Default Credit Card Clients - Predictive model

September 28, 2018

1 Default Credit Card Clients - Predictive model

2 Dataset details

2.1 Default Payments of Credit Card Clients in Taiwan from 2005

(https://www.kaggle.com/uciml/default-of-credit-card-clients-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

2.2 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_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) * 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)

2.3 Acknowledgements

Lichman, M. (2013). UCI Machine Learning Repository [http://archive.ics.uci.edu/ml]. Irvine, CA: University of California, School of Information and Computer Science

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import os
```

3 Data ingestion

In [2]:
```
dataset = pd.read_csv('./data/UCI_Credit_Card.csv')
```

4 Glimpse at the data

In [3]:
```
dataset.head()
```

Out[3]:

	ID	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	\
0	1	20000.0	2	2	1	24	2	2	-1	-1	
1	2	120000.0	2	2	2	26	-1	2	0	0	
2	3	90000.0	2	2	2	34	0	0	0	0	
3	4	50000.0	2	2	1	37	0	0	0	0	
4	5	50000.0	1	2	1	57	-1	0	-1	0	

	...	BILL_AMT4	BILL_AMT5	BILL_AMT6	PAY_AMT1	\
0	...	0.0	0.0	0.0	0.0	
1	...	3272.0	3455.0	3261.0	0.0	
2	...	14331.0	14948.0	15549.0	1518.0	
3	...	28314.0	28959.0	29547.0	2000.0	
4	...	20940.0	19146.0	19131.0	2000.0	

	PAY_AMT2	PAY_AMT3	PAY_AMT4	PAY_AMT5	PAY_AMT6	\
0	689.0	0.0	0.0	0.0	0.0	
1	1000.0	1000.0	1000.0	0.0	2000.0	
2	1500.0	1000.0	1000.0	1000.0	5000.0	
3	2019.0	1200.0	1100.0	1069.0	1000.0	
4	36681.0	10000.0	9000.0	689.0	679.0	

	default.payment.next.month
0	1
1	1
2	0
3	0
4	0

[5 rows x 25 columns]

In [4]:
```
dataset.shape
```

Out[4]: (30000, 25)

In [5]:
```
dataset.describe()
```

Out[5]:

	ID	LIMIT_BAL	SEX	EDUCATION	MARRIAGE
count	30000.000000	30000.000000	30000.000000	30000.000000	30000.000000
mean	15000.500000	167484.322667	1.603733	1.853133	1.551867
std	8660.398374	129747.661567	0.489129	0.790349	0.521970
min	1.000000	10000.000000	1.000000	0.000000	0.000000
25%	7500.750000	50000.000000	1.000000	1.000000	1.000000
50%	15000.500000	140000.000000	2.000000	2.000000	2.000000
75%	22500.250000	240000.000000	2.000000	2.000000	2.000000
max	30000.000000	1000000.000000	2.000000	6.000000	3.000000

	AGE	PAY_0	PAY_2	PAY_3	PAY_4
count	30000.000000	30000.000000	30000.000000	30000.000000	30000.000000
mean	35.485500	-0.016700	-0.133767	-0.166200	-0.220667
std	9.217904	1.123802	1.197186	1.196868	1.169139
min	21.000000	-2.000000	-2.000000	-2.000000	-2.000000
25%	28.000000	-1.000000	-1.000000	-1.000000	-1.000000
50%	34.000000	0.000000	0.000000	0.000000	0.000000
75%	41.000000	0.000000	0.000000	0.000000	0.000000
max	79.000000	8.000000	8.000000	8.000000	8.000000

	...	BILL_AMT4	BILL_AMT5
count	...	30000.000000	30000.000000
mean	...	43262.948967	40311.400967
std	...	64332.856134	60797.155770
min	...	-170000.000000	-81334.000000
25%	...	2326.750000	1763.000000
50%	...	19052.000000	18104.500000
75%	...	54506.000000	50190.500000
max	...	891586.000000	927171.000000

	BILL_AMT6	PAY_AMT1	PAY_AMT2	PAY_AMT3
count	30000.000000	30000.000000	3.000000e+04	30000.00000
mean	38871.760400	5663.580500	5.921163e+03	5225.68150
std	59554.107537	16563.280354	2.304087e+04	17606.96147
min	-339603.000000	0.000000	0.000000e+00	0.00000
25%	1256.000000	1000.000000	8.330000e+02	390.00000
50%	17071.000000	2100.000000	2.009000e+03	1800.00000
75%	49198.250000	5006.000000	5.000000e+03	4505.00000
max	961664.000000	873552.000000	1.684259e+06	896040.00000

	PAY_AMT4	PAY_AMT5	PAY_AMT6	default.payment.next.month
count	30000.000000	30000.000000	30000.000000	30000.000000
mean	4826.076867	4799.387633	5215.502567	0.221200
std	15666.159744	15278.305679	17777.465775	0.415062
min	0.000000	0.000000	0.000000	0.000000
25%	296.000000	252.500000	117.750000	0.000000
50%	1500.000000	1500.000000	1500.000000	0.000000
75%	4013.250000	4031.500000	4000.000000	0.000000

```
max    621000.000000  426529.000000  528666.000000                     1.000000

[8 rows x 25 columns]
```

5 Calculate outstanding amount

In [6]:
```
dataset['APR-Outstanding']= dataset['BILL_AMT6']-dataset['PAY_AMT6']
dataset['MAY-Outstanding']= dataset['BILL_AMT5']-dataset['PAY_AMT5']
dataset['JUN-Outstanding']= dataset['BILL_AMT4']-dataset['PAY_AMT4']
dataset['JUL-Outstanding']= dataset['BILL_AMT3']-dataset['PAY_AMT3']
dataset['AUG-Outstanding']= dataset['BILL_AMT2']-dataset['PAY_AMT2']
dataset['SEP-Outstanding']= dataset['BILL_AMT1']-dataset['PAY_AMT1']
dataset.head(5)
```

Out[6]:
```
   ID  LIMIT_BAL  SEX  EDUCATION  MARRIAGE  AGE  PAY_0  PAY_2  PAY_3  PAY_4  \
0   1    20000.0    2          2         1   24      2      2     -1     -1
1   2   120000.0    2          2         2   26     -1      2      0      0
2   3    90000.0    2          2         2   34      0      0      0      0
3   4    50000.0    2          2         1   37      0      0      0      0
4   5    50000.0    1          2         1   57     -1      0     -1      0

         ...        PAY_AMT4  PAY_AMT5  PAY_AMT6  default.payment.next.month  \
0        ...             0.0       0.0       0.0                           1
1        ...          1000.0       0.0    2000.0                           1
2        ...          1000.0    1000.0    5000.0                           0
3        ...          1100.0    1069.0    1000.0                           0
4        ...          9000.0     689.0     679.0                           0

   APR-Outstanding  MAY-Outstanding  JUN-Outstanding  JUL-Outstanding  \
0              0.0              0.0              0.0            689.0
1           1261.0           3455.0           2272.0           1682.0
2          10549.0          13948.0          13331.0          12559.0
3          28547.0          27890.0          27214.0          48091.0
4          18452.0          18457.0          11940.0          25835.0

   AUG-Outstanding  SEP-Outstanding
0           2413.0           3913.0
1            725.0           2682.0
2          12527.0          27721.0
3          46214.0          44990.0
4         -31011.0           6617.0

[5 rows x 31 columns]
```

6 Data cleanup

```
In [7]: # rename column name
        dataset.rename(columns={'default.payment.next.month':'DefaultPayment'},inplace=True)
        dataset.columns
```

