Predict Default of Credit Card Clients

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Overview

- Data source
- Data cleaning and preprocessing
- Code
- Scaling normalizing data
- Handling imbalanced data
- Feature engineering
- Predictive modeling
- Accuracy and best model

Data source and Problem Statement

- **Data source UCI Machine Learning Repository**

https://archive.ics.uci.edu/ml/datasets/default+of+credit+card+clients

- This research aimed at the case of customers default payments in Taiwan and compares the predictive accuracy of probability of default using various methods

Data Frame

```
#Reading the data using pandas

df = pd.read_excel("default of credit card clients.xls")

#default of credit card clients.xls
```

```
df.head()
```

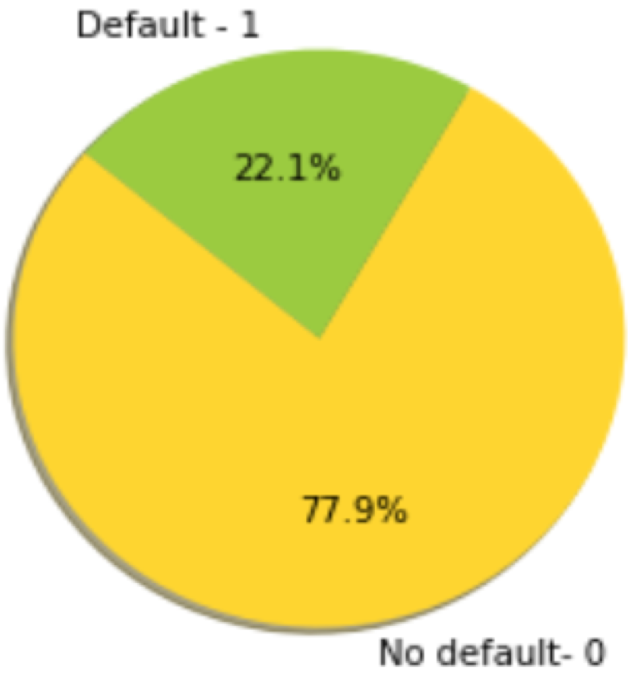
AGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	...	BILL_AMT4	BILL_AMT5	BILL_AMT6	PAY_AMT1	PAY_AMT2	PAY_AMT3	PAY_AMT4	PAY_AMT5	PAY_AMT6	default payment next month
1	24	2	2	-1	-1	...	0	0	0	0	689	0	0	0	0	1
2	26	-1	2	0	0	...	3272	3455	3261	0	1000	1000	1000	0	2000	1
2	34	0	0	0	0	...	14331	14948	15549	1518	1500	1000	1000	1000	5000	0
1	37	0	0	0	0	...	28314	28959	29547	2000	2019	1200	1100	1069	1000	0
1	57	-1	0	-1	0	...	20940	19146	19131	2000	36681	10000	9000	689	679	0

```
#Replacing the column name for convenience

df.rename(columns={"default payment next month": "default"}, inplace = True)
```

```
#checking the columns

df.columns
```

```
Index(['ID', 'LIMIT_BAL', 'SEX', 'EDUCATION', 'MARRIAGE', 'AGE', 'PAY_0',
       'PAY_2', 'PAY_3', 'PAY_4', 'PAY_5', 'PAY_6', 'BILL_AMT1', 'BILL_AMT2',
       'BILL_AMT3', 'BILL_AMT4', 'BILL_AMT5', 'BILL_AMT6', 'PAY_AMT1',
       'PAY_AMT2', 'PAY_AMT3', 'PAY_AMT4', 'PAY_AMT5', 'PAY_AMT6', 'default'],
      dtype='object')
```

Distribution of data (2 categories)



Data is highly imbalanced

78 percent is credit card amount payed duly

22 percent is credit card default

Data Manipulation

Data Manipulation:

Reduced unknown values to category 4 (Education)

```
df['EDUCATION'].unique()
```

```
array([2, 1, 3, 5, 4, 6, 0])
```

```
#Change values for education  (1 = graduate school; 2 = university; 3 = high school; 4 = others)
#Anything other than 4 will be changed to 4

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

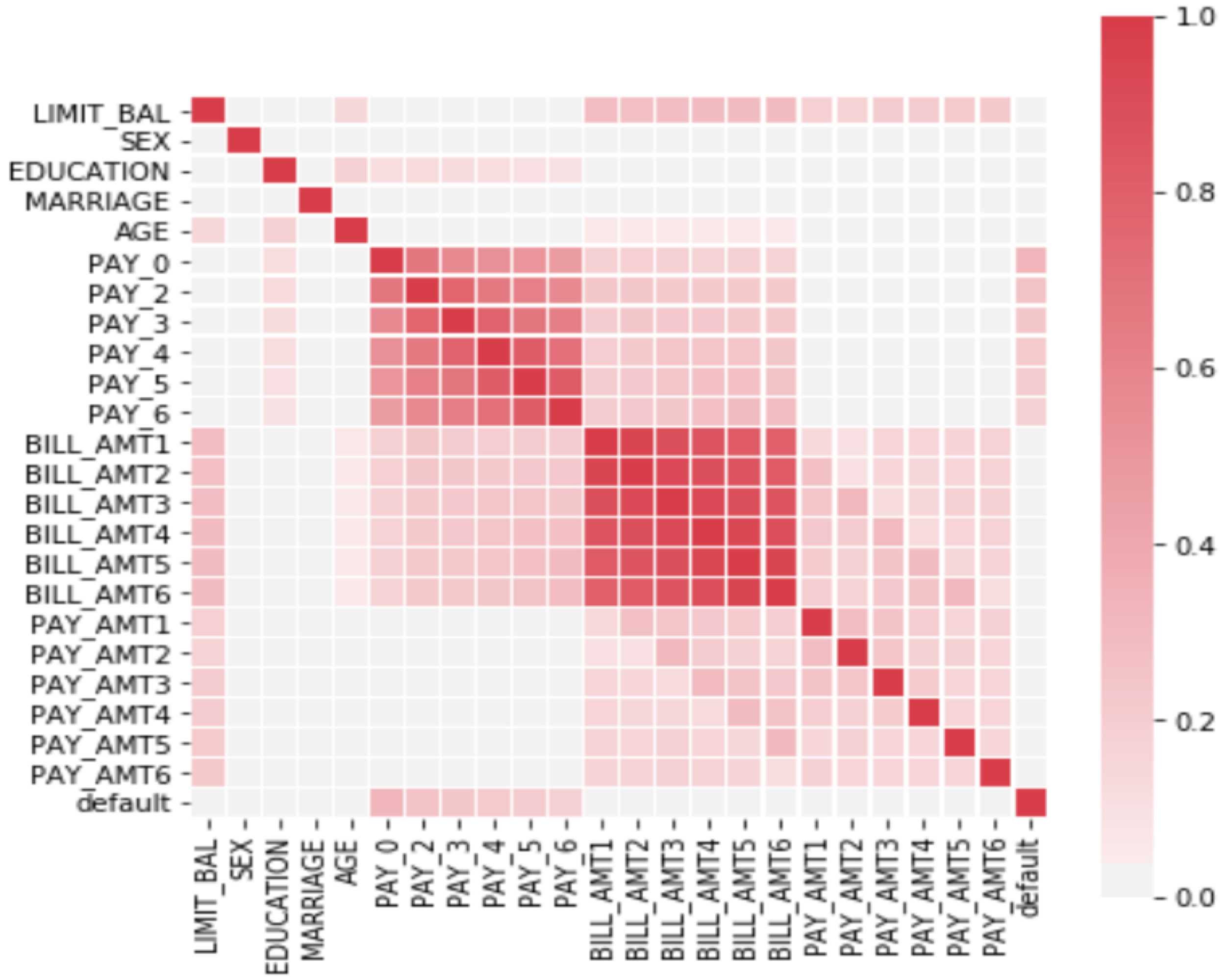
```
2    14030
1    10585
3     4917
4      468
Name: EDUCATION, dtype: int64
```

