Credit card fraud detection using Machine Learning algorithms.

The dataset as such is severely imbalanced with the percentage of fraud transactions being 0.172% of the total data. The dataset contains only transformed numerical features which are a result of a PCA transormation. The original data is not provided to us due to security reasons and to protect the identity of the customers.

Having said that, there are two features which are not transformed using PCA - 'Time' and 'Amount'. These features are given as it is. The 'Time' feature basically says how much time for each transaction has elapsed since the first transaction in the dataset has taken place. The 'Amount' feature gives us information about the transaction amount for each of the transactions. The fraudulent transactions are denoted by class label 1 and the non fraudulent transactions are denoted by class label 0.

What are our main goals for this problem?

1. We will leverage the the very small data that is provided to us.
2. We will implement standard outlier detection algorithms like LOF and see how successful they are in detecting fradulent transactions.
3. For implementing Machine Learning models, we will follow two approaches for resampling ofour data: First, we will undersample the data and create a balanced dataset containing equal number of points from both the classes. Second, we will oversample the dataset by adding synthetic points using SMOTE sampling technique.
4. We will also leverage the concept of Autoencoders and build an encoder-decoder neural network which will be used to learn the low level representations of the transformed PCA data.
5. Lastly, we will compare all our models and see which models turns out to better than the rest.

What is the business problem that we are trying to solve?

Credit card fraud refers to a wide range of activities which includes theft of money using either credit cards or debit cards. The theft can be either online or ofline. An ofline theft generally involves withdrawing money from an ATM machine physically using a stolen credit card. An online theft involves any online transaction using the card without the prior consent of the owner. Both as a customer and as a bank, fraudulent credit card transactions can give you nightmares! From a bank's point of view, it's very essential to identify whether a transaction is fraudulent or not because they don't want to lose money or don't want to lose the faith that there customer has entrusted upon them. In such a scenario it becomes a necessity to build a robust system which can be used to determined fraudulent transactions.

While designing the system we should keep in mind that the cost of misclassification of a fraudulent transaction is very high. We don't to end up with a system which might classify a fradulent transaction as a non-fradulent one. Such a system in machine learning is also called a high recall system. It's important for the bank to know which of the transactions are fraud, at the same time it is important to understand which of the transactions are not fraud.

What are the real world business constraints and what metrics we will use to evaluate our model?

The dataset that we have is a real world dataset which is severely imbalanced. This is expected because if you imagine, the number of valid transactions has to be much much greater than the number of fraud transactions in the world, or else everyone would have been bankrupt by now! Due to the severely imbalanced dataset building the best Machine Learning models will be a challenge. But this is a constraint we have to deal with. Since the dataset is imbalanced we will use roc-auc as our key metric.

Another important factor we must keep in mind is the cost of making an incorrect prediction for the fraudulent class is very very high. It's okay if the model classifies a non-fraudulent transaction as a fraudulent one, but classifying a fraudulent transaction as a non-fradulent one is very very costly, because at the end of the day no one want to lose money. Due to this reason we must always keep a close look at the recall metric and make sure that the false negatives are as low as possible. We will print the confusion matrix and generate classification reports for each models and monitor the false positives.

Exploratory data analysis.

Let's look at the data that is provided to us. The CSV file has been downloaded and renamed to 'data.csv'. The dataset contains 284807 transactions out of which only 492 (0.1727%) transactions are fraud. There are 28 PCA transformed features that are provided to us. These PCA features are not at all interpretable. A high level statistics of the dataset reveals that almost 50% transactions involved 22 dollars or less, almost 75% transactions involves amount less than 77 dollars. The highest transaction amount in a fraudulent scenario is 2125 dollars, whereas the highest transaction recorded in case of a non fraud scenario is 25691 dollars. The median values of all the fraudulent transactions is 9 dollars whereas the median values of all the non fraud transactions is 22 dollars.

In [ ]:

```
#Import the libraries
import pandas as pd
import numpy as np
import seaborn as sn
import matplotlib.pyplot as plt
sn.set(style="darkgrid")
from sklearn.metrics import confusion_matrix
from sklearn.metrics.classification import log_loss
from datetime import datetime as dt
from sklearn import metrics
from sklearn.calibration import CalibratedClassifierCV

import warnings
warnings.filterwarnings("ignore")
```

In [2]:

```
#Read the dataset. Data CSV file has been renamed to data.csv
data=pd.read_csv("data.csv")
data.head()
```

Out[2]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.08510
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.24767
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.37743
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.27053

5 rows × 31 columns

In [3]:

```
#Get the column names
print([i for i in data.columns]) #Here we could have simply done data.columns, but it w
ould have returned a slightly different output. Index and object type additional inform
atinon.
```

```
['Time', 'V1', 'V2', 'V3', 'V4', 'V5', 'V6', 'V7', 'V8', 'V9', 'V10', 'V1
1', 'V12', 'V13', 'V14', 'V15', 'V16', 'V17', 'V18', 'V19', 'V20', 'V21',
'V22', 'V23', 'V24', 'V25', 'V26', 'V27', 'V28', 'Amount', 'Class']
```

Time is basically the number of seconds elapsed between a transaction and the first transaction in the dataset. We will leverage this to build a time based model.

In [4]:

```
#Get high level statistical view of the dataset
data.describe()
```

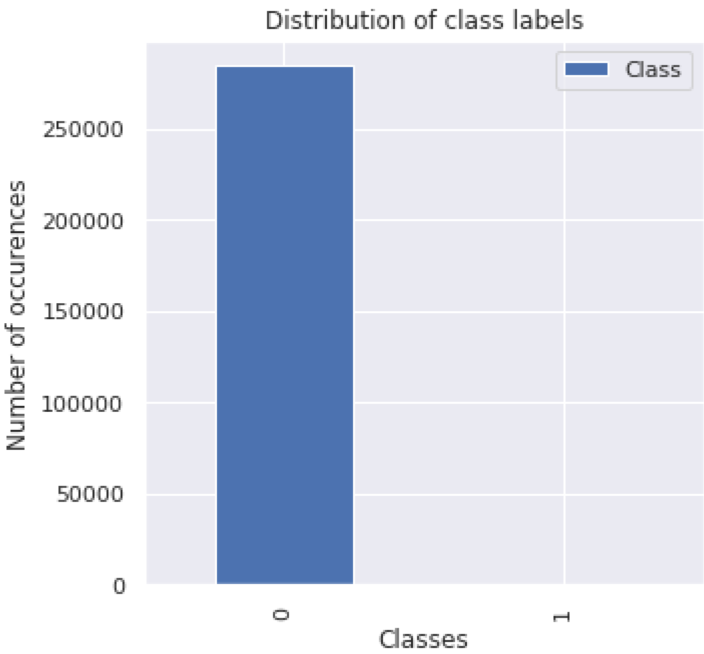
Out[4]:

	Time	V1	V2	V3	V4	
count	284807.000000	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e
mean	94813.859575	3.919560e-15	5.688174e-16	-8.769071e-15	2.782312e-15	-1.552563
std	47488.145955	1.958696e+00	1.651309e+00	1.516255e+00	1.415869e+00	1.380247e
min	0.000000	-5.640751e+01	-7.271573e+01	-4.832559e+01	-5.683171e+00	-1.137433e
25%	54201.500000	-9.203734e-01	-5.985499e-01	-8.903648e-01	-8.486401e-01	-6.915971
50%	84692.000000	1.810880e-02	6.548556e-02	1.798463e-01	-1.984653e-02	-5.433583
75%	139320.500000	1.315642e+00	8.037239e-01	1.027196e+00	7.433413e-01	6.119264
max	172792.000000	2.454930e+00	2.205773e+01	9.382558e+00	1.687534e+01	3.480167e

8 rows × 31 columns

In [5]:

```
#Check the class distribution in the given data
data['Class'].value_counts().plot(figsize=(5,5),kind='bar',legend='True')
plt.title("Distribution of class labels")
plt.xlabel("Classes")
plt.ylabel("Number of occurences")
plt.show()
```



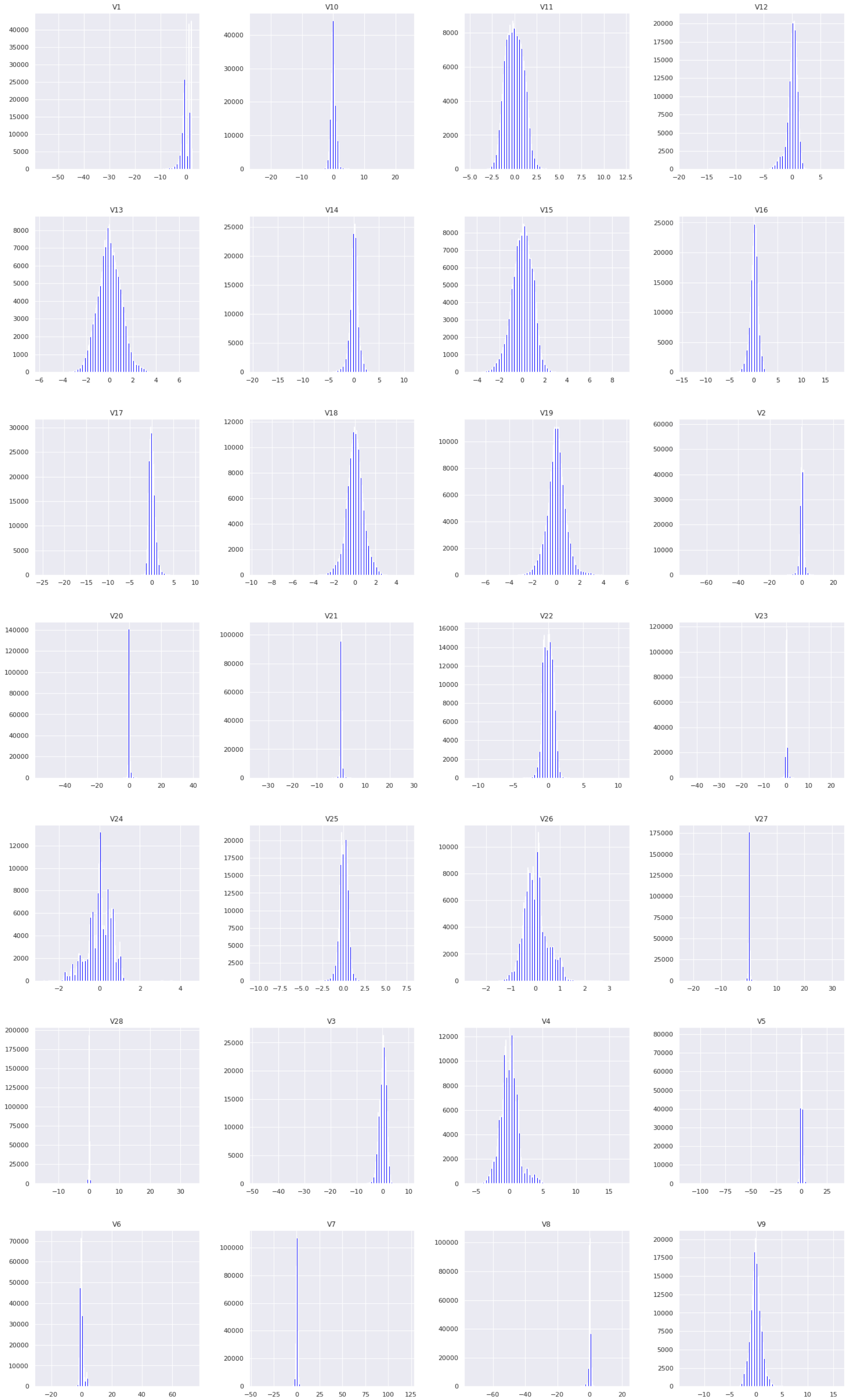
In [6]:

```
#Get percentage fradulent information
not_fraud=data[data['Class']==0].shape[0]
fraud=data[data['Class']==1].shape[0]
total=fraud+not_fraud

print("Percentage of Fradulent transaction: {}".format(np.round(100*fraud/total,4)))
print("Percentage of Non Fradulent transaction: {}".format(np.round(100*not_fraud/total
,4)))
```

```
Percentage of Fradulent transaction: 0.1727
Percentage of Non Fradulent transaction: 99.8273
```

In [7]:

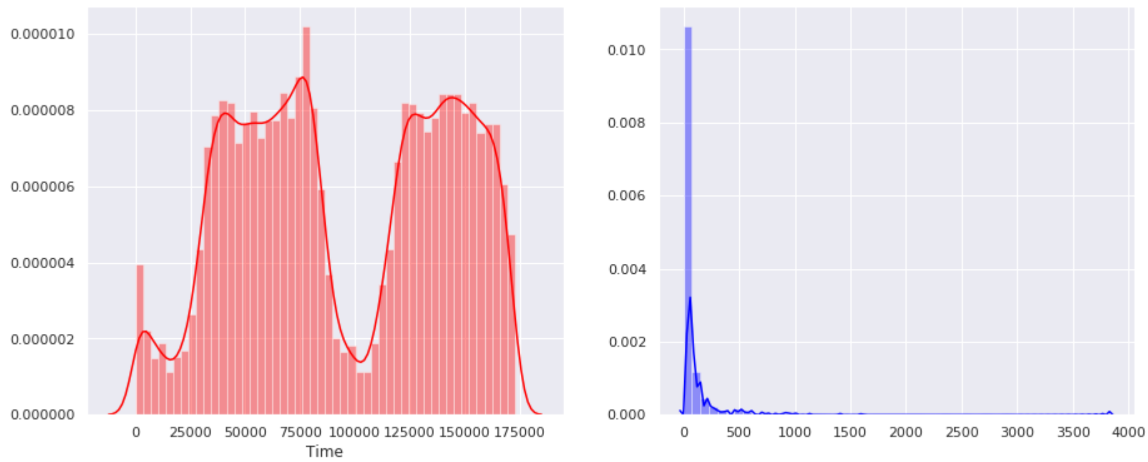
```
#Check the distribution of all the independent variables
data.drop(['Class','Amount','Time'],axis=1).hist(bins=200,color='blue',figsize=(25,50),
layout=(8,4))
plt.show()
```


V1
V10
V11
V12
V13
V14
V15
V16
V17
V18
V19
V2
V20
V21
V22
V23
V24
V25
V26
V27
V28
V3
V4
V5
V6
V7
V8
V9

By looking at the distribution of all the features we can see that there are some features whose distributions are skewed to the left, there are some features whose distributions are skewed to the right and there are some features which appears to have a normal gaussian distribution. Almost all the features have their distributions mean at 0. Some features like V11, V15, V13, V18, V19 has a wider spread compared to other features. Some features like V6, V7, V8 and V28 have a very low spread as compared to other features.

In [8]:

```
#Check the dsitribution of time and amount features
plt.figure(figsize=(15,6))
plt.subplot(1,2,1)
sn.distplot(data['Time'],color='red')
plt.subplot(1,2,2)
sn.distplot(sorted(data['Amount'][0:1000]),color='blue')
plt.show()
```



On EDA of the 'Time' feature, we can see that the number of transactions falls sharply during a particular time interval. There are some regions of time where the number of transactions are very high and there some regions in time where the number of transactions are very low.

On EDA of the 'Amount' features, we see that the distribution is highly skewed towards the left. There are very small number of higher value transactions which happens in the course of 2 days.

In [34]:

```
#Let us get some basic information about the amount columns
print("The lowest transaction amount is: $",data['Amount'].min())
print("The highest transaction amount is: $",data['Amount'].max())
print("The median transaction amount is: $",data['Amount'].median())
print("The average transaction amount is: $",data['Amount'].mean())

print("\nThe lowest transaction amount for fraud transaction is: $",data[data.Class ==
1]['Amount'].min())
print("The highest transaction amount for fraud transaction is: $",data[data.Class == 1
]['Amount'].max())
print("The median transaction amount for fraud transaction is: $",data[data.Class == 1]
['Amount'].median())
print("The average transaction amount for fraud transaction is: $",data[data.Class == 1
]['Amount'].mean())

print("\nThe lowest transaction amount for non fraud transaction is: $",data[data.Class
== 0]['Amount'].min())
print("The highest transaction amount for non fraud transaction is: $",data[data.Class
== 0]['Amount'].max())
print("The median transaction amount for non fraud transaction is: $",data[data.Class =
= 0]['Amount'].median())
print("The average transaction amount for non fraud transaction is: $",data[data.Class
== 0]['Amount'].mean())
```

```
The lowest transaction amount is: $ 0.0
The highest transaction amount is: $ 25691.16
The median transaction amount is: $ 22.0
The average transaction amount is: $ 88.34961925087359

The lowest transaction amount for fraud transaction is: $ 0.0
The highest transaction amount for fraud transaction is: $ 2125.87
The median transaction amount for fraud transaction is: $ 9.25
The average transaction amount for fraud transaction is: $ 122.21132113821
133

The lowest transaction amount for non fraud transaction is: $ 0.0
The highest transaction amount for non fraud transaction is: $ 25691.16
The median transaction amount for non fraud transaction is: $ 22.0
The average transaction amount for non fraud transaction is: $ 88.29102242
225574
```

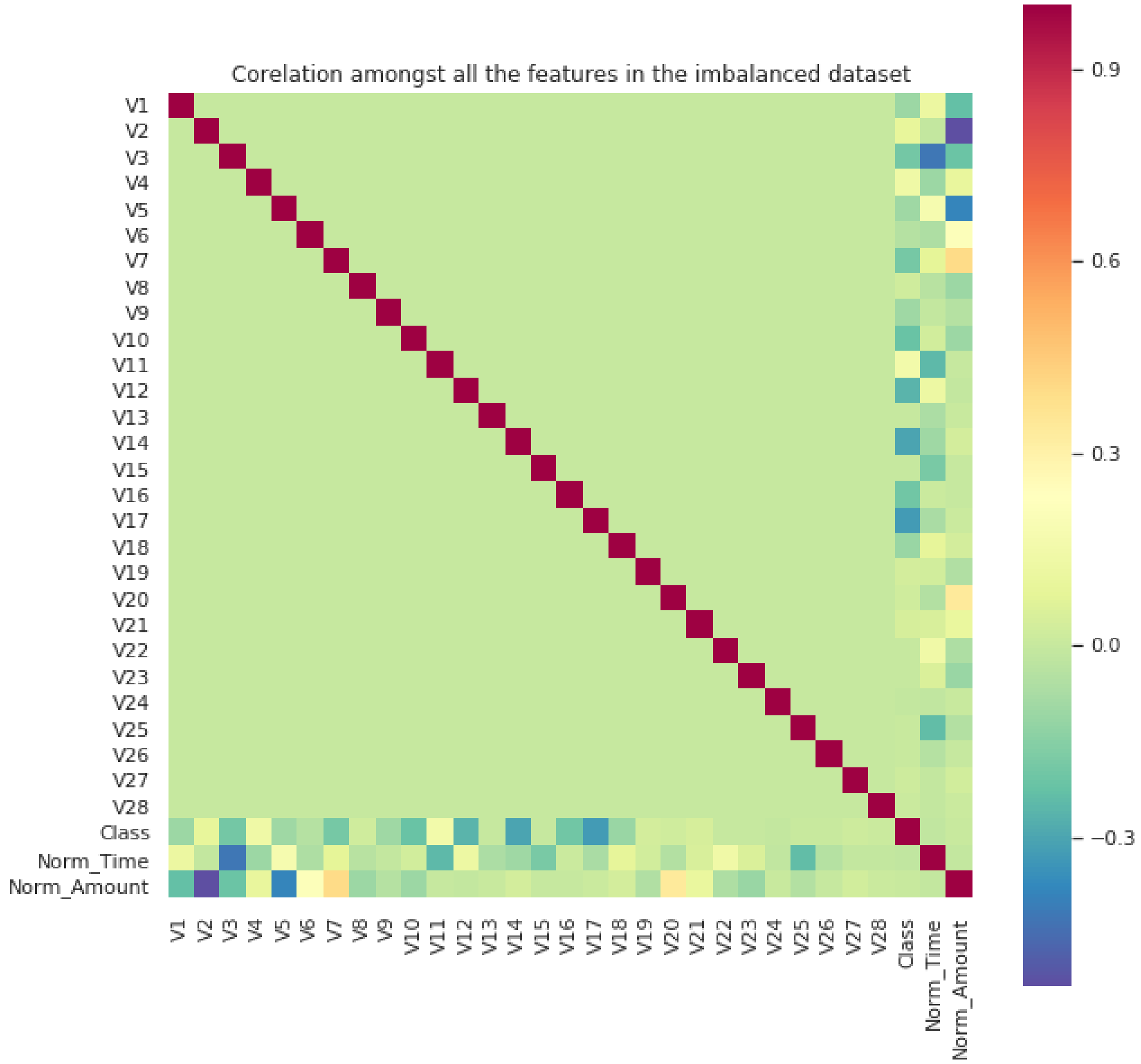
Before proceeding to build ML models we will column standardize both the time as well amount features. In this way we can ensure that both the time and amount features are at scale with the remaining features.

In [9]:

```
#Colum standardize the time and amount column
from sklearn.preprocessing import StandardScaler
data["Norm_Time"]=StandardScaler().fit_transform(data['Time'].values.reshape(-1,1))
data["Norm_Amount"]=StandardScaler().fit_transform(data['Amount'].values.reshape(-1,1))
data=data.drop(["Amount","Time"], axis=1)
```

In [10]:

```
#Get Corelation Matrix between all the features present in the data
cor_matr = data.corr()
plt.figure(figsize=(10,10))
sn.heatmap(cor_matr,square='True',cmap='Spectral_r')
plt.title('Corelation amongst all the features in the imbalanced dataset')
plt.show()
```



Using seaborn we can draw corelation heatmaps which are basically same as corelation matrices. In case of a corelation heatmaps we will use color codings instead of corelation coefficient values to determine whether features have a positive or a negative corelation. A red color indicates the features have a strong positive corelation between them and a blue color indicates that two features have a strong negative corelation between themeselves.

In [11]:

```
#Implement LOF for the imabalanced data set and get information about class
from sklearn.neighbors import LocalOutlierFactor
from sklearn.metrics import classification_report, accuracy_score, recall_score
import gc
X=data.drop(['Class'],axis=1)
y_actual=data['Class'].values

neighbors=[10,20,30,50,70,100,150,200,300, 350, 400, 450, 500, 600]
recall_scores=[]
for n in neighbors:
    model=LocalOutlierFactor(n_neighbors=n,n_jobs=-1,contamination=fraud/total)
    y_pred = model.fit_predict(X)
    # Reshape the prediction values to 0 for valid, 1 for fraud.
    y_pred[y_pred == 1] = 0
    y_pred[y_pred == -1] = 1
    score=recall_score(y_actual,y_pred)
    recall_scores.append(score)
    print("\nRecall scores for neighbors = {} is = {}".format(n,score))
    print("Accuracy scores for neighbors = {} is = {}".format(n,accuracy_score(y_actual
,y_pred)))
    gc.collect()
```

```
Recall scores for neighbors = 10 is = 0.0
Accuracy scores for neighbors = 10 is = 0.9965450287387599

Recall scores for neighbors = 20 is = 0.0
Accuracy scores for neighbors = 20 is = 0.9965450287387599

Recall scores for neighbors = 30 is = 0.0
Accuracy scores for neighbors = 30 is = 0.9965450287387599

Recall scores for neighbors = 50 is = 0.0
Accuracy scores for neighbors = 50 is = 0.9965450287387599

Recall scores for neighbors = 70 is = 0.016260162601626018
Accuracy scores for neighbors = 70 is = 0.9966012071332516

Recall scores for neighbors = 100 is = 0.018292682926829267
Accuracy scores for neighbors = 100 is = 0.9966082294325631

Recall scores for neighbors = 150 is = 0.024390243902439025
Accuracy scores for neighbors = 150 is = 0.9966292963304975

Recall scores for neighbors = 200 is = 0.042682926829268296
Accuracy scores for neighbors = 200 is = 0.9966924970243006

Recall scores for neighbors = 300 is = 0.15040650406504066
Accuracy scores for neighbors = 300 is = 0.9970646788878083

Recall scores for neighbors = 350 is = 0.2032520325203252
Accuracy scores for neighbors = 350 is = 0.9972472586699063

Recall scores for neighbors = 400 is = 0.23373983739837398
Accuracy scores for neighbors = 400 is = 0.9973525931595782

Recall scores for neighbors = 450 is = 0.31910569105691056
Accuracy scores for neighbors = 450 is = 0.9976475297306597

Recall scores for neighbors = 500 is = 0.42886178861788615
Accuracy scores for neighbors = 500 is = 0.9980267338934787

Recall scores for neighbors = 600 is = 0.5447154471544715
Accuracy scores for neighbors = 600 is = 0.9984270049542322
```

Under-sample the dataset to balance the classes

Since the dataset is highly imbalanced there are broadly two strategies we will follow to correctly sample our dataset - under-sampling the dataset and over-sampling the dataset.