```
Out[7]: Index(['ID', 'LIMIT_BAL', 'SEX', 'EDUCATION', 'MARRIAGE', 'AGE', 'PAY_0',
               'PAY_2', 'PAY_3', 'PAY_4', 'PAY_5', 'PAY_6', 'BILL_AMT1', 'BILL_AMT2',
               'BILL_AMT3', 'BILL_AMT4', 'BILL_AMT5', 'BILL_AMT6', 'PAY_AMT1',
               'PAY_AMT2', 'PAY_AMT3', 'PAY_AMT4', 'PAY_AMT5', 'PAY_AMT6',
               'DefaultPayment', 'APR-Outstanding', 'MAY-Outstanding',
               'JUN-Outstanding', 'JUL-Outstanding', 'AUG-Outstanding',
               'SEP-Outstanding'],
              dtype='object')
```

```
In [8]: # check and remove invalid data if any
        print(dataset['SEX'].min(),dataset['SEX'].max())
        print(dataset['SEX'].value_counts())
```

```
1 2
2    18112
1    11888
Name: SEX, dtype: int64
```

```
In [9]: # check for null
        dataset.isnull().any().any()
```

```
Out[9]: False
```

```
In [10]: # check EDUCATION and remove invalid data if any
         print('before\n',dataset['EDUCATION'].value_counts())

         dataset['EDUCATION'] = dataset['EDUCATION'].replace([4,5,6,0], 4)
         print('after\n',dataset['EDUCATION'].value_counts())
```

```
before
 2    14030
1    10585
3     4917
5      280
4      123
6       51
0       14
Name: EDUCATION, dtype: int64
after
 2    14030
1    10585
3     4917
```

```
4      468
Name: EDUCATION, dtype: int64
```

In [11]:
```python
# check MARRIAGE and remove invalid data if any

Before = dataset['MARRIAGE'].value_counts()
dataset = dataset[dataset['MARRIAGE'] > 0]

After = dataset['MARRIAGE'].value_counts()
print('Before\n',Before)
print('After\n',After)
```

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

In [12]:
```python
dataset.head().transpose()
```

Out[12]:

	0	1	2	3	4
ID	1.0	2.0	3.0	4.0	5.0
LIMIT_BAL	20000.0	120000.0	90000.0	50000.0	50000.0
SEX	2.0	2.0	2.0	2.0	1.0
EDUCATION	2.0	2.0	2.0	2.0	2.0
MARRIAGE	1.0	2.0	2.0	1.0	1.0
AGE	24.0	26.0	34.0	37.0	57.0
PAY_0	2.0	-1.0	0.0	0.0	-1.0
PAY_2	2.0	2.0	0.0	0.0	0.0
PAY_3	-1.0	0.0	0.0	0.0	-1.0
PAY_4	-1.0	0.0	0.0	0.0	0.0
PAY_5	-2.0	0.0	0.0	0.0	0.0
PAY_6	-2.0	2.0	0.0	0.0	0.0
BILL_AMT1	3913.0	2682.0	29239.0	46990.0	8617.0
BILL_AMT2	3102.0	1725.0	14027.0	48233.0	5670.0
BILL_AMT3	689.0	2682.0	13559.0	49291.0	35835.0
BILL_AMT4	0.0	3272.0	14331.0	28314.0	20940.0
BILL_AMT5	0.0	3455.0	14948.0	28959.0	19146.0
BILL_AMT6	0.0	3261.0	15549.0	29547.0	19131.0
PAY_AMT1	0.0	0.0	1518.0	2000.0	2000.0
PAY_AMT2	689.0	1000.0	1500.0	2019.0	36681.0

```
PAY_AMT3              0.0     1000.0    1000.0    1200.0  10000.0
PAY_AMT4              0.0     1000.0    1000.0    1100.0   9000.0
PAY_AMT5              0.0        0.0    1000.0    1069.0    689.0
PAY_AMT6              0.0     2000.0    5000.0    1000.0    679.0
DefaultPayment        1.0        1.0       0.0       0.0      0.0
APR-Outstanding       0.0     1261.0   10549.0   28547.0  18452.0
MAY-Outstanding       0.0     3455.0   13948.0   27890.0  18457.0
JUN-Outstanding       0.0     2272.0   13331.0   27214.0  11940.0
JUL-Outstanding     689.0     1682.0   12559.0   48091.0  25835.0
AUG-Outstanding    2413.0      725.0   12527.0   46214.0 -31011.0
SEP-Outstanding    3913.0     2682.0   27721.0   44990.0   6617.0
```

In [13]:
```python
selectedColumns = ['ID','LIMIT_BAL','SEX','EDUCATION','MARRIAGE','AGE','PAY_0','PAY_2
print(selectedColumns)
```

```
['ID', 'LIMIT_BAL', 'SEX', 'EDUCATION', 'MARRIAGE', 'AGE', 'PAY_0', 'PAY_2', 'PAY_3', 'PAY_4',
```

In [14]:
```python
dataset.columns
```

Out[14]:
```
Index(['ID', 'LIMIT_BAL', 'SEX', 'EDUCATION', 'MARRIAGE', 'AGE', 'PAY_0',
       'PAY_2', 'PAY_3', 'PAY_4', 'PAY_5', 'PAY_6', 'BILL_AMT1', 'BILL_AMT2',
       'BILL_AMT3', 'BILL_AMT4', 'BILL_AMT5', 'BILL_AMT6', 'PAY_AMT1',
       'PAY_AMT2', 'PAY_AMT3', 'PAY_AMT4', 'PAY_AMT5', 'PAY_AMT6',
       'DefaultPayment', 'APR-Outstanding', 'MAY-Outstanding',
       'JUN-Outstanding', 'JUL-Outstanding', 'AUG-Outstanding',
       'SEP-Outstanding'],
      dtype='object')
```

In [15]:
```python
data = dataset[selectedColumns]
data.head()
```

Out[15]:
```
   ID  LIMIT_BAL  SEX  EDUCATION  MARRIAGE  AGE  PAY_0  PAY_2  PAY_3  PAY_4  \
0   1    20000.0    2          2         1   24      2      2     -1     -1
1   2   120000.0    2          2         2   26     -1      2      0      0
2   3    90000.0    2          2         2   34      0      0      0      0
3   4    50000.0    2          2         1   37      0      0      0      0
4   5    50000.0    1          2         1   57     -1      0     -1      0

   PAY_5  PAY_6  SEP-Outstanding  AUG-Outstanding  JUL-Outstanding  \
0     -2     -2           3913.0           2413.0            689.0
1      0      2           2682.0            725.0           1682.0
2      0      0          27721.0          12527.0          12559.0
3      0      0          44990.0          46214.0          48091.0
4      0      0           6617.0         -31011.0          25835.0