```
df['MARRIAGE'].unique()
```

```
array([1, 2, 3, 0])
```

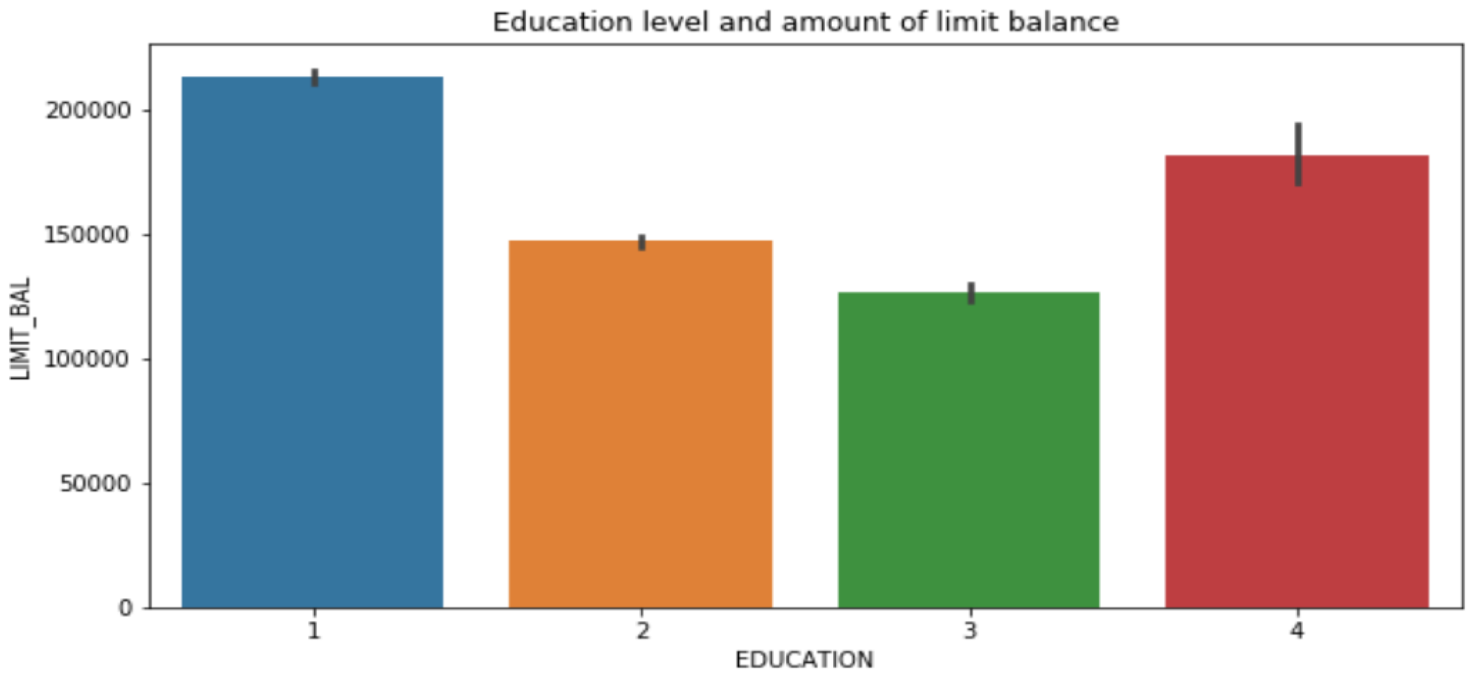
Similar manipulation was performed on various other fields, that had different values other than the ones defined.

Correlation coefficient of variables



Distribution of Education field

1 : graduate school; 2 : university; 3 : high school; 4 : others



Applying Minmax Scaler

```
minmax_scale = preprocessing.MinMaxScaler().fit(df)
df_minmax = minmax_scale.transform(df)
df_minmax = pd.DataFrame(df_minmax, columns= list(df))
df_minmax.hist(figsize=(20,20))
plt.show()
```

Models :(sklearn Library)

- Logistic Regression

Most widely used for Binary classification problem. The sigmoid function snaps values to 0 and 1, and we predict a class value.

- K Nearest Neighbors

For a data point to be classified into two different categories, We find the k nearest neighbors (k is any odd value) Then we use majority voting on the labels. The majority class label is assigned to the data point If k is even then distance is calculated. The shorted distance is used

- Decision Tree Classifier

DTC will segregate the data points based on all values of variables and identify the variable, which creates the best homogeneous sets of data points (which are heterogeneous to each other)

- Random Forest Classifier

Random forests are a way of averaging multiple deep decision trees, trained on different parts of the same training set, with the goal of reducing the variance

Dividing the data into train and test

In [240]:

```
#Perform oversampling to balance the data
X = df_minmax.drop(["default"], axis=1).values #Setting the X to do the split
y = df_minmax["default"].values # transforming the values in array


X_train, X_test, y_train, y_test=train_test_split(X, y, random_state=2, test_size=0.20)


# Separate majority and minority classes
df_majority = df_minmax[df_minmax['default']==0]
df_minority = df_minmax[df_minmax['default']==1]

print(df_majority['default'].count())
print("-----------")
print(df_minority['default'].count())
print("-----------")
print(df['default'].value_counts())
```

```
23364
-----------
6636
-----------
0    23364
1     6636
Name: default, dtype: int64
```

Predictive Modeling on Imbalanced Data

```
from sklearn import linear_model
logreg = linear_model.LogisticRegression(C=1e5)
logreg.fit(X_train, y_train)
prediction = logreg.predict(X_test)
print("accuaracy of model")
a= accuracy_score(y_test, prediction)
a=a*100
print(a)
```

