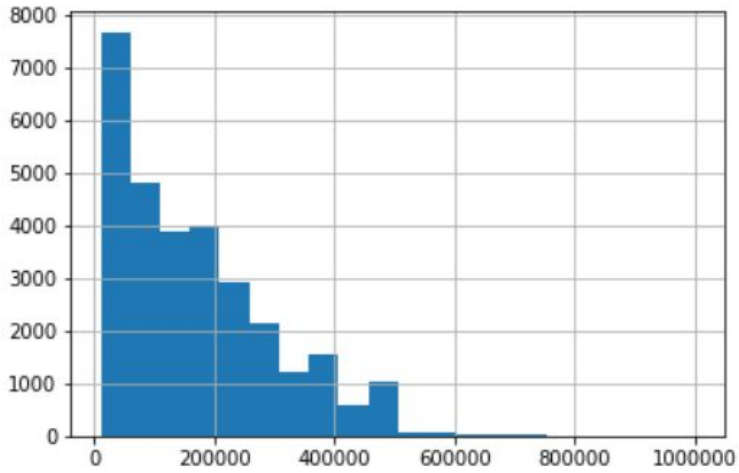
```
In [63]: g = sns.catplot(y="AGE",x="default",data=card_df,kind="box")
```




The Average age of defaulter is almost same as of the average age of Non defaulter

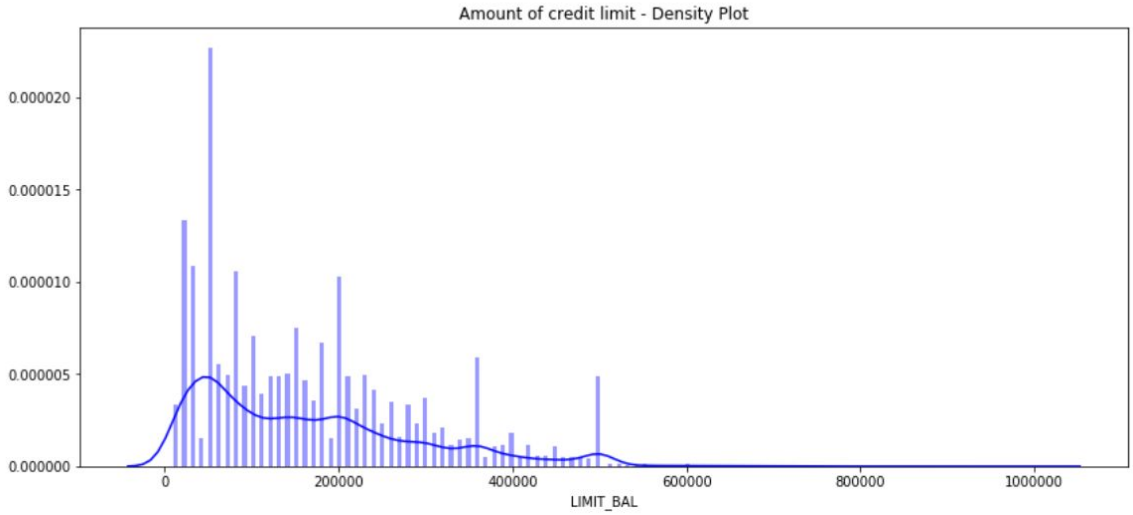
### 4.2.5 Card Balance Limit

```
In [64]: card_df.LIMIT_BAL.hist(bins = 20)
Out[64]: <matplotlib.axes._subplots.AxesSubplot at 0x1ab779686c8>
```



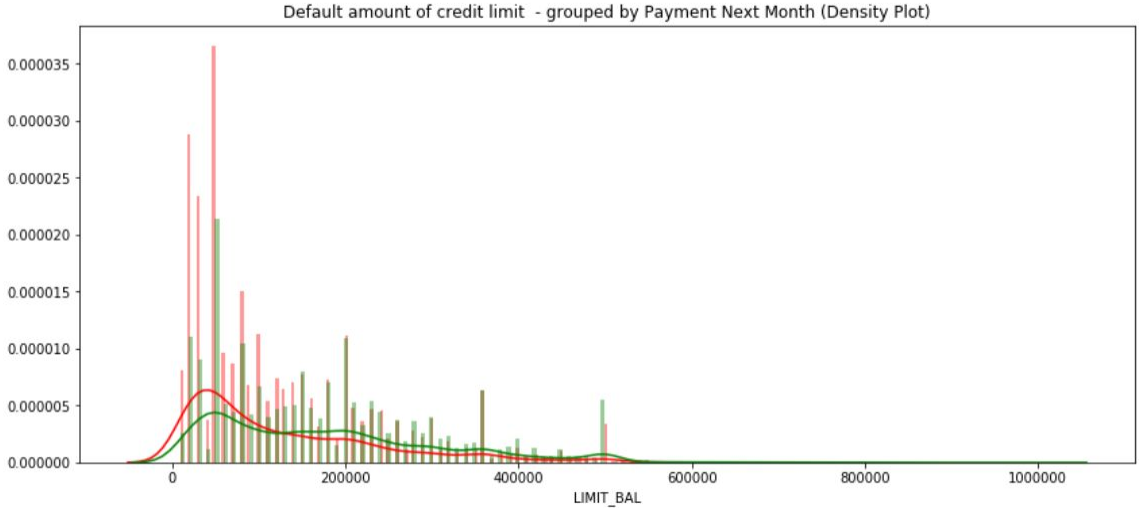

Majority of the Limit balance is less than 4,00,000 with dominant subset is less than 2,00,000

In [65]:
```
plt.figure(figsize = (14,6))
plt.title('Amount of credit limit - Density Plot')
sns.set_color_codes("pastel")
sns.distplot(card_df['LIMIT_BAL'],kde=True,bins=200, color="blue")
plt.show()
```

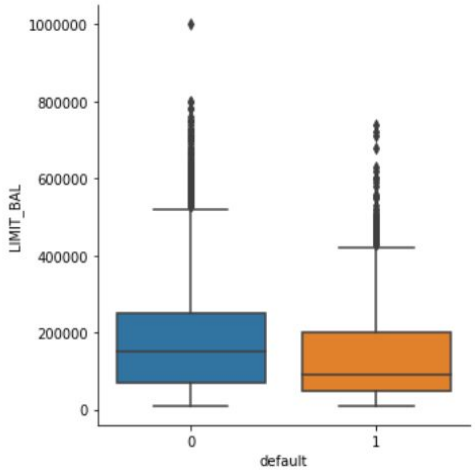



## Density Plot of Amount of Credit Limit (Limit_BAL)

In [69]:
```
class_0 = card_df.loc[card_df['default'] == 0]["LIMIT_BAL"]
class_1 = card_df.loc[card_df['default'] == 1]["LIMIT_BAL"]
plt.figure(figsize = (14,6))
plt.title('Default amount of credit limit  - grouped by Payment Next Month (Density Plot)')
sns.set_color_codes("pastel")
sns.distplot(class_1,kde=True,bins=200, color="red")
sns.distplot(class_0,kde=True,bins=200, color="green")
plt.show()
```

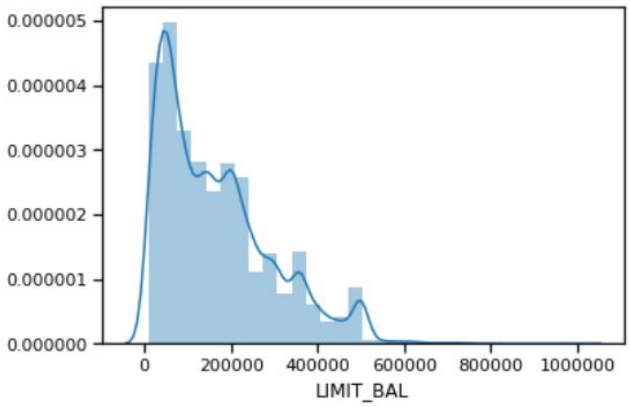


In [66]:
```
g = sns.catplot(y="LIMIT_BAL",x="default",data=card_df,kind="box")
```



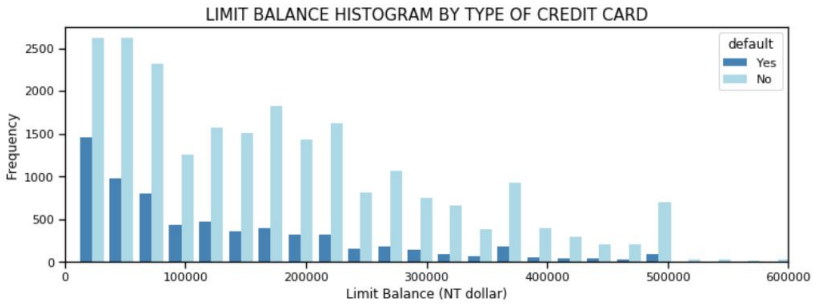

The Non defaulter have higher average Limit Balance than the defaulter

In [107]:
```
sns.distplot(card_df['LIMIT_BAL'],kde=True,bins=30)
plt.show()
```




Majority of the credit card holder have a Limit balance less than 400000 .