   JUN-Outstanding  MAY-Outstanding  APR-Outstanding  DefaultPayment
0              0.0              0.0              0.0               1
1           2272.0           3455.0           1261.0               1
```

2	13331.0	13948.0	10549.0	0
3	27214.0	27890.0	28547.0	0
4	11940.0	18457.0	18452.0	0

In [16]:
```
#data['AvgOS_AMT'] = data[['SEP-Outstanding','AUG-Outstanding','JUL-Outstanding','JUN
```

In [17]:
```
data.describe()
```

Out[17]:

	ID	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	\
count	29946.000000	29946.000000	29946.000000	29946.000000	29946.000000	
mean	14999.138015	167546.573165	1.603486	1.840646	1.554665	
std	8659.571030	129807.831678	0.489182	0.743774	0.518259	
min	1.000000	10000.000000	1.000000	1.000000	1.000000	
25%	7499.250000	50000.000000	1.000000	1.000000	1.000000	
50%	14997.500000	140000.000000	2.000000	2.000000	2.000000	
75%	22495.750000	240000.000000	2.000000	2.000000	2.000000	
max	30000.000000	1000000.000000	2.000000	4.000000	3.000000	

	AGE	PAY_0	PAY_2	PAY_3	PAY_4	\
count	29946.000000	29946.000000	29946.000000	29946.000000	29946.000000	
mean	35.481300	-0.016430	-0.133641	-0.166132	-0.220397	
std	9.218413	1.123467	1.196968	1.196428	1.168882	
min	21.000000	-2.000000	-2.000000	-2.000000	-2.000000	
25%	28.000000	-1.000000	-1.000000	-1.000000	-1.000000	
50%	34.000000	0.000000	0.000000	0.000000	0.000000	
75%	41.000000	0.000000	0.000000	0.000000	0.000000	
max	79.000000	8.000000	8.000000	8.000000	8.000000	

	PAY_5	PAY_6	SEP-Outstanding	AUG-Outstanding	\
count	29946.000000	29946.000000	29946.000000	2.994600e+04	
mean	-0.265945	-0.290857	45619.175015	4.329772e+04	
std	1.133029	1.149773	73212.433876	7.261554e+04	
min	-2.000000	-2.000000	-733744.000000	-1.702347e+06	
25%	-1.000000	-1.000000	750.000000	3.300000e+02	
50%	0.000000	0.000000	18568.500000	1.811900e+04	
75%	0.000000	0.000000	62382.250000	5.924400e+04	
max	8.000000	8.000000	913727.000000	9.332080e+05	

	JUL-Outstanding	JUN-Outstanding	MAY-Outstanding	APR-Outstanding	\
count	2.994600e+04	29946.000000	29946.000000	29946.000000	
mean	4.183537e+04	38477.073432	35547.929173	33690.662359	
std	6.933957e+04	64244.702389	60594.012145	60191.540909	
min	-8.546410e+05	-667000.000000	-414380.000000	-684896.000000	
25%	2.672500e+02	232.000000	0.000000	0.000000	
50%	1.780100e+04	16979.000000	15560.000000	13944.500000	
75%	5.636450e+04	50353.750000	46986.000000	46112.000000	
max	1.542258e+06	841586.000000	877171.000000	911408.000000	

```
       DefaultPayment
count    29946.000000
mean         0.221432
std          0.415218
min          0.000000
25%          0.000000
50%          0.000000
75%          0.000000
max          1.000000
```

7 Outlier treatment

```
In [18]: print(np.percentile(data['SEP-Outstanding'],10),np.percentile(data['SEP-Outstanding']

         MinOutliercondSep= (data['SEP-Outstanding']> np.percentile(data['SEP-Outstanding'],10)
         MaxOutliercondSep= (data['SEP-Outstanding']< np.percentile(data['SEP-Outstanding'],90)


         data= data[MinOutliercondSep & MaxOutliercondSep]
```

```
-896.5 62382.25 134894.0
```

```
In [19]: data.describe()
```

```
Out[19]:                ID      LIMIT_BAL           SEX     EDUCATION      MARRIAGE  \
         count  23956.000000   23956.000000  23956.000000  23956.000000  23956.000000
         mean   14926.754759  144878.610786      1.604024      1.864627      1.564911
         std     8634.851160  119857.561571      0.489070      0.733832      0.518820
         min        1.000000   10000.000000      1.000000      1.000000      1.000000
         25%     7467.250000   50000.000000      1.000000      1.000000      1.000000
         50%    14937.500000  110000.000000      2.000000      2.000000      2.000000
         75%    22309.250000  200000.000000      2.000000      2.000000      2.000000
         max    30000.000000  800000.000000      2.000000      4.000000      3.000000

                        AGE         PAY_0         PAY_2         PAY_3         PAY_4  \
         count  23956.000000  23956.000000  23956.000000  23956.000000  23956.000000
         mean      35.176866      0.040073     -0.060486     -0.135123     -0.181165
         std        9.319899      1.121869      1.228231      1.232781      1.214463
         min       21.000000     -2.000000     -2.000000     -2.000000     -2.000000
         25%       28.000000     -1.000000     -1.000000     -1.000000     -1.000000
         50%       33.000000      0.000000      0.000000      0.000000      0.000000
         75%       41.000000      0.000000      0.000000      0.000000      0.000000
         max       75.000000      8.000000      8.000000      8.000000      8.000000

                      PAY_5         PAY_6  SEP-Outstanding  AUG-Outstanding  \
         count  23956.000000  23956.000000     23956.000000     2.395600e+04
         mean      -0.229838     -0.255260     31707.332192     2.765466e+04
```

```
std         1.178966      1.196043     34603.063009      3.894106e+04
min        -2.000000     -2.000000      -896.000000     -1.024731e+06
25%        -1.000000     -1.000000      2500.000000      0.000000e+00
50%         0.000000      0.000000     18568.500000      1.656750e+04
75%         0.000000      0.000000     49058.250000      4.717450e+04
max         8.000000      8.000000    134886.000000      3.206230e+05

       JUL-Outstanding  JUN-Outstanding  MAY-Outstanding  APR-Outstanding  \
count     23956.000000     23956.000000     23956.000000     23956.000000
mean      27466.613375     25646.122099     24103.911838     23242.997328
std       38479.470290     37019.395019     36023.394211     36973.908497
min     -490073.000000   -502024.000000   -414380.000000   -684896.000000
25%         157.000000       131.250000         0.000000         0.000000
50%       16637.500000     15844.500000     14390.000000     12813.000000
75%       45877.500000     41389.500000     37338.750000     35836.250000
max      854454.000000    434497.000000    492109.000000    484100.000000

       DefaultPayment
count    23956.000000
mean         0.235933
std          0.424589
min          0.000000
25%          0.000000
50%          0.000000
75%          0.000000
max          1.000000
```

```
In [20]: data.shape
```

```
Out[20]: (23956, 19)
```

8 Binning Outstanding amount

```
In [21]: binwidth = round(int((max(data['SEP-Outstanding']) - min(data['SEP-Outstanding']))/5)

         bins = range(int(min(data['SEP-Outstanding'])),int(max(data['SEP-Outstanding'])),binwi
         print(binwidth)
         print(bins)
         group_names=['1','2','3','4']
         group_names=['Below $30k','Between $30k - $60k','Between $60k - $90k','Above $90k']
         data['OS_binned']= pd.cut(data["SEP-Outstanding"],bins,labels=group_names)
```

```
30000
range(-896, 134886, 30000)
```

```
In [22]: data['OS_binned'].value_counts()
```

```
Out[22]: Below $30k              14422
         Between $30k - $60k      4753
         Between $60k - $90k      2559
         Above $90k               1567
         Name: OS_binned, dtype: int64
```

9 Binning Age

```
In [23]: binwidth = 10
         bins = range(min(data['AGE']),max(data['AGE']),binwidth)
         print(binwidth)
         print(bins)
         group_names=['1','2','3','4','5','6','7']
         group_names=['Age 20-30','Age 30-40','Age 40-50','Age 50-60','Age 60-70']
         data['AGEGroup']= pd.cut(data['AGE'],bins,labels=group_names)
```