In this section we will use a data under-sampling technique where we will sample the data based on the number of instances we have in our minority class. In order to create the final dataset, we will take equal number of sample from both the classes, concatenate them into a single dataset and perform random shuffling to shuffle the data. The resultant dataset will contain 50% points from each of the classes.

Under-sampling helps us get rid of the problem of data imbalanced, but at the same time we are discarding huge amount of data to build our models. We can negate this by using certain data over sampling strategies. In a later section, we will implement something called SMOTE algorithm - a technique used to oversample an imbalanced dataset by adding synthetic points. We will discuss about SMOTE when we implement it.

In [11]:

```
state=48
```

In [12]:

```
#Number of data_fraudulent transaction in the whole data
data_fraud=data[data['Class']==1]
data_valid=data[data['Class']==0].sample(data_fraud.shape[0],random_state=state)
data_under=pd.concat([data_fraud,data_valid])

#We will shuffle our dataset after concatenating
data_under = data_under.sample(frac=1).reset_index(drop=True)
data_under.head()
```

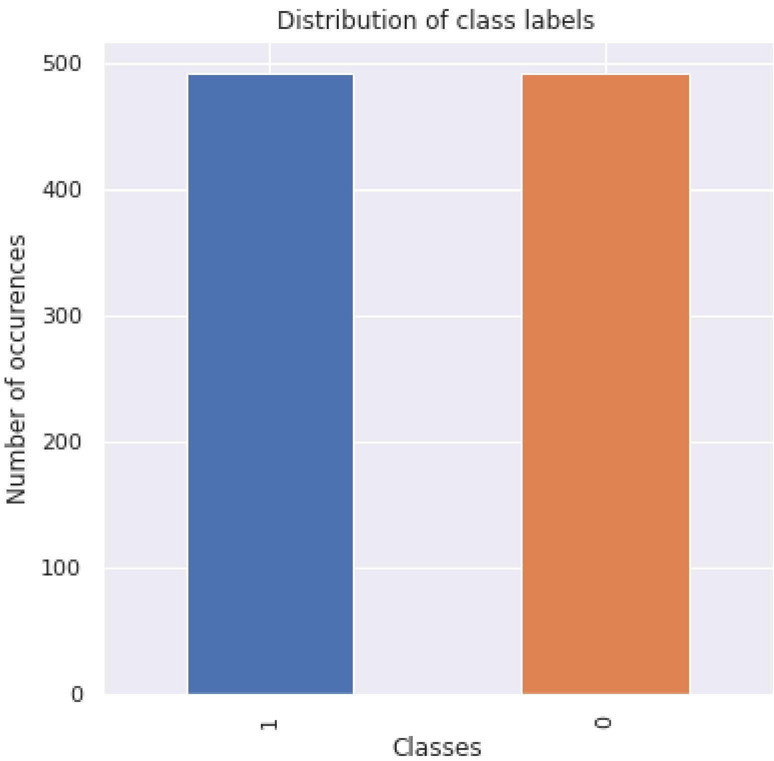
Out[12]:

	V1	V2	V3	V4	V5	V6	V7	V8
0	-1.600211	-3.488130	-6.459303	3.246816	-1.614608	-1.260375	0.288223	-0.048964
1	-24.590245	14.044567	-26.278701	6.320089	-18.224513	-4.609968	-17.681003	16.213627
2	-1.229669	1.956099	-0.851198	2.796987	-1.913977	-0.044934	-1.340739	-0.555548
3	-1.824295	0.403327	-1.994122	2.756558	-3.139064	0.408185	-1.209045	1.095634
4	0.667714	3.041502	-5.845112	5.967587	0.213863	-1.462923	-2.688761	0.677764

5 rows × 31 columns

In [13]:

```
#Check the class distribution in the given data
data_under['Class'].value_counts().plot(figsize=(6,6),kind='bar')
plt.title("Distribution of class labels")
plt.xlabel("Classes")
plt.ylabel("Number of occurences")
plt.show()
```



As we can see, the distribution of class labels is almost equal after we have under-sampled the dataset. This under-sampled dataset now contains 50% class labels from the fraudulent class and 50% class labels from the non fraudulent class.

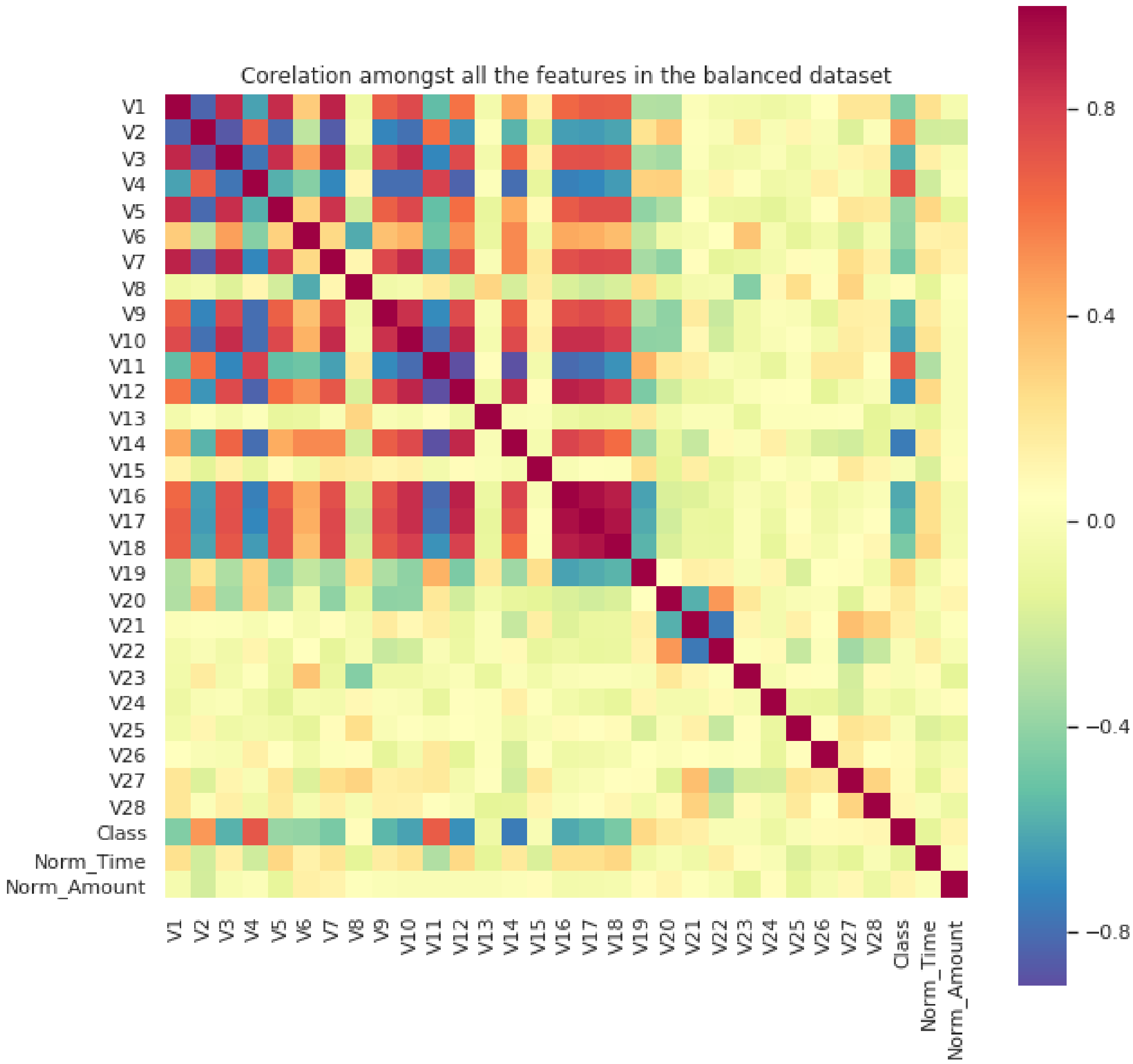
In [14]:

```
#Get percentage fradulent information in the balanced dataset
not_fraud=data_under[data_under['Class']==0].shape[0]
fraud=data_under[data_under['Class']==1].shape[0]
total=fraud+not_fraud

print("Percentage of Fradulent transaction: {}".format(np.round(100*fraud/total,4)))
print("Percentage of Non Fradulent transaction: {}".format(np.round(100*not_fraud/total
,4)))
```

```
Percentage of Fradulent transaction: 50.0
Percentage of Non Fradulent transaction: 50.0
```

In [15]:

```
#Get Corelation Matrix between all the features present in the under sampled data
cor_matr = data_under.corr()
plt.figure(figsize=(10,10))
sn.heatmap(cor_matr,square='True',cmap='Spectral_r')
plt.title('Corelation amongst all the features in the balanced dataset')
plt.show()
```

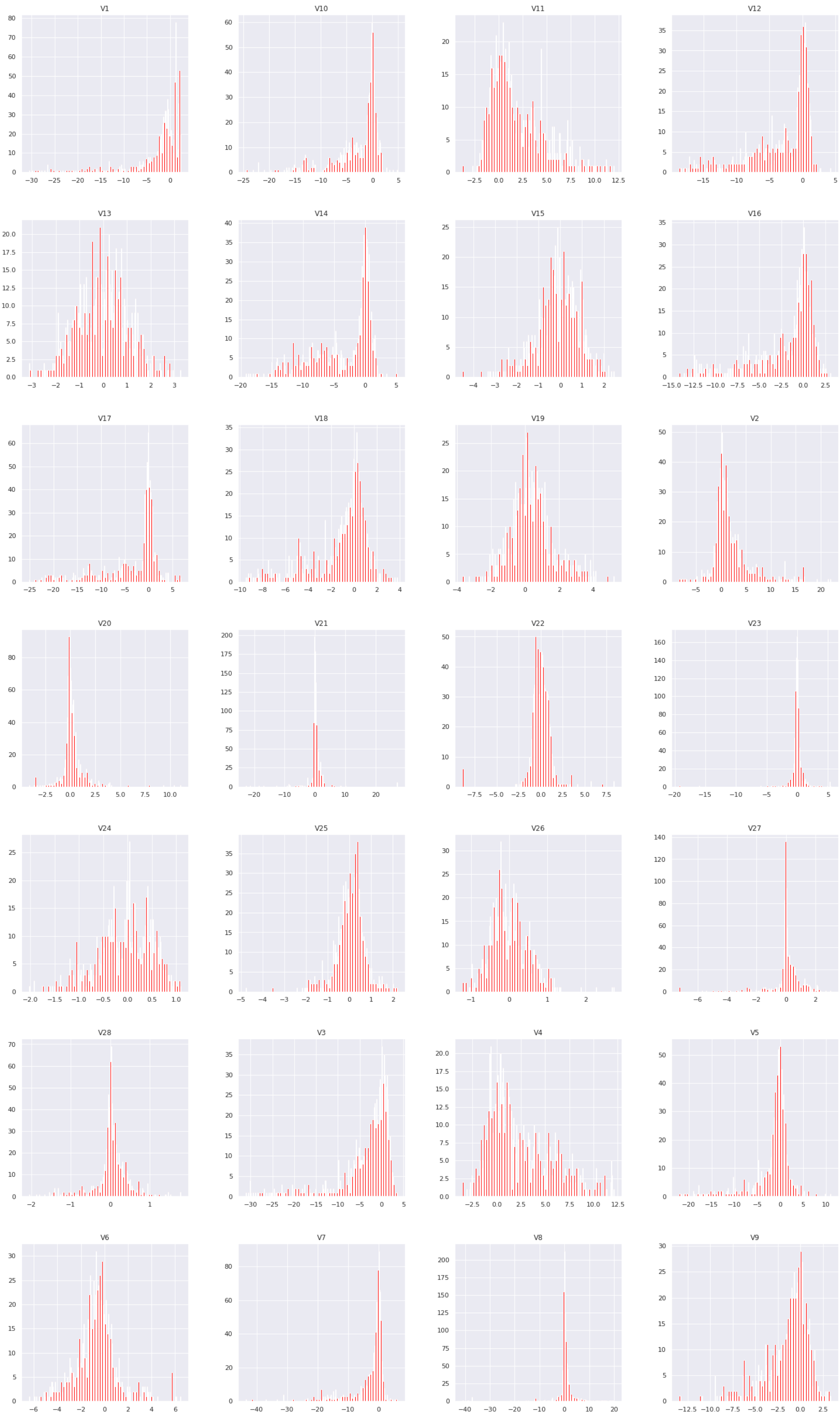


In the corelation heatmap above, we can see that there are some features like V2, V4, V11, V19 which has a strong positive corelation to the class label. This means as the value of these features increases, there is a higher chance that a transaction will be fraudulent one.

The features V3, V10, V12, V14 and V16 seems to have a higher negative corelation to the class labels. This means as these value decreases there is a higher chance that a transaction will be a fraudulent one.

In [29]:

```
#Check the distribution of all the independent variables for the under sampled dataset
data_under.drop(['Class','Norm_Amount','Norm_Time'],axis=1).hist(bins=200,color='red',f
igsize=(25,50),layout=(8,4))
plt.show()
```


V1
V10
V11
V12
V13
V14
V15
V16
V17
V18
V19
V2
V20
V21
V22
V23
V24
V25
V26
V27
V28
V3
V4
V5
V6
V7
V8
V9

In [16]:

```
features=[i for i in data_under.drop(['Class','Norm_Amount','Norm_Time'],axis=1).column
s]
len(features)
```

Out[16]:

28

Box Plots

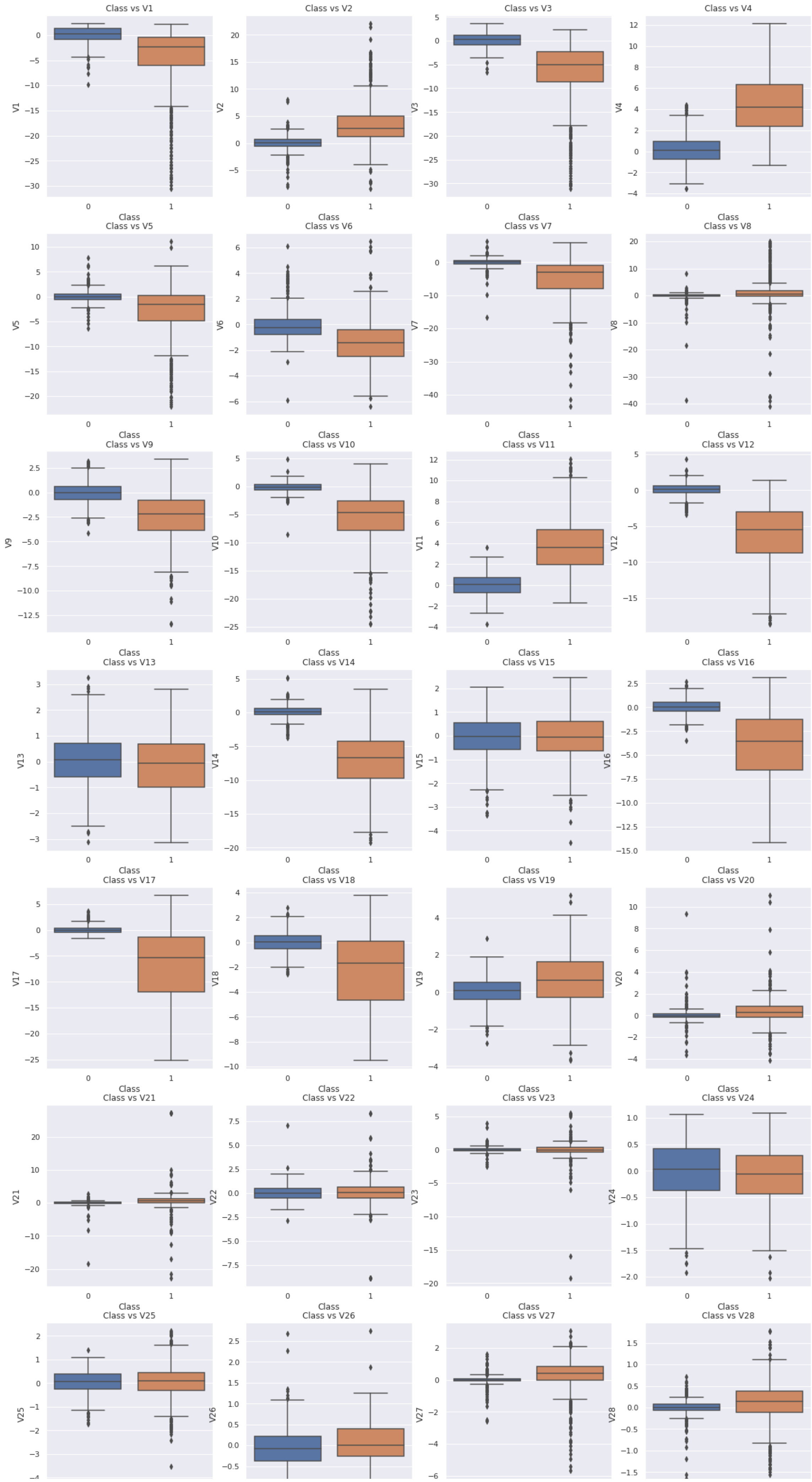
What is a box-plot and why is it useful?

Box plot is a very powerful statistical tool which can be used to represent statistical information like median, quantiles and inter-quartile range in a single plot.

In [17]:

```
#Draw box plots of all the features
plt.figure(figsize=(14, 8))

fig, axes = plt.subplots(nrows=7, ncols=4, figsize=(20,40))

i_ax=0
for i in range(len(features[0:4])):
    sn.boxplot(x="Class", y=features[i], data=data_under, ax=axes[i_ax,i])
    axes[i_ax,i].set_title('Class vs {}'.format(features[i]))

i_ax=1
for i in range(len(features[4:8])):
    sn.boxplot(x="Class", y=features[4+i], data=data_under, ax=axes[i_ax,i])
    axes[i_ax,i].set_title('Class vs {}'.format(features[4+i]))

i_ax=2
for i in range(len(features[8:12])):
    sn.boxplot(x="Class", y=features[8+i], data=data_under, ax=axes[i_ax,i])
    axes[i_ax,i].set_title('Class vs {}'.format(features[8+i]))

i_ax=3
for i in range(len(features[12:16])):
    sn.boxplot(x="Class", y=features[12+i], data=data_under, ax=axes[i_ax,i])
    axes[i_ax,i].set_title('Class vs {}'.format(features[12+i]))

i_ax=4
for i in range(len(features[16:20])):
    sn.boxplot(x="Class", y=features[16+i], data=data_under, ax=axes[i_ax,i])
    axes[i_ax,i].set_title('Class vs {}'.format(features[16+i]))

i_ax=5
for i in range(len(features[20:24])):
    sn.boxplot(x="Class", y=features[20+i], data=data_under, ax=axes[i_ax,i])
    axes[i_ax,i].set_title('Class vs {}'.format(features[20+i]))

i_ax=6
for i in range(len(features[24:28])):
    sn.boxplot(x="Class", y=features[24+i], data=data_under, ax=axes[i_ax,i])
    axes[i_ax,i].set_title('Class vs {}'.format(features[24+i]))

i_ax=7
for i in range(len(features[28:32])):
    sn.boxplot(x="Class", y=features[28+i], data=data_under, ax=axes[i_ax,i])
    axes[i_ax,i].set_title('Class vs {}'.format(features[28+i]))

plt.show()
```

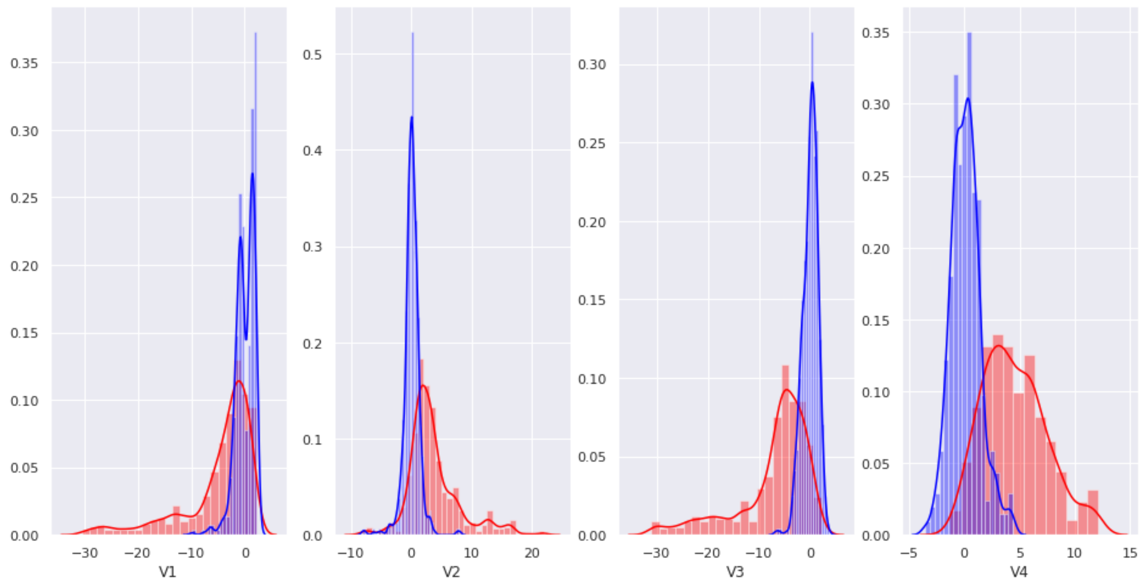
```
<Figure size 1008x576 with 0 Axes>
```


Class vs V1
Class vs V2
Class vs V3
Class vs V4
Class vs V5
Class vs V6
Class vs V7
Class vs V8
Class vs V9
Class vs V10
Class vs V11
Class vs V12
Class vs V13
Class vs V14
Class vs V15
Class vs V16
Class vs V17
Class vs V18
Class vs V19
Class vs V20
Class vs V21
Class vs V22
Class vs V23
Class vs V24
Class vs V25
Class vs V26
Class vs V27
Class vs V28
Class

PDF Distribution

In [18]:

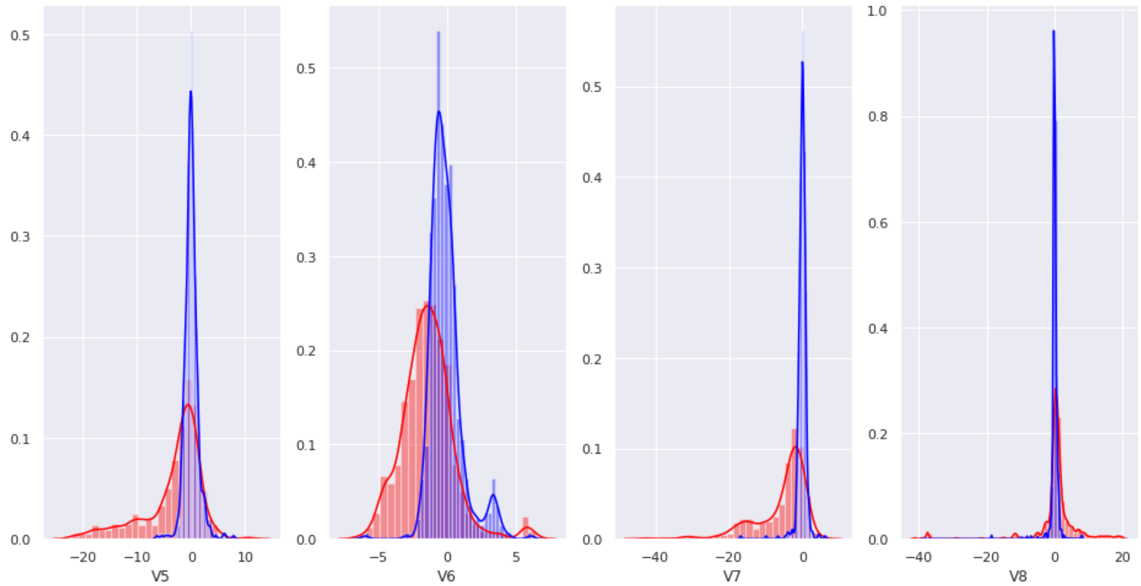
```
plt.figure(figsize=(16, 8))

plt.subplot(1,4,1)
sn.distplot(data_under[data_under['Class'] == 1]['V1'][0:] , label = "1", color = 'red'
)
sn.distplot(data_under[data_under['Class'] == 0]['V1'][0:] , label = "0" , color = 'blu
e' )

plt.subplot(1,4,2)
sn.distplot(data_under[data_under['Class'] == 1]['V2'][0:] , label = "1", color = 'red'
)
sn.distplot(data_under[data_under['Class'] == 0]['V2'][0:] , label = "0" , color = 'blu
e' )

plt.subplot(1,4,3)
sn.distplot(data_under[data_under['Class'] == 1]['V3'][0:] , label = "1", color = 'red'
)
sn.distplot(data_under[data_under['Class'] == 0]['V3'][0:] , label = "0" , color = 'blu
e' )

plt.subplot(1,4,4)
sn.distplot(data_under[data_under['Class'] == 1]['V4'][0:] , label = "1", color = 'red'
)
sn.distplot(data_under[data_under['Class'] == 0]['V4'][0:] , label = "0" , color = 'blu
e' )

plt.show()
```



Here we can see that for features V1, V2, V3 and V4 the class distributions are partially separable. All the distributions are highly skewed. For V4, there is more partial separatability as compared to the other features.

