W3_sundrani_qq301451(Final_v_2)

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1 Classification - Assignment Details

Q1. Build a classification model for the default of credit card clients dataset. More info here: https://archive.ics.uci.edu/ml/datasets/default+of+credit+card+clients

Explore the data Make sure you build a full data pipeline Do you require any data preprocessing? Are all the features useful? (Use only raw features) set the random seed to 123 (For splitting or any other random algorithm) Split data into training (80%) and testing (20%) Follow similar procedure as the one for week 2 (End-to-end Machine Learning Project). Remember apendix B Study the ROC Curve, decide threshold

Use 2 classifiers. Random Forest tune only: n_estimators: {3, 4, 6, 7, 10, 20, 50, 100}

KNN Classfier tune only: n_neighbors: {3, 4, 5, 7, 10, 20, 50}

Which one performs better in the cross validation?

http://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html http://scikit-learn.org/stable/modules/generated/sklearn.neighbors.KNeighborsClassifier.html

Cross-validation with 4-folds. Other paramenters -> Use default

Notes: Make your code modular, the second part of the assignmet you will have to repeat. Include documentation for your code Cross-validation with 5-folds

2 Python Import Details

```
In [0]: import pandas as pd
        import numpy as np

        from sklearn.compose import ColumnTransformer
        from sklearn.pipeline import Pipeline
        from sklearn.impute import SimpleImputer
        from sklearn.preprocessing import StandardScaler, OneHotEncoder
        from sklearn.linear_model import LogisticRegression
        from sklearn.model_selection import train_test_split, GridSearchCV
        from sklearn.ensemble import RandomForestClassifier
        from sklearn.neighbors import KNeighborsClassifier
        from sklearn.model_selection import cross_val_score,cross_val_predict
        from sklearn.metrics import precision_score, recall_score,f1_score,roc_curve,roc_auc_s
```

```
import seaborn as sns
# to make this notebook's output stable across runs
np.random.seed(123)

# To plot pretty figures
%matplotlib inline
import matplotlib
import matplotlib.pyplot as plt
plt.rcParams['axes.labelsize'] = 14
plt.rcParams['xtick.labelsize'] = 12
plt.rcParams['ytick.labelsize'] = 12
```

3 Data Extraction

```
In [0]: !wget https://archive.ics.uci.edu/ml/datasets/default%20of%20credit%20card%20clients.xl

        df=pd.read_excel('default of credit card clients.xls',sheet_name=0,skiprows=1,header=0)

        df_original=df
        df_original.shape
```

```
Out[0]: (30000, 25)
```

4 Data Review

```
In [0]: df.head()
```

```
In [0]: df.info()
```

There are 30K recrods and 25 features. There is no data missing in the file and all of them are int64

```
In [0]: df.describe()
```

```
In [0]: default_ratio=(np.sum(df['default payment next month'])/len(df['default payment next mo
        print('Default Ratio: {}'.format(default_ratio))
```

```
Default Ratio: 22.12
```

Limit Balance: standard deviation is very high which mean the data is not normally distributed. 75% of the clients credit limit is below $250K

Education: Max level is 6, however, in the dataset it was defined upto 4 so need to merge other 2 into 4(others) category.

Marital Status: There are 56 records with '0' status which needs to be merged with status others marked as 3

Age: 75% of the data age limit is 41 or lower.Worth to check default ratio among retire assuming 65 years

Payment status: There is a negative payment status defined in the data set, looks like client credit card balance is negative to represent this. So need to uniform these anamolies as we need to distinguish between default vs non default. Put negative category to zero. **Statement Balance:** 75% of the customers average statement balance is between $49K to $67K. However there are certain accounts have negative balance which is needs to be investigated.

Payments: 75% of clients paid ~$5K which is far different than average statement balance of $67K. Clients majority of the clients paid minimum balance to avoid default

Default Ratio: Overall default ratio is 22.12% over this dataset.

5 Data Clean up

1. **Merge undefined Education 5&6 classification into 4**

In [0]:
```
df['EDUCATION'].value_counts()
```

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

In [0]:
```
Edu_data=(df.EDUCATION==5)|(df.EDUCATION==6)|(df.EDUCATION==0)
df.loc[Edu_data,'EDUCATION']=4
df['EDUCATION'].value_counts()
```

Out[0]:
```
2    14030
1    10585
3     4917
4      468
Name: EDUCATION, dtype: int64
```

2. **Merge undefined marriage classification of '0' into classification 3**

In [0]:
```
df['MARRIAGE'].value_counts()
```

Out[0]:
```
2    15964
1    13659
3      323
0       54
Name: MARRIAGE, dtype: int64
```

In [0]:
```
Mar_data=(df.MARRIAGE==0)
df.loc[Mar_data,'MARRIAGE']=3
df['MARRIAGE'].value_counts()
```

```
Out[0]: 2    15964
        1    13659
        3      377
        Name: MARRIAGE, dtype: int64
```

3. **Create a group of Ages to evaluate results**

```
In [0]:  df.AGE.value_counts()
```

4. **Merge '-1&-2' payment period category into '0' classification to alingn all these payments are made on time**

```
In [0]: #payment categories need to be fixed

        Pay_data0=(df.PAY_0==-1)|(df.PAY_0==-2)
        df.loc[Pay_data0,'PAY_0']=0
        Pay_data2=(df.PAY_2==-1)|(df.PAY_2==-2)
        df.loc[Pay_data2,'PAY_2']=0
        Pay_data3=(df.PAY_3==-1)|(df.PAY_3==-2)
        df.loc[Pay_data3,'PAY_3']=0
        Pay_data4=(df.PAY_4==-1)|(df.PAY_4==-2)
        df.loc[Pay_data4,'PAY_4']=0
        Pay_data5=(df.PAY_5==-1)|(df.PAY_5==-2)
        df.loc[Pay_data5,'PAY_5']=0
        Pay_data6=(df.PAY_6==-1)|(df.PAY_6==-2)
        df.loc[Pay_data6,'PAY_6']=0
```

```
In [0]: df['PAY_6'].value_counts()
```

```
Out[0]: 0    26921
        2     2766
        3      184
        4       49
        7       46
        6       19
        5       13
        8        2
        Name: PAY_6, dtype: int64
```

6 Data Analysis - Individual Variables : Understand relation of individual fields vs default category

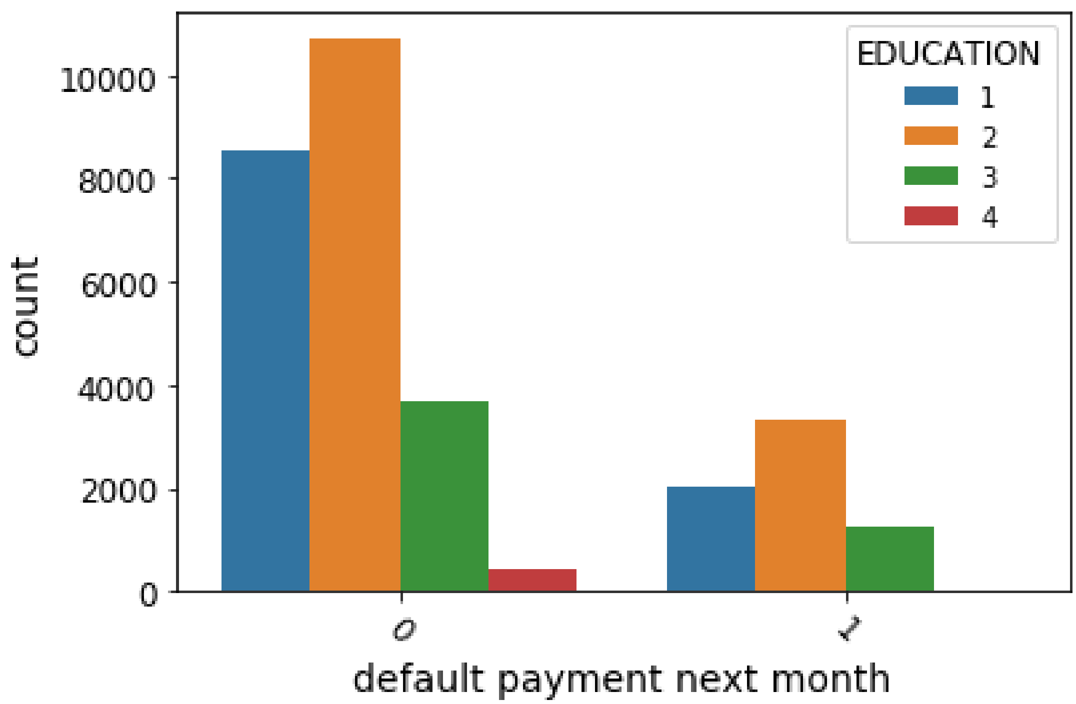
1. Created pivot table to evaluate 'default category' vs ['Education', 'Sex', 'Marriage' & 'Age']

```
In [0]: table_education=pd.pivot_table(df,index=['default payment next month'],values='SEX',co
                                       aggfunc='count',fill_value=0,margins=True)
        print(table_education)
        print('Education: 1 = graduate school; 2 = university; 3 = high school; 4 = others')
```

```
EDUCATION                        1      2     3    4    All
default payment next month
0                             8549  10700  3680  435  23364
1                             2036   3330  1237   33   6636
All                          10585  14030  4917  468  30000
Education: 1 = graduate school; 2 = university; 3 = high school; 4 = others
```

```
In [0]: df1=df
        labels=['Current','Default']
        sns.countplot(x=('default payment next month'),data=df1,hue='EDUCATION')
        plt.xticks(rotation=-45)
```

```
Out[0]: (array([0, 1]), <a list of 2 Text xticklabel objects>)
```



Default ratio is higher amongst university graduate vs others.

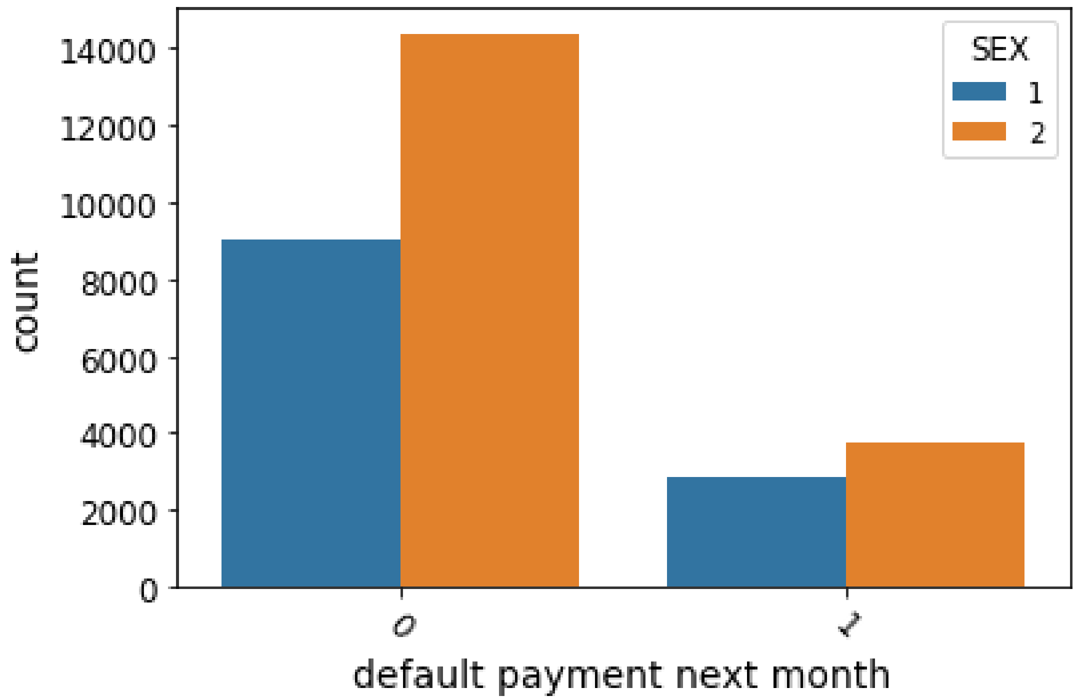
```
In [0]: table_sex=pd.pivot_table(df,index=['default payment next month'],values='EDUCATION',co
                                  aggfunc='count',fill_value=0,margins=True)
        print(table_sex)
        print('1=Male,2=Female')
```

```
SEX                              1      2    All
default payment next month
0                             9015  14349  23364
```

```
1                               2873   3763   6636
All                            11888  18112  30000
1=Male,2=Female
```

```
In [0]: sns.countplot(x=('default payment next month'),data=df1,hue='SEX')
        plt.xticks(rotation=-45)
```

```
Out[0]: (array([0, 1]), <a list of 2 Text xticklabel objects>)
```



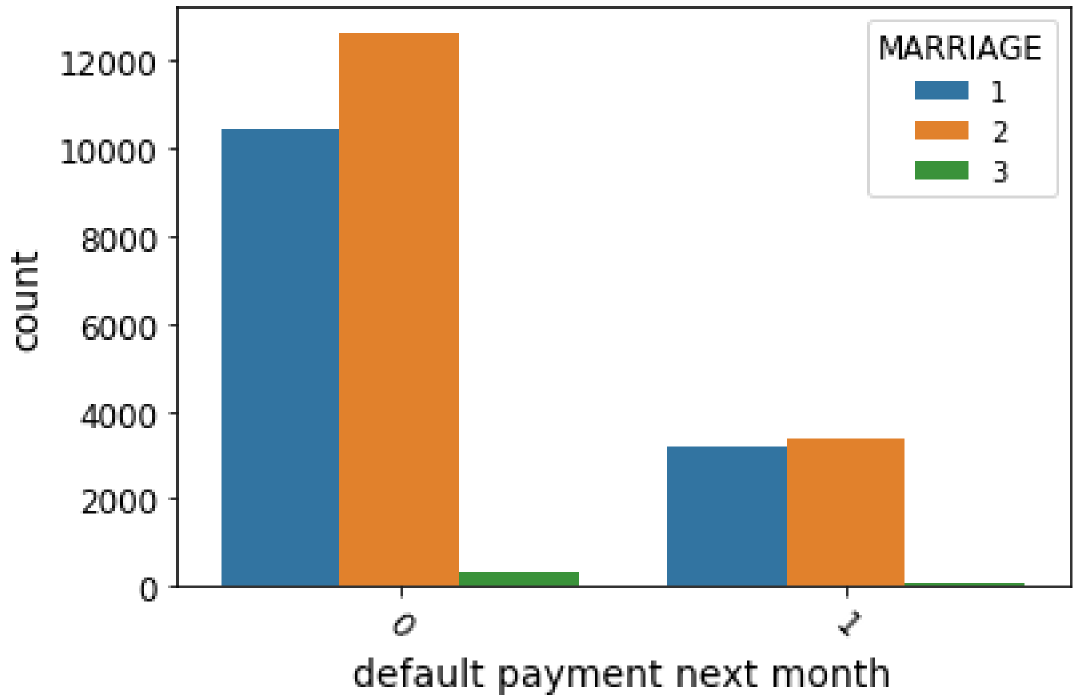
Default ratio amongst female is higher than male.

```
In [0]: table_marriage=pd.pivot_table(df,index=['default payment next month'],values='SEX',colu
                                      aggfunc='count',fill_value=0,margins=True)
        print(table_marriage)
        print('Marital status (1 = married; 2 = single; 3&0 = others)')
```

```
MARRIAGE                           1      2    3    All
default payment next month
0                              10453  12623  288  23364
1                               3206   3341   89   6636
All                            13659  15964  377  30000
Marital status (1 = married; 2 = single; 3&0 = others)
```

```
In [0]: sns.countplot(x=('default payment next month'),data=df1,hue='MARRIAGE')
        plt.xticks(rotation=-45)
```

Out[0]: (array([0, 1]), <a list of 2 Text xticklabel objects>)



Default ratio is almost equal in married vs single status.

