```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

```
data = pd.read_csv("/content/train (2).csv")
data.head()
```

	customer_id	limit_bal	sex	education	marriage	age	pay_1	pay_2	pay_3	pay_4	...	bill_amt4	bill_amt5	bill_amt6	pay_
0	1	1500	2.0	1.0	2.0	23.0	0.0	0.0	0.0	2.0	...	1463	938.0	698.0	
1	2	8500	2.0	2.0	2.0	29.0	0.0	0.0	0.0	0.0	...	8364	8275.0	8425.0	
2	3	1000	1.0	1.0	2.0	22.0	0.0	0.0	0.0	0.0	...	933	772.0	794.0	
3	4	10500	1.0	1.0	1.0	31.0	0.0	0.0	0.0	0.0	...	7190	7229.0	7340.0	
4	5	10500	2.0	2.0	1.0	44.0	0.0	0.0	0.0	0.0	...	3558	3592.0	3496.0	

5 rows × 25 columns

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 24001 entries, 0 to 24000
Data columns (total 25 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   customer_id  24001 non-null  int64
 1   limit_bal    24001 non-null  int64
 2   sex          24001 non-null  float64
 3   education    24001 non-null  float64
 4   marriage     24001 non-null  float64
 5   age          24001 non-null  float64
 6   pay_1        24001 non-null  float64
 7   pay_2        24001 non-null  float64
 8   pay_3        24001 non-null  float64
 9   pay_4        24001 non-null  float64
 10  pay_5        23819 non-null  float64
 11  pay_6        22790 non-null  float64
 12  bill_amt1    24001 non-null  int64
 13  bill_amt2    24001 non-null  int64
 14  bill_amt3    24001 non-null  int64
 15  bill_amt4    24001 non-null  int64
 16  bill_amt5    23819 non-null  float64
 17  bill_amt6    22790 non-null  float64
 18  pay_amt1     24001 non-null  int64
 19  pay_amt2     24001 non-null  int64
 20  pay_amt3     24001 non-null  int64
 21  pay_amt4     24001 non-null  int64
 22  pay_amt5     23819 non-null  float64
 23  pay_amt6     22790 non-null  float64
 24  default_oct  24001 non-null  object
dtypes: float64(14), int64(10), object(1)
memory usage: 4.6+ MB
```

DATA CLEANING

```
data['default_oct'].value_counts()
```

```
no     18692
yes     5309
Name: default_oct, dtype: int64
```

```
data = data.drop(columns = ['customer_id'])
```

```
data.describe()
```

	limit_bal	sex	education	marriage	age	pay_1	pay_2	pay_3	pay_4	p
count	24001.000000	24001.000000	24001.000000	24001.000000	24001.000000	24001.000000	24001.000000	24001.000000	24001.000000	23819.0(
mean	8351.302029	1.604058	1.856839	1.551644	35.498438	-0.015874	-0.132119	-0.166201	-0.215824	-0.2(
std	6475.592450	0.489062	0.792152	0.522663	9.222021	1.123554	1.199237	1.196802	1.173350	1.1(
min	500.000000	1.000000	0.000000	0.000000	21.000000	-2.000000	-2.000000	-2.000000	-2.000000	-2.0(
25%	2500.000000	1.000000	1.000000	1.000000	28.000000	-1.000000	-1.000000	-1.000000	-1.000000	-1.0(
50%	7000.000000	2.000000	2.000000	2.000000	34.000000	0.000000	0.000000	0.000000	0.000000	0.0(
75%	12000.000000	2.000000	2.000000	2.000000	41.000000	0.000000	0.000000	0.000000	0.000000	0.0(
max	50000.000000	2.000000	6.000000	3.000000	79.000000	8.000000	8.000000	8.000000	8.000000	8.0(

8 rows × 23 columns

```
data.isnull().sum()
```

```
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           182
pay_6          1211
bill_amt1         0
bill_amt2         0
bill_amt3         0
bill_amt4         0
bill_amt5       182
bill_amt6      1211
pay_amt1          0
pay_amt2          0
pay_amt3          0
pay_amt4          0
pay_amt5        182
pay_amt6       1211
default_oct       0
dtype: int64
```

```
missing_proportion = data.isnull().sum() / len(data)

columns_to_process = ['pay_5', 'pay_6', 'bill_amt5', 'bill_amt6', 'pay_amt5', 'pay_amt6']

columns_to_remove = []
columns_to_impute = []

for col in columns_to_process:
    if missing_proportion[col] > 0.1: # if missing values in a columns are more than 10% of total values
        columns_to_remove.append(col)
    else:
        columns_to_impute.append(col)

if columns_to_remove:
    data.drop(columns_to_remove, axis=1, inplace=True)
    print("Columns removed:", columns_to_remove)

# Impute missing values in remaining columns
for col in columns_to_impute:
    # Here you can choose different imputation methods like mean, median, mode, or others
    # For simplicity, let's use median imputation


#The median is less sensitive to outliers and extreme values compared to the mean

#The median is a better measure of central tendency for skewed distributions because it doesn't assume the data is symmetric, ur
    median_value = data[col].median()
    data[col].fillna(median_value, inplace=True)
    print("Missing values in", col, "imputed with median value:", median_value)

# Now you have a DataFrame 'df' with missing values handled
```

```
Missing values in pay_5 imputed with median value: 0.0
Missing values in pay_6 imputed with median value: 0.0
Missing values in bill_amt5 imputed with median value: 906.0
Missing values in bill_amt6 imputed with median value: 855.5
Missing values in pay_amt5 imputed with median value: 75.0
Missing values in pay_amt6 imputed with median value: 75.0
```

```
data.head(5)
```

	limit_bal	sex	education	marriage	age	pay_1	pay_2	pay_3	pay_4	pay_5	...	bill_amt4	bill_amt5	bill_amt6	pay_amt1
0	1500	2.0	1.0	2.0	23.0	0.0	0.0	0.0	2.0	2.0	...	1463	938.0	698.0	75
1	8500	2.0	2.0	2.0	29.0	0.0	0.0	0.0	0.0	0.0	...	8364	8275.0	8425.0	300
2	1000	1.0	1.0	2.0	22.0	0.0	0.0	0.0	0.0	0.0	...	933	772.0	794.0	150
3	10500	1.0	1.0	1.0	31.0	0.0	0.0	0.0	0.0	0.0	...	7190	7229.0	7340.0	255
4	10500	2.0	2.0	1.0	44.0	0.0	0.0	0.0	0.0	0.0	...	3558	3592.0	3496.0	180