In [19]:

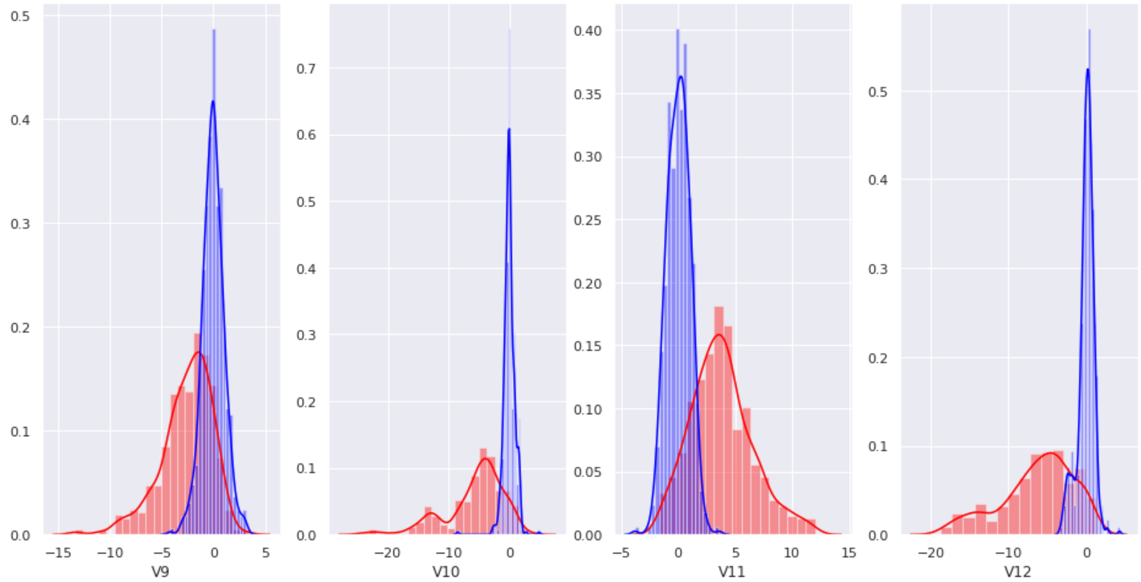
```
plt.figure(figsize=(16, 8))

plt.subplot(1,4,1)
sn.distplot(data_under[data_under['Class'] == 1]['V5'][0:] , label = "1", color = 'red'
)
sn.distplot(data_under[data_under['Class'] == 0]['V5'][0:] , label = "0" , color = 'blu
e' )

plt.subplot(1,4,2)
sn.distplot(data_under[data_under['Class'] == 1]['V6'][0:] , label = "1", color = 'red'
)
sn.distplot(data_under[data_under['Class'] == 0]['V6'][0:] , label = "0" , color = 'blu
e' )

plt.subplot(1,4,3)
sn.distplot(data_under[data_under['Class'] == 1]['V7'][0:] , label = "1", color = 'red'
)
sn.distplot(data_under[data_under['Class'] == 0]['V7'][0:] , label = "0" , color = 'blu
e' )

plt.subplot(1,4,4)
sn.distplot(data_under[data_under['Class'] == 1]['V8'][0:] , label = "1", color = 'red'
)
sn.distplot(data_under[data_under['Class'] == 0]['V8'][0:] , label = "0" , color = 'blu
e' )

plt.show()
```



For V5 and V6, the class distributions are partially separable. For V7 and V8 the class distributions are almost overlapping and there is no clear way of separating these features based on their class labels.

In [20]:

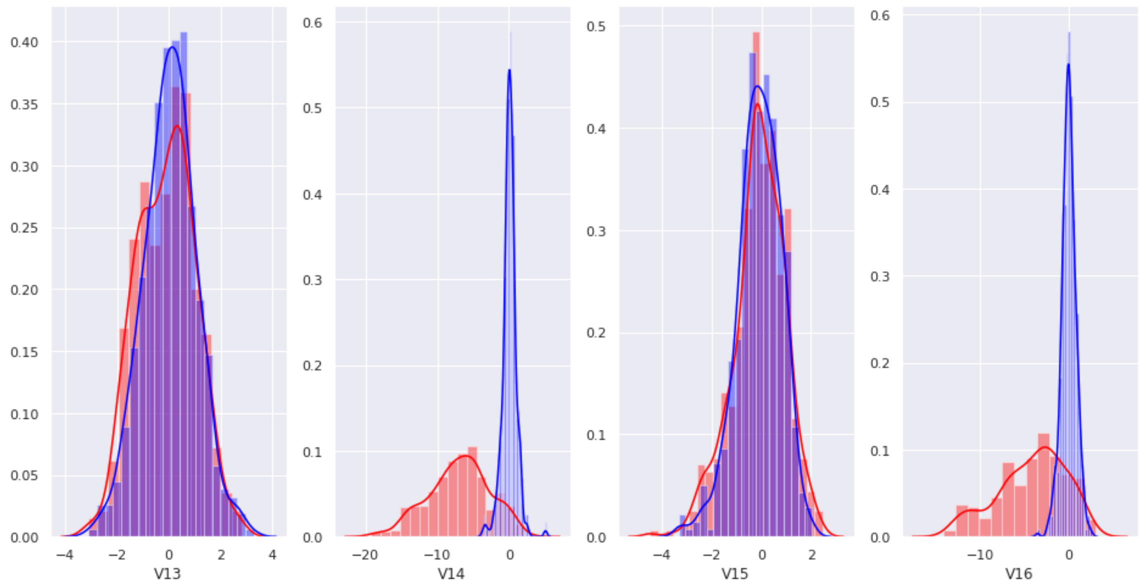
```
plt.figure(figsize=(16, 8))

plt.subplot(1,4,1)
sn.distplot(data_under[data_under['Class'] == 1]['V9'][0:] , label = "1", color = 'red'
)
sn.distplot(data_under[data_under['Class'] == 0]['V9'][0:] , label = "0" , color = 'blu
e' )

plt.subplot(1,4,2)
sn.distplot(data_under[data_under['Class'] == 1]['V10'][0:] , label = "1", color = 're
d')
sn.distplot(data_under[data_under['Class'] == 0]['V10'][0:] , label = "0" , color = 'bl
ue' )

plt.subplot(1,4,3)
sn.distplot(data_under[data_under['Class'] == 1]['V11'][0:] , label = "1", color = 're
d')
sn.distplot(data_under[data_under['Class'] == 0]['V11'][0:] , label = "0" , color = 'bl
ue' )

plt.subplot(1,4,4)
sn.distplot(data_under[data_under['Class'] == 1]['V12'][0:] , label = "1", color = 're
d')
sn.distplot(data_under[data_under['Class'] == 0]['V12'][0:] , label = "0" , color = 'bl
ue' )

plt.show()
```



Here again, we see a lot of partial separability between the class labels for all four of these features.

In [21]:

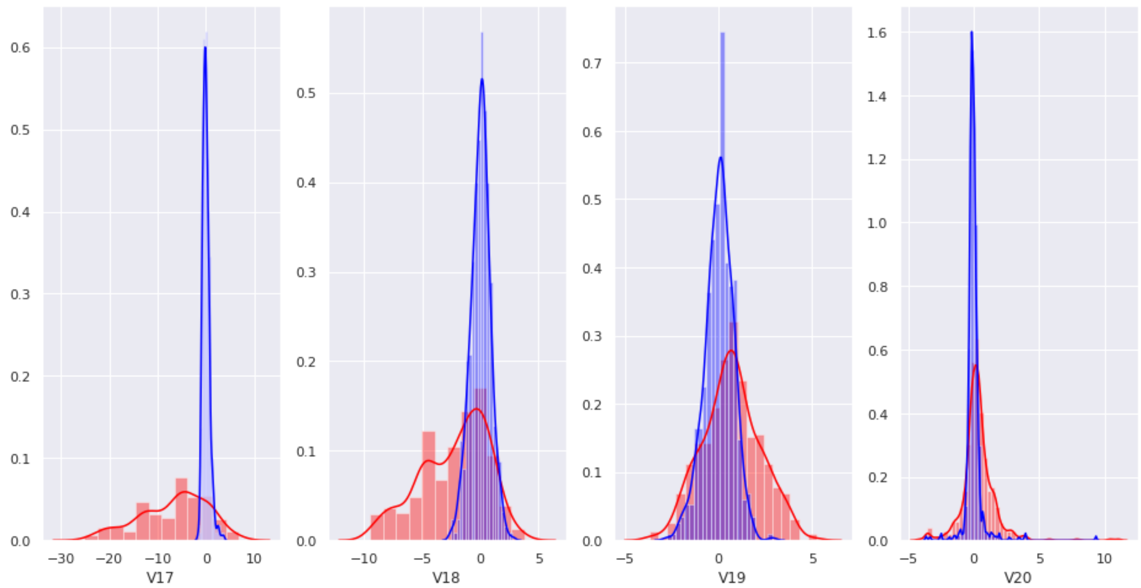
```
plt.figure(figsize=(16, 8))

plt.subplot(1,4,1)
sn.distplot(data_under[data_under['Class'] == 1]['V13'][0:] , label = "1", color = 're
d')
sn.distplot(data_under[data_under['Class'] == 0]['V13'][0:] , label = "0" , color = 'bl
ue' )

plt.subplot(1,4,2)
sn.distplot(data_under[data_under['Class'] == 1]['V14'][0:] , label = "1", color = 're
d')
sn.distplot(data_under[data_under['Class'] == 0]['V14'][0:] , label = "0" , color = 'bl
ue' )

plt.subplot(1,4,3)
sn.distplot(data_under[data_under['Class'] == 1]['V15'][0:] , label = "1", color = 're
d')
sn.distplot(data_under[data_under['Class'] == 0]['V15'][0:] , label = "0" , color = 'bl
ue' )

plt.subplot(1,4,4)
sn.distplot(data_under[data_under['Class'] == 1]['V16'][0:] , label = "1", color = 're
d')
sn.distplot(data_under[data_under['Class'] == 0]['V16'][0:] , label = "0" , color = 'bl
ue' )

plt.show()
```



V13, V15 features are highly overlapping as far as their class label is concerned. V14 and V16 features has some partial separability as far as their class label is concerned.

In [22]:

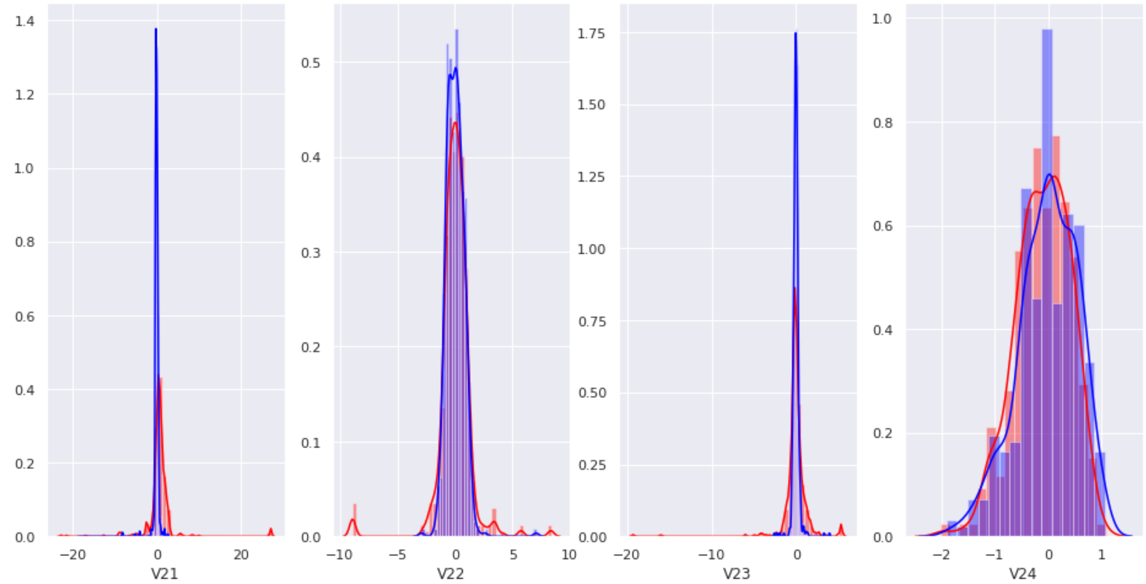
```
plt.figure(figsize=(16, 8))

plt.subplot(1,4,1)
sn.distplot(data_under[data_under['Class'] == 1]['V17'][0:] , label = "1", color = 're
d')
sn.distplot(data_under[data_under['Class'] == 0]['V17'][0:] , label = "0" , color = 'bl
ue' )

plt.subplot(1,4,2)
sn.distplot(data_under[data_under['Class'] == 1]['V18'][0:] , label = "1", color = 're
d')
sn.distplot(data_under[data_under['Class'] == 0]['V18'][0:] , label = "0" , color = 'bl
ue' )

plt.subplot(1,4,3)
sn.distplot(data_under[data_under['Class'] == 1]['V19'][0:] , label = "1", color = 're
d')
sn.distplot(data_under[data_under['Class'] == 0]['V19'][0:] , label = "0" , color = 'bl
ue' )

plt.subplot(1,4,4)
sn.distplot(data_under[data_under['Class'] == 1]['V20'][0:] , label = "1", color = 're
d')
sn.distplot(data_under[data_under['Class'] == 0]['V20'][0:] , label = "0" , color = 'bl
ue' )

plt.show()
```



Here the spread of the fraudulent class is more as compared to the spread in non fraudulent class.

In [23]:

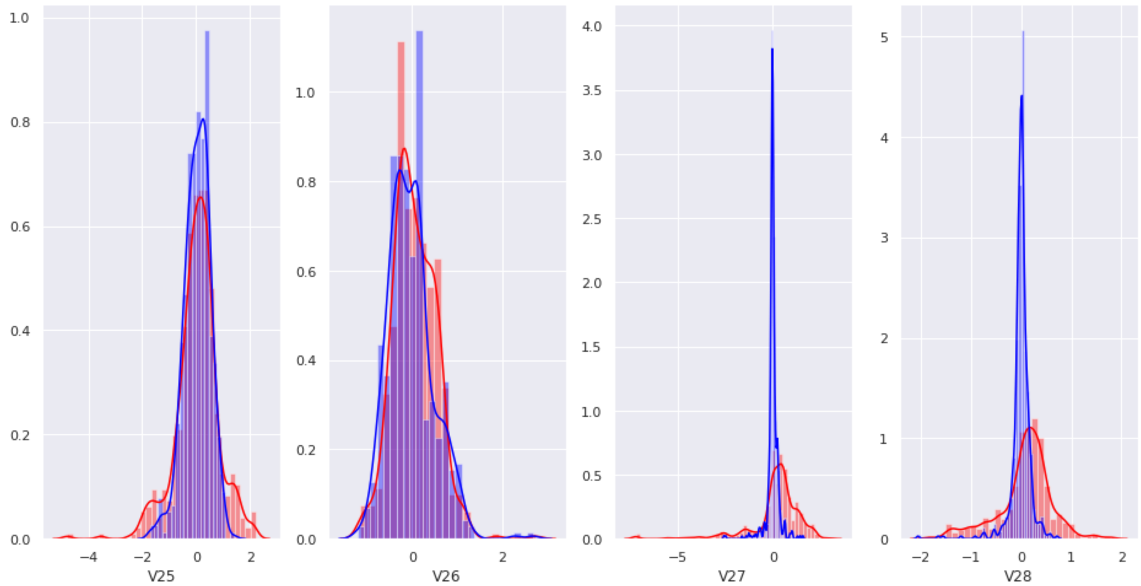
```
plt.figure(figsize=(16, 8))

plt.subplot(1,4,1)
sn.distplot(data_under[data_under['Class'] == 1]['V21'][0:] , label = "1", color = 're
d')
sn.distplot(data_under[data_under['Class'] == 0]['V21'][0:] , label = "0" , color = 'bl
ue' )

plt.subplot(1,4,2)
sn.distplot(data_under[data_under['Class'] == 1]['V22'][0:] , label = "1", color = 're
d')
sn.distplot(data_under[data_under['Class'] == 0]['V22'][0:] , label = "0" , color = 'bl
ue' )

plt.subplot(1,4,3)
sn.distplot(data_under[data_under['Class'] == 1]['V23'][0:] , label = "1", color = 're
d')
sn.distplot(data_under[data_under['Class'] == 0]['V23'][0:] , label = "0" , color = 'bl
ue' )

plt.subplot(1,4,4)
sn.distplot(data_under[data_under['Class'] == 1]['V24'][0:] , label = "1", color = 're
d')
sn.distplot(data_under[data_under['Class'] == 0]['V24'][0:] , label = "0" , color = 'bl
ue' )

plt.show()
```



The class distribution of these features - V21, V22, V23 and V24 are completely inseparable. The distributions are highly overlapping with no way to separate the class labels.

In [24]:

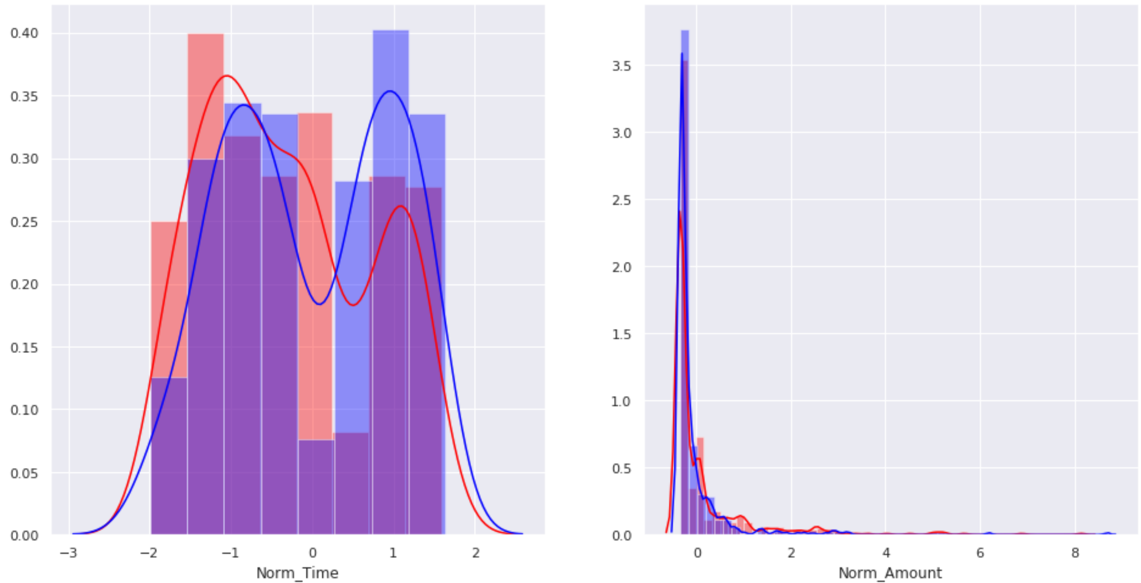
```
plt.figure(figsize=(16, 8))

plt.subplot(1,4,1)
sn.distplot(data_under[data_under['Class'] == 1]['V25'][0:] , label = "1", color = 're
d')
sn.distplot(data_under[data_under['Class'] == 0]['V25'][0:] , label = "0" , color = 'bl
ue' )

plt.subplot(1,4,2)
sn.distplot(data_under[data_under['Class'] == 1]['V26'][0:] , label = "1", color = 're
d')
sn.distplot(data_under[data_under['Class'] == 0]['V26'][0:] , label = "0" , color = 'bl
ue' )

plt.subplot(1,4,3)
sn.distplot(data_under[data_under['Class'] == 1]['V27'][0:] , label = "1", color = 're
d')
sn.distplot(data_under[data_under['Class'] == 0]['V27'][0:] , label = "0" , color = 'bl
ue' )

plt.subplot(1,4,4)
sn.distplot(data_under[data_under['Class'] == 1]['V28'][0:] , label = "1", color = 're
d')
sn.distplot(data_under[data_under['Class'] == 0]['V28'][0:] , label = "0" , color = 'bl
ue' )

plt.show()
```



Here again we see that these features cannot be separated well based on their class labels. The class distributions are highly overlapping.

In [25]:

```
plt.figure(figsize=(16, 8))

plt.subplot(1,2,1)
sn.distplot(data_under[data_under['Class'] == 1]['Norm_Time'][0:] , label = "1", color
= 'red')
sn.distplot(data_under[data_under['Class'] == 0]['Norm_Time'][0:] , label = "0" , color
= 'blue' )

plt.subplot(1,2,2)
sn.distplot(data_under[data_under['Class'] == 1]['Norm_Amount'][0:] , label = "1", colo
r = 'red')
sn.distplot(data_under[data_under['Class'] == 0]['Norm_Amount'][0:] , label = "0" , col
or = 'blue' )


plt.show()
```



Splitting the data into train and test datasets

Before building our machine learning models, we will split the dataset in such a way that 80% of the undersample data goes to our training set and 20% data from the undersampled class goes to our test set. We will make use of the 'stratify' argument to make sure we have equal distribution of class labels in both the training as well as test sets.

After the initial splitting, we have 787 points in our training dataset and 197 points in our test dataset. We will build machine learning models using these 787 points and then evaluate the performance of each of our models on the test set.

In [26]:

```
from sklearn.model_selection import train_test_split

X=data_under.drop("Class", axis=1)
y=data_under['Class']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, stratify=y, r
andom_state=state)

print('Number of data points in train data:', X_train.shape[0])
print('Number of data points in test data:', X_test.shape[0])
```

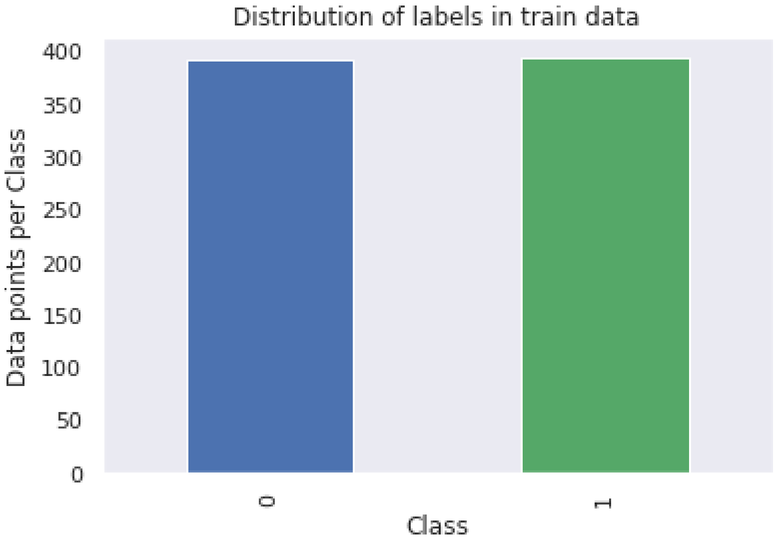
```
Number of data points in train data: 787
Number of data points in test data: 197
```

Check the distribution of train and test data after splitting the original dataset

This is a sanity check we need to perform to check if the distribution of class labels is same in both the training as well as the test set. We can see that in both the train as well as the test sets, the class labels are distributed almost equally at 50% data points from each of the classes.

