Data Preprocessing

B.Charan Sai

19314,CSE-D

Data Loading

In [62]:
```
import pandas as pd
import numpy as np
import matplotlib
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
%matplotlib inline
warnings.filterwarnings('ignore')
```

In [63]:
```
df = pd.read_csv("UCI_Credit_Card.csv")
# Reading the data
```

Check the data

In [64]:
```
df.dtypes
# checking the datatypes of columns
```

Out[64]:
```
ID                              int64
LIMIT_BAL                     float64
SEX                             int64
EDUCATION                       int64
MARRIAGE                        int64
AGE                             int64
PAY_0                           int64
PAY_2                           int64
PAY_3                           int64
PAY_4                           int64
PAY_5                           int64
PAY_6                           int64
BILL_AMT1                     float64
BILL_AMT2                     float64
BILL_AMT3                     float64
BILL_AMT4                     float64
BILL_AMT5                     float64
BILL_AMT6                     float64
PAY_AMT1                      float64
PAY_AMT2                      float64
PAY_AMT3                      float64
PAY_AMT4                      float64
PAY_AMT5                      float64
PAY_AMT6                      float64
default.payment.next.month      int64
dtype: object
```

In [65]:
```
df.rename(columns={'default.payment.next.month':'Target'},inplace=True)
#Renaming the target varible column name
```

Finding missing values

In [66]:
```
# Checking any null values are present in the data
# No missing values are there
total = df.isnull().sum().sort_values(ascending = False)
percent = (df.isnull().sum()/df.isnull().count()*100).sort_values(ascending = False)
pd.concat([total, percent], axis=1, keys=['Total', 'Percent'])
```

Out[66]:

	Total	Percent
Target	0	0.0
PAY_6	0	0.0
LIMIT_BAL	0	0.0
SEX	0	0.0
EDUCATION	0	0.0
MARRIAGE	0	0.0
AGE	0	0.0
PAY_0	0	0.0
PAY_2	0	0.0
PAY_3	0	0.0
PAY_4	0	0.0
PAY_5	0	0.0
BILL_AMT1	0	0.0
PAY_AMT6	0	0.0
BILL_AMT2	0	0.0

	Total	Percent
BILL_AMT3	0	0.0
BILL_AMT4	0	0.0
BILL_AMT5	0	0.0
BILL_AMT6	0	0.0
PAY_AMT1	0	0.0
PAY_AMT2	0	0.0
PAY_AMT3	0	0.0
PAY_AMT4	0	0.0
PAY_AMT5	0	0.0
ID	0	0.0

Standardization of the data

In [67]:
```
from sklearn import preprocessing
std_scale = preprocessing.StandardScaler().fit_transform(df)
data_df = pd.DataFrame(std_scale, columns=df.columns)
data_df.head()
```

Out[67]:

	ID	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	...	BILL_AMT4	BILL_AMT5	BILL_AMT6
0	-1.731993	-1.136720	0.810161	0.185828	-1.057295	-1.246020	1.794564	1.782348	-0.696663	-0.666599	...	-0.672497	-0.663059	-0.652724
1	-1.731878	-0.365981	0.810161	0.185828	0.858557	-1.029047	-0.874991	1.782348	0.138865	0.188746	...	-0.621636	-0.606229	-0.597966
2	-1.731762	-0.597202	0.810161	0.185828	0.858557	-0.161156	0.014861	0.111736	0.138865	0.188746	...	-0.449730	-0.417188	-0.391630
3	-1.731647	-0.905498	0.810161	0.185828	-1.057295	0.164303	0.014861	0.111736	0.138865	0.188746	...	-0.232373	-0.186729	-0.156579
4	-1.731531	-0.905498	-1.234323	0.185828	-1.057295	2.334029	-0.874991	0.111736	-0.696663	0.188746	...	-0.346997	-0.348137	-0.331482

5 rows × 25 columns

Data Summarization

In [68]:
```
df.head()
```

Out[68]:

	ID	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	...	BILL_AMT4	BILL_AMT5	BILL_AMT6	PAY_AMT1	PAY_AMT2	PA
0	1	20000.0	2	2	1	24	2	2	-1	-1	...	0.0	0.0	0.0	0.0	689.0	
1	2	120000.0	2	2	2	26	-1	2	0	0	...	3272.0	3455.0	3261.0	0.0	1000.0	
2	3	90000.0	2	2	2	34	0	0	0	0	...	14331.0	14948.0	15549.0	1518.0	1500.0	
3	4	50000.0	2	2	1	37	0	0	0	0	...	28314.0	28959.0	29547.0	2000.0	2019.0	
4	5	50000.0	1	2	1	57	-1	0	-1	0	...	20940.0	19146.0	19131.0	2000.0	36681.0	

5 rows × 25 columns

In [69]:
```
print("Credit Card Clients data -  rows:",df.shape[0]," columns:", data_df.shape[1])
```

```
Credit Card Clients data -  rows: 30000  columns: 25
```

In [70]:
```
df.describe(include='all').T # Descriptive analysis
```

Out[70]:

	count	mean	std	min	25%	50%	75%	max
ID	30000.0	15000.500000	8660.398374	1.0	7500.75	15000.5	22500.25	30000.0
LIMIT_BAL	30000.0	167484.322667	129747.661567	10000.0	50000.00	140000.0	240000.00	1000000.0
SEX	30000.0	1.603733	0.489129	1.0	1.00	2.0	2.00	2.0
EDUCATION	30000.0	1.853133	0.790349	0.0	1.00	2.0	2.00	6.0
MARRIAGE	30000.0	1.551867	0.521970	0.0	1.00	2.0	2.00	3.0
AGE	30000.0	35.485500	9.217904	21.0	28.00	34.0	41.00	79.0
PAY_0	30000.0	-0.016700	1.123802	-2.0	-1.00	0.0	0.00	8.0
PAY_2	30000.0	-0.133767	1.197186	-2.0	-1.00	0.0	0.00	8.0
PAY_3	30000.0	-0.166200	1.196868	-2.0	-1.00	0.0	0.00	8.0
PAY_4	30000.0	-0.220667	1.169139	-2.0	-1.00	0.0	0.00	8.0
PAY_5	30000.0	-0.266200	1.133187	-2.0	-1.00	0.0	0.00	8.0
PAY_6	30000.0	-0.291100	1.149988	-2.0	-1.00	0.0	0.00	8.0
BILL_AMT1	30000.0	51223.330900	73635.860576	-165580.0	3558.75	22381.5	67091.00	964511.0

