UCLA Extension Data Science Certificate - Final Exam

Proposal

Prepare a proposal in which you describe work to be done in analysis of the following dataset:
https://archive.ics.uci.edu/ml/datasets/default+of+credit+card+clients (https://archive.ics.uci.edu/ml/datasets/default+of+credit+card+clients)

Domain Background

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.

This research aimed at the case of customersâ€™ default payments in Taiwan and compares the predictive accuracy of probability of default among six data mining methods.

From the perspective of risk management, the result of predictive accuracy of the estimated probability of default will be more valuable than the binary result of classification - credible or not credible clients. Because the real probability of default is unknown, this study presented the novel â€œSorting Smoothing Methodâ€ to estimate the real probability of default.

With the real probability of default as the response variable (Y), and the predictive probability of default as the independent variable (X), the simple linear regression result (Y = A + BX) shows that the forecasting model produced by artificial neural network has the highest coefficient of determination; its regression intercept (A) is close to zero, and regression coefficient (B) to one.

Therefore, among the six data mining techniques, artificial neural network is the only one that can accurately estimate the real probability of default.

Import Libraries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

Get the Data

In [2]:
```
credit_card = pd.read_excel('..\data\\default of credit card clients.xls',header= 1)
```

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

Out[3]:

	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	...	BILL_AMT4	BILL_AMT5	BILL_AMT6	PA
	20000	2	2	1	24	2	2	-1	-1	...	0	0	0	0
	120000	2	2	2	26	-1	2	0	0	...	3272	3455	3261	0
200	90000	2	2	2	34	0	0	0	0	...	14331	14948	15549	15
200	50000	2	2	1	37	0	0	0	0	...	28314	28959	29547	
	50000	1	2	1	57	-1	0	-1	0	...	20940	19146	19131	

s × 25 columns

Attribute Information:

This research employed a binary variable, default payment (Yes = 1, No = 0), as the response variable.

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)

default.payment.next.month is the target variable.

Problem Statement

In the given problem we need to classify client based on 23 variables / attributes provided to predict if a client will be a defaulter in payment next month. Using EDA & close look at the data we will analyze the features which will have impact on target variable. Since this is a clearly defined problem & Discrete target we can use classification models to predict if a client will default or not.

Classification models include linear models like Logistic Regression, SVM, and nonlinear ones like K-NN, Kernel SVM and Random Forests.

Machine Learning Classification models:

1. Logistic Regression
2. K-Nearest Neighbors K-NN
3. Support Vector Machine (SVM)
4. Kernel SVM
5. Naive Bayes
6. Decision Tree Classification
7. Random Forest Classification

Metrics

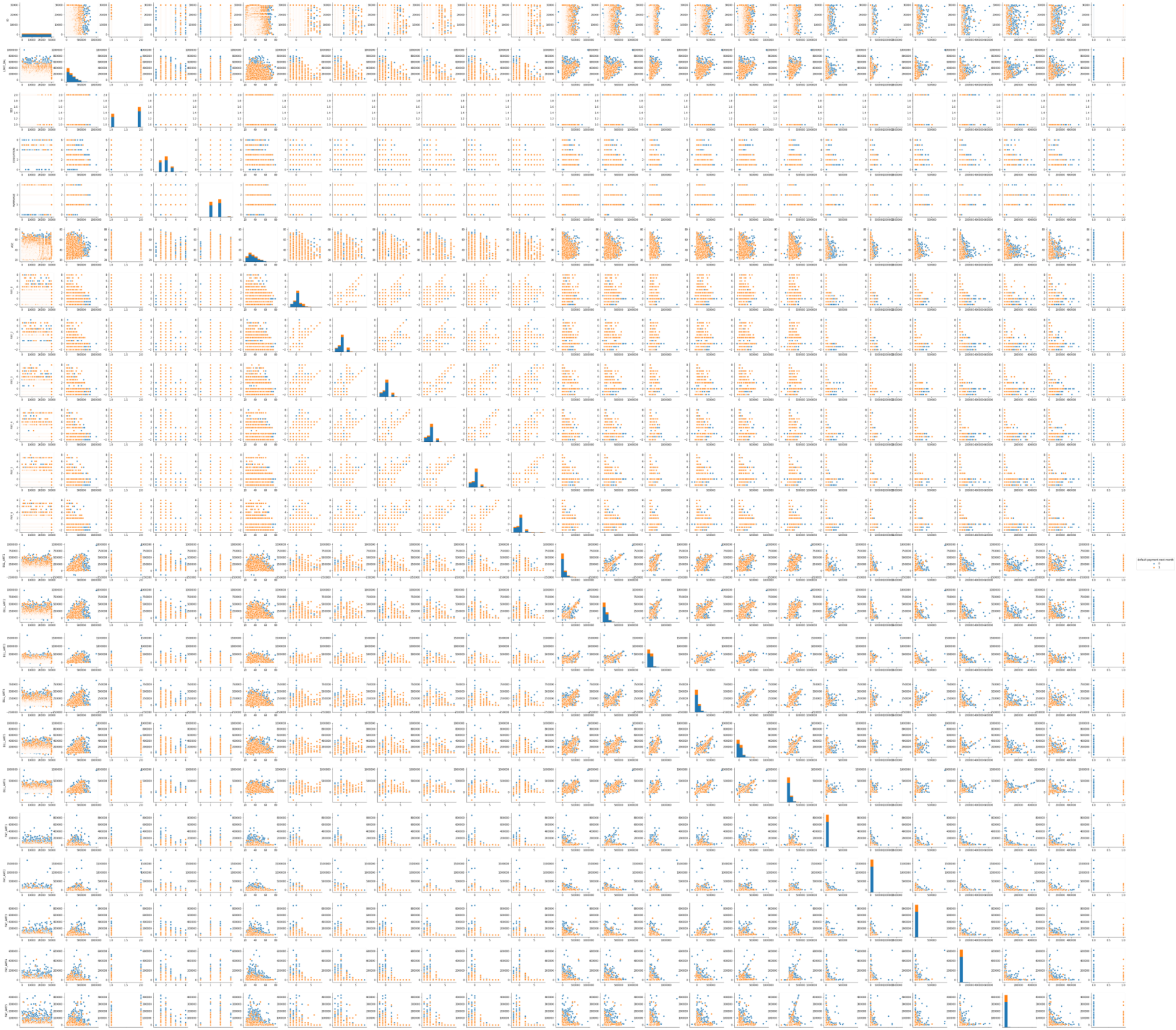
Classification performance can be measured using metrics such as Log-Loss, Accuracy, AUC(Area under Curve) etc.