5 rows × 24 columns

```
data.isnull().sum()
```

```
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
default_oct    0
dtype: int64
```

```
data = data.drop_duplicates()
```

DATA PREPROCESSING

sex: Gender (1 = male; 2 = female).

education: Education (1 = graduate school; 2 = university; 3 = high school; 4 = others).

marriage: Marital status (1 = married; 2 = single; 3 = others).

age: Age (year).

```
print(data['sex'].unique())
print(data['marriage'].unique()) #checking categories
print(data['education'].unique())
```

```
[2. 1.]
[2. 1. 3. 0.]
[1. 2. 3. 5. 0. 6. 4.]
```

```
# replace 4,5,6 values with 4 in education column
for index in data.loc[data['education'] > 4].index:
  data.loc[index,['education']] = 4.
```

```
# replace 0 value with 3 in marriage column
for index in data.loc[data['marriage'] == 0].index:
  data.loc[index,['marriage']] = 3
```

```
#convert each categorical column to object type
data['marriage'] = data['marriage'].astype('object')
data['sex'] = data['sex'].astype('object')
data['education'] = data['education'].astype('object')
```

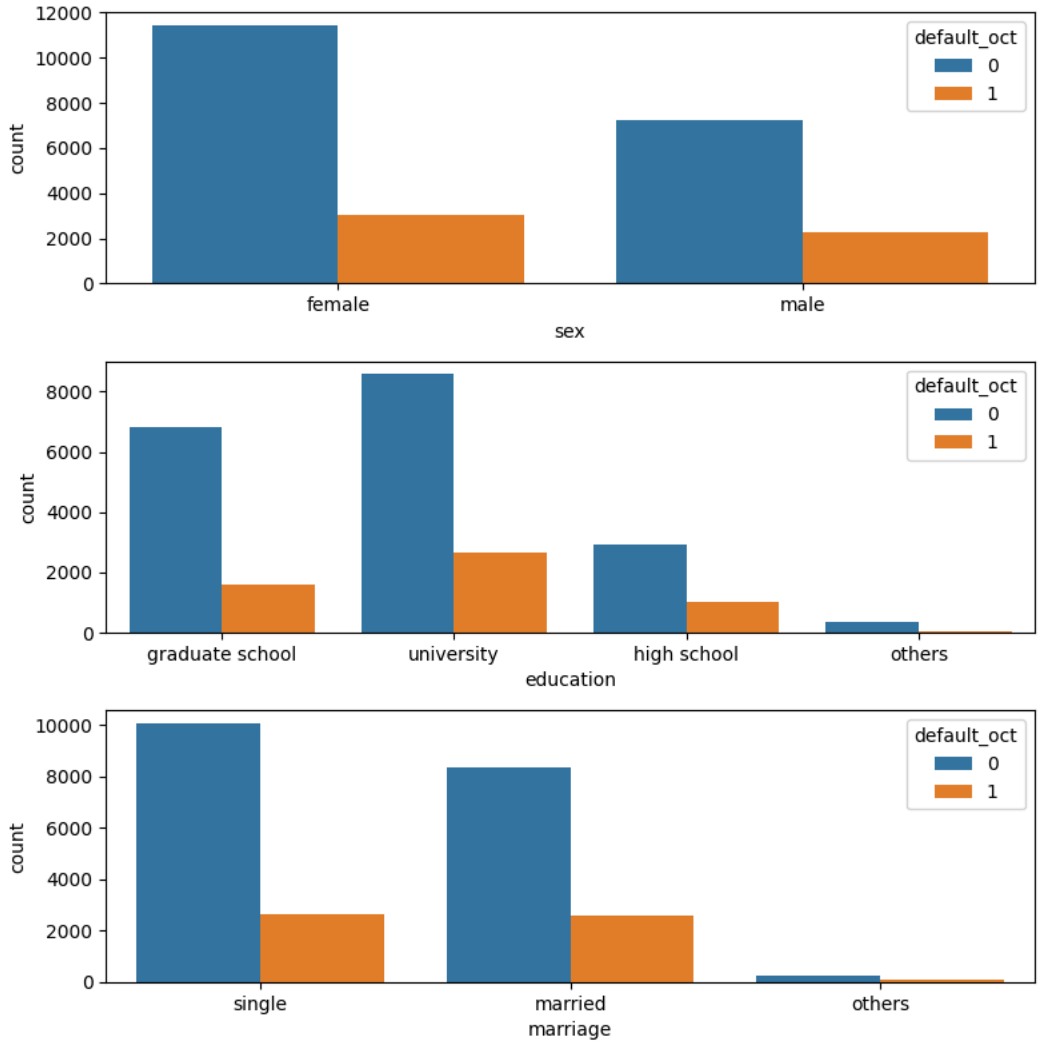
```
data['default_oct'] = data['default_oct'].replace({'yes': 1, 'no' : 0}).astype(int)
```

```
data['marriage'] = data['marriage'].replace({1 : 'married', 2 : 'single', 3 : 'others'})
data['sex'] = data['sex'].replace({1 : 'male', 2 : 'female',3 : 'others'})
data['education'] = data['education'].replace({0: 'others', 1 : 'graduate school', 2 : 'university', 3 : 'high school', 4 :'othe
```

```
from scipy.stats import chi2_contingency
from scipy.stats import chi2
#statistical hypothesis
```

CATEGORICAL FEATURE ANALYSIS

```
#count plot
fig,axes=plt.subplots(3,figsize=(8,8))
cols=['sex', 'education', 'marriage']

for i,col in enumerate(cols):

    sns.countplot(x=col, hue="default_oct",data=data,ax=axes[i]);

plt.tight_layout()
plt.savefig("1.png")
```



ANALYSIS - SEX VARIABLE

Statistical hypothesis on sex

Individual groups or characteristics like race, ethnicity, gender, religion, and age should not lead the model to make unfair predictions.

Ethically, sex should not impact the model to predit default customers

So, it is important to do statistical hypothesis on variable 'sex'

To check if this variable data distribution will influence the chances of customer being a default customer, it is important to perform tests..

If it is a numerical variable, z-test or t-test can be used.

If it is a categorical variable, chisquare test can be used.