	count	mean	std	min	25%	50%	75%	max
BILL_AMT2	30000.0	49179.075167	71173.768783	-69777.0	2984.75	21200.0	64006.25	983931.0
BILL_AMT3	30000.0	47013.154800	69349.387427	-157264.0	2666.25	20088.5	60164.75	1664089.0
BILL_AMT4	30000.0	43262.948967	64332.856134	-170000.0	2326.75	19052.0	54506.00	891586.0
BILL_AMT5	30000.0	40311.400967	60797.155770	-81334.0	1763.00	18104.5	50190.50	927171.0
BILL_AMT6	30000.0	38871.760400	59554.107537	-339603.0	1256.00	17071.0	49198.25	961664.0
PAY_AMT1	30000.0	5663.580500	16563.280354	0.0	1000.00	2100.0	5006.00	873552.0
PAY_AMT2	30000.0	5921.163500	23040.870402	0.0	833.00	2009.0	5000.00	1684259.0
PAY_AMT3	30000.0	5225.681500	17606.961470	0.0	390.00	1800.0	4505.00	896040.0
PAY_AMT4	30000.0	4826.076867	15666.159744	0.0	296.00	1500.0	4013.25	621000.0
PAY_AMT5	30000.0	4799.387633	15278.305679	0.0	252.50	1500.0	4031.50	426529.0
PAY_AMT6	30000.0	5215.502567	17777.465775	0.0	117.75	1500.0	4000.00	528666.0
Target	30000.0	0.221200	0.415062	0.0	0.00	0.0	0.00	1.0

In [71]:
```
df['LIMIT_BAL'].value_counts().shape
```

Out[71]:
```
(81,)
```

In [72]:
```
df['LIMIT_BAL'].value_counts().head(5)
```

Out[72]:
```
50000.0     3365
20000.0     1976
30000.0     1610
80000.0     1567
200000.0    1528
Name: LIMIT_BAL, dtype: int64
```

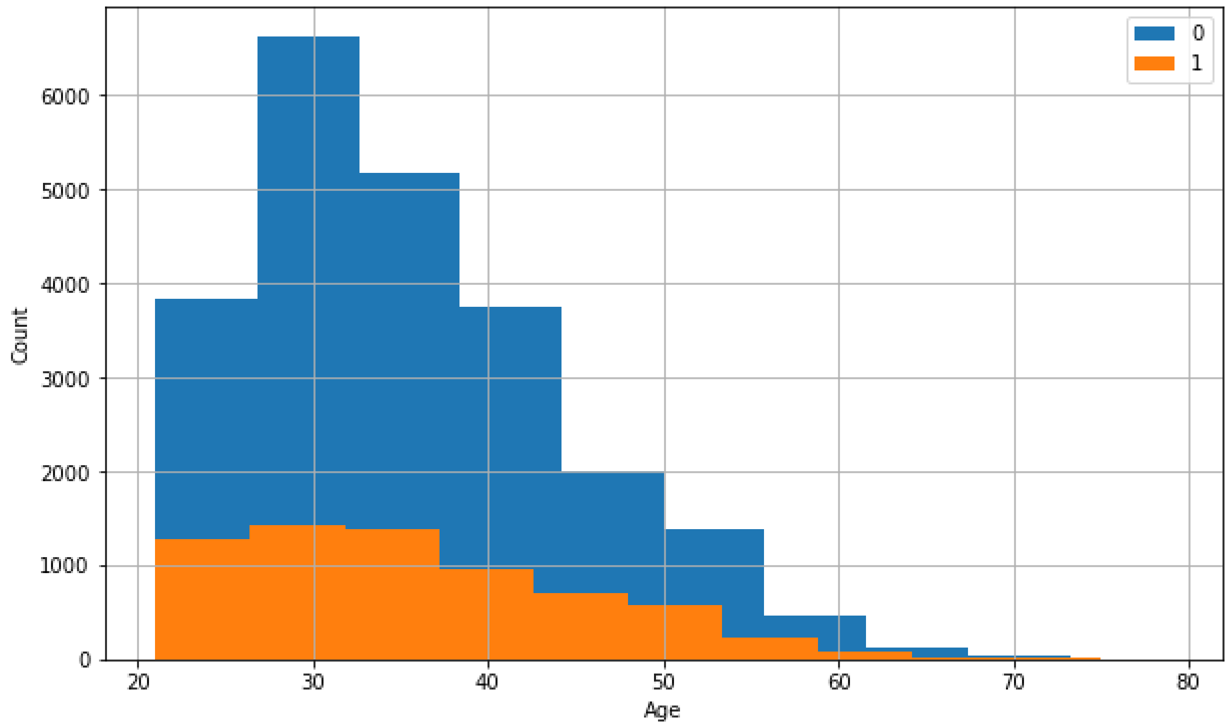
In [73]:
```
# Variance Inflation Factor (VIF) is used to detect the presence of multicollinearity.
# Variance inflation factors (VIF) measure how much the variance of the estimated regression
# coefficients are inflated as compared to when the predictor variables are not linearly related.

from statsmodels.stats.outliers_influence import variance_inflation_factor
data= df.drop(['Target','ID'],1)
factor = pd.DataFrame()
factor['Features']= data.columns
factor['VIF']= [variance_inflation_factor(data.values,i) for i in range(data.shape[1])]
factor
```