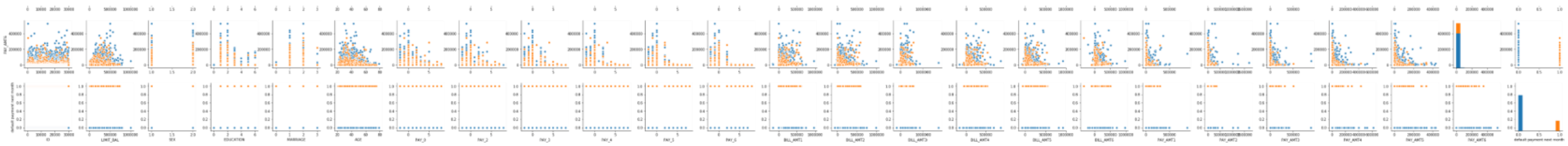
1. Confusion Matrix
2. Accuracy - is the number of correct predictions made by the model over all kinds predictions made. (True Positive & True Negative) (TP+TN)/(TP+TN+FP+FN)
3. Precision - Precision is a measure that tells us what proportion of client that we predicted to defaulter, actually are defaulter.
4. Recall or Sensitivity - Recall is a measure that tells us what proportion of client that actually are defaulter was predicted by the algorithm as defaulter.
5. F1 Score - Single score that kind of represents both Precision(P) and Recall(R)

Data Exploration

The Data provide to us as a CSV file has 25 attributes with 23 attributes features & 1 target. All attributes are numerical features with each attribute having 30K record. This dataset is clean without any missing value. There are no categorical variables since all categorical variable are already converted to numeric data (e.g Sex, Education, Martial Status etc)

In [4]:
```
sns.pairplot(credit_card, hue='default payment next month')
```





In [5]:
```
credit_card.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30000 entries, 0 to 29999
Data columns (total 25 columns):
ID                             30000 non-null int64
LIMIT_BAL                      30000 non-null int64
SEX                            30000 non-null int64
EDUCATION                      30000 non-null int64
MARRIAGE                       30000 non-null int64
AGE                            30000 non-null int64
PAY_0                          30000 non-null int64
PAY_2                          30000 non-null int64
PAY_3                          30000 non-null int64
PAY_4                          30000 non-null int64
PAY_5                          30000 non-null int64
PAY_6                          30000 non-null int64
BILL_AMT1                      30000 non-null int64
BILL_AMT2                      30000 non-null int64
BILL_AMT3                      30000 non-null int64
BILL_AMT4                      30000 non-null int64
BILL_AMT5                      30000 non-null int64
BILL_AMT6                      30000 non-null int64
PAY_AMT1                       30000 non-null int64
PAY_AMT2                       30000 non-null int64
PAY_AMT3                       30000 non-null int64
PAY_AMT4                       30000 non-null int64
PAY_AMT5                       30000 non-null int64
PAY_AMT6                       30000 non-null
int64 default payment next month    30000 non-
null int64 dtypes: int64(25) memory usage: 5.7 MB
```

In [6]:
```
credit_card.describe().T
```

Out[6]:

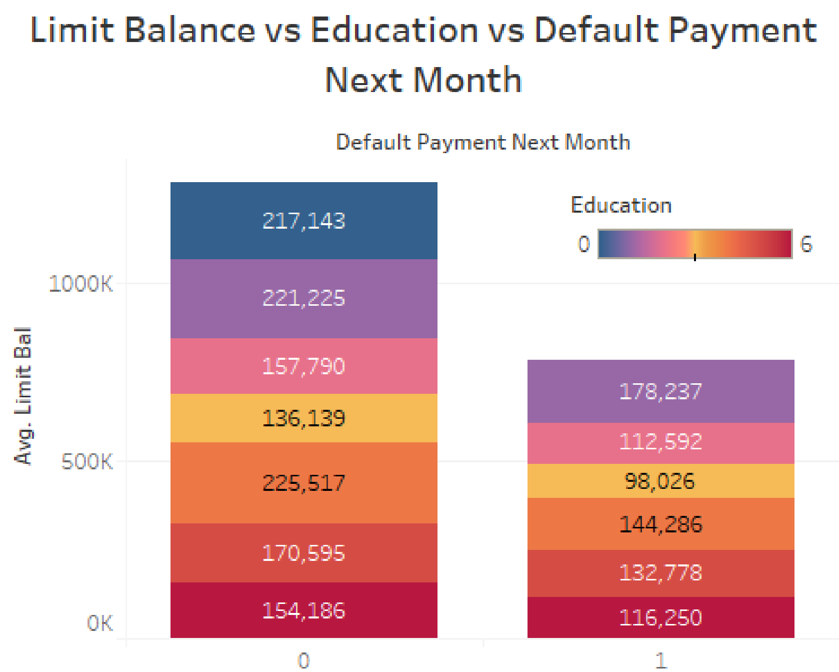
	count	mean	std	min	25%	50%	75%	max
ID	30000.0	15000.500000	8660.398374	1.0	7500.75	15000.5	22500.25	30000.0
LIMIT_BAL	30000.0	167484.322667	129747.661567	10000.0	50000.00	140000.0	240000.00	1000000.0
SEX	30000.0	1.603733	0.489129	1.0	1.00	2.0	2.00	2.0
EDUCATION	30000.0	1.853133	0.790349	0.0	1.00	2.0	2.00	6.0
MARRIAGE	30000.0	1.551867	0.521970	0.0	1.00	2.0	2.00	3.0
AGE	30000.0	35.485500	9.217904	21.0	28.00	34.0	41.00	79.0
PAY_0	30000.0	-0.016700	1.123802	-2.0	-1.00	0.0	0.00	8.0
PAY_2	30000.0	-0.133767	1.197186	-2.0	-1.00	0.0	0.00	8.0
PAY_3	30000.0	-0.166200	1.196868	-2.0	-1.00	0.0	0.00	8.0
PAY_4	30000.0	-0.220667	1.169139	-2.0	-1.00	0.0	0.00	8.0
PAY_5	30000.0	-0.266200	1.133187	-2.0	-1.00	0.0	0.00	8.0
PAY_6	30000.0	-0.291100	1.149988	-2.0	-1.00	0.0	0.00	8.0
BILL_AMT1	30000.0	51223.330900	73635.860576	-165580.0	3558.75	22381.5	67091.00	964511.0
BILL_AMT2	30000.0	49179.075167	71173.768783	-69777.0	2984.75	21200.0	64006.25	983931.0
BILL_AMT3	30000.0	47013.154800	69349.387427	-157264.0	2666.25	20088.5	60164.75	1664089.0
BILL_AMT4	30000.0	43262.948967	64332.856134	-170000.0	2326.75	19052.0	54506.00	891586.0
BILL_AMT5	30000.0	40311.400967	60797.155770	-81334.0	1763.00	18104.5	50190.50	927171.0
BILL_AMT6	30000.0	38871.760400	59554.107537	-339603.0	1256.00	17071.0	49198.25	961664.0