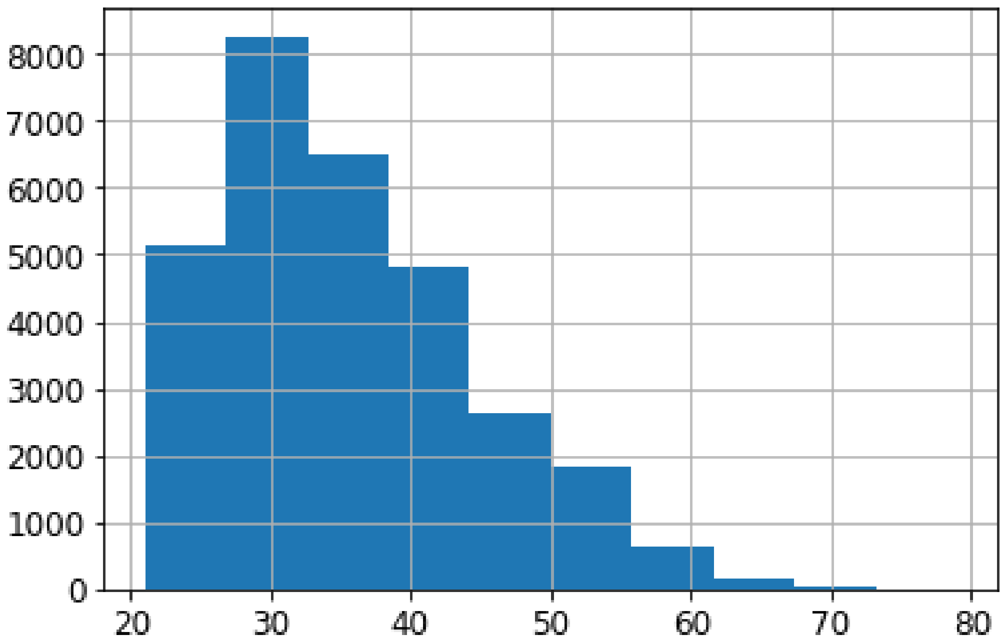
In [0]:
```
table_age1=pd.pivot_table(df,index=['default payment next month'],values='SEX',columns=
                          aggfunc='count',fill_value=0,margins=True)
table_age1
```

Out[0]:
```
AGE                         21   22   23    24    25  ...  73  74  75  79    All
default payment next month                            ...
0                           53  391  684   827   884  ...   1   1   2   1  23364
1                           14  169  247   300   302  ...   3   0   1   0   6636
All                         67  560  931  1127  1186  ...   4   1   3   1  30000

[3 rows x 57 columns]
```

In [0]:
```
df.AGE.hist()
```

Out[0]: <matplotlib.axes._subplots.AxesSubplot at 0x7fca4afad630>

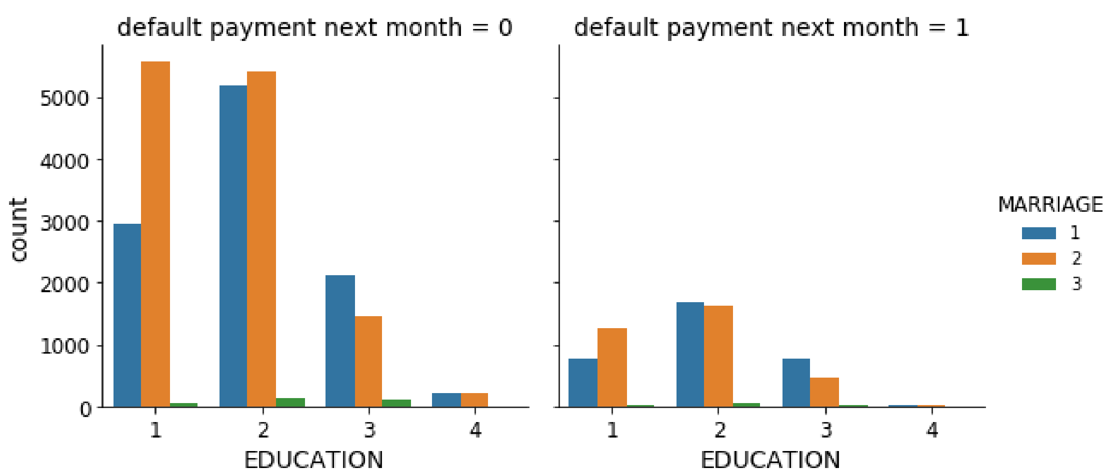


Majority of age groups between 20 to 45 years. Ratio of retires are very minimal

7 DATA Analysis - Combination of variables vs default to identify outliers

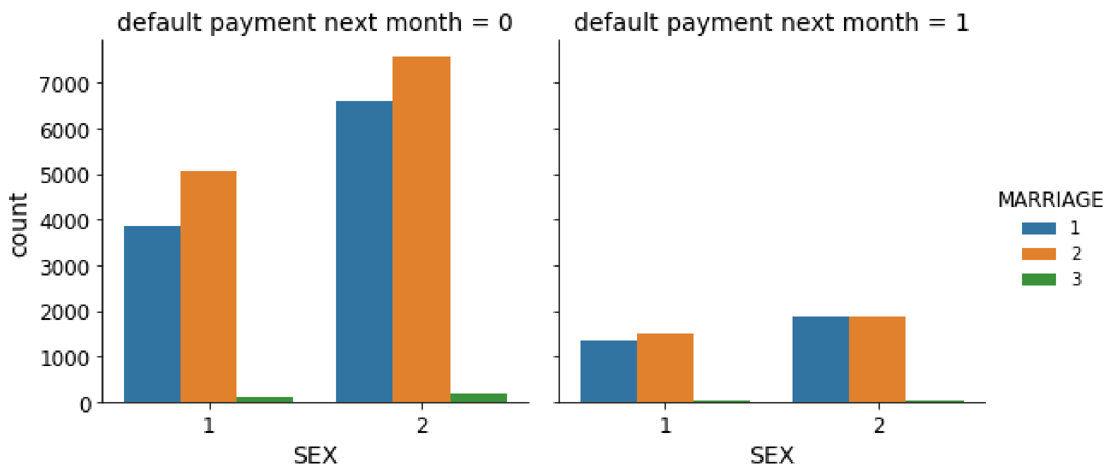
1. Review relationship between Education & Marriage Vs Default

```
In [0]: g = sns.catplot(x="EDUCATION", hue="MARRIAGE", col='default payment next month',
        ...                   data=df1, kind="count",
        ...                   height=4, aspect=1);
```



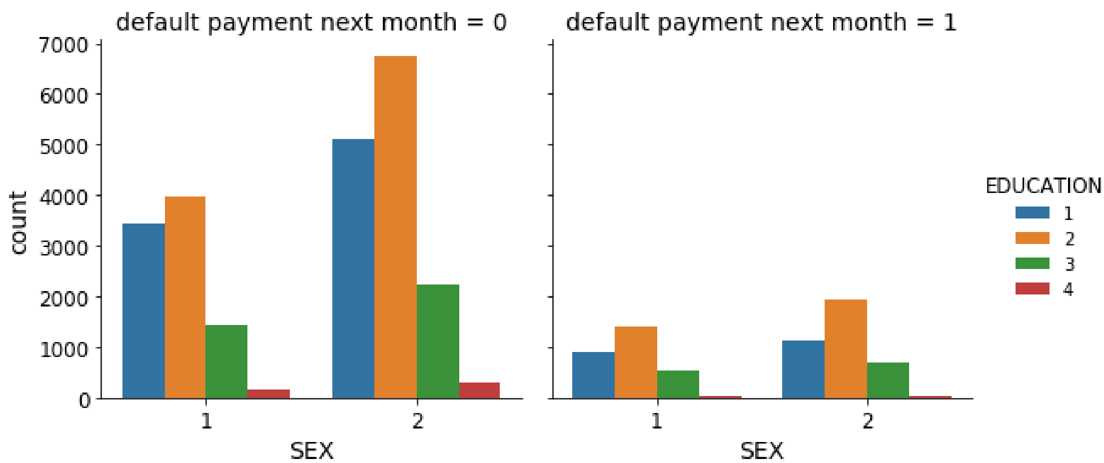
Overall university degree candidates are in high default category.

```
In [0]: g = sns.catplot(x="SEX", hue="MARRIAGE", col='default payment next month',
    ...                   data=df1, kind="count",
    ...                   height=4, aspect=1);
```



No outliers between sex & marriage. This is just for FYI

```
In [0]: g = sns.catplot(x="SEX", hue="EDUCATION", col='default payment next month',
    ...                   data=df1, kind="count",
    ...                   height=4, aspect=1);
```



Overall Female with university degree has overall high default ration

In [0]:
```python
from pandas.plotting import scatter_matrix
df1=df[['default payment next month','SEX','EDUCATION','MARRIAGE','AGE']]
scatter_matrix(df1, alpha=0.2, figsize=(12, 12))
```

2. Analysis of payment period of customers

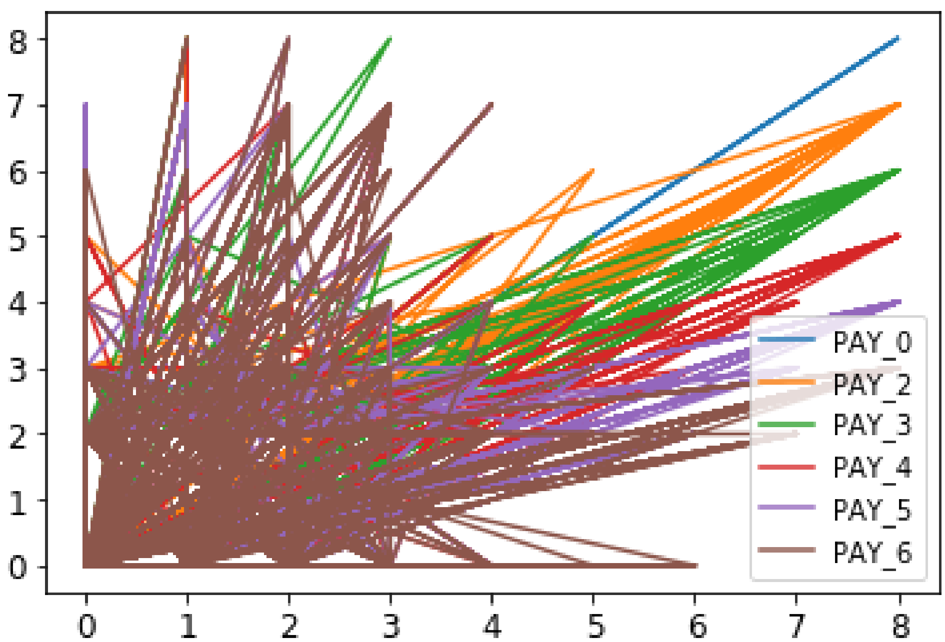
In [0]:
```python
from pandas.plotting import scatter_matrix
df1=df[['default payment next month','PAY_0','PAY_2','PAY_3','PAY_4','PAY_5','PAY_6']]
scatter_matrix(df1, alpha=0.2, figsize=(12, 12))
```

In [0]:
```python
plt.subplots()

plt.plot(df['PAY_0'],df['PAY_0'])
plt.plot(df['PAY_0'],df['PAY_2'])
plt.plot(df['PAY_0'],df['PAY_3'])
plt.plot(df['PAY_0'],df['PAY_4'])
plt.plot(df['PAY_0'],df['PAY_5'])
plt.plot(df['PAY_0'],df['PAY_6'])

plt.legend(loc='lower right')
```

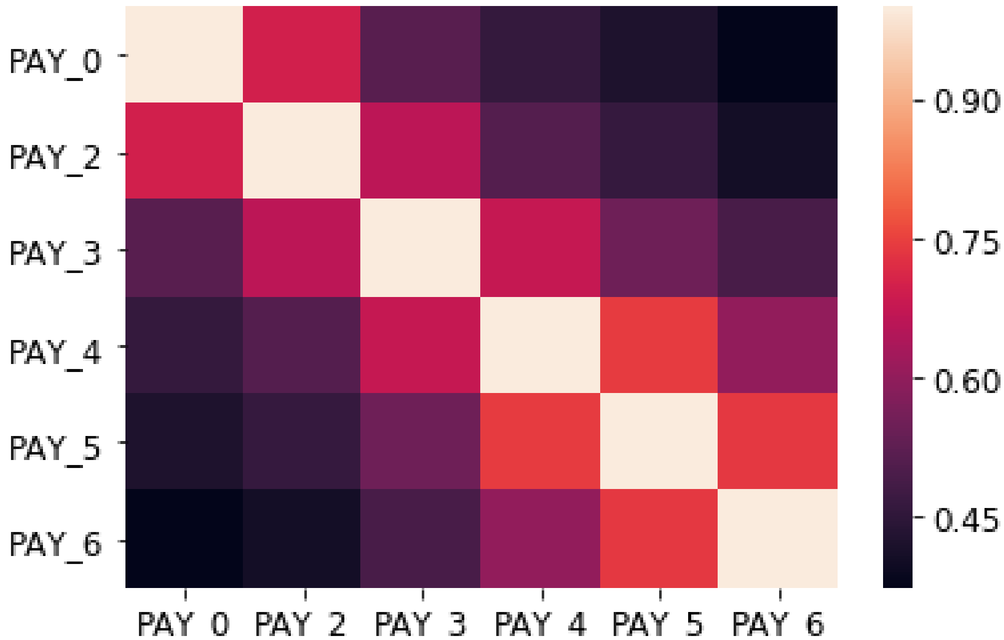
Out[0]:
```
<matplotlib.legend.Legend at 0x7fca4b1e5668>
```



In [0]:
```python
# Calculate correlations
corr = df1[['PAY_0','PAY_2','PAY_3','PAY_4','PAY_5','PAY_6']].corr()

# Heatmap
sns.heatmap(corr)
```