In [117]:
```
x1 = list(card_df[card_df['default'] == 1]['LIMIT_BAL'])
x2 = list(card_df[card_df['default'] == 0]['LIMIT_BAL'])

plt.figure(figsize=(12,4))

plt.hist([x1, x2], bins = 40, normed=False, color=['steelblue', 'lightblue'])
plt.xlim([0,600000])
plt.legend(['Yes', 'No'], title = 'default', loc='upper right', facecolor='white')
plt.xlabel('Limit Balance (NT dollar)')
plt.ylabel('Frequency')
plt.title('LIMIT BALANCE HISTOGRAM BY TYPE OF CREDIT CARD', SIZE=15)
plt.savefig('ImageName', format='png', dpi=200, transparent=True);
```



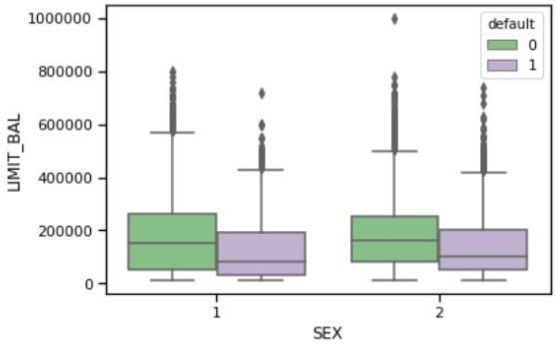

The likelihood of defaulter is less when the Limit Balance is quite high

# 4.3 Visualizing features in pairs

## Sex vs Balance Limit

```
In [111]: sns.boxplot(x='SEX',hue='default', y='LIMIT_BAL',data=card_df,palette='Accent')
```

```
Out[111]: <matplotlib.axes._subplots.AxesSubplot at 0x1ab7747a588>
```

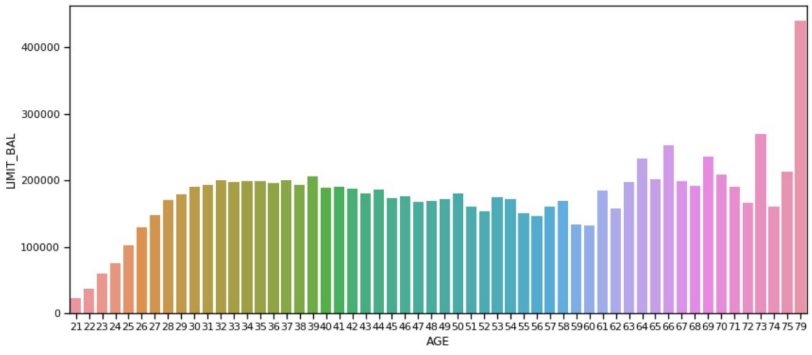



The limit credit amount is quite balanced between sexes. The males have a slightly smaller Q2 and larger Q3 and Q4 and a lower mean. The female have a larger outlier max value (1M NT dollars)

## Age vs Balance Limit

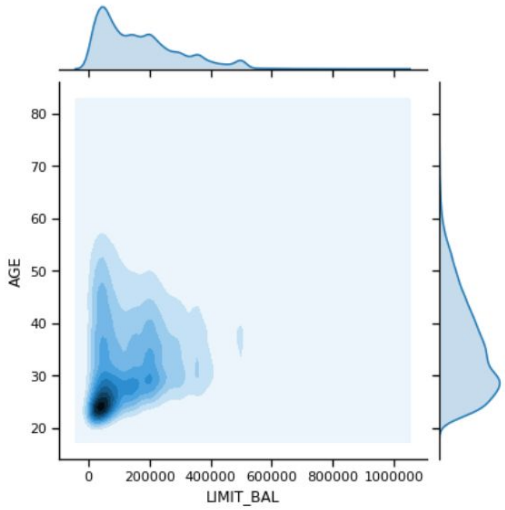
```
In [108]: age_df = card_df.groupby('AGE')['LIMIT_BAL'].mean().reset_index()
          fig_dims = (14, 6)
          fig, ax = plt.subplots(figsize=fig_dims)
          sns.barplot(x='AGE',y='LIMIT_BAL',ax=ax,data=age_df)
```

```
Out[108]: <matplotlib.axes._subplots.AxesSubplot at 0x1ab7729abc8>
```



The Limit balance is almost increasing linearly till around 29 to 30 and then it is slightly decreasing till around 60 and then increasing again.The Limit Balance of the age 79 is exceptionally high.

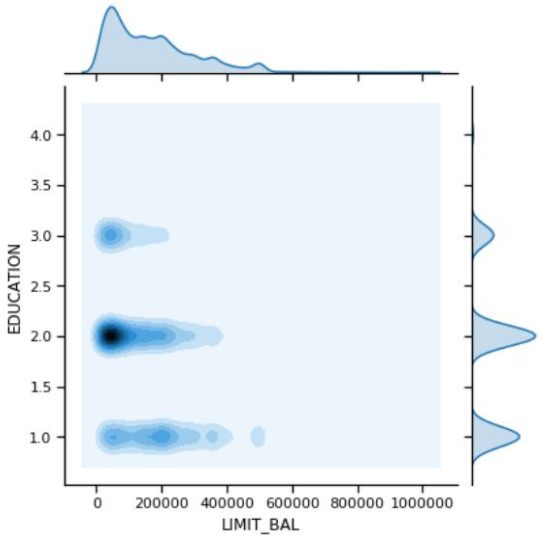
```
In [113]: sns.jointplot(x ='LIMIT_BAL', y ='AGE', data = card_df,kind='kde')
Out[113]: <seaborn.axisgrid.JointGrid at 0x1ab77faa5c8>
```




There is a very high majority of people around the age range 20-30 with Limit Balance  less than 1,50,000

## Education vs Balance Limit

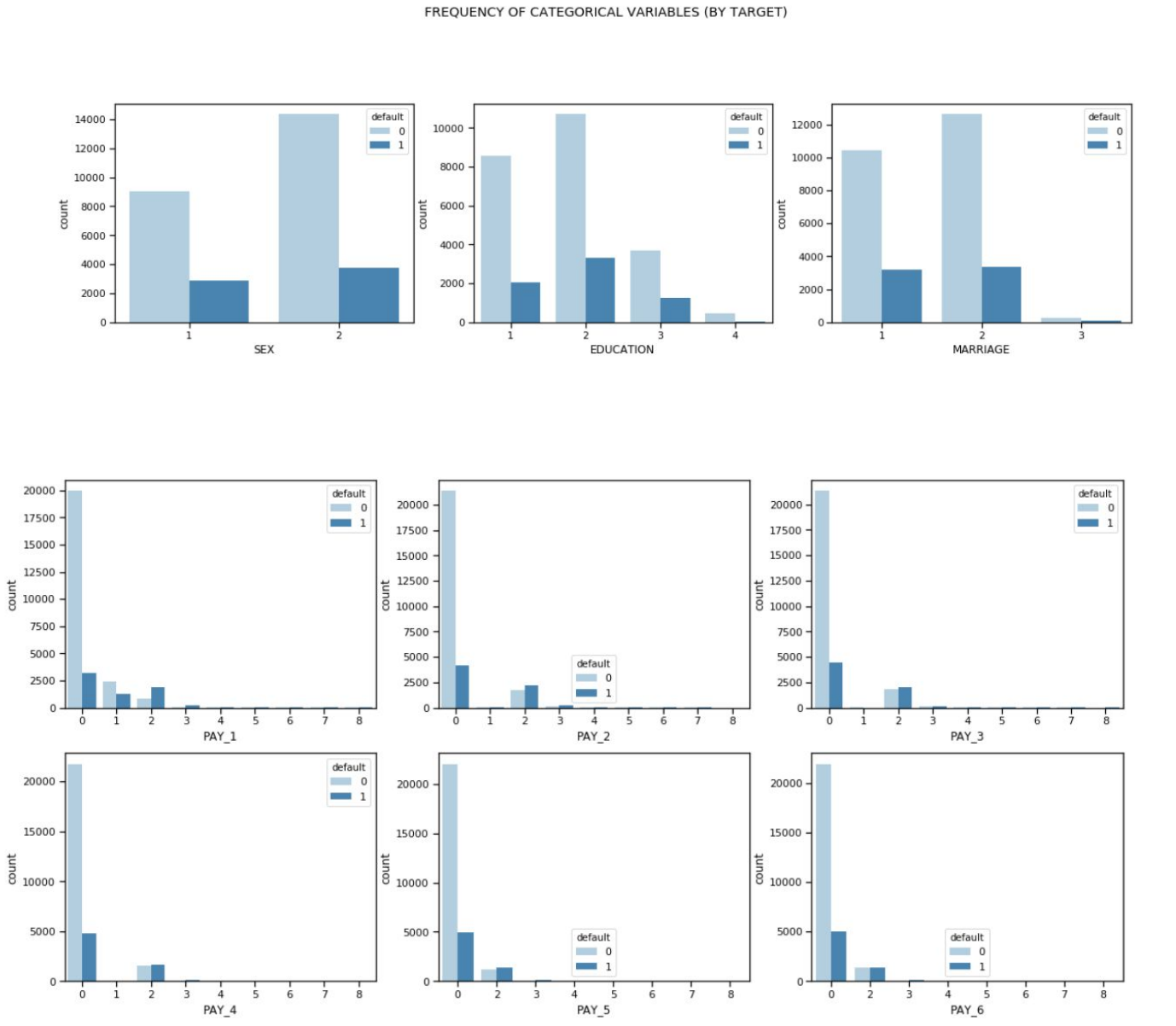
```
In [115]: sns.jointplot(x ='LIMIT_BAL', y ='EDUCATION', data = card_df,kind='kde')
Out[115]: <seaborn.axisgrid.JointGrid at 0x1ab77035d08>
```