```
accuaracy of model
81.01666666666667
```

Conclusion of running model on imbalanced data:

Since distribution is 78:22 ratio, so running a model yeilds an 80 percent accuarcy. So it makes no sense to run a model on imbalanced data. Even random guess will give this result.

No other model was tried, cause running model on imbalanced data doesn’t serve the purpose.

Random Oversampling of Minority

In [243]:
```
from sklearn.utils import resample

# Upsample minority class
df_minority_oversampling = resample(df_minority,
                                 replace=True,     # sample with replacement
                                 n_samples=22677,    # to match majority class
                                 random_state=587) # reproducible results
# Combine majority class with upsampled minority class
df_oversample = pd.concat([df_majority, df_minority_oversampling])
# Display new class counts
print("Now the distribution of non default and default are almost close")
df_oversample['default'].value_counts()
```

```
Now the distribution of non default and default are almost close
```

Out[243]:
```
0.0    23364
1.0    22677
Name: default, dtype: int64
```

Splitting into train and test 80 percent train, 20 percent test

In [244]:
```
#using the new data frame - oversampled dataframe --- oversampling of minority class

X = df_oversample.drop(["default"], axis=1).values #Setting the X to do the split
y = df_oversample["default"].values # transforming the values in array
X_train, X_test, y_train, y_test=train_test_split(X, y, random_state=2, test_size=0.20)
```

Logistic Regression

[245]:
```
# Create dictionary for storing values of all models

prediction = dict()

#Run the logistic Regression model
#import the linear_model class from sklearn package
from sklearn import linear_model

#create an object of the class, logreg is the object of class LogisticRegression
logreg = linear_model.LogisticRegression(C=1e5)

#call object.fir on (X_train----Set of predictors, Y_train ------target variable. 80 percent is used for training)
logreg.fit(X_train, y_train)
#Model learns from training process
#After training the model -- predict the the class for rest of 20 percent of data
prediction['Logistic'] = logreg.predict(X_test)

#after predicting we check for the accuracy
#Accuracy is defined as comparison between the actual class of target variable from the test data vs predicted
print("accuaracy of model")
a= accuracy_score(y_test, prediction['Logistic'])
a=a*100
print(a)


#Print the confusion matrix
#Confusion matrix is classifying Actual and predicted
#False negative ---Predicted as negative but actually positive
#True Positive ----Predicted as positive and actually positive
#True Negative ---- Predicted as negative  and actually negative
#False Positive----Predicted as positive but actually negative
from sklearn.metrics import confusion_matrix
confusion_matrix = confusion_matrix(y_test,prediction['Logistic'])
```

K Nearest Neighbors

In [246]:

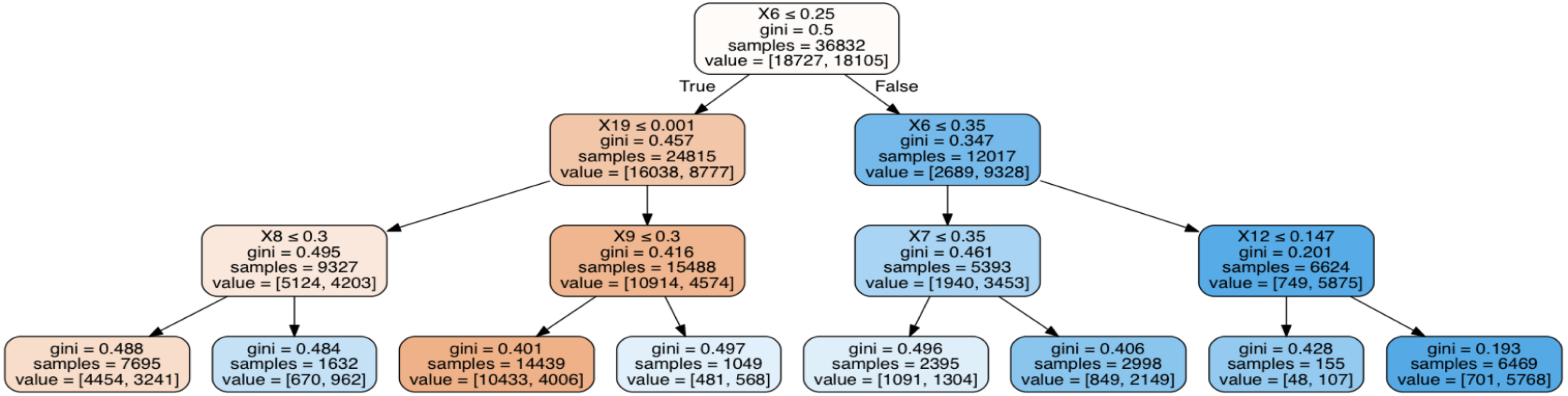
```
from sklearn.neighbors import KNeighborsClassifier
classifier = KNeighborsClassifier(n_neighbors=5)
classifier.fit(X_train, y_train)
prediction['KNN']= classifier.predict(X_test)
print("accuaracy of model")
a= accuracy_score(y_test, prediction['KNN'])
a=a*100
print(a)


from sklearn.metrics import confusion_matrix
confusion_matrix = confusion_matrix(y_test,prediction['KNN'])