Chisquare contingency test is a non parametric test that can be used for categorical variables

So, lets check if the distribution of these variables is normal/gaussian.

```
count_oct=data.groupby('sex')[['default_oct']].agg(['count','sum'])
count_oct
```

	default_oct	
	count	sum
sex		
female	14479	3027
male	9497	2279

```
default_count=count_oct['default_oct']['sum'].values
print(default_count)
non_default_count=(count_oct['default_oct']['count']-count_oct['default_oct']['sum']).values
print(non_default_count)
```

```
[3027 2279]
[11452  7218]
```

```
contingency_table=pd.DataFrame({"Non-defaulter":non_default_count,
                                        "Defaulter":default_count},
                                        index=["Male","Female"])

stat, p, dof, expected = chi2_contingency(contingency_table)

expected_table=pd.DataFrame(expected,columns=["Non-defaulter","Defaulter"],
                            index=["Male","Female"])

print('sex','\n\nObserved Table\n',contingency_table,'\n\nExpected Table\n',expected_table)

# test-statistic

critical = chi2.ppf(0.95, dof)
if abs(stat) >= critical:
        print('\n')
        print('stat=',stat)
        print("A person's gender has impact on a customer defaulting")
else:
        print("A person's gender has no impact on a customer defaulting ")

print('\nSignificance=%.3f, p=%.3f' % (0.05,p))
if p <= 0.05:
        print("A person's gender has impact on a customer defaulting")
else:
        print("A person's gender has no impact on a customer defaulting ")
```

```
sex

Observed Table
         Non-defaulter  Defaulter
Male            11452       3027
Female           7218       2279

Expected Table
         Non-defaulter    Defaulter
Male     11274.730147  3204.269853
Female    7395.269853  2101.730147


stat= 31.616225650307857
A person's gender has impact on a customer defaulting

Significance=0.050, p=0.000
A person's gender has impact on a customer defaulting
```

It can be concluded that the variable 'sex' can influence model's predictions. So, it cannot be ignored because of ethical consideration.

```
#Violinp plot
plt.figure(figsize=(5,5))
sns.violinplot(x="sex", y="age",hue = 'default_oct',split=True,data=data)

# Adding labels and title
plt.xlabel("Sex/Gender", fontsize=14)
plt.ylabel("Age", fontsize=14)
plt.title("Distribution of Age by Sex/Gender", fontsize=16)
```

```
Text(0.5, 1.0, 'Distribution of Age by Sex/Gender')
```

NOTE: To calculate probability we can multiply probability of males defaulting by probability of customer being male....

But looking at the distributions we can assume that the probability is fair(0.5) for a customer being male or female.

So, to determine probability of males/ females defaulting..using ratio of male/female defaulters by total number of males/females could be appropriate.

```
# ratio of male defaulters by total number of males
len(data[data['default_oct'] ==1].loc[data['sex'] == 'male'])/len(data.loc[data['sex'] == 'male'])
```

```
0.23997051700537012
```

```
# ratio of female defaulters by total number of females
len(data[data['default_oct'] ==1].loc[data['sex'] == 'female'])/len(data.loc[data['sex'] == 'female'])
```

```
0.20906139926790523
```

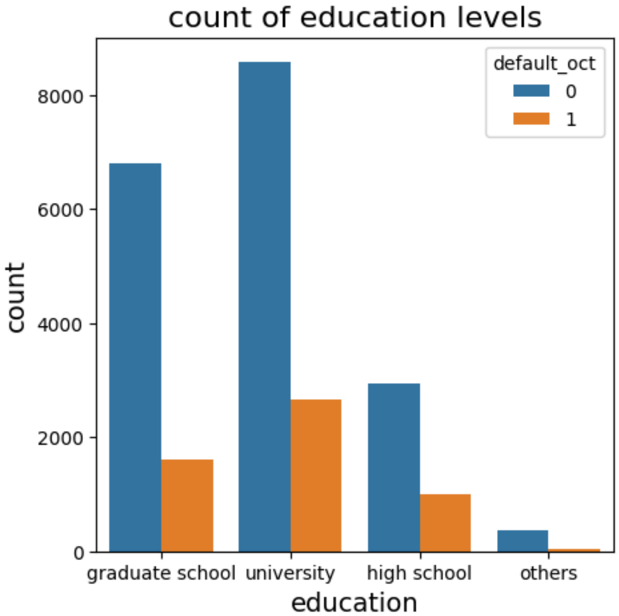
Count of female defaulters are more than male defaulters.

But based on above calculated probabilities, males have comparatively higher chance of defaulting

ANALYSIS - EDUCATION

```
#count plot of education categories
plt.figure(figsize=(5,5))
sns.countplot(x="education",hue = 'default_oct',data=data)

# Adding labels and title
plt.xlabel("education", fontsize=14)
plt.ylabel("count", fontsize=14)
plt.title("count of education levels", fontsize=16)
```

```
Text(0.5, 1.0, 'count of education levels')
```




```
#defaulters education categories count
data[data['default_oct'] == 1 ].groupby('education')['default_oct'].count()
```

```
education
graduate school    1612
high school        1000
others               29
university         2665
Name: default_oct, dtype: int64
```

```
1000/len(data[data['education'] == 'high school']) # probability of high school students defaulting
```

```
0.2537427048972342
```

```
2665/len(data[data['education'] == 'university'])  # probability of university students defaulting
```

```
0.2371207402793843
```

```
1612/len(data[data['education'] == 'graduate school']) # probability of graduate students defaulting
```