There is a very high majority of people with university level education and limit balance less than 1,50,000

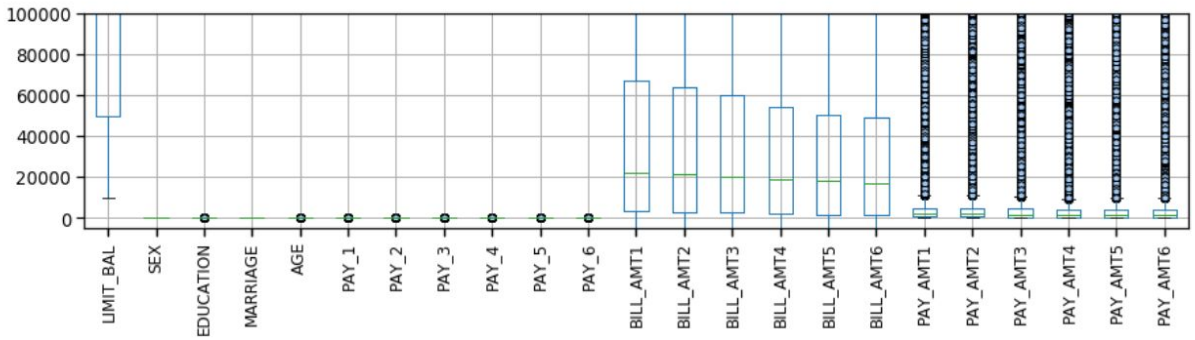
In [81]:

```
# Creating a new dataframe with categorical variables
subset = card_df[['SEX', 'EDUCATION', 'MARRIAGE', 'PAY_1', 'PAY_2', 'PAY_3', 'PAY_4','PAY_5', 'PAY_6', 'default']]

f, axes = plt.subplots(3, 3, figsize=(20, 15), facecolor='white')
f.suptitle('FREQUENCY OF CATEGORICAL VARIABLES (BY TARGET)')

ax1 = sns.countplot(x="SEX", hue="default", data=subset, palette="Blues", ax=axes[0,0])
ax2 = sns.countplot(x="EDUCATION", hue="default", data=subset, palette="Blues",ax=axes[0,1])
ax3 = sns.countplot(x="MARRIAGE", hue="default", data=subset, palette="Blues",ax=axes[0,2])
ax4 = sns.countplot(x="PAY_1", hue="default", data=subset, palette="Blues", ax=axes[1,0])
ax5 = sns.countplot(x="PAY_2", hue="default", data=subset, palette="Blues", ax=axes[1,1])
ax6 = sns.countplot(x="PAY_3", hue="default", data=subset, palette="Blues", ax=axes[1,2])
ax7 = sns.countplot(x="PAY_4", hue="default", data=subset, palette="Blues", ax=axes[2,0])
ax8 = sns.countplot(x="PAY_5", hue="default", data=subset, palette="Blues", ax=axes[2,1])
ax9 = sns.countplot(x="PAY_6", hue="default", data=subset, palette="Blues", ax=axes[2,2]);
```

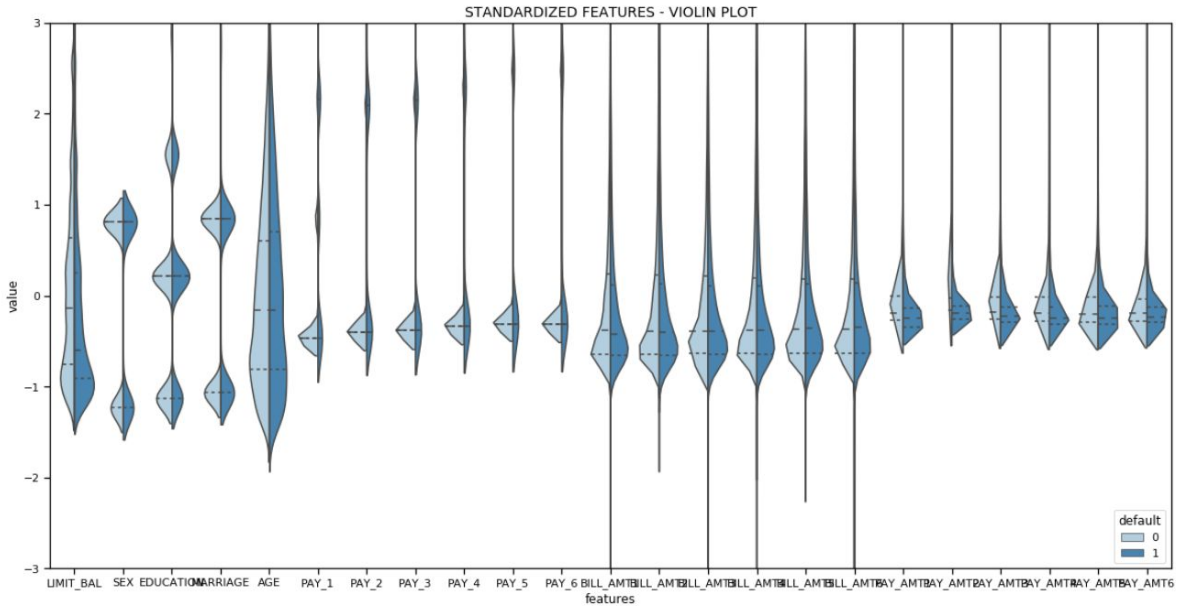


In [84]:
```
## data are distributed in a wide range (below), need to be normalizded.
plt.figure(figsize=(15,3))
ax= card_df.drop('default', axis=1).boxplot(card_df.columns.name, rot=90)
outliers = dict(markerfacecolor='b', marker='p')
ax= features.boxplot(features.columns.name, rot=90, flierprops=outliers)
plt.xticks(size=12)
ax.set_ylim([-5000,100000])
```

Out[84]: (-5000, 100000)



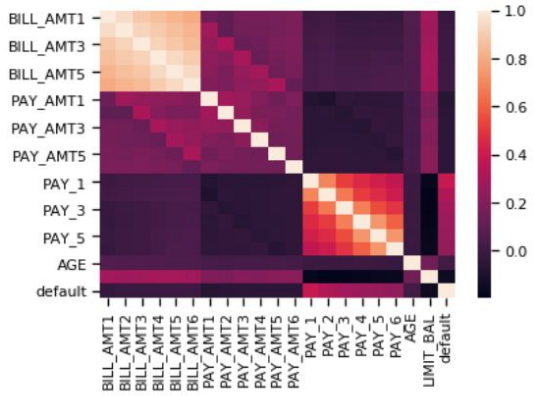

In [85]:
```
stdX = (features - features.mean()) / (features.std())              # standardization
data_st = pd.concat([y,stdX.iloc[:,:]],axis=1)
data_st = pd.melt(data_st,id_vars="default",
                  var_name="features",
                  value_name='value')
plt.figure(figsize=(20,10))
sns.set_context('notebook', font_scale=1)
sns.violinplot(y="value", x="features", hue="default", data=data_st,split=True,
               inner="quart", palette='Blues')
plt.legend(loc=4, title= 'default', facecolor='white')
plt.ylim([-3,3])
plt.title('STANDARDIZED FEATURES - VIOLIN PLOT', size=14)
plt.savefig('ImageName', format='png', dpi=200, transparent=False);
```