In [27]:

```
# it returns a dict, keys as class labels and values as the number of data points in th
at class
train_class_distribution = y_train.value_counts().sortlevel()
test_class_distribution = y_test.value_counts().sortlevel()

my_colors = ["b","g"]
train_class_distribution.plot(kind='bar', color=my_colors)
plt.xlabel('Class')
plt.ylabel('Data points per Class')
plt.title('Distribution of labels in train data')
plt.grid()
plt.show()


# -(train_class_distribution.values): the minus sign will give us in decreasing order
sorted_yi = np.argsort(-train_class_distribution.values)
for i in sorted_yi:
    print('Number of data points in class', i+1, ':',train_class_distribution.values[i
], '(', np.round((train_class_distribution.values[i]/y_train.shape[0]*100), 3), '%)')

print('-'*80)
test_class_distribution.plot(kind='bar', color=my_colors)
plt.xlabel('Class')
plt.ylabel('Data points per Class')
plt.title('Distribution of labels in test data')
plt.grid()
plt.show()


# -(train_class_distribution.values): the minus sign will give us in decreasing order
sorted_yi = np.argsort(-test_class_distribution.values)
for i in sorted_yi:
    print('Number of data points in class', i+1, ':',test_class_distribution.values[i],
'(', np.round((test_class_distribution.values[i]/y_test.shape[0]*100), 3), '%)')
```




```
Number of data points in class 2 : 394 ( 50.064 %)
Number of data points in class 1 : 393 ( 49.936 %)
---------------------------------------------------------------------------
------
```


```
Number of data points in class 1 : 99 ( 50.254 %)
Number of data points in class 2 : 98 ( 49.746 %)
```

Dimensionality reduction using TSNE

T-SNE stands for t-distributed Stochastic Neighbor Embedding.

T-SNE is a tool which is used to visualize high dimensional data in 2 or 3 dimensions. In this section we will try to visualize the high dimensional data in a 2D plot. T-SNE tries to preserve the neighborhood distances between each of the data points when we project them onto a lower dimensional space. We will try plotting the T-SNE with various values of perplexities and see if the resultant plot can separate the positive and negative classes well.

In [42]:

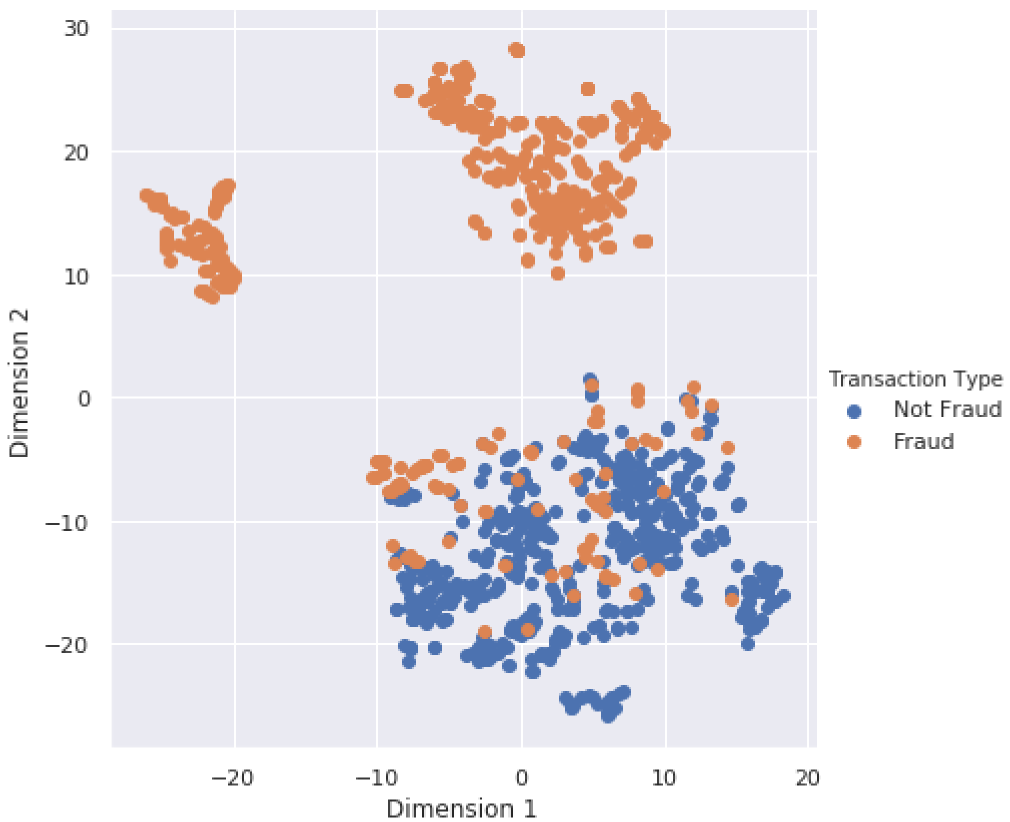
```
from MulticoreTSNE import MulticoreTSNE as TSNE
def tsne(dataset, labels, perplexity):
    labels=labels.apply(lambda x: 'Fraud' if x==1.0 else 'Not Fraud')
    '''This function is used to plot the t-sne for any input dataset using their corres
ponding class labels,
    using two dimensions.'''

    #Starting TSNE dataset transform
    model = TSNE(n_components=2, init='random', random_state=0, verbose=2, n_jobs=-1, a
ngle=0.5, method='barnes_hut', perplexity=perplexity, n_iter=2000)
    tsne_data = model.fit_transform(dataset)

    #Creating a new data frame which help us in ploting the result data
    tsne_data = np.vstack((tsne_data.T, labels)).T
    tsne_df = pd.DataFrame(data=tsne_data, columns=("Dimension 1", "Dimension 2", "Tran
saction Type"))

    #Info
    print("\nT-SNE Plot for perplexity = {}".format(perplexity))

    # Ploting the result of tsne
    sn.FacetGrid(tsne_df, hue="Transaction Type", height=6).map(plt.scatter, 'Dimension
1', 'Dimension 2').add_legend()
    plt.show()
```

In [43]:

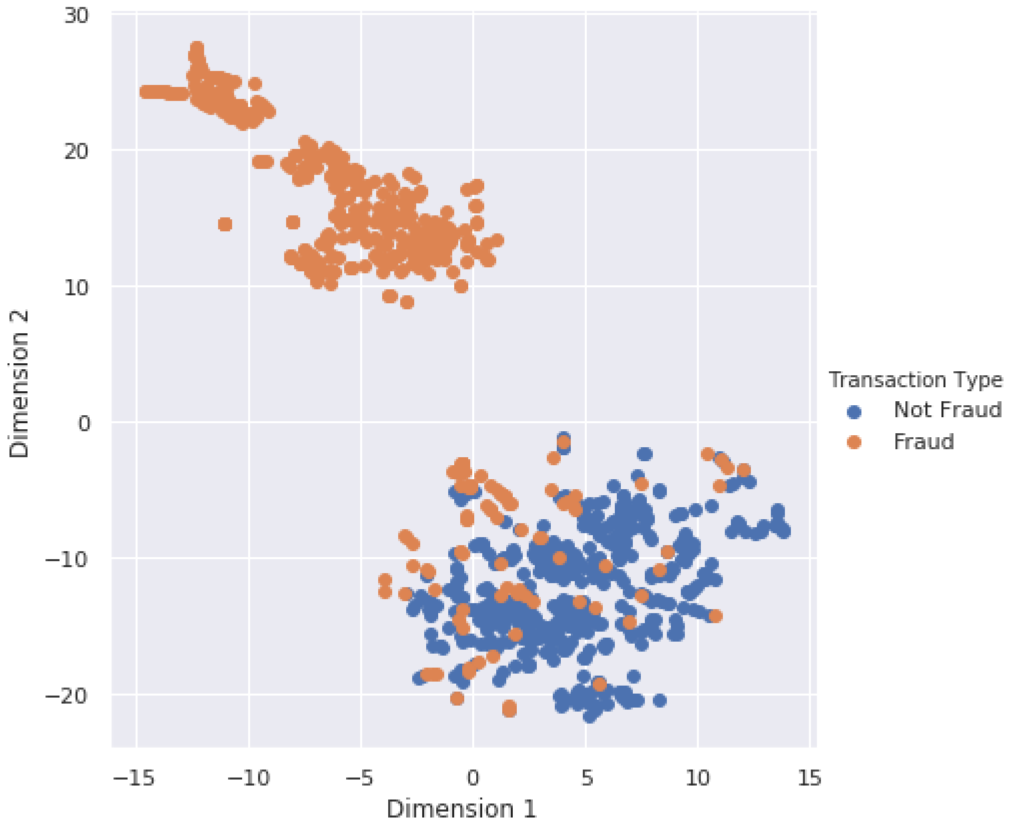
```
tsne(X, y, 5)
tsne(X, y, 50)
tsne(X, y, 100)
tsne(X, y, 150)
```

T-SNE Plot for perplexity = 5

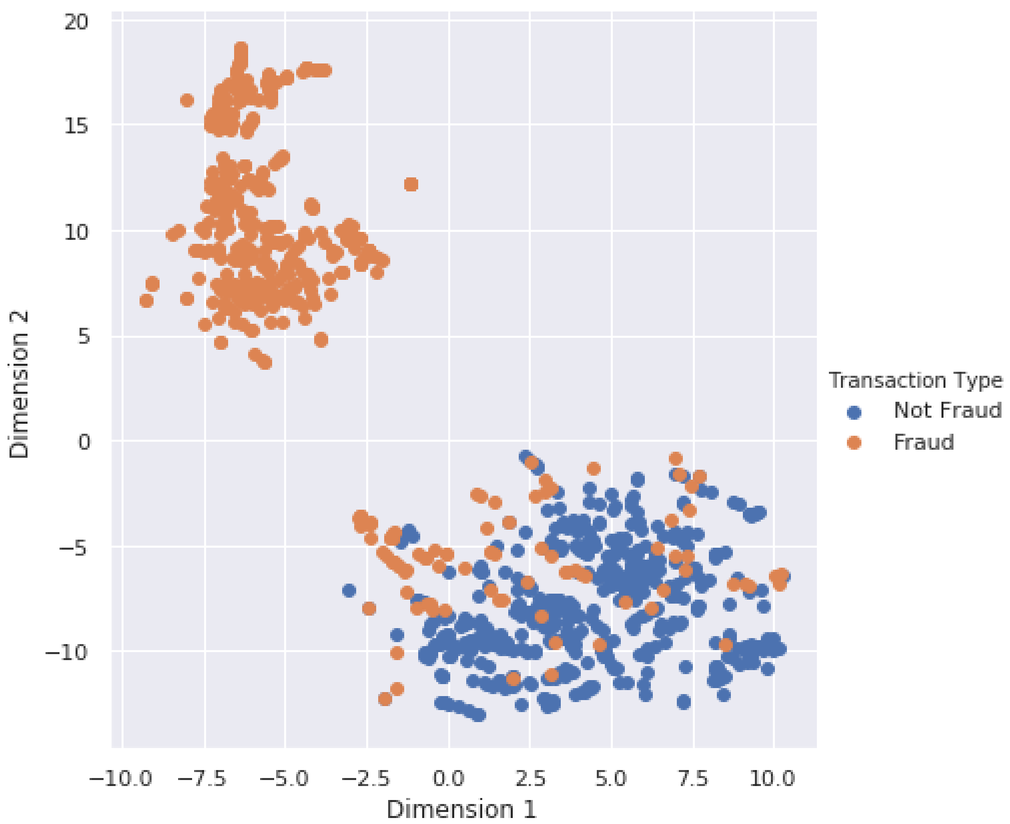
T-SNE Plot for perplexity = 50



T-SNE Plot for perplexity = 100




```
T-SNE Plot for perplexity = 150
```



Observations:

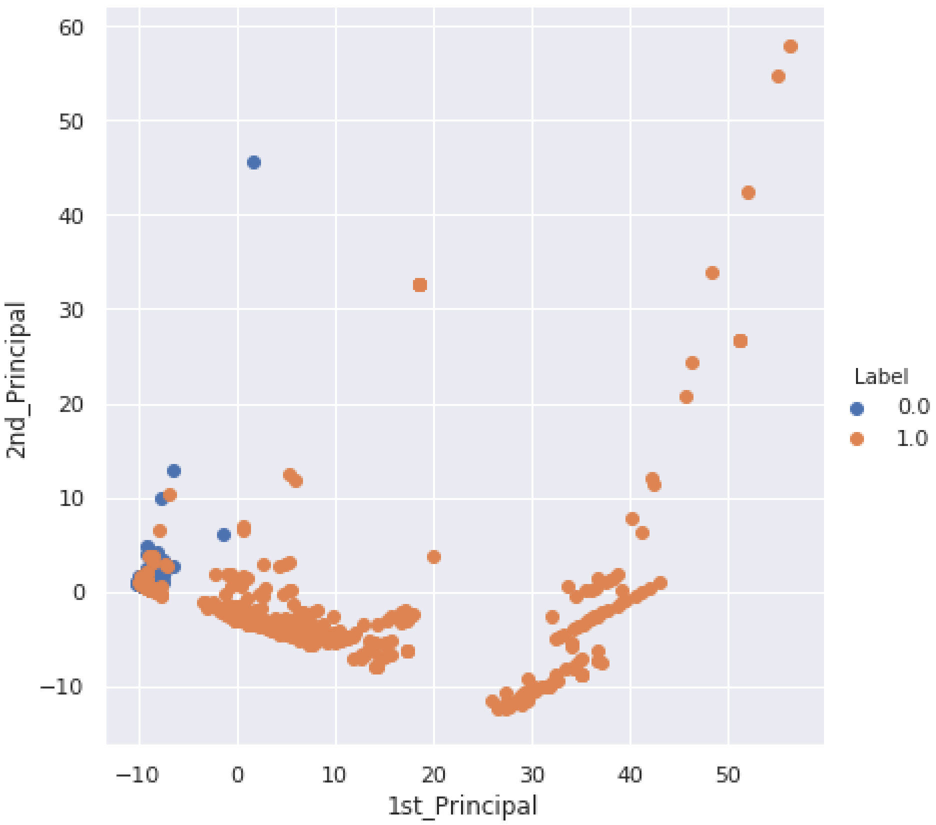
Here we have run the algorithm for various values of perplexities. Perplexity values basically tells the T-SNE algorithm the number of neighborhood distances it should preserve. Here we can see that T-SNE plots are able to accurately cluster the data points at various values of perplexity based on whether or not they are fraudulent transactions. A partial separability suggest that our Machine Learning models should perform well on the given dataset.

Dimensionality Reduction using PCA

In [44]:

```
#Initialize the PCA
from sklearn import decomposition
pca = decomposition.PCA()

#Configure the parameteres: Number of components = 2
pca.n_components = 2
pca_data = pca.fit_transform(X_train)

#pca_data will contain the 2-D projections of X_train
print("Shape of the Data Matrix before reducing dimension: ",X_train.shape)
print("Shape of the Data Matrix after reducing dimension: ",pca_data.shape)

#Attaching the label for each 2D data point.
pca_data = np.vstack((pca_data.T, y_train)).T

#Creating a new dataframe which help us in ploting the result data. The new dataframe c
ontains the reduced dimension of X_train along with the class label.
pca_df = pd.DataFrame(data=pca_data, columns=("1st_Principal", "2nd_Principal", "Label"
))
sn.FacetGrid(pca_df, hue="Label", size=6).map(plt.scatter, '1st_Principal', '2nd_Princi
pal').add_legend()
plt.show()
```

```
Shape of the Data Matrix before reducing dimension:  (787, 30)
Shape of the Data Matrix after reducing dimension:  (787, 2)
```



Functioin to plot Confusion Matrix, Precision Matrix, Recall Matrix

We will use this function to draw the confusion matrix, precision matrix and the recall matrix. We will use the confusion matrix to keep an eye on the false positive values and the recall values. Our main objective of this case study is to build a model which has a high recall value.

Confusion Matrix is a tool which helps us to evaluate the performance of our classification model on unseen data. It's a very important tool to evaluate metrics such as Precision, Recall, Accuracy and Area under the ROC curve using these four values - False Positives (FP), False Negatives (FN), True Positives (TP) and True Negatives (TN).

Let us understand these four metrics in a bit more detail with regards to the given problem.

True Positives (TP): Here the model has predicted the transaction to be fraudulent and in real life the transaction is fraudulent.

True Negatives (TN): Here the model has predicted a transaction to be a non-fraudulent one and in real life the transaction is non-fraudulent.

False Positives (FP): Here the model has predicted the transactions to be fraudulent whereas in real life the given transaction is not fraudulent. These are also known as Type 1 errors.

False Negatives (FN): Here the model has predicted the transactions to be non-fraudulent where as in real life the transactions are fraudulent. These are also known as Type 2 errors.

Ideally, for a perfect model, we would want the values of TPs and TNs to be very high and our FPs and FNs to be very low. Also, for this problem it's an absolute necessity to keep the False Negative values as low as possible. In the real world Type 2 errors are much more sever than Type 1 errors. Imagine this scenario - our model predicts a fraudulent transaction as a non fraudulent one. This is much more severe than predicting a non-fraudulent transaction as a fraudulent one.

Recall tells us that out of the total number of actual/correctly classified classes how many did our model predicted to belong to the correctly classified class?

Precision tells us that out of the total number of predictions how many of them are actually predicted to be true?

In [12]:

```
# This function plots the confusion matrices given y_i, y_i_hat.
def plot_confusion_matrix(test_y, predict_y):
    C = confusion_matrix(test_y, predict_y)
    # C = 9,9 matrix, each cell (i,j) represents number of points of class i are predic
ted class j

    A =(((C.T)/(C.sum(axis=1))).T)
    #divid each element of the confusion matrix with the sum of elements in that column

    # C = [[1, 2],
    #     [3, 4]]
    # C.T = [[1, 3],
    #        [2, 4]]
    # C.sum(axis = 1)  axis=0 corresonds to columns and axis=1 corresponds to rows in t
wo diamensional array
    # C.sum(axix =1) = [[3, 7]]
    # ((C.T)/(C.sum(axis=1))) = [[1/3, 3/7]
    #                            [2/3, 4/7]]

    # ((C.T)/(C.sum(axis=1))).T = [[1/3, 2/3]
    #                            [3/7, 4/7]]
    # sum of row elements = 1

    B =(C/C.sum(axis=0))
    #divid each element of the confusion matrix with the sum of elements in that row
    # C = [[1, 2],
    #     [3, 4]]
    # C.sum(axis = 0)  axis=0 corresonds to columns and axis=1 corresponds to rows in t
wo diamensional array
    # C.sum(axix =0) = [[4, 6]]
    # (C/C.sum(axis=0)) = [[1/4, 2/6],
    #                       [3/4, 4/6]]
    plt.figure(figsize=(20,4))

    labels = [0,1]
    # representing A in heatmap format
    cmap=sn.light_palette("blue")
    plt.subplot(1, 3, 1)
    sn.heatmap(C, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels, yticklabels=lab
els)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.title("Confusion matrix")

    plt.subplot(1, 3, 2)
    sn.heatmap(B, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels, yticklabels=lab
els)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.title("Precision matrix")

    plt.subplot(1, 3, 3)
    # representing B in heatmap format
    sn.heatmap(A, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels, yticklabels=lab
els)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.title("Recall matrix")
```

```
    plt.show()
```

Function to plot the ROC-AUC Curve

ROC curve stands for Receiver operating characteristic curve. In machine learning, ROC curves helps us evaluate our models performance at various threshold settings. ROC curves is a probability curve and AUC stands for the area under the ROC curve. Generally a ROC-AUC curves gives us an idea about how well our model is capable of distinguishing between various class labels. IN ROC-AUC curve, the value of the true positive rates and false positive rates are plotted against each other at various threshold settings. Higher the value of an ROC-AUC curve, the better will be our model in predicting a class 0 label as class 0 and class 1 label as class 1. For this case study, class 1 signifies a fraudulent transaction and class 0 signifies a non-fraudulent transaction.

While plotting the ROC-AUC curve, the TPR is taken in Y-Axis and the FPR is taken at X-axis. TPR is also known ans Recall. Mathematically TPR is defined as (TP/TP+FN), and FPR is defined as (FP/TN+FP). We will have to optimize our Machine Learning models such that they maximize the ROC-AUC score.

In [13]:

```
def plot_roc_curve(classifier, X_train, y_train, X_test, y_test):
    from sklearn.metrics import roc_curve, auc
    fpr = dict()
    tpr = dict()
    roc_auc = dict()

    '''TEST DATA ROC CURVE'''
    #Use probability scores to compute the ROC Curve
    class_probabilities = classifier.predict_proba(X_test)
    y_probs = class_probabilities[:,1]
    fpr["Test"], tpr["Test"], threshold = roc_curve(y_test, y_probs)
    roc_auc["Test"] = auc(fpr["Test"], tpr["Test"])

    '''TRAIN DATA ROC CURVE'''
    #Use probability scores to compute the ROC Curve
    class_probabilities = classifier.predict_proba(X_train)
    y_probs = class_probabilities[:,1]
    fpr["Train"], tpr["Train"], threshold = roc_curve(y_train, y_probs)
    roc_auc["Train"] = auc(fpr["Train"], tpr["Train"])

    plt.figure(figsize=(15,10))
    linewidth = 2
    plt.plot(fpr["Test"], tpr["Test"], color='green', lw=linewidth, label='ROC curve Te
st Data (area = %0.2f)' % roc_auc["Test"])
    plt.plot(fpr["Train"], tpr["Train"], color='red', lw=linewidth, label='ROC curve Tr
ain Data (area = %0.2f)' % roc_auc["Train"])
    plt.plot([0, 1], [0, 1], color='navy', lw=linewidth, linestyle='--', label='Baselin
e ROC curve (area = 0.5)')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver operating characteristic example')
    plt.legend(loc="lower right")
    plt.show()
```

Generic function to run any model and print the classification metrics

This function is used to evaluate our model on unseen data. We will first obtain the best estimator using either grid search or random search. We will use the best estimator from our model to print the roc-auc scores, the accuracy scores, the recall score and the f1 score. F1 score as we know is the harmonic mean between precision and recall scores. We will also use this function to generate the classification report for each of our models.