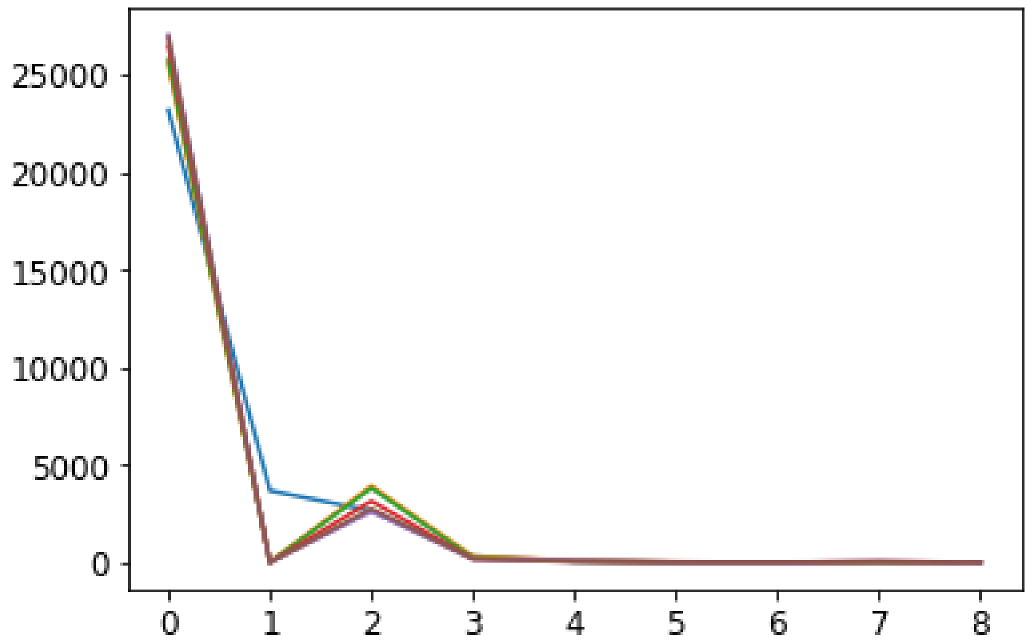
Out[0]: <matplotlib.axes._subplots.AxesSubplot at 0x7fca4b176e80>



In [0]:
```
plt.subplots()
x=(0,1,2,3,4,5,6,7,8)
y_month1=(23182,3688,2667,322,76,26,11,9,19) #driven from value counts command i.e. df
y_month2=(25562,28,3927,326,99,25,12,20,1)# manual input
y_month3=(25787,4,3819,240,76,21,23,27,3)
y_month4=(26490,2,3159,180,69,35,5,58,2)
y_month5=(27032,0,2626,178,84,17,4,58,1)
y_month6=(26921,0,2766,184,49,13,19,46,2)

plt.plot(x,y_month1)
plt.plot(x,y_month2)
plt.plot(x,y_month3)
plt.plot(x,y_month4)
plt.plot(x,y_month5)
plt.plot(x,y_month6)
```

Out[0]: [<matplotlib.lines.Line2D at 0x7fca4b054748>]



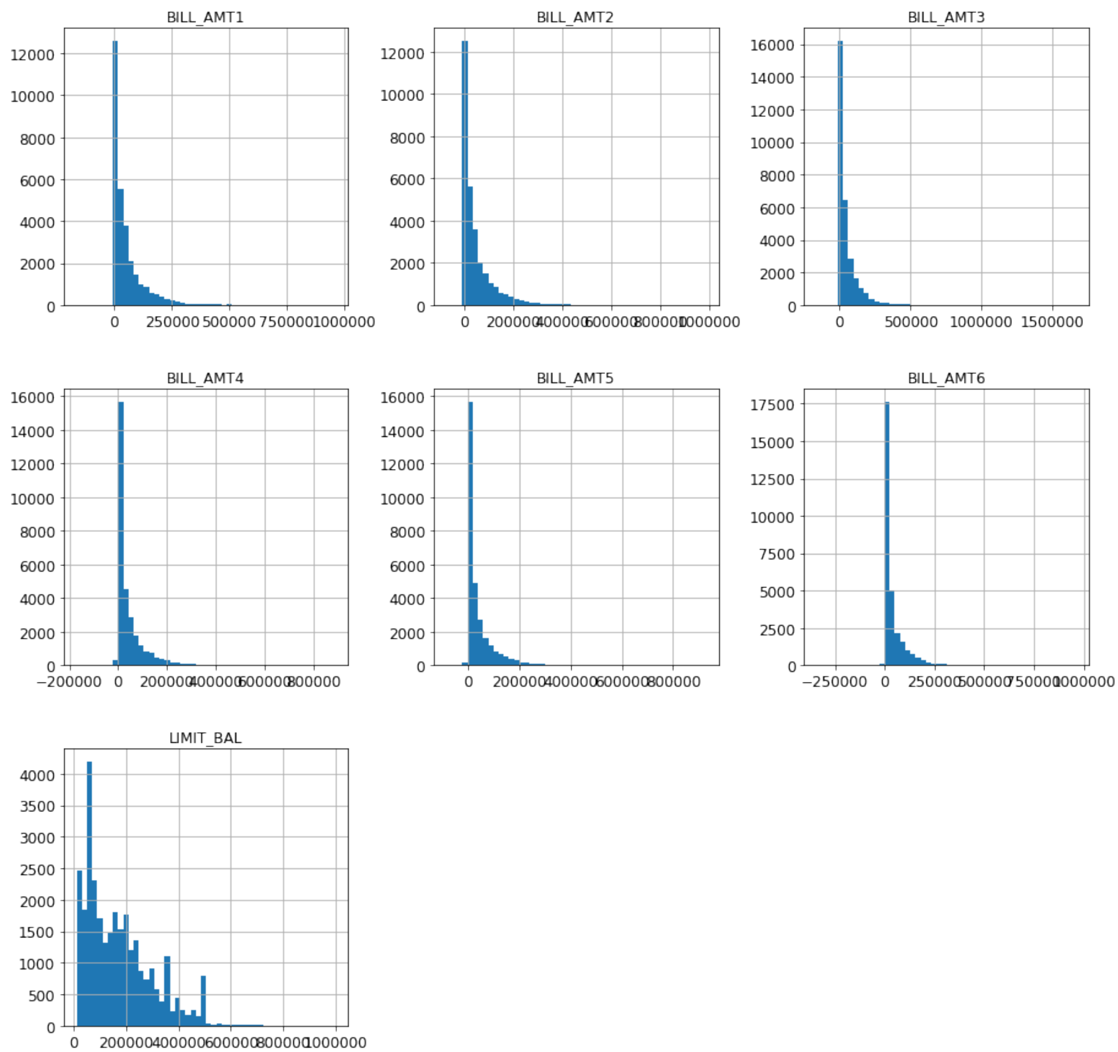
The monthly count of payment timeline shows that majority of the default category is in month 2 which is close to 5K records. Remaining counts of default are not in high numbers

3. Analysis of credit balance versus limit

In [0]:
```
from pandas.plotting import scatter_matrix
df1=df[['LIMIT_BAL','BILL_AMT1','BILL_AMT2','BILL_AMT3','BILL_AMT4','BILL_AMT5','BILL_
scatter_matrix(df1, alpha=0.2, figsize=(12, 12))
```

In [0]:
```
df[['LIMIT_BAL','BILL_AMT1', 'BILL_AMT2','BILL_AMT3','BILL_AMT4','BILL_AMT5','BILL_AMT
```

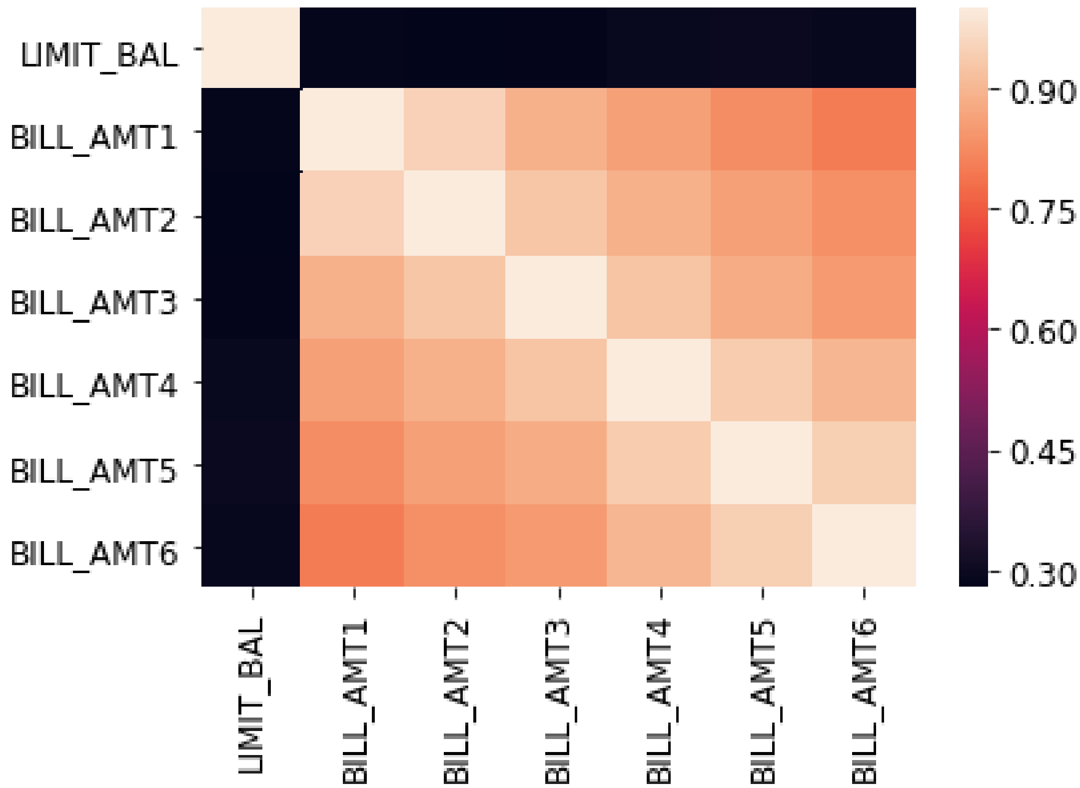
Out[0]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7fca4b097978>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fca4b046048>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fca4afeb5c0>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7fca49502b38>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fca495330f0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fca494db668>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7fca49483be0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fca494b11d0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fca494b1208>]],
      dtype=object)
```



In [0]:
```
# Calculate correlations
corr = df1[['LIMIT_BAL','BILL_AMT1','BILL_AMT2','BILL_AMT3','BILL_AMT4','BILL_AMT5','BI

# Heatmap
sns.heatmap(corr)
```

Out[0]: <matplotlib.axes._subplots.AxesSubplot at 0x7fca488d1a90>

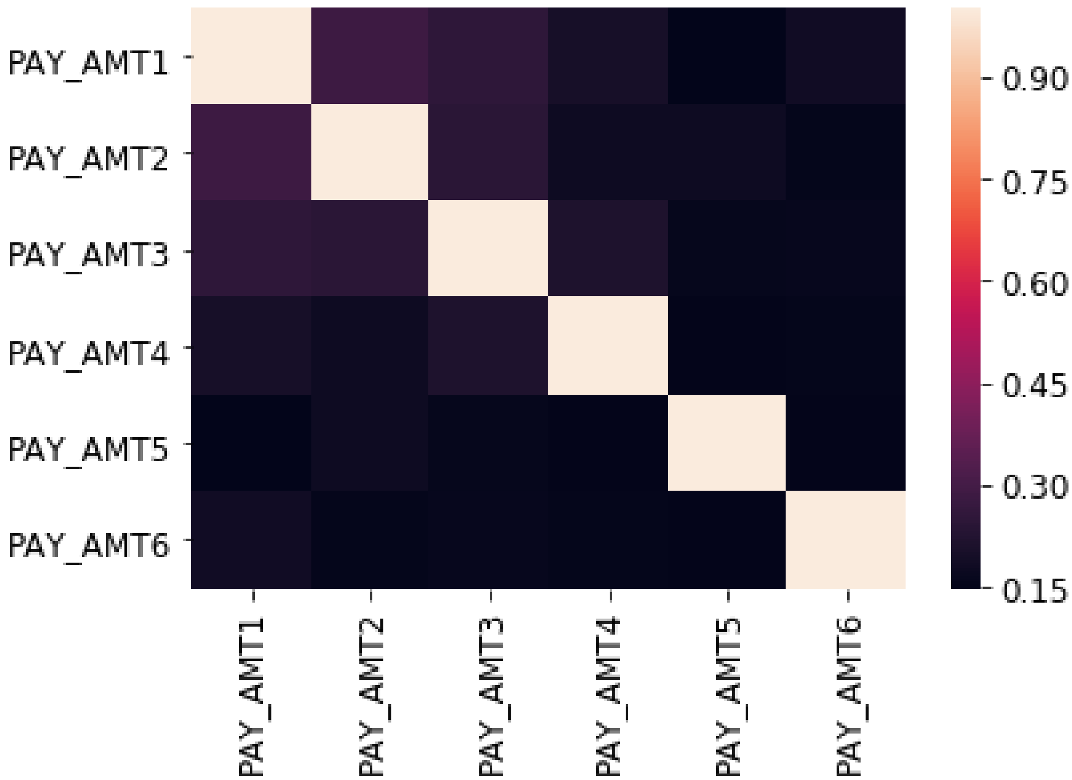


The above chart shows there is high corelation in monthly balance over the period which means customers are accumulating debt over the period. Below chart also support this fact as monthly payments are flat.

In [0]:
```
# Calculate correlations
corr = df[['PAY_AMT1','PAY_AMT2','PAY_AMT3','PAY_AMT4','PAY_AMT5','PAY_AMT6']].corr()

# Heatmap
sns.heatmap(corr)
```

Out[0]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fca489c75c0>
```



This chart is showing that there is no corelation in monthly payments over the period which in contrast to the debt balance chart which shows that customers monthly balances have high corelation. In summary customers are paying minimum payment to avoid default.

