Project Name : - Credit Card Default EDA & FE .

1) Problem statement .

- This dataset comprises of Credit Card Default Dataset taken from Kaggle .
- Link of the dataset is as follows :- https://www.kaggle.com/datasets/uciml/default-of-credit-card-clients-dataset .

2) Data Collection.

- This dataset comprises of Flight Fare data taken from Kaggle
- The data consists of 25 column and 30,000 rows.

2.1 Import Data and Required Packages

Importing Necessary Libraries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
pd.set_option("display.max_columns", None)
import warnings
warnings.filterwarnings("ignore", category=FutureWarning)
%matplotlib inline
```

Loading the Credit Card Default DataSet

In [2]:
```
df=pd.read_csv("UCI_Credit_Card.csv")
```

In [3]:
```
df
```

Out[3]:

	ID	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	PAY_5	PAY_6	BILL_A
0	1	20000.0	2	2	1	24	2	2	-1	-1	-2	-2	39
1	2	120000.0	2	2	2	26	-1	2	0	0	0	2	26
2	3	90000.0	2	2	2	34	0	0	0	0	0	0	292
3	4	50000.0	2	2	1	37	0	0	0	0	0	0	469
4	5	50000.0	1	2	1	57	-1	0	-1	0	0	0	86
...	...	...	...	...	...	...	...	...	...	...	...	...	
29995	29996	220000.0	1	3	1	39	0	0	0	0	0	0	1889
29996	29997	150000.0	1	3	2	43	-1	-1	-1	-1	0	0	16
29997	29998	30000.0	1	2	2	37	4	3	2	-1	0	0	35
29998	29999	80000.0	1	3	1	41	1	-1	0	0	0	-1	-16

	ID	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	PAY_5	PAY_6	BILL_A
29999	30000	50000.0	1	2	1	46	0	0	0	0	0	0	479

30000 rows × 25 columns

About Dataset

Dataset Information 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.

Content

There are 25 variables:

ID: ID of each client .

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

SEX: Gender (1=male, 2=female) .

EDUCATION: (1=graduate school, 2=university, 3=high school, 4=others, 5=unknown, 6=unknown) .

MARRIAGE: Marital status (1=married, 2=single, 3=others) .

AGE: Age in years .

PAY_1: Repayment status in September, 2005 (-2= no credit to pay,-1=pay duly,0= minimum payment is met, 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) .

PAY_2: Repayment status in August, 2005 (scale same as above) .

PAY_3: Repayment status in July, 2005 (scale same as above) .

PAY_4: Repayment status in June, 2005 (scale same as above) .

PAY_5: Repayment status in May, 2005 (scale same as above) .

PAY_6: Repayment status in April, 2005 (scale same as above) .

BILL_AMT1: Amount of bill statement in September, 2005 (NT dollar) .

BILL_AMT2: Amount of bill statement in August, 2005 (NT dollar) .

BILL_AMT3: Amount of bill statement in July, 2005 (NT dollar) .

BILL_AMT4: Amount of bill statement in June, 2005 (NT dollar) .

BILL_AMT5: Amount of bill statement in May, 2005 (NT dollar) .

BILL_AMT6: Amount of bill statement in April, 2005 (NT dollar) .

PAY_AMT1: Amount of previous payment in September, 2005 (NT dollar) .

PAY_AMT2: Amount of previous payment in August, 2005 (NT dollar) .

PAY_AMT3: Amount of previous payment in July, 2005 (NT dollar) .

PAY_AMT4: Amount of previous payment in June, 2005 (NT dollar) .

PAY_AMT5: Amount of previous payment in May, 2005 (NT dollar) .

PAY_AMT6: Amount of previous payment in April, 2005 (NT dollar) .

default.payment.next.month: Default payment (1=yes, 0=no) .

In [ ]:

```

```

There are categorical columns which are encoded as Follows

SEX: Gender

```
1 = Male
2 = Female
```

EDUCATION:

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

MARRIAGE: Marital status

```
1 = married
2 = single
3 = others
```

PAY_1,2,3,4,5,6: Repayment status in September 2005, August 2005, July 2005, June 2005, May 2005, April 2005 (respectivey)

```
-2= no credit to pay
-1= pay duly
0= minimum payment is met
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
```

Data Cleaning

In [4]:

```
#Dropping the Id column as it will be of no use to us in further EDA & Model Building
```

In [5]:

```
df.drop('ID',axis=1,inplace=True)
```

In [6]:

```
df.rename(columns={"PAY_0":"PAY_1",'default.payment.next.month':'defaulter_or_not'},inplac
```

Shape of the DataSet

In [7]:

```
df.shape
```

Out[7]:

```
(30000, 24)
```

Summary of the DataSet

In [8]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30000 entries, 0 to 29999
Data columns (total 24 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   LIMIT_BAL         30000 non-null  float64
 1   SEX               30000 non-null  int64
 2   EDUCATION         30000 non-null  int64
 3   MARRIAGE          30000 non-null  int64
 4   AGE               30000 non-null  int64
 5   PAY_1             30000 non-null  int64
 6   PAY_2             30000 non-null  int64
 7   PAY_3             30000 non-null  int64
 8   PAY_4             30000 non-null  int64
 9   PAY_5             30000 non-null  int64
 10  PAY_6             30000 non-null  int64
 11  BILL_AMT1         30000 non-null  float64
 12  BILL_AMT2         30000 non-null  float64
 13  BILL_AMT3         30000 non-null  float64
 14  BILL_AMT4         30000 non-null  float64
 15  BILL_AMT5         30000 non-null  float64
 16  BILL_AMT6         30000 non-null  float64
 17  PAY_AMT1          30000 non-null  float64
 18  PAY_AMT2          30000 non-null  float64
 19  PAY_AMT3          30000 non-null  float64
 20  PAY_AMT4          30000 non-null  float64
 21  PAY_AMT5          30000 non-null  float64
 22  PAY_AMT6          30000 non-null  float64
 23  defaulter_or_not  30000 non-null  int64
dtypes: float64(13), int64(11)
memory usage: 5.5 MB
```

In [9]:

```
df.describe()
```

Out[9]:

	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_1	PAY_2	P
count	30000.000000	30000.000000	30000.000000	30000.000000	30000.000000	30000.000000	30000.000000	30000.00
mean	167484.322667	1.603733	1.853133	1.551867	35.485500	-0.016700	-0.133767	-0.16
std	129747.661567	0.489129	0.790349	0.521970	9.217904	1.123802	1.197186	1.19
min	10000.000000	1.000000	0.000000	0.000000	21.000000	-2.000000	-2.000000	-2.00
25%	50000.000000	1.000000	1.000000	1.000000	28.000000	-1.000000	-1.000000	-1.00

	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_1	PAY_2	I
50%	140000.000000	2.000000	2.000000	2.000000	34.000000	0.000000	0.000000	0.0(
75%	240000.000000	2.000000	2.000000	2.000000	41.000000	0.000000	0.000000	0.0(
max	1000000.000000	2.000000	6.000000	3.000000	79.000000	8.000000	8.000000	8.0(

In [10]:

```
df.isnull().sum()
```

Out[10]:

```
LIMIT_BAL          0
SEX                0
EDUCATION          0
MARRIAGE           0
AGE                0
PAY_1              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
defaulter_or_not   0
dtype: int64
```

Proportion of count data for each columns

In [11]:

```
for col in df:
    print(df[col ].value_counts(normalize=True)*100)
    print('----------------------------')
```

```
50000.0      11.216667
20000.0       6.586667
30000.0       5.366667
80000.0       5.223333
200000.0      5.093333
                ...
730000.0      0.006667
1000000.0     0.003333
327680.0      0.003333
760000.0      0.003333
690000.0      0.003333
Name: LIMIT_BAL, Length: 81, dtype: float64
----------------------------
2    60.373333
1    39.626667
Name: SEX, dtype: float64
----------------------------
2    46.766667
1    35.283333
3    16.390000
5     0.933333
4     0.410000
```

```
6     0.170000
0     0.046667
Name: EDUCATION, dtype: float64
----------------------------
2    53.213333
1    45.530000
3     1.076667
0     0.180000
Name: MARRIAGE, dtype: float64
----------------------------
29    5.350000
27    4.923333
28    4.696667
30    4.650000
26    4.186667
31    4.056667
25    3.953333
34    3.873333
32    3.860000
33    3.820000
24    3.756667
35    3.710000
36    3.693333
37    3.470000
39    3.180000
38    3.146667
23    3.103333
40    2.900000
41    2.746667
42    2.646667
44    2.333333
43    2.233333
45    2.056667
46    1.900000
22    1.866667
47    1.670000
48    1.553333
49    1.506667
50    1.370000
51    1.133333
53    1.083333
52    1.013333
54    0.823333
55    0.696667
56    0.593333
58    0.406667
57    0.406667
59    0.276667
60    0.223333
21    0.223333
61    0.186667
62    0.146667
63    0.103333
64    0.103333
66    0.083333
65    0.080000
67    0.053333
69    0.050000
70    0.033333
68    0.016667
73    0.013333
72    0.010000
75    0.010000
71    0.010000
79    0.003333
74    0.003333
```

```
Name: AGE, dtype: float64
----------------------------
 0    49.123333
-1    18.953333
 1    12.293333
-2     9.196667
 2     8.890000
 3     1.073333
 4     0.253333
 5     0.086667
 8     0.063333
 6     0.036667
 7     0.030000
Name: PAY_1, dtype: float64
----------------------------
 0    52.433333
-1    20.166667
 2    13.090000
-2    12.606667
 3     1.086667
 4     0.330000
 1     0.093333
 5     0.083333
 7     0.066667
 6     0.040000
 8     0.003333
Name: PAY_2, dtype: float64
----------------------------
 0    52.546667
-1    19.793333
-2    13.616667
 2    12.730000
 3     0.800000
 4     0.253333
 7     0.090000
 6     0.076667
 5     0.070000
 1     0.013333
 8     0.010000
Name: PAY_3, dtype: float64
----------------------------
 0    54.850000
-1    18.956667
-2    14.493333
 2    10.530000
 3     0.600000
 4     0.230000
 7     0.193333
 5     0.116667
 6     0.016667
 1     0.006667
 8     0.006667
Name: PAY_4, dtype: float64
----------------------------
 0    56.490000
-1    18.463333
-2    15.153333
 2     8.753333
 3     0.593333
 4     0.280000
 7     0.193333
 5     0.056667
 6     0.013333
 8     0.003333
Name: PAY_5, dtype: float64
----------------------------
```

```
 0    54.286667
-1    19.133333
-2    16.316667
 2     9.220000
 3     0.613333
 4     0.163333
 7     0.153333
 6     0.063333
 5     0.043333
 8     0.006667
Name: PAY_6, dtype: float64
----------------------------
0.0         6.693333
390.0       0.813333
780.0       0.253333
326.0       0.240000
316.0       0.210000
              ...
11636.0     0.003333
146034.0    0.003333
20817.0     0.003333
1351.0      0.003333
47929.0     0.003333
Name: BILL_AMT1, Length: 22723, dtype: float64
----------------------------
0.0        8.353333
390.0      0.770000
326.0      0.250000
780.0      0.250000
316.0      0.240000
             ...
26357.0    0.003333
85195.0    0.003333
6889.0     0.003333
11004.0    0.003333
48905.0    0.003333
Name: BILL_AMT2, Length: 22346, dtype: float64
----------------------------
0.0         9.566667
390.0       0.916667
780.0       0.246667
326.0       0.210000
316.0       0.206667
              ...
19580.0     0.003333
45129.0     0.003333
227807.0    0.003333
39330.0     0.003333
49764.0     0.003333
Name: BILL_AMT3, Length: 22026, dtype: float64
----------------------------
0.0         10.650000
390.0        0.820000
780.0        0.336667
316.0        0.226667
326.0        0.206667
              ...
97189.0      0.003333
118839.0     0.003333
23567.0      0.003333
18377.0      0.003333
36535.0      0.003333
Name: BILL_AMT4, Length: 21548, dtype: float64
----------------------------
0.0        11.686667
390.0       0.783333
```

```
780.0       0.313333
316.0       0.263333
326.0       0.206667
              ...
19341.0     0.003333
66726.0     0.003333
80682.0     0.003333
28508.0     0.003333
32428.0     0.003333
Name: BILL_AMT5, Length: 21010, dtype: float64
----------------------------
0.0         13.400000
390.0        0.690000
780.0        0.286667
150.0        0.260000
316.0        0.256667
               ...
26852.0      0.003333
108660.0     0.003333
480.0        0.003333
15298.0      0.003333
15313.0      0.003333
Name: BILL_AMT6, Length: 20604, dtype: float64
----------------------------
0.0        17.496667
2000.0      4.543333
3000.0      2.970000
5000.0      2.326667
1500.0      1.690000
              ...
3391.0      0.003333
7785.0      0.003333
66022.0     0.003333
10121.0     0.003333
85900.0     0.003333
Name: PAY_AMT1, Length: 7943, dtype: float64
----------------------------
0.0        17.986667
2000.0      4.300000
3000.0      2.856667
5000.0      2.390000
1000.0      1.980000
              ...
7866.0      0.003333
6206.0      0.003333
10529.0     0.003333
21300.0     0.003333
3526.0      0.003333
Name: PAY_AMT2, Length: 7899, dtype: float64
----------------------------
0.0        19.893333
2000.0      4.283333
1000.0      3.676667
3000.0      2.900000
5000.0      2.403333
              ...
5102.0      0.003333
5368.0      0.003333
28138.0     0.003333
549.0       0.003333
25128.0     0.003333
Name: PAY_AMT3, Length: 7518, dtype: float64
----------------------------
0.0        21.360000
1000.0      4.646667
2000.0      4.046667
```

```
3000.0      2.956667
5000.0      2.700000
              ...
18916.0     0.003333
3468.0      0.003333
11476.0     0.003333
4363.0      0.003333
8049.0      0.003333
Name: PAY_AMT4, Length: 6937, dtype: float64
----------------------------
0.0        22.343333
1000.0      4.466667
2000.0      4.410000
3000.0      3.156667
5000.0      2.713333
              ...
9111.0      0.003333
16496.0     0.003333
4819.0      0.003333
10078.0     0.003333
52964.0     0.003333
Name: PAY_AMT5, Length: 6897, dtype: float64
----------------------------
0.0        23.910000
1000.0      4.330000
2000.0      4.316667
3000.0      3.046667
5000.0      2.693333
              ...
7329.0      0.003333
6862.0      0.003333
6525.0      0.003333
11894.0     0.003333
16080.0     0.003333
Name: PAY_AMT6, Length: 6939, dtype: float64
----------------------------
0    77.88
1    22.12
Name: defaulter_or_not, dtype: float64
----------------------------
```