```
10
range(21, 75, 10)
```

```
In [24]: data['AGEGroup'].value_counts()
```

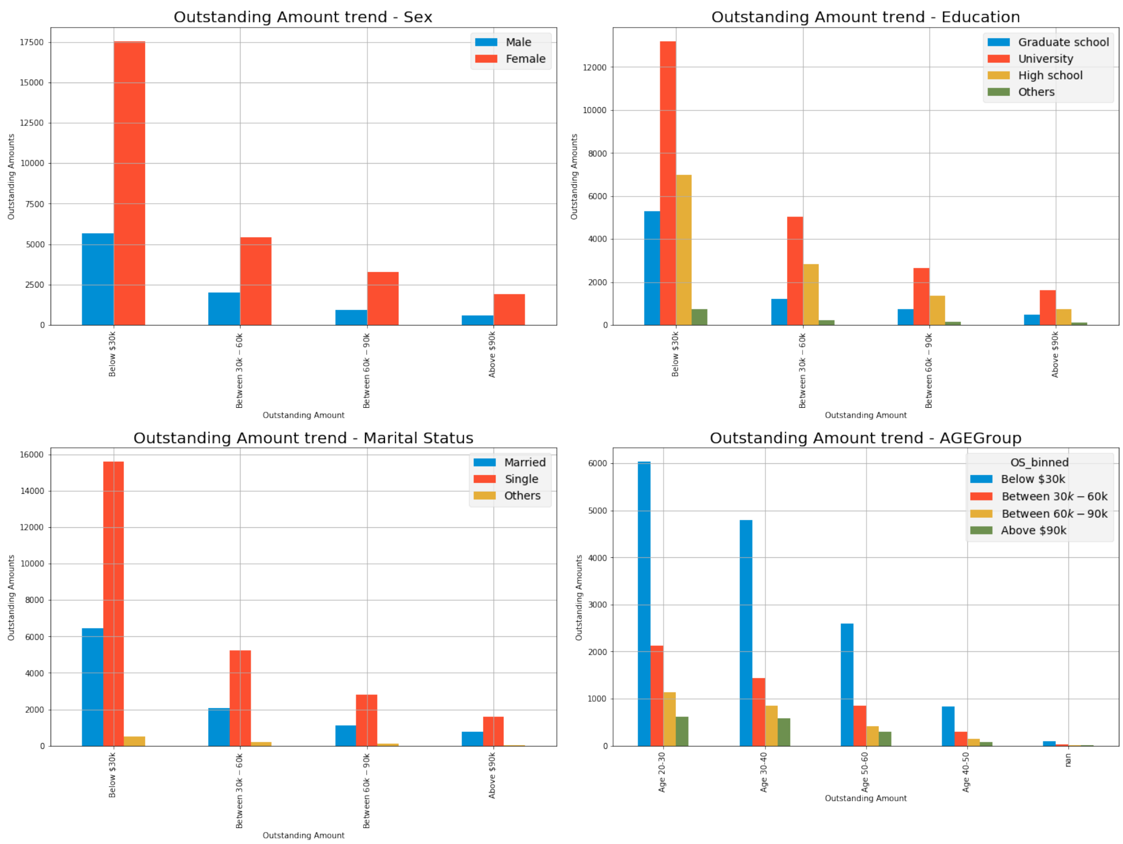
```
Out[24]: Age 20-30    10161
         Age 30-40     7912
         Age 40-50     4273
         Age 50-60     1383
         Age 60-70      154
         Name: AGEGroup, dtype: int64
```

10 Analyze the trend on outstanding amount for the bank

11 1. Overall outstanding amount trend

```
In [25]: fig = plt.figure(figsize=(20,15))
         ax1 = fig.add_subplot(221)
         ax2 = fig.add_subplot(222)
         ax3 = fig.add_subplot(223)
         ax4 = fig.add_subplot(224)

         plt.style.use('fivethirtyeight') # using the fivethirtyeight matplotlib theme

         # plot 1 - Outstanding trend - Sex

         DefaultgroupBySexBucket = data[['OS_binned','SEX']].groupby(['OS_binned','SEX'])
         DefaultgroupBySexBucketSum = DefaultgroupBySexBucket['SEX'].aggregate(np.sum).unstack
         DefaultgroupBySexBucketSum.plot(kind='bar',title='Outstanding Amount: By Sex', ax=ax1
         L=ax1.legend()
```

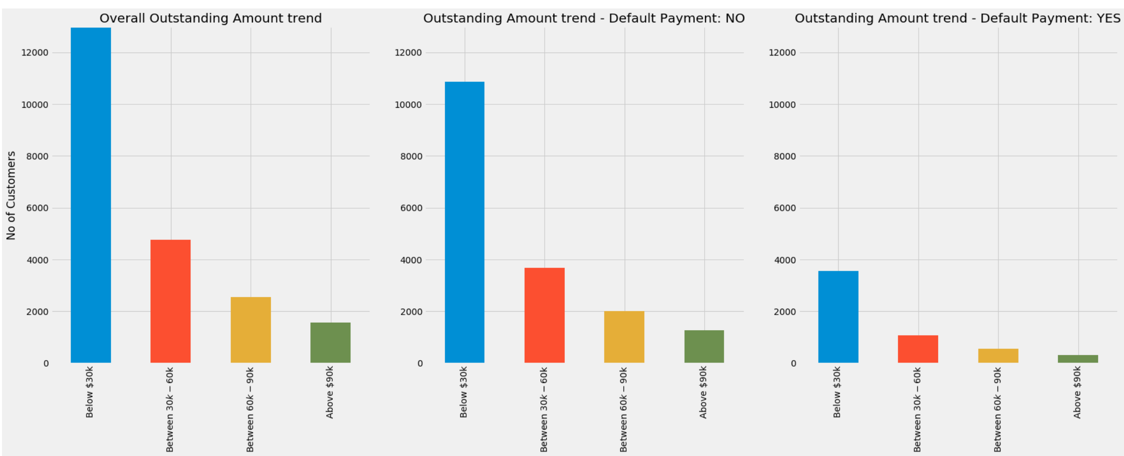
```
L.get_texts()[0].set_text('Male')
L.get_texts()[1].set_text('Female')

ax1.set(title='Outstanding Amount trend - Sex', xlabel='Outstanding Amount', ylabel='(

# plot 2 - Outstanding trend - Education
DefaultgroupByEDUBucket = data[['OS_binned','EDUCATION']].groupby(['OS_binned','EDUCAT
DefaultgroupByEDUBucketSum = DefaultgroupByEDUBucket['EDUCATION'].aggregate(np.sum).un
DefaultgroupByEDUBucketSum.plot(kind='bar',title='Outstanding Amount: By EDUCATION',ax
L2=ax2.legend()
L2.get_texts()[0].set_text('Graduate school')
L2.get_texts()[1].set_text('University')
L2.get_texts()[2].set_text('High school')
L2.get_texts()[3].set_text('Others')

ax2.set(title='Outstanding Amount trend - Education', xlabel='Outstanding Amount', yla

# plot 3 - Outstanding trend - Marital Status

DefaultgroupByMARBucket = data[['OS_binned','MARRIAGE']].groupby(['OS_binned','MARRIAG
DefaultgroupByMARBucketSum = DefaultgroupByMARBucket['MARRIAGE'].aggregate(np.sum).uns
DefaultgroupByMARBucketSum.plot(kind='bar',title='Outstanding Amount: By Marital Statu
L3=ax3.legend()
L3.get_texts()[0].set_text('Married')
L3.get_texts()[1].set_text('Single')
L3.get_texts()[2].set_text('Others')
ax3.set(title='Outstanding Amount trend - Marital Status', xlabel='Outstanding Amount

# plot 4 - Outstanding trend - Age

DefaultgroupByAgeBucket = pd.crosstab(data['AGEGroup'],data['OS_binned'])
#DefaultgroupByAgeBucket = pd.crosstab(data['OS_binned'],data['AGEGroup'])
DefaultgroupByAgeBucket.plot(kind='bar',title='Outstanding Amount: By AGEGroup',ax=ax4

ax4.set(title='Outstanding Amount trend - AGEGroup', xlabel='Outstanding Amount', ylab

fig.tight_layout()
plt.show()
```



12 2. Number of customers with outstanding amount (in different outstanding amount buckets)

In [26]:
```
# Plot1: Outstanding Amount trend
fig = plt.figure(figsize=(25, 10))

ax1=fig.add_subplot(131)
var = data['OS_binned'].value_counts()

plt.style.use('fivethirtyeight') # using the fivethirtyeight matplotlib theme


var.plot(x = 'OutStanding Amount',kind='bar',title='Overall Outstanding Amount trend'

# Plot2: Outstanding Amount trend - DefaultPayment: NO
ax2=fig.add_subplot(132)

dataDefault0=data[data['DefaultPayment']==0]
dataDefault1=data[data['DefaultPayment']==1]
```

```
var0 = dataDefault0['OS_binned'].value_counts()
var1 = dataDefault1['OS_binned'].value_counts()

#plt.xlabel('Outstanding amount bucket')
#plt.ylabel('No of Customers')