Out[73]:

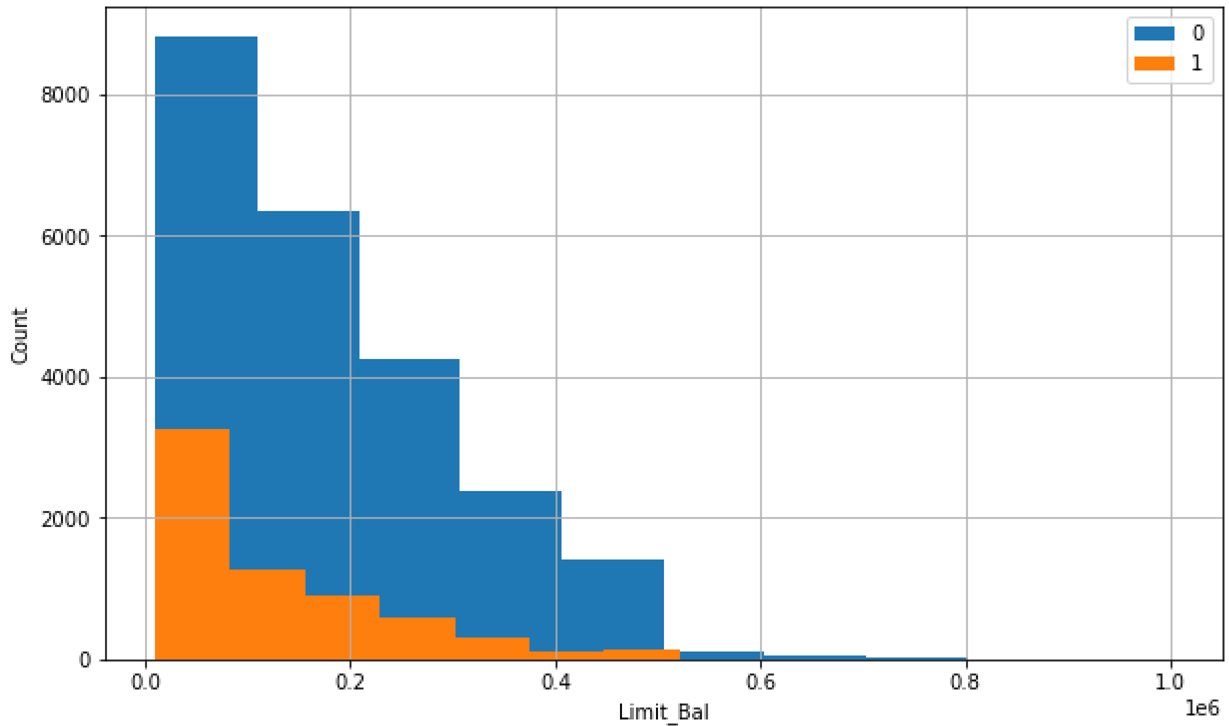
	Features	VIF
0	LIMIT_BAL	4.037479
1	SEX	9.092210
2	EDUCATION	6.731119
3	MARRIAGE	6.265388
4	AGE	10.857679
5	PAY_0	1.918276
6	PAY_2	3.211217
7	PAY_3	3.727427
8	PAY_4	4.440120
9	PAY_5	4.985856
10	PAY_6	3.463800
11	BILL_AMT1	20.823400
12	BILL_AMT2	38.214225
13	BILL_AMT3	31.783029
14	BILL_AMT4	29.548135
15	BILL_AMT5	35.986369
16	BILL_AMT6	21.426076
17	PAY_AMT1	1.907500
18	PAY_AMT2	2.384860
19	PAY_AMT3	1.911689
20	PAY_AMT4	1.805048
21	PAY_AMT5	1.854229
22	PAY_AMT6	1.270665

Data Visualization

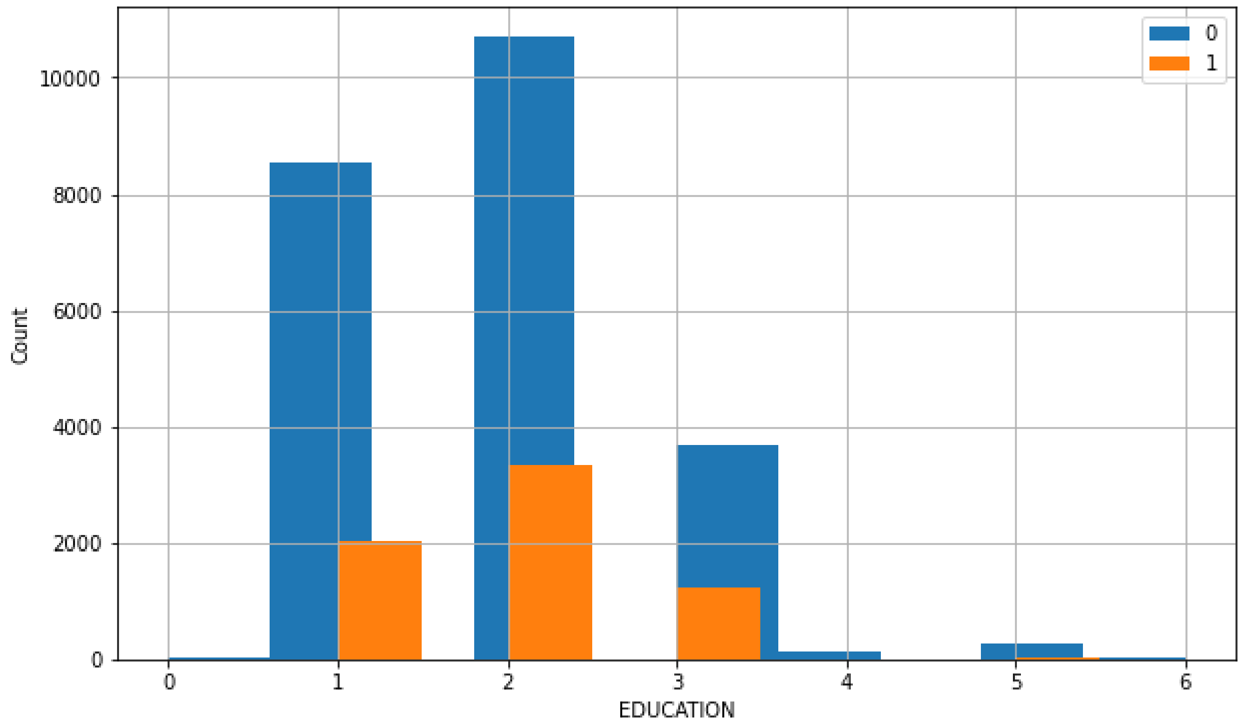
In [74]:
```python
# Histogram analysis Count and Age
plt.figure(figsize=(10,6))
df.groupby('Target')['AGE'].hist(legend=True)
plt.xlabel('Age')
plt.ylabel('Count')
plt.show()
```