8 Data Preprocessing and Pipeline

```
In [0]: numeric_features = ['LIMIT_BAL','BILL_AMT1', 'BILL_AMT2','BILL_AMT3','BILL_AMT4','BILL_
        numeric_transformer = Pipeline(steps=[
            ('imputer', SimpleImputer(strategy='median')),
            ('scaler', StandardScaler())])
```

```
In [0]: categorical_features = ['SEX', 'EDUCATION', 'MARRIAGE','AGE','PAY_0','PAY_2','PAY_3','I
        categorical_transformer = Pipeline(steps=[('onehot', OneHotEncoder(handle_unknown='igno
```

```
In [0]: preprocessor = ColumnTransformer(
            transformers=[
                ('num', numeric_transformer, numeric_features),
                ('cat', categorical_transformer, categorical_features)])
```

```
In [0]: Kneighbors_clf= Pipeline(steps=[('preprocessor', preprocessor),
                              ('classifier', KNeighborsClassifier(),)])
        Randomforest_clf= Pipeline(steps=[('preprocessor', preprocessor),
                              ('classifier', RandomForestClassifier(),)])
```

9 Data Split - Target & Train_Test_Split

```
In [0]: X = df.drop('default payment next month', axis=1)
        y = df['default payment next month']
        print(X.shape)
        print(y.shape)
```

```
(30000, 24)
(30000,)
```

```
In [0]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
        print(X_train.shape,y_train.shape)
        print(X_test.shape,y_test.shape)
```

```
(24000, 24) (24000,)
(6000, 24) (6000,)
```

```
In [0]: X_scaled=preprocessor.fit_transform(X_train)
        X_test_scaled=preprocessor.transform(X_test)
```

10 GridSearchCV -Best Parameters

KNeighbors and Random Classifiers

```
In [0]: # KNEIGHBORS CLASSIFIER

        para_grid={'n_neighbors':[3, 4, 5, 7, 10, 20, 50]}

        gs=GridSearchCV(KNeighborsClassifier(),para_grid,cv=4,verbose=1,n_jobs=-1)
        gs_results=gs.fit(X_scaled,y_train)
```

```
Fitting 4 folds for each of 7 candidates, totalling 28 fits


[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done  28 out of  28 | elapsed:  4.0min finished
```

```
In [0]: [gs_results.best_score_,gs_results.best_params_,gs_results.best_estimator_]
```

```
Out[0]: [0.808875,
         {'n_neighbors': 20},
         KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                              metric_params=None, n_jobs=None, n_neighbors=20, p=2,
                              weights='uniform')]
```

```
In [0]: random_clf=RandomForestClassifier()
        param_grid={'n_estimators':[3, 4, 6, 7, 10, 20, 50, 100]}
        grid_search=GridSearchCV(random_clf,param_grid,cv=4,verbose=1,n_jobs=-1)
        grid_randaom=grid_search.fit(X_scaled,y_train)
```

```
Fitting 4 folds for each of 8 candidates, totalling 32 fits


[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done  32 out of  32 | elapsed:  2.1min finished
```

```
In [0]: [grid_randaom.best_score_,grid_randaom.best_params_,grid_randaom.best_estimator_]
```

```
Out[0]: [0.8162916666666666,
         {'n_estimators': 50},
         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=50,
                                n_jobs=None, oob_score=False, random_state=None,
                                verbose=0, warm_start=False)]
```

```
In [0]: i=gs_results.best_params_
        j=grid_randaom.best_params_
```

11 DEF for Graphs

```
In [0]: def plot_precision_recall_vs_threshold(precisions, recalls, thresholds):
            plt.plot(thresholds, precisions[:-1], "b--", label="Precision", linewidth=2)
            plt.plot(thresholds, recalls[:-1], "g-", label="Recall", linewidth=2)
            plt.legend(loc="upper right", fontsize=16)
            plt.xlabel("Threshold", fontsize=16)
            plt.grid(True)
            plt.axis([0, 1, 0, 1])

        def plot_roc_curve(fpr, tpr, label=None):
            plt.plot(fpr, tpr, linewidth=2, label=label)
            plt.plot([0, 1], [0, 1], 'k--') # dashed diagonal
            plt.axis([0, 1, 0, 1])
            plt.xlabel('False Positive Rate (Fall-Out)', fontsize=16)
            plt.ylabel('True Positive Rate (Recall)', fontsize=16)
            plt.legend()
            plt.grid(True)
```

12 KNEIGHBORS - WITHOUT AND WITH DATA SCALING

1. WITHOUT DATA SCALING PERFORMANCE METRICS: KNN Score, Cross Validation Score, Confusion Matrix, Precision/Recall/F1 Scores, Precision_Recall_Curve,ROC_AUC Score & ROC_Curve

In [0]:
```
# KNN best fit evaluation without DATA SCALING

knn_clf=KNeighborsClassifier(n_neighbors=i['n_neighbors'])
knn_clf.fit(X_train,y_train)
cv=4

print('KNN Score: {}'.format(knn_clf.score(X_train,y_train)))

print('CROSS_VAL Score: {}'.format(cross_val_score(knn_clf, X_train, y_train, cv=cv, sc

y_train_predict=cross_val_predict(knn_clf,X_train,y_train,cv=cv)
cm_train_knn1=confusion_matrix(y_train,y_train_predict)
print(cm_train_knn1)
print('Precision Score: {}'.format(precision_score(y_train,y_train_predict)))
print('Recall Score: {}'.format(recall_score(y_train,y_train_predict)))
print('F1 Score: {}'.format(f1_score(y_train,y_train_predict)))

sns.heatmap(cm_train_knn1, annot=True,  fmt='.2f', xticklabels = ["Not Default", "Defau
plt.ylabel('Actual label', fontsize=18)
plt.xlabel('Predicted label',fontsize=18)
plt.show()

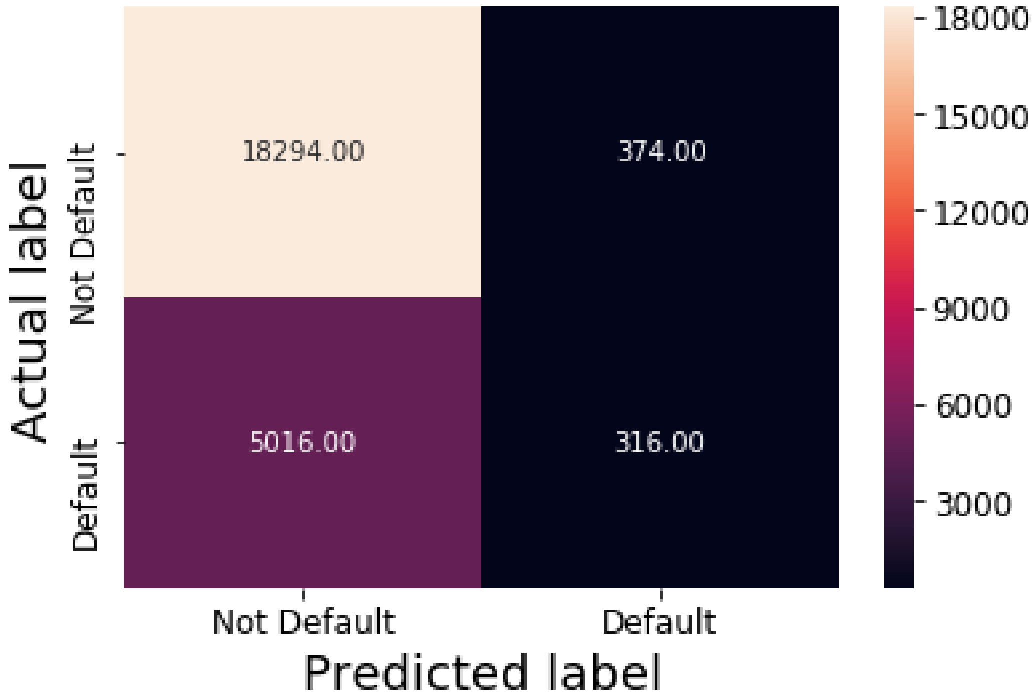
precisions, recalls, thresholds = precision_recall_curve(y_train, y_train_predict)
plt.figure(figsize=(8, 4))
plot_precision_recall_vs_threshold(precisions, recalls, thresholds)
plt.show()

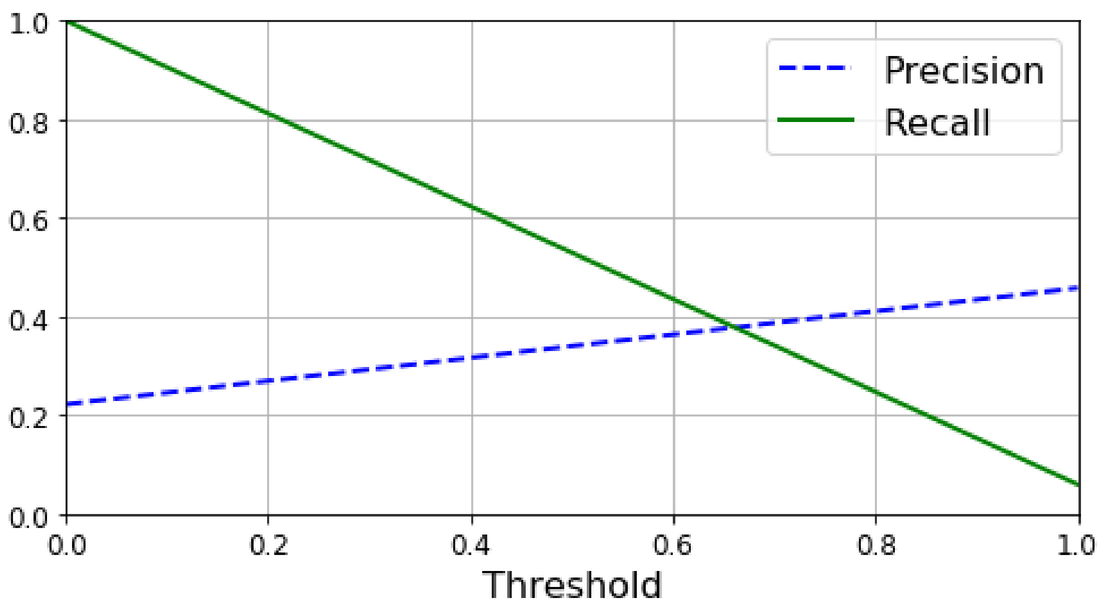
y_train_predict_proba=cross_val_predict(knn_clf, X_train, y_train, cv=cv, method="predi
y_scores_forest = y_train_predict_proba[:, 1] # score = proba of positive class
fpr_forest, tpr_forest, thresholds_forest = roc_curve(y_train,y_scores_forest)
print('ROC_AUC Score: {}'.format(roc_auc_score(y_train, y_scores_forest)))

plt.figure(figsize=(8, 6))
plot_roc_curve(fpr_forest, tpr_forest)
plt.show()
```

```
KNN Score: 0.78575
CROSS_VAL Score: [0.77616667 0.77383333 0.77783333 0.77383333]
[[18294   374]
 [ 5016   316]]
Precision Score: 0.4579710144927536
Recall Score: 0.05926481620405101
```

```
F1 Score: 0.10494852208568581
```





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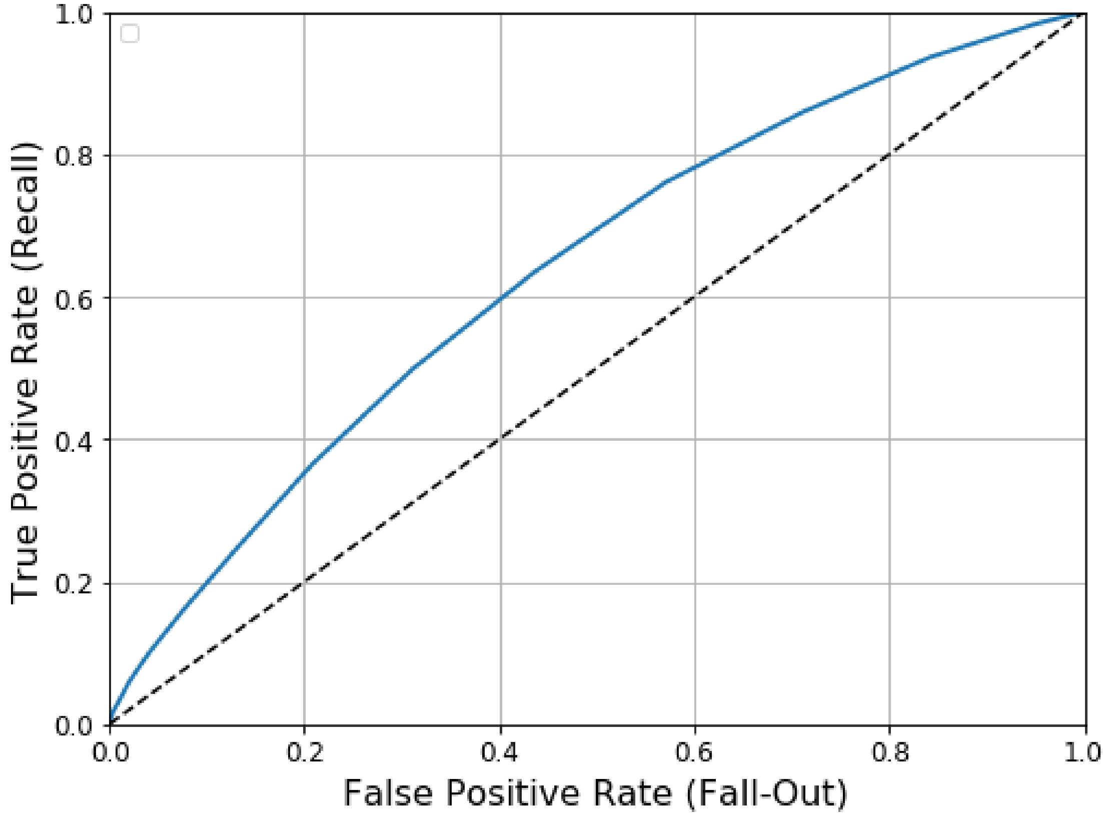
ROC_AUC Score: 0.6355235674544305
```




```
In [0]: print('Summary: Without Feature Scaling ROC_AUC Score: {}'.format(roc_auc_score(y_trai
```

```
Summary: Without Feature Scaling ROC_AUC Score: 0.6355235674544305
```

2. WITH DATA SCALING PERFORMANCE METRICS: KNN Score, Cross Validation Score, Confusion Matrix, Precision/Recall/F1 Scores, Precision_Recall_Curve,ROC_AUC Score & ROC_Curve

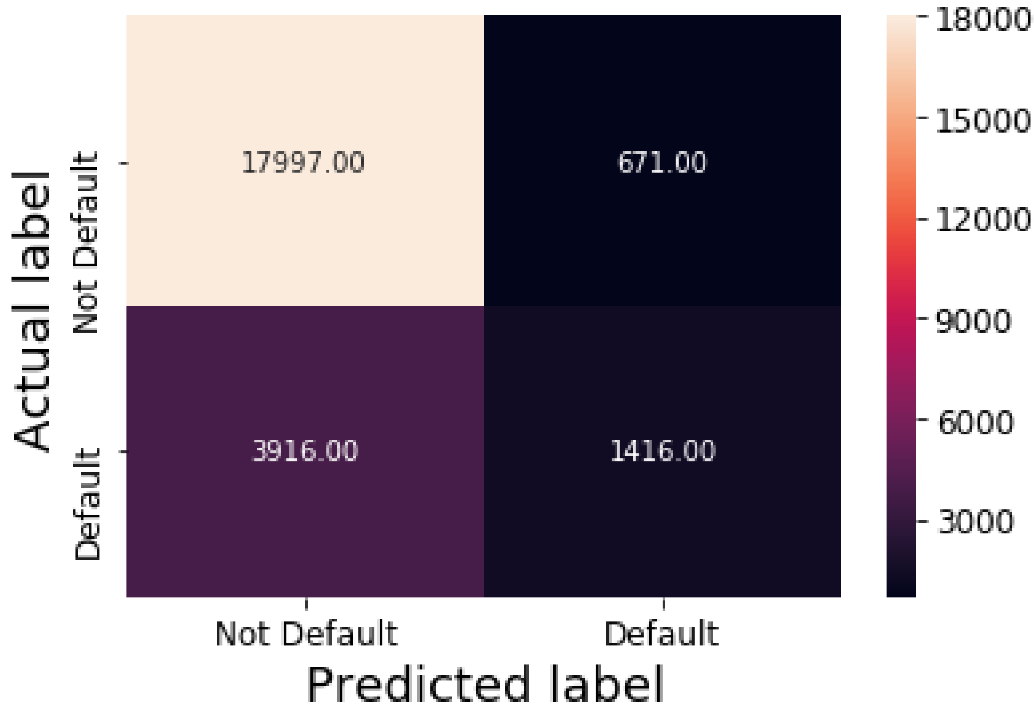
```
In [0]: # KNN best fit evaluation with DATA SCALING