#p1 = var0.plot(x = 'OutStanding Amount',kind='bar',title='Overall Outstanding Amount
var0.plot(x = 'OutStanding Amount',kind='bar',title='Outstanding Amount trend - Defau
#plt.show()

# Plot3: Outstanding Amount trend - DefaultPayment: YES

ax3=fig.add_subplot(133)

#fig = plt.figure(figsize=(10, 5))
#p2 = var1.plot(x = 'OutStanding Amount',kind='bar',title='Overall Outstanding Amount
var1.plot(x = 'OutStanding Amount',kind='bar',title='Outstanding Amount trend - Defau

ax1.set(ylabel='No of Customers')
plt.tight_layout()
plt.show()
```



13 3. Age of outstanding amount analysis

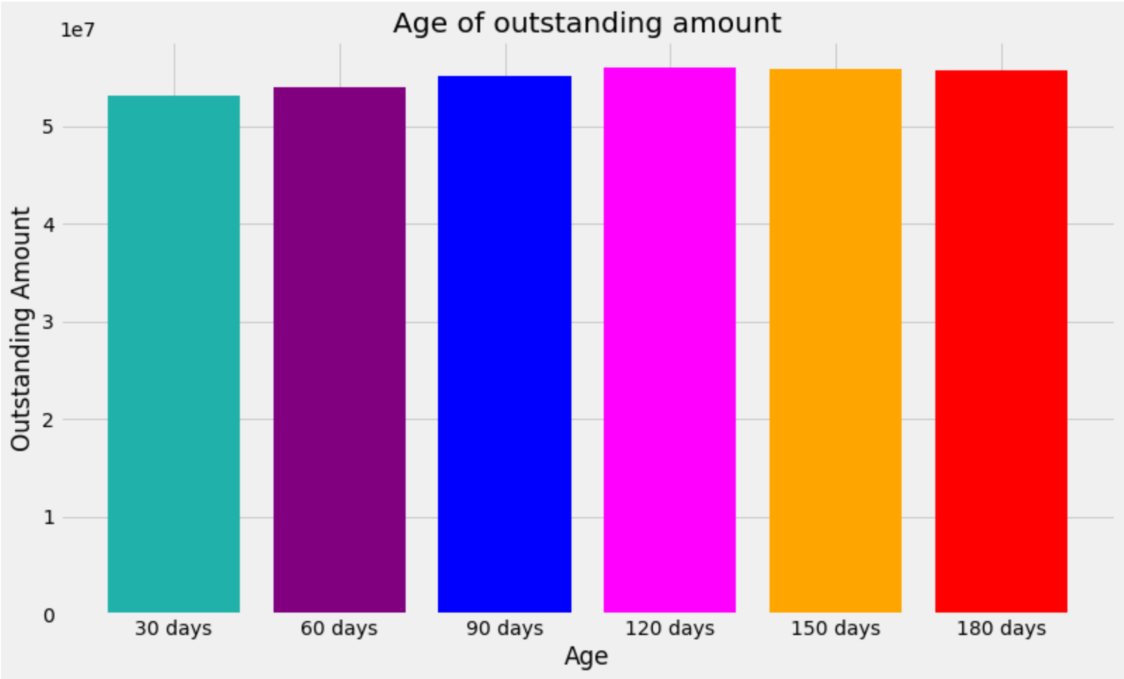
In [27]:
```
AgeDF = data.copy()
AgeDF.columns
```

Out[27]:
```
Index(['ID', 'LIMIT_BAL', 'SEX', 'EDUCATION', 'MARRIAGE', 'AGE', 'PAY_0',
       'PAY_2', 'PAY_3', 'PAY_4', 'PAY_5', 'PAY_6', 'SEP-Outstanding',
       'AUG-Outstanding', 'JUL-Outstanding', 'JUN-Outstanding',
       'MAY-Outstanding', 'APR-Outstanding', 'DefaultPayment', 'OS_binned',
```

```
             'AGEGroup'],
            dtype='object')
```

```
In [28]: AgeDF = AgeDF[(AgeDF['PAY_0'] > 0) & (AgeDF['PAY_2'] > 0) & (AgeDF['PAY_3'] > 0) & (Ag
```

```
In [29]: fig= plt.figure(figsize = (12,7))
         ax1=fig.add_subplot(111)
         df = AgeDF[['SEP-Outstanding','AUG-Outstanding','JUL-Outstanding','JUN-Outstanding','M
         df.rename(index={'SEP-Outstanding':'30 days','AUG-Outstanding':'60 days','JUL-Outstanc
         x= df.index
         y=df
         ax1.bar(x,y,color=['lightseagreen', 'Purple', 'Blue', 'magenta', 'Orange', 'Red'])
         ax1.set(Title="Age of outstanding amount",xlabel="Age",ylabel="Outstanding Amount")
         plt.show()
```



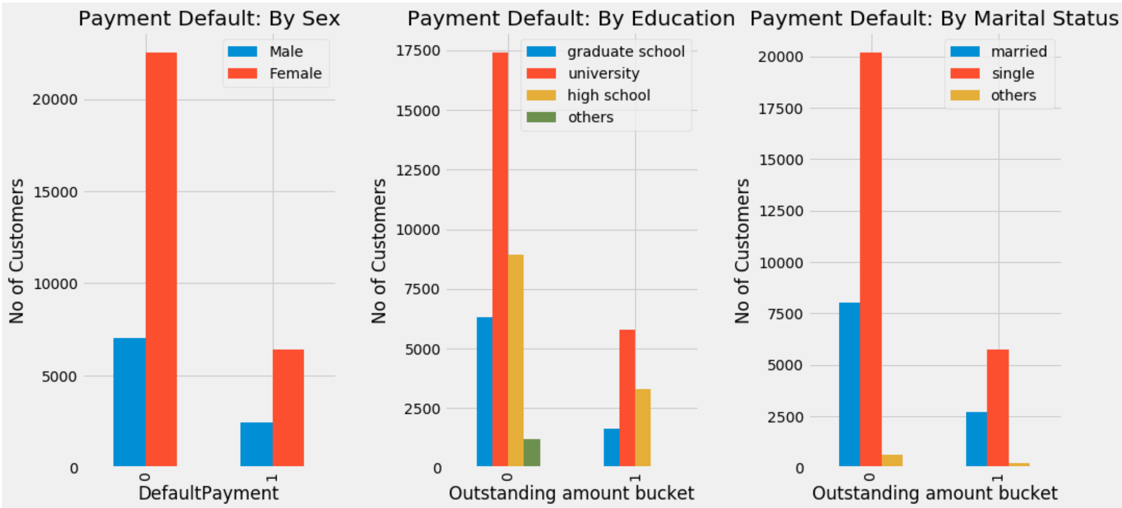
** No significant behaviour observed of outstanding amount / trend affect on the default behavior in next month

14 Is there any relationship between in outstanding amount / trend with respect to age, education, marriage, credit limit?

15 a. Default payment by demographic variables

```
In [30]: fig= plt.figure(figsize=(15,7))
```

```
# Payment Default: By Sex

ax1= fig.add_subplot(131)

DefaultgroupBySexBucket = data[['DefaultPayment','SEX']].groupby(['DefaultPayment','SE
DefaultgroupBySexBucketSum = DefaultgroupBySexBucket['SEX'].aggregate(np.sum).unstack
DefaultgroupBySexBucketSum.plot(kind='bar',title='Payment Default: By Sex',ax=ax1)
L=ax1.legend()
L.get_texts()[0].set_text('Male')
L.get_texts()[1].set_text('Female')
#plt.xlabel('Outstanding amount bucket')
plt.ylabel('No of Customers')


# Payment Default: By EDUCATION
ax2= fig.add_subplot(132)
DefaultgroupByEduBucket = data[['DefaultPayment','EDUCATION']].groupby(['DefaultPaymen
DefaultgroupByEduBucketSum = DefaultgroupByEduBucket['EDUCATION'].aggregate(np.sum).un
DefaultgroupByEduBucketSum.plot(kind='bar',title='Payment Default: By Education',ax=a
L=ax2.legend()
L.get_texts()[0].set_text('graduate school')
L.get_texts()[1].set_text('university')
L.get_texts()[2].set_text('high school')
L.get_texts()[3].set_text('others')
plt.xlabel('Outstanding amount bucket')
plt.ylabel('No of Customers')