In [75]:
```python
plt.figure(figsize=(10,6))
df.groupby('Target')['LIMIT_BAL'].hist(legend=True)
plt.xlabel('Limit_Bal')
plt.ylabel('Count')
plt.show()
```

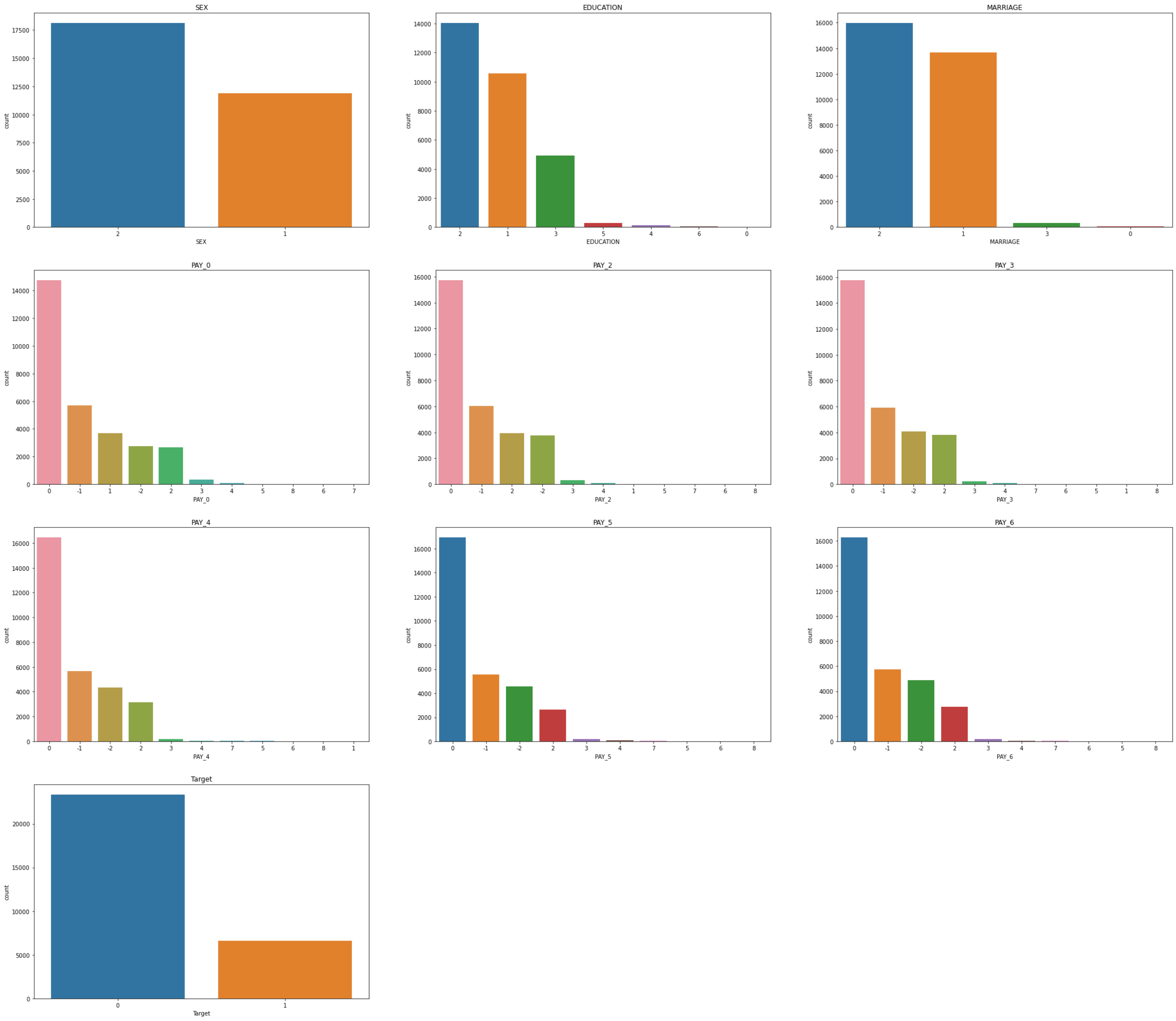


In [76]:
```python
plt.figure(figsize=(10,6))
df.groupby('Target')['EDUCATION'].hist(legend=True)
plt.xlabel('EDUCATION')
plt.ylabel('Count')
plt.show()
```