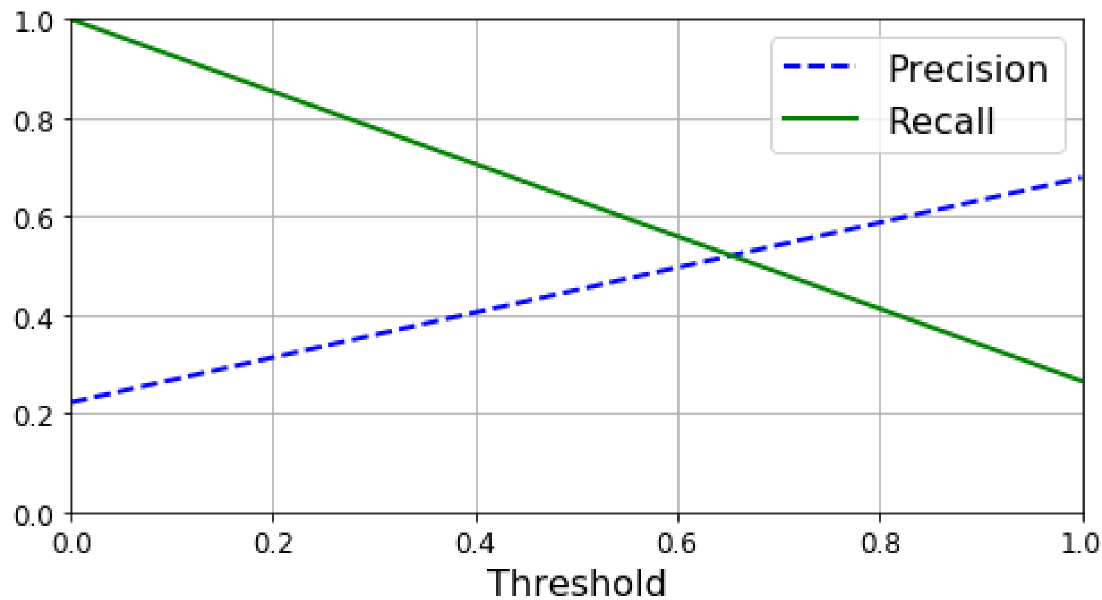
        knn_clf=KNeighborsClassifier(n_neighbors=i['n_neighbors'])
        knn_clf.fit(X_scaled,y_train)
        print('KNN Score: {}'.format(knn_clf.score(X_scaled,y_train)))

        print('CROSS_VAL Score: {}'.format(cross_val_score(knn_clf, X_scaled, y_train, cv=cv, s
```

```python
y_train_predict=cross_val_predict(knn_clf,X_scaled,y_train,cv=cv)
cm_train_knn2=confusion_matrix(y_train,y_train_predict)
print(cm_train_knn2)
print('Precision Score: {}'.format(precision_score(y_train,y_train_predict)))
print('Recall Score: {}'.format(recall_score(y_train,y_train_predict)))
print('F1 Score: {}'.format(f1_score(y_train,y_train_predict)))

sns.heatmap(cm_train_knn2, annot=True,  fmt='.2f', xticklabels = ["Not Default", "Defau
plt.ylabel('Actual label', fontsize=18)
plt.xlabel('Predicted label',fontsize=18)
plt.show()

precisions1, recalls1, thresholds1 = precision_recall_curve(y_train, y_train_predict)
plt.figure(figsize=(8, 4))
plot_precision_recall_vs_threshold(precisions1, recalls1, thresholds1)
plt.show()

y_train_predict_proba=cross_val_predict(knn_clf, X_scaled, y_train, cv=cv, method="pred
y_scores_forest1 = y_train_predict_proba[:, 1] # score = proba of positive class
fpr_forest1, tpr_forest1, thresholds_forest1 = roc_curve(y_train,y_scores_forest1)
print('ROC_AUC Score: {}'.format(roc_auc_score(y_train, y_scores_forest1)))

plt.figure(figsize=(8, 6))
plot_roc_curve(fpr_forest1, tpr_forest1)
plt.show()
```

```
KNN Score: 0.8179166666666666
CROSS_VAL Score: [0.807      0.80966667 0.812      0.80683333]
[[17997   671]
 [ 3916  1416]]
Precision Score: 0.678485864877815
Recall Score: 0.26556639159789946
F1 Score: 0.38172260412454506
```



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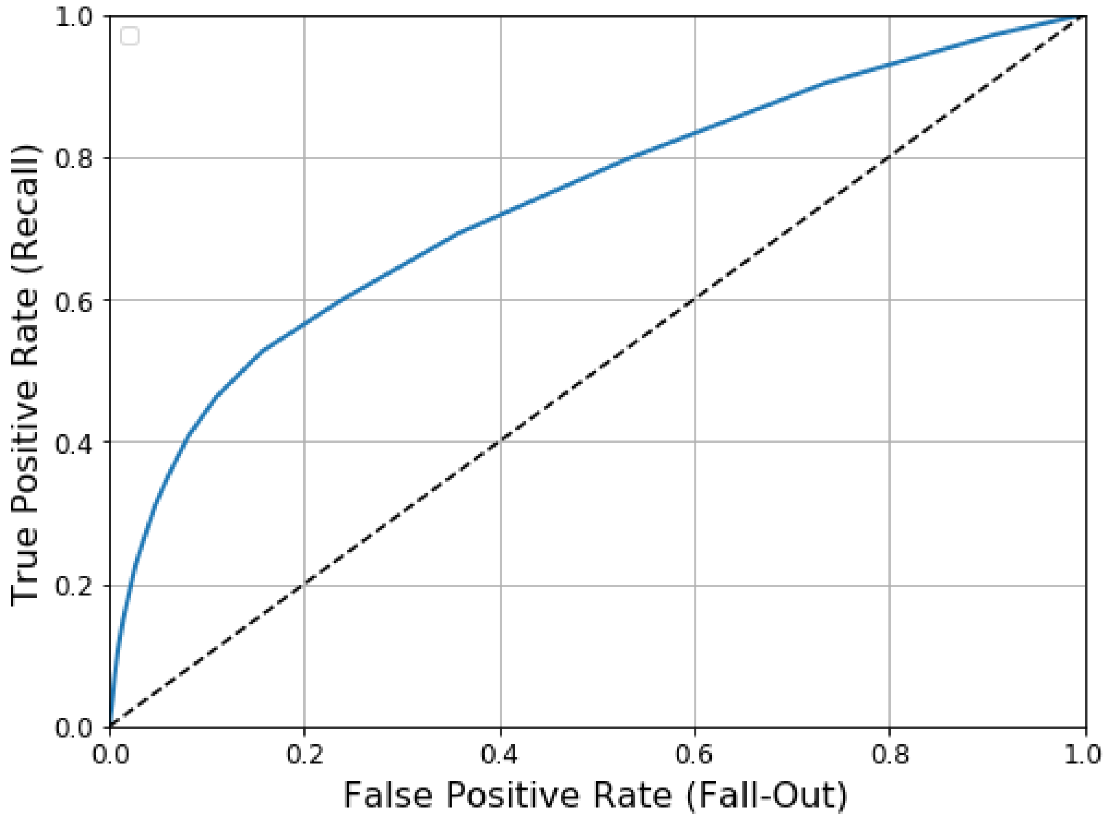
```
ROC_AUC Score: 0.7353515011225487
```




```
In [0]: print('Summary: KNN With Feature Scaling ROC_AUC Score: {}'.format(roc_auc_score(y_trai
        print('Summary: KNN Without Feature Scaling ROC_AUC Score: {}'.format(roc_auc_score(y_t
```

```
Summary: KNN With Feature Scaling ROC_AUC Score: 0.7353515011225487
Summary: KNN Without Feature Scaling ROC_AUC Score: 0.6355235674544305
```

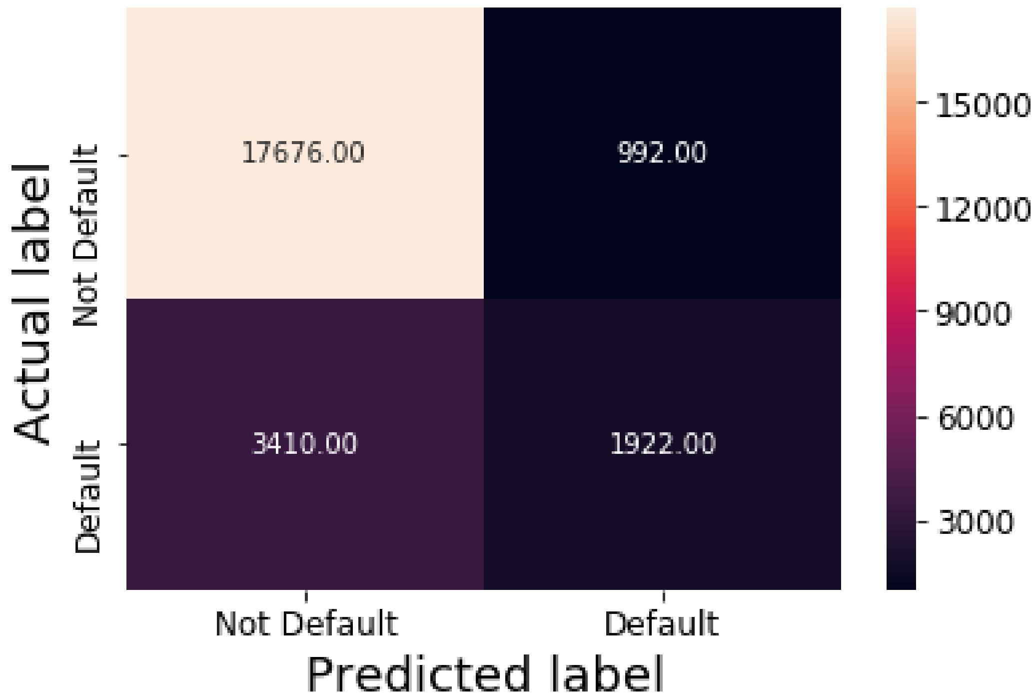
AUC score improve by 0.1 once applied scalling on the data.

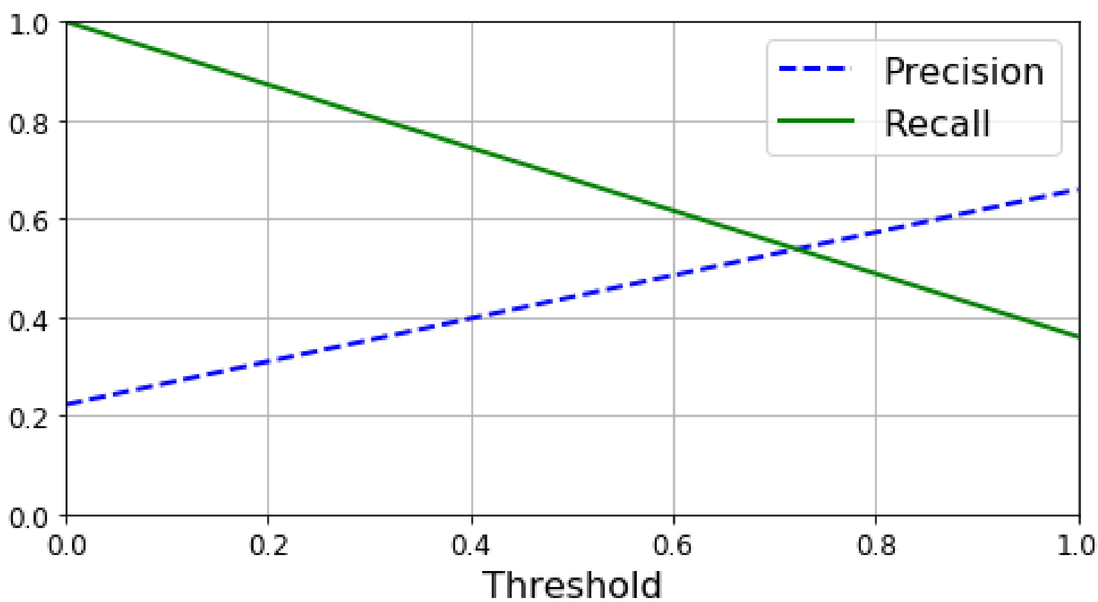
13 RANDOM FOREST - WITHOUT AND WITH DATA SCALING

```
In [0]: # Random Forest with No Data Scaling

        random_clf = RandomForestClassifier(n_estimators=j['n_estimators'])
        random_clf.fit(X_train,y_train)
        print('Random CLF Score: {}'.format(random_clf.score(X_train,y_train)))

        print(cross_val_score(random_clf, X_train, y_train, cv=cv, scoring="accuracy"))
```