# Payment Default: By Marital Status

ax3= fig.add_subplot(133)
DefaultgroupByMarriageBucket = data[['DefaultPayment','MARRIAGE']].groupby(['DefaultPa
DefaultgroupByMarriageBucketSum = DefaultgroupByMarriageBucket['MARRIAGE'].aggregate(n
DefaultgroupByMarriageBucketSum.plot(kind='bar',title='Payment Default: By Marital Sta
L=ax3.legend()
L.get_texts()[0].set_text('married')
L.get_texts()[1].set_text('single')
L.get_texts()[2].set_text('others')
plt.xlabel('Outstanding amount bucket')
plt.ylabel('No of Customers')

plt.tight_layout()
plt.show()
```



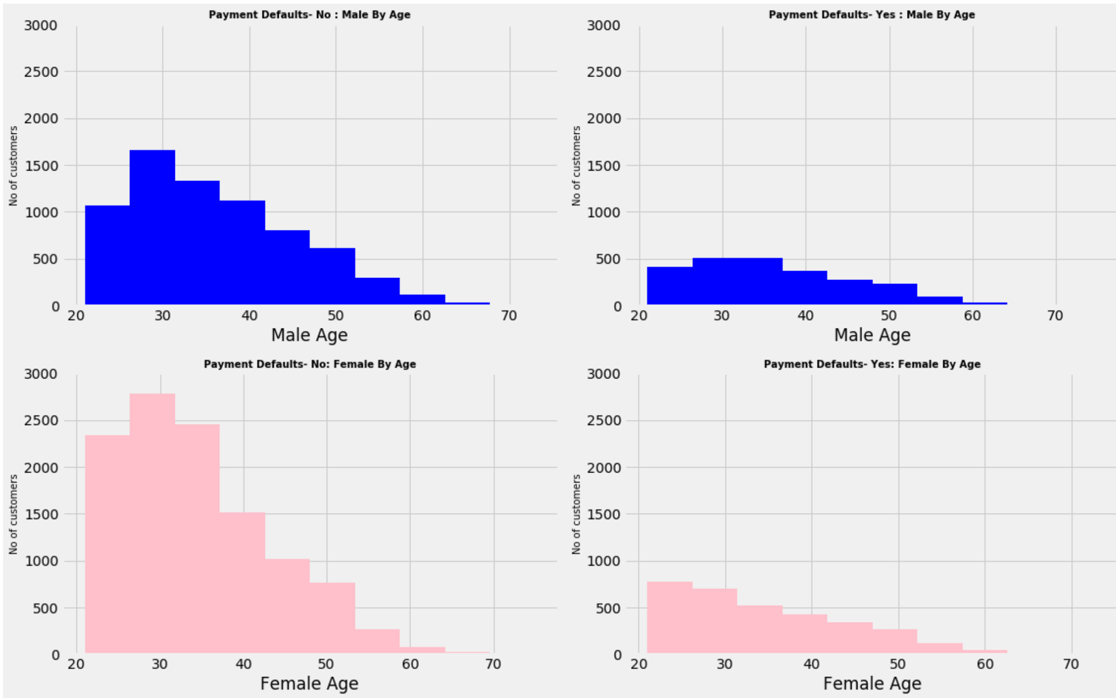
**The above plots do not show any significant impact of demographic variables on Default Payment

16 b. Default payment by age & sex

In [31]:
```
# Default payment by Age and Sex
datasetDefaultNo = data.query('DefaultPayment==0')
datasetDefaultYes = data.query('DefaultPayment==1')

datasetDefaultNoMale = datasetDefaultNo.query('SEX==1')
datasetDefaultNoFemale = datasetDefaultNo.query('SEX==2')

datasetDefaultYesMale = datasetDefaultYes.query('SEX==1')
datasetDefaultYesFemale = datasetDefaultYes.query('SEX==2')
```

In [32]:
```
from matplotlib import gridspec

fig = plt.figure(figsize=(16, 10))
plt.style.use('fivethirtyeight') # using the fivethirtyeight matplotlib theme
#gs = gridspec.GridSpec(1, 2, width_ratios=[1, 1])
gs = gridspec.GridSpec(2, 2)#, width_ratios=[1, 1])

### Plot 1 "Male By Age"
ax0 = plt.subplot(gs[0,0])
ax0.set_title('Payment Defaults- No : Male By Age', fontsize=10,fontweight="bold")

ax0.set_xlabel('Male Age')
ax0.set_ylabel('No of customers',fontsize=10)

ax0.set_ylim(0, 3000)
```

```
plt.hist(datasetDefaultNoMale['AGE'],bins=10, histtype='bar', color='blue')

### Plot 2 "Male By Age"
ax1 = plt.subplot(gs[0,1])
ax1.set_title('Payment Defaults- Yes : Male By Age', fontsize=10,fontweight="bold")

ax1.set_xlabel('Male Age')
ax1.set_ylabel('No of customers',fontsize=10)

ax1.set_ylim(0, 3000)

plt.hist(datasetDefaultYesMale['AGE'],bins=10, histtype='bar', color='blue')

### Plot 3 "Female By Age"
ax2 = plt.subplot(gs[1,0])
ax2.set_title('Payment Defaults- No: Female By Age', fontsize=10,fontweight="bold")

ax2.set_xlabel('Female Age')
ax2.set_ylabel('No of customers',fontsize=10)
ax2.set_ylim(0, 3000)

plt.hist(datasetDefaultNoFemale['AGE'],bins=10, histtype='bar', color='pink')

### Plot 4 "Female By Age"

ax3 = plt.subplot(gs[1,1])
ax3.set_title('Payment Defaults- Yes: Female By Age', fontsize=10,fontweight="bold")

ax3.set_xlabel('Female Age')
ax3.set_ylabel('No of customers',fontsize=10)
ax3.set_ylim(0, 3000)

plt.hist(datasetDefaultYesFemale['AGE'],bins=10, histtype='bar', color='pink')

plt.tight_layout()
plt.show()
```



** The above plots do not show any significant impact of age and sex on Default Payment

17 c. Outstanding amount Vs Credit Limit

In [33]:
```
dataset['AboveLimit']= dataset['SEP-Outstanding'] - dataset['LIMIT_BAL']
dataset.head()
```

Out[33]:

	ID	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	\
0	1	20000.0	2	2	1	24	2	2	-1	-1	
1	2	120000.0	2	2	2	26	-1	2	0	0	
2	3	90000.0	2	2	2	34	0	0	0	0	
3	4	50000.0	2	2	1	37	0	0	0	0	
4	5	50000.0	1	2	1	57	-1	0	-1	0	

	...	PAY_AMT5	PAY_AMT6	DefaultPayment	APR-Outstanding	\
0	...	0.0	0.0	1	0.0	
1	...	0.0	2000.0	1	1261.0	
2	...	1000.0	5000.0	0	10549.0	
3	...	1069.0	1000.0	0	28547.0	
4	...	689.0	679.0	0	18452.0	

	MAY-Outstanding	JUN-Outstanding	JUL-Outstanding	AUG-Outstanding	\
0	0.0	0.0	689.0	2413.0	
1	3455.0	2272.0	1682.0	725.0	
2	13948.0	13331.0	12559.0	12527.0	

```
3          27890.0          27214.0          48091.0          46214.0
4          18457.0          11940.0          25835.0         -31011.0

   SEP-Outstanding  AboveLimit
0           3913.0    -16087.0
1           2682.0   -117318.0
2          27721.0    -62279.0
3          44990.0     -5010.0
4           6617.0    -43383.0