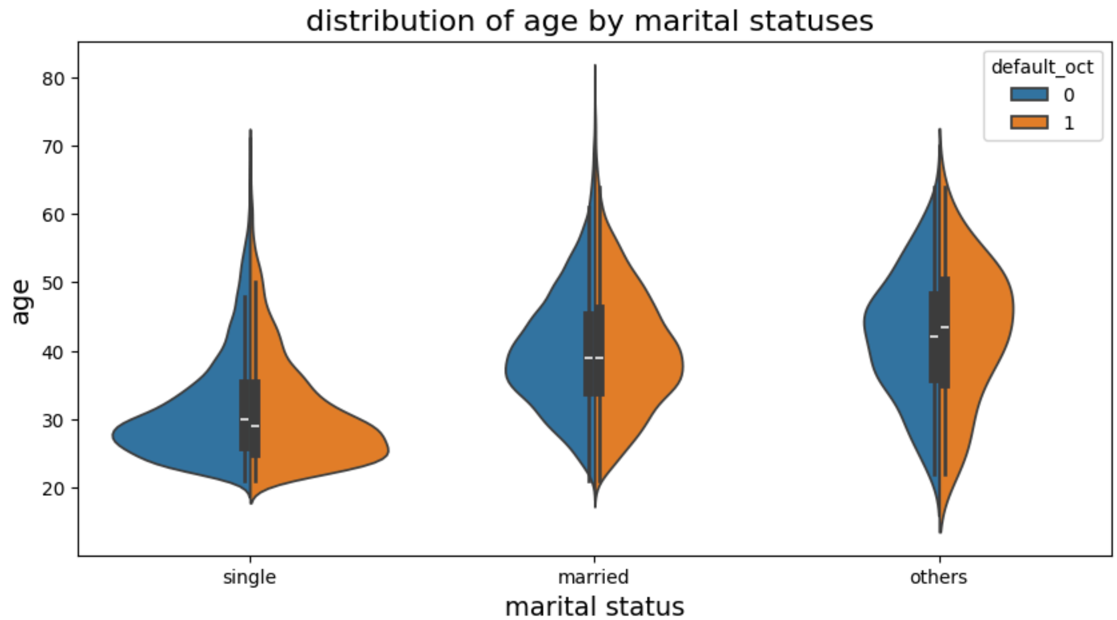
```
0.19169936972291593
```

As education level increases, probability of defaulting decreases

ANALYSIS - MARITAL STATUS

```
#violin plot wrt marital status
plt.figure(figsize=(10,5))
sns.violinplot(x="marriage",y= 'age',hue = 'default_oct',split = True,data=data)

# Adding labels and title
plt.xlabel("marital status", fontsize=14)
plt.ylabel("age", fontsize=14)
plt.title("distribution of age by marital statuses ", fontsize=16)
```

```
Text(0.5, 1.0, 'distribution of age by marital statuses ')
```




```
# ratio of single defaulters by total number of single people
len(data[data['default_oct'] ==1].loc[data['marriage'] == 'single'])/len(data.loc[data['marriage'] == 'single'])
```

```
0.2090009425070688
```

```
# ratio of married defaulters by total number of married people
len(data[data['default_oct'] ==1].loc[data['marriage'] == 'married'])/len(data.loc[data['marriage'] == 'married'])
```

```
0.23513810133528443
```

```
# ratio of other category defaulters by total number of other category people
len(data[data['default_oct'] ==1].loc[data['marriage'] == 'others'])/len(data.loc[data['marriage'] == 'others'])
```

```
0.23870967741935484
```

As shown above, singles and married people are likely to become default customers and singles have less probability of defaulting compared to married people.

Mainly singles aged between 20 to 30 years are more likely to default.

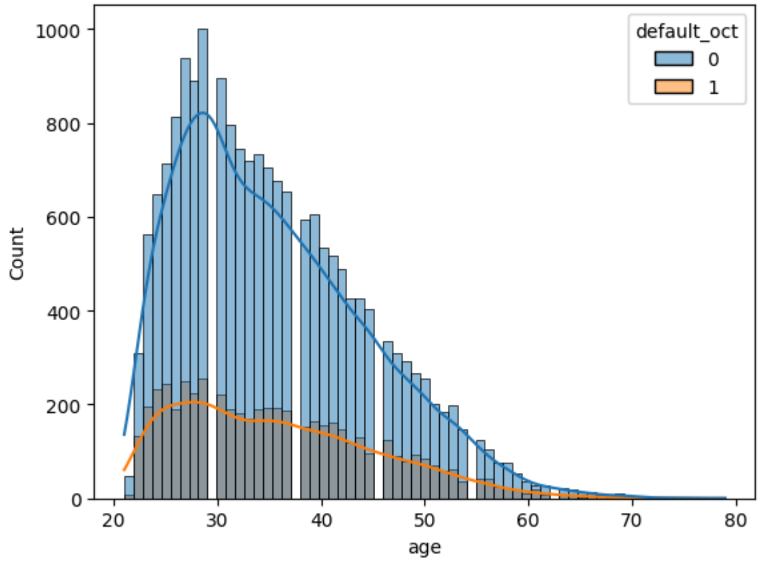
```
#defaulters grouped by marriage and qualification
data[data['default_oct'] == 1].groupby(['marriage','education'])['default_oct'].count()
```

```
marriage  education
married   graduate school     613
          high school         619
          others               14
          university         1325
others    graduate school      10
          high school          26
          university           38
single    graduate school     989
          high school         355
          others               15
          university         1302
Name: default_oct, dtype: int64
```

Both married and single univeristy graduates have high chances of defaulting payments

NUMERICAL VARIABLE ANALYSIS

```
#histogram of age distribution
sns.histplot(x='age',hue='default_oct',data=data,kde=True);
```



most of the customers fall under middle age category.(25-35 years)

```
#Grouping age variable with ranges (age bins)
data['AgeBin'] = pd.cut(data['age'],[20, 25, 30, 35, 40, 50, 60, 80])
print(data['AgeBin'].value_counts())
```