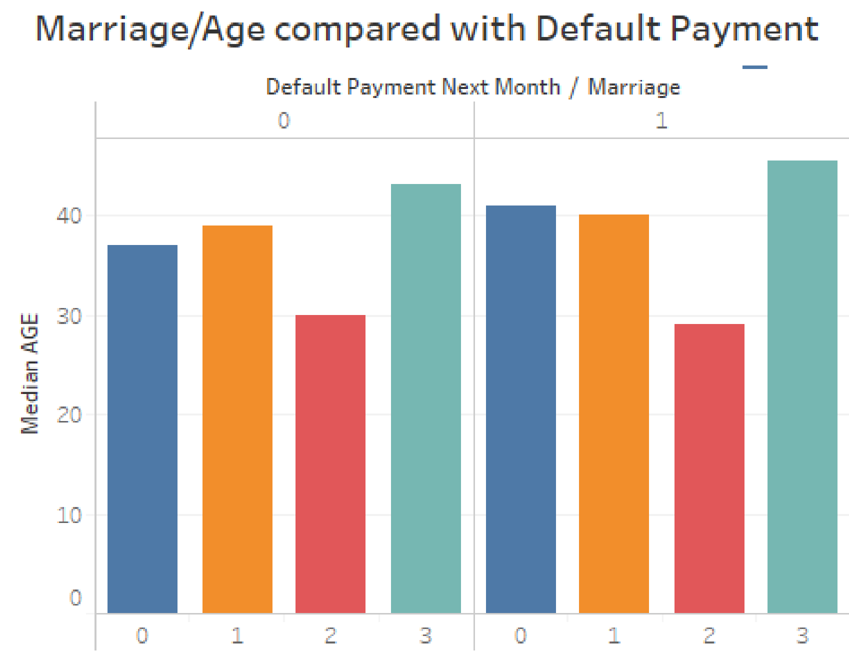
	count	mean	std	min	25%	50%	75%	max
PAY_AMT1	30000.0	5663.580500	16563.280354	0.0	1000.00	2100.0	5006.00	873552.0
PAY_AMT2	30000.0	5921.163500	23040.870402	0.0	833.00	2009.0	5000.00	1684259.0
PAY_AMT3	30000.0	5225.681500	17606.961470	0.0	390.00	1800.0	4505.00	896040.0
PAY_AMT4	30000.0	4826.076867	15666.159744	0.0	296.00	1500.0	4013.25	621000.0
PAY_AMT5	30000.0	4799.387633	15278.305679	0.0	252.50	1500.0	4031.50	426529.0
PAY_AMT6	30000.0	5215.502567	17777.465775	0.0	117.75	1500.0	4000.00	528666.0
default payment next month	30000.0	0.221200	0.415062	0.0	0.00	0.0	0.00	1.0

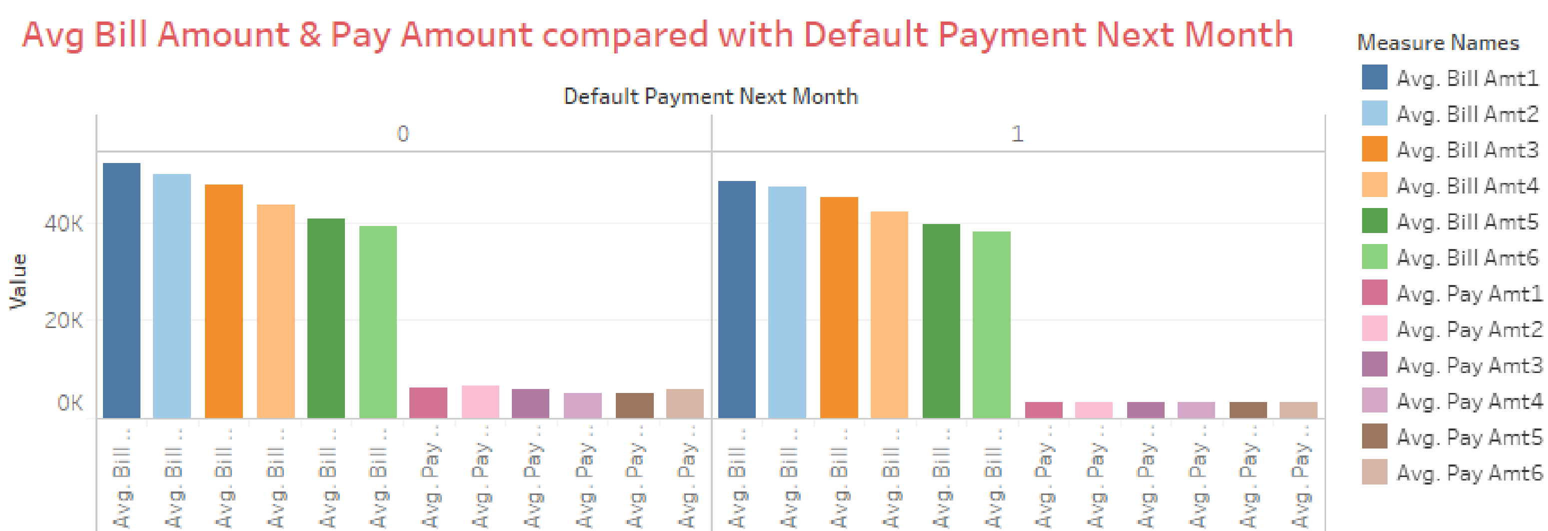
Exploratory Visualization

We have carried out several EDA to find out the data correlation & extract relevant characteristic or feature about the data. Below plot between LimitBalance & Sex shows that number of female are more & have higher limit balance. Plot below that visualizes Education with Default Payment next month, which clearly shows that higher the education less likelihood of default in payment. The KDE plot below shows the more concentration of client are of Age around 20-25 & people with Age around 30 to 35 have higher limit balance. As age increase beyond 40 balance reduces. The correlation plot shows high correlation of Bill amounts and also high correlation among Pay.