[5 rows x 32 columns]
```

In [34]:
```
# function to check the limit
def limitCheck(df, C, X):
    df_copy = df.copy()
    # 1 if crossed else 0
    df_copy['LimitExceed'] = (df_copy[C] >= X)*1
    return df_copy
```

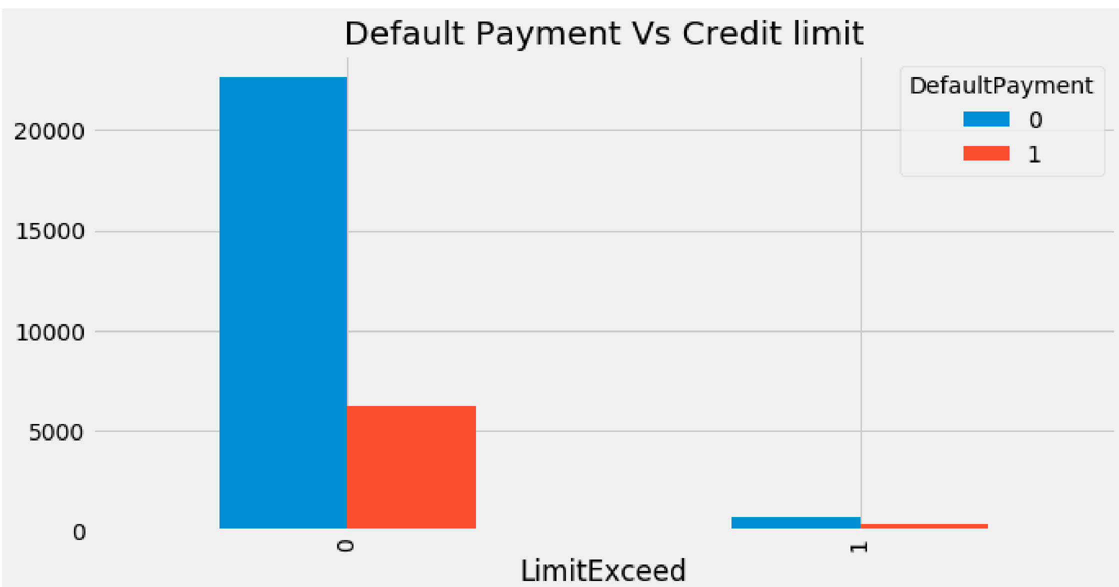
In [35]:
```
dataset = limitCheck(dataset,'AboveLimit',0)
```

In [36]:
```
dataset['LimitExceed'].value_counts()
```

Out[36]:
```
0    28935
1     1011
Name: LimitExceed, dtype: int64
```

In [37]:
```
DFct = pd.crosstab(dataset['LimitExceed'],dataset['DefaultPayment'])
```

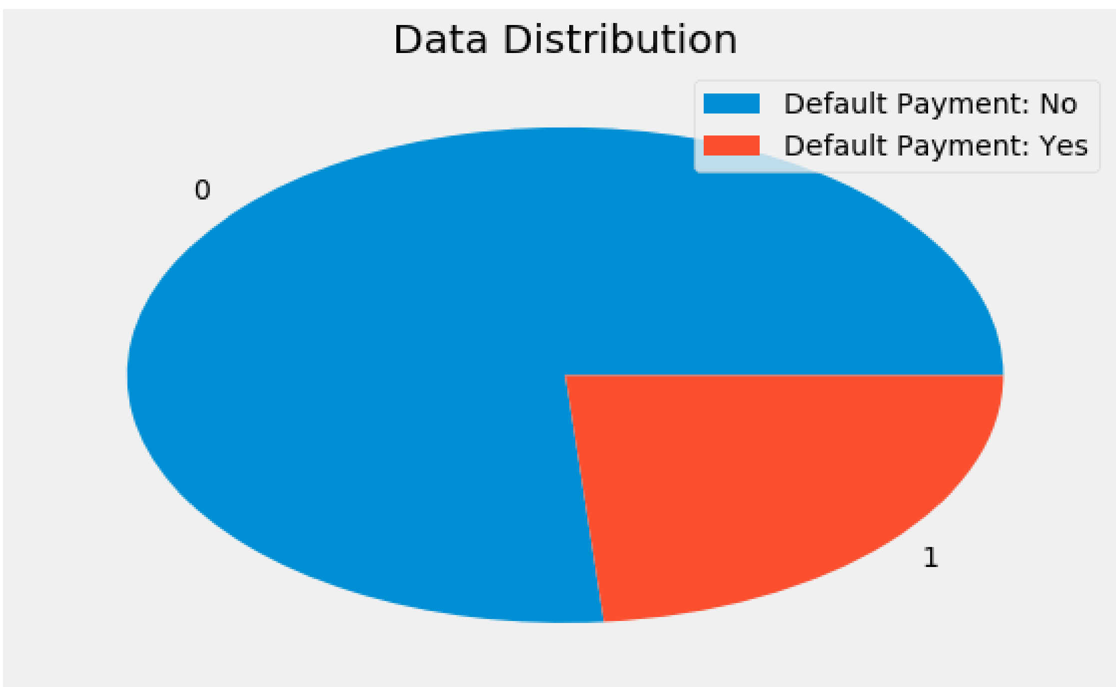
In [38]:
```
fig = plt.figure(figsize=(10,5))
ax1 = fig.add_subplot(111)
DFct.plot(kind='bar',ax=ax1)
ax1.set(title='Default Payment Vs Credit limit')
plt.show()
```



** The above plot does not show any significant impact of customer's outstanding amount (exceeding their limit) on Default Payment

18 Target data distribution

In [39]:
```
fig = plt.figure(figsize=(8,5))
datatemp = data['DefaultPayment'].value_counts()
datatemp.plot(kind = 'pie', title = 'Data Distribution')
L=plt.legend()
L.get_texts()[0].set_text('Default Payment: No')
L.get_texts()[1].set_text('Default Payment: Yes')
plt.ylabel('')

plt.tight_layout()
plt.show()
```



19 Correlation

In [40]:
```
corr = data.corr()
corr.style.background_gradient().set_precision(2)
```

Out[40]: <pandas.io.formats.style.Styler at 0x1c8817ebb70>

20 Feature selction - based on correlation

In [41]:
```
# top features correated with DefaultPayments
SelectFeatures = ['PAY_0','PAY_2','PAY_3','PAY_4','PAY_5','PAY_6','DefaultPayment']
```

In [42]:
```
FinalData = data[SelectFeatures]
FinalData.head()
```

Out[42]:

	PAY_0	PAY_2	PAY_3	PAY_4	PAY_5	PAY_6	DefaultPayment
0	2	2	-1	-1	-2	-2	1
1	-1	2	0	0	0	2	1
2	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0
4	-1	0	-1	0	0	0	0

21 Prediction model: Default Payment using Machine Learning

In [43]:
```
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
```

In [44]:
```
FinalData.describe()
```

Out[44]:

	PAY_0	PAY_2	PAY_3	PAY_4	PAY_5 \
count	23956.000000	23956.000000	23956.000000	23956.000000	23956.000000
mean	0.040073	-0.060486	-0.135123	-0.181165	-0.229838
std	1.121869	1.228231	1.232781	1.214463	1.178966
min	-2.000000	-2.000000	-2.000000	-2.000000	-2.000000
25%	-1.000000	-1.000000	-1.000000	-1.000000	-1.000000
50%	0.000000	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	0.000000	0.000000
max	8.000000	8.000000	8.000000	8.000000	8.000000

	PAY_6	DefaultPayment
count	23956.000000	23956.000000
mean	-0.255260	0.235933
std	1.196043	0.424589
min	-2.000000	0.000000
25%	-1.000000	0.000000
50%	0.000000	0.000000
75%	0.000000	0.000000
max	8.000000	1.000000

In [45]:
```
# drop instances that have NA
before_rows = data.shape[0]
FinalData = FinalData.dropna()
after_rows = data.shape[0]
before_rows,after_rows,FinalData.shape
```