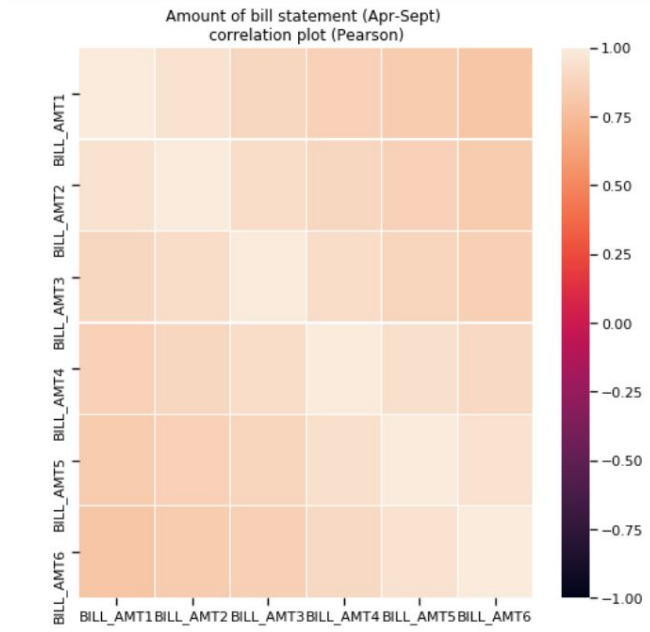
# 4.4 Correlations

## All numerical columns with Target default

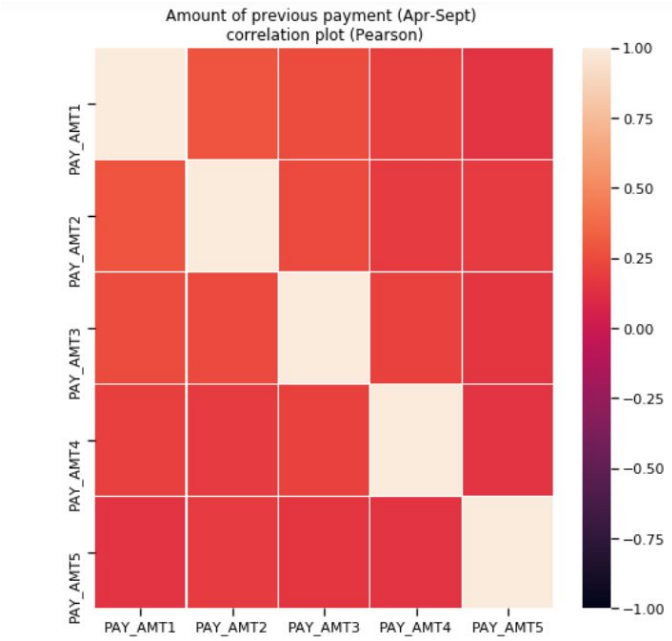
In [86]:
```
# Correlation matrix between numerical values (SibSp Parch Age and Fare values) and Survived
g = sns.heatmap(card_df[['BILL_AMT1','BILL_AMT2', 'BILL_AMT3', 'BILL_AMT4', 'BILL_AMT5', 'BILL_AMT6',
                         'PAY_AMT1','PAY_AMT2', 'PAY_AMT3', 'PAY_AMT4', 'PAY_AMT5', 'PAY_AMT6' ,
                         'PAY_1','PAY_2','PAY_3','PAY_4','PAY_5','PAY_6','AGE','LIMIT_BAL','default']].corr(),annot=False,fmt
```



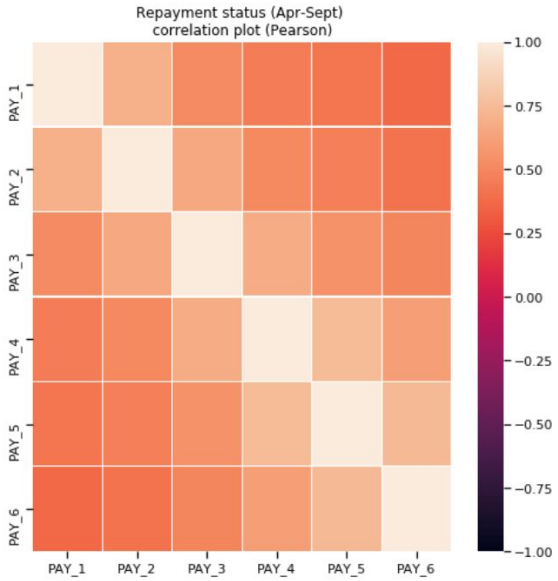

In [87]:
```
var = ['BILL_AMT1','BILL_AMT2','BILL_AMT3','BILL_AMT4','BILL_AMT5','BILL_AMT6']

plt.figure(figsize = (8,8))
plt.title('Amount of bill statement (Apr-Sept) \ncorrelation plot (Pearson)')
corr = card_df[var].corr()
sns.heatmap(corr,xticklabels=corr.columns,yticklabels=corr.columns,linewidths=.1,vmin=-1, vmax=1)
plt.show()
```



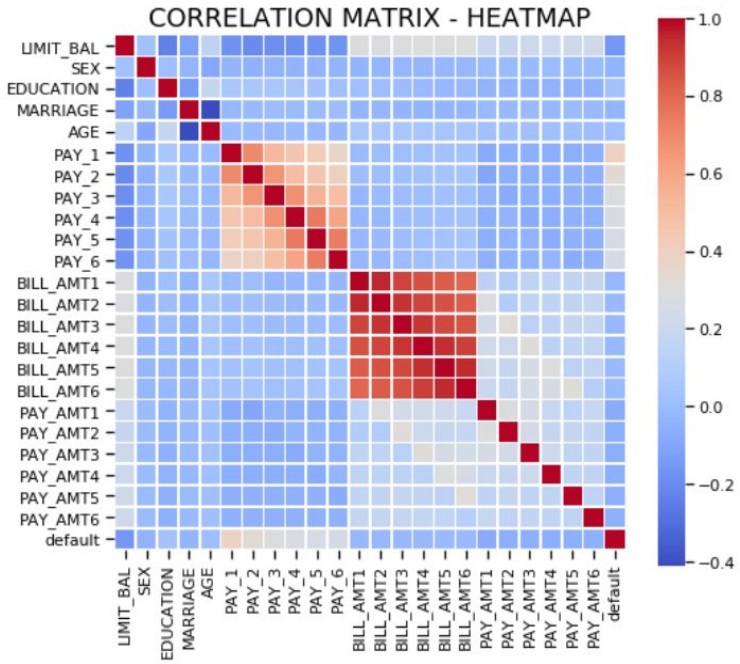
In [88]:
```
var = ['PAY_AMT1', 'PAY_AMT2', 'PAY_AMT3', 'PAY_AMT4', 'PAY_AMT5']

plt.figure(figsize = (8,8))
plt.title('Amount of previous payment (Apr-Sept) \ncorrelation plot (Pearson)')
corr = card_df[var].corr()
sns.heatmap(corr,xticklabels=corr.columns,yticklabels=corr.columns,linewidths=.1,vmin=-1, vmax=1)
plt.show()
```




In [89]:
```
var = ['PAY_1','PAY_2', 'PAY_3', 'PAY_4', 'PAY_5', 'PAY_6']

plt.figure(figsize = (8,8))
plt.title('Repayment status (Apr-Sept) \ncorrelation plot (Pearson)')
corr = card_df[var].corr()
sns.heatmap(corr,xticklabels=corr.columns,yticklabels=corr.columns,linewidths=.1,vmin=-1, vmax=1)
plt.show()
```



In [90]:
```
#  looking at correlations matrix, defined via Pearson function
corr = card_df.corr() # .corr is used to find corelation
f,ax = plt.subplots(figsize=(8, 7))
sns.heatmap(corr, cbar = True,  square = True, annot = False, fmt= '.1f',
            xticklabels= True, yticklabels= True
            ,cmap="coolwarm", linewidths=.5, ax=ax)
plt.title('CORRELATION MATRIX - HEATMAP', size=18);
```




# 5. Data Processing

## 5.1 Test Train Split

In [121]:
```
#Splitting dataset into Trainset and Testset
X_train,X_test,y_train,y_test=train_test_split(features,y,test_size=0.2,random_state=4)
print("Number transactions X_train dataset: ", X_train.shape)
print("Number transactions y_train dataset: ", y_train.shape)
print("Number transactions X_test dataset: ", X_test.shape)
print("Number transactions y_test dataset: ", y_test.shape)
```

```
Number transactions X_train dataset:  (24000, 23)
Number transactions y_train dataset:  (24000,)
Number transactions X_test dataset:  (6000, 23)
Number transactions y_test dataset:  (6000,)
```

## 5.2 Data Normalization

In [123]:
```
to_normalize = X_train.columns
norm_X_train = X_train.copy()
norm_X_test = X_test.copy()
#min_max_scaler = preprocessing.MinMaxScaler()
scaler = StandardScaler()

for var in to_normalize:
    x_train_scaled = scaler.fit_transform(np.array(X_train[var]).reshape(-1, 1))
    x_test_scaled = scaler.transform(np.array(X_test[var]).reshape(-1, 1))
    norm_X_train.drop([var],axis=1)
    norm_X_train[var] = x_train_scaled
    norm_X_test.drop([var],axis=1)
    norm_X_test[var] = x_test_scaled
```

In [124]:
```
X_train = norm_X_train
X_test = norm_X_test
```

In [125]:
```
X_train
```

Out[125]:

| ID | LIMIT_BAL | SEX | EDUCATION | MARRIAGE | AGE | PAY_1 | PAY_2 | PAY_3 | PAY_4 | PAY_5 | ... | BILL_AMT3 | BILL_AMT4 | BILL |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **15660** | -0.367600 | 0.809075 | 1.550481 | -1.068822 | 0.163804 | -0.467335 | -0.399559 | -0.383834 | -0.337526 | -0.307145 | ... | -0.679607 | -0.668750 | -0. |
| **12752** | 2.563303 | -1.235980 | -1.128247 | 0.853232 | -0.706387 | -0.467335 | -0.399559 | -0.383834 | -0.337526 | -0.307145 | ... | 4.530949 | 4.690449 | 3. |
| **27301** | -0.136213 | -1.235980 | 0.211117 | -1.068822 | 1.360317 | -0.467335 | -0.399559 | -0.383834 | -0.337526 | -0.307145 | ... | 1.107622 | 0.369784 | 0. |
| **18340** | -1.138890 | 0.809075 | 2.889845 | 0.853232 | -1.467804 | -0.467335 | -0.399559 | -0.383834 | -0.337526 | -0.307145 | ... | -0.454719 | -0.646489 | -0. |
| **16077** | -0.521858 | 0.809075 | 0.211117 | -1.068822 | 0.707674 | -0.467335 | -0.399559 | -0.383834 | -0.337526 | -0.307145 | ... | -0.543285 | -0.513487 | -0. |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| **22402** | -0.136213 | 0.809075 | 0.211117 | 0.853232 | -0.815161 | 2.129571 | 2.076725 | 2.132422 | 2.283185 | 2.463046 | ... | 1.443296 | 1.626588 | 1. |
| **17094** | -0.676116 | 0.809075 | 0.211117 | -1.068822 | -1.250256 | -0.467335 | -0.399559 | -0.383834 | -0.337526 | -0.307145 | ... | 0.454833 | 0.548269 | 0. |
| **27064** | -0.984632 | -1.235980 | -1.128247 | 0.853232 | 1.033995 | -0.467335 | -0.399559 | -0.383834 | -0.337526 | -0.307145 | ... | -0.629954 | -0.671031 | -0. |
| **8367** | -0.136213 | 0.809075 | -1.128247 | 0.853232 | 0.055031 | -0.467335 | -0.399559 | -0.383834 | -0.337526 | -0.307145 | ... | -0.679607 | -0.668750 | -0. |