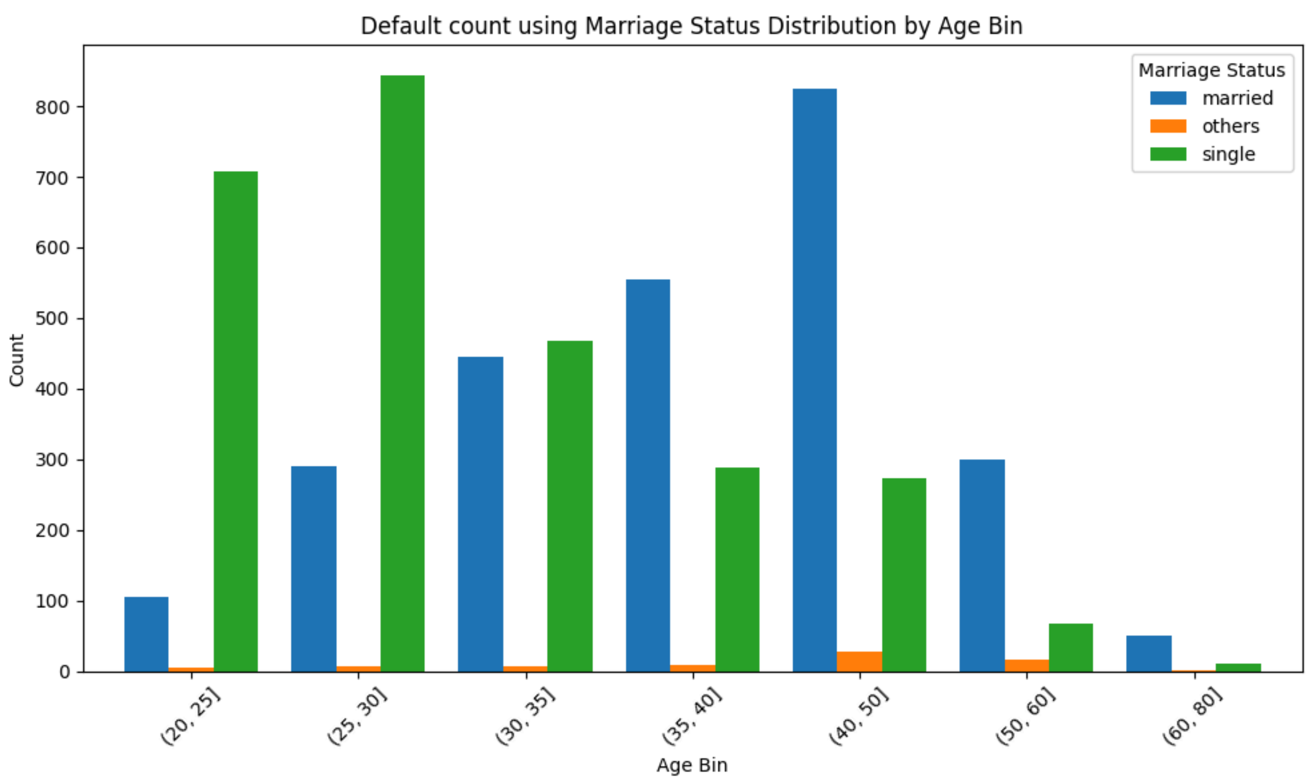
```
(25, 30]    5682
(40, 50]    4849
(30, 35]    4621
(35, 40]    3918
(20, 25]    3101
(50, 60]    1583
(60, 80]     222
Name: AgeBin, dtype: int64
```

```
#Grouping age bins with marital status categories
data[data['default_oct']==1].groupby(['AgeBin','marriage'])['default_oct'].count()
```

```
AgeBin    marriage
(20, 25]  married     105
          others        5
          single      708
(25, 30]  married     291
          others        7
          single      844
(30, 35]  married     446
          others        7
          single      468
(35, 40]  married     555
          others        9
          single      288
(40, 50]  married     825
          others       28
          single      274
(50, 60]  married     299
          others       17
          single       68
(60, 80]  married      50
          others        1
          single       11
Name: default_oct, dtype: int64
```

Plotting age bins with marital status categories

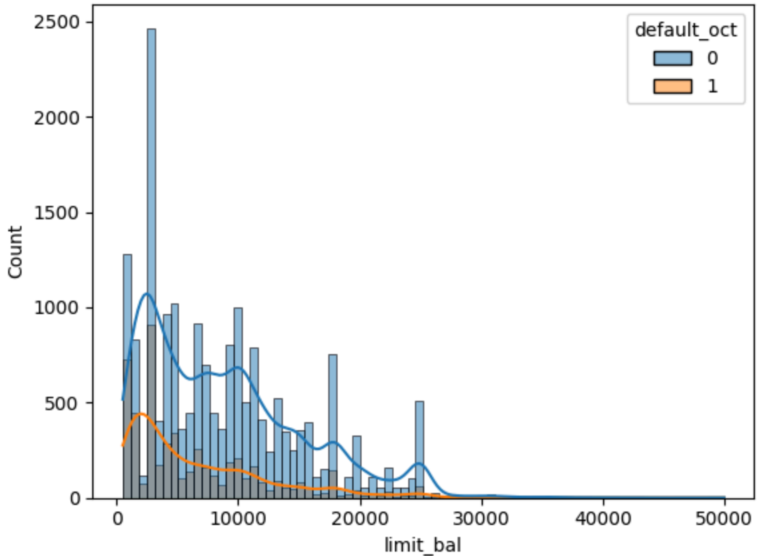
```
d = {
    'AgeBin': ['(20, 25]', '(20, 25]', '(20, 25]', '(25, 30]', '(25, 30]', '(25, 30]', '(30, 35]', '(30, 35]', '(30, 35]',
               '(35, 40]', '(35, 40]', '(35, 40]', '(40, 50]', '(40, 50]', '(40, 50]', '(50, 60]', '(50, 60]', '(50, 60]',
               '(60, 80]', '(60, 80]', '(60, 80]'],
    'Marriage': ['married', 'others', 'single', 'married', 'others', 'single', 'married', 'others', 'single',
                 'married', 'others', 'single', 'married', 'others', 'single', 'married', 'others', 'single',
                 'married', 'others', 'single'],
    'Count': [105, 5, 708, 291, 7, 844, 446, 7, 468, 555, 9, 288, 825, 28, 274, 299, 17, 68, 50, 1, 11]
}

# Creating DataFrame
df = pd.DataFrame(d)

# Pivot the DataFrame to get 'AgeBin' on x-axis, 'Marriage' categories as legend, and 'Count' as bar heights
pivot_df = df.pivot(index='AgeBin', columns='Marriage', values='Count')

# Plotting
pivot_df.plot(kind='bar', figsize=(10, 6), width=0.8)
plt.title('Default count using Marriage Status Distribution by Age Bin')
plt.xlabel('Age Bin')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.legend(title='Marriage Status')
plt.tight_layout()

# Display the plot
plt.show()
```



As you can see single people having age 20 to 30 years and married people having 40 to 50 years of age have high chance of defaulting

Count of the number of customers who default the payment is inversely proportional to the increase in age factor.

```
#histogram plot of limit balance
sns.histplot(x='limit_bal',hue='default_oct',data=data,kde=True);
```



Most of the customers possess limit balance less than

Limit_Bal and Age are highly skewed.

```
ncol = data.select_dtypes('integer') #numerical columns
```

```
ccol = data.select_dtypes('object') #categorical columns
```