Categorical Features

Univariate Analysis

- The term univariate analysis refers to the analysis of one variable prefix “uni” means “one.” The purpose of univariate analysis is to understand the distribution of values for a single variable.

Multivariate Analysis

Check Multicollinearity for Categorical features

- Multivariate analysis is the analysis of more than one variable.

- **A chi-squared test (also chi-square or χ2 test) is a statistical hypothesis test that is valid to perform when the test statistic is chi-squared distributed under the null hypothesis, specifically Pearson's chi-squared test**

- **A chi-square statistic is one way to show a relationship between two categorical variables.**
- **Here we test correlation of Categorical columns with Target column i.e defaulter_or_not**

In [12]:

```
categorical_features=[i for i in df[['SEX', 'EDUCATION', 'MARRIAGE', 'PAY_1', 'PAY_2', 'PA
                'PAY_5', 'PAY_6']]]
```

In [13]:

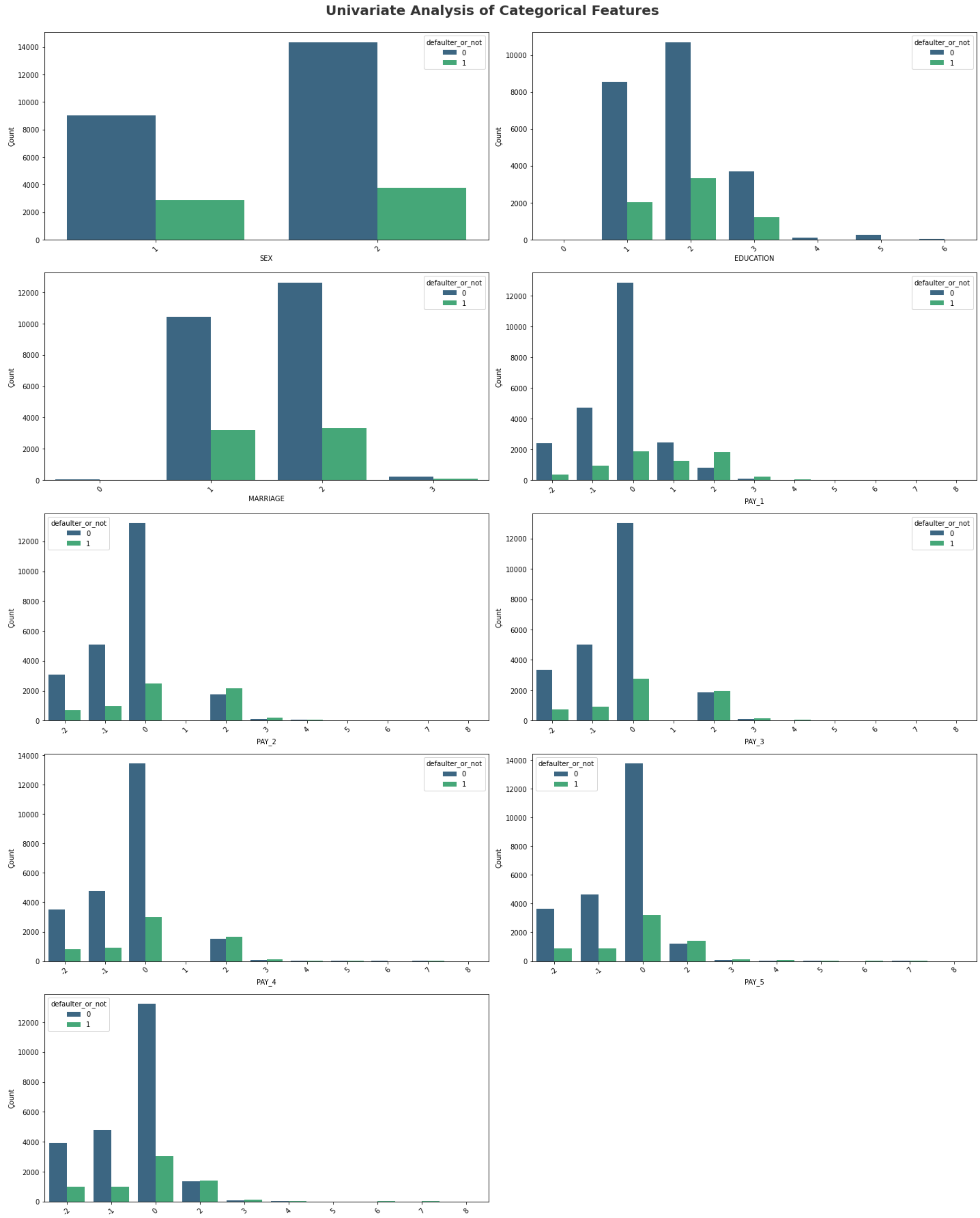
```
from scipy.stats import chi2_contingency
chi2_test=[]
for feature in categorical_features:
    if chi2_contingency(pd.crosstab(df['defaulter_or_not'],df[feature]))[1] <0.05:
        chi2_test.append('Rejet Null Hypothesis')
    else:
        chi2_test.append('Fail to Reject Null Hypothesis')
result=pd.DataFrame(data=[categorical_features,chi2_test]).T
result.columns=['Column','Hypothesis Result']
result
```

Out[13]:

	Column	Hypothesis Result
0	SEX	Rejet Null Hypothesis
1	EDUCATION	Rejet Null Hypothesis
2	MARRIAGE	Rejet Null Hypothesis
3	PAY_1	Rejet Null Hypothesis
4	PAY_2	Rejet Null Hypothesis
5	PAY_3	Rejet Null Hypothesis
6	PAY_4	Rejet Null Hypothesis
7	PAY_5	Rejet Null Hypothesis
8	PAY_6	Rejet Null Hypothesis

In [14]:

```
plt.figure(figsize=(20,25))
plt.suptitle('Univariate Analysis of Categorical Features', fontsize=20, fontweight='bold'
categorical = [ 'SEX', 'EDUCATION', 'MARRIAGE', 'PAY_1', 'PAY_2', 'PAY_3', 'PAY_4',
               'PAY_5', 'PAY_6']
for i in range(0, len(categorical)):
    plt.subplot(5,2,i+1)
    sns.countplot(x=df[categorical[i]],hue=df['defaulter_or_not'],palette='viridis')
    plt.xlabel(categorical[i])
    plt.ylabel('Çount')
    plt.xticks(rotation=45)
    plt.tight_layout()
```



Meaning of X axis numeric values is given below:-

SEX: Gender

1 = Male
2 = Female

EDUCATION:

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

MARRIAGE: Marital status

1 = married 2 = single 3 = others

PAY_1,2,3,4,5,6: Repayment status in September 2005, August 2005, July 2005, June 2005, May 2005, April 2005 (respectivey)

-2= no credit to pay

-1= pay duly

0 = minimum payment is met

1 = payment delay for one month

2 = payment delay for two months

3 = payment delay for three months

4 = payment delay for four months

5 = payment delay for five months

6 = payment delay for six months

7 = payment delay for seven months

8 = payment delay for eight months

9 = payment delay for nine months and above

Defaulter or not

0 = Non Defaulters

1 = Defauters

Visualizing the Data

Limit Balance

In [15]:

```
df["LIMIT_BAL"].value_counts()
```

Out[15]:

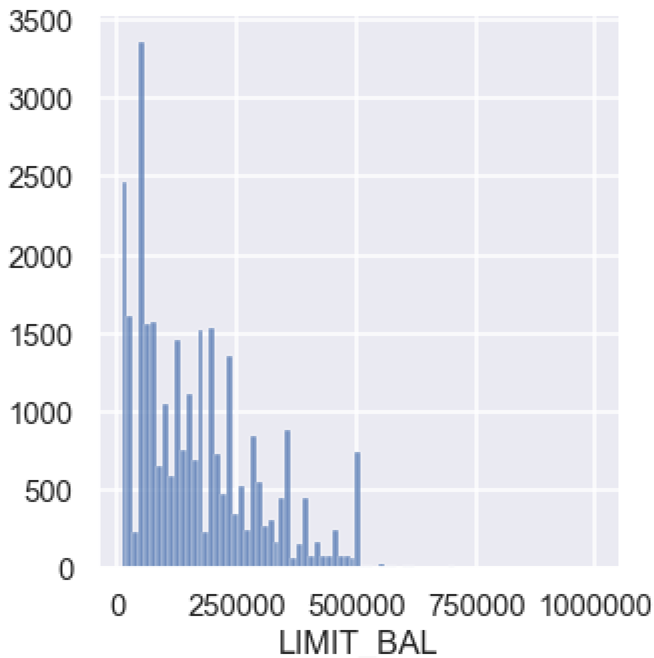
```
50000.0      3365
20000.0      1976
30000.0      1610
80000.0      1567
```

```
200000.0     1528
             ...
730000.0        2
1000000.0       1
327680.0        1
760000.0        1
690000.0        1
Name: LIMIT_BAL, Length: 81, dtype: int64
```

In [16]:

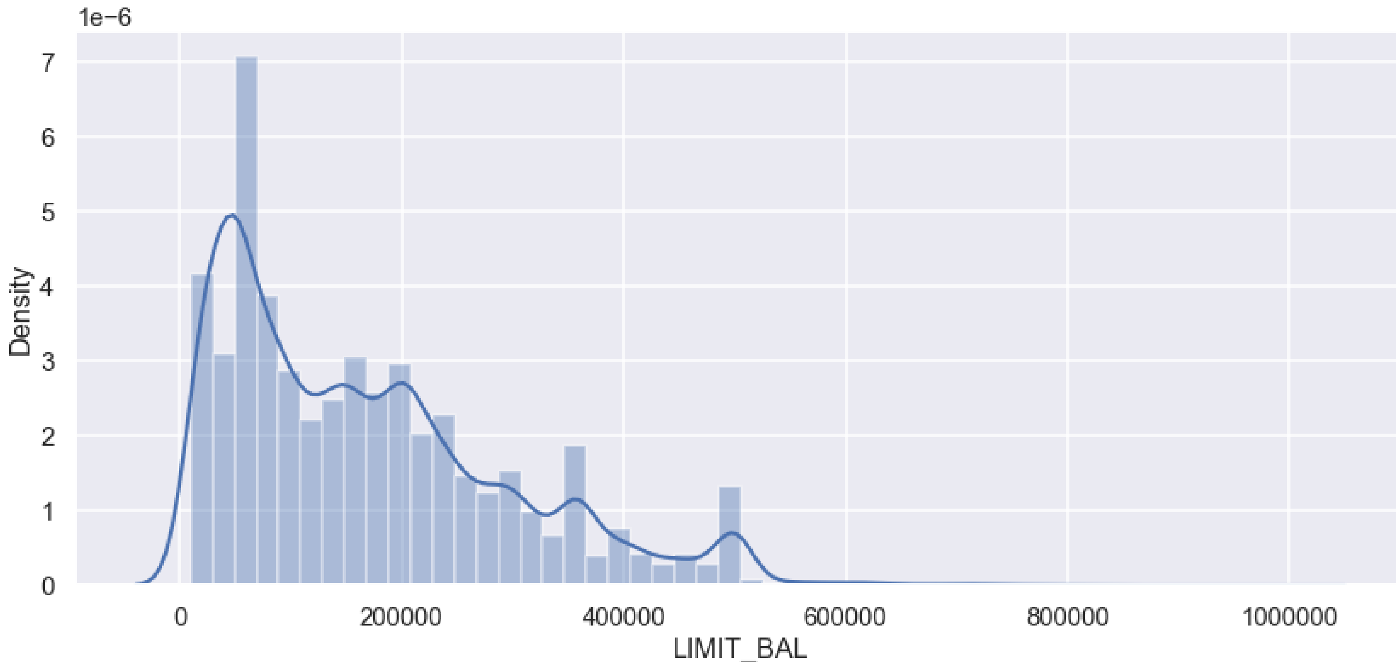
```
sns.set(rc={'figure.figsize' : (15,15)})
sns.set_context('talk',font_scale=0.9)
plt.figure(figsize=(14,4))
sns.displot(df['LIMIT_BAL'])
plt.ticklabel_format(style='plain',axis='x')
plt.ylabel('')
plt.show()
```

```
<Figure size 1008x288 with 0 Axes>
```

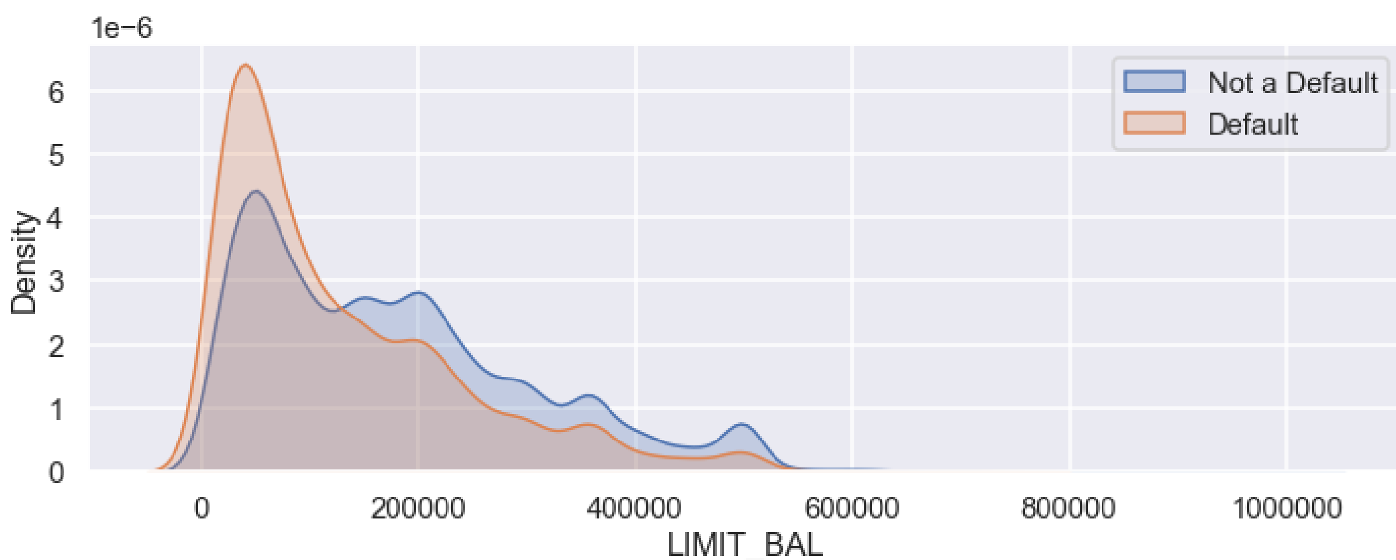


In [17]:

```
plt.figure(figsize=(14,6))
sns.distplot(df['LIMIT_BAL'])
plt.ticklabel_format(style='plain', axis='x')
plt.show()
```

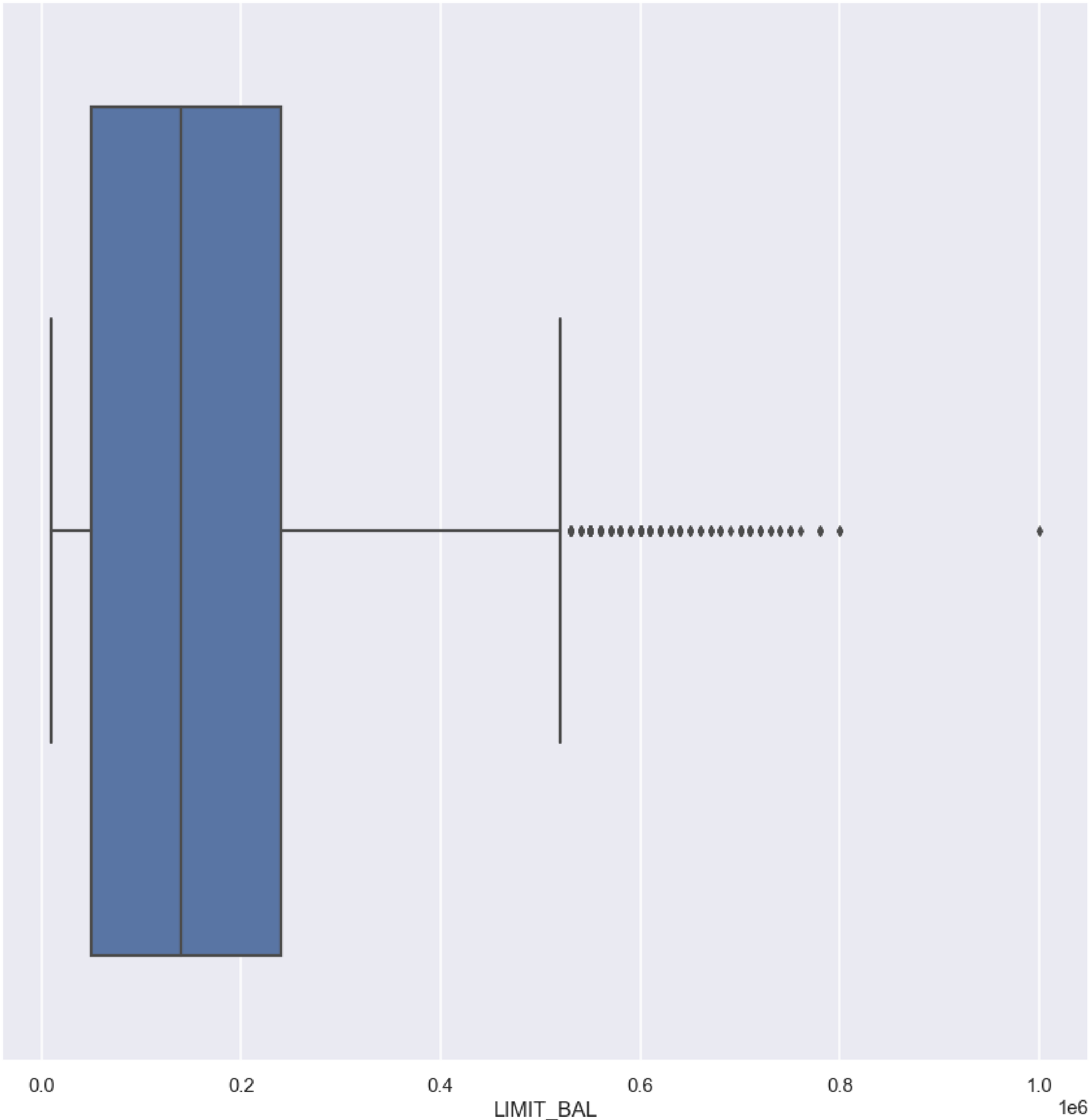


In [18]:
```
plt.figure(figsize=(12,4))
sns.kdeplot(df.loc[(df['defaulter_or_not'] == 0),"LIMIT_BAL"],label="Not a Default" ,shade
sns.kdeplot(df.loc[(df['defaulter_or_not'] == 1),"LIMIT_BAL"],label="Default" ,shade=True)
plt.ticklabel_format(style='plain', axis='x')
plt.legend()
plt.show()
```



