panek_tanyuk_wall_davieau_lab1

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1 First Project Work Week Assignment

1.1 Business Understanding

Business applications of predicting an overall default rate could include capcacity planning and financial reporting. However, the ability to predict whether an individual customer will default is also an important aspect of managing the profitability of a credit card business.

Projecting the likelihood of default for a given customer can be used to:

1. Determine the collection strategy if a customer misses a payment
2. Determine the appropriate credit limit for that customer

Use of inaccurate predictions to determine how a customer will be treated can adversely impact profitability. - If the risk is overestimated, collection efforts may be too intense thereby alienating customers and unnecessarily constraining credit lines. Restricing credit lines too much may inhibit customers' ability and willingness to use the product. - If the risk is underestimated, the bank will incur higher losses than it might otherwise. We expect that a more acceptable bias would be to overestimate the likelihood of default rather than underestimate it.

**** Goal ** The goal of this analysis is to identify basic patterns in the data.** In subsequent studies we will predict the probablity of default for credit card customers. We will set aside a portion of the data for validation (the test set), and use Logistic Regression on the remaining training set.

The effectiveness of the model in predicting an overall default rate will be measured by its performance when applied to the test data set. If the actual results are within 10% of the estimate, we will deem it to be successful. We will also use the AUC against the test set. Judgmentally, we will consider an AUC of 80% or more acceptable.

To test the effectiveness of the model for use in determining the course of action with respect to a specific customer we will look for specificity and sensitivity rates at certain probabilities of default. In order to determine whether a "lighter" collection strategy should be used, we will look for those probabilities where the sensitivity (true positive rate) is greater than 90%. In order to determine that a request to increase credit will be declined, we will look for those probabilities where the specificity is 90% or more.

1.2 Data Meaning Type

Attribute Information The data used is "Default of Credit Card Clients" from UCI. It was attained by I-Cheng Yeh with Chung Hua University and Tamkang University in Taiwan. The original goal was to predict default rates.

The data has a 6 month history of 30,000 Taiwanese credit account balances and transactions. Each observation contains a binary reponse variable "default" with values 1 indicating a default occured and 0 indicating no default occured.

The following explanatory variables are included:

- LIMIT_BAL = Total credit amount allowed
- SEX
  - 1 = Male
  - 2 = Female
- EDUCATION
  - 1 = Graduate School
  - 2 = University
  - 3 = High School
  - 4 = Other
- MARRIAGE
  - 1 = Married
  - 2 = Single
  - 3 = Other
- AGE = Credit holder age in years

Payment history (2005) - PAY_0 = September - PAY_2 = August - PAY_3 = July - PAY_4 = June - PAY_5 = May - PAY_6 = April - -1 = payment received on time - 1 = payment received one month late - 2 = payment received two months late - "......" - 9 = payment received nine months late or more

Statement amount (NT dollars, 2005) - BILL_AMT1 = September - BILL_AMT2 = August - BILL_AMT3 = July - BILL_AMT4 = June - BILL_AMT5 = May - BILL_AMT6 = April

Payment amount (NT dollars, 2005). - PAY_AMT1 = September - PAY_AMT2 = August - PAY_AMT3 = July - PAY_AMT4 = June - PAY_AMT5 = May - PAY_AMT6 = April

Original Source Data Set Information
https://archive.ics.uci.edu/ml/datasets/default+of+credit+card+clients#

In [1]:
```
#import libraries
import pandas as pd
import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt
import warnings
warnings.simplefilter('ignore', DeprecationWarning)
```

```
#import the data
df = pd.read_csv('Input/DefaultCreditcardClients.csv')
df.rename(columns={'default payment next month':'default'}, inplace=True)
df.index = df.ID
if 'ID' in df:
    del df['ID']
df.head()
```

Out[1]:

```
    LIMIT_BAL  SEX  EDUCATION  MARRIAGE  AGE  PAY_0  PAY_2  PAY_3  PAY_4  \
ID
1       20000    2          2         1   24      2      2     -1     -1
2      120000    2          2         2   26     -1      2      0      0
3       90000    2          2         2   34      0      0      0      0
4       50000    2          2         1   37      0      0      0      0
5       50000    1          2         1   57     -1      0     -1      0

    PAY_5   ...     BILL_AMT4  BILL_AMT5  BILL_AMT6  PAY_AMT1  PAY_AMT2  \
ID          ...
1      -2   ...             0          0          0         0       689
2       0   ...          3272       3455       3261         0      1000
3       0   ...         14331      14948      15549      1518      1500
4       0   ...         28314      28959      29547      2000      2019
5       0   ...         20940      19146      19131      2000     36681

    PAY_AMT3  PAY_AMT4  PAY_AMT5  PAY_AMT6  default
ID
1          0         0         0         0        1
2       1000      1000         0      2000        1
3       1000      1000      1000      5000        0
4       1200      1100      1069      1000        0
5      10000      9000       689       679        0

[5 rows x 24 columns]
```

The table above shows a peek at the first 5 records in the dataset.

In [2]:
```
df.dtypes
```

Out[2]:
```
LIMIT_BAL     int64
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    int64
BILL_AMT2    int64
BILL_AMT3    int64
BILL_AMT4    int64
BILL_AMT5    int64
BILL_AMT6    int64
PAY_AMT1     int64
PAY_AMT2     int64
PAY_AMT3     int64
PAY_AMT4     int64
PAY_AMT5     int64
PAY_AMT6     int64
default      int64
dtype: object
```

Pandas defaulted all data types to integer. The source has no explicit data type descriptions but there is enough context to safely change the datatypes of all continuous variables to floats.

```
In [3]: #Create Lists for Analysis
        BillsAndPayments=['BILL_AMT1','BILL_AMT2','BILL_AMT3','BILL_AMT4','BILL_AMT5','BILL_AM
        Bills=['LIMIT_BAL','BILL_AMT1','BILL_AMT2','BILL_AMT3','BILL_AMT4','BILL_AMT5','BILL_AM
        Payments=['PAY_AMT1','PAY_AMT2','PAY_AMT3','PAY_AMT4','PAY_AMT5','PAY_AMT6','default']
        PayStatus=['PAY_0','PAY_2','PAY_3','PAY_4','PAY_5','PAY_6','default']
        PayStausOnly = ['PAY_0','PAY_2','PAY_3','PAY_4','PAY_5','PAY_6']
        continuous_features = ['LIMIT_BAL', 'BILL_AMT1', 'BILL_AMT2','BILL_AMT3',
                               'BILL_AMT4', 'BILL_AMT5', 'BILL_AMT6', 'PAY_AMT1',
                               'PAY_AMT2', 'PAY_AMT3', 'PAY_AMT4', 'PAY_AMT5',
                               'PAY_AMT6']
        ordinal_features = ['EDUCATION', 'MARRIAGE', 'AGE', 'PAY_0','PAY_2', 'PAY_3', 'PAY_4',
        pca_features = ['LIMIT_BAL','BILL_AMT1', 'BILL_AMT2','BILL_AMT3','BILL_AMT4', 'BILL_AM
                        'PAY_AMT1','PAY_AMT2', 'PAY_AMT3', 'PAY_AMT4', 'PAY_AMT5','PAY_AMT6']
        #Convert datatypes
        df[continuous_features] = df[continuous_features].astype(np.float64)
        df[ordinal_features] = df[ordinal_features].astype(np.int64)
        df_pca = df[pca_features].astype(np.int64)
        df.dtypes

Out[3]: 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        int64
dtype: object
```

1.3 Data Quality

There were no missing values identified. However in cases where the bill amount is $0 and the payment amount is $0 presented challenges which are addressed only when necessary in each portion of analysis.

Field definitions and naming:

1. The payment fields range from PAY_0 to PAY_6. There is no PAY_1 named field. This raises suspicion; we will assume that there is no missing column and proceed with caution.
2. The descriptions of values -2 and 0 in the pay fields are not provided. Based on visual inspection, a value of -2 appears to indicate that no payment is due because the account has a credit balance. Because a value of -1 means "Paid on time" and a value of 1 means one month late, we are assuming that a value of zero means less than one month late. It may be that these are missing values coded as 0. About half of the data set has a value of 0 for these attributes.
3. The value 0 is found in the marriage attribute but is not defined. There are only 54 instances. We added these to the "Other" category.

Suspicious values:

1. There are only 34 instances where the payment status had a value of 1 for two months in a row. This is highly unusual given the propensity for customers with status values of 1 or 2 to remain in their current payment status for one month.
2. It appears that the first month the value of 1 is used is in PAY_0 with only a few observations prior to that. Therfore it seems that there is a methodology change part-way through the data series. We will proceed with caution since the number of observations is small.
3. There are nonsensical instances where the Payment Status implies late payment but the amount billed was zero or less. There are 1,769 such cases out of 150,000 possible payments.

Outliers: The range of values in the Payment, Amount Billed and Credit Limit fields are extremely wide and right-skewed. We explored a sample of outliers and concluded that the observations were legitimate. High payments were consistent with amounts billed and high balances were often recurring which is consistent with the credit limits.

The distributions of other variables seem reasonable.

1.4 Simple Statistics

Visualize appropriate statistics (e.g., range, mode, mean, median, variance, counts) for a subset of attributes. Describe anything meaningful you found from this or if you found something potentially interesting. Note: You can also use data from other sources for comparison. Explain why the statistics run are meaningful.

In [4]:
```
# Describing the data set in two sections so we can see the values for all columnts.
df[['EDUCATION', 'MARRIAGE', 'AGE', 'PAY_0','PAY_2', 'PAY_3', 'PAY_4', 'PAY_5', 'PAY_6
```

Out[4]:

	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2
count	30000.000000	30000.000000	30000.000000	30000.000000	30000.000000
mean	1.853133	1.551867	35.485500	-0.016700	-0.133767
std	0.790349	0.521970	9.217904	1.123802	1.197186
min	0.000000	0.000000	21.000000	-2.000000	-2.000000
25%	1.000000	1.000000	28.000000	-1.000000	-1.000000
50%	2.000000	2.000000	34.000000	0.000000	0.000000
75%	2.000000	2.000000	41.000000	0.000000	0.000000
max	6.000000	3.000000	79.000000	8.000000	8.000000

	PAY_3	PAY_4	PAY_5	PAY_6	default
count	30000.000000	30000.000000	30000.000000	30000.000000	30000.000000
mean	-0.166200	-0.220667	-0.266200	-0.291100	0.221200
std	1.196868	1.169139	1.133187	1.149988	0.415062
min	-2.000000	-2.000000	-2.000000	-2.000000	0.000000
25%	-1.000000	-1.000000	-1.000000	-1.000000	0.000000
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	1.000000

In [5]:
```
df[continuous_features].describe()
```

Out[5]:

	LIMIT_BAL	BILL_AMT1	BILL_AMT2	BILL_AMT3
count	30000.000000	30000.000000	30000.000000	3.000000e+04
mean	167484.322667	51223.330900	49179.075167	4.701315e+04
std	129747.661567	73635.860576	71173.768783	6.934939e+04
min	10000.000000	-165580.000000	-69777.000000	-1.572640e+05
25%	50000.000000	3558.750000	2984.750000	2.666250e+03
50%	140000.000000	22381.500000	21200.000000	2.008850e+04
75%	240000.000000	67091.000000	64006.250000	6.016475e+04
max	1000000.000000	964511.000000	983931.000000	1.664089e+06

	BILL_AMT4	BILL_AMT5	BILL_AMT6	PAY_AMT1
count	30000.000000	30000.000000	30000.000000	30000.000000
mean	43262.948967	40311.400967	38871.760400	5663.580500
std	64332.856134	60797.155770	59554.107537	16563.280354
min	-170000.000000	-81334.000000	-339603.000000	0.000000

```
25%      2326.750000    1763.000000    1256.000000    1000.000000
50%     19052.000000   18104.500000   17071.000000    2100.000000
75%     54506.000000   50190.500000   49198.250000    5006.000000
max    891586.000000  927171.000000  961664.000000  873552.000000

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

The tables above show summary statistics for all the variables in the data set.

Some Noted Observations: - We can see that the average person is a 35 year old woman who graduated school and pays her bills on time. - Continuous variables appear right-skewed with large ranges. - Billed amounts seem to be increasing with time but the pattern appears less clear with payment amounts.