```
Out[45]: (23956, 23956, (23956, 7))
```

```
In [46]: FinalData.columns
```

```
Out[46]: Index(['PAY_0', 'PAY_2', 'PAY_3', 'PAY_4', 'PAY_5', 'PAY_6', 'DefaultPayment'], dtype=
```

```
In [47]: y = FinalData.iloc[:,6].values
         y
```

```
Out[47]: array([1, 1, 0, ..., 0, 1, 1], dtype=int64)
```

```
In [48]: FeatuesPredictors = ['PAY_0','PAY_2','PAY_3','PAY_4','PAY_5','PAY_6']
         X=FinalData[FeatuesPredictors].values
         X
```

```
Out[48]: array([[ 2,  2, -1, -1, -2, -2],
                [-1,  2,  0,  0,  0,  2],
                [ 0,  0,  0,  0,  0,  0],
                ...,
                [-1, -1, -1, -1,  0,  0],
                [ 4,  3,  2, -1,  0,  0],
                [ 0,  0,  0,  0,  0,  0]], dtype=int64)
```

21.0.1 More Importance to closest months

```
In [49]: Importance = np.array([1.2,1.0,0.6,0.4,0.2,0.05])
```

```
In [50]: X = X*Importance
         X
```

```
Out[50]: array([[ 2.4,  2. , -0.6, -0.4, -0.4, -0.1],
                [-1.2,  2. ,  0. ,  0. ,  0. ,  0.1],
                [ 0. ,  0. ,  0. ,  0. ,  0. ,  0. ],
                ...,
                [-1.2, -1. , -0.6, -0.4,  0. ,  0. ],
                [ 4.8,  3. ,  1.2, -0.4,  0. ,  0. ],
                [ 0. ,  0. ,  0. ,  0. ,  0. ,  0. ]])
```

22 Data split: Training set and Test set

```
In [51]: X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.3, random_state=123)
```

```
In [52]: # scale
         from sklearn.preprocessing import StandardScaler
         sc_X = StandardScaler()
         X_train = sc_X.fit_transform(X_train)
         X_test = sc_X.fit_transform(X_test)
```

23 Final Model

In [53]:
```
# Fit Random forest to the training set
from sklearn.ensemble import RandomForestClassifier
RF_classifier = RandomForestClassifier(n_estimators = 50,criterion='entropy',random_s
#RF_classifier = RandomForestClassifier(n_estimators = 5,random_state=0)
RF_classifier.fit(X_train,y_train)
```

Out[53]:
```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='entropy',
            max_depth=None, max_features='auto', 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, n_estimators=50, n_jobs=1,
            oob_score=False, random_state=0, verbose=0, warm_start=False)
```

In [54]:
```
y_RFpredictions = RF_classifier.predict(X_test)
```

In [55]:
```
# Measures Accuracy of the Classifier
RFAccuracy = round(accuracy_score(y_true=y_test,y_pred=y_RFpredictions),3)
RFAccuracy
```

Out[55]:
```
0.807
```

In [56]:
```
# Confusion matrix
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test,y_RFpredictions)
cm
```

Out[56]:
```
array([[5159,  331],
       [1055,  642]], dtype=int64)
```

In [57]:
```
from sklearn.metrics import roc_curve
fpr, tpr, _ =roc_curve(y_test,y_RFpredictions)
```

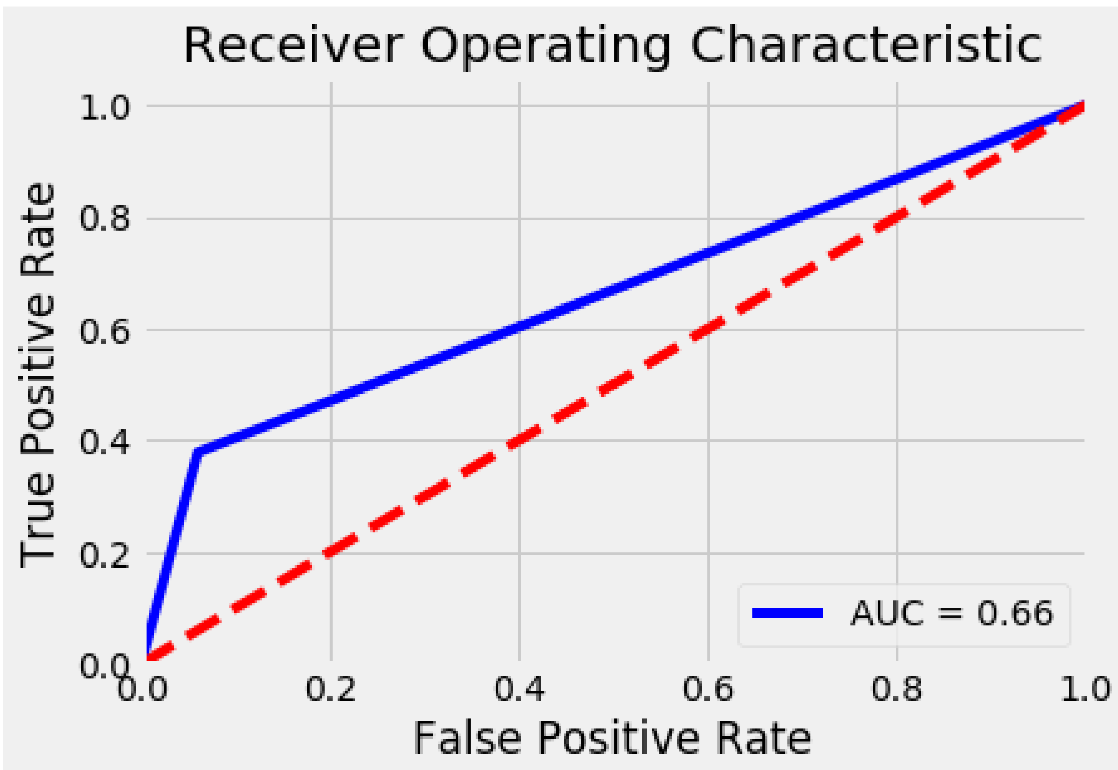
In [58]:
```
from sklearn.metrics import auc
roc_auc = auc(fpr, tpr)
print(roc_auc)
```

```
0.6590116169861525
```

In [59]:
```
from sklearn.metrics import precision_recall_fscore_support
report_lr= precision,recall,fbeta_score,support = precision_recall_fscore_support(y_te

precision,recall,fbeta_score,support
```

Out[59]:
```
(array([0.83022208, 0.65981501]),
 array([0.93970856, 0.37831467]),
 array([0.88157895, 0.48089888]),
 array([5490, 1697], dtype=int64))
```

```
In [60]: import matplotlib.pyplot as plt

         plt.title('Receiver Operating Characteristic')
         plt.plot(fpr, tpr, 'b',label = 'AUC = %0.2f' % roc_auc)
         plt.legend(loc = 'lower right')
         plt.plot([0, 1], [0, 1],'r--')
         plt.xlim([0, 1])
         plt.ylim([0, 1.05])
         plt.ylabel('True Positive Rate')
         plt.xlabel('False Positive Rate')
         plt.show()
```



24 model statistics

```
In [61]: print('******************************************************************************

         print('--- Confusion Matrix ---\n')

         print(cm)

         print('\n --- Accuracy ---\n')
```

```python
print(RFAccuracy*100,'%')

print('\n --- Classification Report ---\n')

from sklearn.metrics import classification_report
target=['0','1']
print(classification_report(y_test,y_RFpredictions, target_names=target))

print('******************************************************************************
```

```
*******************************************************************************************
--- Confusion Matrix ---

[[5159  331]
 [1055  642]]

 --- Accuracy ---

80.7 %

 --- Classification Report ---

             precision    recall  f1-score   support

          0       0.83      0.94      0.88      5490
          1       0.66      0.38      0.48      1697

avg / total       0.79      0.81      0.79      7187

*******************************************************************************************
```