# 6 . Data Modeling

## 6.1 Logistic Regression

Logistic regression is the appropriate regression analysis to conduct when the dependent variable is dichotomous (binary). Like all regression analyses, the logistic regression is a predictive analysis. In Logistic Regression, we wish to model a dependent variable(Y) in terms of one or more independent variables(X). It is a method for classification. This algorithm is used for the dependent variable that is Categorical.

- **Fitting the Model on Train Set**

We create an instance of Logistic Regression( ) available in the sklearn library. The object is initialized with parameters C and solver. C is the inverse of regularization strength and is initialized

with 0.01. The solver is the algorithm used for optimization and is initialized with ‘liblinear’ as it is preferred for relatively small datasets.

In [272]:
```
from sklearn.linear_model import LogisticRegression

lr=LogisticRegression(C=0.01,solver='liblinear',random_state =1)
lr.fit(X_train,y_train)
```

Out[272]:
```
LogisticRegression(C=0.01, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=1, solver='liblinear', tol=0.0001, verbose=0,
                   warm_start=False)
```

- **Predicting the Model on Test Set and produce Confusion Matrix**

After training the model on the train set, we predict the test set using it. The predict( ) gives a class label as output whereas the predict_proba( ) gives the probability for an example to be in each of the output class categories. The class label with maximum probability is outputted in predict( ).

In [273]:
```
y_pred = lr.predict(X_test)
y_pred_prob = lr.predict_proba(X_test)
```

In [274]:
```
CM1 = metrics.confusion_matrix(y_test, y_pred)
print("Confusion Matrix:" "\n",CM1 )
print()
```

```
Confusion Matrix:
 [[4443  195]
 [ 934  428]]
```

The confusion matrix shows that the number of :

- ❖ True Positives ( Actually 1 and Predicted 1 ) - 4443
- ❖ False Positives ( Actually 0 and Predicted 1 ) - 195
- ❖ False Negatives ( Actually 1 and Predicted 0 ) - 934
- ❖ False Positives ( Actually 0 and Predicted 0 ) - 428

- **Classification Report**

In [275]:
```
C1=metrics.classification_report(y_test,y_pred)
print("Classification Report : ",C1)
print()
```

```
Classification Report :               precision    recall  f1-score   support

           0       0.83      0.96      0.89      4638
           1       0.69      0.31      0.43      1362

    accuracy                           0.81      6000
   macro avg       0.76      0.64      0.66      6000
weighted avg       0.79      0.81      0.78      6000
```

- **Model Evaluation**

In [276]:
```
from sklearn.metrics import  accuracy_score, f1_score, precision_score, recall_score, roc_auc_score,log_loss

roc=roc_auc_score(y_test, y_pred)
acc = accuracy_score(y_test, y_pred)
prec = precision_score(y_test, y_pred)
rec = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)
err=(y_pred != y_test).sum()
loglos = log_loss(y_test,y_pred)

results = pd.DataFrame([['Logistic Regression', acc, err, prec, rec, f1, roc]],
               columns = ['Model', 'Accuracy', 'Number of Errors','Precision', 'Recall', 'F1 Score','ROC'])
final_report = results
results
```

Out[276]:

| | Model | Accuracy | Number of Errors | Precision | Recall | F1 Score | ROC |
|---|---|---|---|---|---|---|---|
| **0** | Logistic Regression | 0.811833 | 1129 | 0.686998 | 0.314244 | 0.431234 | 0.6361 |

**Model : Logistic Regression**
**No. of Errors : 1129**
**Accuracy : 81.2%**

# 6.2 K Nearest Neighbors

The KNN algorithm assumes that similar things exist in close proximity. In other words, similar things are near to each other.

Iterating from the n_neighbors to be 0 to 25 skipping the even numbers, we fit the model using that neighbors and compute the corresponding error rate.

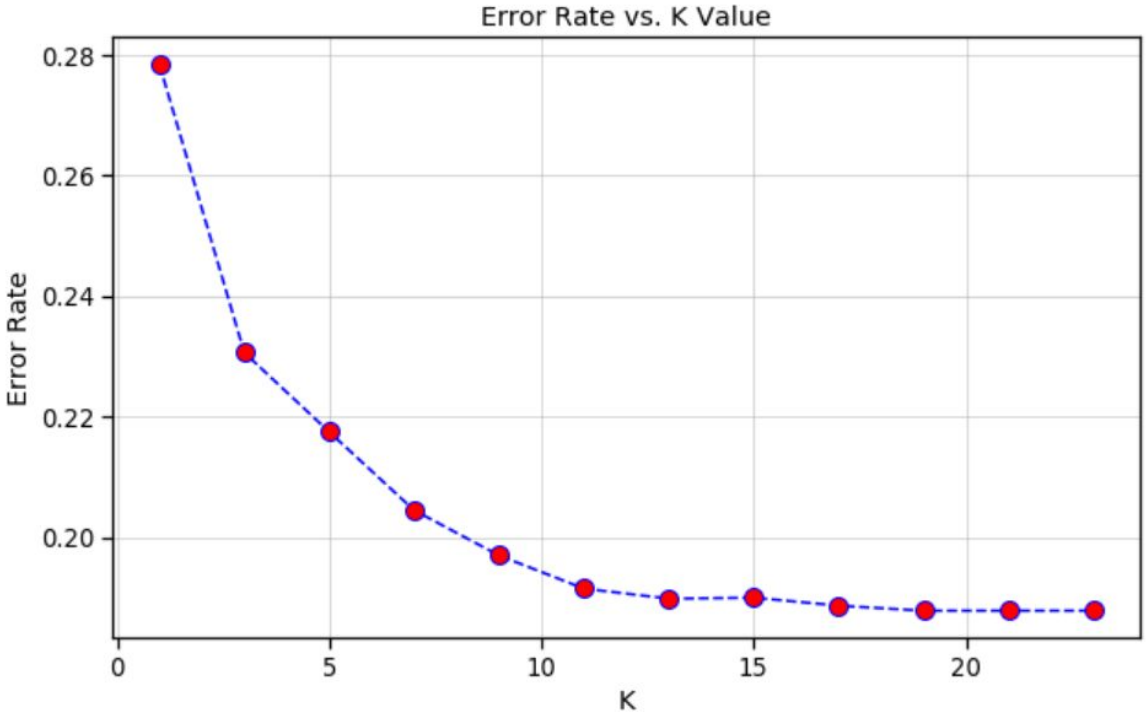
- **Selecting the best value of n_neighbors**

In [279]:
```
myList = list(range(0,25))
neighbors = list(filter(lambda x: x%2!=0, myList))  #This will give a list of odd numbers only

error_rate = []

for k in neighbors:
    knn = KNeighborsClassifier(n_neighbors = k, algorithm = 'kd_tree')
    knn.fit(X_train,y_train)
    pred = knn.predict(X_test)
    error_rate.append(np.mean(pred != y_test))

```

- **Plot K-Valur vs Error-rate**

```
plt.figure(figsize=(10,6))
plt.plot(neighbors,error_rate,color='blue', linestyle='dashed', marker='o',markerfacecolor='red', markersize=10)
plt.title('Error Rate vs. K Value')
plt.xlabel('K')
plt.ylabel('Error Rate')

plt.grid(linestyle='-', linewidth=0.5)

```

The plot represents Error rate on the Y-axis and K no. of neighbors on the X Axis. The best value of K is selected using the Elbow method. Thus the best value of n_neighbors can be considered between 8 to 12.




- **Fitting the Model on Train Set**

We create an instance of KNeighborsClassifier ( ) available in the sklearn library. The object is initialized with the parameter n_neighbors which specifies the number of neighbors. It is initialized with the best value 8.