```
In [6]: %matplotlib inline
        # find the percentage of people who were default
        percentDefault = float(len(df[df.default != 0]))/len(df) * 100
        print (percentDefault)
```

```
22.12
```

Overall, the percentage of clients in the data set who defaulted on their credit cards is 22.12%. This matches the mean from the data frame describe() function in the table above. It gives us an indication of the robustness of the data set in terms of the variable we will be predicting.

```
In [1]: (130109.65-178099.72)/178099.72

Out[1]: -0.26945617881937156
```

The average credit limit (LIMIT_BAL) for clients who defaulted is 26.94% lower than those who did not. The bank may be successfully limiting credit to those it deems riskier.

History of delinquency in the above table (PAY_0 - PAY_6) confirms that late payments seem to be related to default.

```
In [9]: df.groupby(by=df.EDUCATION).mean()

Out[9]:                LIMIT_BAL       SEX  MARRIAGE        AGE     PAY_0     PAY_2  \
        EDUCATION
        0          217142.857143  1.428571  1.714286  38.857143 -0.500000 -1.000000
        1          212956.069910  1.588663  1.652338  34.231838 -0.233916 -0.408125
        2          147062.437634  1.616964  1.523022  34.722096  0.102210  0.022523
```

```
3          126550.270490  1.595282  1.421192  40.299980  0.132805  0.040879
4          220894.308943  1.658537  1.601626  33.853659 -0.504065 -0.772358
5          168164.285714  1.660714  1.475000  35.600000 -0.121429 -0.303571
6          148235.294118  1.509804  1.490196  43.901961 -0.176471 -0.313725

              PAY_3     PAY_4     PAY_5     PAY_6    ...        BILL_AMT4  \
EDUCATION                                            ...
0         -0.928571 -0.857143 -1.071429 -1.357143    ...     13350.214286
1         -0.425886 -0.461974 -0.479074 -0.485971    ...     42931.065187
2         -0.018532 -0.083036 -0.141411 -0.170848    ...     44748.779758
3          0.002644 -0.066504 -0.139313 -0.183649    ...     38718.582266
4         -0.764228 -0.813008 -0.780488 -0.739837    ...     39570.268293
5         -0.375000 -0.375000 -0.389286 -0.521429    ...     62275.767857
6         -0.372549 -0.411765 -0.509804 -0.647059    ...     54259.490196

              BILL_AMT5     BILL_AMT6     PAY_AMT1      PAY_AMT2     PAY_AMT3  \
EDUCATION
0           7409.071429   5272.928571  5945.785714  13030.928571  8825.142857
1          40388.891261  38668.076051  6780.933585   7306.622201  6560.585735
2          41588.566287  40431.943835  5080.463293   5106.711333  4556.800000
3          35957.469392  34704.597315  4866.397397   5053.454139  3964.056742
4          33840.113821  32136.130081  5450.512195   6555.008130  9990.626016
5          53568.014286  46083.860714  5970.714286   8912.921429  7718.510714
6          44510.745098  39578.509804  9780.450980   6176.431373  7644.941176

              PAY_AMT4      PAY_AMT5      PAY_AMT6   default
EDUCATION
0          3620.571429   2541.714286   3007.214286  0.000000
1          5804.565612   5776.562211   6422.554842  0.192348
2          4375.387313   4452.678689   4716.487028  0.237349
3          3992.658532   3599.658938   3825.749034  0.251576
4          5104.861789   5991.642276   4284.967480  0.056911
5          4927.332143   4633.246429   7772.114286  0.064286
6          5179.490196  11691.137255  14773.901961  0.156863

[7 rows x 23 columns]
```

Those with a only high school education have the highest default rate at 25.15%. The "Other/undefined" categories are the lowest.

1.5 Visualize Attributes

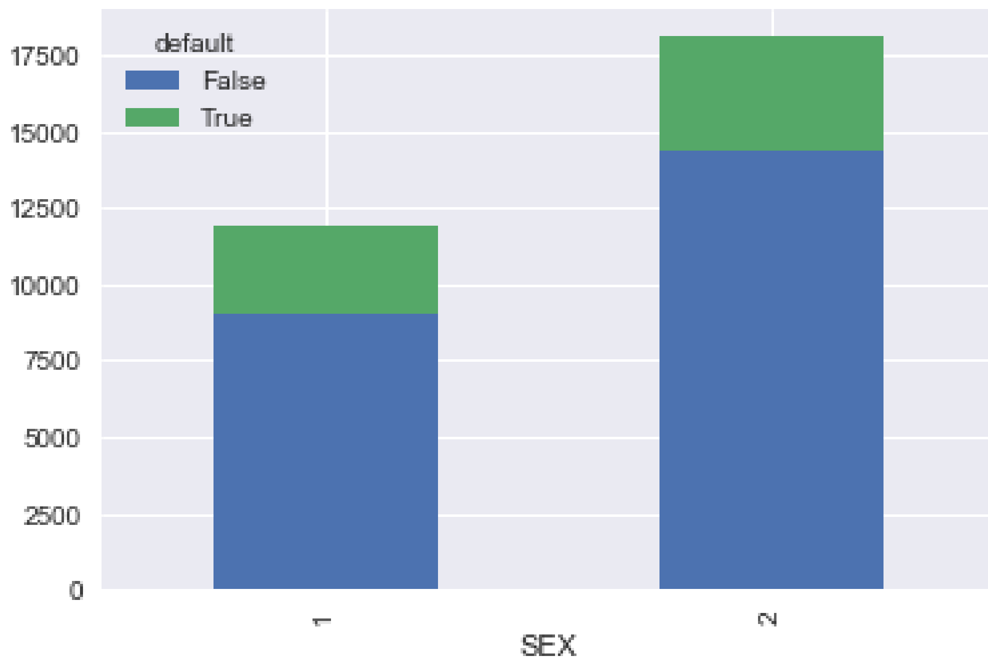
In [10]:
```
df.groupby(by=df.SEX).mean()
```

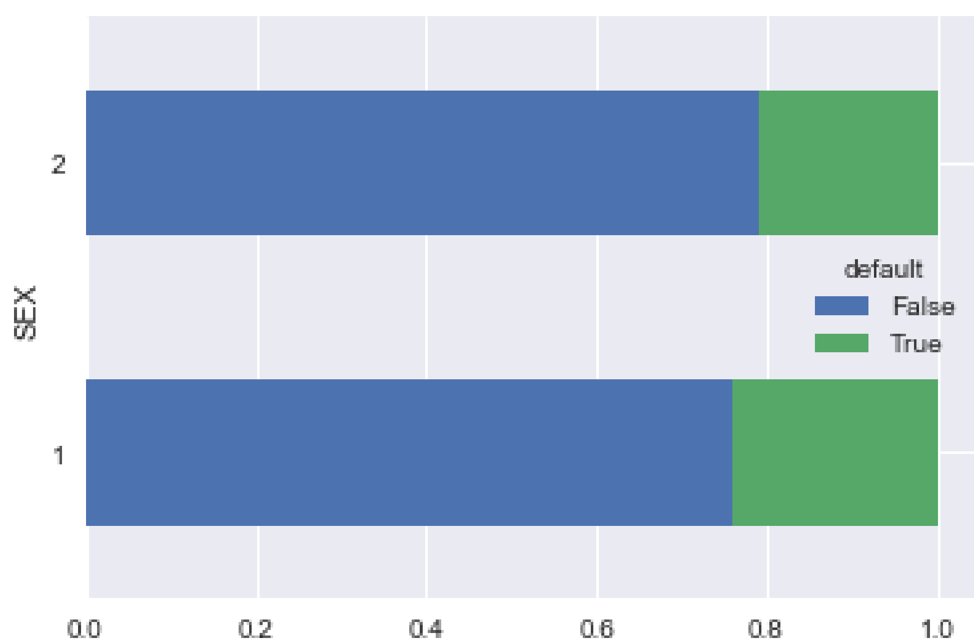
Out[10]:
```
         LIMIT_BAL  EDUCATION  MARRIAGE        AGE     PAY_0     PAY_2  \
SEX
1    163519.825034   1.839250  1.572090  36.519431  0.063257 -0.029189
2    170086.462014   1.862246  1.538593  34.806868 -0.069181 -0.202407
```

```
        PAY_3     PAY_4     PAY_5     PAY_6    ...       BILL_AMT4  \
SEX                                            ...
1    -0.068557 -0.133832 -0.189182 -0.228634    ...    45000.331090
2    -0.230289 -0.277661 -0.316751 -0.332100    ...    42122.600099

        BILL_AMT5     BILL_AMT6     PAY_AMT1     PAY_AMT2     PAY_AMT3  \
SEX
1     41587.504963  40101.775320  5668.537264  5960.720138  5412.506057
2     39473.816807  38064.427286  5660.327076  5895.200088  5103.057255

        PAY_AMT4     PAY_AMT5     PAY_AMT6   default
SEX
1     4869.177995  4830.827052  5276.196753  0.241672
2     4797.786992  4778.752043  5175.665305  0.207763

[2 rows x 23 columns]
```

In [42]:
```
warnings.simplefilter('ignore', DeprecationWarning)
%matplotlib inline
Default_counts = pd.crosstab([df['SEX']], df.default.astype(bool))
# Default_counts.plot(kind='bar', stacked=True, color=['grey','blue'])
Default_counts.plot(kind='bar', stacked=True)

# divide the counts to get rates
Default_rate = Default_counts.div(Default_counts.sum(1).astype(float),axis=0)
# Default_rate.plot(kind='barh', stacked=True, color=['grey','blue'])
Default_rate.plot(kind='barh', stacked=True)
```

Out[42]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1d458abc160>
```