In [14]:

```
def model_report(rsearch_cv, X_train, y_train, X_test, y_test, class_labels):

    #To store results at various phases during training as well as cross validation sta
ges
    results = dict()
    model = rsearch_cv.best_estimator_

    #Time at which model starts training
    train_start_time = dt.now()
    print('Training the model...')
    model.fit(X_train, y_train)
    print('Training completed... \n \n')
    train_end_time = dt.now()
    results['Training_Time'] =  train_end_time - train_start_time
    print('Training Time (HH:MM:SS.ms) -- {}\n\n'.format(results['Training_Time']))


    #Predict the test data
    print('Predicting test data...')
    test_start_time = dt.now()
    y_pred = model.predict(X_test)
    test_end_time = dt.now()
    print('Predicting test data completed... \n \n')
    results['Testing_Time'] = test_end_time - test_start_time
    print('Testing Time(HH:MM:SS:ms) -- {}\n\n'.format(results['Testing_Time']))
    results['Predicted'] = y_pred


    #Compute the F1 score
    f1_score = metrics.f1_score(y_true=y_test, y_pred=y_pred, average='micro') #F1 = 2
 * (precision * recall) / (precision + recall)

    #Store F1 Score in results
    results['F1_Score'] = f1_score
    print('----------------------')
    print('|      F1 Score      |')
    print('----------------------')
    print('\n    {}\n\n'.format(f1_score))


    #Calculate overall accuracy of the model
    accuracy = metrics.accuracy_score(y_true=y_test, y_pred=y_pred)

    #Store the accuracy in results
    results['Accuracy'] = accuracy
    print('----------------------')
    print('|      Accuracy      |')
    print('----------------------')
    print('\n    {}\n\n'.format(accuracy))

    #Calculate overall recall_score of the model
    recall = metrics.recall_score(y_true=y_test, y_pred=y_pred)

    #Store the accuracy in results
    results['Recall'] = recall
    print('----------------------')
    print('|      Recall        |')
    print('----------------------')
    print('\n    {}\n\n'.format(recall))
```

```
    #Calculate overall roc-auc of the model
    #Calibrate the model
    sig_clf = CalibratedClassifierCV(model, method="sigmoid")
    sig_clf.fit(X_train, y_train)
    class_probabilities = sig_clf.predict_proba(X_test)
    y_probs = class_probabilities[:,1]
    roc_auc = metrics.roc_auc_score(y_true=y_test, y_score=y_probs)

    #Store the ROC-AUC in results
    results['ROC-AUC'] = roc_auc
    print('---------------------')
    print('|       ROC AUC       |')
    print('---------------------')
    print('\n    {}\n\n'.format(roc_auc))

    #Display the classification report having individual class recalls and precision va
lues.
    print('-------------------------')
    print('| Classifiction Report  |')
    print('-------------------------')
    classification_report = metrics.classification_report(y_test, y_pred)

    #Store report in results
    results['Classification_Report'] = classification_report
    print(classification_report)

    #Add the trained  model to the results
    results['Model'] = model

    #Plot the confusion matrix curve
    plot_confusion_matrix(y_test, y_pred)

    return results, model
```

Generic function to print grid/random search results/attributes

This function will be used to print the best estimator obtained using grid search/random search. For each estimator, we will print the best parameters for a given function along with their best scores on the cross validation dataset.

In [15]:

```
def print_grid_search_attributes(model):
    #Estimator that gave highest score among all the estimators formed in GridSearch
    print('--------------------------')
    print('|      Best Estimator     |')
    print('--------------------------')
    print('\n\t{}\n'.format(model.best_estimator_))

    #Parameters that gave best results while performing grid search
    print('--------------------------')
    print('|     Best parameters     |')
    print('--------------------------')
    print('\tParameters of best estimator : \n\n\t{}\n'.format(model.best_params_))

    #Number of cross validation splits
    print('---------------------------------')
    print('|   No of CrossValidation sets   |')
    print('--------------------------------')
    print('\n\tTotal numbre of cross validation sets: {}\n'.format(model.n_splits_))

    #Average cross validated score of the best estimator, from the Grid Search
    print('--------------------------')
    print('|        Best Score       |')
    print('--------------------------')
    print('\n\tAverage Cross Validate scores of best estimator : \n\n\t{}\n'.format(mod
el.best_score_))
```

Machine Learning Models

1. Logistic Regression Classifier

In [32]:

```
from sklearn.model_selection import RandomizedSearchCV
from sklearn.linear_model import LogisticRegression
from datetime import datetime as dt

st=dt.now()

tuned_parameters = {'C': np.logspace(-4,3,50),
                     'penalty': ['l1','l2'] } #C values used for cross validation

model = LogisticRegression(n_jobs=-1, random_state=state)
rsearch_cv = RandomizedSearchCV(estimator=model,
                                param_distributions=tuned_parameters,
                                cv=3, scoring='roc_auc',
                                verbose=5,
                                n_jobs=-1,
                                random_state=state)
rsearch_cv.fit(X_train, y_train)

print("Time taken to complete random search: ",dt.now()-st)
```

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent worker
s.
[Parallel(n_jobs=-1)]: Done   2 tasks      | elapsed:    1.7s
[Parallel(n_jobs=-1)]: Done  22 out of  30 | elapsed:    1.8s remaining:
0.7s
[Parallel(n_jobs=-1)]: Done  30 out of  30 | elapsed:    1.9s finished


Time taken to complete random search:  0:00:01.904716
```

In [33]:

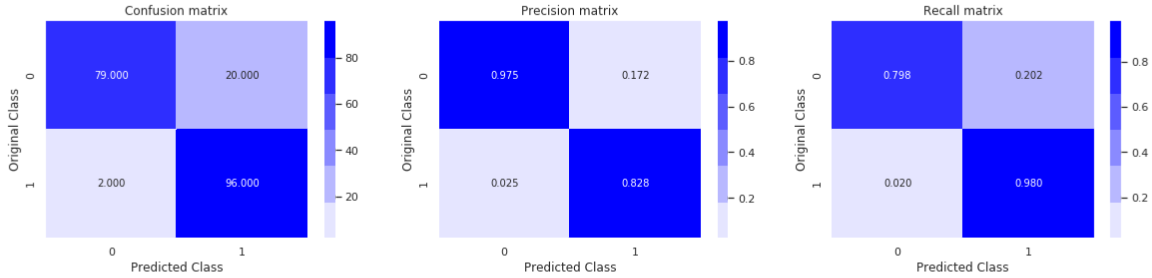
```
print_grid_search_attributes(rsearch_cv)
```

```
--------------------------
|      Best Estimator     |
--------------------------

        LogisticRegression(C=0.0003727593720314938, class_weight=None, dua
l=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='warn', n_jobs=-1, penalty='l2', random_state=48,
          solver='warn', tol=0.0001, verbose=0, warm_start=False)

--------------------------
|     Best parameters     |
--------------------------
        Parameters of best estimator : 

        {'penalty': 'l2', 'C': 0.0003727593720314938}

---------------------------------
|   No of CrossValidation sets   |
--------------------------------

        Total numbre of cross validation sets: 3

--------------------------
|        Best Score       |
--------------------------

        Average Cross Validate scores of best estimator : 

        0.9767022877249171
```

In [37]:

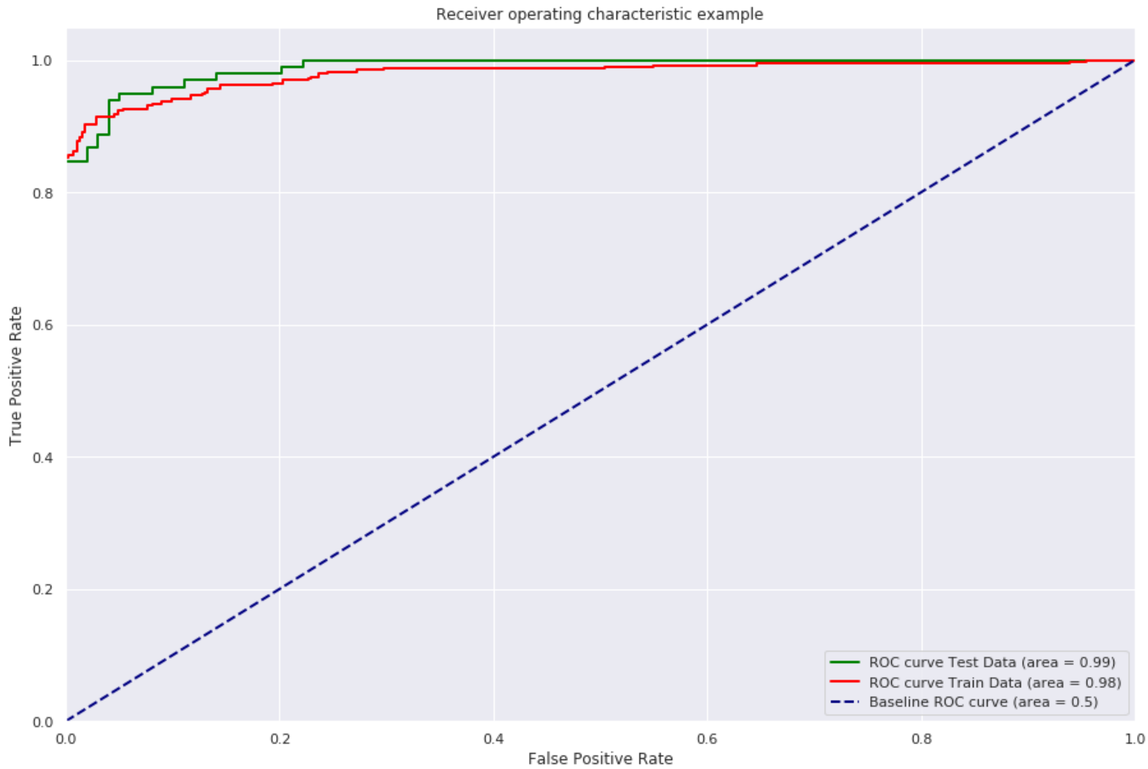
```
log_reg_grid_results, trained_model =  model_report(rsearch_cv, X_train, y_train, X_tes
t, y_test, class_labels=y_train.values)
```

```
Training the model...
Training completed...


Training Time (HH:MM:SS.ms) -- 0:00:00.008919


Predicting test data...
Predicting test data completed...


Testing Time(HH:MM:SS:ms) -- 0:00:00.001629


---------------------
|      F1 Score      |
---------------------

    0.8883248730964467


---------------------
|      Accuracy      |
---------------------

    0.8883248730964467


---------------------
|      Recall        |
---------------------

    0.9795918367346939


---------------------
|      ROC AUC       |
---------------------

    0.9886621315192744


-------------------------
| Classifiction Report  |
-------------------------
              precision    recall  f1-score   support

           0       0.98      0.80      0.88        99
           1       0.83      0.98      0.90        98

   micro avg       0.89      0.89      0.89       197
   macro avg       0.90      0.89      0.89       197
weighted avg       0.90      0.89      0.89       197
```



In [38]:

```
#Calibrate the model
sig_clf = CalibratedClassifierCV(trained_model, method="sigmoid")
sig_clf.fit(X_train, y_train)

#Plot the ROC curve
plot_roc_curve(sig_clf, X_train, y_train, X_test, y_test)
```



2. KNN Classifier

In [39]:

```
from sklearn.neighbors import KNeighborsClassifier

st=dt.now()

tuned_parameters = {'n_neighbors': [3,5,7,9,11,13,15],
                    'weights': ['uniform','distance'],
                    'algorithm': ['ball_tree','kd_tree','brute'] }

model = KNeighborsClassifier(n_jobs=-1, p=2, metric='minkowski')

rsearch_cv = RandomizedSearchCV(estimator=model,
                                param_distributions=tuned_parameters,
                                cv=3, scoring='roc_auc',
                                verbose=5,
                                n_jobs=-1,
                                random_state=state)

rsearch_cv.fit(X_train, y_train)

print("Time taken to complete random search: ",dt.now()-st)
```

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent worker
s.
[Parallel(n_jobs=-1)]: Done   2 tasks      | elapsed:    0.3s
[Parallel(n_jobs=-1)]: Done  22 out of  30 | elapsed:    0.8s remaining:
0.3s

Time taken to complete random search:  0:00:01.003091

[Parallel(n_jobs=-1)]: Done  30 out of  30 | elapsed:    1.0s finished
```

In [40]:

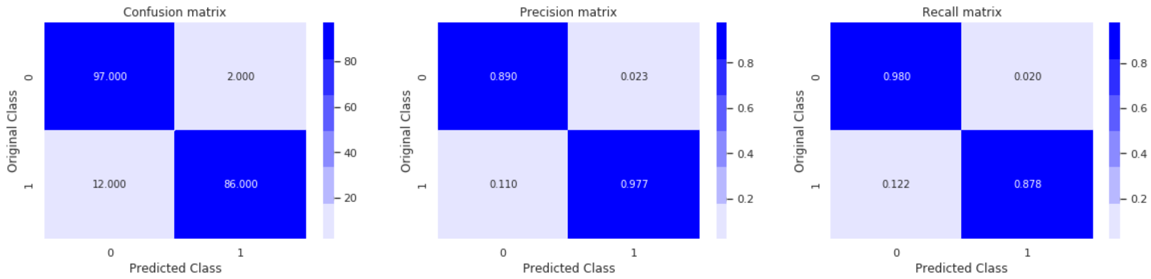
```
print_grid_search_attributes(rsearch_cv)
```

```
--------------------------
|      Best Estimator     |
--------------------------

        KNeighborsClassifier(algorithm='kd_tree', leaf_size=30, metric='mi
nkowski',
           metric_params=None, n_jobs=-1, n_neighbors=13, p=2,
           weights='distance')

--------------------------
|     Best parameters     |
--------------------------
        Parameters of best estimator : 

        {'weights': 'distance', 'n_neighbors': 13, 'algorithm': 'kd_tree'}

---------------------------------
|   No of CrossValidation sets   |
--------------------------------

        Total numbre of cross validation sets: 3

--------------------------
|        Best Score       |
--------------------------

        Average Cross Validate scores of best estimator : 

        0.9755376739939822
```

In [41]:

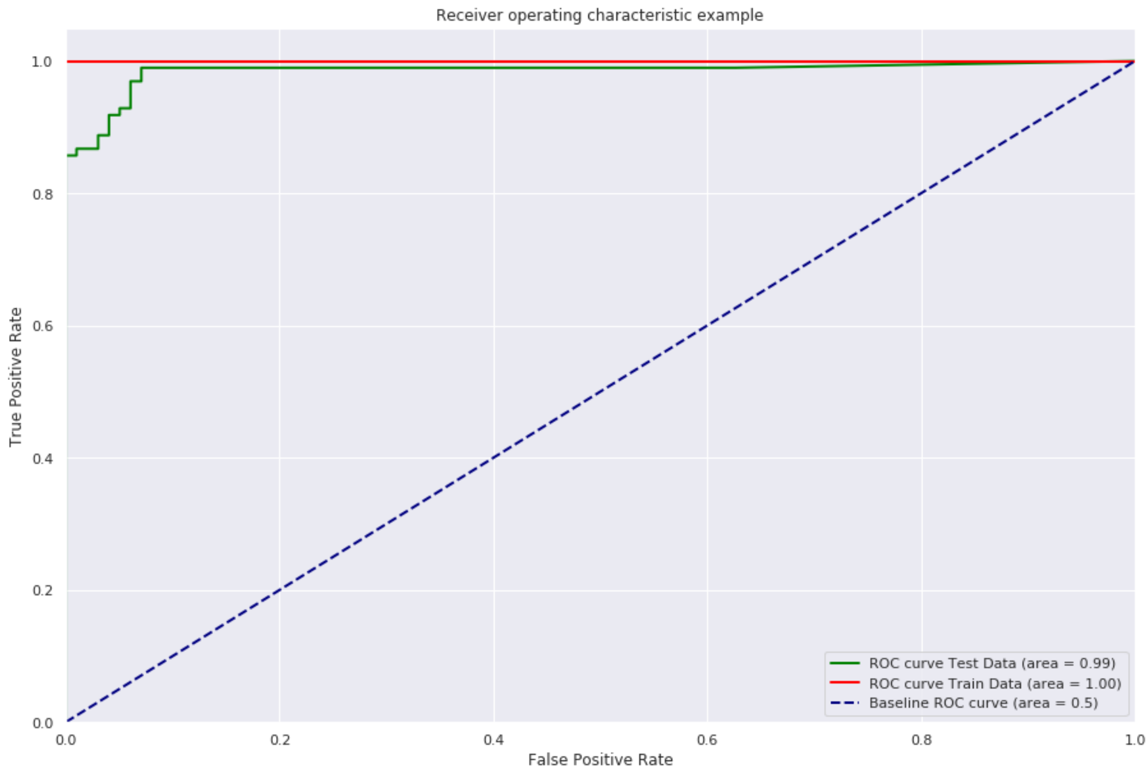
```
knn_grid_results, trained_model =  model_report(rsearch_cv, X_train, y_train, X_test, y
_test, class_labels=y_train.values)
```

```
Training the model...
Training completed...


Training Time (HH:MM:SS.ms) -- 0:00:00.003352


Predicting test data...
Predicting test data completed...


Testing Time(HH:MM:SS:ms) -- 0:00:00.107235


---------------------
|      F1 Score      |
---------------------

    0.9289340101522843


---------------------
|      Accuracy      |
---------------------

    0.9289340101522843


---------------------
|      Recall        |
---------------------

    0.8775510204081632


---------------------
|      ROC AUC       |
---------------------

    0.985312306740878


-------------------------
| Classifiction Report  |
-------------------------
              precision    recall  f1-score   support

           0       0.89      0.98      0.93        99
           1       0.98      0.88      0.92        98

   micro avg       0.93      0.93      0.93       197
   macro avg       0.93      0.93      0.93       197
weighted avg       0.93      0.93      0.93       197
```



In [42]:

```
#Calibrate the model
from sklearn.calibration import CalibratedClassifierCV
sig_clf = CalibratedClassifierCV(trained_model, method="sigmoid")
sig_clf.fit(X_train, y_train)

#Plot the ROC curve
plot_roc_curve(sig_clf, X_train, y_train, X_test, y_test)
```



3. Decision Trees Classifier

In [43]:

```
from sklearn.tree import DecisionTreeClassifier


st=dt.now()

tuned_parameters = {'max_depth': np.arange(1,10,1),
                    'criterion': ['gini','entropy'],
                    'min_samples_split': np.arange(0.1,1.0,0.1),
                    'min_samples_leaf' : np.arange(1,10,1),
                    'min_weight_fraction_leaf' : [0.0,0.1,0.2,0.3,0.4],
                    'max_features': ['auto','sqrt','log2']}

model = DecisionTreeClassifier(random_state=state)
rsearch_cv = RandomizedSearchCV(estimator=model,
                                param_distributions=tuned_parameters,
                                cv=3, scoring='roc_auc',
                                verbose=5,
                                n_jobs=-1,
                                random_state=state)

rsearch_cv.fit(X_train, y_train)

print("Time taken to complete random search: ",dt.now()-st)
```

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits
Time taken to complete random search:  0:00:00.181862

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent worker
s.
[Parallel(n_jobs=-1)]: Done   2 tasks      | elapsed:    0.0s
[Parallel(n_jobs=-1)]: Done   8 out of  30 | elapsed:    0.1s remaining:
0.2s
[Parallel(n_jobs=-1)]: Done  15 out of  30 | elapsed:    0.1s remaining:
0.1s
[Parallel(n_jobs=-1)]: Done  30 out of  30 | elapsed:    0.2s finished
```

In [44]:

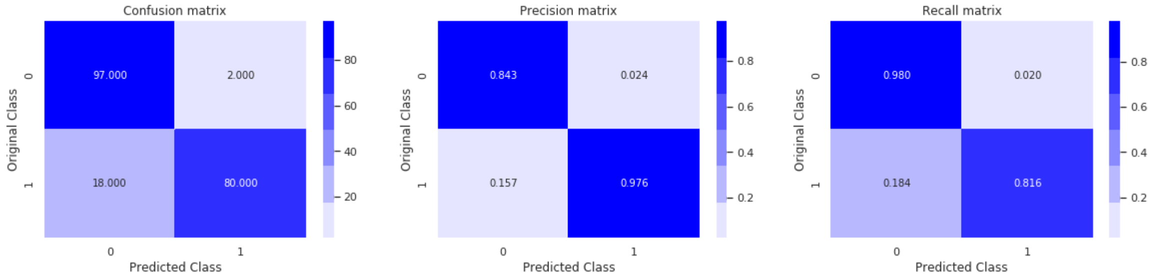
```
print_grid_search_attributes(rsearch_cv)
```

```
--------------------------
|      Best Estimator     |
--------------------------

        DecisionTreeClassifier(class_weight=None, criterion='gini', max_de
pth=3,
            max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=5, min_samples_split=0.1,
            min_weight_fraction_leaf=0.1, presort=False, random_state=48,
            splitter='best')

--------------------------
|     Best parameters     |
--------------------------
        Parameters of best estimator :

        {'min_weight_fraction_leaf': 0.1, 'min_samples_split': 0.1, 'min_s
amples_leaf': 5, 'max_features': 'auto', 'max_depth': 3, 'criterion': 'gin
i'}

---------------------------------
|   No of CrossValidation sets   |
--------------------------------

        Total numbre of cross validation sets: 3

--------------------------
|        Best Score       |
--------------------------

        Average Cross Validate scores of best estimator :

        0.9402813428718644
```

In [45]:

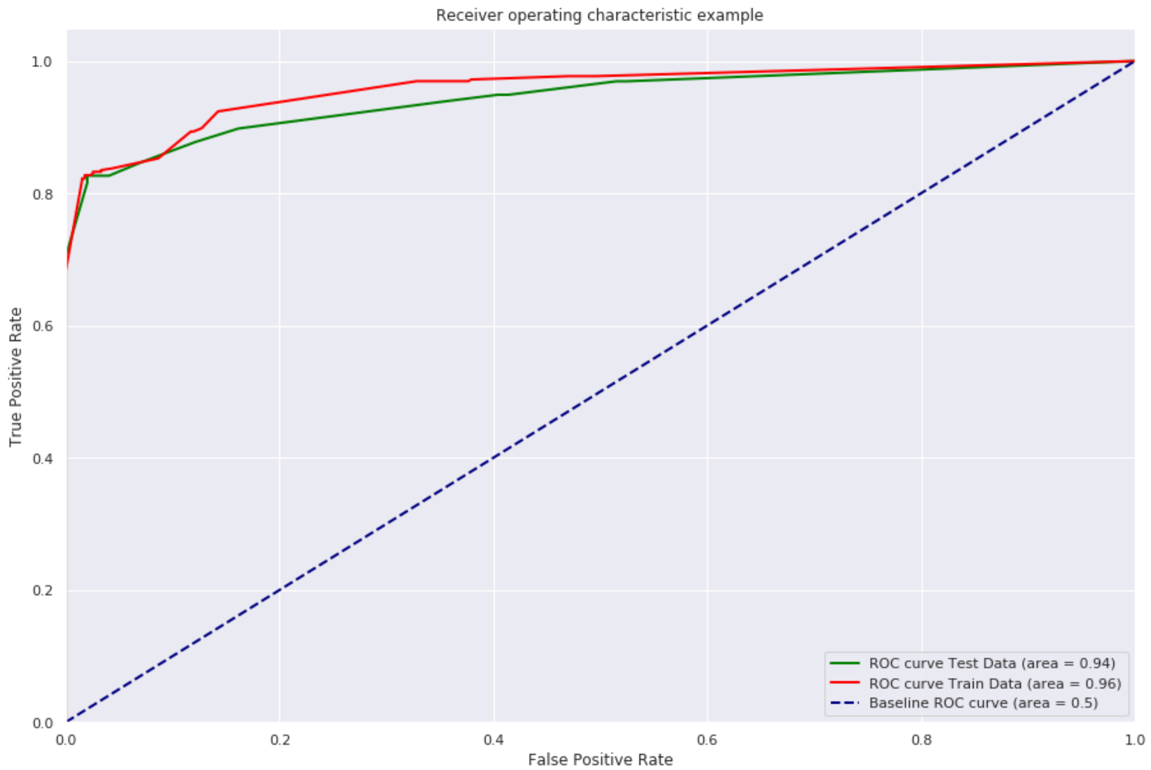
```
dt_grid_results, trained_model =  model_report(rsearch_cv, X_train, y_train, X_test, y_
test, class_labels=y_train.values)
```

```
Training the model...
Training completed...


Training Time (HH:MM:SS.ms) -- 0:00:00.003679


Predicting test data...
Predicting test data completed...