In [19]:
```
sns.boxplot(df["LIMIT_BAL"])
```

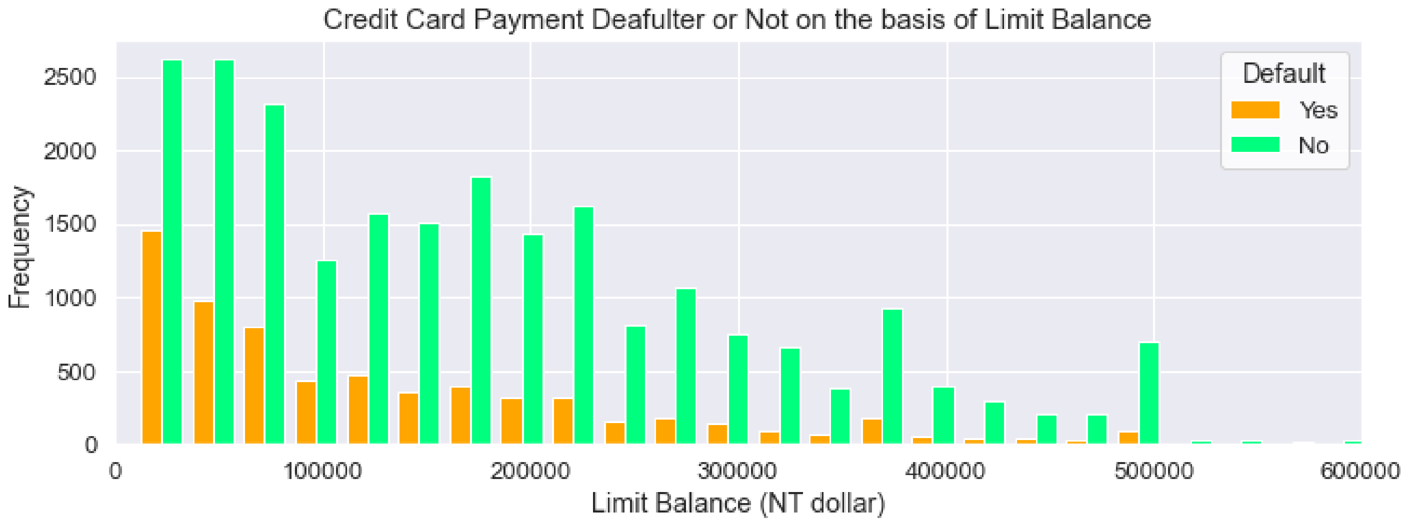
Out[19]: <AxesSubplot:xlabel='LIMIT_BAL'>



In [20]:

```
defaulter = list(df[df['defaulter_or_not'] == 1]['LIMIT_BAL'])
non_defaulter = list(df[df['defaulter_or_not'] == 0]['LIMIT_BAL'])

plt.figure(figsize=(12,4))
sns.set_context('notebook', font_scale=1.2)
plt.hist([defaulter, non_defaulter], bins = 40, color=['orange', 'springgreen'])
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('Credit Card Payment Deafulter or Not on the basis of Limit Balance', size=15)
plt.show()
#plt.box(False)
#plt.savefig('ImageName', format='png', dpi=200, transparent=True)
```



In [21]:

```
print(df["LIMIT_BAL"].max())
print(df["LIMIT_BAL"].min())
```

```
1000000.0
10000.0
```

In [22]:

```
df['bin_limit']=pd.cut(df['LIMIT_BAL'],bins=[10000,100000,200000,300000,400000,500000,600(
```

In [23]:

```
df['bin_limit'].value_counts()
```

Out[23]:

```
(10000, 100000]       12005
(100000, 200000]       7880
(200000, 300000]       5059
(300000, 400000]       2759
(400000, 500000]       1598
(500000, 600000]        127
(600000, 700000]         56
(700000, 800000]         22
(900000, 1000000]         1
(800000, 900000]          0
Name: bin_limit, dtype: int64
```

In [24]:

```
df.head()
```

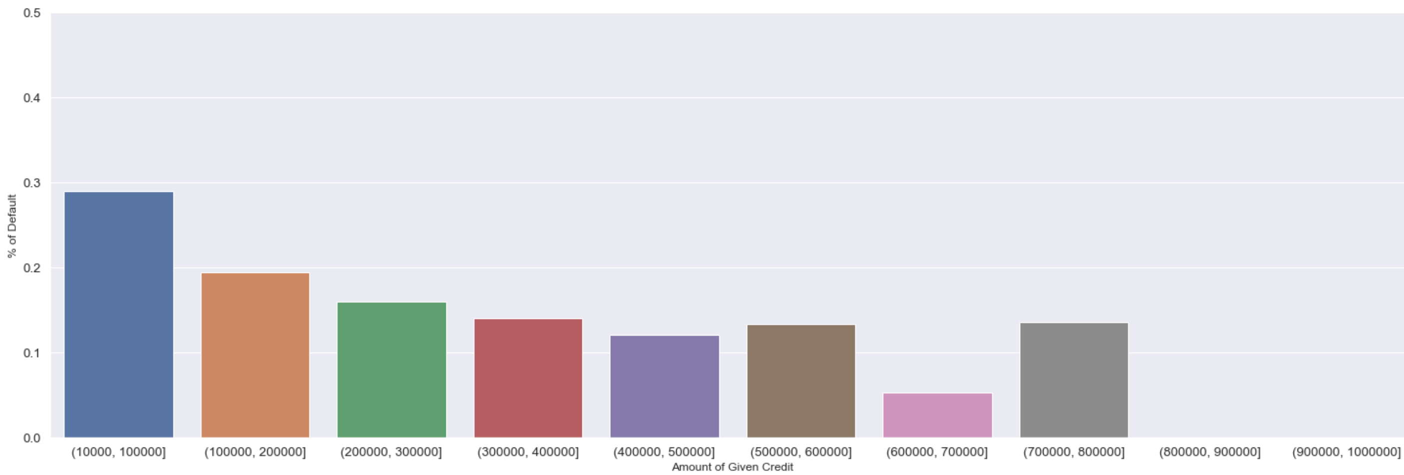
Out[24]:

	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_1	PAY_2	PAY_3	PAY_4	PAY_5	PAY_6	BILL_AMT1	BILL_A
0	20000.0	2	2	1	24	2	2	-1	-1	-2	-2	3913.0	3
1	120000.0	2	2	2	26	-1	2	0	0	0	2	2682.0	1
2	90000.0	2	2	2	34	0	0	0	0	0	0	29239.0	14
3	50000.0	2	2	1	37	0	0	0	0	0	0	46990.0	48
4	50000.0	1	2	1	57	-1	0	-1	0	0	0	8617.0	5

In [25]:

```
plt.figure(figsize=(25,8))
sns.barplot(x=df["bin_limit"],y=df["defaulter_or_not"]==1, ci = None)
```

```
plt.xlabel("Amount of Given Credit", fontsize= 12)
plt.ylabel("% of Default", fontsize= 12)
plt.ylim(0,0.5)
plt.show()
```



Conclusion:-

- 30% of Credit Card Holders are Deafault whose Limit is Below 1 Lakh .
- Credit Card holders with Limit below 1,00,000 has higher default as compared to Credit Card holders having a limit balance beyond Rs 1,00,000 .

SEX

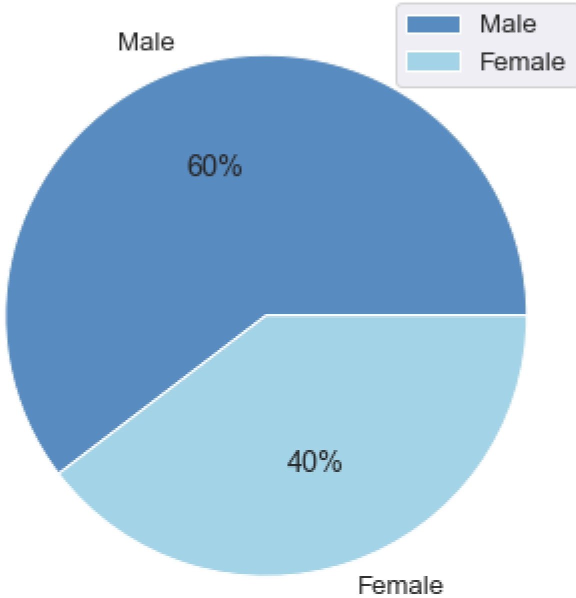
In [26]:
```
df['SEX'].value_counts(normalize=True)
```

Out[26]:
```
2    0.603733
1    0.396267
Name: SEX, dtype: float64
```

In [27]:
```
df['defaulter_or_not'].groupby(df['SEX']).value_counts(normalize=True)
```