#print(confusion_matrix)
import scikitplot as skplt
skplt.metrics.plot_confusion_matrix(y_test, prediction['KNN'])
plt.show()

skplt.metrics.plot_confusion_matrix(y_test, prediction['KNN'],normalize=True)
plt.show()


average_precision = average_precision_score(y_test,prediction['KNN'])

print('Average precision-recall score: {0:0.2f}'.format(
      average_precision))
```

Decision Tree Classifier

In [247]:

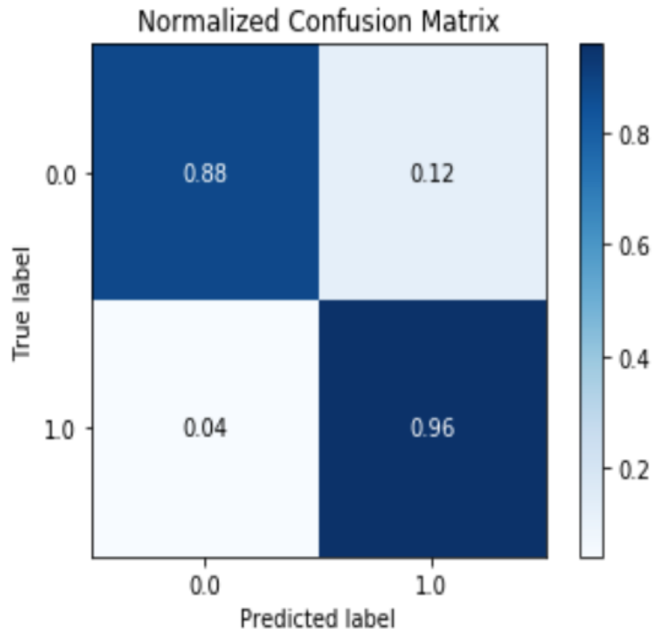
```
#Calling the Decision TRee Classifier class
clf_gini = DecisionTreeClassifier(criterion = "gini", random_state = 100,
                               max_depth=3, min_samples_leaf=5)
clf_gini.fit(X_train, y_train)

prediction['DecisionTree'] = clf_gini.predict(X_test)
print("accuracy of the model")
a=accuracy_score(y_test, prediction['DecisionTree'])
a=a*100
print(a)
```

Out[248]:



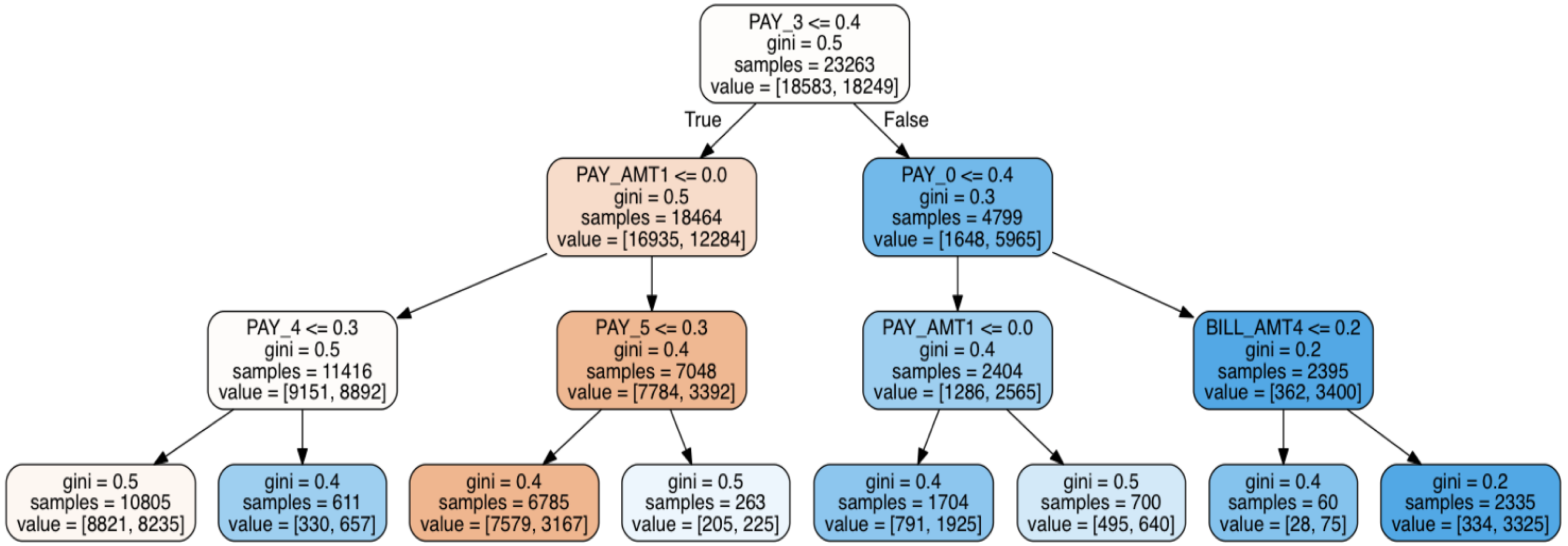
Random Forest Classifier