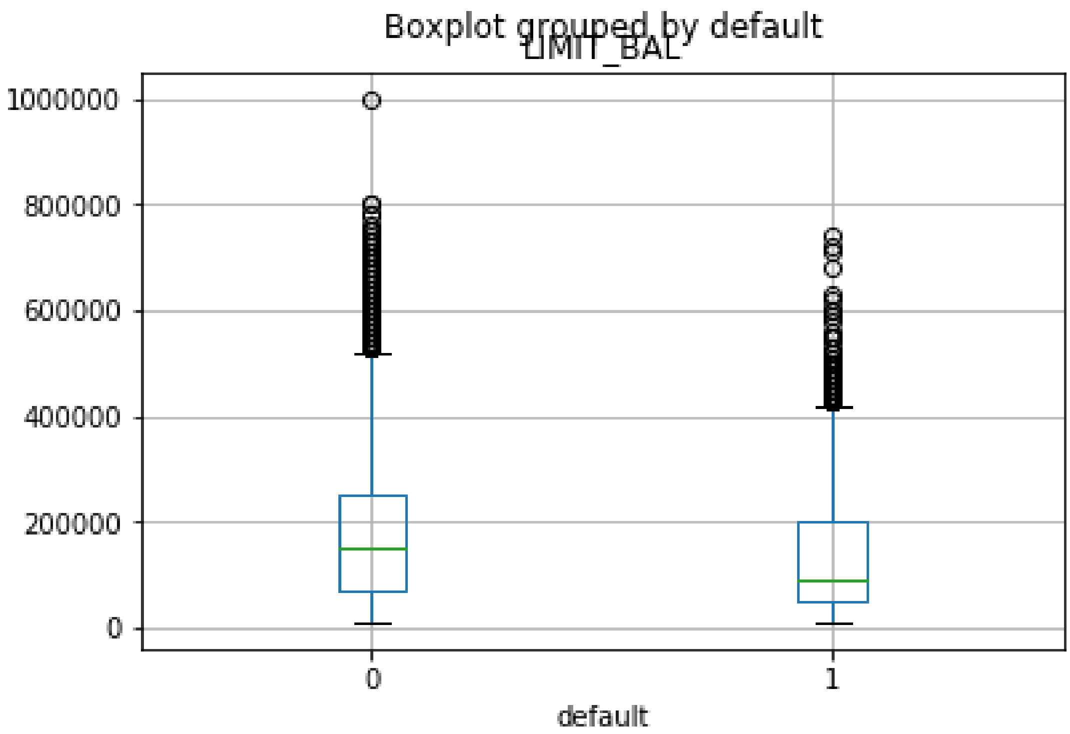




It satisfies our curiosity that 21% of women default while 24% of men default. It is also interesting that 60% of the data set is women. It is not clear from these statistics alone whether gender is a meaningful factor in estimating default rates after other variables are considered.

```
In [12]: a = df.boxplot(column='LIMIT_BAL', by = 'default')
         a.set_yscale
```

```
Out[12]: <bound method _AxesBase.set_yscale of <matplotlib.axes._subplots.AxesSubplot object a
```

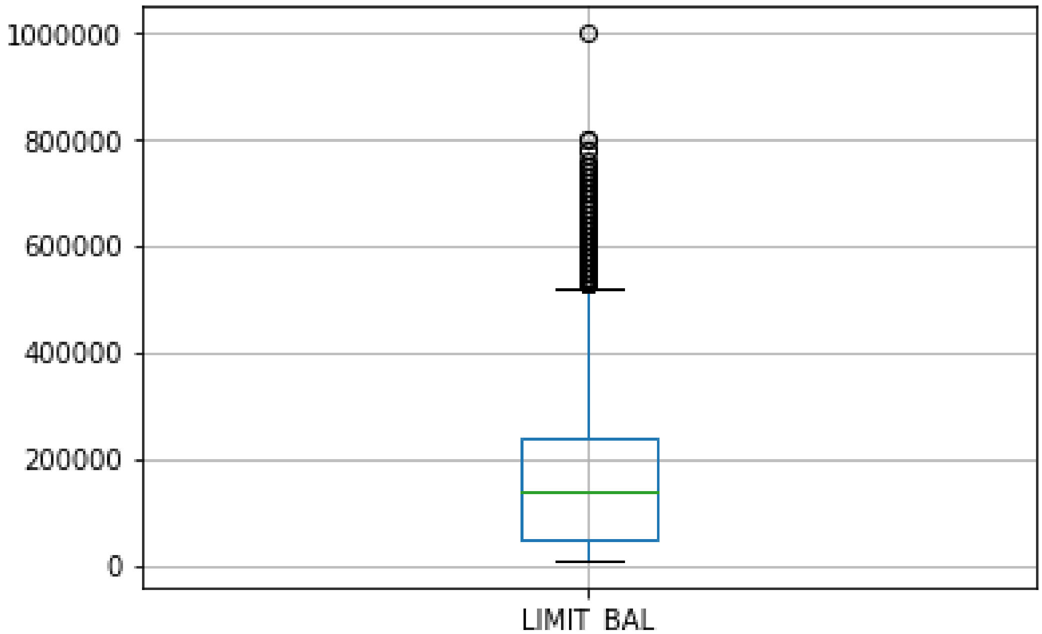


The boxplot above shows that credit limits (LIMIT_BAL) tend to be lower overall for those who default than those who don't. It is not just a matter of the average being 26.94% lower as noted earlier.

This could be interesting because the bank may be successfully managing its risk through limits, which could indicate factors at work in the data other than the attributes provided. The limits could be set on variables not provided, and changes in their credit granting processes could impact the default rates without change in the attributes provided. It also shows that the credit limit could provide value as an explanatory variable.

```
In [13]: b = df.boxplot(column='LIMIT_BAL')
         b.set_yscale
```

```
Out[13]: <bound method _AxesBase.set_yscale of <matplotlib.axes._subplots.AxesSubplot object a
```



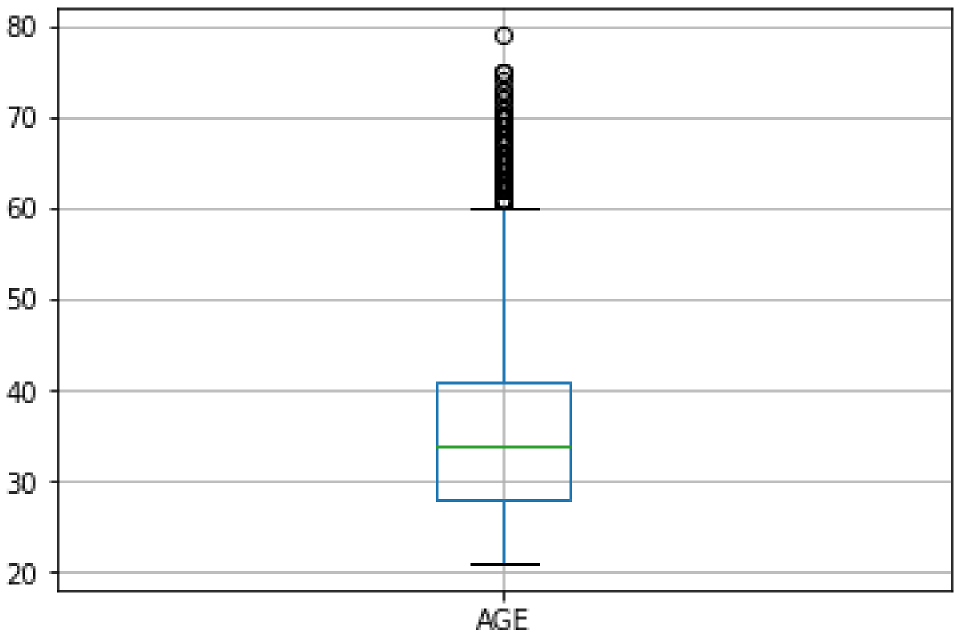
From the boxplot above we see that credit limits are right-skewed. The max for the top 90% of the data is approximately 500,000 a median of 140,000 and a potential outlier at 1 million.

We believe that the 1 million point is valid because billed amounts are consistent with that limit. We also checked some of the others and didn't see any potential data issues.

We may want to be mindful of the extreme spread in credit limits. Such a spread may create modelling issues and we may want to cluster customers into similar groups.

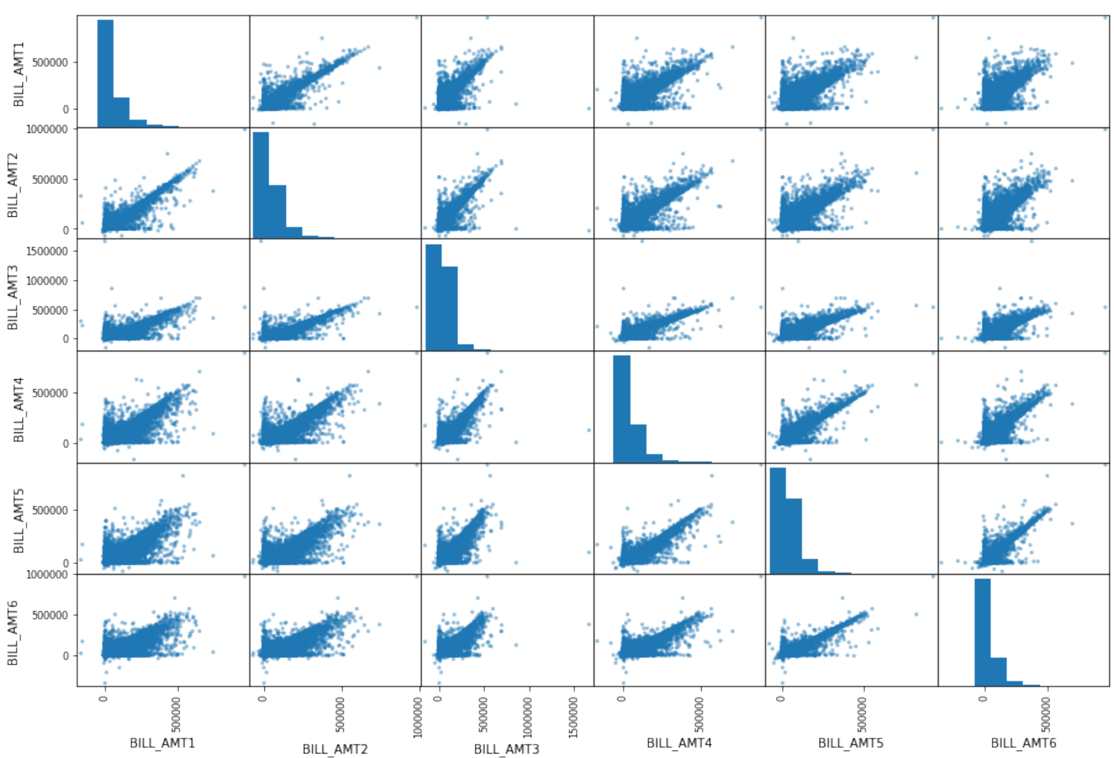
```
In [14]: c = df.boxplot(column='AGE')
         c.set_yscale
```

```
Out[14]: <bound method _AxesBase.set_yscale of <matplotlib.axes._subplots.AxesSubplot object a
```



The age variable seems pretty clean. 90% of the observations are between 21 and 60. Mean age is 35 and the median is 34. The skew doesn't seem to dominate most of the data.