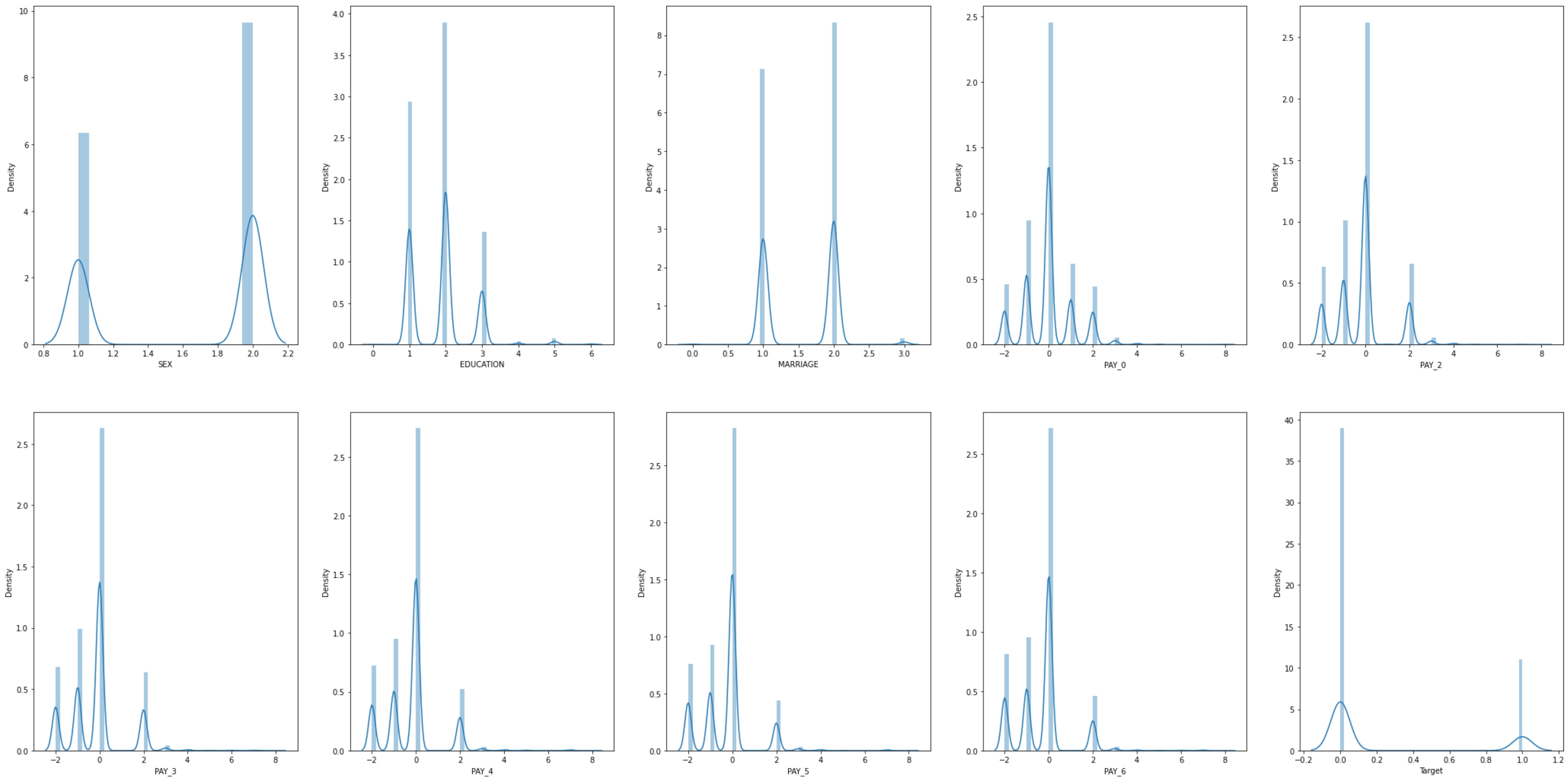
In [77]:
```python
data= df.drop(['ID'],1)
nuniq = data.nunique()
```

```python
data = df[[col for col in data if nuniq[col]>1 and nuniq[col]<50]]
row, cols = data.shape
colnames = list(data)
graph_perrow = 3
graph_row = (cols+graph_perrow-1)/ graph_perrow
max_graph = 20
plt.figure(figsize=(graph_perrow*12,graph_row*8))
for i in range(min(cols,max_graph)):
    plt.subplot(graph_row,graph_perrow,i+1)
    coldf = data.iloc[:,i]
    if (not np.issubdtype(type(coldf),np.number)):
        sns.countplot(colnames[i],data= data, order= data[colnames[i]].value_counts().index)
    else:
        coldf.hist()
    plt.title(colnames[i])
plt.show()
```