```
In [249]: #calling the RandomForest Classifier


          clf = RandomForestClassifier(n_jobs=1000,
                                       random_state=9,
                                       #criterion=RFC_METRIC,
                                       n_estimators=11,
                                       verbose=False)
          clf.fit(X_train,y_train)
          prediction['RandomForest'] = clf.predict(X_test)
          a= accuracy_score(prediction['RandomForest'], y_test)
          a= a*100
          print(a)


          from sklearn.metrics import confusion_matrix
          confusion_matrix = confusion_matrix(y_test,prediction['RandomForest']
```



Random Forest Tree

Out[250]:

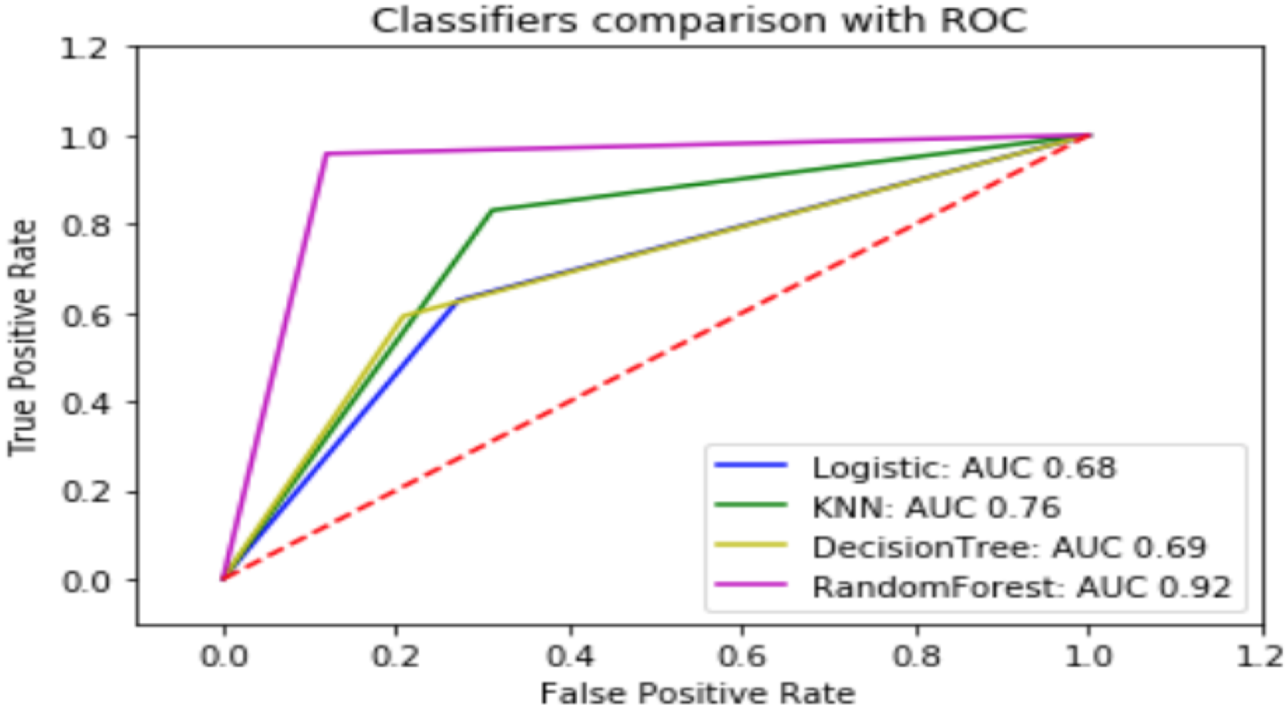


Running model on Randomly Oversampled Data