```
y_train_predict2=cross_val_predict(random_clf,X_train,y_train,cv=cv)
cm_train_random1=confusion_matrix(y_train,y_train_predict2)
print(cm_train_random1)
print('Precision Score: {}'.format(precision_score(y_train,y_train_predict2)))
print('Recall Score: {}'.format(recall_score(y_train,y_train_predict2)))
print('F1 Score: {}'.format(f1_score(y_train,y_train_predict2)))

sns.heatmap(cm_train_random1, annot=True,  fmt='.2f', xticklabels = ["Not Default", "De
plt.ylabel('Actual label', fontsize=18)
plt.xlabel('Predicted label',fontsize=18)
plt.show()

precisionsR, recallsR, thresholdsR = precision_recall_curve(y_train, y_train_predict2)
plt.figure(figsize=(8, 4))
plot_precision_recall_vs_threshold(precisionsR, recallsR, thresholdsR)
plt.show()

y_train_predict_proba2=cross_val_predict(random_clf, X_train, y_train, cv=cv, method="
y_scores_forest2 = y_train_predict_proba2[:, 1] # score = proba of positive class
fpr_forestR, tpr_forestR, thresholds_forestR = roc_curve(y_train,y_scores_forest2)
print('ROC_AUC Score: {}'.format(roc_auc_score(y_train, y_scores_forest2)))

plt.figure(figsize=(8, 6))
plot_roc_curve(fpr_forestR, tpr_forestR)
plt.show()
```

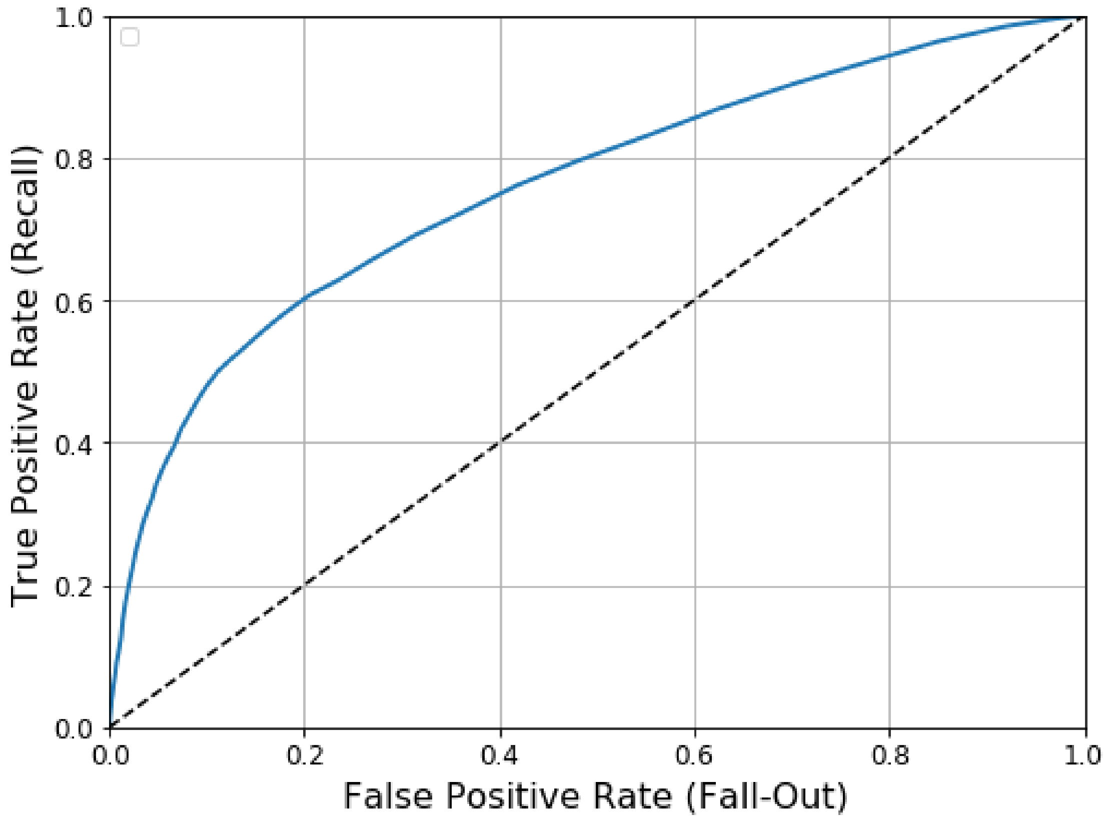
```
Random CLF Score: 0.9991666666666666
[0.811      0.81133333 0.82816667 0.81733333]
[[17676   992]
 [ 3410  1922]]
Precision Score: 0.6595744680851063
Recall Score: 0.36046511627906974
F1 Score: 0.4661654135338345
```






```
ROC_AUC Score: 0.7584216167337312
```

```
No handles with labels found to put in legend.
```

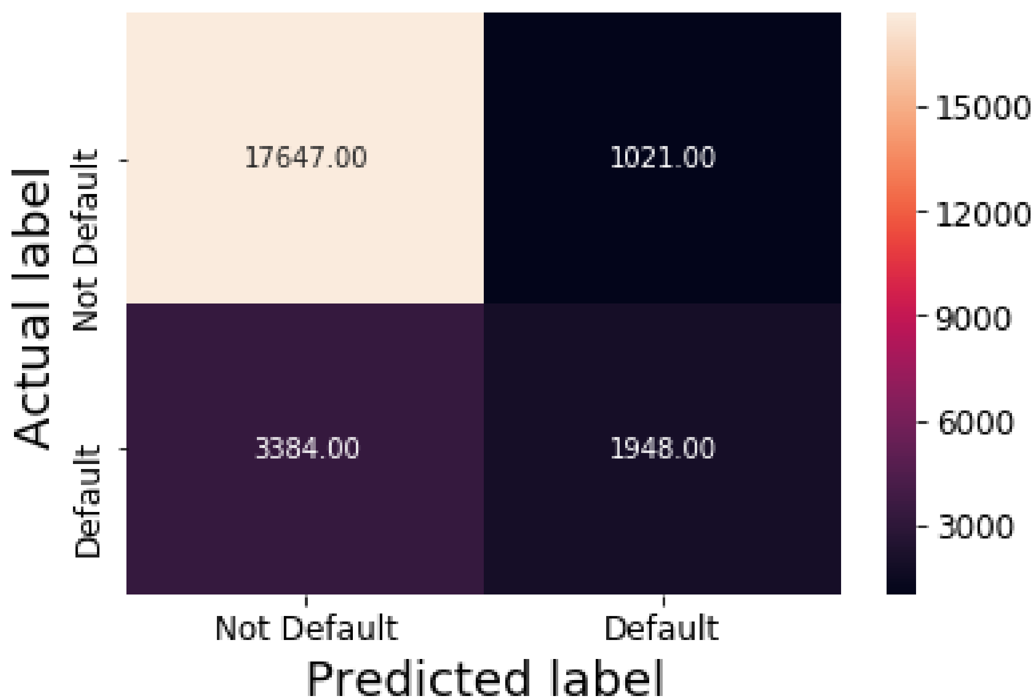


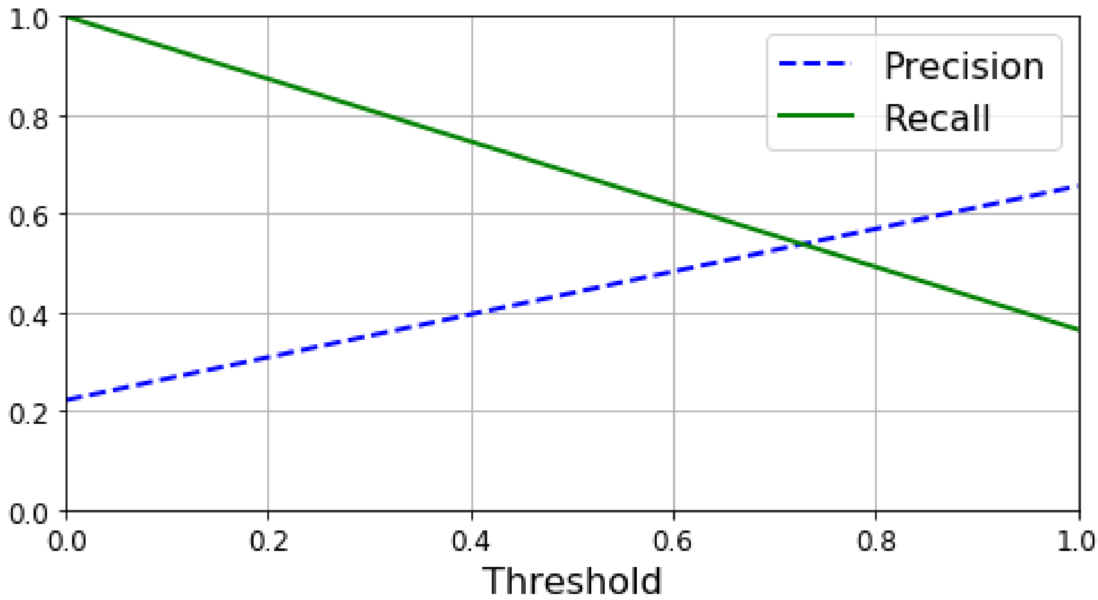
RANDOM FOREST WITH DATA SCALING

```
In [0]: # Random Forest with  Data Scaling
        random_clf = RandomForestClassifier(n_estimators=j['n_estimators'])
        random_clf.fit(X_scaled,y_train)
        print('Random CLF Score: {}'.format(random_clf.score(X_scaled,y_train)))

        print(cross_val_score(random_clf, X_scaled, y_train, cv=cv, scoring="accuracy"))

        y_train_predict2=cross_val_predict(random_clf,X_scaled,y_train,cv=cv)
        cm_train_random2=confusion_matrix(y_train,y_train_predict2)
        print(cm_train_random2)
        print('Precision Score: {}'.format(precision_score(y_train,y_train_predict2)))
        print('Recall Score: {}'.format(recall_score(y_train,y_train_predict2)))
        print('F1 Score: {}'.format(f1_score(y_train,y_train_predict2)))

        sns.heatmap(cm_train_random2, annot=True,  fmt='.2f', xticklabels = ["Not Default", "De
        plt.ylabel('Actual label', fontsize=18)
        plt.xlabel('Predicted label',fontsize=18)
```

```
plt.show()

precisionsR1, recallsR1, thresholdsR1 = precision_recall_curve(y_train, y_train_predic
plt.figure(figsize=(8, 4))
plot_precision_recall_vs_threshold(precisionsR1, recallsR1, thresholdsR1)
plt.show()

y_train_predict_proba2=cross_val_predict(random_clf, X_scaled, y_train, cv=cv, method=
y_scores_forest3 = y_train_predict_proba2[:, 1] # score = proba of positive class
fpr_forestR1, tpr_forestR1, thresholds_forestR1 = roc_curve(y_train,y_scores_forest3)
print('ROC_AUC Score: {}'.format(roc_auc_score(y_train, y_scores_forest3)))

plt.figure(figsize=(8, 6))
plot_roc_curve(fpr_forestR1, tpr_forestR1)
plt.show()
```

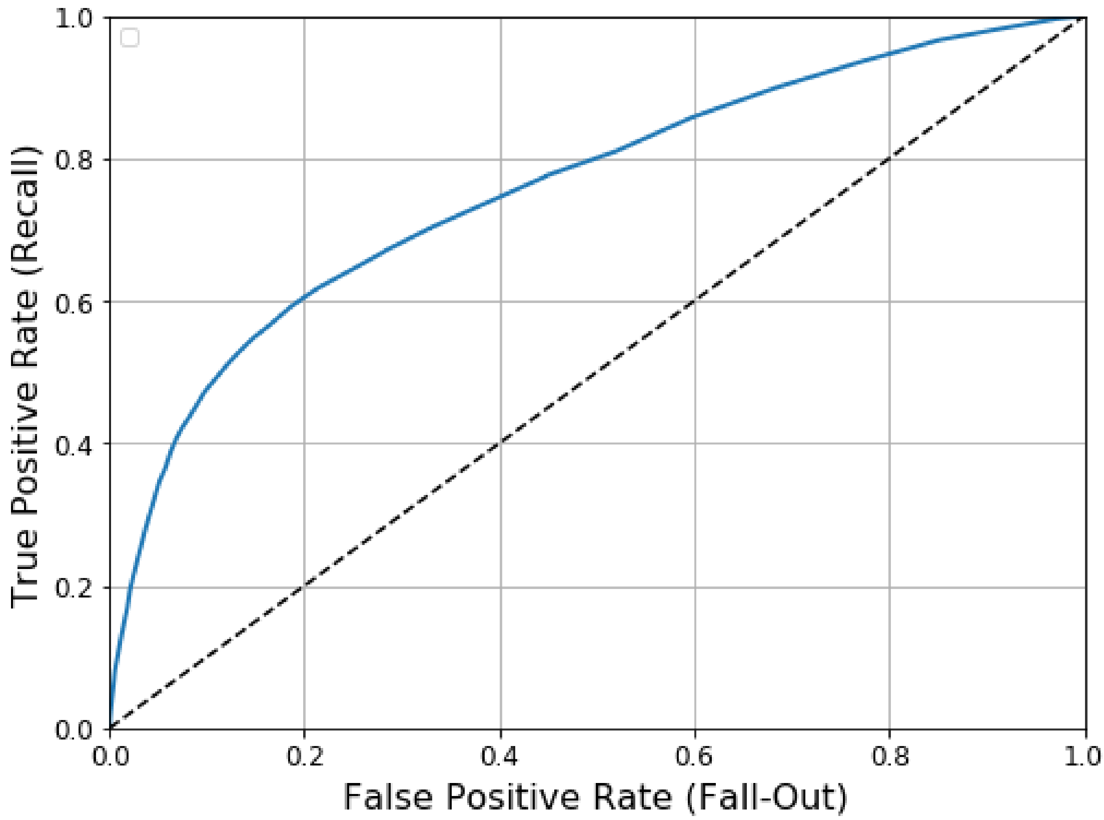
```
Random CLF Score: 0.99875
[0.812      0.81283333 0.82483333 0.81366667]
[[17647  1021]
 [ 3384  1948]]
Precision Score: 0.6561131694173122
Recall Score: 0.36534133533383345
F1 Score: 0.46934104324780146
```