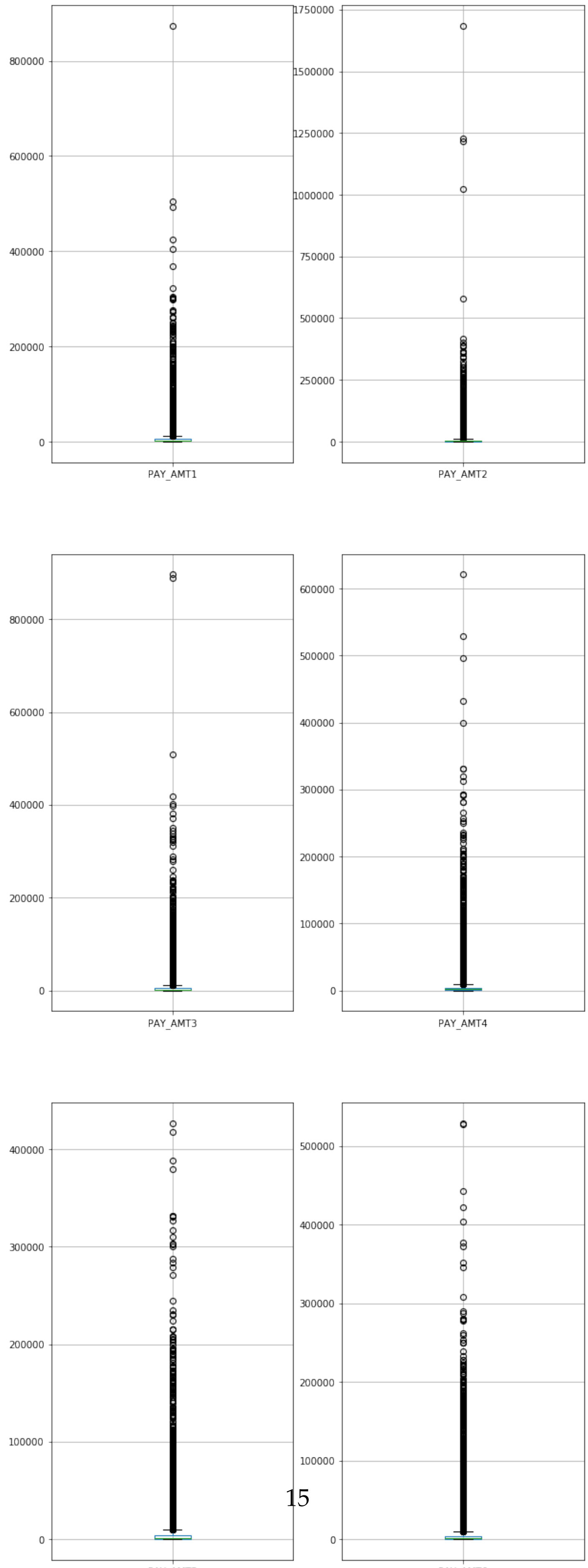
```
In [15]: from pandas.plotting import scatter_matrix
         ax=scatter_matrix(df[["BILL_AMT1","BILL_AMT2","BILL_AMT3","BILL_AMT4","BILL_AMT5","BI
```



We see on the scatter matrix high correlation between amounts of bill statements. All BILL_AMT distributions are right skewed. There are also indications of outliers. We looked at a small sample, and saw no reason to question the data.

We may use a log transform for this data in subsequent analysis.

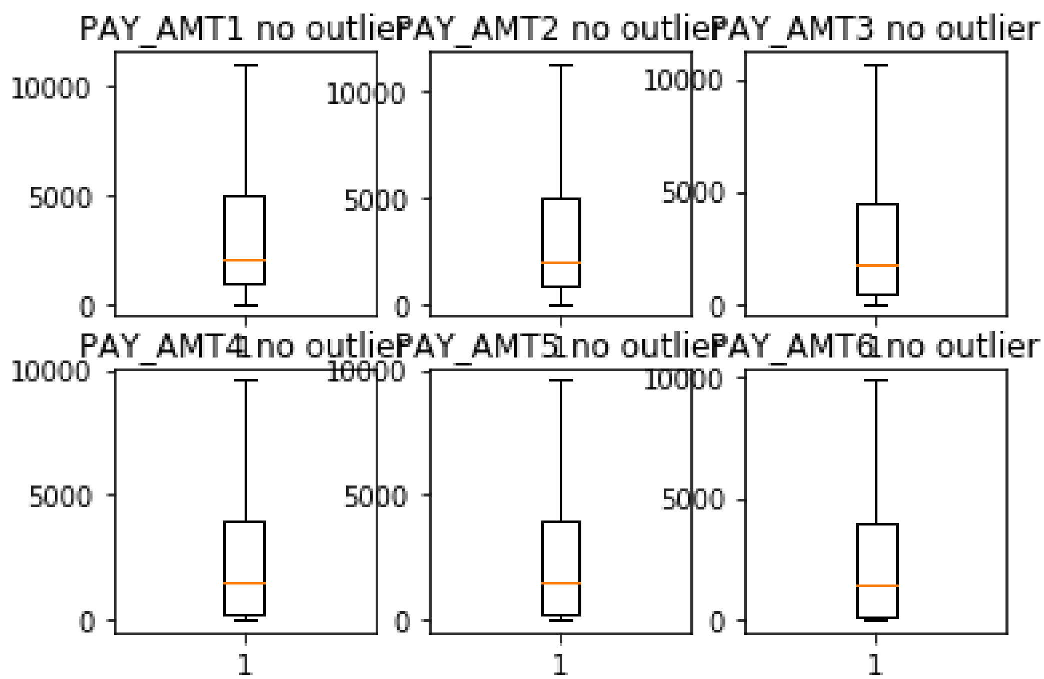
```
In [16]: vars_to_plot_separate = [['PAY_AMT1'],['PAY_AMT2'],['PAY_AMT3'],['PAY_AMT4'],['PAY_AM
         plt.figure(figsize=(10,30))
         for index, plot_vars in enumerate (vars_to_plot_separate):
             plt.subplot(len(vars_to_plot_separate)/2,
                         2,
                         index+1)
             ax=df.boxplot(column=plot_vars)

         plt.show()
```


800000
600000
400000
200000
0
PAY_AMT1
1750000
1500000
1250000
1000000
750000
500000
250000
0
PAY_AMT2
800000
600000
400000
200000
0
PAY_AMT3
600000
500000
400000
300000
200000
100000
0
PAY_AMT4
400000
300000
200000
100000
0
PAY_AMT5
500000
400000
300000
200000
100000
0
PAY_AMT6

As observed previously the range of values in the amount of payments made is extremely wide. This makes visualization and potentially modeling difficult. Again log or some other transforms may be necessary but we will keep the scale for the purposes of visualization.

```
In [17]: fig, axs = plt.subplots(2, 3)
         axs[0, 0].boxplot(df.PAY_AMT1, 0, '')
         axs[0, 0].set_title("PAY_AMT1 no outlier")
         axs[0, 1].boxplot(df.PAY_AMT2, 0, '')
         axs[0, 1].set_title("PAY_AMT2 no outlier")
         axs[0, 2].boxplot(df.PAY_AMT3, 0, '')
         axs[0, 2].set_title("PAY_AMT3 no outlier")
         axs[1, 0].boxplot(df.PAY_AMT4, 0, '')
         axs[1, 0].set_title("PAY_AMT4 no outlier")
         axs[1, 1].boxplot(df.PAY_AMT4, 0, '')
         axs[1, 1].set_title("PAY_AMT5 no outlier")
         axs[1, 2].boxplot(df.PAY_AMT6, 0, '')
         axs[1, 2].set_title("PAY_AMT6 no outlier")
```

```
Out[17]: Text(0.5,1,'PAY_AMT6 no outlier')
```



Removal of outliers above $10,000 (about the 90th percentile) makes the box-plots more interpretable. The plots look similar from month to month, but the skew seems to be decreasing with time. This point will be important for modeling.

1.6 Explore Joint Attributes

Overview Amount Billed, Payment Amount, and Pay(Delinquency Status) are time series. We examined for autocorrelation by reviewing scatterplots, correlation matrices and cross-tabs.

There are assumed structural relationships between some of the attributes: 1. The amount of a payment is likely related to the Amount Billed in the prior month 2. The Amount Billed is likely limited by the Credit Limit

Serial Correlation Analysis: Payments

In [18]:
```
%matplotlib inline
sns.set()
g = sns.pairplot(df[Payments],hue = 'default',size = 2)
```