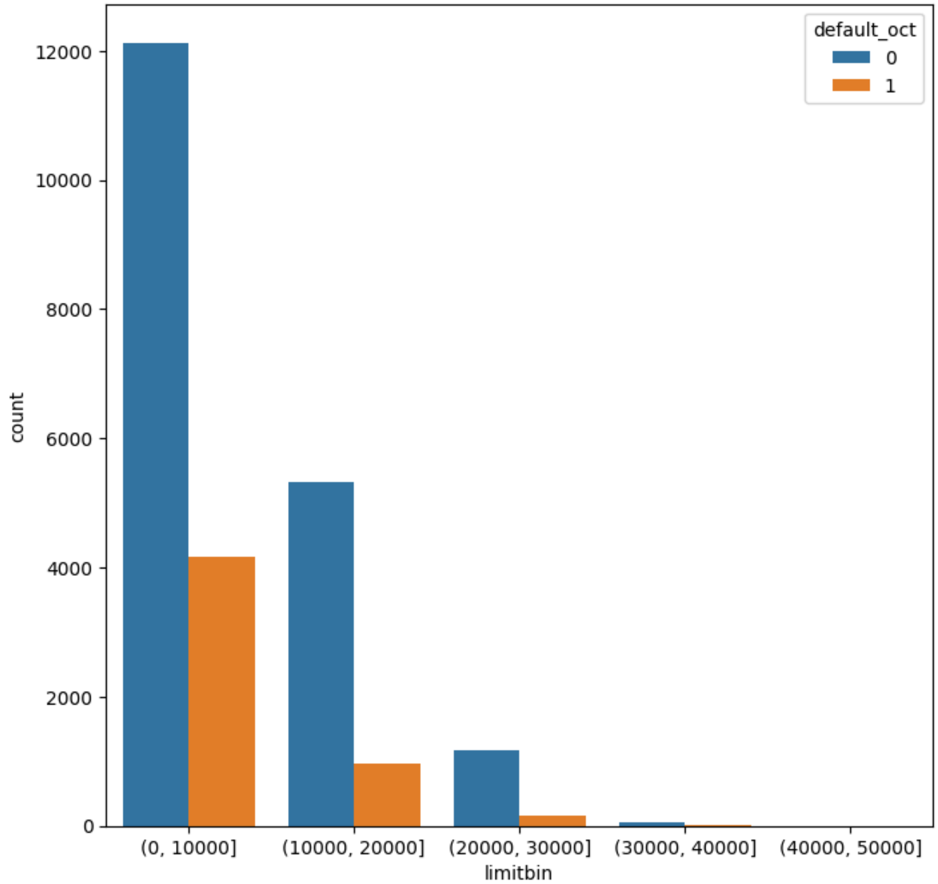
```
# Grouping limit balance to bins using ranges.
data['limitbin'] = pd.cut(data['limit_bal'],[0,10000, 20000, 30000, 40000, 50000])
print(data['limitbin'].value_counts())
```

```
(0, 10000]        16295
(10000, 20000]     6272
(20000, 30000]     1346
(30000, 40000]       62
(40000, 50000]        1
Name: limitbin, dtype: int64
```

```
d1 = data.groupby(['limitbin','default_oct'])['sex'].count().reset_index().rename(columns = {'sex' : 'count'})
```

```
#bar plot of limit balance with default count as hue
plt.figure(figsize = (8,8))
sns.barplot(x = 'limitbin',y = 'count',hue = 'default_oct',data = d1)
```

```
<Axes: xlabel='limitbin', ylabel='count'>
```



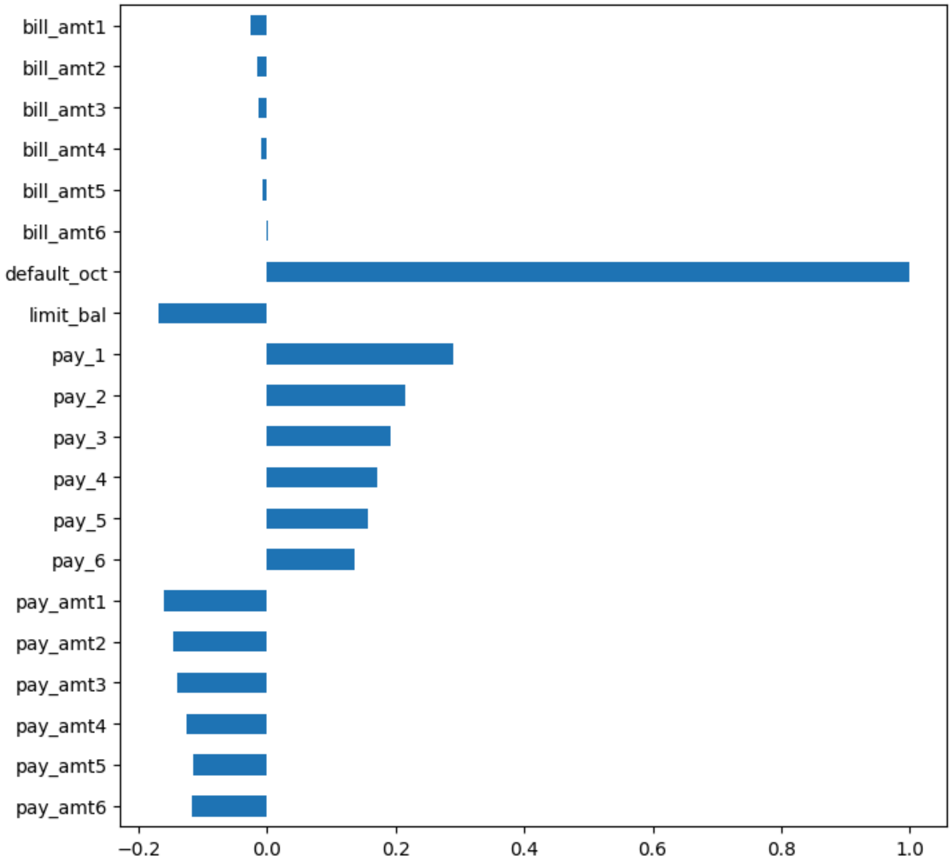
Most of the defaulting customers have limit balance less than 10000

ANALYSIS OF PAYMENT AND BILL AMOUNT VARIABLES

```
data['pay_1'] = data['pay_1'].astype(int)
data['pay_2'] = data['pay_2'].astype(int)
data['pay_3'] = data['pay_3'].astype(int)# These values are of float type. So these are converted to integer types.
data['pay_4'] = data['pay_4'].astype(int)
data['pay_5'] = data['pay_5'].astype(int)
data['pay_6'] = data['pay_6'].astype(int)
data['pay_amt5'] = data['pay_amt5'].astype(int)
data['pay_amt6'] = data['pay_amt6'].astype(int)
data['bill_amt5'] = data['bill_amt5'].astype(int)
data['bill_amt6'] = data['bill_amt6'].astype(int)
```

```
 #considering the numerical columns again as few columns are converted to integer type above
ncol = data.select_dtypes('integer')
```

```
#Numerical columns correlation with target variable

plt.figure(figsize=(8,8))
g=ncol.corrwith(data['default_oct'],method='spearman').sort_index(ascending=False)
g.plot(kind='barh');
plt.savefig("3.png")
```



If pay amount is increased, it means due amount is being paid which is a good sign and hence chances of default decreases.