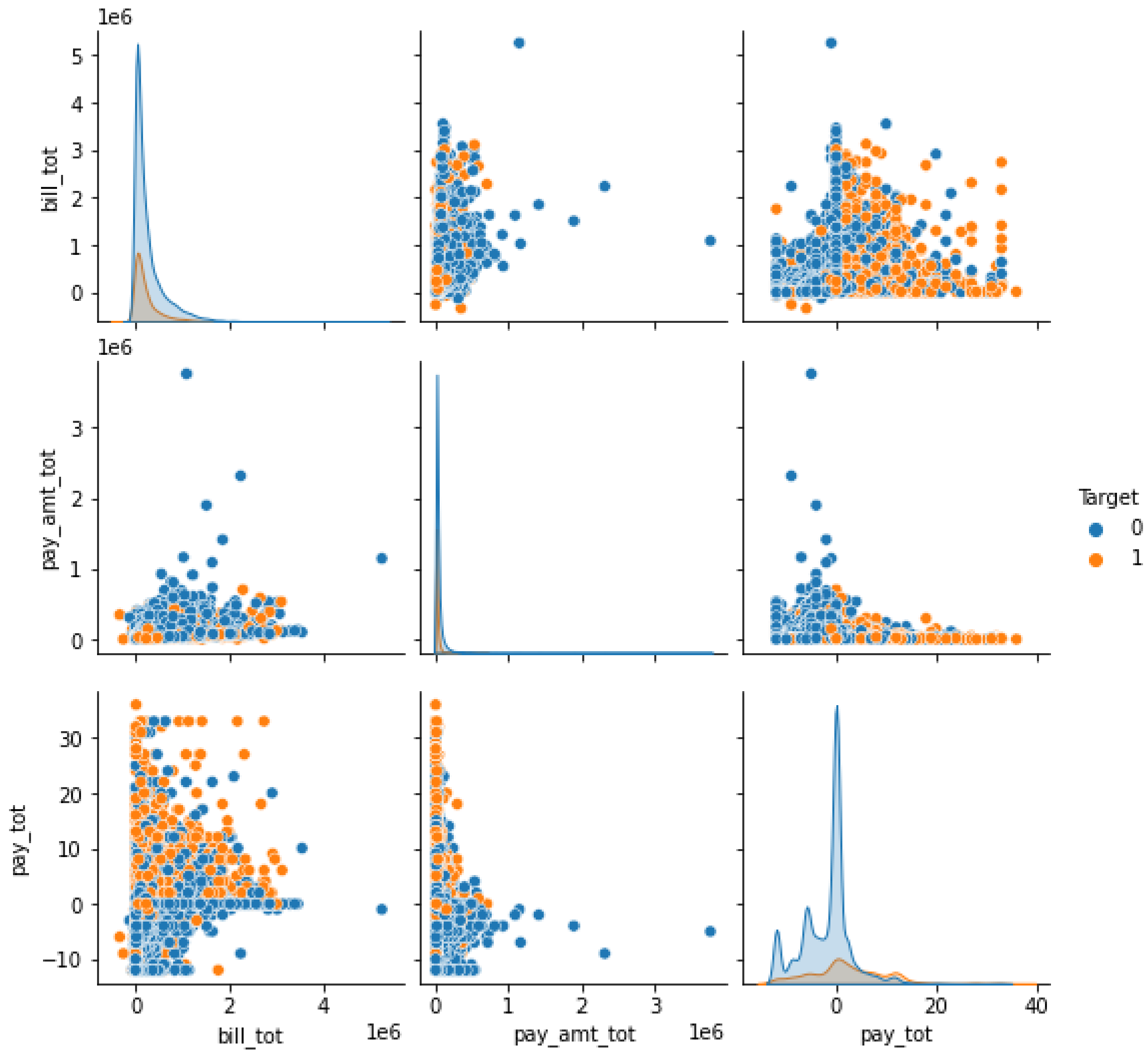
In [78]:

```python
# Density vs Data Features
cont = data.select_dtypes(exclude='object').columns
nrow = (len(cont)+5-1)/5
plt.figure(figsize=(12*3,6*3))
for i,j in enumerate(cont):
    plt.subplot(nrow,5,i+1)
    sns.distplot(df[j])
plt.show()
```

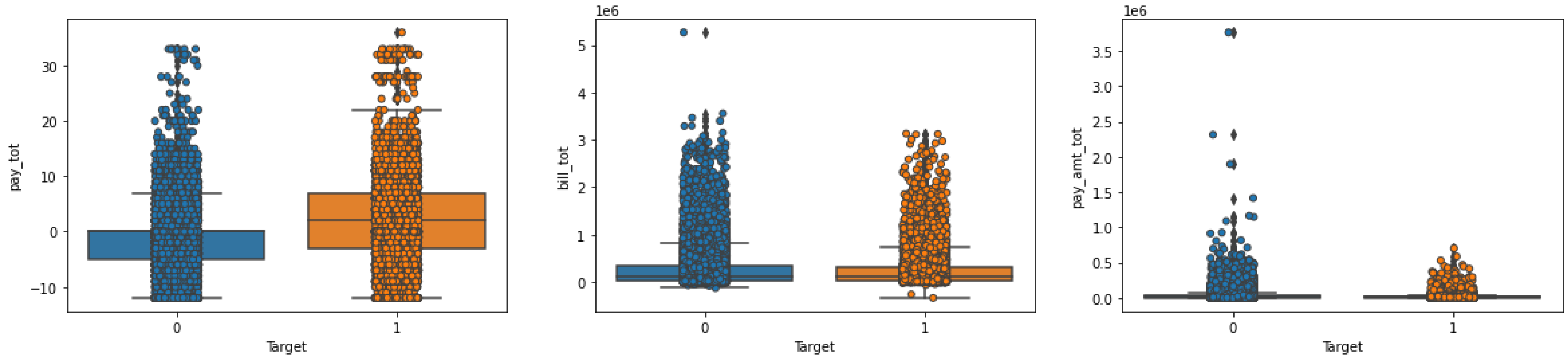


In [79]:
```
# Merging the Bill amount columns,Pay coulmns and Pay amount columns as different total one column respectively.

bill_tot = pd.DataFrame(df['BILL_AMT1']+df['BILL_AMT2']+df['BILL_AMT3']+df['BILL_AMT4']+df['BILL_AMT5']+df['BILL_AMT6'],columns=['
pay_tot =pd.DataFrame(df['PAY_0']+df['PAY_2']+df['PAY_3']+df['PAY_4']+df['PAY_5']+df['PAY_6'],columns=['pay_tot'])
pay_amt_tot = pd.DataFrame(df['PAY_AMT1']+df['PAY_AMT2']+df['PAY_AMT3']+df['PAY_AMT4']+df['PAY_AMT5']+df['PAY_AMT6'],columns=['pay
frames=[bill_tot,pay_tot,pay_amt_tot,df['Target']]
total = pd.concat(frames,axis=1)
```