In [19]:
```
df[Payments].corr()
```

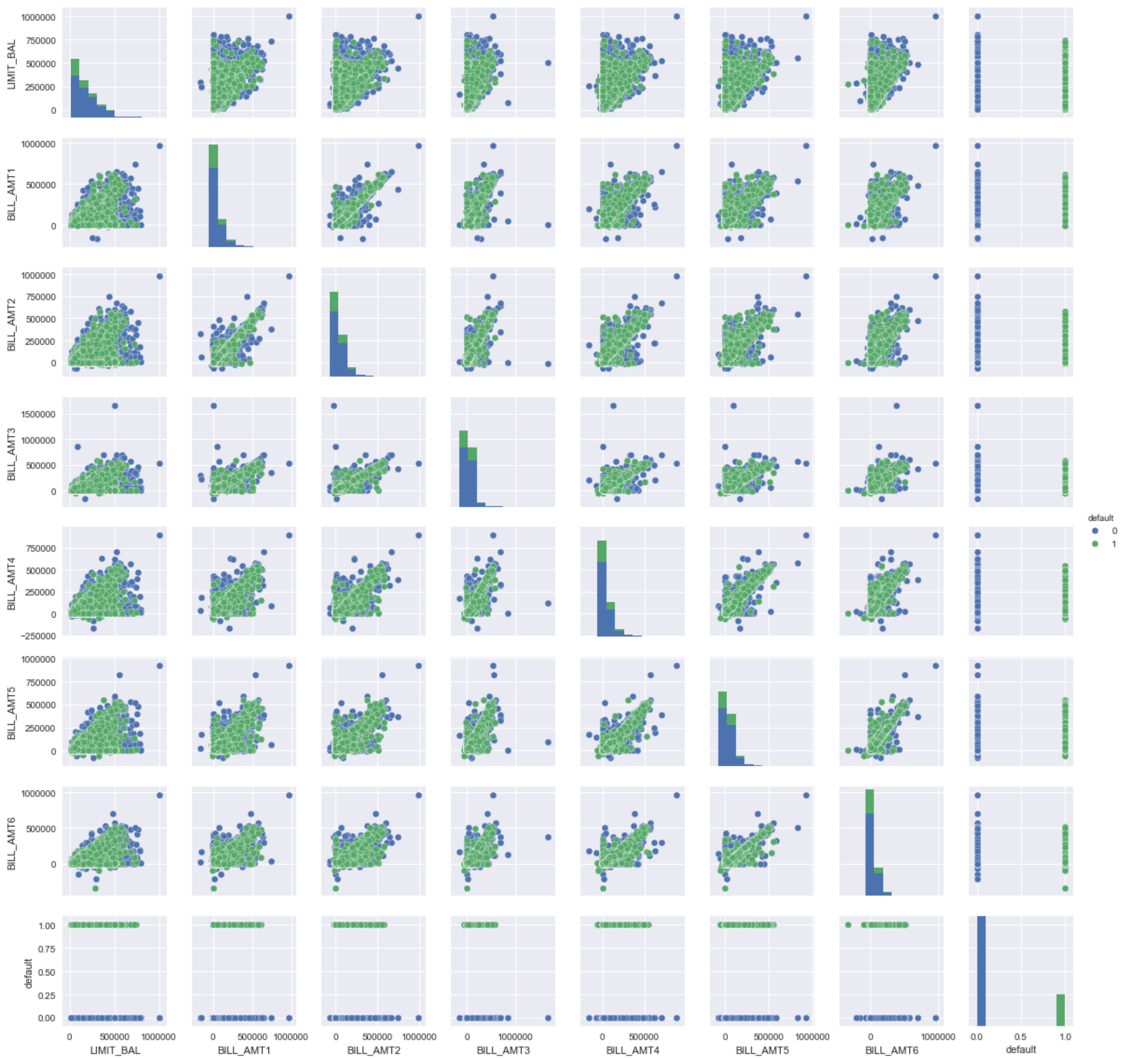
```
Out[19]:           PAY_AMT1  PAY_AMT2  PAY_AMT3  PAY_AMT4  PAY_AMT5  PAY_AMT6   default
         PAY_AMT1  1.000000  0.285576  0.252191  0.199558  0.148459  0.185735 -0.072929
         PAY_AMT2  0.285576  1.000000  0.244770  0.180107  0.180908  0.157634 -0.058579
         PAY_AMT3  0.252191  0.244770  1.000000  0.216325  0.159214  0.162740 -0.056250
         PAY_AMT4  0.199558  0.180107  0.216325  1.000000  0.151830  0.157834 -0.056827
         PAY_AMT5  0.148459  0.180908  0.159214  0.151830  1.000000  0.154896 -0.055124
         PAY_AMT6  0.185735  0.157634  0.162740  0.157834  0.154896  1.000000 -0.053183
         default  -0.072929 -0.058579 -0.056250 -0.056827 -0.055124 -0.053183  1.000000
```

A visual review of the scatter plots above does not show obvious serial correlation in payments. However, correlation coefficients approaching 30% in certain cases as indicated in the table above indicate that this is something we need to consider in the modelling phase.

Serial Correlation Analysis: Billed Amounts and Credit Limits

```
In [20]: %matplotlib inline
         sns.set()
         sns.pairplot(df[Bills],hue = 'default',size = 2)
```

```
Out[20]: <seaborn.axisgrid.PairGrid at 0x1d43ca312b0>
```



In [21]:
```
df[Bills].corr()
```

Out[21]:
```
           LIMIT_BAL  BILL_AMT1  BILL_AMT2  BILL_AMT3  BILL_AMT4  BILL_AMT5  \
LIMIT_BAL   1.000000   0.285430   0.278314   0.283236   0.293988   0.295562
BILL_AMT1   0.285430   1.000000   0.951484   0.892279   0.860272   0.829779
BILL_AMT2   0.278314   0.951484   1.000000   0.928326   0.892482   0.859778
BILL_AMT3   0.283236   0.892279   0.928326   1.000000   0.923969   0.883910
BILL_AMT4   0.293988   0.860272   0.892482   0.923969   1.000000   0.940134
BILL_AMT5   0.295562   0.829779   0.859778   0.883910   0.940134   1.000000
BILL_AMT6   0.290389   0.802650   0.831594   0.853320   0.900941   0.946197
default    -0.153520  -0.019644  -0.014193  -0.014076  -0.010156  -0.006760

           BILL_AMT6   default
LIMIT_BAL   0.290389 -0.153520
BILL_AMT1   0.802650 -0.019644
```

```
BILL_AMT2   0.831594 -0.014193
BILL_AMT3   0.853320 -0.014076
BILL_AMT4   0.900941 -0.010156
BILL_AMT5   0.946197 -0.006760
BILL_AMT6   1.000000 -0.005372
default    -0.005372  1.000000
```

A visual review of the scatter plots above shows clear indication of correlation in Billed Amounts across different months. It also shows that the Billed Amounts tend to be bound by the Credit Limit.

This is confirmed by the high correlation coefficients in the table above. We will need to consider mitigation methods in the modelling phase.

Serial Correlation Analysis: PAY ("Payment Delinquency Status")

In [22]:
```
# Creating a cross-tab of counts by the value of the ordinal variable to check autoco
#Payment Status.
# We are showing the migration of statuses from one period to the next.
# The rows are the first period status and the columns are the next period status.
# This requires re-shaping (stacking) data.

# First, create a single column of all Initial time period statuses,
#regardless of attribute name (month).
InitialList = ['PAY_6','PAY_5','PAY_4','PAY_3','PAY_2']
dfFirstStatus = df[InitialList]
StatusStacked = pd.DataFrame({'First':dfFirstStatus.stack()})
StatusStacked = StatusStacked.reset_index(drop=True)

# Then, create a single column of all subsequent time period statuses, regardless
#of attribute name (month).
NextList = ['PAY_5','PAY_4','PAY_3','PAY_2','PAY_0']
dfNextStatus = df[NextList]
NextStatusStacked = pd.DataFrame({'Next':dfNextStatus.stack()})
NextStatusStacked = NextStatusStacked.reset_index(drop=True)

# Combining the two columns into a single df.
StatusStacked['Next'] = NextStatusStacked['Next']
pd.crosstab(StatusStacked['First'],StatusStacked['Next'])
```

Out[22]:

Next / First	-2	-1	0	1	2	3	4	5	6	7	8
-2	17602	1477	1091	1233	253	0	0	0	0	0	0
-1	1904	21915	3476	621	1038	0	0	0	0	0	0
0	4	4106	72148	6	4918	0	0	0	0	0	0
1	0	0	0	34	0	0	0	0	0	0	0
2	10	1306	2814	1676	9460	1031	0	0	0	0	0
3	0	84	92	109	362	176	285	0	0	0	0
4	0	8	8	32	85	29	106	109	0	0	0

5	0	3	3	7	18	7	11	12	50	0	0
6	0	1	1	2	5	1	1	3	4	45	0
7	0	0	0	1	56	2	0	0	1	126	23
8	0	0	0	1	3	0	1	0	0	1	3

The table above shows the propensity of an account to remain in the same status in some cases. We will illustrate how the table above works by describing the first row. The table shows that there were 17,602+1,477+1,091+1,233+253=21,656 instances where an account had a Pay Status of -2 in a month where the status in the next month is available. Of those instances, 17,602 also had a Status of -2 in the folowing month, and 1,477 had a Status of -1 in the following month and so on.

The table shows that accounts with initial Statuses of -2 through 2 tend to stay in that status the following month. Status 1 seems to be a special case discussed in ***Data Quality***. We will need to account for this in the modelling phase.

```
In [23]: df[PayStausOnly].apply(pd.value_counts)
```

Out[23]:

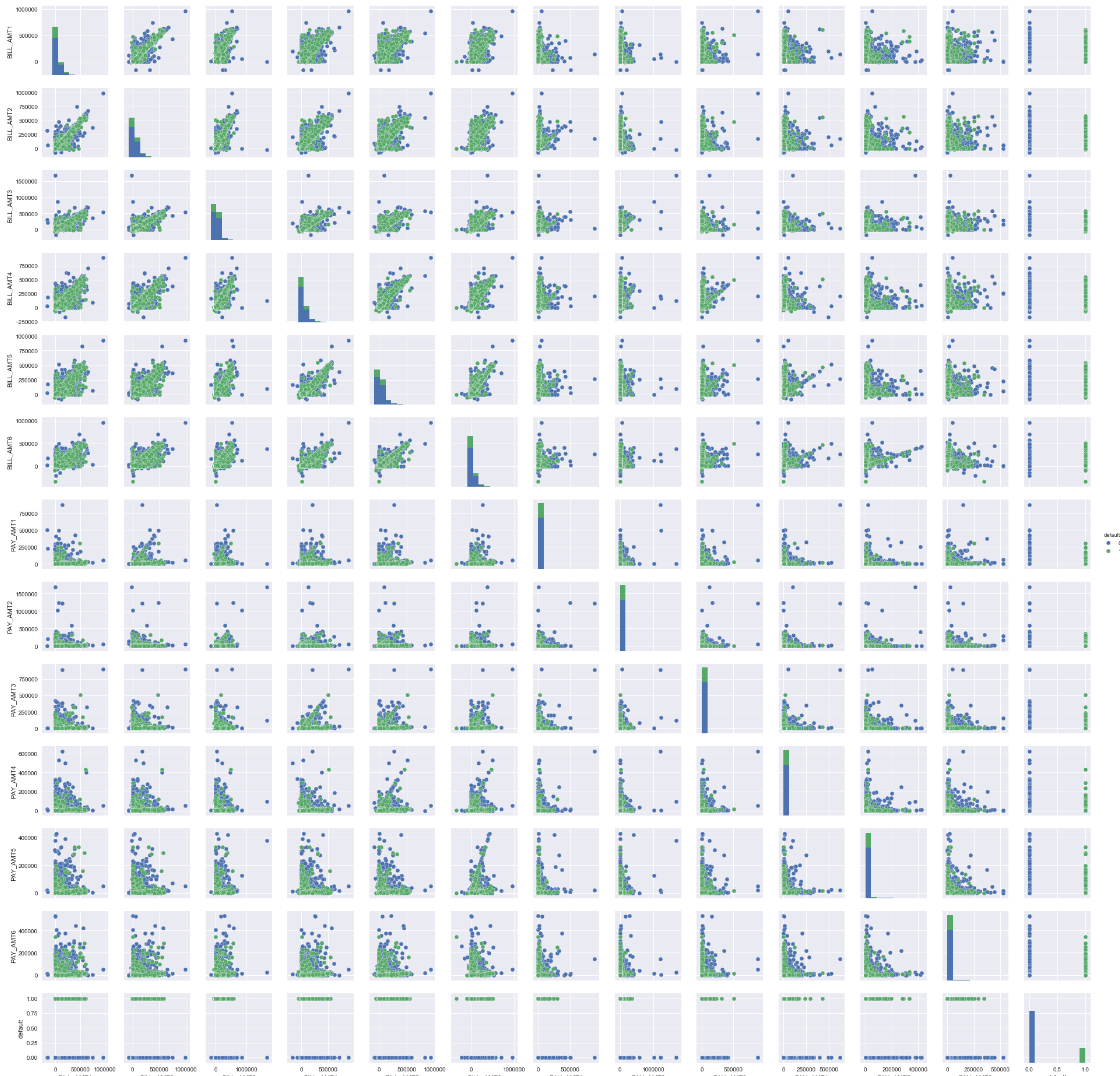
	PAY_0	PAY_2	PAY_3	PAY_4	PAY_5	PAY_6
-2	2759	3782	4085	4348	4546.0	4895.0
-1	5686	6050	5938	5687	5539.0	5740.0
0	14737	15730	15764	16455	16947.0	16286.0
1	3688	28	4	2	NaN	NaN
2	2667	3927	3819	3159	2626.0	2766.0
3	322	326	240	180	178.0	184.0
4	76	99	76	69	84.0	49.0
5	26	25	21	35	17.0	13.0
6	11	12	23	5	4.0	19.0
7	9	20	27	58	58.0	46.0
8	19	1	3	2	1.0	2.0

The table above shows that a value of 1 for this variable only appears in meaningful amounts in the PAY_0, the most recent month. It could be that this indicates the creation of a new "Status" or a data issue.