Similarily if pay increases, it means the number of months of payment delay for previous months debt is increasing which in turn increases the chances of default.

Only recent months Bill amount is having little influence the target variable and also only last three months(SEP, AUG, JUL) payments and due statuses are influencing the output variable

From above correlations, bill_amt,pay and pay_amt features for last 3 months are least correlated with target variable.

We can consider removing these variables if their data distributions over the time frame (months) are same.

To check if their respective distributions are same, we can use normality test

USE NORMALITY TEST TO CHECK IF VARIABLES FOLLOW NORMAL DISTRIBUTION.

```
from scipy.stats import normaltest


ncolumns=["pay_1","limit_bal","bill_amt1", "pay_amt1","age"]

for nc in ncolumns:
    stat, p = normaltest(data[nc])
    alpha = 0.05
    if p > alpha:
        print('Sample looks Gaussian for',nc,'column: (fail to reject H0)')
    else:
        print('Sample does not look Gaussian for',nc,'column: (reject H0)')
```

```
Sample does not look Gaussian for pay_1 column: (reject H0)
Sample does not look Gaussian for limit_bal column: (reject H0)
Sample does not look Gaussian for bill_amt1 column: (reject H0)
Sample does not look Gaussian for pay_amt1 column: (reject H0)
Sample does not look Gaussian for age column: (reject H0)
```

AS SHOWN ABOVE ALL NUMERICAL VARIABLE DISTRIBUTIONS ARE NON GAUSSIAN. SO NON PARAMETRIC VARIABLE SUCH AS FRIEDMAN CHI SQUARE TESTS SHOULD BE USED TO CHECK IF VARIABLES CONTAIN SAME DISTRIBUTION.

```
from scipy.stats import friedmanchisquare
# this test is used to check if variables contain same distribution
```

```
stat, p = friedmanchisquare(data["pay_1"], data["pay_2"], data["pay_3"], data["pay_4"], data["pay_5"], data["pay_6"])

print('Stat:',stat,'p-value:',p)
if p > 0.05:
    print('distributions are same\n\n')
else:
    print('distributions are different\n\n')
```

```
Stat: 1502.0653470782693 p-value: 0.0
distributions are different
```

```
stat, p = friedmanchisquare(data["pay_amt1"], data["pay_amt2"], data["pay_amt3"],data["pay_amt4"], data["pay_amt5"], data["pay_a

print('Stat:',stat,'p-value:',p)
if p > 0.05:
    print('distributions are same\n\n')
else:
    print('distributions are different\n\n')
```

```
Stat: 7345.173564487524 p-value: 0.0
distributions are different
```

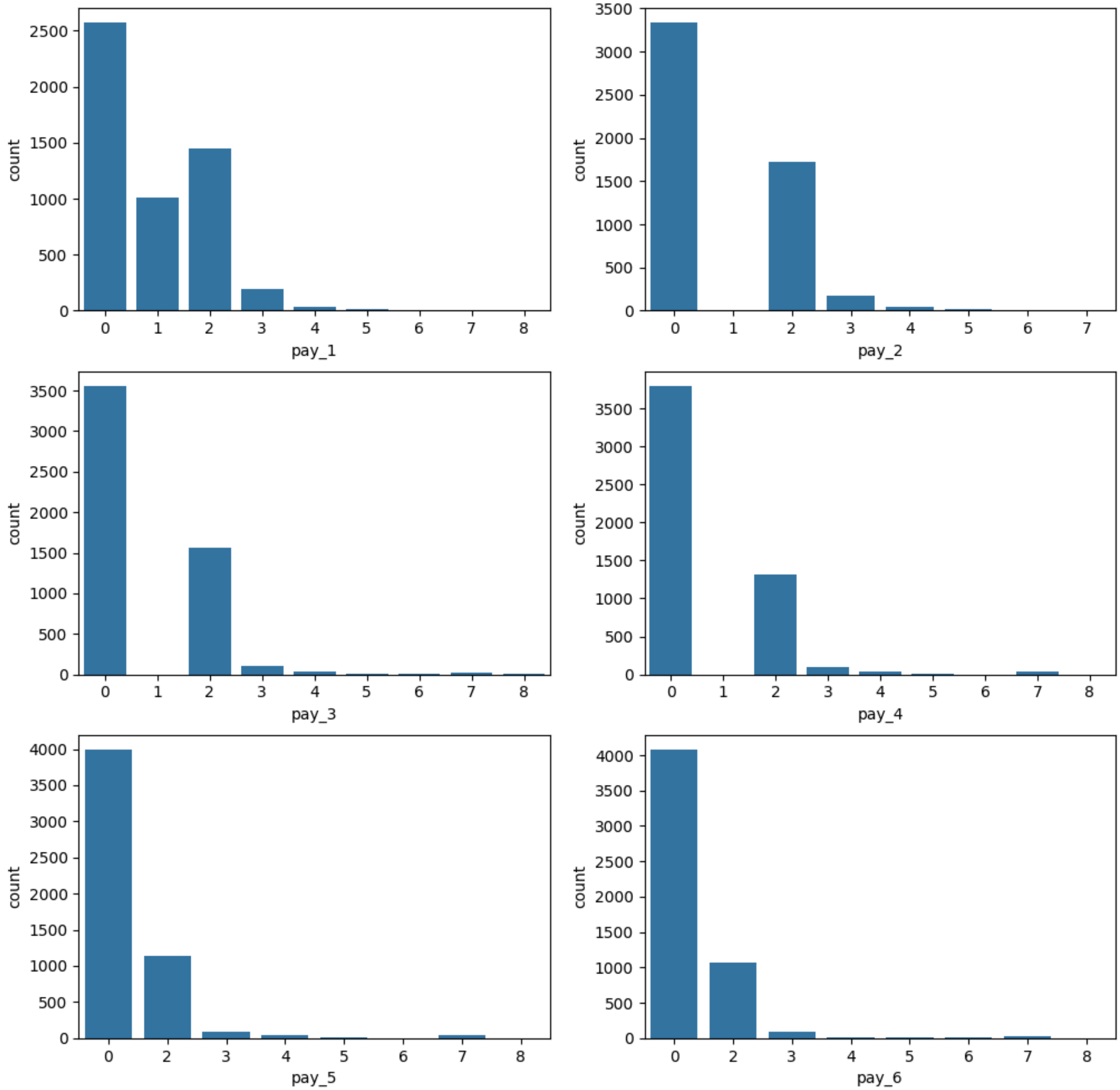
```
stat, p = friedmanchisquare(data["bill_amt1"], data["bill_amt2"], data["bill_amt3"], data["bill_amt4"], data["bill_amt5"], data[

print('Stat:',stat,'p-value:',p)
if p > 0.05:
    print('distributions are same\n\n')
else:
    print('distributions are different\n\n')
```

```
Stat: 1506.3550084085332 p-value: 0.0
distributions are different
```