```
No handles with labels found to put in legend.
```

```
ROC_AUC Score: 0.7583778695236271
```



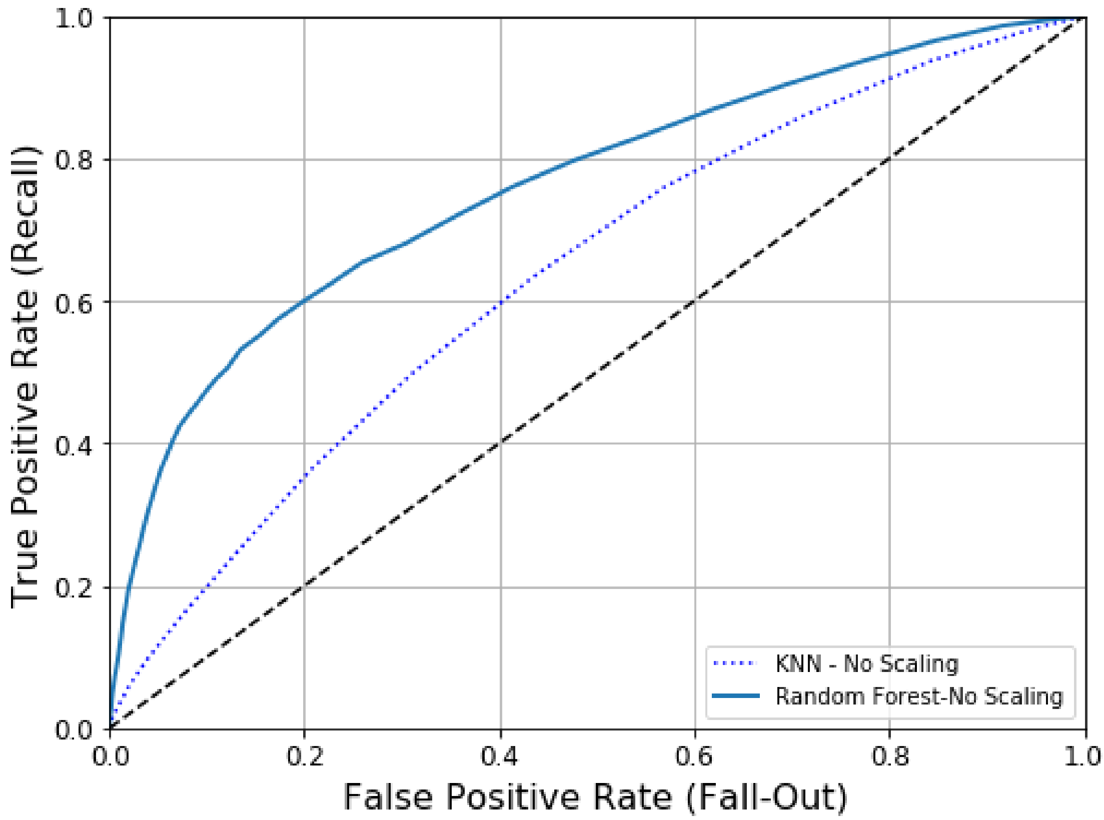

```
In [0]: print('ROC_AUC Score Random Forest with Scaling: {}'.format(roc_auc_score(y_train, y_sc
        print('ROC_AUC Score Random Forest without Scaling: {}'.format(roc_auc_score(y_train, y
```

```
ROC_AUC Score Random Forest with Scaling: 0.7583778695236271
ROC_AUC Score Random Forest without Scaling: 0.7584216167337312
```

AUC area of without scaling is slightly higher than with data scalling. Almost no impact of scalling.

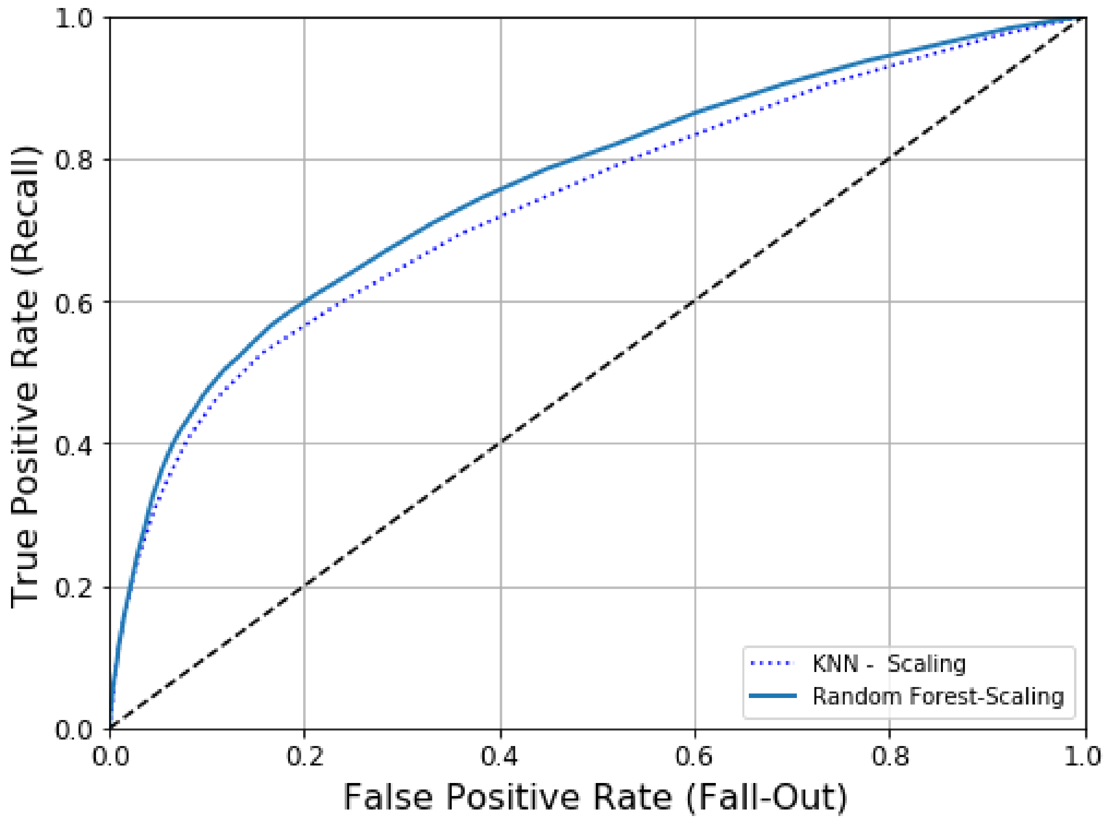
14 KNN VS RANDOM FOREST - ROC_CURVE AND AUC_RUC SCORE

```
In [0]: plt.figure(figsize=(8, 6))                              # Not shown
        plt.plot(fpr_forest, tpr_forest,'b:',label='KNN - No Scaling')
        plot_roc_curve(fpr_forestR, tpr_forestR,'Random Forest-No Scaling')
        plt.legend(loc='lower right')
        plt.show()
```



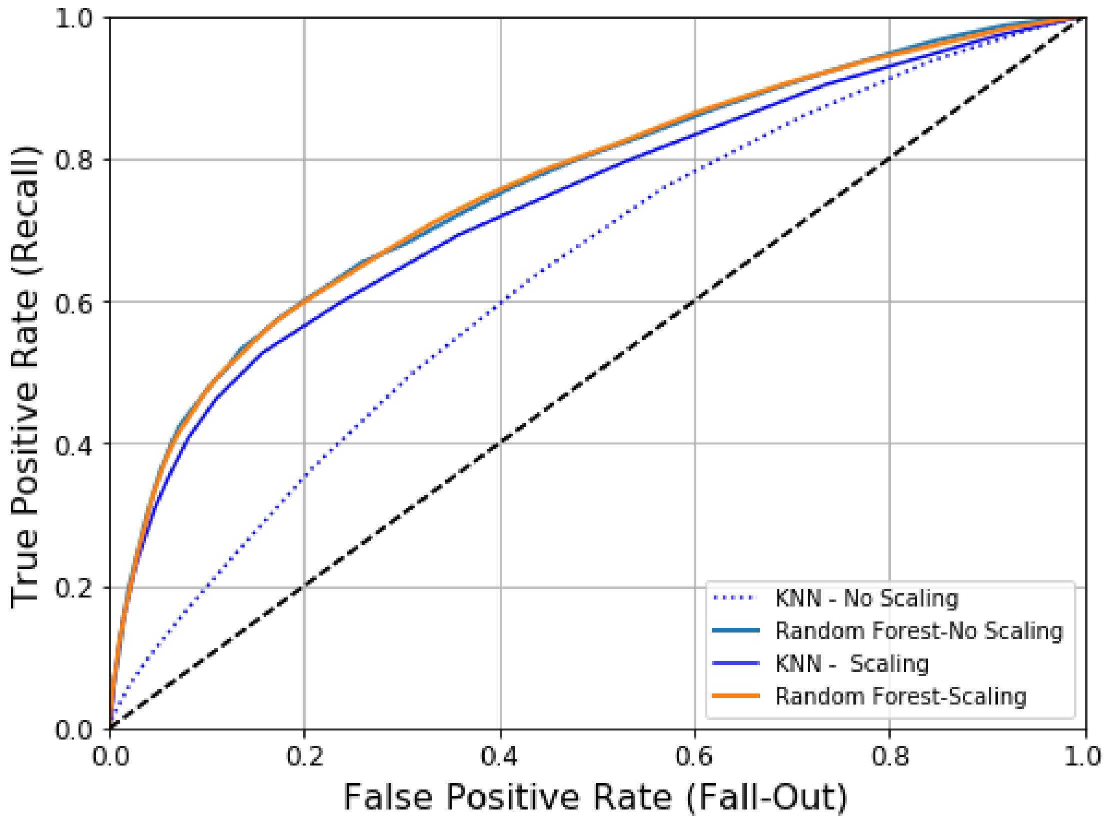
AUC area is much higer in Random Forest before applying any scaling.

In [0]:
```
plt.figure(figsize=(8, 6))
plt.plot(fpr_forest1, tpr_forest1,'b:',label='KNN -  Scaling')
plot_roc_curve(fpr_forestR1, tpr_forestR1,'Random Forest-Scaling')
plt.legend(loc='lower right')
plt.show()
```



With Scaling KNN has imporved but Random Forest has not changed much.

```
In [0]: plt.figure(figsize=(8, 6))                          # Not shown
        plt.plot(fpr_forest, tpr_forest,'b:',label='KNN - No Scaling')
        plot_roc_curve(fpr_forestR, tpr_forestR,'Random Forest-No Scaling')
        plt.plot(fpr_forest1, tpr_forest1,'b-',label='KNN -  Scaling')
        plot_roc_curve(fpr_forestR1, tpr_forestR1,'Random Forest-Scaling')
        plt.legend(loc='lower right')
        plt.show()
```



In [0]:
```
print('Summary: KNN With Feature Scaling ROC_AUC Score: {}'.format(roc_auc_score(y_trai
print('Summary: KNN Without Feature Scaling ROC_AUC Score: {}'.format(roc_auc_score(y_t


print('Summary: Random Forest With Feature Scaling ROC_AUC Score:: {}'.format(roc_auc_s
print('Summary: Random Forest Without Feature Scaling ROC_AUC Score:: {}'.format(roc_au
```

```
Summary: KNN With Feature Scaling ROC_AUC Score: 0.7353515011225487
Summary: KNN Without Feature Scaling ROC_AUC Score: 0.6355235674544305
Summary: Random Forest With Feature Scaling ROC_AUC Score:: 0.7601789395013206
Summary: Random Forest Without Feature Scaling ROC_AUC Score:: 0.7600251134805343
```

15 Conclusion :

Random Forest without scaling AUC_ROC_Score is highest and should be selected for test model

16 TEST SET -Results

In [0]:
```
random_clf.predict(X_test_scaled)
print('Random CLF Score: {}'.format(random_clf.score(X_test_scaled,y_test)))
```

```python
        print(cross_val_score(random_clf, X_test_scaled,y_test, cv=cv, scoring="accuracy"))
        y_test_predict=cross_val_predict(random_clf,X_test_scaled,y_test,cv=cv)
        cm_test=confusion_matrix(y_test,y_test_predict)
        print(cm_test)
        print('Precision Score: {}'.format(precision_score(y_test,y_test_predict)))
        print('Recall Score: {}'.format(recall_score(y_test,y_test_predict)))
        print('F1 Score: {}'.format(f1_score(y_test,y_test_predict)))

        sns.heatmap(cm_test, annot=True,  fmt='.2f', xticklabels = ["Not Default", "Default"]
        plt.ylabel('Actual label', fontsize=18)
        plt.xlabel('Predicted label',fontsize=18)
        plt.show()

        precisionsR1T, recallsR1T, thresholdsR1T = precision_recall_curve(y_test,y_test_predic
        plt.figure(figsize=(8, 4))
        plot_precision_recall_vs_threshold(precisionsR1T, recallsR1T, thresholdsR1T)
        plt.show()

        y_test_predict_proba2T=cross_val_predict(random_clf, X_test_scaled,y_test, cv=cv, metho
        y_scores_forest3T = y_test_predict_proba2T[:, 1] # score = proba of positive class
        fpr_forestR1T, tpr_forestR1T, thresholds_forestR1T = roc_curve(y_test,y_scores_forest3

        plt.figure(figsize=(8, 6))
        plot_roc_curve(fpr_forestR1T, tpr_forestR1T)
        plt.show()