Used Tableau to create Visualization

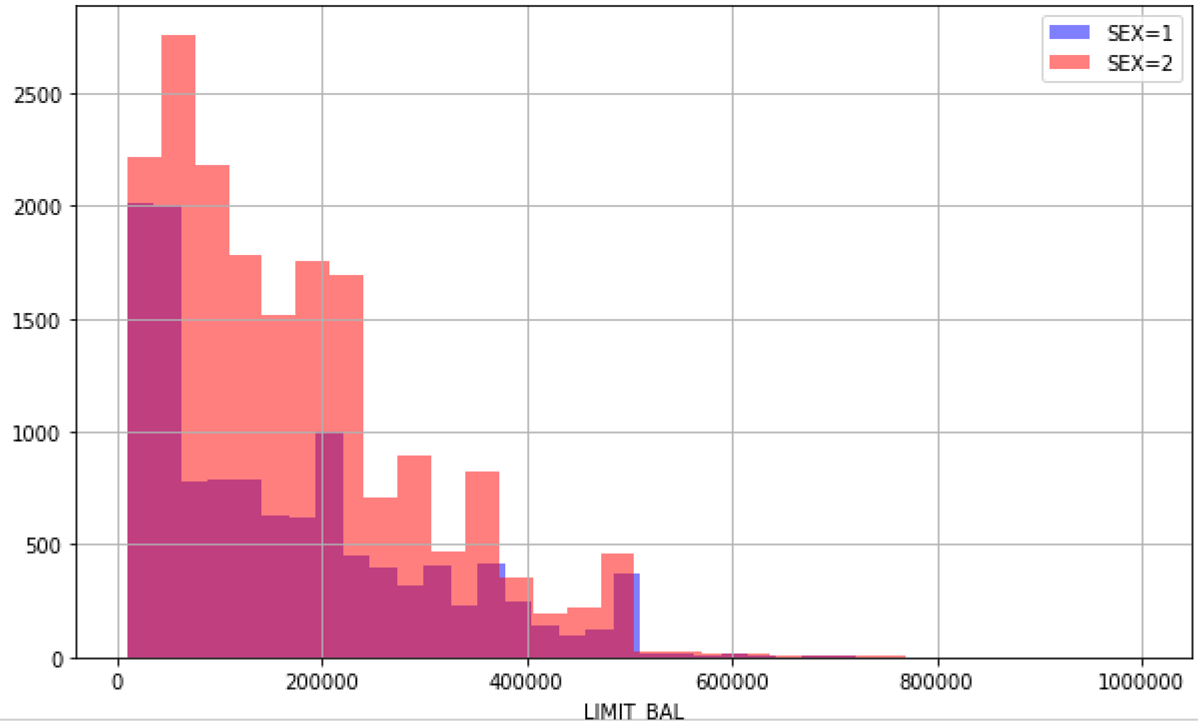

Limit Balance vs Education vs Default Payment Next Month
Default Payment Next Month
Education
0
6
Avg. Limit Bal
1000K
500K
0K
217,143
221,225
157,790
136,139
225,517
170,595
154,186
178,237
112,592
98,026
144,286
132,778
116,250
0
1


Marriage/Age compared with Default Payment
Default Payment Next Month / Marriage
0
1
Median AGE
40
30
20
10
0
0
1
2
3
0
1
2
3


Avg Bill Amount & Pay Amount compared with Default Payment Next Month
Default Payment Next Month
0
1
Value
40K
20K
0K
Avg. Bill ..
Avg. Pay ..
Measure Names
Avg. Bill Amt1
Avg. Bill Amt2
Avg. Bill Amt3
Avg. Bill Amt4
Avg. Bill Amt5
Avg. Bill Amt6
Avg. Pay Amt1
Avg. Pay Amt2
Avg. Pay Amt3
Avg. Pay Amt4
Avg. Pay Amt5
Avg. Pay Amt6