Serial Correlation Analysis: Billed Amounts and Payment Amounts

```
In [24]: %matplotlib inline
         sns.set()
         sns.pairplot(df[BillsAndPayments],hue = 'default',size = 2)
```

```
Out[24]: <seaborn.axisgrid.PairGrid at 0x1d4449ee080>
```



In [25]:
```
df[BillsAndPayments].corr()
```

Out[25]:

	BILL_AMT1	BILL_AMT2	BILL_AMT3	BILL_AMT4	BILL_AMT5	BILL_AMT6 \
BILL_AMT1	1.000000	0.951484	0.892279	0.860272	0.829779	0.802650
BILL_AMT2	0.951484	1.000000	0.928326	0.892482	0.859778	0.831594
BILL_AMT3	0.892279	0.928326	1.000000	0.923969	0.883910	0.853320
BILL_AMT4	0.860272	0.892482	0.923969	1.000000	0.940134	0.900941
BILL_AMT5	0.829779	0.859778	0.883910	0.940134	1.000000	0.946197
BILL_AMT6	0.802650	0.831594	0.853320	0.900941	0.946197	1.000000
PAY_AMT1	0.140277	0.280365	0.244335	0.233012	0.217031	0.199965
PAY_AMT2	0.099355	0.100851	0.316936	0.207564	0.181246	0.172663
PAY_AMT3	0.156887	0.150718	0.130011	0.300023	0.252305	0.233770
PAY_AMT4	0.158303	0.147398	0.143405	0.130191	0.293118	0.250237
PAY_AMT5	0.167026	0.157957	0.179712	0.160433	0.141574	0.307729

```
PAY_AMT6     0.179341   0.174256   0.182326   0.177637   0.164184   0.115494
default     -0.019644  -0.014193  -0.014076  -0.010156  -0.006760  -0.005372

           PAY_AMT1  PAY_AMT2  PAY_AMT3  PAY_AMT4  PAY_AMT5  PAY_AMT6  \
BILL_AMT1  0.140277  0.099355  0.156887  0.158303  0.167026  0.179341
BILL_AMT2  0.280365  0.100851  0.150718  0.147398  0.157957  0.174256
BILL_AMT3  0.244335  0.316936  0.130011  0.143405  0.179712  0.182326
BILL_AMT4  0.233012  0.207564  0.300023  0.130191  0.160433  0.177637
BILL_AMT5  0.217031  0.181246  0.252305  0.293118  0.141574  0.164184
BILL_AMT6  0.199965  0.172663  0.233770  0.250237  0.307729  0.115494
PAY_AMT1   1.000000  0.285576  0.252191  0.199558  0.148459  0.185735
PAY_AMT2   0.285576  1.000000  0.244770  0.180107  0.180908  0.157634
PAY_AMT3   0.252191  0.244770  1.000000  0.216325  0.159214  0.162740
PAY_AMT4   0.199558  0.180107  0.216325  1.000000  0.151830  0.157834
PAY_AMT5   0.148459  0.180908  0.159214  0.151830  1.000000  0.154896
PAY_AMT6   0.185735  0.157634  0.162740  0.157834  0.154896  1.000000
default   -0.072929 -0.058579 -0.056250 -0.056827 -0.055124 -0.053183

            default
BILL_AMT1 -0.019644
BILL_AMT2 -0.014193
BILL_AMT3 -0.014076
BILL_AMT4 -0.010156
BILL_AMT5 -0.006760
BILL_AMT6 -0.005372
PAY_AMT1  -0.072929
PAY_AMT2  -0.058579
PAY_AMT3  -0.056250
PAY_AMT4  -0.056827
PAY_AMT5  -0.055124
PAY_AMT6  -0.053183
default    1.000000
```

A visual review of the scatterplots above show that there is a potential relationship between the Billed Amount in one month (e.g. BILL_AMT6) and the resulting payment (e.g. PAY_AMT5). This is confirmed by the correlation matrix, which indicates that the correlation between the billed amount and the resulting payment is in the 30% range.

```
In [26]: #Adding Prior Period Balances to table used for evaluating Status accuracy
         BillList = ['BILL_AMT6','BILL_AMT5','BILL_AMT4','BILL_AMT3','BILL_AMT2']
         dfPriorBill = df[BillList]

         BillStacked = pd.DataFrame({'Billed':dfPriorBill.stack()})
         BillStacked = BillStacked.reset_index(drop=True)
         StatusStacked['Billed'] = BillStacked['Billed']
```

```
In [27]: ## Checking instances of an account coded as delinquent when Billed amount was zero o
         ProblemCountV_Minus1 = 0
```

```
    ProblemCountV_Zero = 0

    # Checking Delinquency if Status 0 is Delinquent:
    for i in np.arange(0,len(StatusStacked)):
        if StatusStacked['Billed'][i] < 1 and StatusStacked['Next'][i]>-1:
            ProblemCountV_Minus1 = ProblemCountV_Minus1 + 1

    # Checking Delinquency if Status 1 only is Delinquent:
    for i in np.arange(0,len(StatusStacked)):
        if StatusStacked['Billed'][i] < 1 and StatusStacked['Next'][i]>0:
            ProblemCountV_Zero = ProblemCountV_Zero + 1


    print("Versus -1: ", ProblemCountV_Minus1,"Versus 0: ", ProblemCountV_Zero)
```

```
Versus -1:  4702 Versus 0:  1769
```

As mentioned in the "Suspicious Values" section of this analysis: The data points above show that there are instances where the Payment Status implies late payment but the amount billed was zero or less. This seems nonsensical. There are 1,769 such cases (out of 150,000 possible payments: 30,000 accounts and 5 months of validatable data) if measured against payment statuses defined as delinquent by the data providers, and 4,702 if we consider Payment Status of zero as delinquent.

1.7 Explore Attributes and Class

In this section we review the various relationships between our various features and there relationship to our target class (default =1). This will allow us to understand certain features or potentially identify new features for use in our model.

We began by exploring the relationships between the available demographic data to the default class.

Customer Demographics and Default

```
In [28]: #do some transformations
         #convert any non-identified education categories to 'OTHER'
         df['EDUCATION'] = df['EDUCATION'].replace(to_replace=(0,5,6),value=4)

         #convert any non-identified marriage categories to 'OTHER'
         df['MARRIAGE'] = df['MARRIAGE'].replace(to_replace=(0),value=3)

         #calculate the credit usage values
         df['USAGE_1'] = df['BILL_AMT1']/df['LIMIT_BAL']
         df['USAGE_2'] = df['BILL_AMT2']/df['LIMIT_BAL']
         df['USAGE_3'] = df['BILL_AMT3']/df['LIMIT_BAL']
         df['USAGE_4'] = df['BILL_AMT4']/df['LIMIT_BAL']
         df['USAGE_5'] = df['BILL_AMT5']/df['LIMIT_BAL']
         df['USAGE_6'] = df['BILL_AMT6']/df['LIMIT_BAL']
```

```
payments = ['PAY_0','PAY_2','PAY_3','PAY_4','PAY_5','PAY_6']
df['TotalMonthsLate'] = df[payments].sum(axis=1)
#transform continuous variables as they each have a mostly exponential distribution
df[continuous_features] = df[continuous_features].replace(to_replace=0,value=np.nan).a
```

In [29]:
```
# this python magics will allow plot to be embedded into the notebook
%matplotlib inline
# cross tabs provide a quick view of the relationships between characteristics of the
#borrower & our target
plotVar = ['SEX','EDUCATION','MARRIAGE','AGE']

fig, axes = plt.subplots(nrows=len(plotVar), ncols=2, figsize=(15, 25))

for fi,feature in enumerate(plotVar):
    Counts = pd.crosstab(df[feature],df.default.astype(bool))
    Counts.plot(kind='bar', stacked=True, ax=axes[fi,0])

    Rate = Counts.div(Counts.sum(1).astype(float),axis=0)
    Rate.plot(kind='barh', stacked=True, ax=axes[fi,1])

plt.show()
```

default
False
True
17500
15000
12500
10000
7500
5000
2500
0
1
2
SEX
SEX
0.0
0.2
0.4
0.6
0.8
1.0
14000
12000
10000
8000
6000
4000
2000
3
4
EDUCATION
EDUCATION
16000
MARRIAGE
MARRIAGE
1600
1400
1200
1000
800
600
400
200
AGE
AGE

After reviewing the features from above there are a couple relationships that stand out when comparing the demographic features and the proportion of defaults for our sample. The review of this data below simply addresses the variable relationships to the default class. It does not address the potential ethical or legal concerns of using a customer's demographic information to influence a bank's decision on credit limits or interest rates.

Sex - There does not appear to be a noticeable difference in the default rates by gender based on a visual inspections.

Education - There does seem to pattern between the amount of education people receive and the default rates. Based on the visual inspection of the above data there is some indication that people with higher levels of education default at lower rates.

Marriage - There does not seem to be any obvious discernable trends based on Marital Status

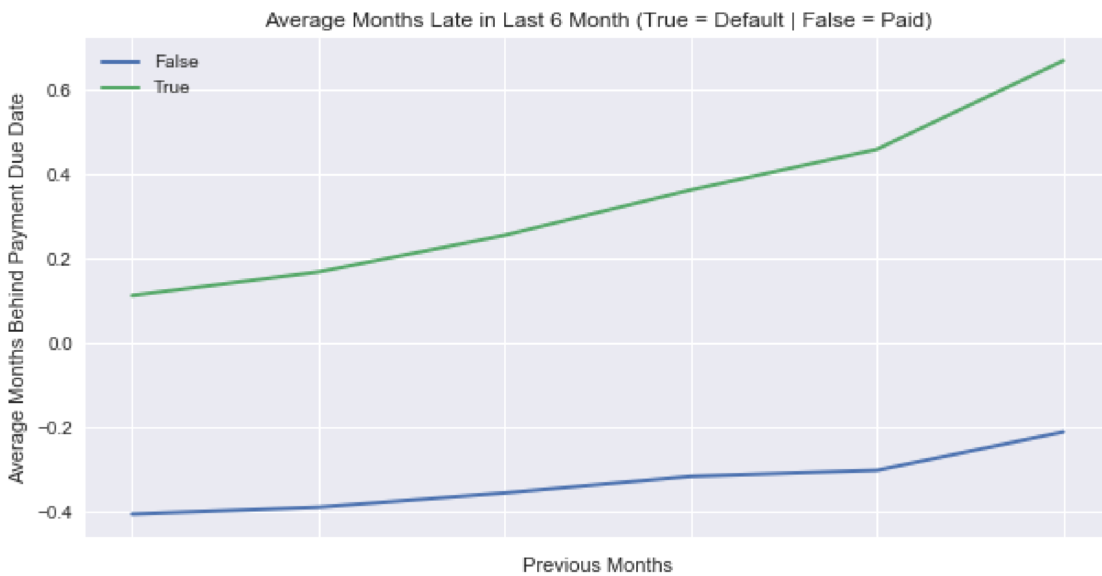
Age: - Based on the age variables there is potentially some indications that people in there early 20's are more succeptible to defaulting, however this variable may need to be bucketed differently to better interpret the succeptible age groups. We will cover this in our 'New Features' section.