In [281]:
```
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors=8)
knn.fit(X_train,y_train)
```

Out[281]:
```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                     metric_params=None, n_jobs=None, n_neighbors=8, p=2,
                     weights='uniform')
```

- **Predicting the Model on Test Set and produce Confusion Matrix**

In [282]:
```
y_pred = knn.predict(X_test)
```

In [283]:
```
CM1 = metrics.confusion_matrix(y_test, y_pred)
print("Confusion Matrix:" "\n",CM1 )
print()
```

```
Confusion Matrix:
 [[4422  216]
 [ 984  378]]
```

The confusion matrix shows that the number of :

- True Positives ( Actually 1 and Predicted 1 ) - 4422
- False Positives ( Actually 0 and Predicted 1 ) - 216
- False Negatives ( Actually 1 and Predicted 0 ) - 984
- False Positives ( Actually 0 and Predicted 0 ) - 378

- **Classification Report**

In [284]:
```
C1=metrics.classification_report(y_test,y_pred)
print("Classification Report : ",C1)
print()
```

```
Classification Report :                precision    recall  f1-score   support

           0       0.82      0.95      0.88      4638
           1       0.64      0.28      0.39      1362

    accuracy                           0.80      6000
   macro avg       0.73      0.62      0.63      6000
weighted avg       0.78      0.80      0.77      6000
```

- **Model Evaluation**

```
from sklearn.metrics import  accuracy_score, f1_score, precision_score, recall_score, roc_auc_score

roc=roc_auc_score(y_test, y_pred)
acc = accuracy_score(y_test, y_pred)
prec = precision_score(y_test, y_pred)
rec = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)
err=(y_pred != y_test).sum()

res = pd.DataFrame([['K-Nearest Neighbour', err,acc,prec,rec, f1,roc]],
              columns = ['Model','Number of Errors' ,'Accuracy', 'Precision', 'Recall', 'F1 Score','ROC'])
final_report = final_report.append(res, ignore_index = True)
res
```

Out[285]:

| | Model | Number of Errors | Accuracy | Precision | Recall | F1 Score | ROC |
|---|---|---|---|---|---|---|---|
| 0 | K-Nearest Neighbour | 1200 | 0.8 | 0.636364 | 0.277533 | 0.386503 | 0.615481 |

**Model : K Nearest Neighbors**
**No. of Errors : 1200**
**Accuracy :80.0%**

# 6.3 Naive Bayes Classifier

Naive Bayes algorithm is a supervised learning algorithm, which is based on Bayes Theorem and used for solving classification problems. Gaussian Naive Bayes is a variant of Naive Bayes that follows Gaussian normal distribution and supports continuous data.

We create an instance of GaussianNB( ) from the sklearn library and fit it with the training data.

- **Fitting the Model on Train Set**

```
In [286]:
1 from sklearn.naive_bayes import GaussianNB
2 naive_bayes = GaussianNB()
3 naive_bayes.fit(X_train,y_train)

Out[286]: GaussianNB(priors=None, var_smoothing=1e-09)
```

- **Predicting the Model on Test Set and produce Confusion Matrix**

```
In [287]:
1 y_pred =naive_bayes.predict(X_test)
```

```
In [288]:
1 pred_score=naive_bayes.predict_proba(X_test)
2 pred_score[0:10]

Out[288]: array([[9.51801945e-01, 4.81980547e-02],
       [9.99803726e-01, 1.96273989e-04],
       [9.47960850e-01, 5.20391499e-02],
       [9.73198275e-01, 2.68017248e-02],
       [3.00763266e-05, 9.99969924e-01],
       [7.12785069e-12, 1.00000000e+00],
       [9.55921118e-01, 4.40788824e-02],
       [7.51576737e-02, 9.24842326e-01],
       [1.00000000e+00, 4.72849207e-81],
       [9.54883560e-01, 4.51164402e-02]])
```

```
In [289]:
1 CM1 = metrics.confusion_matrix(y_test, y_pred)
2 print("Confusion Matrix:" "\n",CM1 )
3 print()

Confusion Matrix:
 [[3833  805]
 [ 599  763]]
```

The confusion matrix shows that the number of :

- True Positives ( Actually 1 and Predicted 1 ) - 3833
- False Positives ( Actually 0 and Predicted 1 ) - 805
- False Negatives ( Actually 1 and Predicted 0 ) - 599
- False Positives ( Actually 0 and Predicted 0 ) - 763

- **Classification Report**

In [290]:
```
C1=metrics.classification_report(y_test,y_pred)
print("Classification Report : ",C1)
print()
```

```
Classification Report :               precision    recall  f1-score   support

           0       0.86      0.83      0.85      4638
           1       0.49      0.56      0.52      1362

    accuracy                           0.77      6000
   macro avg       0.68      0.69      0.68      6000
weighted avg       0.78      0.77      0.77      6000
```

- **Model Evaluation**

```
from sklearn.metrics import  accuracy_score, f1_score, precision_score, recall_score, roc_auc_score
roc=roc_auc_score(y_test, y_pred)
acc = accuracy_score(y_test, y_pred)
prec = precision_score(y_test, y_pred)
rec = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)
err =(y_pred != y_test).sum()

res= pd.DataFrame([['Gaussian Naive Bayes', err,acc,prec,rec, f1,roc]],
               columns = ['Model', 'Number of Errors','Accuracy', 'Precision', 'Recall', 'F1 Score','ROC'])
final_report = final_report.append(res, ignore_index = True)
res
```

Out[291]:

| | Model | Number of Errors | Accuracy | Precision | Recall | F1 Score | ROC |
|---|---|---|---|---|---|---|---|
| 0 | Gaussian Naive Bayes | 1404 | 0.766 | 0.486607 | 0.560206 | 0.520819 | 0.69332 |

**Model : Naive Bayes**
**No. of Errors : 1404**
**Accuracy : 76.6%**

# 6.4 Decision Tree Classifier

Decision Tree is a Supervised learning technique that can be used for both classification and Regression problems, but mostly it is preferred for solving Classification problems. It is a tree-structured classifier, where internal nodes represent the features of a dataset, branches represent the decision rules and each leaf node represents the outcome.

The idea of a decision tree is to divide the data set into smaller data sets based on the descriptive features until you reach a small enough set that contains data points that fall under one label.

- **Fitting the Model on Train Set**

We create an object of Decision Tree Classifier from the sklearn library. The criterion parameter determines the function to measure the quality of a split. Supported criteria are “gini” for the Gini impurity and “entropy” for the information gain.

In [292]:
```
from sklearn.tree import DecisionTreeClassifier
dt = DecisionTreeClassifier(criterion = 'entropy',random_state = 0)
```

In [293]:
```
dt.fit(X_train,y_train)
```

Out[293]:
```
DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, criterion='entropy',
                       max_depth=None, max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort='deprecated',
                       random_state=0, splitter='best')
```

- **Predicting the Model on Test Set and Confusion Matrix**

In [294]:
```
y_pred = dt.predict(X_test)
```

In [295]:
```
CM1 = metrics.confusion_matrix(y_test, y_pred)
print("Confusion Matrix:" "\n",CM1 )
print()
```

```
Confusion Matrix:
 [[3826  812]
 [ 809  553]]
```

The confusion matrix shows that the number of :

- True Positives ( Actually 1 and Predicted 1 ) - 3826
- False Positives ( Actually 0 and Predicted 1 ) - 812
- False Negatives ( Actually 1 and Predicted 0 ) - 809
- False Positives ( Actually 0 and Predicted 0 ) - 553

- **Classification Report**

In [296]:
```
C1=metrics.classification_report(y_test,y_pred)
print("Classification Report : ",C1)
print()

```

```
Classification Report :               precision    recall  f1-score   support

           0       0.83      0.82      0.83      4638
           1       0.41      0.41      0.41      1362

    accuracy                           0.73      6000
   macro avg       0.62      0.62      0.62      6000
weighted avg       0.73      0.73      0.73      6000
```

- **Model Evaluation**

```
from sklearn.metrics import  accuracy_score, f1_score, precision_score, recall_score, roc_auc_score
roc=roc_auc_score(y_test, y_pred)
acc = accuracy_score(y_test, y_pred)
prec = precision_score(y_test, y_pred)
rec = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)
err =(y_pred != y_test).sum()

res= pd.DataFrame([['Decision Tree Classifier', err,acc,prec,rec, f1,roc]],
               columns = ['Model', 'Number of Errors','Accuracy', 'Precision', 'Recall', 'F1 Score','ROC'])
final_report = final_report.append(res, ignore_index = True)
res
```

Out[297]:

| | Model | Number of Errors | Accuracy | Precision | Recall | F1 Score | ROC |
|---|---|---|---|---|---|---|---|
| 0 | Decision Tree Classifier | 1621 | 0.729833 | 0.405128 | 0.406021 | 0.405574 | 0.615473 |

**Model : Decision Tree**
**No. of Errors : 1621**
**Accuracy : 72.9%**

# 6.5 Random Forest Classifier

Random Forest is a popular machine learning algorithm that belongs to the supervised learning technique. It can be used for both Classification and Regression problems in ML. It is based on the concept of ensemble learning, which is a process of combining multiple classifiers to solve a complex problem and to improve the performance of the model.

As the name suggests, "Random Forest is a classifier that contains a number of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset." Instead of relying on one decision tree, the random forest takes the prediction from each tree and based on the majority votes of predictions, and it predicts the final output.

- **Fitting the Model on Train Set**

We instantiate an object of RandomForestClassifier with the required parameters. N_estimators denote the number of tree in the model. Criterion is the function to measure the quality of a split. Supported criteria are “gini” for the Gini impurity and “entropy” for the information gain.