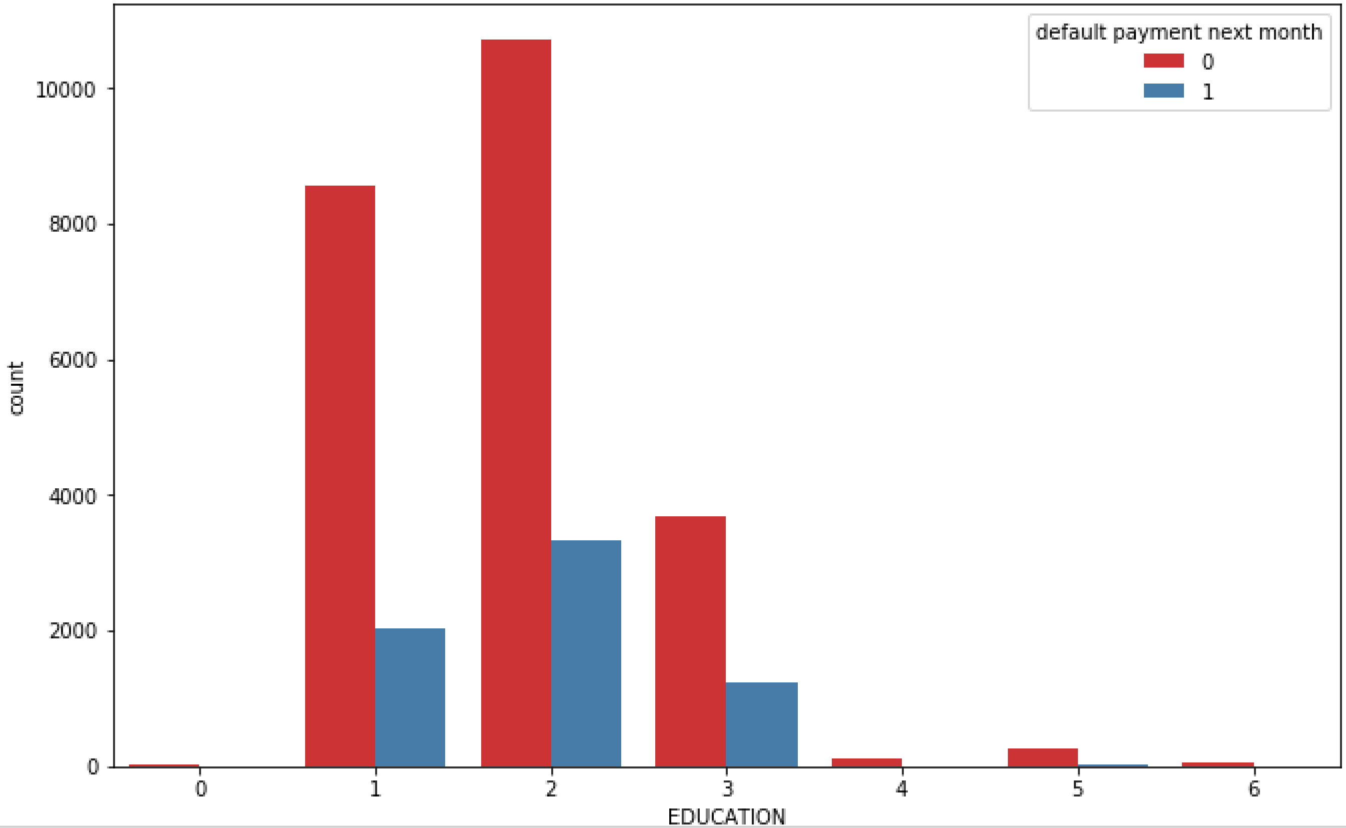
In [7]:
```
plt.figure(figsize=(10,6))
credit_card[credit_card['SEX']==1]['LIMIT_BAL'].hist(alpha=0.5,color='blue',
bins=30,label='SEX=1')
credit_card[credit_card['SEX']==2]['LIMIT_BAL'].hist(alpha=0.5,color='red',
                                              bins=30,label='SEX=2')
plt.legend() plt.xlabel('LIMIT_BAL')
```

Out[7]: Text(0.5,0,'LIMIT_BAL')



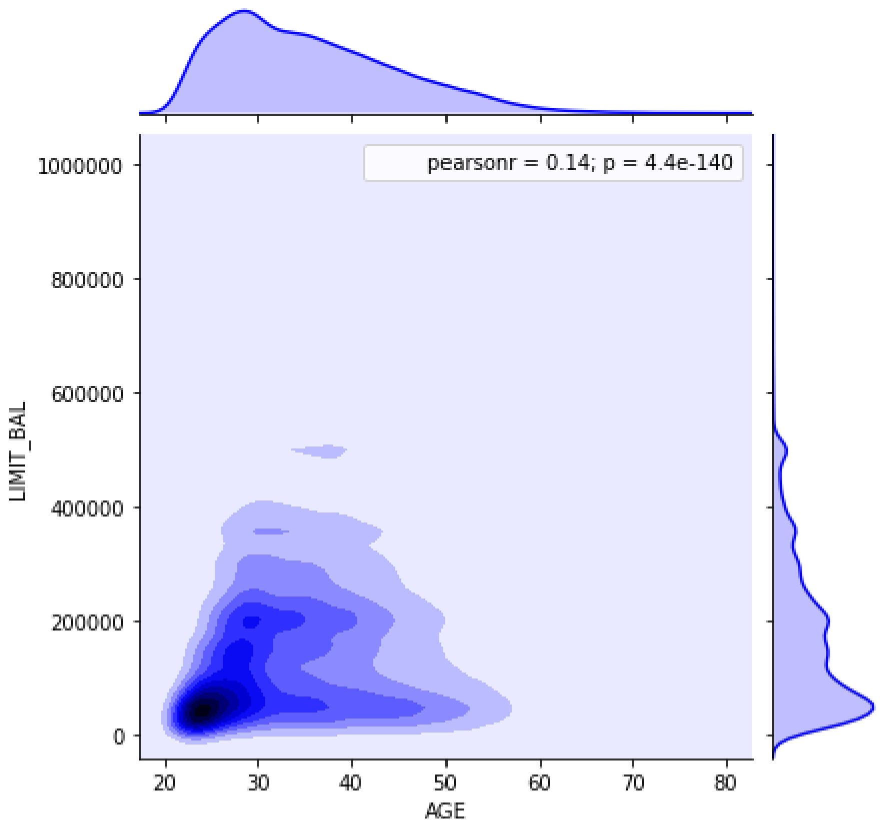
In [8]:
```
plt.figure(figsize=(11,7)) sns.countplot(x='EDUCATION',hue='default payment next
month',data=credit_card,palette='Set1')
```