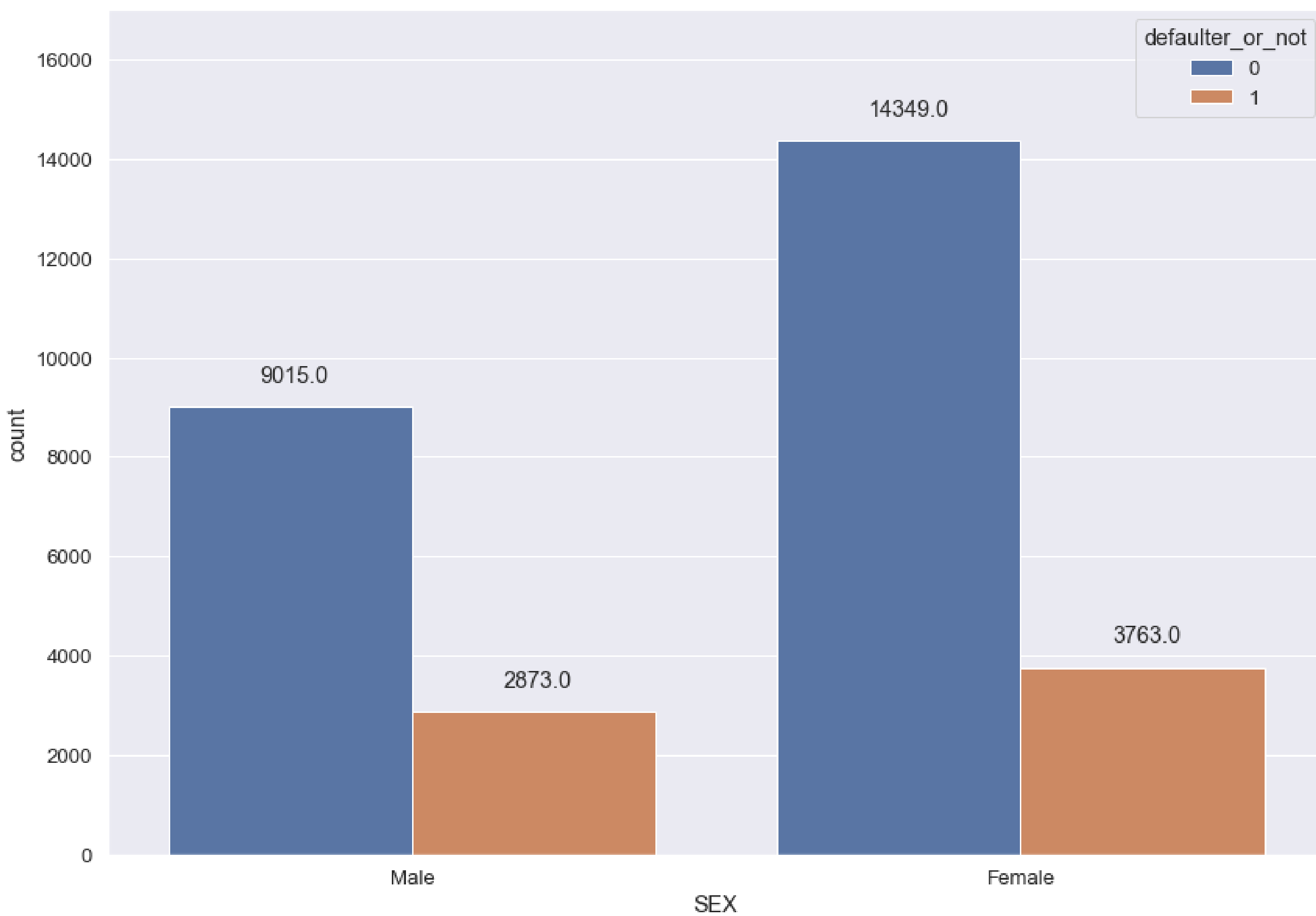
Out[27]:
```
SEX  defaulter_or_not
1    0                   0.758328
     1                   0.241672
2    0                   0.792237
     1                   0.207763
Name: defaulter_or_not, dtype: float64
```

In [28]:
```
plt.figure(figsize = (15,6))
palette_color = sns.color_palette('RdYlBu_r')
keys=['Male','Female']
plt.pie(df["SEX"].value_counts(), labels=keys, colors=palette_color, autopct='%.0f%%')
plt.legend()
plt.show()
```



In [29]:

```
plt.figure(figsize=(14,10))
ax=sns.countplot('SEX',data=df,hue='defaulter_or_not')
plt.xticks(ticks=[1,0],labels=['Female','Male'])
plt.ylim(0,17000)
for i in ax.patches:
    ax.annotate('{:.1f}'.format(i.get_height()),(i.get_x()+0.15,i.get_height()+500))
plt.show()
```



Conclusion:-

- 60% Credit Card Holders are Male & 40% Credit Card Holders are Female .
- Female Defaulters are marginally high as compares to male .

Education

In [30]:
```
#(1=graduate school, 2=university, 3=high school, 4=others, 5=unknown, 6=unknown)
df['EDUCATION'].value_counts()
```

Out[30]:
```
2    14030
1    10585
3     4917
5      280
4      123
6       51
0       14
Name: EDUCATION, dtype: int64
```

Since 5 is representing unknown education & 6 is also representing unknown education,so we will replace 6 with 5,and also as we do not have any information about 0,so we will be replacing also it with 5

In [31]:
```
df.loc[:,'EDUCATION']=df.loc[:,'EDUCATION'].replace(0,5)
df.loc[:,'EDUCATION']=df.loc[:,'EDUCATION'].replace(6,5)
```

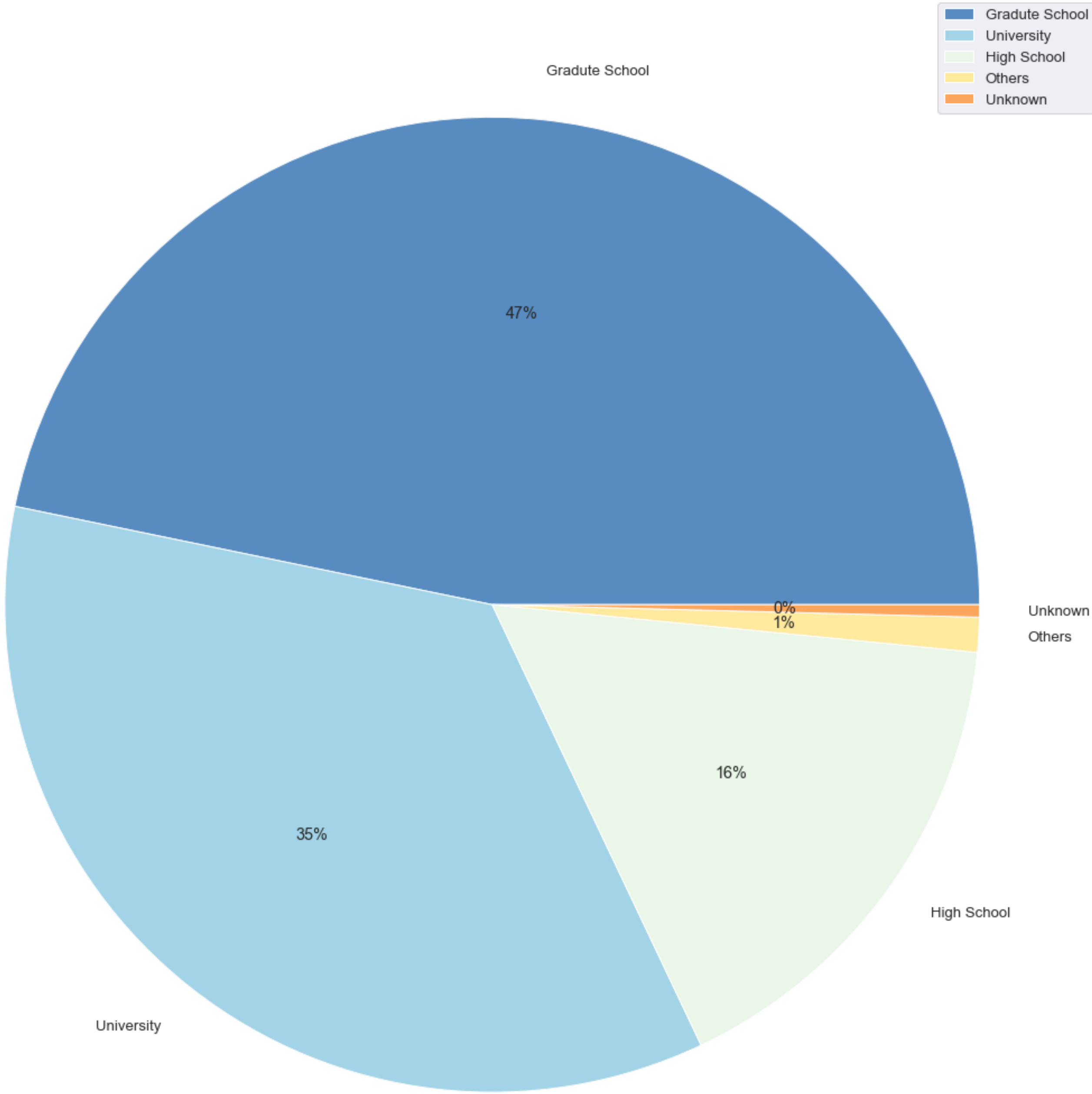
In [32]:
```
df['EDUCATION'].value_counts()
```

Out[32]:
```
2    14030
1    10585
3     4917
5      345
4      123
Name: EDUCATION, dtype: int64
```

In [33]:
```
df['defaulter_or_not'].groupby(df['EDUCATION']).value_counts()
```

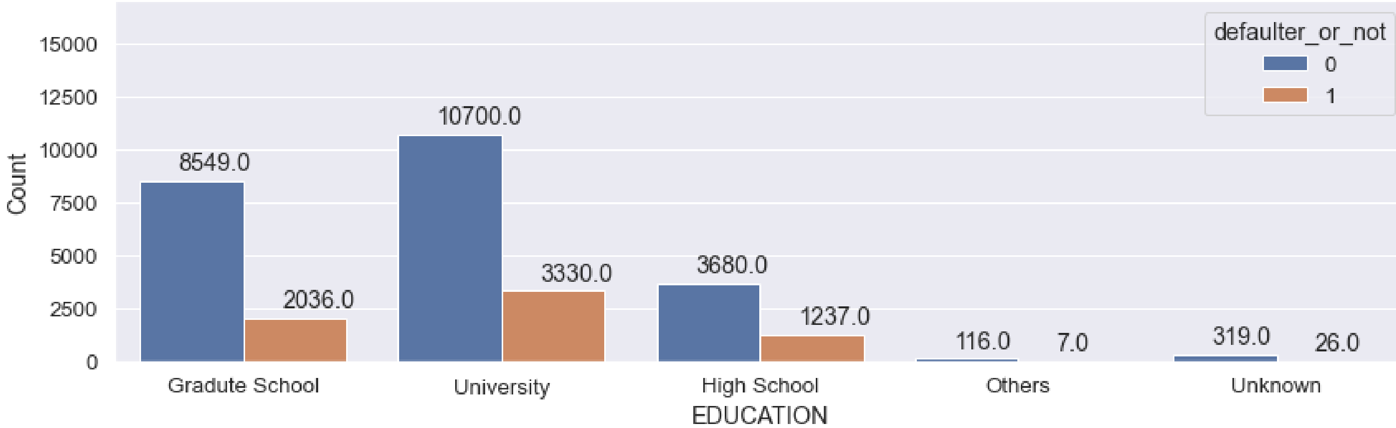
Out[33]:
```
EDUCATION  defaulter_or_not
1          0                    8549
           1                    2036
2          0                   10700
           1                    3330
3          0                    3680
           1                    1237
4          0                     116
           1                       7
5          0                     319
           1                      26
Name: defaulter_or_not, dtype: int64
```

In [34]:
```
plt.figure(figsize = (20,20))
palette_color = sns.color_palette('RdYlBu_r')
keys=['Gradute School','University','High School','Others','Unknown']
plt.pie(df["EDUCATION"].value_counts(), labels=keys, colors=palette_color, autopct='%.0f%%
plt.legend()
plt.show()
```



In [35]:

```
plt.figure(figsize=(14,4))
ax=sns.countplot("EDUCATION",data=df,hue='defaulter_or_not')
plt.xticks(ticks=[1,0,2,3,4],labels=['University','Gradute School','High School','Others',
plt.ylabel('Count')
plt.ylim(0,17000)
for i in ax.patches:
    ax.annotate('{:.1f}'.format(i.get_height()),(i.get_x()+0.15,i.get_height()+500))
plt.show()
#(1=graduate school, 2=university, 3=high school, 4=others, 5=unknown, 6=unknown)
```



In [36]:

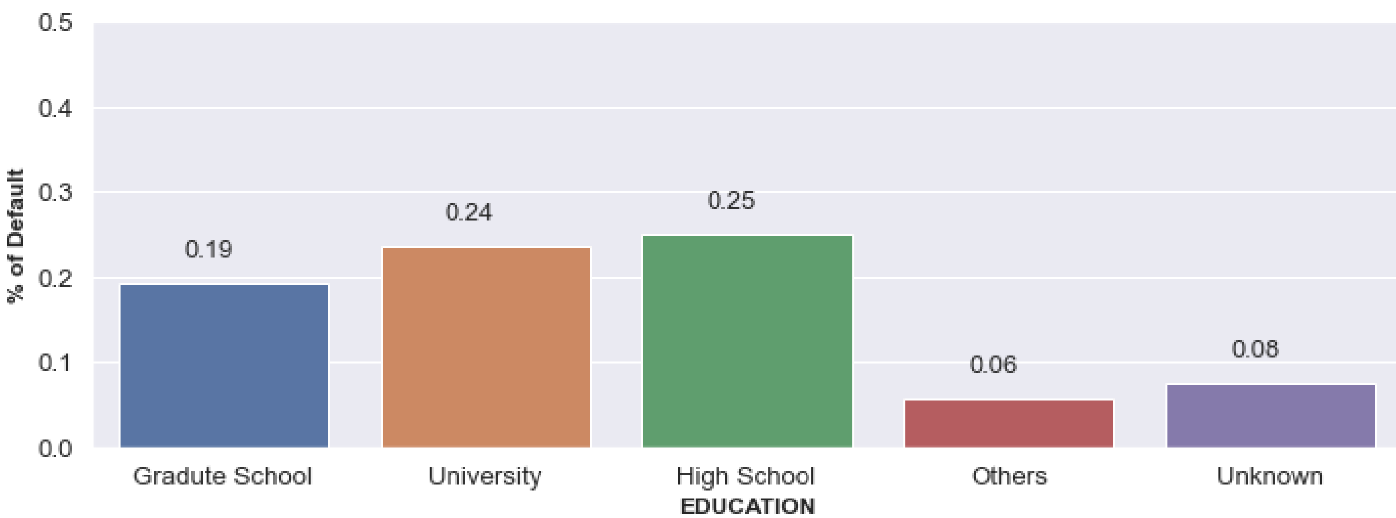
```
plt.figure(figsize=(12,4))

ax = sns.barplot(x = df["EDUCATION"], y = df["defaulter_or_not"]==1 , ci = None)
plt.xticks(ticks=[1,0,2,3,4],labels=['University','Gradute School','High School','Others',

plt.xlabel("EDUCATION", fontsize= 12,weight='bold')
plt.ylabel("% of Default", fontsize= 12,weight='bold')
plt.ylim(0,0.5)

for p in ax.patches:
    ax.annotate("%.2f" %(p.get_height()), (p.get_x()+0.25, p.get_height()+0.03),fontsize=1

plt.show()
```



Conclusion:-

- Majority of Credit Card Holders have Education as Graduate School,followed by University & High School Education .
- On the basis of Education High School defaulters are high followed by University & Graduate School .

MARITAL STATUS

In [37]:

```
df['MARRIAGE'].value_counts()
```

Out[37]:

```
2    15964
1    13659
3      323
0       54
Name: MARRIAGE, dtype: int64
```

In [38]:
```
df['defaulter_or_not'].groupby(df['MARRIAGE']).value_counts()
```

Out[38]:
```
MARRIAGE  defaulter_or_not
0         0                      49
          1                       5
1         0                   10453
          1                    3206
2         0                   12623
          1                    3341
3         0                     239
          1                      84
Name: defaulter_or_not, dtype: int64
```

In [39]:
```
df['defaulter_or_not'].groupby(df['MARRIAGE']).value_counts(normalize=True)
```

Out[39]:
```
MARRIAGE  defaulter_or_not
0         0                   0.907407
          1                   0.092593
1         0                   0.765283
          1                   0.234717
2         0                   0.790717
          1                   0.209283
3         0                   0.739938
          1                   0.260062
Name: defaulter_or_not, dtype: float64
```

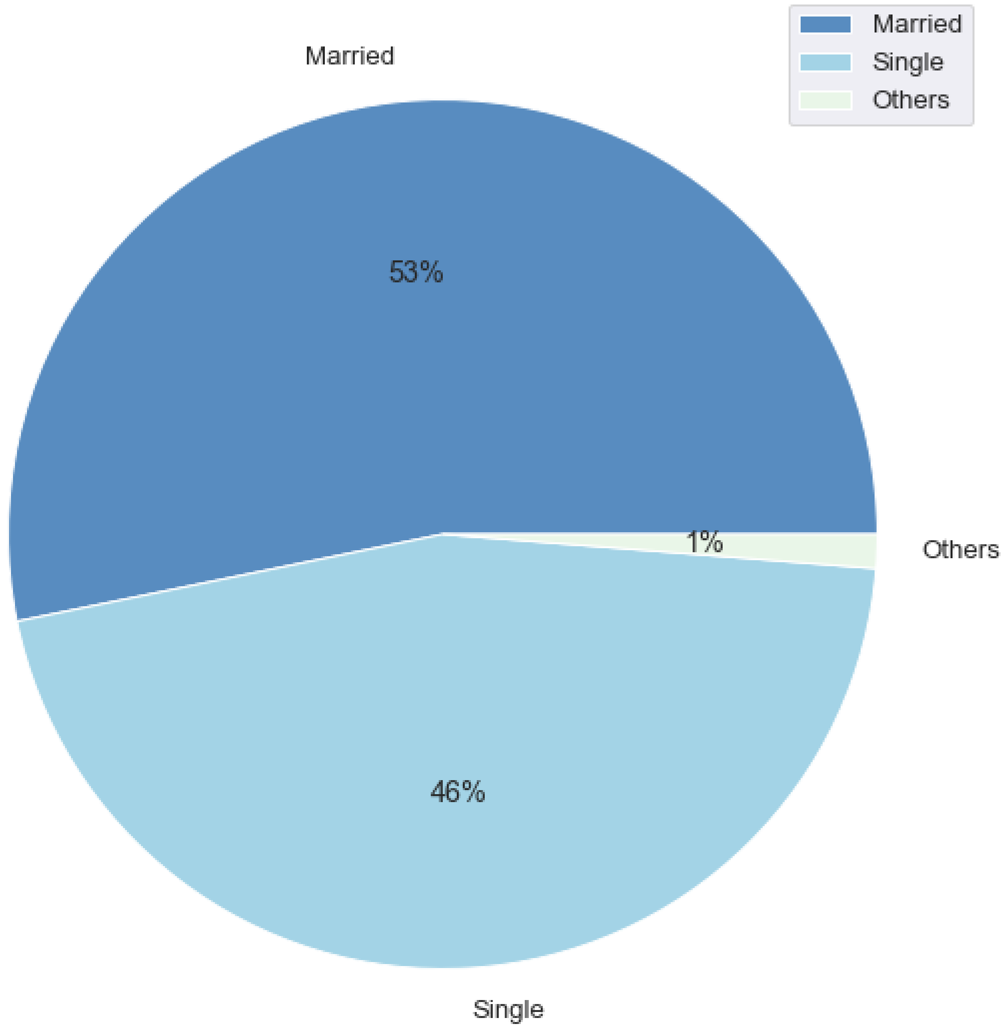
Since we do not have any information about what 0 is representing ,so we will replace 0 with 3,and consider only 3 values under marital status i.e 1,2,3

In [40]:
```
df.loc[:,'MARRIAGE']=df.loc[:,'MARRIAGE'].replace(0,3)
```

In [41]:
```
df['defaulter_or_not'].groupby(df['MARRIAGE']).value_counts(normalize=True)
```

Out[41]:
```
MARRIAGE  defaulter_or_not
1         0                   0.765283
          1                   0.234717
2         0                   0.790717
          1                   0.209283
3         0                   0.763926
          1                   0.236074
Name: defaulter_or_not, dtype: float64
```

In [42]:
```
plt.figure(figsize = (20,10))
palette_color = sns.color_palette('RdYlBu_r')
keys=['Married','Single','Others']
plt.pie(df["MARRIAGE"].value_counts(), labels=keys, colors=palette_color, autopct='%.0f%%'
plt.legend()
plt.show()
```



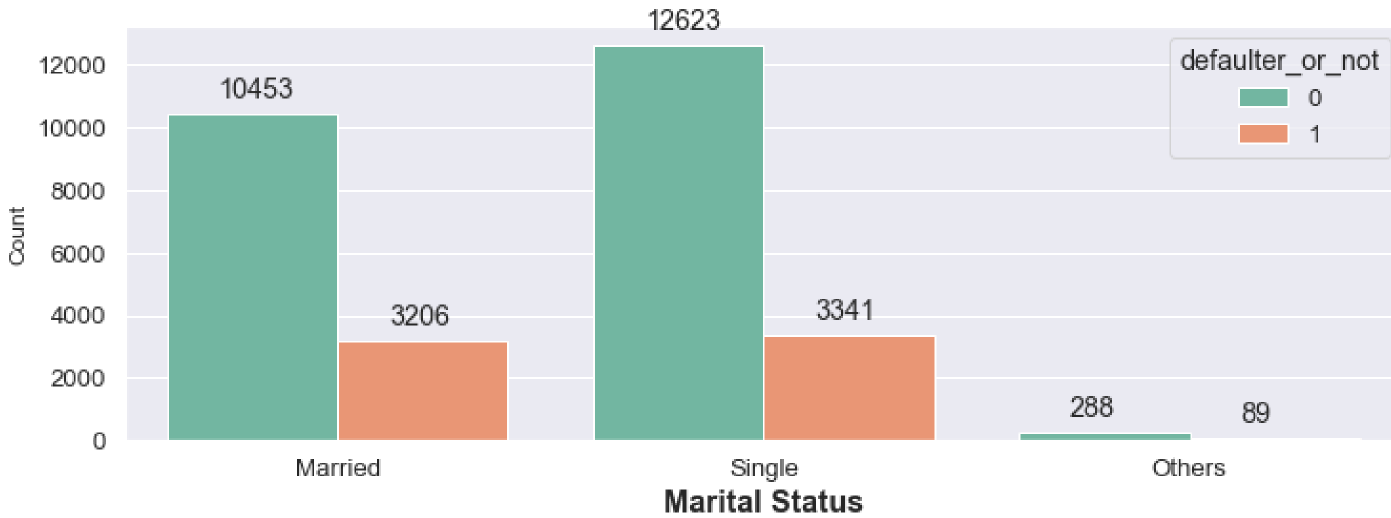
In [43]:
```
plt.figure(figsize=(12,4))

ax = sns.countplot(data = df, x = 'MARRIAGE', hue="defaulter_or_not", palette = 'Set2')

plt.xlabel("Marital Status", fontsize= 16,weight='bold')
plt.ylabel("Count", fontsize= 12)
plt.xticks(ticks=[0,1,2],labels=['Married','Single','Others'])

for p in ax.patches:
    ax.annotate((p.get_height()), (p.get_x()+0.12, p.get_height()+500))

plt.show()
```



Conclusion:-

- No of Credit Card Holders having Marital Status as Married are 56% followed by Single (46%) & Others(1%) .
- On the basis of Marital Status,Single Defaulters are marginally high as compared to married .