As the distributions of these variables over different months are not same, we consider using 6 months transaction data.

```
# For pay variables -2,-1 AND 0 COME UNDER SAME CATEGORY(due cleared soon)
for i in range(1,7):
 for index in data.loc[data[str('pay_') + str(i)] < 0].index:
  data.loc[index,[str('pay_') + str(i)]] = 0
```

```
# Count plot of defaulters pay status for 6 months
i = 1
plt.figure(figsize=(12, 12))
for c in range(1,7):
    plt.subplot(3, 2, i)
    sns.countplot(x=data[data['default_oct'] ==1][str('pay_') + str(c)],data = data)
    i+=1
```



The majority of customers are responsibly settling their credit card bills, indicating a significantly reduced likelihood of default compared to others.

Given the limited number of customers experiencing delays of four months or more in all PAY_X features, consolidating them for a new analysis would provide a more meaningful average default rate for this subgroup.

```
data['pay_amt1'].sort_values()
```

```
7063         0
3486         0
17654        0
3484         0
11752        0
         ...
21667    20250
14115    21195
15361    24667
15026    25250
18874    43677
Name: pay_amt1, Length: 23976, dtype: int64
```

Most of the payments fall below 1000. So lets consider payment ranges:

0-250

250-500

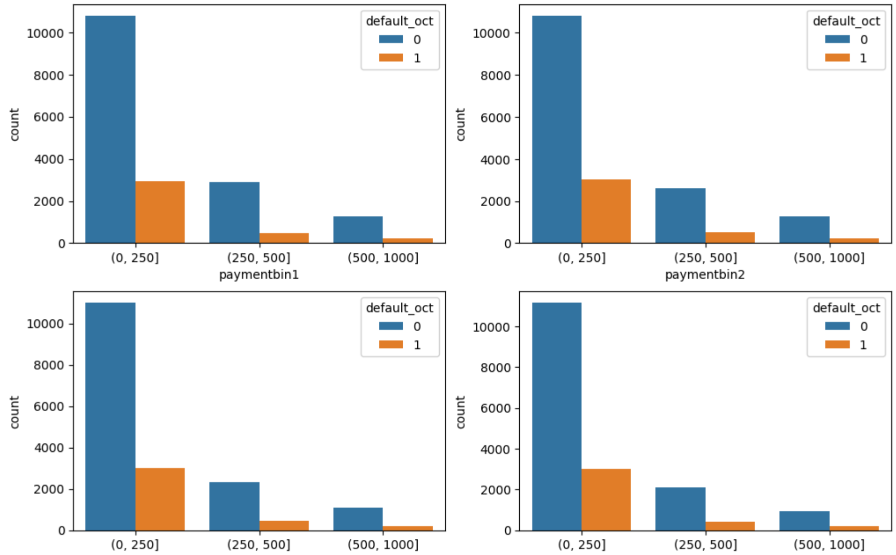
500-750

750-1000

```
data['paymentbin1'] = pd.cut(data['pay_amt1'],[0, 250,500, 1000])
#print(data['paymentbin1'].value_counts())
data[data['default_oct']==1].groupby(['paymentbin1'])['default_oct'].count()

data['paymentbin2'] = pd.cut(data['pay_amt2'],[0, 250,500, 1000])
#print(data['paymentbin2'].value_counts())
data[data['default_oct']==1].groupby(['paymentbin2'])['default_oct'].count()

data['paymentbin3'] = pd.cut(data['pay_amt3'],[0, 250,500, 1000])
#print(data['paymentbin1'].value_counts())
data[data['default_oct']==1].groupby(['paymentbin3'])['default_oct'].count()

data['paymentbin4'] = pd.cut(data['pay_amt4'],[0, 250,500, 1000])
#print(data['paymentbin1'].value_counts())
data[data['default_oct']==1].groupby(['paymentbin4'])['default_oct'].count()

data['paymentbin5'] = pd.cut(data['pay_amt5'],[0, 250,500, 1000])
#print(data['paymentbin5'].value_counts())
data[data['default_oct']==1].groupby(['paymentbin5'])['default_oct'].count()

data['paymentbin6'] = pd.cut(data['pay_amt6'],[0, 250,500, 1000])
#print(data['paymentbin5'].value_counts())
data[data['default_oct']==1].groupby(['paymentbin6'])['default_oct'].count()
```

```
paymentbin6
(0, 250]       3092
(250, 500]      373
(500, 1000]     129
Name: default_oct, dtype: int64
```

```
# Count plot of defaulters payment ranges for 6 months
i = 1
plt.figure(figsize=(12, 12))
for c in range(1,7):
    plt.subplot(3, 2, i)
    sns.countplot(x=data[str('paymentbin') + str(i)],hue = 'default_oct',data = data)
    i+=1
```



Across all the months, it is clear that most of the defaulters fall in payment range 0-250.

Recommendation:

Minimum payment range

```
plt.figure(figsize = (18,15))

sns.heatmap(data.corr(),annot = True)
```

```
<ipython-input-60-adaae945c41a>:3: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a fu
  sns.heatmap(data.corr(),annot = True)
<Axes: >
```