Out[8]: <matplotlib.axes._subplots.AxesSubplot at 0x20c04e80>



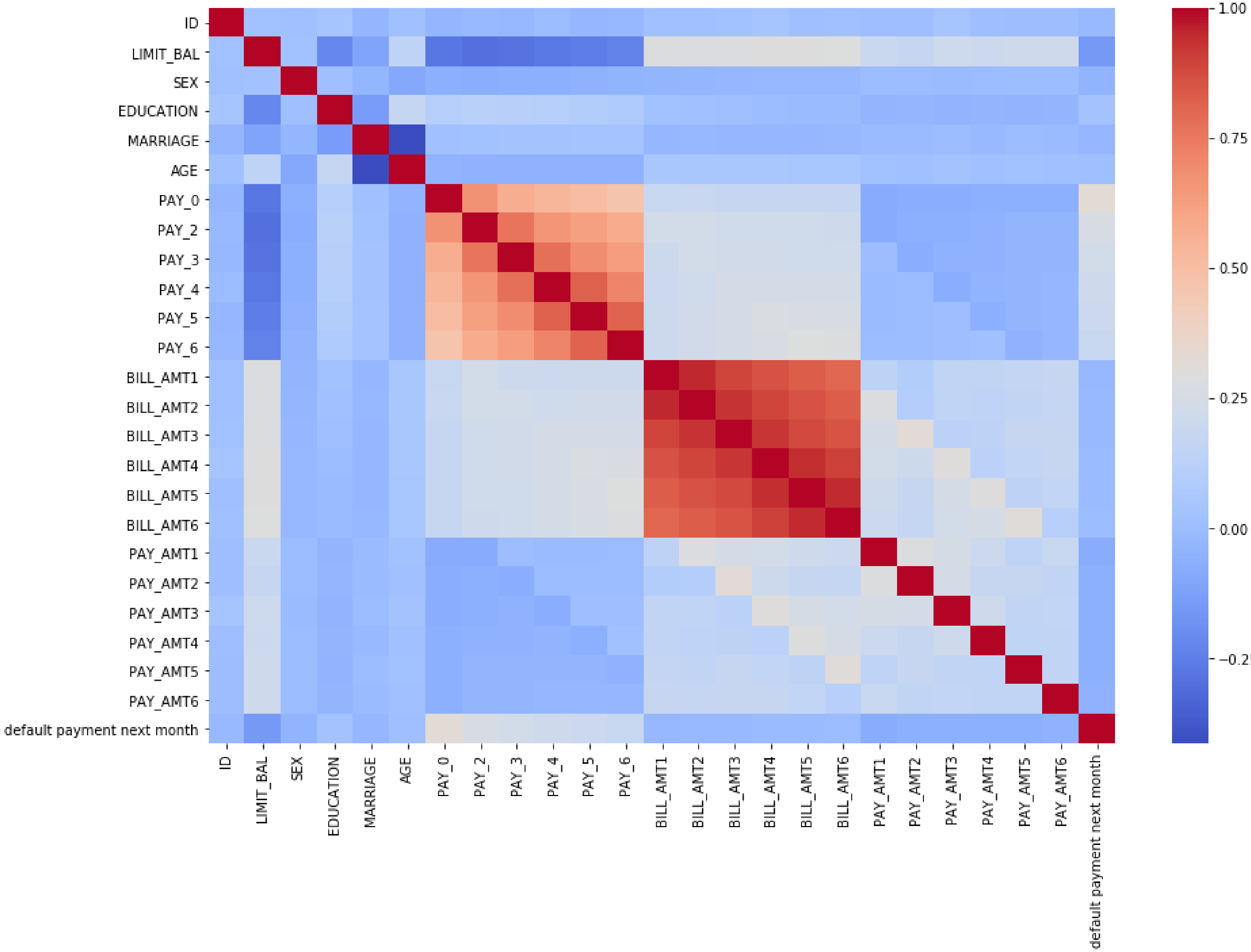
In [9]:
```
sns.jointplot(y='LIMIT_BAL',x='AGE',kind= 'kde',data=credit_card,color='blue')
```

Out[9]: <seaborn.axisgrid.JointGrid at 0x23277b38>



In [10]:
```
f, ax = plt.subplots(figsize=(15,10))
sns.heatmap(credit_card.corr(),cmap = 'coolwarm')
```

Out[10]: <matplotlib.axes._subplots.AxesSubplot at 0x47b56da0>



Solution Statement

Solution for this Classification problem can be Logistic Regression, K-Nearest Neighbors K-NN, Decision Tree Classification, Random Forest Classification, Gradient Boost etc.