Payment History and Default After looking through the customers demographic history we wanted to explore the relationships between the customers bill payment history to identify any patterns that emerge.

We begin with the relationship between prior payment status (late payments vs ontime)

In [30]:
```
plotVar = ['PAY_0','PAY_2','PAY_3','PAY_4','PAY_5','PAY_6','default']
plotDF = df[plotVar]

meanDF = plotDF.groupby(by='default').mean().T.reset_index()
meanDF['Month'] = [9,8,7,6,5,4]
meanDF.columns = ['PreviousMonths', 'False', 'True', 'Month']
meanDF = meanDF.sort_values(by=['Month'], ascending=True)

meanDF.plot(x='PreviousMonths', y=['False', 'True'], figsize=(10,5), grid=True, lw = 
plt.title('Average Months Late in Last 6 Month (True = Default | False = Paid)')
plt.xlabel('Previous Months')
plt.ylabel('Average Months Behind Payment Due Date')
```

Out[30]:
```
Text(0,0.5,'Average Months Behind Payment Due Date')
```



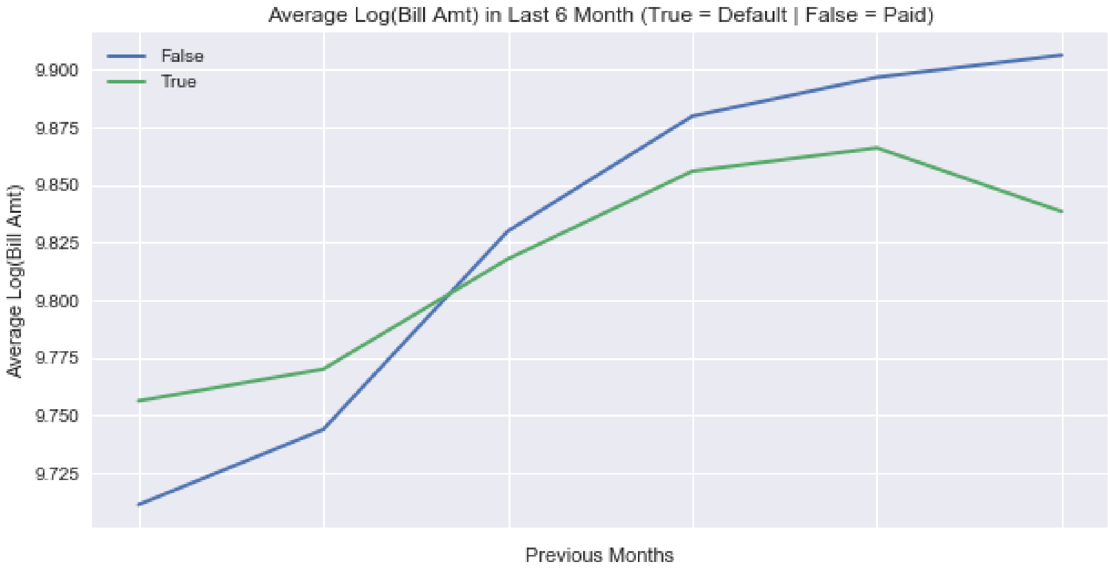
From above the customers that defaulted paid there previous bill between .2 to .7 months late on average. Additionally, it appears that as we move closer to the month we are predicting(left to right), the timeliness of the bill payments seems to be getting worse for both groups.

Logically we interpret this to support the notion that people who have trouble paying there previous bills will likely have similar difficulties paying in the future.

This lends to the potential for a new features that better captures the timeliness of previous payments as well as the status of the last payment (paid or still outstanding).

In order to understand why, we will look at the average of the log transformed bill amounts to see if there is any identifiable pattern.

```
In [31]: plotVar = ['BILL_AMT1', 'BILL_AMT2','BILL_AMT3','BILL_AMT4', 'BILL_AMT5', 'BILL_AMT6'
         plotDF = df[plotVar]

         meanDF = plotDF.groupby(by='default').mean().T.reset_index()
         meanDF['Month'] = [9,8,7,6,5,4]
         meanDF.columns = ['PreviousMonths', 'False', 'True', 'Month']
         meanDF = meanDF.sort_values(by=['Month'], ascending=True)

         meanDF.plot(x='PreviousMonths', y=['False', 'True'], figsize=(10,5), grid=True, lw = 
         plt.title('Average Log(Bill Amt) in Last 6 Month (True = Default | False = Paid)')
         plt.xlabel('Previous Months')
         plt.ylabel('Average Log(Bill Amt)')

Out[31]: Text(0,0.5,'Average Log(Bill Amt)')
```

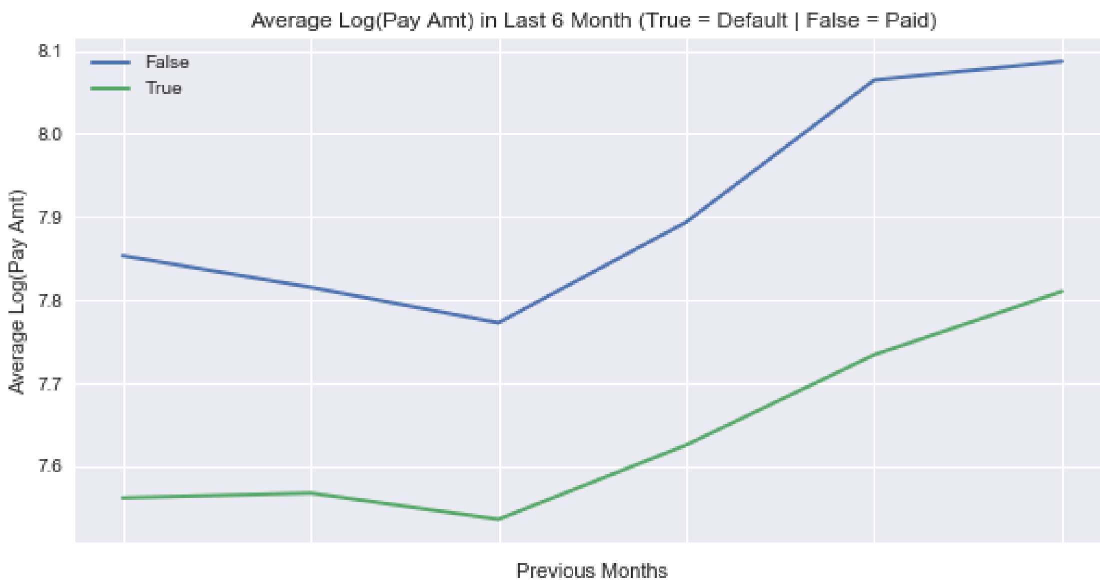


Interestingly, when looking at the bill amount from the previous months there does not seem to be a considerable difference between the median bill amount between customers that default and those that don't.

Based on this it would seem that the actual bill amount by itself will offer little insight into the likelihood of default. This is perhaps an indication that it should be considered relative to the total available credit and the prior payments.

Next we look deeper that log transformed payment amounts.

```
In [32]: plotVar = ['PAY_AMT1', 'PAY_AMT2','PAY_AMT3','PAY_AMT4', 'PAY_AMT5', 'PAY_AMT6','defau
         plotDF = df[plotVar]

         meanDF = plotDF.groupby(by='default').mean().T.reset_index()
         meanDF['Month'] = [9,8,7,6,5,4]
         meanDF.columns = ['PreviousMonths', 'False', 'True', 'Month']
         meanDF = meanDF.sort_values(by=['Month'], ascending=True)

         meanDF.plot(x='PreviousMonths', y=['False', 'True'], figsize=(10,5), grid=True, lw = 
         plt.title('Average Log(Pay Amt) in Last 6 Month (True = Default | False = Paid)')
         plt.xlabel('Previous Months')
         plt.ylabel('Average Log(Pay Amt)')

Out[32]: Text(0,0.5,'Average Log(Pay Amt)')
```



There does appear to be a difference in the median payment amount between the customers that defaulted and those that did not.

It appears that customers that did not default make higher payments against their credit on average than those that do default.

This leads us to question if customers that default are paying less, but maintain a similar bill amount then they are likely using a higher proportion of there credit. We will introduce a new feature that will measure the customer's credit usage in the 'New Features' section.

Summary Based on the reviews of the features above it appears that we have several features that have a relationship to our target class. Additionally, we identified several limitations of our current features and have decided to include a several new features that could potentially improve our model.

1.8 New Features

Based on the above analysis we believe we idenfied several new features that we will derive from our existing data. Below we explain the variable and the code used to create it.

Bucketed Age Group This will allow us to pick up some of the traits of different age groups and life events. For example young adults (21-28) will likely have a different financial situation than a retiree.

```
In [33]: # Creating Age Buckets
         df['Agegroup'] = df['AGE']//10
```

Credit Usage History Using the billed amounts relative to the total available credit for each of the customers gives us information on how much available credit they are using and carrying over month to month. This feature will allow us to determine how high consistently high credit usage effects a customer's likelihood of defaulting.

```
In [34]: #calculate the credit usage values
         df['USAGE_1'] = df['BILL_AMT1']/df['LIMIT_BAL']
         df['USAGE_2'] = df['BILL_AMT2']/df['LIMIT_BAL']
         df['USAGE_3'] = df['BILL_AMT3']/df['LIMIT_BAL']
         df['USAGE_4'] = df['BILL_AMT4']/df['LIMIT_BAL']
         df['USAGE_5'] = df['BILL_AMT5']/df['LIMIT_BAL']
         df['USAGE_6'] = df['BILL_AMT6']/df['LIMIT_BAL']
```

Late Payments Total How many times has a customer been late on a payment in the last six months? We saw in the section above that a history of late payments does appear to have a strong relationship with our target variable default.