Testing Time(HH:MM:SS:ms) -- 0:00:00.001357


---------------------
|      F1 Score      |
---------------------

    0.8984771573604061


---------------------
|      Accuracy      |
---------------------

    0.8984771573604061


---------------------
|      Recall        |
---------------------

    0.8163265306122449


---------------------
|      ROC AUC       |
---------------------

    0.9444959802102658


-------------------------
| Classifiction Report  |
-------------------------
              precision    recall  f1-score   support

           0       0.84      0.98      0.91        99
           1       0.98      0.82      0.89        98

   micro avg       0.90      0.90      0.90       197
   macro avg       0.91      0.90      0.90       197
weighted avg       0.91      0.90      0.90       197
```



In [46]:

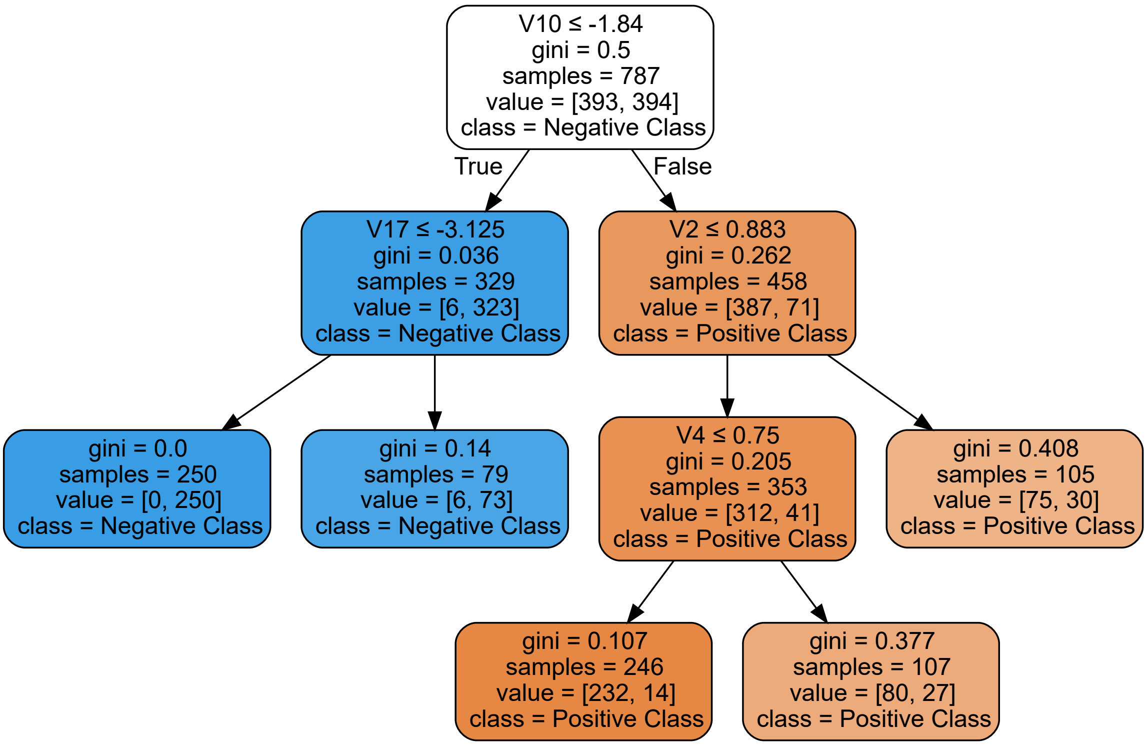
```
#Calibrate the model
from sklearn.calibration import CalibratedClassifierCV
sig_clf = CalibratedClassifierCV(trained_model, method="sigmoid")
sig_clf.fit(X_train, y_train)

#Plot the ROC curve
plot_roc_curve(sig_clf, X_train, y_train, X_test, y_test)
```



In [47]:

```
def visualize_tree(trained_clf, f_names, filename):
    from sklearn import tree
    import graphviz
    dot_data = tree.export_graphviz(decision_tree=trained_clf, out_file=None, max_depth
=3, filled=True, rounded=True, special_characters=True, impurity=True, feature_names=f_
names, class_names=['Positive Class','Negative Class'])
    graph = graphviz.Source(dot_data)
    graph.render(filename, format='png')
    return graph

#Call the function above and pass a filename onto it.
f_names=[i for i in X_train.columns]

graph=visualize_tree(trained_model, f_names, 'Credit_Card_Tree.png')
graph
```

Out[47]:



4. Linear SVM Classifier

In [48]:

```
from sklearn.svm import SVC

st=dt.now()
tuned_parameters = {'C':np.logspace(-3,4,25),
                    'gamma':np.logspace(-3,1,8)}

model = SVC(random_state=state)

rsearch_cv = RandomizedSearchCV(estimator=model,
                                param_distributions=tuned_parameters,
                                cv=3, scoring='roc_auc',
                                verbose=5,
                                n_jobs=-1,
                                random_state=state)
rsearch_cv.fit(X_train, y_train)

print("Time taken to complete random search: ",dt.now()-st)
```

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent worker
s.
[Parallel(n_jobs=-1)]: Done   2 tasks      | elapsed:    0.1s

Time taken to complete random search:  0:00:00.425082

[Parallel(n_jobs=-1)]: Done  15 out of  30 | elapsed:    0.2s remaining:
0.2s
[Parallel(n_jobs=-1)]: Done  22 out of  30 | elapsed:    0.3s remaining:
0.1s
[Parallel(n_jobs=-1)]: Done  30 out of  30 | elapsed:    0.4s finished
```

In [49]:

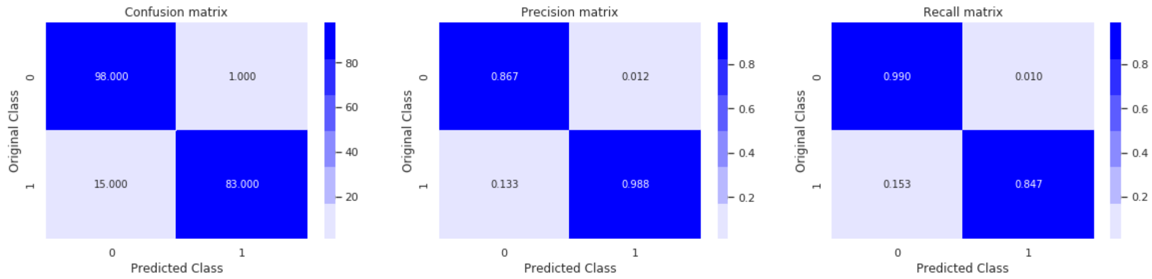
```
print_grid_search_attributes(rsearch_cv)
```

```
--------------------------
|      Best Estimator     |
--------------------------

        SVC(C=0.028729848333536655, cache_size=200, class_weight=None, coe
f0=0.0,
  decision_function_shape='ovr', degree=3, gamma=0.003727593720314938,
  kernel='rbf', max_iter=-1, probability=False, random_state=48,
  shrinking=True, tol=0.001, verbose=False)

--------------------------
|     Best parameters     |
--------------------------
        Parameters of best estimator :

        {'gamma': 0.003727593720314938, 'C': 0.028729848333536655}

---------------------------------
|   No of CrossValidation sets   |
--------------------------------

        Total numbre of cross validation sets: 3

--------------------------
|        Best Score       |
--------------------------

        Average Cross Validate scores of best estimator :

        0.9706541441848967
```

In [50]:

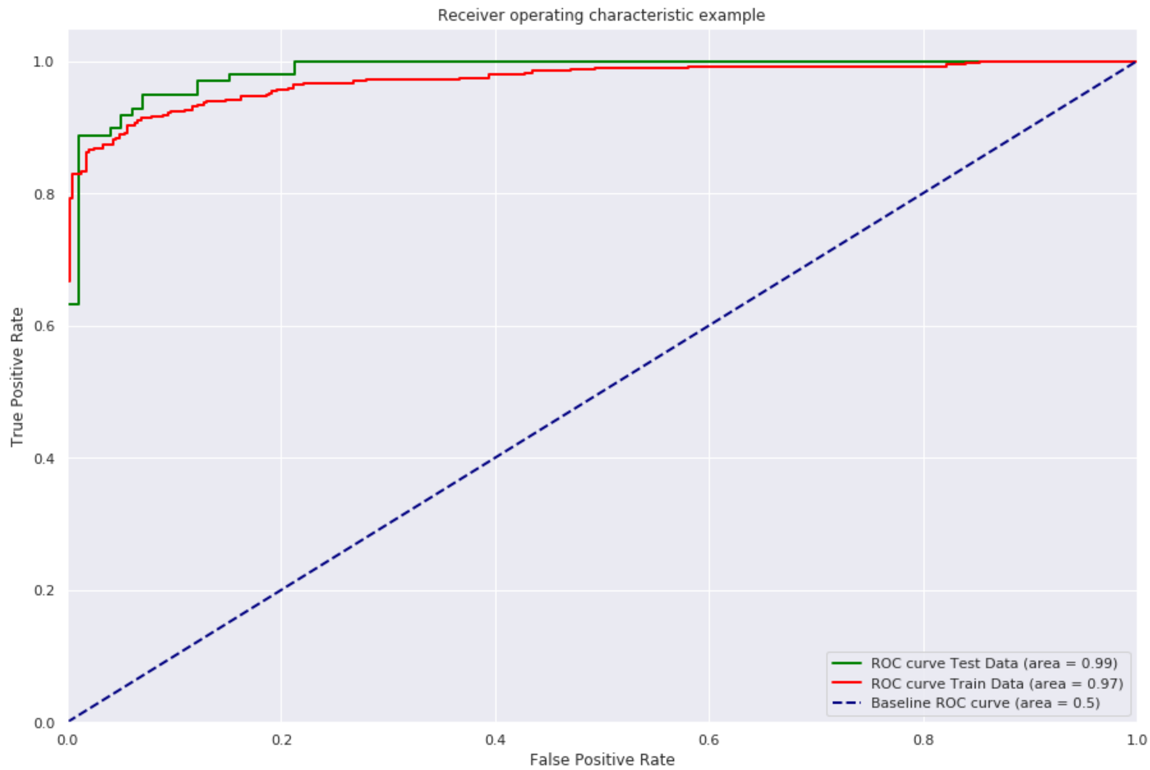
```
svc_grid_results, trained_model =  model_report(rsearch_cv, X_train, y_train, X_test, y
_test, class_labels=y_train.values)
```

```
Training the model...
Training completed...


Training Time (HH:MM:SS.ms) -- 0:00:00.038415


Predicting test data...
Predicting test data completed...


Testing Time(HH:MM:SS:ms) -- 0:00:00.007886


---------------------
|      F1 Score     |
---------------------

    0.9187817258883249


---------------------
|      Accuracy     |
---------------------

    0.9187817258883249


---------------------
|      Recall       |
---------------------

    0.8469387755102041


---------------------
|      ROC AUC      |
---------------------

    0.9855699855699855


-------------------------
| Classifiction Report  |
-------------------------
              precision    recall  f1-score   support

           0       0.87      0.99      0.92        99
           1       0.99      0.85      0.91        98

   micro avg       0.92      0.92      0.92       197
   macro avg       0.93      0.92      0.92       197
weighted avg       0.93      0.92      0.92       197
```



In [51]:

```
#Calibrate the model
from sklearn.calibration import CalibratedClassifierCV
sig_clf = CalibratedClassifierCV(trained_model, method="sigmoid")
sig_clf.fit(X_train, y_train)

#Plot the ROC curve
plot_roc_curve(sig_clf, X_train, y_train, X_test, y_test)
```



5. Random Forest Classifier

In [52]:

```
from sklearn.ensemble import RandomForestClassifier

st=dt.now()
tuned_parameters = {'max_depth':[3,4,5,6,7,8,9,10],
                    'criterion':['gini','entropy'],
                    'min_samples_split':[2,3,5,7,9],
                    'max_features':['auto','sqrt', 'log2'],
                    'min_samples_leaf':[1, 10, 25, 50, 75, 100],
                    'n_estimators':[10,20,30,40,50,60,80,100,500,1000,1500,2000,3000],
                    'max_leaf_nodes':[None, 10, 25, 50, 100, 500]}

model = RandomForestClassifier(random_state=state)
rsearch_cv = RandomizedSearchCV(estimator=model,
                                param_distributions=tuned_parameters,
                                cv=3, scoring='roc_auc',
                                verbose=5,
                                n_jobs=-1,
                                random_state=state)
rsearch_cv.fit(X_train, y_train)

print("Time taken to complete random search: ",dt.now()-st)
```

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent worker
s.
[Parallel(n_jobs=-1)]: Done   2 tasks      | elapsed:    4.4s
[Parallel(n_jobs=-1)]: Done  22 out of  30 | elapsed:    8.6s remaining:
3.1s
[Parallel(n_jobs=-1)]: Done  30 out of  30 | elapsed:   10.6s finished

Time taken to complete random search:  0:00:15.309435
```

In [53]:

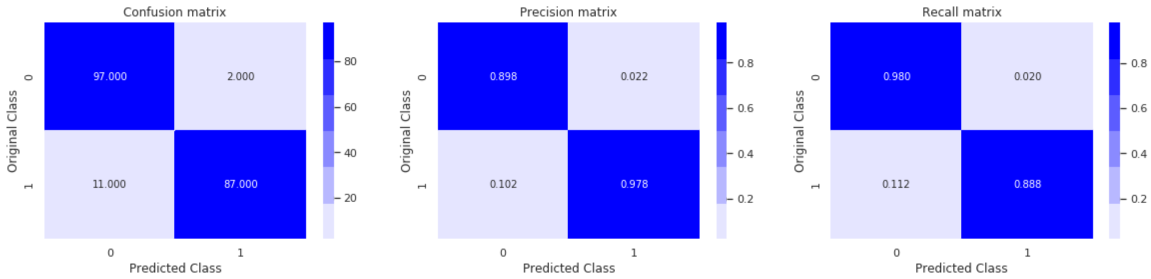
```
print_grid_search_attributes(rsearch_cv)
```

```
--------------------------
|      Best Estimator     |
--------------------------

        RandomForestClassifier(bootstrap=True, class_weight=None, criterio
n='entropy',
            max_depth=7, max_features='log2', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=10, min_samples_split=3,
            min_weight_fraction_leaf=0.0, n_estimators=1500, n_jobs=None,
            oob_score=False, random_state=48, verbose=0, warm_start=False)

--------------------------
|     Best parameters     |
--------------------------
        Parameters of best estimator :

        {'n_estimators': 1500, 'min_samples_split': 3, 'min_samples_leaf':
10, 'max_leaf_nodes': None, 'max_features': 'log2', 'max_depth': 7, 'crite
rion': 'entropy'}

---------------------------------
|   No of CrossValidation sets   |
--------------------------------

        Total numbre of cross validation sets: 3

--------------------------
|        Best Score       |
--------------------------

        Average Cross Validate scores of best estimator :

        0.9774326972451068
```

In [54]:

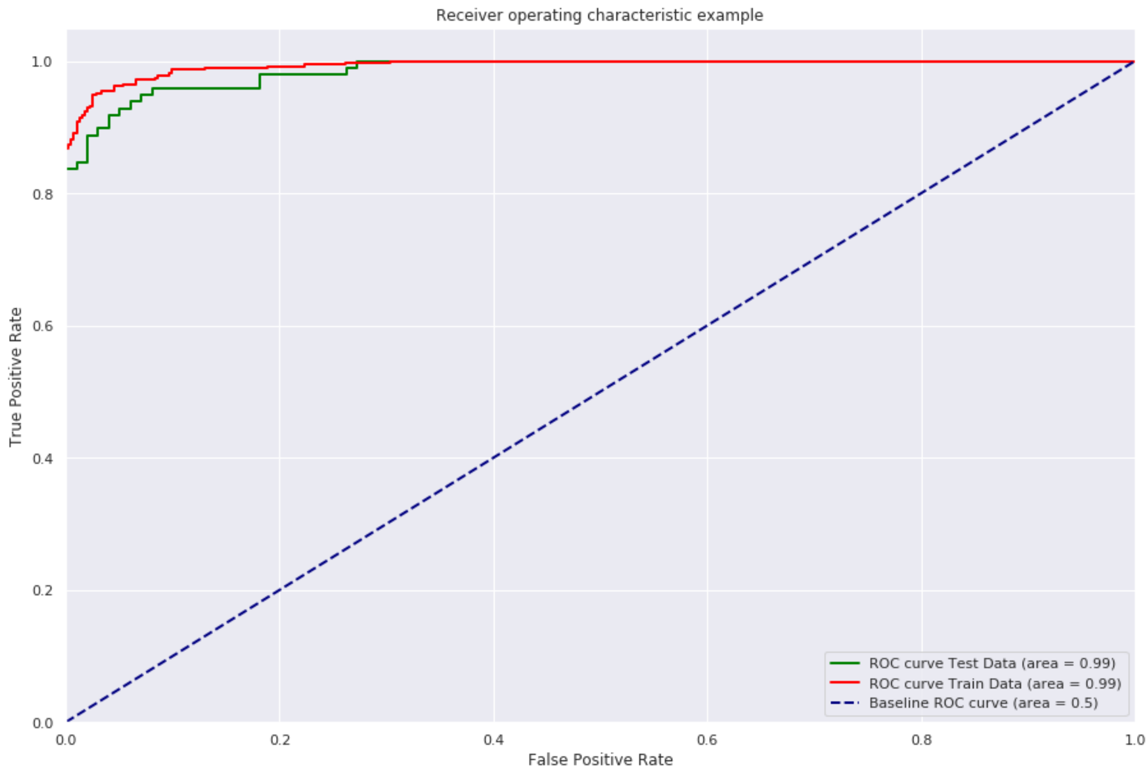
```
rf_grid_results, trained_model =  model_report(rsearch_cv, X_train, y_train, X_test, y_
test, class_labels=y_train.values)
```

```
Training the model...
Training completed...


Training Time (HH:MM:SS.ms) -- 0:00:04.717364


Predicting test data...
Predicting test data completed...


Testing Time(HH:MM:SS:ms) -- 0:00:00.157480


---------------------
|      F1 Score      |
---------------------

    0.934010152284264


---------------------
|      Accuracy      |
---------------------

    0.934010152284264


---------------------
|      Recall        |
---------------------

    0.8877551020408163


---------------------
|      ROC AUC       |
---------------------

    0.9860853432282004


-------------------------
| Classifiction Report  |
-------------------------
              precision    recall  f1-score   support

           0       0.90      0.98      0.94        99
           1       0.98      0.89      0.93        98

   micro avg       0.93      0.93      0.93       197
   macro avg       0.94      0.93      0.93       197
weighted avg       0.94      0.93      0.93       197
```



In [55]:

```
#Calibrate the model
from sklearn.calibration import CalibratedClassifierCV
sig_clf = CalibratedClassifierCV(trained_model, method="sigmoid")
sig_clf.fit(X_train, y_train)

#Plot the ROC curve
plot_roc_curve(sig_clf, X_train, y_train, X_test, y_test)
```



6. XGBoost Classifier

In [59]:

```
from xgboost import XGBClassifier

st=dt.now()
tuned_parameters = {'learning_rate':[0.1,0.01,0.001,0.0001],
                    'n_estimators':[10,25,50,100,250,500,650,750,850,1000,1500,2000,300
0],
                    'subsample':[0.6,0.7,0.8],
                    'min_child_weight':[3,5,7,9],
                    'max_depth': [3,4,5,6,7,9,11,13,15,17,20,25,50],
                    'colsample_bytree':[0.6,0.7,0.8],
                    'gamma':[0,0.25,0.4,0.5,0.55,0.7,1]}

model = XGBClassifier(random_state=state)

rsearch_cv = RandomizedSearchCV(estimator=model,
                                param_distributions=tuned_parameters,
                                cv=3, scoring='roc_auc',
                                verbose=5,
                                n_jobs=-1,
                                random_state=state)
rsearch_cv.fit(X_train, y_train)

print("Time taken to complete random search: ",dt.now()-st)
```

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent worker
s.
[Parallel(n_jobs=-1)]: Done   2 tasks      | elapsed:    0.7s
[Parallel(n_jobs=-1)]: Done  22 out of  30 | elapsed:    1.5s remaining:
0.6s
[Parallel(n_jobs=-1)]: Done  30 out of  30 | elapsed:    3.2s finished

Time taken to complete random search:  0:00:04.625647
```

In [60]:

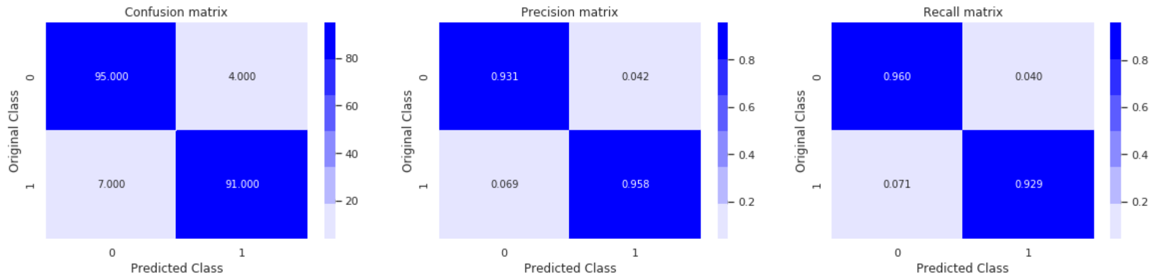
```
print_grid_search_attributes(rsearch_cv)
```

```
--------------------------
|      Best Estimator     |
--------------------------

        XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=
1,
       colsample_bytree=0.8, gamma=0.25, learning_rate=0.01,
       max_delta_step=0, max_depth=17, min_child_weight=3, missing=None,
       n_estimators=850, n_jobs=1, nthread=None,
       objective='binary:logistic', random_state=48, reg_alpha=0,
       reg_lambda=1, scale_pos_weight=1, seed=None, silent=True,
       subsample=0.6)

--------------------------
|     Best parameters     |
--------------------------
        Parameters of best estimator : 

        {'subsample': 0.6, 'n_estimators': 850, 'min_child_weight': 3, 'ma
x_depth': 17, 'learning_rate': 0.01, 'gamma': 0.25, 'colsample_bytree': 0.
8}

---------------------------------
|   No of CrossValidation sets   |
--------------------------------

        Total numbre of cross validation sets: 3

--------------------------
|        Best Score       |
--------------------------

        Average Cross Validate scores of best estimator : 

        0.9796251015151662
```

In [61]:

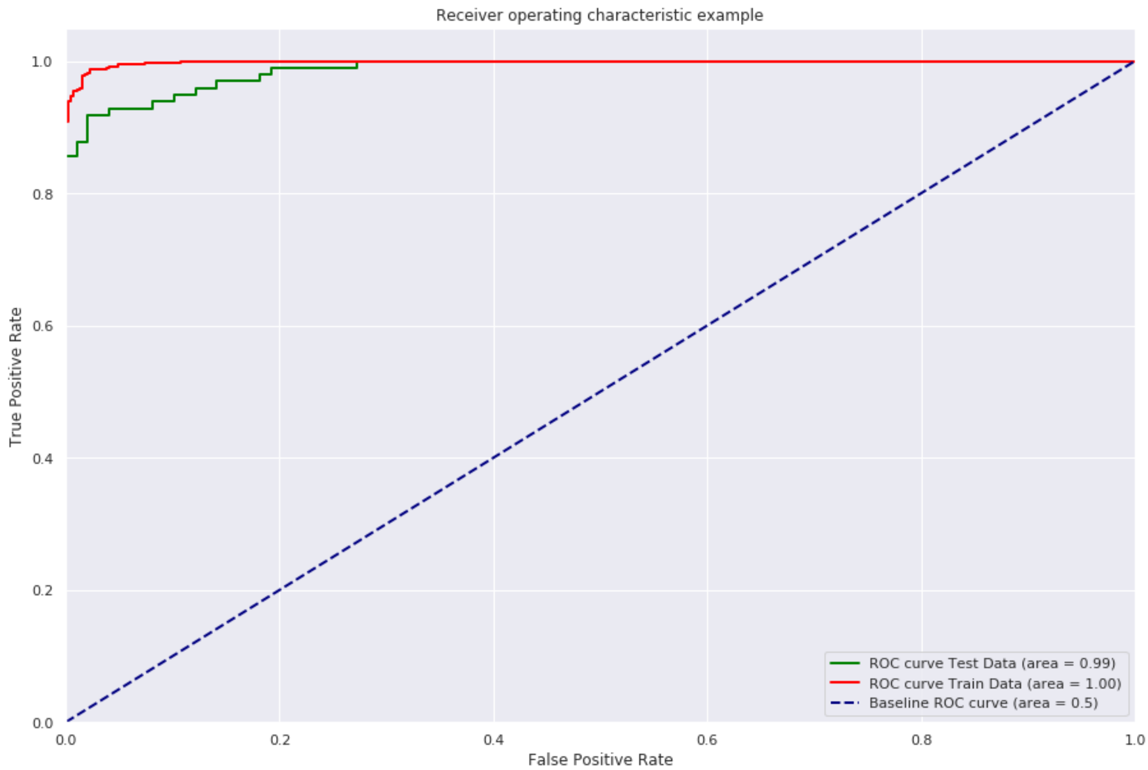
```
xgb_grid_results, trained_model =  model_report(rsearch_cv, X_train, y_train, X_test, y
_test, class_labels=y_train.values)
```

```
Training the model...
Training completed...


Training Time (HH:MM:SS.ms) -- 0:00:01.452918


Predicting test data...
Predicting test data completed...


Testing Time(HH:MM:SS:ms) -- 0:00:00.009262


---------------------
|      F1 Score      |
---------------------

    0.9441624365482234


---------------------
|      Accuracy      |
---------------------

    0.9441624365482234


---------------------
|      Recall        |
---------------------

    0.9285714285714286


---------------------
|      ROC AUC       |
---------------------

    0.9874252731395589


-------------------------
| Classifiction Report  |
-------------------------
              precision    recall  f1-score   support

           0       0.93      0.96      0.95        99
           1       0.96      0.93      0.94        98

   micro avg       0.94      0.94      0.94       197
   macro avg       0.94      0.94      0.94       197
weighted avg       0.94      0.94      0.94       197
```