Age

In [44]:

```
df['AGE'].min()
```

Out[44]:

```
21
```

In [45]:

```
df['AGE'].max()
```

Out[45]:

```
79
```

In [46]:

```
df['bin_age'] = pd.cut(df['AGE'],[15, 20,25, 30, 35, 40, 50, 60, 80])
print(df['bin_age'].value_counts())
```

```
(25, 30]     7142
(40, 50]     6005
(30, 35]     5796
(35, 40]     4917
(20, 25]     3871
(50, 60]     1997
(60, 80]      272
(15, 20]        0
Name: bin_age, dtype: int64
```

In [47]:

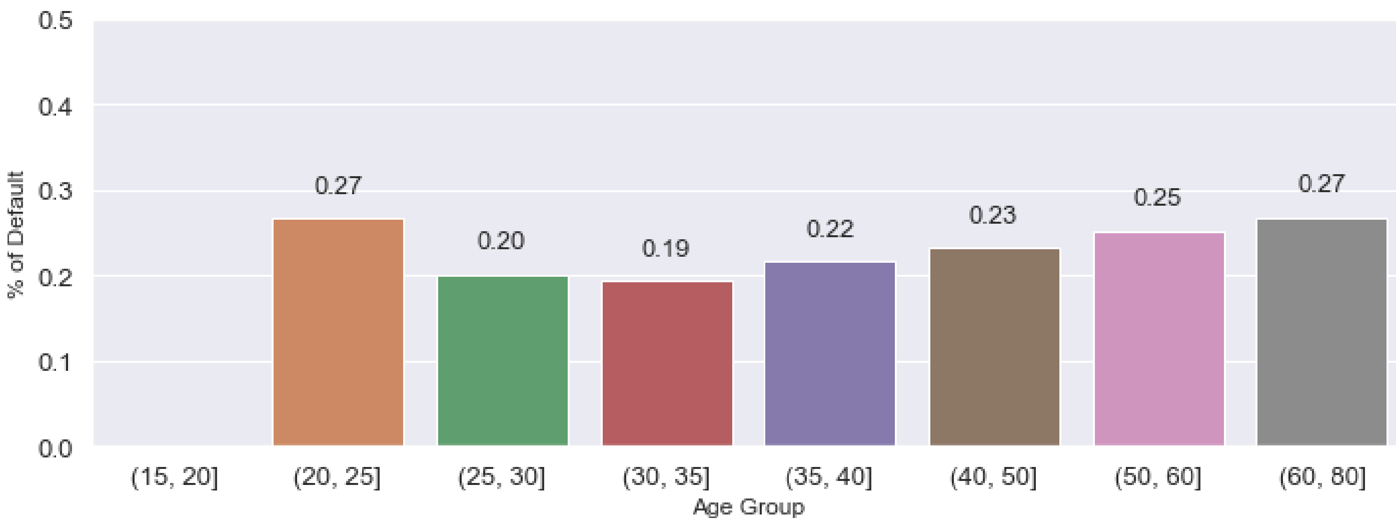
```
plt.figure(figsize=(12,4))

ax = sns.barplot(x = df["bin_age"], y = df["defaulter_or_not"]==1 , ci = None)

plt.xlabel("Age Group", fontsize= 12)
plt.ylabel("% of Default", fontsize= 12)
plt.ylim(0,0.5)

for p in ax.patches:
    ax.annotate("%.2f" %(p.get_height()), (p.get_x()+0.25, p.get_height()+0.03),fontsize=1

plt.show()
```



Conclusion:-

- Age Group of 30 to 35 has lowest number of Credit Card payment Defaulters followed by Age Group of 25 to 30 and 35 to 40 .
- Age Group of 20 to 25 and 60 to 80 has highest number of credit card payment defaulters followed by Age Group of 50 to 60 and 40 to 50 .

Repayment status

In [48]:
```
df[["PAY_1","PAY_2","PAY_3","PAY_4","PAY_5","PAY_6"]].value_counts()
```

Out[48]:
```
PAY_1  PAY_2  PAY_3  PAY_4  PAY_5  PAY_6
 0      0      0      0      0      0        9821
-2     -2     -2     -2     -2     -2        2109
-1     -1     -1     -1     -1     -1        1992
 1     -2     -2     -2     -2     -2         651
 2      2      2      2      2      2         530
                                             ...
       -1      2      2      2      0           1
                            -1      0           1
                            -2     -1           1
                                   -2           1
 1     -1      2      2      2     -1           1
Length: 1106, dtype: int64
```

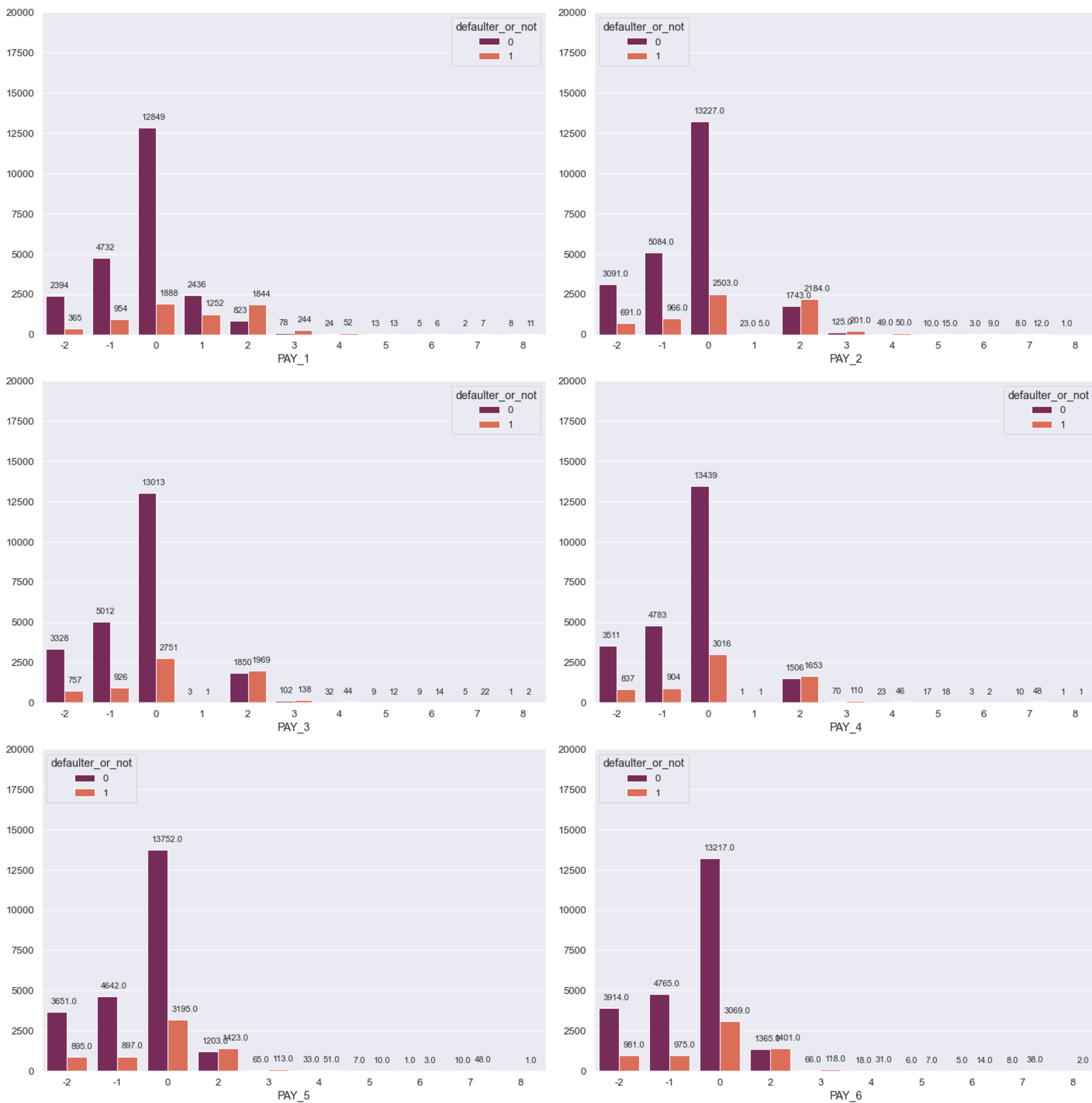
-2 = no credit to pay,-1=pay duly, 0=minimum payment is met,1=payment delay for one month, 2=payment delay for two months, ... 8=payment delay for eight months, 9=payment delay for nine months and above

In [49]:
```
pay_x_fts = ['PAY_1', 'PAY_2', 'PAY_3', 'PAY_4', 'PAY_5', 'PAY_6']
plt.figure(figsize=(20,20))

for i,col in enumerate(pay_x_fts):
    plt.subplot(3,2,i + 1)
    ax = sns.countplot(df.loc[:,col], palette = 'rocket',data=df,hue='defaulter_or_not')
    plt.ylim(0,20000)
    plt.ylabel('')
    plt.tight_layout()

    for p in ax.patches:
        ax.annotate((p.get_height()), (p.get_x()+0.08, p.get_height()+500), fontsize = 11)

plt.show()
```



PAY_1,2,3,4,5,6: Repayment status in September 2005, August 2005, July 2005, June 2005, May 2005, April 2005 (respectivey)

-2= no credit to pay

-1= pay duly

0= minimum payment is met

1 = payment delay for one month

2 = payment delay for two months

3 = payment delay for three months

4 = payment delay for four months

5 = payment delay for five months

6 = payment delay for six months

7 = payment delay for seven months

8 = payment delay for eight months

9 = payment delay for nine months and above

Conclusion:-

- From above we can conclude that majority of customers are paying minimum amount due .