In [80]:
```
sns.pairplot(total[['bill_tot','pay_amt_tot','pay_tot','Target']],hue='Target')
plt.show()
```

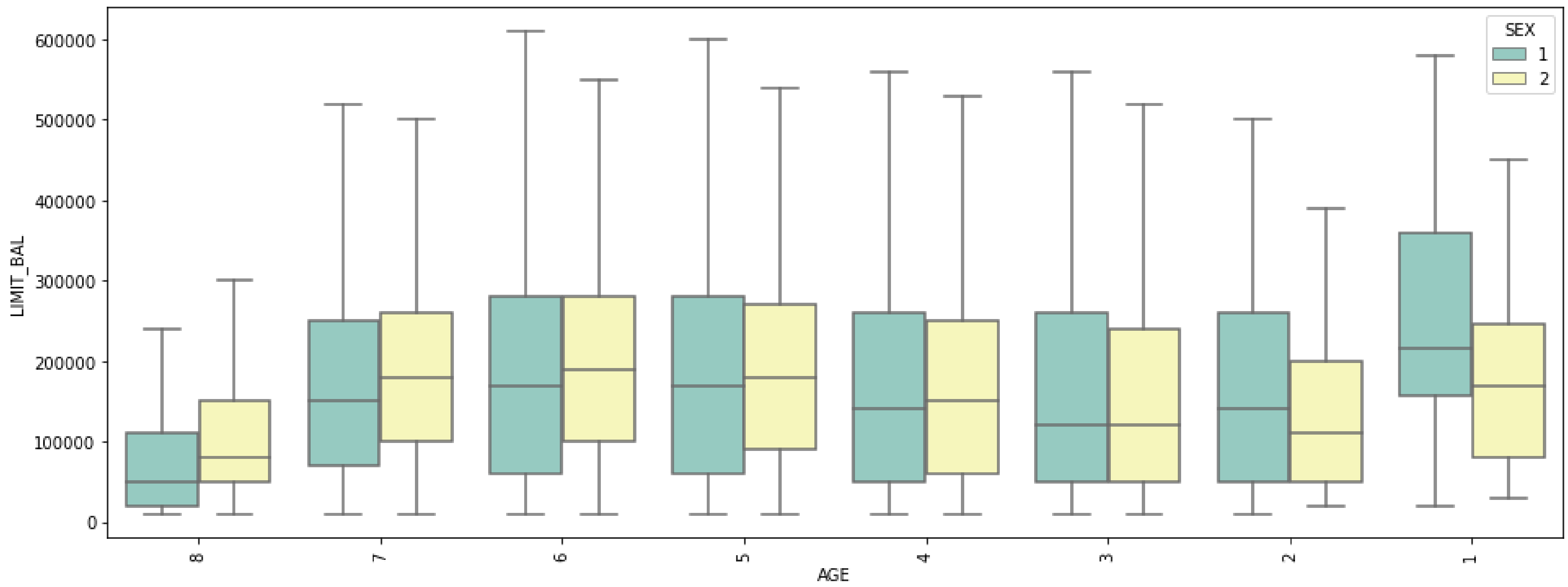


In [81]:
```
plt.figure(figsize=(20,4))
plt.subplot(131)
sns.boxplot(x='Target',y='pay_tot',data = total)
sns.stripplot(x='Target',y='pay_tot',data = total,linewidth=1)

plt.subplot(132)
sns.boxplot(x='Target', y='bill_tot',data=total)
sns.stripplot(x='Target', y='bill_tot',data=total,linewidth=1)

plt.subplot(133)
sns.boxplot(x='Target', y='pay_amt_tot',data=total)
sns.stripplot(x='Target', y='pay_amt_tot',data=total,linewidth=1)
plt.show()
```