```
from sklearn.metrics import accuracy_score

cmp = 0
for model, predicted in prediction.items():
    accuracy = accuracy_score(y_test, predicted)
    accuracy
    print(model, accuracy*100)
    cmp += 1
```

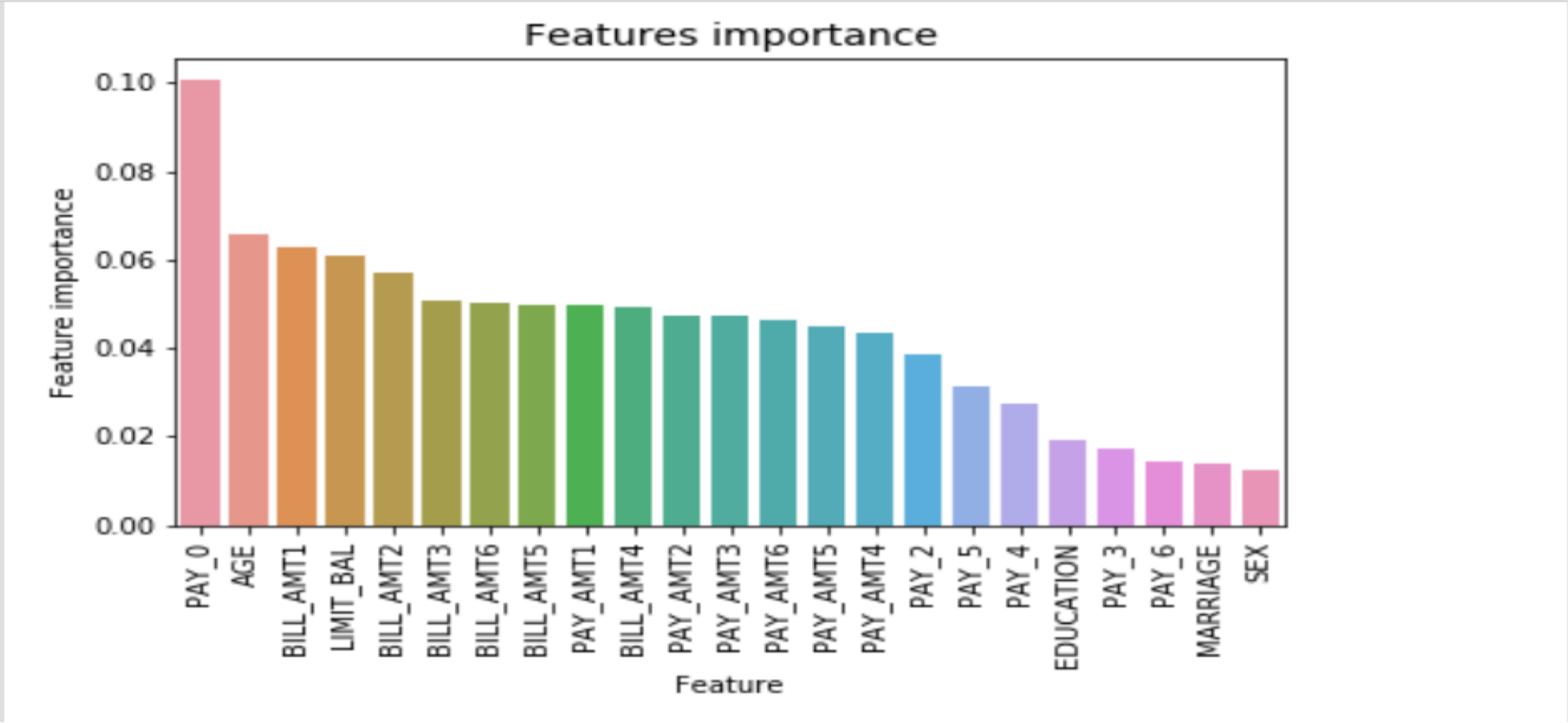
```
Logistic 67.86838961885113
KNN 75.93658377674014
DecisionTree 69.26919318058421
RandomForest 91.91008795743295
```

Receiver Operator Characteristic
(Area under curve)



Feature Selection

- We can select the best features based on the correlation coefficient of predictors with target . (forward ,backward, automated(random forest))



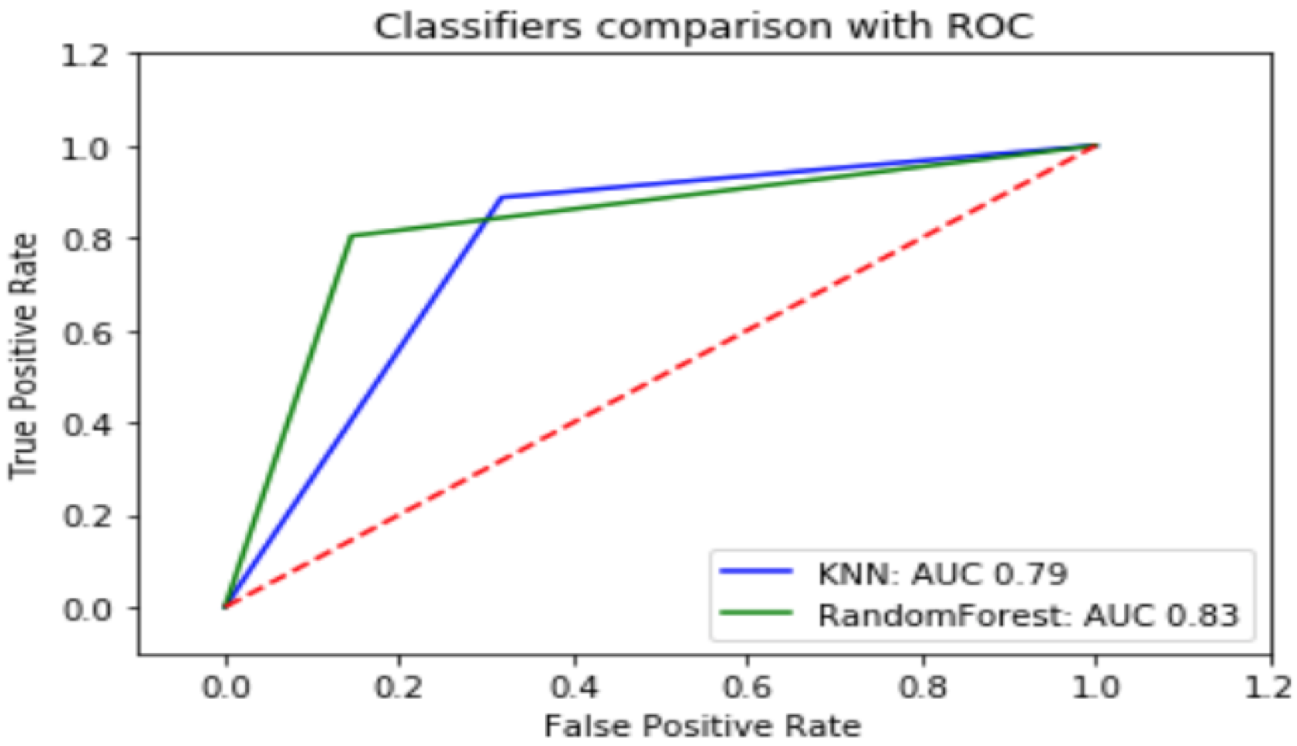
SMOTE

- **Using SMOTE - Synthetic Minority Oversampling Technique**
- over-sampling approach in which the minority class is over-sampled by creating synthetic examples , that is learning from the data and generating data points.
- Reduces the chance of overfitting
- Accuracy

➢ KNN 78.45067408517012

➢ Random Forest -83.59726086026107

Receiver Operator Characteristic (Area under curve)



Learning Processes

- Using MinMax Scaler to Normalize data.
- Understanding the effect of unbalanced data
- Random oversampling of minority class, under sampling of majority class, SMOTE.
- Using Sklearn library for running various models.
- Using feature engineering.
- Understanding confusion matrix , accuracy and Receiver Operator characteristic concepts.(precision /recall)
- Understanding the concepts behind each model
- Logistic Regression (sigmoid function)
- KNN – Nearest neighbors, odd value of K and majority vote.
- Decision Tree/ Random Forest – Condition based classification, with second being more deeper.

Conclusion

- The most important parameters in determining default of credit cards are the Repayment status variable.
- With Random oversampling of data and Random Forest classifier, achieves the best accuracy of 91 percent , with precision – recall score of 0.87 and area under curve of 0.92
- With , SMOTE Random Forest Classifier , achieves the best accuracy of 82 percent , with precision – recall score of 0.79 and area under curve of 0.83
- KNN is the next best model.
- Random Under sampling didn't yield great results because of less data points.