Changes in Client Behavior Trends in Billed Amounts or % of Billed Amounts paid may prove to be related to the propensity to default.

```
In [35]: transformVar = ['PAY_0','PAY_2','PAY_3','PAY_4','PAY_5','PAY_6']

         for fi,feature in enumerate(transformVar):
             df[feature] = pd.cut(df[feature], [-3,-1,8], 2, labels=[0,1]).astype(np.int64)

         df['TotalMonthsLate'] = df[transformVar].sum(axis=1)
```

1.9 Exceptional Work

```
In [36]: df = pd.read_csv('Input/DefaultCreditcardClients.csv')
         df.rename(columns={'default payment next month':'default'}, inplace=True)
         df.index = df.ID
         if 'ID' in df:
             del df['ID']

         df["log_LIMIT_BAL"]=np.log(df.LIMIT_BAL)
         df["log_PAY_AMT1"]=np.log(df.PAY_AMT1+1)
         df["log_PAY_AMT2"]=np.log(df.PAY_AMT2+1)
         df["log_PAY_AMT3"]=np.log(df.PAY_AMT3+1)
         df["log_PAY_AMT4"]=np.log(df.PAY_AMT4+1)
         df["log_PAY_AMT5"]=np.log(df.PAY_AMT5+1)
         df["log_PAY_AMT6"]=np.log(df.PAY_AMT6+1)

         from sklearn.decomposition import PCA
         pca=PCA(n_components=4)
         X=df[['log_LIMIT_BAL', 'BILL_AMT1', 'BILL_AMT2','BILL_AMT3','BILL_AMT4', 'BILL_AMT5',
                         'log_PAY_AMT1','log_PAY_AMT2', 'log_PAY_AMT3', 'log_PAY_AMT4', 'log_P
         X_pca = pca.fit(X).transform(X)
         print ('pca:', pca.components_)
```

```
pca: [[ 1.82072365e-06  4.47584136e-01  4.41765411e-01  4.29686609e-01
   3.97979144e-01  3.69918767e-01  3.53063573e-01  6.69199565e-06
   6.94605205e-06  7.48699545e-06  7.87942983e-06  7.79690911e-06
```

```
  7.83768078e-06]
 [-3.36391191e-07  5.53642823e-01  3.91611377e-01  7.51240163e-02
  -2.67274713e-01 -4.50579053e-01 -5.09920857e-01  4.57022076e-06
  -1.29278520e-06 -7.60193355e-06 -1.05517954e-05 -1.09800464e-05
  -7.43284675e-06]
 [-1.42657603e-06 -4.49920270e-01 -3.35071473e-02  7.17866806e-01
   2.91213435e-01 -1.73749572e-01 -4.07580779e-01  5.45394684e-06
   1.85954127e-05  3.88365681e-06 -6.73941550e-06 -9.32576735e-06
  -3.24824575e-06]
 [-4.45743980e-07 -1.92812760e-01  1.68834826e-01  4.13771338e-01
  -7.06454730e-01 -1.56148804e-01  4.89541199e-01  6.18075806e-06
   5.90076772e-06 -2.24234453e-05  5.05479320e-06  2.06556973e-05
   5.94049376e-06]]
```

In [37]:
```python
from sklearn.preprocessing import StandardScaler
features = ['log_LIMIT_BAL', 'BILL_AMT1', 'BILL_AMT2','BILL_AMT3','BILL_AMT4', 'BILL_A
                'log_PAY_AMT1','log_PAY_AMT2', 'log_PAY_AMT3', 'log_PAY_AMT4', 'log_P
x = df.loc[:, features].values
y = df.loc[:,['default']].values
x = StandardScaler().fit_transform(x)

from sklearn.decomposition import PCA
pca = PCA(n_components=7)
principalComponents = pca.fit_transform(x)
principalDf = pd.DataFrame(data = principalComponents
             , columns = ['principal component 1', 'principal component 2', 'principal
                          'principal component 5','principal component 6', 'principal
principalDf.head()
```

Out[37]:
```
   principal component 1  principal component 2  principal component 3  \
0              -3.500827               2.365336               1.480592
1              -1.857898               0.154172              -0.510818
2              -0.545440              -1.180344               0.045414
3               0.000963              -0.737854               0.860512
4              -0.225923              -1.794903               0.952715

   principal component 4  principal component 5  principal component 6  \
0               0.362212               1.284113               0.873443
1               0.931328               1.141986               0.412477
2               0.257409               0.025700              -0.222169
3               0.156770               0.033502              -0.092137
4              -0.020841               0.571804               0.419759

   principal component 7
0               0.331434
1              -1.674209
2               0.095423
```

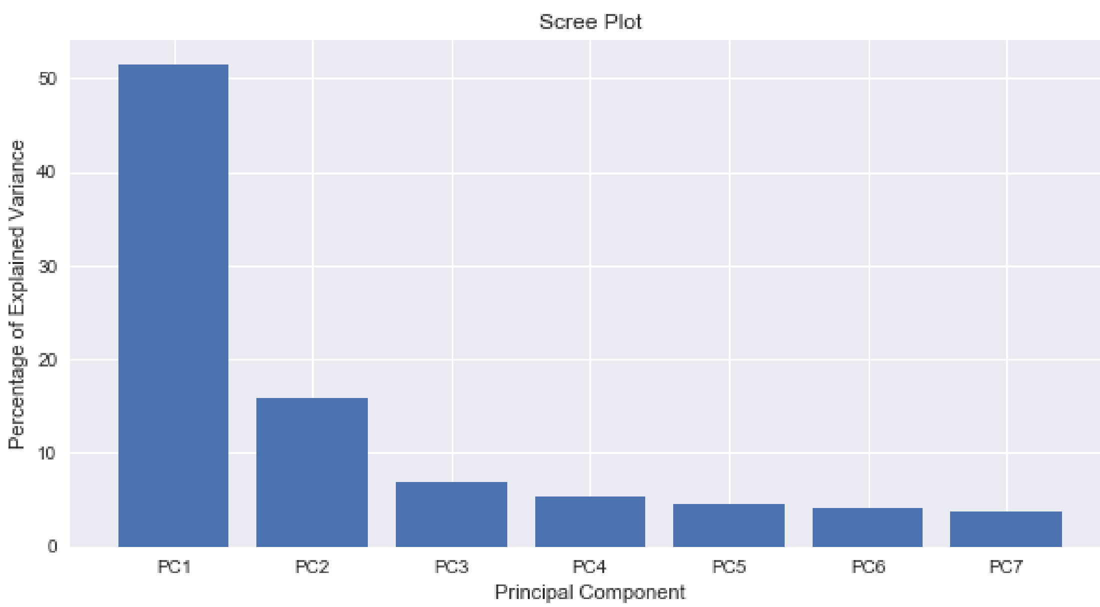
```
3                0.117068
4               -0.507973
```

```
In [38]: finalDf = pd.concat([principalDf, df[['default']]], axis = 1)
```

```
In [39]: pca.explained_variance_ratio_
```

```
Out[39]: array([0.51460566, 0.15764278, 0.06993085, 0.05446773, 0.04516576,
                0.04217214, 0.03813215])
```

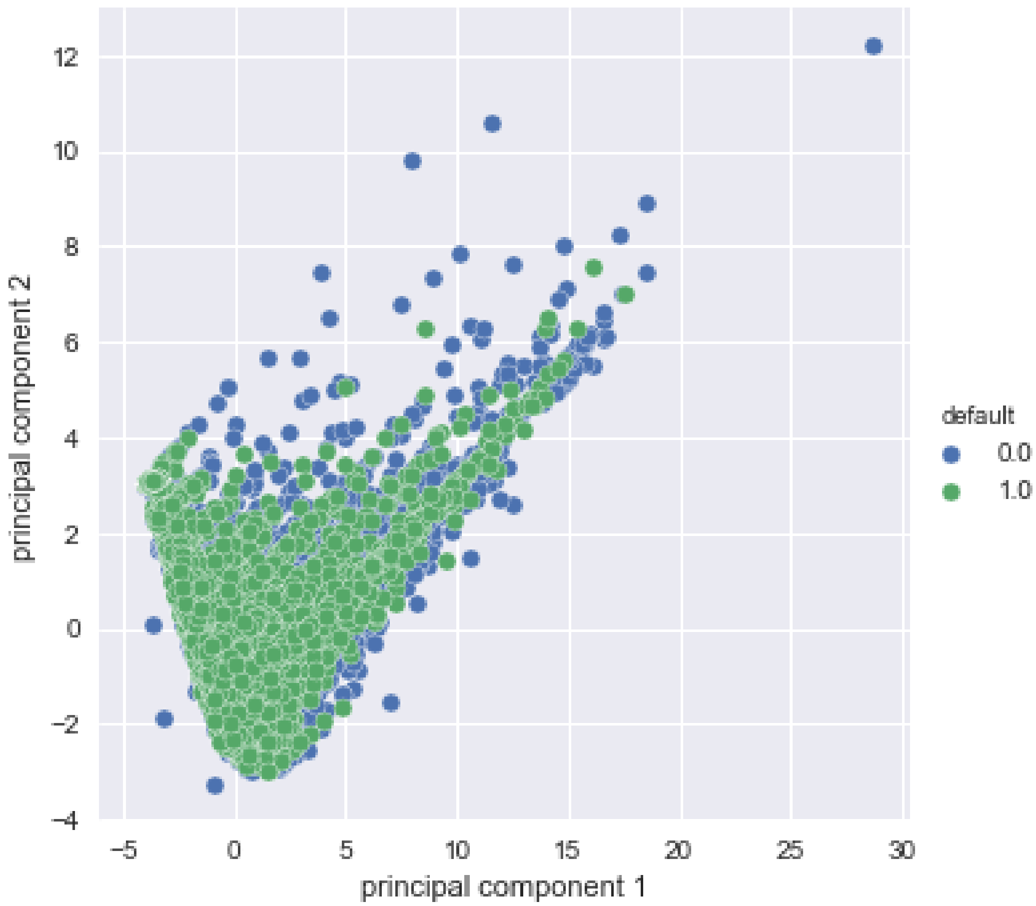
```
In [40]: #Scree plot
         plt.rcParams['figure.figsize'] = [10, 5]
         #Calculate % that each comp accounts for
         per_var = np.round(pca.explained_variance_ratio_*100, decimals=1)
         #Create labels
         labels = ['PC' + str(x) for x in range(1, len(per_var)+1)]
         #Create matplotlib bar (scree) plot
         plt.bar(x=range(1,len(per_var)+1), height=per_var, tick_label=labels)
         plt.ylabel('Percentage of Explained Variance')
         plt.xlabel('Principal Component')
         plt.title('Scree Plot')
         plt.show()
```



The Percentage of Explained Variance in the plot above tells us how much information (variance) can be attributed to each of the principal components. This is important as while we can convert 13 dimensional space to 7 dimensional space, we lose some of the variance (information) when we do this. By using the attribute explained_variance_ratio_, we can see that the first principal component contains 51.46% of the variance, the second principal component contains 15.76% of the variance and the third principal component contains 6.99% of the variance and so on. Together these seven components explain 92.18% of the variance.

```
In [41]: sns.pairplot(x_vars=["principal component 1"], y_vars=["principal component 2"], data=
```

```
Out[41]: <seaborn.axisgrid.PairGrid at 0x1d457017240>
```



Above scatterplot represents 67.21% of the continuus features variance just using only the first 2 principal components.