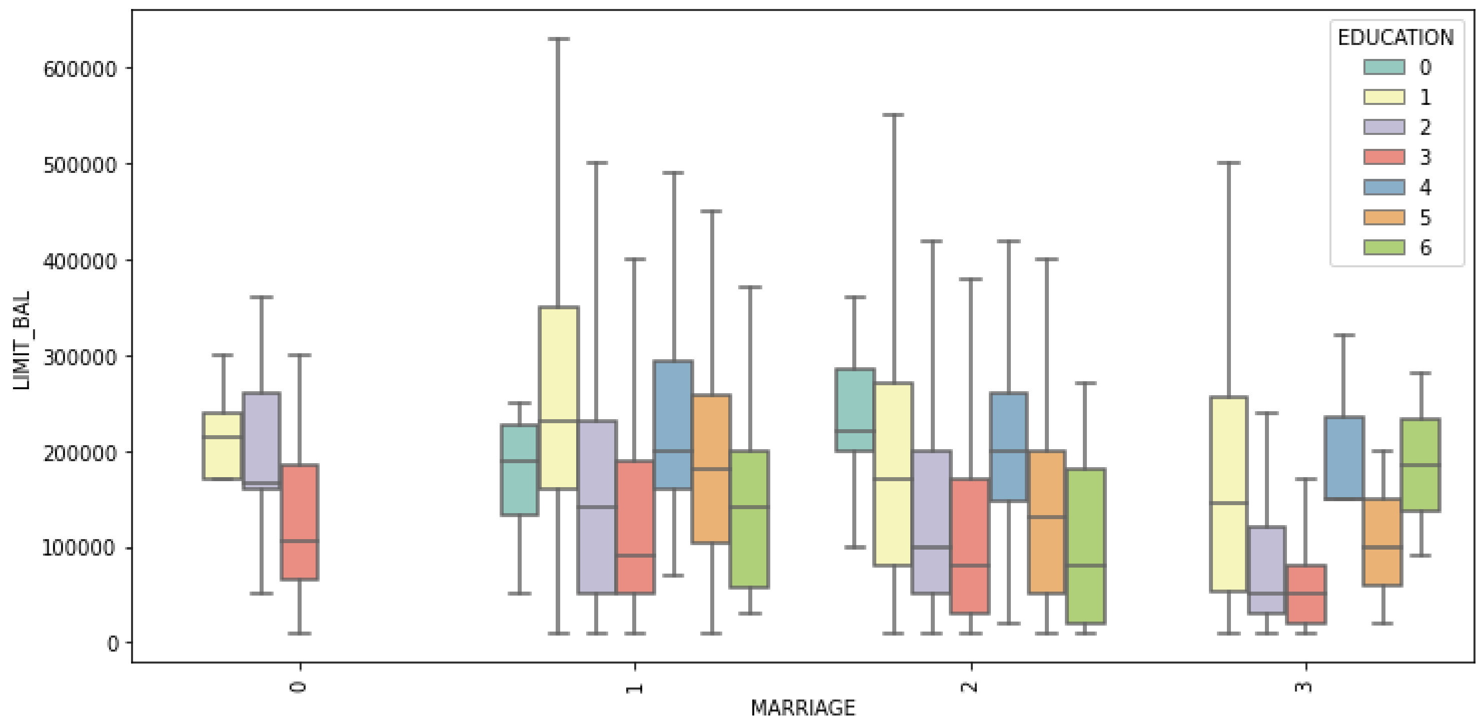


In [82]:
```
age = [20,27,32,37,42,48,58,64,80]
lab = [8,7,6,5,4,3,2,1]
df['AGE'] = pd.cut(df['AGE'],bins= age,labels=lab)
```

In [83]:
```
def boxplot_variation(feature1, feature2, feature3, width=16):
    fig, ax1 = plt.subplots(ncols=1, figsize=(width,6))
    s = sns.boxplot(ax = ax1, x=feature1, y=feature2, hue=feature3,
                data=df, palette="Set3",showfliers=False)
    s.set_xticklabels(s.get_xticklabels(),rotation=90)
    plt.show()

boxplot_variation('AGE','LIMIT_BAL', 'SEX',16)
```



In [84]:
```
boxplot_variation('MARRIAGE','LIMIT_BAL', 'EDUCATION',12)
```



Data Interpretation

- Raw Data Contains rows: 30000 columns: 25
- There are 30,000 distinct credit card clients.
- The average value for the amount of credit card limit is 167,484.
- The standard deviation is unusually large, max value being 1M.
- Education level is mostly graduate school and university.
- Most of the clients are either marrined or single (less frequent the other status).
- Average age is 35.5 years, with a standard deviation of 9.2.
- As the value 0 for Target means 'not default' and value 1 means 'default', the mean of 0.221 means that there are 22.1% of credit card contracts that will default next month (will verify this in the next sections of this analysis).
- There are 81 distinct values for amount of credit limit.

- Indeed, the largest number of credit cards are with limit of 50,000 (3365), followed by 20,000 (1976) and 30,000 (1610). Credit limit distinct values and count
- Marriage status meaning is:
  - 0 : unknown (let's consider as others as well)
  - 1 : married
  - 2 : single
  - 3 : others
- Sex status meaning is:
  - 1 : male
  - 2 : female
- Education status meaning is:
  - 1 : graduate school
  - 2 : university
  - 3 : high school
  - 4 : others
  - 5 : unknown
  - 6 : unknow
- from the data summary the datset doesnt contain any missing values and all are numeric values
- Most of the people fall between 20 and 40 years of age age
- from the above,we can see that we have maximum clients from 20-30 age group followed by 31-40.
- Hence with increasing age group the number of clients that will default the payment next month is decreasing.
- Hence we can see that Age is important feature to predict the default payment for next month.
- From the above VIF we can see that there are some multicolinearity(values >10) in the data which we can handle.
- we know that the Bill_AMT is the most correlated column so using that we create a data.
- As a thumb rule, any variable with VIF > 1.5 is avoided in a regression analysis. Sometimes the condition is relaxed to 2, instead of 1.5.

In [85]:
```
df= pd.concat([bill_tot,df],1)
df= df.drop(['BILL_AMT1','BILL_AMT2','BILL_AMT3','BILL_AMT4','BILL_AMT5','BILL_AMT6'],1)
```

In [86]:
```
df_fact = pd.DataFrame()
df_fact['Features']= df.columns
df_fact['VIF']= [variance_inflation_factor(df.values,i) for i in range(df.shape[1])]
df_fact
```

Out[86]:

	Features	VIF
0	bill_tot	2.204331
1	ID	3.811546
2	LIMIT_BAL	3.667109
3	SEX	9.814152
4	EDUCATION	5.288997
5	MARRIAGE	10.757710
6	AGE	14.245275
7	PAY_0	1.996823
8	PAY_2	3.193387
9	PAY_3	3.709471
10	PAY_4	4.434841
11	PAY_5	4.966761
12	PAY_6	3.409306
13	PAY_AMT1	1.358967
14	PAY_AMT2	1.263243
15	PAY_AMT3	1.302529
16	PAY_AMT4	1.256366
17	PAY_AMT5	1.221195
18	PAY_AMT6	1.204328
19	Target	1.428712

- above we can see that now our data doesn't have multicollinearty(no values >10)
- for age we divided it into different groups and labelled it with values
  - 8 : 20-26
  - 7 : 27-31
  - 6 : 32-36
  - 5 : 37-41
  - 4 : 42-47

        - 3 : 48-57
        - 2 : 58-63
        - 1 : 64-max
- Histograms ,density and boxplots are plotted according to the data values.
- The new processed data is stored in a new csv file under name Cleaned_data.csv
- The shape of the new data is rows:30000 columns:20

In [94]:
```
df.to_csv('Cleaned_data.csv')
```

In [93]:
```
df.shape
```

Out[93]:
```
(30000, 20)
```