In [62]:

```
#Calibrate the model
from sklearn.calibration import CalibratedClassifierCV
sig_clf = CalibratedClassifierCV(trained_model, method="sigmoid")
sig_clf.fit(X_train, y_train)

#Plot the ROC curve
plot_roc_curve(sig_clf, X_train, y_train, X_test, y_test)
```



7. Neural Networks

In [63]:

```
import keras
from keras.models import Sequential
from keras.layers import Activation
from keras.layers.core import Dense, Dropout
from keras import optimizers
from keras.metrics import binary_crossentropy
from keras.utils import to_categorical
```

```
Using TensorFlow backend.
```

In [65]:

```
import warnings
warnings.filterwarnings("ignore")

#Initializing parameters
epochs = 50
batch_size = 16
first_layer_input = X_train.shape[1]

#Define the neural network architecture
model = Sequential()
model.add(Dense(32, input_shape=(first_layer_input, ), activation='relu', kernel_initia
lizer='he_uniform'))
model.add(Dense(32, activation='relu',kernel_initializer='he_uniform'))
model.add(Dense(1, activation='sigmoid', kernel_initializer='glorot_uniform'))
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_4 (Dense)              (None, 32)                992       
_________________________________________________________________
dense_5 (Dense)              (None, 32)                1056      
_________________________________________________________________
dense_6 (Dense)              (None, 1)                 33        
=================================================================
Total params: 2,081
Trainable params: 2,081
Non-trainable params: 0
_________________________________________________________________
```

In [66]:

```
#Define optimzers for training the neural network
optim=optimizers.Adam(lr=0.001)
model.compile(optimizer=optim, loss='binary_crossentropy', metrics=['accuracy'])
```

In [68]:

```
#Start training the neural network
model.fit(X_train, y_train, batch_size=batch_size, epochs=epochs, validation_split=0.3,
shuffle=True)
```

```
Train on 550 samples, validate on 237 samples
Epoch 1/50
550/550 [==============================] - 0s 131us/step - loss: 0.0176 -
acc: 0.9945 - val_loss: 0.2642 - val_acc: 0.9241
Epoch 2/50
550/550 [==============================] - 0s 132us/step - loss: 0.0173 -
acc: 0.9927 - val_loss: 0.2713 - val_acc: 0.9241
Epoch 3/50
550/550 [==============================] - 0s 137us/step - loss: 0.0160 -
acc: 0.9964 - val_loss: 0.2747 - val_acc: 0.9241
Epoch 4/50
550/550 [==============================] - 0s 124us/step - loss: 0.0153 -
acc: 0.9982 - val_loss: 0.2781 - val_acc: 0.9283
Epoch 5/50
550/550 [==============================] - 0s 117us/step - loss: 0.0141 -
acc: 0.9982 - val_loss: 0.2814 - val_acc: 0.9283
Epoch 6/50
550/550 [==============================] - 0s 118us/step - loss: 0.0135 -
acc: 0.9982 - val_loss: 0.2865 - val_acc: 0.9283
Epoch 7/50
550/550 [==============================] - 0s 118us/step - loss: 0.0127 -
acc: 0.9982 - val_loss: 0.2913 - val_acc: 0.9283
Epoch 8/50
550/550 [==============================] - 0s 125us/step - loss: 0.0121 -
acc: 0.9982 - val_loss: 0.2936 - val_acc: 0.9283
Epoch 9/50
550/550 [==============================] - 0s 121us/step - loss: 0.0113 -
acc: 0.9982 - val_loss: 0.2991 - val_acc: 0.9283
Epoch 10/50
550/550 [==============================] - 0s 115us/step - loss: 0.0107 -
acc: 0.9982 - val_loss: 0.3040 - val_acc: 0.9283
Epoch 11/50
550/550 [==============================] - 0s 141us/step - loss: 0.0103 -
acc: 0.9982 - val_loss: 0.3107 - val_acc: 0.9241
Epoch 12/50
550/550 [==============================] - 0s 136us/step - loss: 0.0098 -
acc: 0.9982 - val_loss: 0.3121 - val_acc: 0.9283
Epoch 13/50
550/550 [==============================] - 0s 130us/step - loss: 0.0092 -
acc: 0.9982 - val_loss: 0.3178 - val_acc: 0.9241
Epoch 14/50
550/550 [==============================] - 0s 132us/step - loss: 0.0087 -
acc: 0.9982 - val_loss: 0.3206 - val_acc: 0.9283
Epoch 15/50
550/550 [==============================] - 0s 114us/step - loss: 0.0084 -
acc: 1.0000 - val_loss: 0.3255 - val_acc: 0.9241
Epoch 16/50
550/550 [==============================] - 0s 125us/step - loss: 0.0081 -
acc: 1.0000 - val_loss: 0.3311 - val_acc: 0.9241
Epoch 17/50
550/550 [==============================] - 0s 142us/step - loss: 0.0076 -
acc: 1.0000 - val_loss: 0.3348 - val_acc: 0.9241
Epoch 18/50
550/550 [==============================] - 0s 135us/step - loss: 0.0071 -
acc: 1.0000 - val_loss: 0.3392 - val_acc: 0.9241
Epoch 19/50
550/550 [==============================] - 0s 137us/step - loss: 0.0068 -
acc: 1.0000 - val_loss: 0.3386 - val_acc: 0.9241
Epoch 20/50
550/550 [==============================] - 0s 143us/step - loss: 0.0064 -
acc: 1.0000 - val_loss: 0.3442 - val_acc: 0.9241
```

```
Epoch 21/50
550/550 [==============================] - 0s 125us/step - loss: 0.0062 -
acc: 1.0000 - val_loss: 0.3502 - val_acc: 0.9241
Epoch 22/50
550/550 [==============================] - 0s 130us/step - loss: 0.0063 -
acc: 1.0000 - val_loss: 0.3540 - val_acc: 0.9241
Epoch 23/50
550/550 [==============================] - 0s 142us/step - loss: 0.0056 -
acc: 1.0000 - val_loss: 0.3590 - val_acc: 0.9241
Epoch 24/50
550/550 [==============================] - 0s 124us/step - loss: 0.0054 -
acc: 1.0000 - val_loss: 0.3639 - val_acc: 0.9241
Epoch 25/50
550/550 [==============================] - 0s 121us/step - loss: 0.0051 -
acc: 1.0000 - val_loss: 0.3665 - val_acc: 0.9241
Epoch 26/50
550/550 [==============================] - 0s 125us/step - loss: 0.0049 -
acc: 1.0000 - val_loss: 0.3710 - val_acc: 0.9241
Epoch 27/50
550/550 [==============================] - 0s 132us/step - loss: 0.0046 -
acc: 1.0000 - val_loss: 0.3772 - val_acc: 0.9241
Epoch 28/50
550/550 [==============================] - 0s 140us/step - loss: 0.0044 -
acc: 1.0000 - val_loss: 0.3795 - val_acc: 0.9241
Epoch 29/50
550/550 [==============================] - 0s 137us/step - loss: 0.0042 -
acc: 1.0000 - val_loss: 0.3852 - val_acc: 0.9241
Epoch 30/50
550/550 [==============================] - 0s 112us/step - loss: 0.0041 -
acc: 1.0000 - val_loss: 0.3892 - val_acc: 0.9241
Epoch 31/50
550/550 [==============================] - 0s 119us/step - loss: 0.0039 -
acc: 1.0000 - val_loss: 0.3914 - val_acc: 0.9241
Epoch 32/50
550/550 [==============================] - 0s 148us/step - loss: 0.0039 -
acc: 1.0000 - val_loss: 0.4012 - val_acc: 0.9241
Epoch 33/50
550/550 [==============================] - 0s 125us/step - loss: 0.0036 -
acc: 1.0000 - val_loss: 0.4016 - val_acc: 0.9241
Epoch 34/50
550/550 [==============================] - 0s 133us/step - loss: 0.0034 -
acc: 1.0000 - val_loss: 0.4057 - val_acc: 0.9241
Epoch 35/50
550/550 [==============================] - 0s 144us/step - loss: 0.0034 -
acc: 1.0000 - val_loss: 0.4064 - val_acc: 0.9241
Epoch 36/50
550/550 [==============================] - 0s 125us/step - loss: 0.0031 -
acc: 1.0000 - val_loss: 0.4111 - val_acc: 0.9241
Epoch 37/50
550/550 [==============================] - 0s 122us/step - loss: 0.0030 -
acc: 1.0000 - val_loss: 0.4161 - val_acc: 0.9241
Epoch 38/50
550/550 [==============================] - 0s 114us/step - loss: 0.0029 -
acc: 1.0000 - val_loss: 0.4188 - val_acc: 0.9241
Epoch 39/50
550/550 [==============================] - 0s 135us/step - loss: 0.0029 -
acc: 1.0000 - val_loss: 0.4241 - val_acc: 0.9241
Epoch 40/50
550/550 [==============================] - 0s 121us/step - loss: 0.0027 -
acc: 1.0000 - val_loss: 0.4282 - val_acc: 0.9241
Epoch 41/50
```

```
550/550 [==============================] - 0s 140us/step - loss: 0.0025 - acc: 1.0000 - val_loss: 0.4294 - val_acc: 0.9241
Epoch 42/50
550/550 [==============================] - 0s 133us/step - loss: 0.0024 - acc: 1.0000 - val_loss: 0.4352 - val_acc: 0.9241
Epoch 43/50
550/550 [==============================] - 0s 119us/step - loss: 0.0024 - acc: 1.0000 - val_loss: 0.4386 - val_acc: 0.9241
Epoch 44/50
550/550 [==============================] - 0s 114us/step - loss: 0.0022 - acc: 1.0000 - val_loss: 0.4390 - val_acc: 0.9241
Epoch 45/50
550/550 [==============================] - 0s 119us/step - loss: 0.0022 - acc: 1.0000 - val_loss: 0.4458 - val_acc: 0.9241
Epoch 46/50
550/550 [==============================] - 0s 110us/step - loss: 0.0021 - acc: 1.0000 - val_loss: 0.4490 - val_acc: 0.9241
Epoch 47/50
550/550 [==============================] - 0s 126us/step - loss: 0.0020 - acc: 1.0000 - val_loss: 0.4483 - val_acc: 0.9241
Epoch 48/50
550/550 [==============================] - 0s 142us/step - loss: 0.0020 - acc: 1.0000 - val_loss: 0.4541 - val_acc: 0.9241
Epoch 49/50
550/550 [==============================] - 0s 126us/step - loss: 0.0018 - acc: 1.0000 - val_loss: 0.4564 - val_acc: 0.9241
Epoch 50/50
550/550 [==============================] - 0s 124us/step - loss: 0.0019 - acc: 1.0000 - val_loss: 0.4594 - val_acc: 0.9241
```

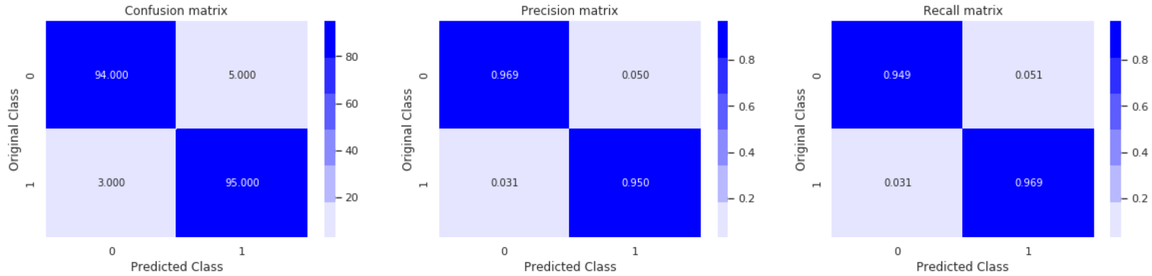
Out[68]:

```
<keras.callbacks.History at 0x7fec01702208>
```

In [75]:

```
nn_results = dict()

#Compute the F1 score
f1_score = metrics.f1_score(y_true=y_test, y_pred=y_pred, average='micro') #F1 = 2 * (p
recision * recall) / (precision + recall)
nn_results['F1_Score'] = f1_score
print('\nF1 Score = {}'.format(f1_score))


#Calculate overall accuracy of the model
accuracy = metrics.accuracy_score(y_true=y_test, y_pred=y_pred)
nn_results['Accuracy'] = accuracy
print('\nAccuracy = {}'.format(accuracy))

#Calculate overall recall_score of the model
recall = metrics.recall_score(y_true=y_test, y_pred=y_pred)
nn_results['Recall'] = recall
print('\nRecall = {}'.format(recall))

#Calculate overall roc-auc of the model
#Calibrate the model
roc_auc = metrics.roc_auc_score(y_true=y_test, y_score=y_pred)
nn_results['ROC-AUC'] = roc_auc
print('\nROC-AUC = {}\n'.format(roc_auc))

#Display the classification report having individual class recalls and precision value
s.
print('------------------------')
print('| Classifiction Report  |')
print('------------------------')
classification_report = metrics.classification_report(y_test, y_pred)

#Store report in nn_results
nn_results['Classification_Report'] = classification_report
print(classification_report)

#Add the trained  model to the nn_results
nn_results['Model'] = model

#Plot the confusion matrix curve
plot_confusion_matrix(y_test, y_pred)
```

```
F1 Score = 0.9593908629441623

Accuracy = 0.9593908629441624

Recall = 0.9693877551020408

ROC-AUC = 0.959441352298495

-------------------------
| Classifiction Report  |
-------------------------
              precision    recall  f1-score   support

           0       0.97      0.95      0.96        99
           1       0.95      0.97      0.96        98

   micro avg       0.96      0.96      0.96       197
   macro avg       0.96      0.96      0.96       197
weighted avg       0.96      0.96      0.96       197
```



In [98]:

```
print('\n                          Accuracy        Recall      ROC-AUC')
print('                         ----------      --------    --------')

print('Logistic Regression        : {:.04}%          {:.04}%       {:.04}'.format(log_r
eg_grid_results['Accuracy'] * 100,
                                                                              log_r
eg_grid_results['Recall'] * 100,
                                                                              log_r
eg_grid_results['ROC-AUC']))
print('KNN Classifier             : {:.04}%          {:.04}%       {:.04}'.format(knn_g
rid_results['Accuracy'] * 100,
                                                                              knn_g
rid_results['Recall'] * 100,
                                                                              knn_g
rid_results['ROC-AUC']))
print('Decision Trees Classifier  : {:.04}%          {:.04}%       {:.04}'.format(dt_gr
id_results['Accuracy'] * 100,
                                                                              dt_gr
id_results['Recall'] * 100,
                                                                              dt_gr
id_results['ROC-AUC']))
print('Linear SVC                 : {:.04}%          {:.04}%       {:.04}'.format(svc_g
rid_results['Accuracy'] * 100,
                                                                              svc_g
rid_results['Recall'] * 100,
                                                                              svc_g
rid_results['ROC-AUC']))
print('Random Forest Classifier   : {:.04}%           {:.04}%       {:.04}'.format(rf_g
rid_results['Accuracy'] * 100,
                                                                              rf_gr
id_results['Recall'] * 100,
                                                                              rf_gr
id_results['ROC-AUC']))
print('XGBoost Classifier         : {:.04}%          {:.04}%       {:.04}'.format(xgb_g
rid_results['Accuracy'] * 100,
                                                                              xgb_g
rid_results['Recall'] * 100,
                                                                              xgb_g
rid_results['ROC-AUC']))
print('Neural Networks            : {:.04}%          {:.04}%       {:.04}'.format(nn_re
sults['Accuracy'] * 100,
                                                                              nn_re
sults['Recall'] * 100,
                                                                              nn_re
sults['ROC-AUC']))
```

```
                             Accuracy        Recall      ROC-AUC
                            ----------      --------    --------
Logistic Regression        : 88.83%          97.96%       0.9887
KNN Classifier             : 92.89%          87.76%       0.9853
Decision Trees Classifier  : 89.85%          81.63%       0.9445
Linear SVC                 : 91.88%          84.69%       0.9856
Random Forest Classifier   : 93.4%           88.78%       0.9861
XGBoost Classifier         : 94.42%          92.86%       0.9874
Neural Networks            : 95.94%          96.94%       0.9594
```

Perform threshold analysis using Logistic Regression model

In [ ]:

```

```

Split the original imbalanced dataset into train and test set

In [16]:

```
from sklearn.model_selection import train_test_split

print("Shape of the original dataset: ", data.shape)

X=data.drop("Class", axis=1)
y=data['Class']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, stratify=y, ra
ndom_state=state)

print('\nNumber of data points in train data:', X_train.shape[0])
print('Number of data points in test data:', X_test.shape[0])
```

```
Shape of the original dataset:  (284807, 31)

Number of data points in train data: 227845
Number of data points in test data: 56962
```

Data Oversampling using SMOTE

In [17]:

```
#Get information about the class labels before applying SMOTE
print("Before oversampling, number of fraud transactions: ",y_train.value_counts()[1])
print("Before oversampling, number of non fraud transactions: ",y_train.value_counts()[
0])
```

```
Before oversampling, number of fraud transactions:  394
Before oversampling, number of non fraud transactions:  227451
```

In [18]:

```
from imblearn.over_sampling import SMOTE
smote_obj = SMOTE(sampling_strategy='minority',random_state=state)

#Adding synthetic points at this stage
X_train, y_train = smote_obj.fit_sample(X_train, y_train)
```

In [19]:

```
print("After oversampling, number of fraud transactions: ",sum(y_train==1))
print("After oversampling, number of non fraud transactions: ",sum(y_train==0))
```

```
After oversampling, number of fraud transactions:  227451
After oversampling, number of non fraud transactions:  227451
```

1. Logistic Regression Classifier

In [21]:

```
from sklearn.model_selection import RandomizedSearchCV
from sklearn.linear_model import LogisticRegression
from datetime import datetime as dt
from scipy import stats

st=dt.now()

tuned_parameters = {'C': stats.uniform(0,10000),
                    'penalty': ['l1','l2'] } #C values used for cross validation

model = LogisticRegression(n_jobs=-1, random_state=state)
rsearch_cv = RandomizedSearchCV(estimator=model,
                                param_distributions=tuned_parameters,
                                cv=5, scoring='roc_auc',
                                n_jobs=-1,
                                verbose=5,
                                random_state=state)
rsearch_cv.fit(X_train, y_train)

print("Time taken to complete random search: ",dt.now()-st)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent worker
s.
[Parallel(n_jobs=-1)]: Done   2 tasks      | elapsed:   34.9s
[Parallel(n_jobs=-1)]: Done  46 out of  50 | elapsed:  6.9min remaining:
36.0s
[Parallel(n_jobs=-1)]: Done  50 out of  50 | elapsed:  7.3min finished

Time taken to complete random search:  0:07:29.236845
```

In [22]:

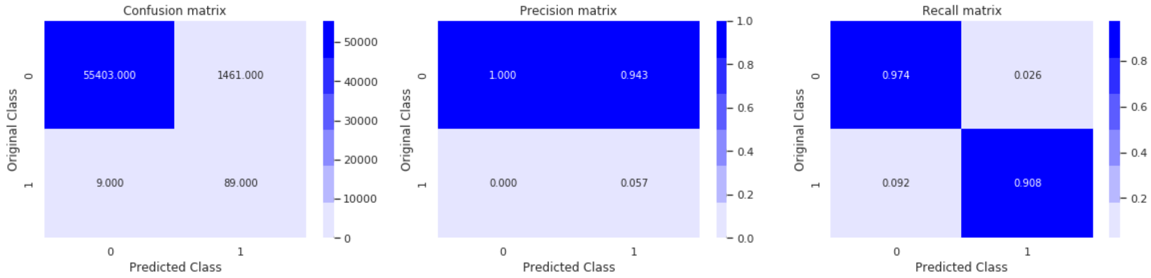
```
print_grid_search_attributes(rsearch_cv)
```

```
--------------------------
|      Best Estimator     |
--------------------------

        LogisticRegression(C=174.90270931152628, class_weight=None, dual=F
alse,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='warn', n_jobs=-1, penalty='l2', random_state=48,
          solver='warn', tol=0.0001, verbose=0, warm_start=False)

--------------------------
|     Best parameters     |
--------------------------
        Parameters of best estimator :

        {'C': 174.90270931152628, 'penalty': 'l2'}

---------------------------------
|   No of CrossValidation sets   |
--------------------------------

        Total numbre of cross validation sets: 5

--------------------------
|        Best Score       |
--------------------------

        Average Cross Validate scores of best estimator :

        0.9909727979229617
```

In [23]:

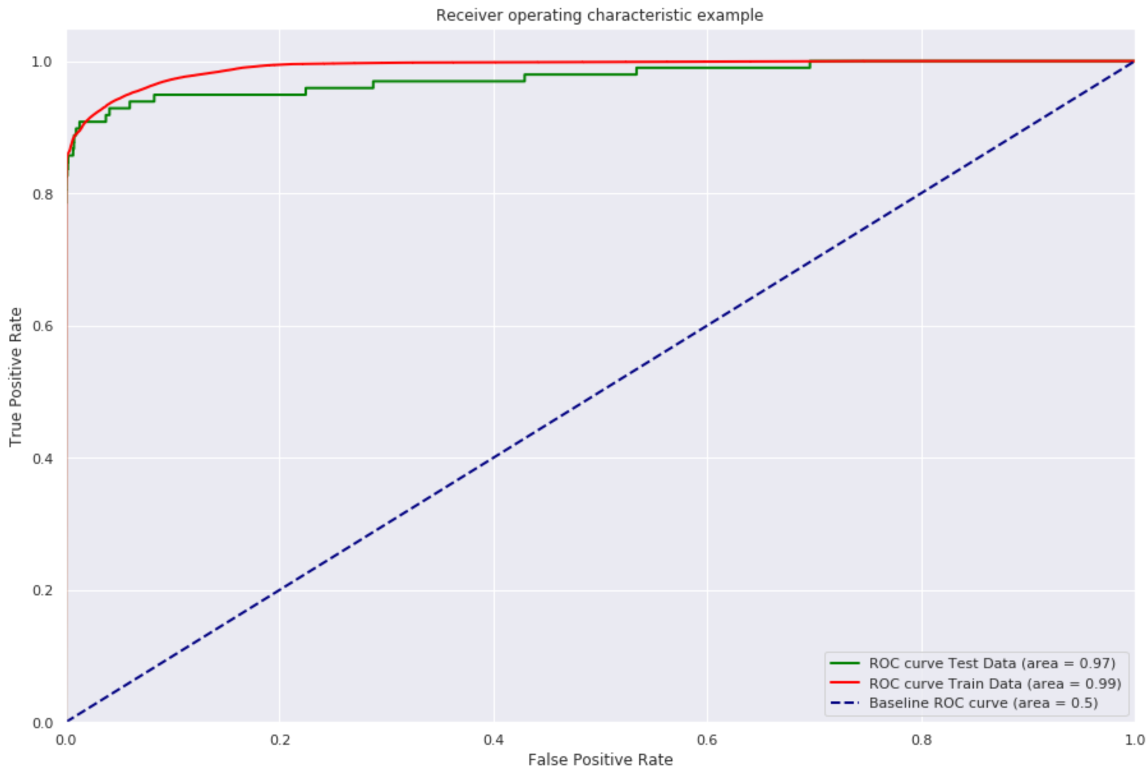
```
log_reg_grid_results, trained_model =  model_report(rsearch_cv, X_train, y_train, X_tes
t, y_test, class_labels=y_train)
```

```
Training the model...
Training completed...


Training Time (HH:MM:SS.ms) -- 0:00:10.079332


Predicting test data...
Predicting test data completed...


Testing Time(HH:MM:SS:ms) -- 0:00:00.005715


---------------------
|      F1 Score      |
---------------------

    0.9741933218636986


---------------------
|      Accuracy      |
---------------------

    0.9741933218636986


---------------------
|      Recall        |
---------------------

    0.9081632653061225


---------------------
|      ROC AUC       |
---------------------

    0.9749633568959379


-------------------------
| Classifiction Report  |
-------------------------
              precision    recall  f1-score   support

           0       1.00      0.97      0.99     56864
           1       0.06      0.91      0.11        98

   micro avg       0.97      0.97      0.97     56962
   macro avg       0.53      0.94      0.55     56962
weighted avg       1.00      0.97      0.99     56962
```