In [316]:
```
from sklearn.ensemble import RandomForestClassifier
rdf = RandomForestClassifier(n_estimators = 100,criterion = 'entropy',random_state = 0)
rdf.fit(X_train, y_train)
```

Out[316]:
```
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None,
                       criterion='entropy', max_depth=None, max_features='auto',
                       max_leaf_nodes=None, max_samples=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=100,
                       n_jobs=None, oob_score=False, random_state=0, verbose=0,
                       warm_start=False)
```

- **Predicting the Model on Test Set and produce Confusion Matrix**

In [299]:
```
y_pred = rdf.predict(X_test)
```

In [300]:
```
CM1 = metrics.confusion_matrix(y_test, y_pred)
print("Confusion Matrix:" "\n",CM1 )
print()
```

```
Confusion Matrix:
 [[4389  249]
 [ 878  484]]
```

The confusion matrix shows that the number of :

- True Positives ( Actually 1 and Predicted 1 ) - 4389
- False Positives ( Actually 0 and Predicted 1 ) - 249
- False Negatives ( Actually 1 and Predicted 0 ) - 878
- False Positives ( Actually 0 and Predicted 0 ) - 484

- **Classification Report**

In [301]:
```
C1=metrics.classification_report(y_test,y_pred)
print("Classification Report : ",C1)
print()
```

```
Classification Report :                precision    recall  f1-score   support

           0       0.83      0.95      0.89      4638
           1       0.66      0.36      0.46      1362

    accuracy                           0.81      6000
   macro avg       0.75      0.65      0.67      6000
weighted avg       0.79      0.81      0.79      6000
```

- **Model Evaluation**

```
from sklearn.metrics import  accuracy_score, f1_score, precision_score, recall_score, roc_auc_score
roc=roc_auc_score(y_test, y_pred)
acc = accuracy_score(y_test, y_pred)
prec = precision_score(y_test, y_pred)
rec = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)
err =(y_pred != y_test).sum()

res= pd.DataFrame([['Random Forest Classifier', err,acc,prec,rec, f1,roc]],
                  columns = ['Model', 'Number of Errors','Accuracy', 'Precision', 'Recall', 'F1 Score','ROC'])
final_report = final_report.append(res, ignore_index = True)
res
```

Out[302]:

| | Model | Number of Errors | Accuracy | Precision | Recall | F1 Score | ROC |
|---|---|---|---|---|---|---|---|
| 0 | Random Forest Classifier | 1127 | 0.812167 | 0.6603 | 0.35536 | 0.462053 | 0.650836 |

**Model : Random Forest**
**No. of Errors : 1127**
**Accuracy : 81.2%**

**This is the final report which depicts the classifier model and the corresponding evaluation metrics like Accuracy, Number of errors, Precision, Recall , F1-score and ROC value.**

| | Model | Accuracy | Number of Errors | Precision | Recall | F1 Score | ROC |
|---|---|---|---|---|---|---|---|
| 0 | Logistic Regression | 0.811833 | 1129 | 0.686998 | 0.314244 | 0.431234 | 0.636100 |
| 1 | K-Nearest Neighbour | 0.800000 | 1200 | 0.636364 | 0.277533 | 0.386503 | 0.615481 |
| 2 | Gaussian Naive Bayes | 0.766000 | 1404 | 0.486607 | 0.560206 | 0.520819 | 0.693320 |
| 3 | Decision Tree Classifier | 0.729833 | 1621 | 0.405128 | 0.406021 | 0.405574 | 0.615473 |
| 4 | Random Forest Classifier | 0.812167 | 1127 | 0.660300 | 0.355360 | 0.462053 | 0.650836 |

# 7 . HyperParameter Tuning

Hyperparameter optimization or tuning is the problem of choosing a set of optimal hyperparameters for a learning algorithm. A hyperparameter is a parameter whose value is used to control the learning process.

Hyperparameters are crucial as they control the overall behaviour of a machine learning model. The ultimate goal is to find an optimal combination of hyperparameters that minimizes a predefined loss function to give better results.

## 7.1 Tuning Logistic Regression Classifier

- **Forming Grid of Parameters and fit the Train Set**

```
[305]: lr_params = {'C': [0.001, 0.01, 0.1, 1, 10], 'class_weight': [None, 'balanced'], 'penalty': ['l1', 'l2']}

[306]: grid_search_log = GridSearchCV(estimator=lr,param_grid=lr_params,scoring='accuracy',cv=10,n_jobs=-1)

[307]: grid_search_log = grid_search_log.fit(X_train,y_train)
```

- **Finding the best accuracy and best set of parameters**

```
In [308]: best_accuracy = grid_search_log.best_score_
          print('Accuracy on Cross Validation set :',best_accuracy)

Accuracy on Cross Validation set : 0.8185416666666667

In [309]: best_parameters = grid_search_log.best_params_
          best_parameters

Out[309]: {'C': 0.1, 'class_weight': None, 'penalty': 'l1'}
```

- **Evaluating model on best parameters**

**Model : Naive Bayes**
**No. of Errors : 1404**
**Accuracy : 76.6%**

# 7.2 Tuning KNN Classifier

- **Forming Grid of Parameters and fit the Train Set**

```
In [311]: k_range = list(range(1, 30 , 3))
          leaf_size = list(range(1,30 , 5))
          weight_options = ['uniform', 'distance']
          knn_param = {'leaf_size': leaf_size, 'weights': weight_options}

In [312]: grid_search_knn = GridSearchCV(estimator = knn,param_grid = knn_param,scoring='accuracy',cv=5,n_jobs=-1)
          grid_search_knn = grid_search_knn.fit(X_train,y_train)
```

- **Finding the best accuracy and best set of parameters**

```
In [313]: best_accuracy = grid_search_knn.best_score_
          print('Accuracy on Cross Validation set :',best_accuracy)

Accuracy on Cross Validation set : 0.8081250000000001

In [314]: best_parameters = grid_search_knn.best_params_
          best_parameters

Out[314]: {'leaf_size': 11, 'weights': 'uniform'}
```

- **Evaluating model on best parameters**

```
y_pred_KNN = grid_search_knn.predict(X_test)
roc=roc_auc_score(y_test, y_pred_KNN)
acc = accuracy_score(y_test, y_pred_KNN)
prec = precision_score(y_test, y_pred_KNN)
rec = recall_score(y_test, y_pred_KNN)
f1 = f1_score(y_test, y_pred_KNN)
err =(y_pred_KNN != y_test).sum()

model =  pd.DataFrame([['KNN Model Tuned',err, acc,prec,rec, f1,roc]],
              columns = ['Model','Number of Errors', 'Accuracy', 'Precision', 'Recall', 'F1 Score','ROC'])
final_report = final_report.append(model, ignore_index = True)
model
```

Out[315]:

| | Model | Number of Errors | Accuracy | Precision | Recall | F1 Score | ROC |
|---|---|---|---|---|---|---|---|
| 0 | KNN Model Tuned | 1200 | 0.8 | 0.636364 | 0.277533 | 0.386503 | 0.615481 |

**Model : Tuned K Nearest Neighbors**
**No. of Errors : 1200**
**Accuracy : 80.0%**

# 7.3 Tuning Naive Bayes Classifier

- **Forming Grid of Parameters and fit the Train Set**
- **Finding the best accuracy and best set of parameters**
- **Evaluating model on best parameters**

# 7.4 Tuning Decision Tree Classifier

- **Forming Grid of Parameters and fit the Train Set**

```
dt_parameters = {'max_depth':[2,4,6,8,10],'min_samples_leaf':[2,4,6,8,10], 'min_samples_split':[2,4,6,8,10]}
grid_search_dt = GridSearchCV(estimator=dt,param_grid=dt_parameters,scoring = 'accuracy',cv=5,n_jobs=-1)
grid_search_dt = grid_search_dt.fit(X_train,y_train)
```

- **Finding the best accuracy and best set of parameters**

In [226]:
```
best_accuracy = grid_search_dt.best_score_
print('Accuracy on Cross Validation set :',best_accuracy)
```

```
Accuracy on Cross Validation set : 0.8212083333333334
```

In [227]:
```
best_parameters = grid_search_dt.best_params_
best_parameters
```

Out[227]:
```
{'max_depth': 4, 'min_samples_leaf': 10, 'min_samples_split': 2}
```

- **Evaluating model on best parameters**

```
y_pred_dct = grid_search_dt.predict(X_test)

roc=roc_auc_score(y_test, y_pred_dct)
acc = accuracy_score(y_test, y_pred_dct)
prec = precision_score(y_test, y_pred_dct)
rec = recall_score(y_test, y_pred_dct)
f1 = f1_score(y_test, y_pred_dct)
err =(y_pred_dct != y_test).sum()

model =  pd.DataFrame([['Decision Tree Tuned',err, acc,prec,rec, f1,roc]],
              columns = ['Model','Number of Errors','Accuracy', 'Precision', 'Recall', 'F1 Score','ROC'])
final_report = final_report.append(model, ignore_index = True)
model
```

Out[228]:

| | Model | Number of Errors | Accuracy | Precision | Recall | F1 Score | ROC |
|---|---|---|---|---|---|---|---|
| 0 | Decision Tree Tuned | 1094 | 0.817667 | 0.710692 | 0.331865 | 0.452452 | 0.646096 |