        print('ROC_AUC Score: {}'.format(roc_auc_score(y_test, y_scores_forest3T)))
```

```
Random CLF Score: 0.9993333333333333
[0.82066667 0.81333333 0.80733333 0.82      ]
[[4436  260]
 [ 860  444]]
Precision Score: 0.6306818181818182
Recall Score: 0.34049079754601225
F1 Score: 0.44223107569721115
```

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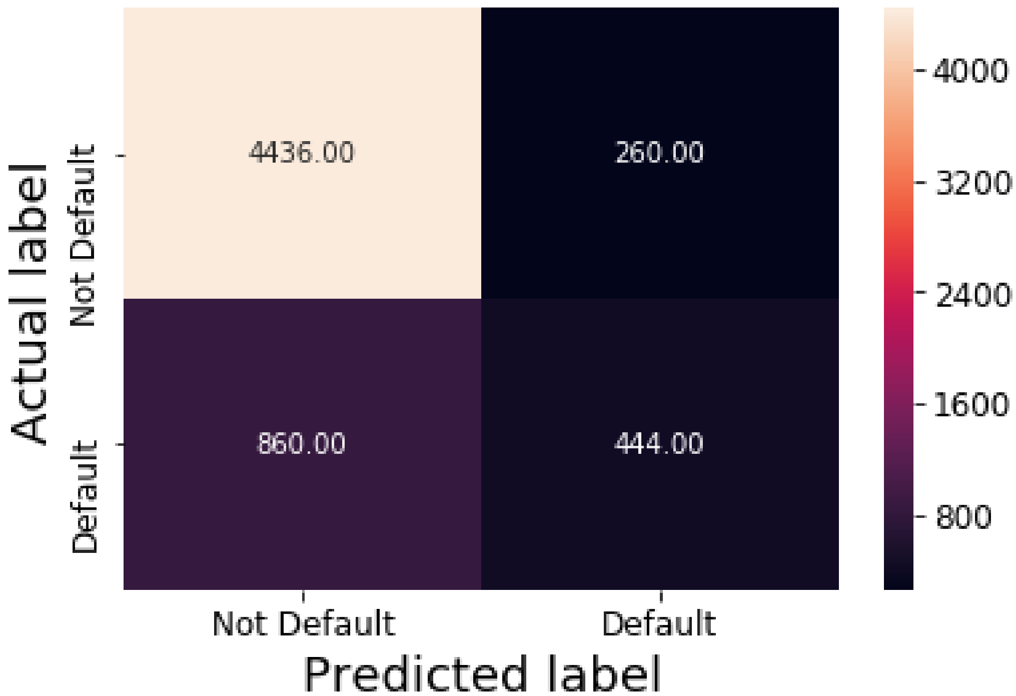
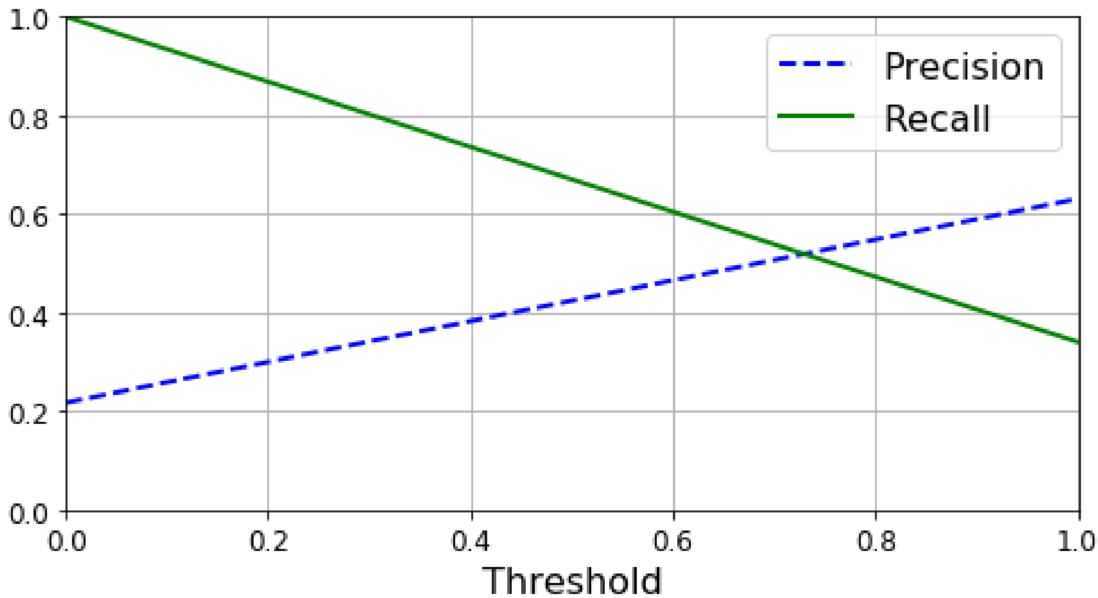
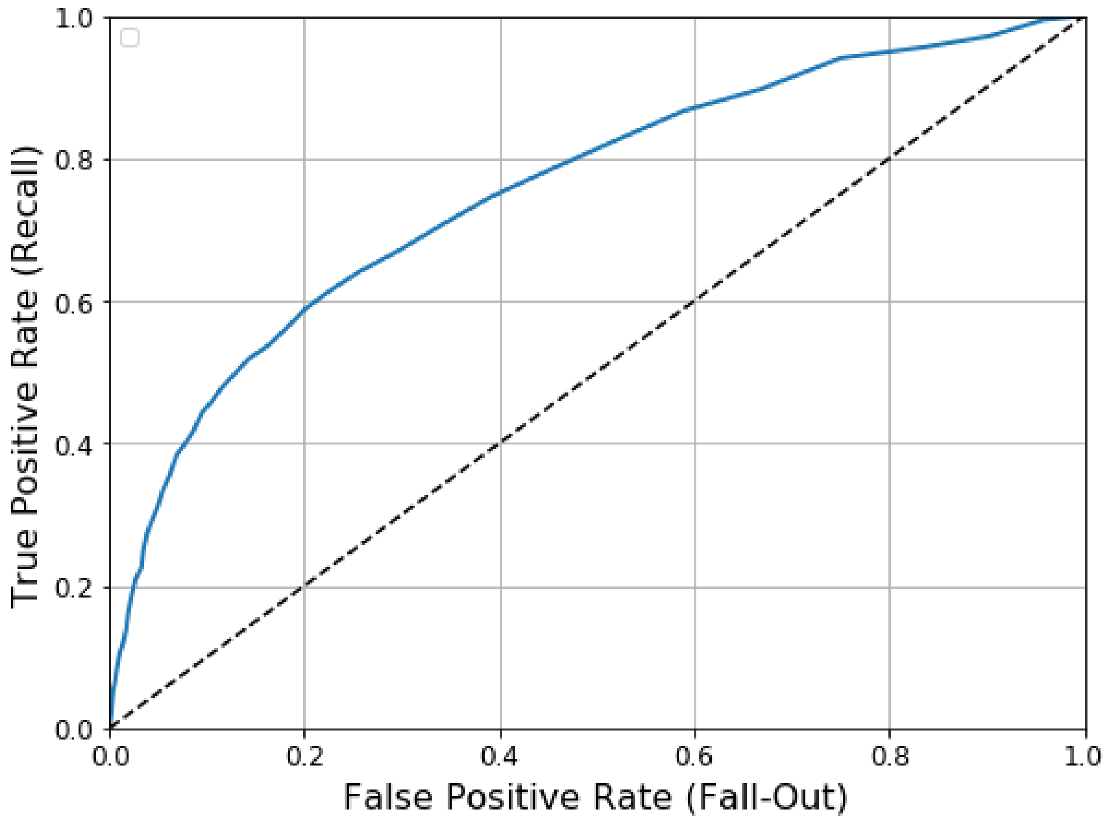




No handles with labels found to put in legend.




```
ROC_AUC Score: 0.7558901780395271
```

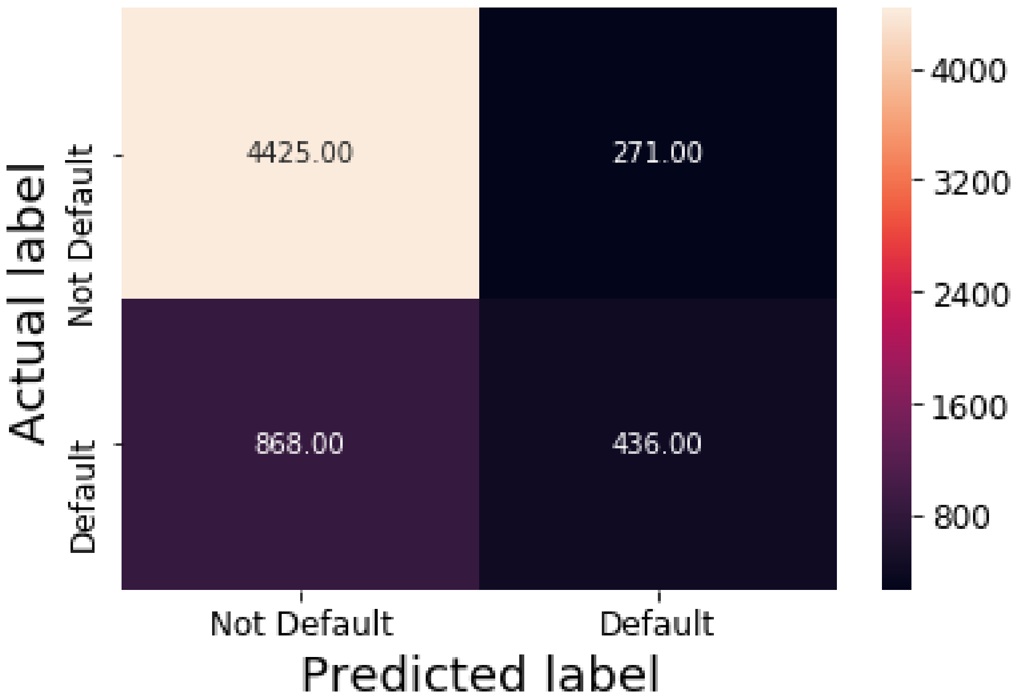
AUC Score - Training 0.7600 vs Test 0.756. Overall test result is performing as predicted by training. Looks like it is neither underfitting (test is not performing to well vs train) not overfitting(test is performing poorly vs train). Further evaluation required to see if this can be improved.

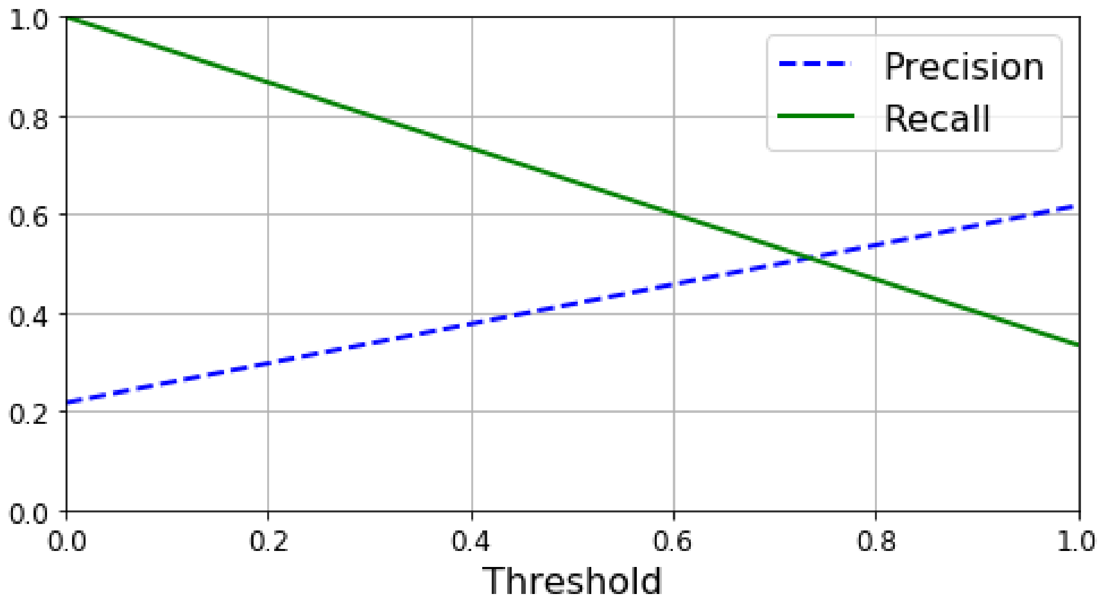
In [0]:
```
# CV=5 Validation Scenario
cv1=5

random_clf.predict(X_test_scaled)
print('Random CLF Score: {}'.format(random_clf.score(X_test_scaled,y_test)))

print(cross_val_score(random_clf, X_test_scaled,y_test, cv=cv1, scoring="accuracy"))

y_test_predict=cross_val_predict(random_clf,X_test_scaled,y_test,cv=cv1)
cm_test2=confusion_matrix(y_test,y_test_predict)
print(cm_test2)
print('Precision Score: {}'.format(precision_score(y_test,y_test_predict)))
print('Recall Score: {}'.format(recall_score(y_test,y_test_predict)))
print('F1 Score: {}'.format(f1_score(y_test,y_test_predict)))
```

```
sns.heatmap(cm_test2, annot=True,  fmt='.2f', xticklabels = ["Not Default", "Default"]
plt.ylabel('Actual label', fontsize=18)
plt.xlabel('Predicted label',fontsize=18)
plt.show()

precisionsR1T, recallsR1T, thresholdsR1T = precision_recall_curve(y_test,y_test_predic
plt.figure(figsize=(8, 4))
plot_precision_recall_vs_threshold(precisionsR1T, recallsR1T, thresholdsR1T)
plt.show()

y_test_predict_proba2T=cross_val_predict(random_clf, X_test_scaled,y_test, cv=cv1, met
y_scores_forest3T = y_test_predict_proba2T[:, 1] # score = proba of positive class
fpr_forestR1T, tpr_forestR1T, thresholds_forestR1T = roc_curve(y_test,y_scores_forest3

plt.figure(figsize=(8, 6))
plot_roc_curve(fpr_forestR1T, tpr_forestR1T)
plt.show()

print('ROC_AUC Score: {}'.format(roc_auc_score(y_test, y_scores_forest3T)))
```

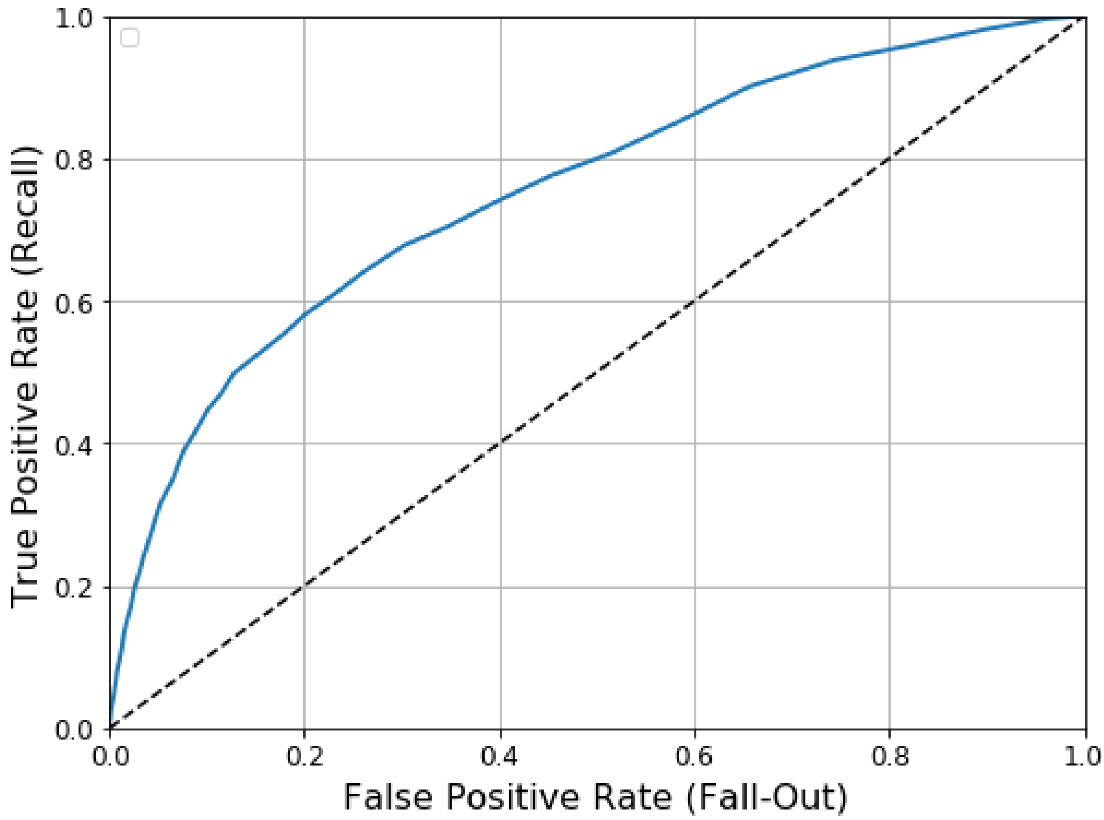
```
Random CLF Score: 0.9993333333333333
[0.8143214  0.80083333 0.8125     0.79666667 0.81984987]
[[4425  271]
 [ 868  436]]
Precision Score: 0.6166902404526167
Recall Score: 0.3343558282208589
F1 Score: 0.4336151168572849
```

No handles with labels found to put in legend.





No handles with labels found to put in legend.




```
ROC_AUC Score: 0.7529009155422708
```

With CV=5 the AUC score 0.7529 not imporved from 0.7560. However, this is close to training prediction 0.7658. Not much change.