IMBALANCED DATA

In [50]:

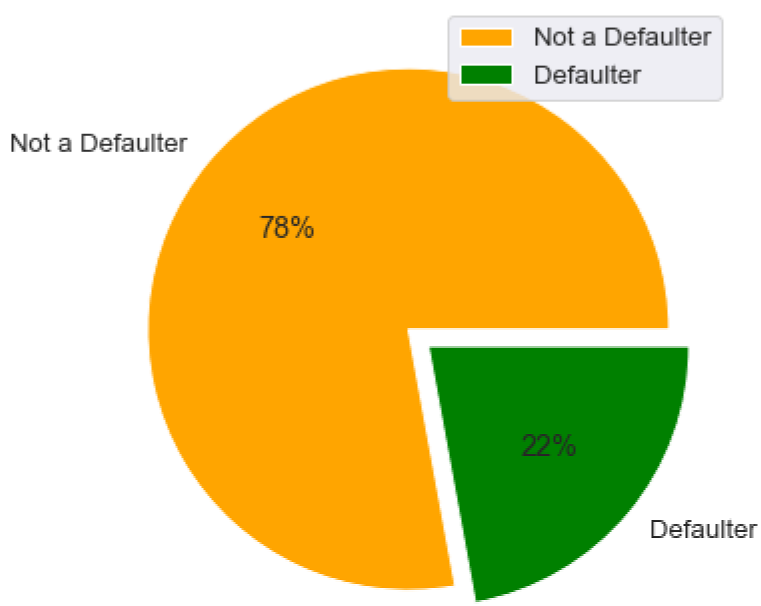
```
#Default payment (1=yes, 0=no)
df["defaulter_or_not"].value_counts()
```

Out[50]:

```
0    23364
1     6636
Name: defaulter_or_not, dtype: int64
```

In [51]:

```
plt.figure(figsize = (15,6))
palette_color = sns.color_palette('rocket',as_cmap=True)
keys=['Not a Defaulter','Defaulter']
plt.pie(df["defaulter_or_not"].value_counts(), labels=keys, autopct='%.0f%%',colors = ["or
plt.legend()
plt.show()
```

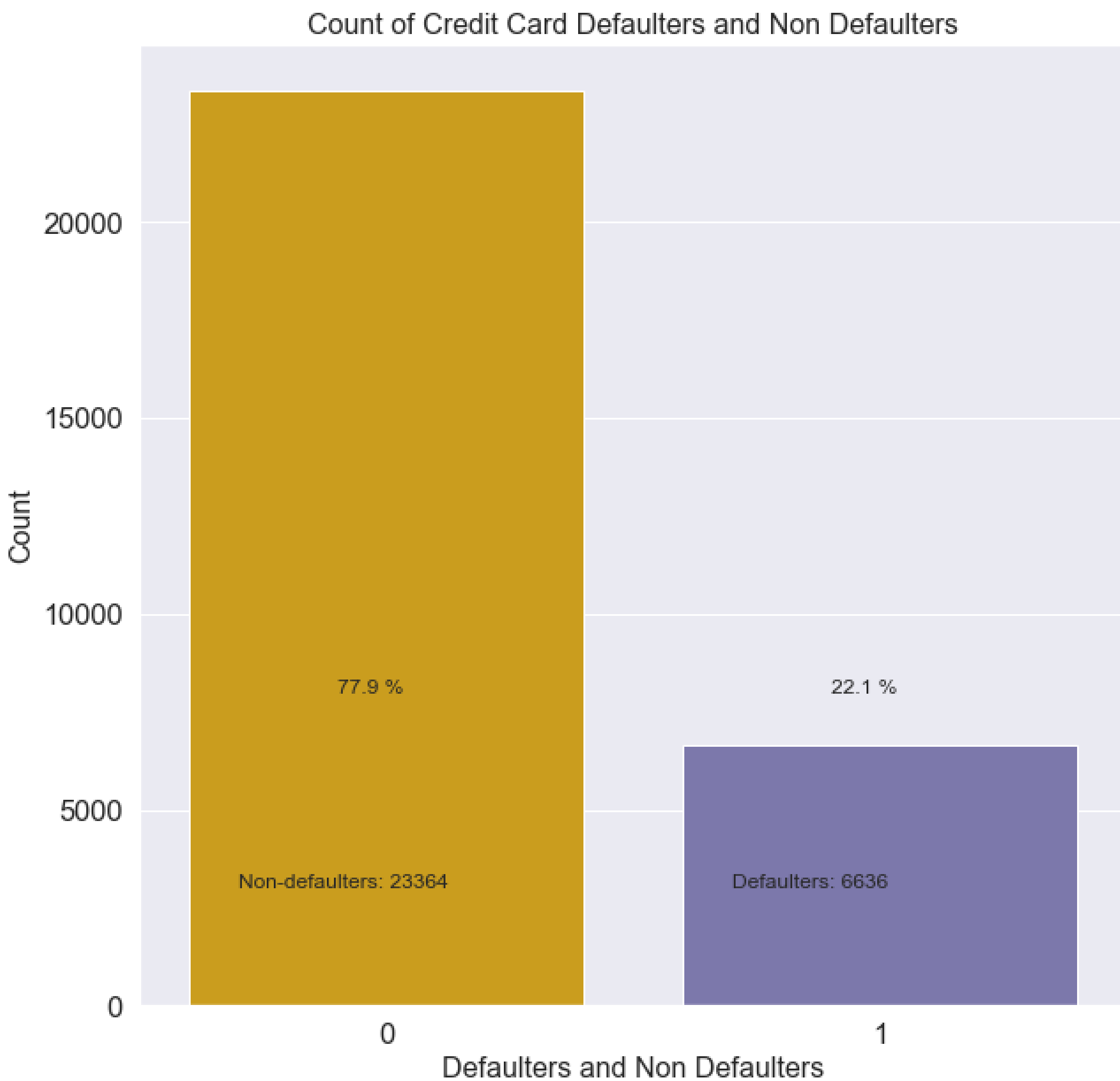


In [52]:

```
#the frequency of default & non default
defaulter=df.defaulter_or_not.sum()
non_defaulter=len(df)-defaulter

#converting into percentage
defaulter_percentage=round(defaulter/len(df)*100,1)
non_defaulter_percentage=round(non_defaulter/len(df)*100,1)
```

```
#plotting the graph
plt.figure(figsize=(10,10))
sns.set_context('notebook', font_scale=1.5)
sns.countplot('defaulter_or_not',data=df, palette="Dark2_r")
plt.annotate('Non-defaulters: {}'.format(non_defaulter), xy=(-0.3, 15000), xytext=(-0.3, 3
plt.annotate('Defaulters: {}'.format(defaulter), xy=(0.7, 15000), xytext=(0.7, 3000), size
plt.annotate(str(non_defaulter_percentage)+" %", xy=(-0.3, 15000), xytext=(-0.1, 8000), si
plt.annotate(str(defaulter_percentage)+" %", xy=(0.7, 15000), xytext=(0.9, 8000), size=12)
plt.title('Count of Credit Card Defaulters and Non Defaulters', size=16)
plt.xlabel("Defaulters and Non Defaulters",fontsize=16)
plt.ylabel("Count",fontsize=16)
plt.show()
```



In above graph:-

- 0 means Non Defaulters
- 1 means Defauters

Conclusion:-

- From the above proportion we can see that there are around 22 % defaulters for credit card payments out of sample size of 30,000 credit card holders .

Multicolinearity

- In simple words,we say there is a multicolinearity if there is a correlation between 2 or more features .

Correlation:

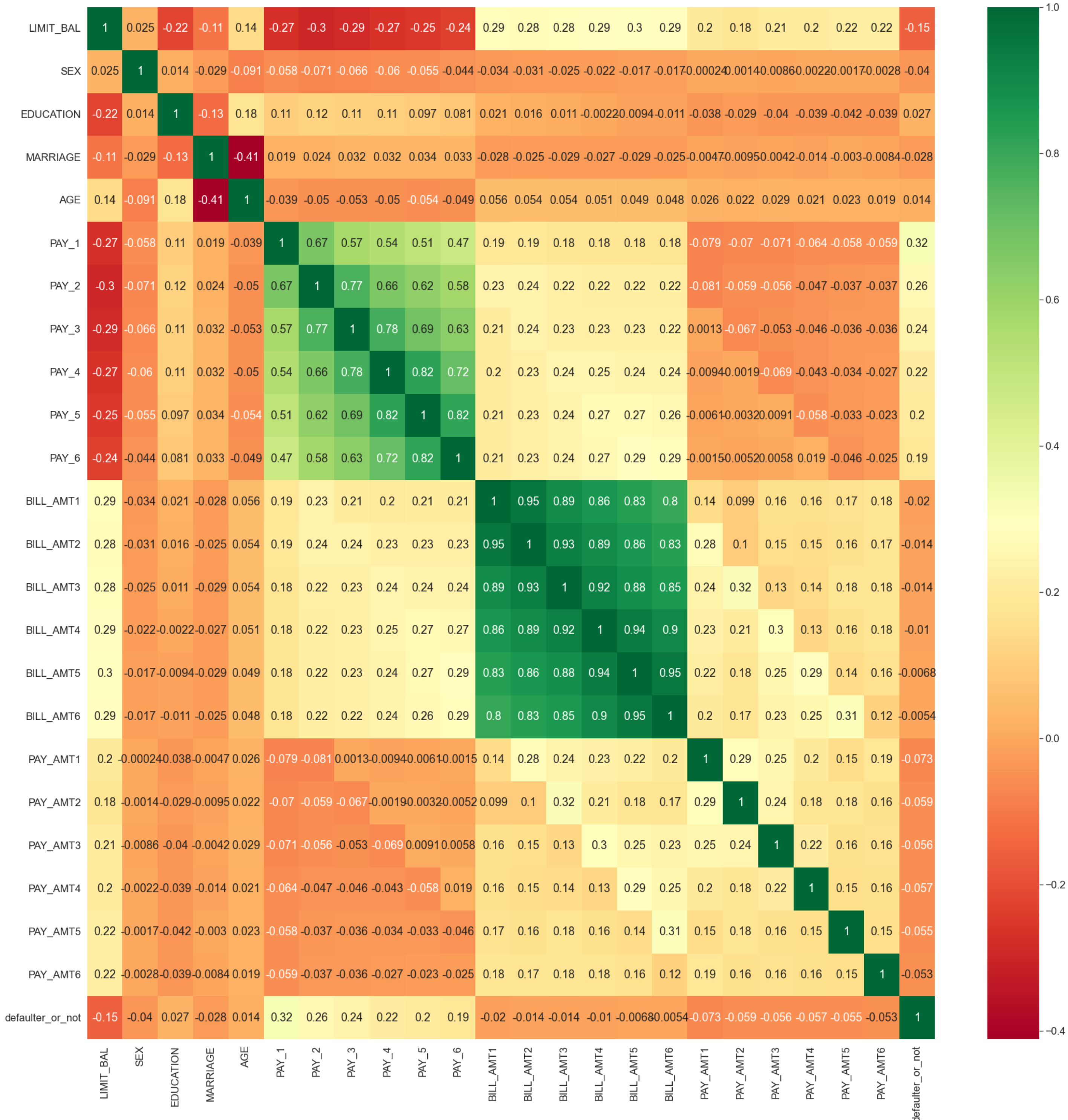
- Correlation is a technique for determining the link between two variables, which is useful in real life since it allows us to forecast the value of one variable using other factors that are connected with it. Because two variables are involved, it is a sort of bivariate statistic.

In [53]:

```
# Heatmap
plt.figure(figsize=(30,30))
sns.heatmap(df.corr(),annot = True, cmap = "RdYlGn")
```

Out[53]:

```
<AxesSubplot:>
```



Conclusion:-

- From the correlation heatmap above, it can be seen that there are some relationships between the feature columns, they are not entirely independent.
- But in this scenario, there is a correlation because a customer who was not able to pay the bill for 1 month was again not able to pay it for the subsequent months and hence the correlation.
- Again for the bill amount column, the same has happened. If the customer was not able to pay the bill, then the bill amount almost remained the same, or if the customer was able to pay then the bill amount got reduced.
- We remove columns when they convey the same information. But here, dropping the columns shall result in the loss of bill and payment history data. So, we don't need to drop any column although there is a correlation.