**Model : Tuned Decision Tree**
**No. of Errors : 1094**
**Accuracy : 81.77%**

# 7.5 Tuning Random Forest Classifier

- **Forming Grid of Parameters and fit the Train Set**

```
param_grid_rf = {'n_estimators': [200, 400, 600, 1000], # It is going to be a long search
              'criterion': ['entropy', 'gini'],
              'class_weight' : ['balanced',None]}
grid_search_rf = GridSearchCV(estimator=rdf,param_grid=param_grid_rf,scoring='accuracy',cv=5,n_jobs=-1)
grid_search_rf = grid_search_rf.fit(X_train,y_train)
```

- **Finding the best accuracy and best set of parameters**

```
best_accuracy = grid_search_rf.best_score_
print('Accuracy on Cross Validation set :',best_accuracy)
```

```
Accuracy on Cross Validation set : 0.8168333333333333
```

```
best_parameters = grid_search_rf.best_params_
best_parameters
```

```
{'class_weight': None, 'criterion': 'gini', 'n_estimators': 400}
```

- **Evaluating model on best parameters**

```
y_pred_rv = grid_search_rf.predict(X_test)

roc=roc_auc_score(y_test, y_pred_rv)
acc = accuracy_score(y_test, y_pred_rv)
prec = precision_score(y_test, y_pred_rv)
rec = recall_score(y_test, y_pred_rv)
f1 = f1_score(y_test, y_pred_rv)
err =(y_pred_rv != y_test).sum()

model =  pd.DataFrame([['Random Forest Tuned',err, acc,prec,rec, f1,roc]],
              columns = ['Model','Number of Errors', 'Accuracy', 'Precision', 'Recall', 'F1 Score','ROC'])
final_report = final_report.append(model, ignore_index = True)
model
```

Out[233]:

| | Model | Number of Errors | Accuracy | Precision | Recall | F1 Score | ROC |
|---|---|---|---|---|---|---|---|
| 0 | Random Forest Tuned | 1119 | 0.8135 | 0.667125 | 0.356094 | 0.464337 | 0.651958 |

**Model : Naive Bayes**
**No. of Errors : 1404**
**Accuracy : 76.6%**

# 8. Comparison of Classifiers

**This is the final report which shows the Model Classifiers along with their corresponding evaluation metrics like accuracy , precision , F-Score etc.**

**Also it shows the evaluation parameters after Tuning each of the Classifiers.**

In [69]:
```
final_report
```

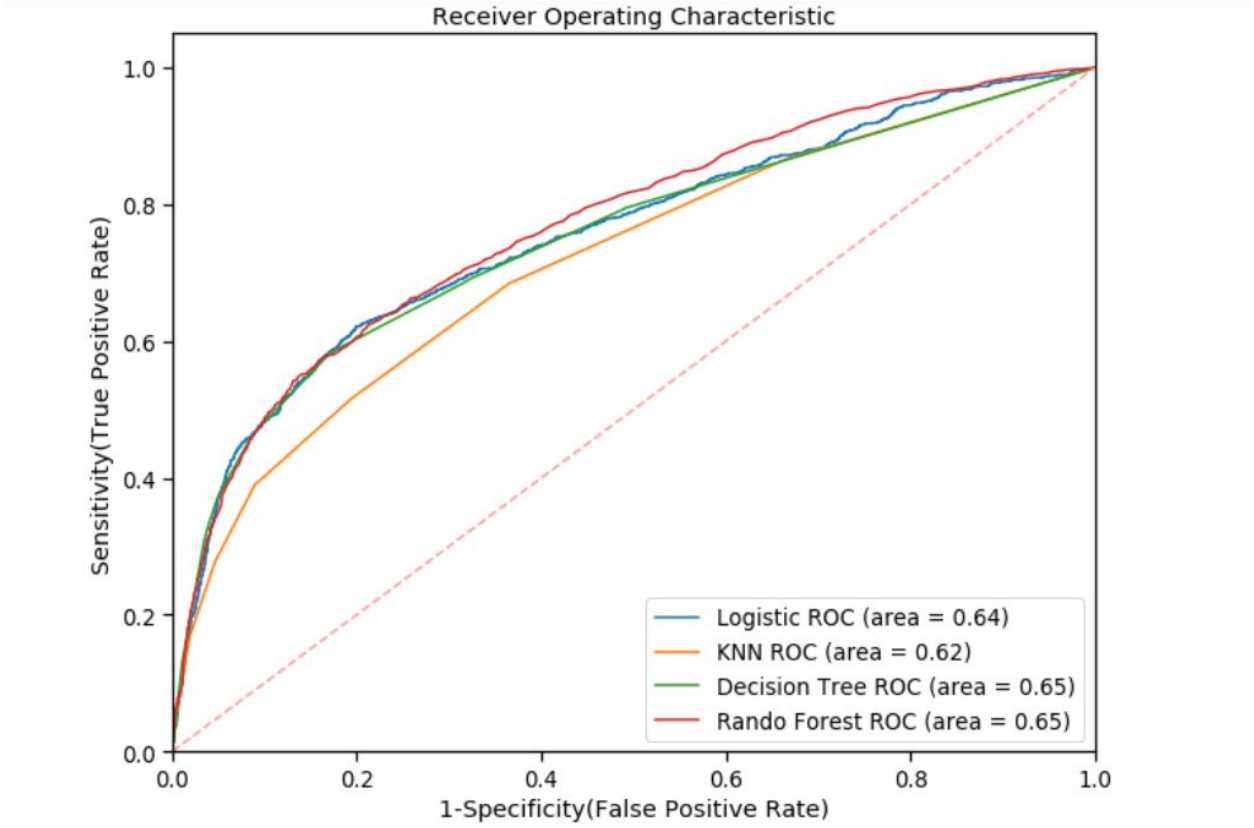
Out[69]:

| | Accuracy | F1 Score | Model | Number of Errors | Precision | ROC | Recall |
|---|---|---|---|---|---|---|---|
| 0 | 0.811833 | 0.431234 | Logistic Regression | 1129 | 0.686998 | 0.636100 | 0.314244 |
| 1 | 0.800000 | 0.386503 | K-Nearest Neighbour | 1200 | 0.636364 | 0.615481 | 0.277533 |
| 2 | 0.766000 | 0.520819 | Gaussian Naive Bayes | 1404 | 0.486607 | 0.693320 | 0.560206 |
| 3 | 0.729833 | 0.405574 | Decision Tree Classifier | 1621 | 0.405128 | 0.615473 | 0.406021 |
| 4 | 0.812167 | 0.462053 | Random Forest Classifier | 1127 | 0.660300 | 0.650836 | 0.355360 |
| 5 | 0.814000 | 0.438632 | Logistic Regression Tuned | 1116 | 0.696486 | 0.639576 | 0.320117 |
| 6 | 0.800000 | 0.386503 | KNN Model Tuned | 1200 | 0.636364 | 0.615481 | 0.277533 |
| 7 | 0.817667 | 0.452452 | Decision Tree Tuned | 1094 | 0.710692 | 0.646096 | 0.331865 |
| 8 | 0.814167 | 0.464200 | Random Forest Tuned | 1115 | 0.671766 | 0.651871 | 0.354626 |

In [235]:
```
y_pred_log_p =grid_search_log.predict_proba(X_test)[:,1]
y_pred_knn_p =grid_search_knn.predict_proba(X_test)[:,1]
y_pred_dt_p =grid_search_dt.predict_proba(X_test)[:,1]
y_pred_rf_p =grid_search_rf.predict_proba(X_test)[:,1]
```

In [237]:
```
model = [grid_search_log,grid_search_knn,grid_search_dt,grid_search_rf]

models=[y_pred_log_p,y_pred_knn_p,y_pred_dt_p,y_pred_rf_p]
label=['Logistic','KNN','Decision Tree','Rando Forest']

# plotting ROC curves
plt.figure(figsize=(10, 8))
m=np.arange(4)
for m in m:
    fpr, tpr,thresholds= metrics.roc_curve(y_test,models[m])
    auc = metrics.roc_auc_score(y_test,model[m].predict(X_test))
    plt.plot(fpr, tpr, label='%s ROC (area = %0.2f)' % (label[m], auc))
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('1-Specificity(False Positive Rate)')
plt.ylabel('Sensitivity(True Positive Rate)')
plt.title('Receiver Operating Characteristic')
plt.legend(loc="lower right")
plt.show()
```

## ROC Curve




An **ROC curve** (**receiver operating characteristic curve**) is a **graph** showing the performance of a classification model at all classification thresholds. This **curve** plots two parameters: True Positive Rate. False Positive Rate.

## Interpretation from ROC Curve

The ROC curve shows the trade-off between sensitivity (or TPR) and specificity (1 – FPR). Classifiers that give curves closer to the top-left corner indicate a better performance. As a baseline, a random classifier is expected to give points lying along the diagonal (FPR = TPR). The closer the curve comes to the 45-degree diagonal of the ROC space, the less accurate the test.

An ROC curve plots TPR vs. FPR at different classification thresholds. Lowering the classification threshold classifies more items as positive, thus increasing both False Positives and True Positives.

**Random Forest and Decision Tree Classifier gives the maximum area under the curve.**