For our case we will use classic Decision Tree Classification & then use ensemble method using Random Forest. Entropy and Information Gain are the Mathematical Methods of choosing the best split.

For Random Forest, we will use many trees with a random sample of features chosen as the split.

- A new random sample of features is chosen for every single tree at every single split.
- For classification, m is typically chosen to be the square root of p.

Algorithms and Techniques

In the tree we built, every leaf consisted entirely of True inputs or entirely of False inputs. This means that the tree predicts perfectly on the training data set

Bagging, random forests, and boosting use trees as building blocks to construct more powerful prediction models.

Training a Decision Tree Model

Let's start by training a single decision tree first!

Import DecisionTreeClassifier

In [11]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
```

In [12]:
```
X = credit_card.drop(['ID','default payment next month'],axis=1) y
= credit_card['default payment next month']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30, random_state=805)
```

In [13]:
```
dtree = DecisionTreeClassifier()
```

In [14]:
```
dtree.fit(X_train,y_train)
```

Out[14]:
```
DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=None,
 max_features=None, 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, presort=False, random_state=None,
 splitter='best')
```

Predictions and Evaluation of Decision Tree

Create predictions from the test set and create a classification report and a confusion matrix.

In [15]:
```
predictions = dtree.predict(X_test)
```

In [16]:
```
from sklearn.metrics import classification_report,confusion_matrix
```

In [17]:
```
print(classification_report(y_test,predictions))
```

```
             precision    recall  f1-score   support
0       0.84      0.81      0.82      6994
1       0.40      0.44      0.42      2006

avg / total       0.74      0.73      0.73      9000
```

In [18]:
```
print(confusion_matrix(y_test,predictions))
```

```
[[5682 1312]
 [1116  890]]
```

Benchmark Model

Here we are using Logistic Regression as our Benchmark Model. The Sigmoid Function takes in any value and outputs it to be between 0 and 1. We can use a confusion matrix to evaluate our model

In [27]:
```
from sklearn.linear_model import LogisticRegression
```

In [28]:
```
logmodel = LogisticRegression()
logmodel.fit(X_train,y_train)
```

Out[28]:
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
 intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
 penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
 verbose=0, warm_start=False)
```

In [29]:
```
predictions = logmodel.predict(X_test)
```

In [30]:
```
print(classification_report(y_test,predictions))
```

```
             precision    recall  f1-score   support
```

```
             0       0.78      1.00      0.87      6994
          1       0.00      0.00      0.00      2006

avg / total       0.60      0.78      0.68      9000

C:\Users\asrath\AppData\Local\Continuum\anaconda3\lib\site-packages\sklearn\metrics\classification.py:1135: U
ndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted
samples.
  'precision', 'predicted', average, warn_for)
```

Project Design

We can use several models to find the best fit for the project, we are using Random Forest from Sklearn Ensemble to find out the prediction model if the client will default next month or not. We have used all features & since it's a Random forest model we don't need any scaling of data.

Training the Random Forest model

Now it's time to train our model!

Create an instance of the RandomForestClassifier class and fit it to our training data from the previous step.

In [19]:
```
from sklearn.ensemble import RandomForestClassifier
```

In [20]:
```
rfc = RandomForestClassifier(n_estimators=600)
```

In [21]:
```
rfc.fit(X_train,y_train)
```

Out[21]:
```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
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=600, n_jobs=1,
oob_score=False, random_state=None, verbose=0,
warm_start=False)
```

Predictions and Evaluation of Random Forest

Let's predict off the y_test values and evaluate our model.

Predict default payment next month for the X_test data.

In [22]:
```
predictions = rfc.predict(X_test)
```

In [23]:
```
print(classification_report(y_test,predictions))
```

```
             precision    recall  f1-score   support

          0       0.84      0.95      0.89      6994
          1       0.66      0.38      0.48      2006

avg / total       0.80      0.82      0.80      9000
```

In [24]:
```
print(confusion_matrix(y_test,predictions))
```

```
[[6612  382]
 [1253  753]]
```

Conclusion

Model worked well with Random Forest with a F1 score of .8 , precision of .8 & recall of .82 We can try Gradient boost & other boosting model to check if that can perform better with our model.