In [24]:

```
#Calibrate the model
from sklearn.calibration import CalibratedClassifierCV
sig_clf = CalibratedClassifierCV(trained_model, method="sigmoid")
sig_clf.fit(X_train, y_train)

#Plot the ROC curve
plot_roc_curve(sig_clf, X_train, y_train, X_test, y_test)
```



In [25]:

```
import gc
gc.collect()

del(model, trained_model, rsearch_cv)
```

In [26]:

```
log_reg_grid_results
```

Out[26]:

```
{'Training_Time': datetime.timedelta(seconds=10, microseconds=79332),
 'Testing_Time': datetime.timedelta(microseconds=5715),
 'Predicted': array([0, 0, 0, ..., 0, 0, 0]),
 'F1_Score': 0.9741933218636986,
 'Accuracy': 0.9741933218636986,
 'Recall': 0.9081632653061225,
 'ROC-AUC': 0.9749633568959379,
 'Classification_Report': '              precision    recall  f1-score   s
upport\n\n           0       1.00      0.97      0.99     56864\n
1       0.06      0.91      0.11        98\n\n   micro avg       0.97
0.97      0.97     56962\n   macro avg       0.53      0.94      0.55
56962\nweighted avg       1.00      0.97      0.99     56962\n',
 'Model': LogisticRegression(C=174.90270931152628, class_weight=None, dual
=False,
           fit_intercept=True, intercept_scaling=1, max_iter=100,
           multi_class='warn', n_jobs=-1, penalty='l2', random_state=48,
           solver='warn', tol=0.0001, verbose=0, warm_start=False)}
```

2. KNN Classifier

In [27]:

```
from sklearn.neighbors import KNeighborsClassifier

st=dt.now()

tuned_parameters = {'n_neighbors': [3,5,7,9,11,13],
                    'weights': ['uniform','distance']}

model = KNeighborsClassifier(n_jobs=-1, p=2, metric='minkowski')

rsearch_cv = RandomizedSearchCV(estimator=model,
                                param_distributions=tuned_parameters,
                                cv=5, scoring='roc_auc',
                                n_jobs=-1,
                                verbose=5,
                                random_state=state)
rsearch_cv.fit(X_train, y_train)

print("Time taken to complete random search: ",dt.now()-st)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent worker
s.
[Parallel(n_jobs=-1)]: Done   2 tasks      | elapsed: 32.4min
[Parallel(n_jobs=-1)]: Done  46 out of  50 | elapsed: 177.6min remaining:
15.4min
[Parallel(n_jobs=-1)]: Done  50 out of  50 | elapsed: 181.6min finished

Time taken to complete random search:  3:01:41.284961
```

In [28]:

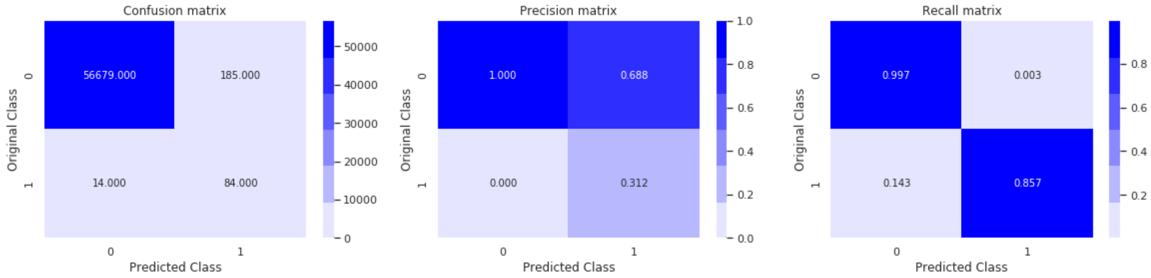
```
print_grid_search_attributes(rsearch_cv)
```

```
--------------------------
|      Best Estimator     |
--------------------------

        KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minko
wski',
           metric_params=None, n_jobs=-1, n_neighbors=13, p=2,
           weights='distance')

--------------------------
|     Best parameters     |
--------------------------
        Parameters of best estimator : 

        {'weights': 'distance', 'n_neighbors': 13}

---------------------------------
|   No of CrossValidation sets   |
--------------------------------

        Total numbre of cross validation sets: 5

--------------------------
|       Best Score        |
--------------------------

        Average Cross Validate scores of best estimator : 

        0.9996812500274784
```

In [29]:

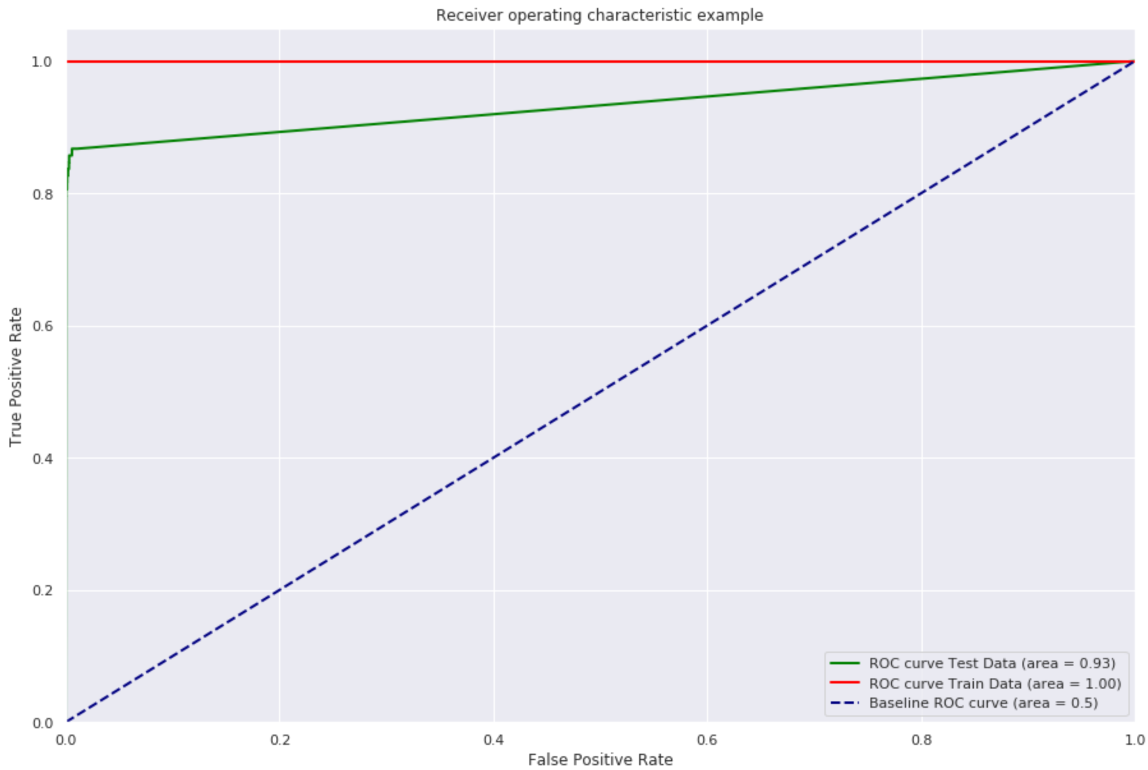
```
knn_grid_results, trained_model =  model_report(rsearch_cv, X_train, y_train, X_test, y
_test, class_labels=y_train)
```

```
Training the model...
Training completed...


Training Time (HH:MM:SS.ms) -- 0:00:02.305079


Predicting test data...
Predicting test data completed...


Testing Time(HH:MM:SS:ms) -- 0:02:39.129933


---------------------
|      F1 Score      |
---------------------

    0.9965064428917524


---------------------
|      Accuracy      |
---------------------

    0.9965064428917524


---------------------
|      Recall        |
---------------------

    0.8571428571428571


---------------------
|      ROC AUC       |
---------------------

    0.9326478393129903


-------------------------
| Classifiction Report  |
-------------------------
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56864
           1       0.31      0.86      0.46        98

   micro avg       1.00      1.00      1.00     56962
   macro avg       0.66      0.93      0.73     56962
weighted avg       1.00      1.00      1.00     56962
```



In [30]:

```
#Calibrate the model
from sklearn.calibration import CalibratedClassifierCV
sig_clf = CalibratedClassifierCV(trained_model, method="sigmoid")
sig_clf.fit(X_train, y_train)

#Plot the ROC curve
plot_roc_curve(sig_clf, X_train, y_train, X_test, y_test)
```



3. Decision Trees Classifier

In [31]:

```
from sklearn.tree import DecisionTreeClassifier


st=dt.now()

tuned_parameters = {'max_depth': np.arange(1,10,1),
                    'criterion': ['gini','entropy'],
                    'min_samples_split': np.arange(0.1,1.0,0.1),
                    'min_samples_leaf' : np.arange(1,10,1),
                    'min_weight_fraction_leaf' : [0.0,0.1,0.2,0.3,0.4],
                    'max_features': ['auto','sqrt','log2']}

model = DecisionTreeClassifier(random_state=state)
rsearch_cv = RandomizedSearchCV(estimator=model,
                                param_distributions=tuned_parameters,
                                cv=5, scoring='roc_auc',
                                n_jobs=-1,
                                verbose=5,
                                random_state=state)
rsearch_cv.fit(X_train, y_train)

print("Time taken to complete random search: ",dt.now()-st)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent worker
s.
[Parallel(n_jobs=-1)]: Done   2 tasks      | elapsed:    4.8s
[Parallel(n_jobs=-1)]: Done  46 out of  50 | elapsed:   15.6s remaining:
1.4s
[Parallel(n_jobs=-1)]: Done  50 out of  50 | elapsed:   16.1s finished

Time taken to complete random search:  0:00:17.730190
```

In [32]:

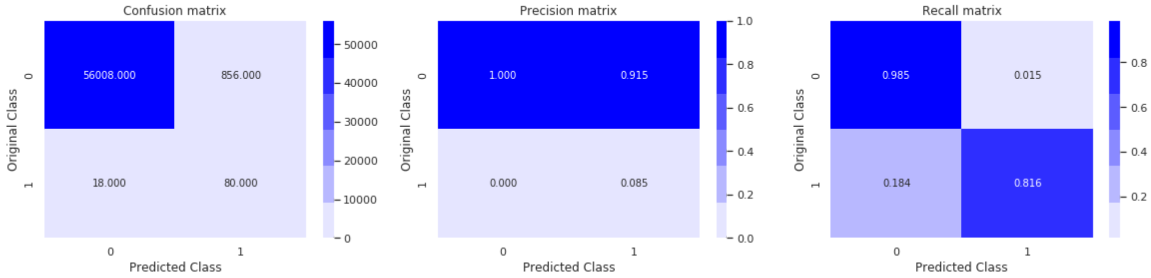
```
print_grid_search_attributes(rsearch_cv)
```

```
--------------------------
|      Best Estimator     |
--------------------------

        DecisionTreeClassifier(class_weight=None, criterion='gini', max_de
pth=3,
            max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=5, min_samples_split=0.1,
            min_weight_fraction_leaf=0.1, presort=False, random_state=48,
            splitter='best')

--------------------------
|     Best parameters     |
--------------------------
        Parameters of best estimator :

        {'min_weight_fraction_leaf': 0.1, 'min_samples_split': 0.1, 'min_s
amples_leaf': 5, 'max_features': 'auto', 'max_depth': 3, 'criterion': 'gin
i'}

---------------------------------
|   No of CrossValidation sets   |
--------------------------------

        Total numbre of cross validation sets: 5

--------------------------
|        Best Score       |
--------------------------

        Average Cross Validate scores of best estimator :

        0.9636516148000225
```

In [33]:

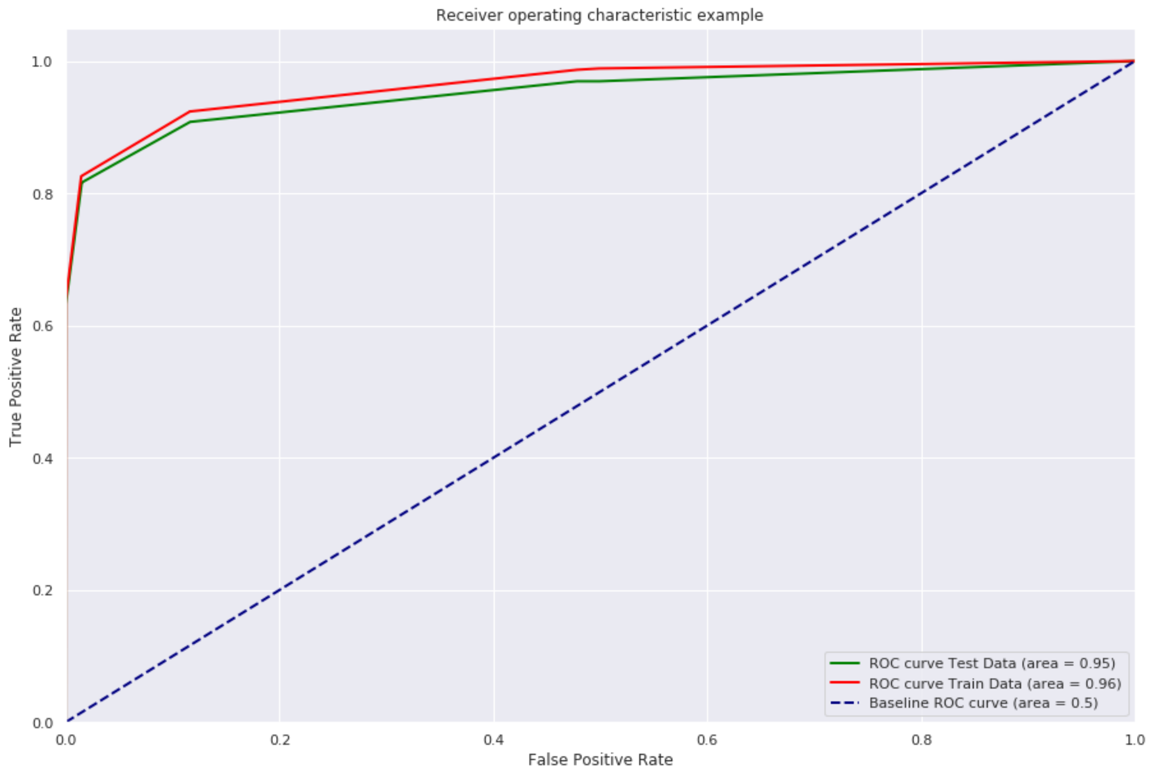
```
dt_grid_results, trained_model =  model_report(rsearch_cv, X_train, y_train, X_test, y_
test, class_labels=y_train)
```

```
Training the model...
Training completed...


Training Time (HH:MM:SS.ms) -- 0:00:01.498290


Predicting test data...
Predicting test data completed...


Testing Time(HH:MM:SS:ms) -- 0:00:00.006884


---------------------
|      F1 Score      |
---------------------

    0.9846564376250834


---------------------
|      Accuracy      |
---------------------

    0.9846564376250834


---------------------
|      Recall        |
---------------------

    0.8163265306122449


---------------------
|      ROC AUC       |
---------------------

    0.9513398599451034


-------------------------
| Classifiction Report  |
-------------------------
              precision    recall  f1-score   support

           0       1.00      0.98      0.99     56864
           1       0.09      0.82      0.15        98

   micro avg       0.98      0.98      0.98     56962
   macro avg       0.54      0.90      0.57     56962
weighted avg       1.00      0.98      0.99     56962
```



In [34]:

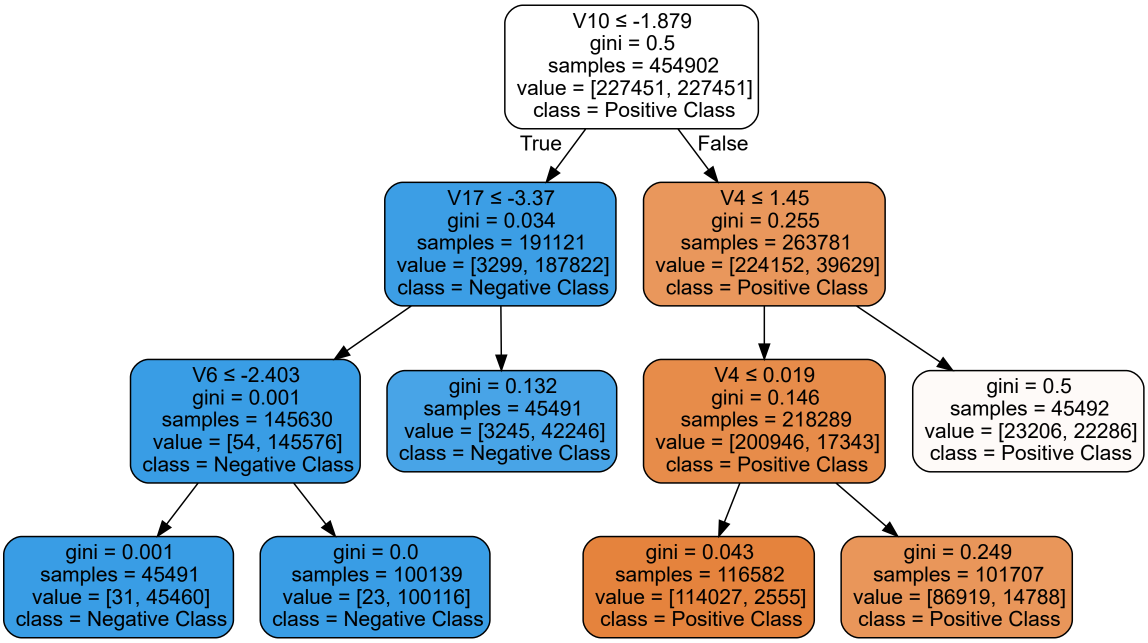
```
#Calibrate the model
from sklearn.calibration import CalibratedClassifierCV
sig_clf = CalibratedClassifierCV(trained_model, method="sigmoid")
sig_clf.fit(X_train, y_train)

#Plot the ROC curve
plot_roc_curve(sig_clf, X_train, y_train, X_test, y_test)
```



In [36]:

```
def visualize_tree(trained_clf, f_names, filename):
    from sklearn import tree
    import graphviz
    dot_data = tree.export_graphviz(decision_tree=trained_clf, out_file=None, max_depth
=3, filled=True, rounded=True, special_characters=True, impurity=True, feature_names=f_
names, class_names=['Positive Class','Negative Class'])
    graph = graphviz.Source(dot_data)
    graph.render(filename, format='png')
    return graph

#Call the function above and pass a filename onto it.
f_names=[i for i in X.columns]

graph=visualize_tree(trained_model, f_names, 'Credit_Card_Tree.png')
graph
```

Out[36]:



In [37]:

```
import gc
gc.collect()

del(model, trained_model, rsearch_cv)
```

4. Linear SVM Classifier

In [ ]:

```
from sklearn.svm import SVC

st=dt.now()
tuned_parameters = {'C':np.logspace(-3,4,25),
                    'gamma':np.logspace(-3,1,8)}

model = SVC(kernel='linear',random_state=state)
rsearch_cv = RandomizedSearchCV(estimator=model,
                                param_distributions=tuned_parameters,
                                cv=5, scoring='roc_auc',
                                n_jobs=-1,
                                verbose=5,
                                random_state=state)
rsearch_cv.fit(X_train, y_train)

print("Time taken to complete random search: ",dt.now()-st)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent worker
s.
[Parallel(n_jobs=-1)]: Done   2 tasks      | elapsed: 483.8min
```

In [ ]:

```
print_grid_search_attributes(rsearch_cv)
```

In [ ]:

```
svc_grid_results, trained_model =  model_report(rsearch_cv, X_train, y_train, X_test, y
_test, class_labels=y_train)
```

In [ ]:

```
#Calibrate the model
from sklearn.calibration import CalibratedClassifierCV
sig_clf = CalibratedClassifierCV(trained_model, method="sigmoid")
sig_clf.fit(X_train, y_train)

#Plot the ROC curve
plot_roc_curve(sig_clf, X_train, y_train, X_test, y_test)
```

In [ ]:

```
import gc
gc.collect()

del(model, trained_model, rsearch_cv)
```

5. Random Forest Classifier

In [38]:

```
from sklearn.ensemble import RandomForestClassifier

st=dt.now()
tuned_parameters = {'max_depth':[3,4,5,6,7,8,9,10],
                    'criterion':['gini','entropy'],
                    'min_samples_split':[2,3,5,7,9],
                    'max_features':['auto','sqrt', 'log2'],
                    'min_samples_leaf':[1, 10, 25, 50, 75, 100],
                    'n_estimators':[10,20,30,40,50,60,80,100,500,1000,1500,2000,3000],
                    'max_leaf_nodes':[None, 10, 25, 50, 100, 500]}

model = RandomForestClassifier(random_state=state)
rsearch_cv = RandomizedSearchCV(estimator=model,
                                param_distributions=tuned_parameters,
                                cv=5, scoring='roc_auc',
                                n_jobs=-1,
                                verbose=5,
                                random_state=state)
rsearch_cv.fit(X_train, y_train)

print("Time taken to complete random search: ",dt.now()-st)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent worker
s.
[Parallel(n_jobs=-1)]: Done   2 tasks      | elapsed: 40.0min
[Parallel(n_jobs=-1)]: Done  46 out of  50 | elapsed: 252.8min remaining:
22.0min
[Parallel(n_jobs=-1)]: Done  50 out of  50 | elapsed: 261.0min finished

Time taken to complete random search:  4:24:21.229768
```

In [39]:

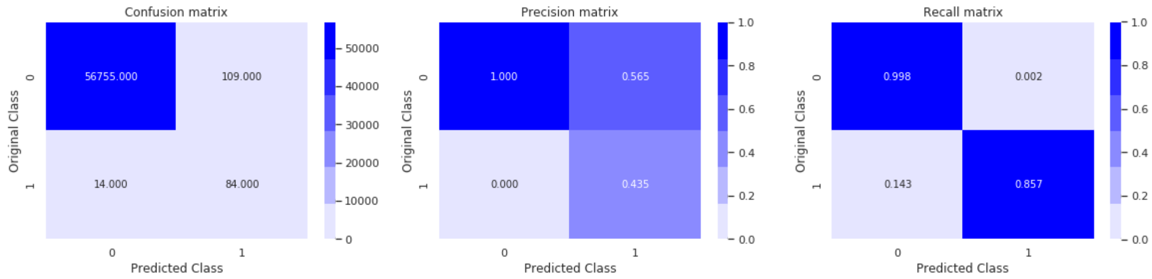
```
print_grid_search_attributes(rsearch_cv)
```

```
--------------------------
|      Best Estimator     |
--------------------------

        RandomForestClassifier(bootstrap=True, class_weight=None, criterio
n='entropy',
            max_depth=8, max_features='sqrt', max_leaf_nodes=500,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=25, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=50, n_jobs=None,
            oob_score=False, random_state=48, verbose=0, warm_start=False)

--------------------------
|     Best parameters     |
--------------------------
        Parameters of best estimator :

        {'n_estimators': 50, 'min_samples_split': 2, 'min_samples_leaf': 2
5, 'max_leaf_nodes': 500, 'max_features': 'sqrt', 'max_depth': 8, 'criteri
on': 'entropy'}

---------------------------------
|   No of CrossValidation sets   |
--------------------------------

        Total numbre of cross validation sets: 5

--------------------------
|        Best Score       |
--------------------------

        Average Cross Validate scores of best estimator :

        0.9996593533102067
```

In [40]:

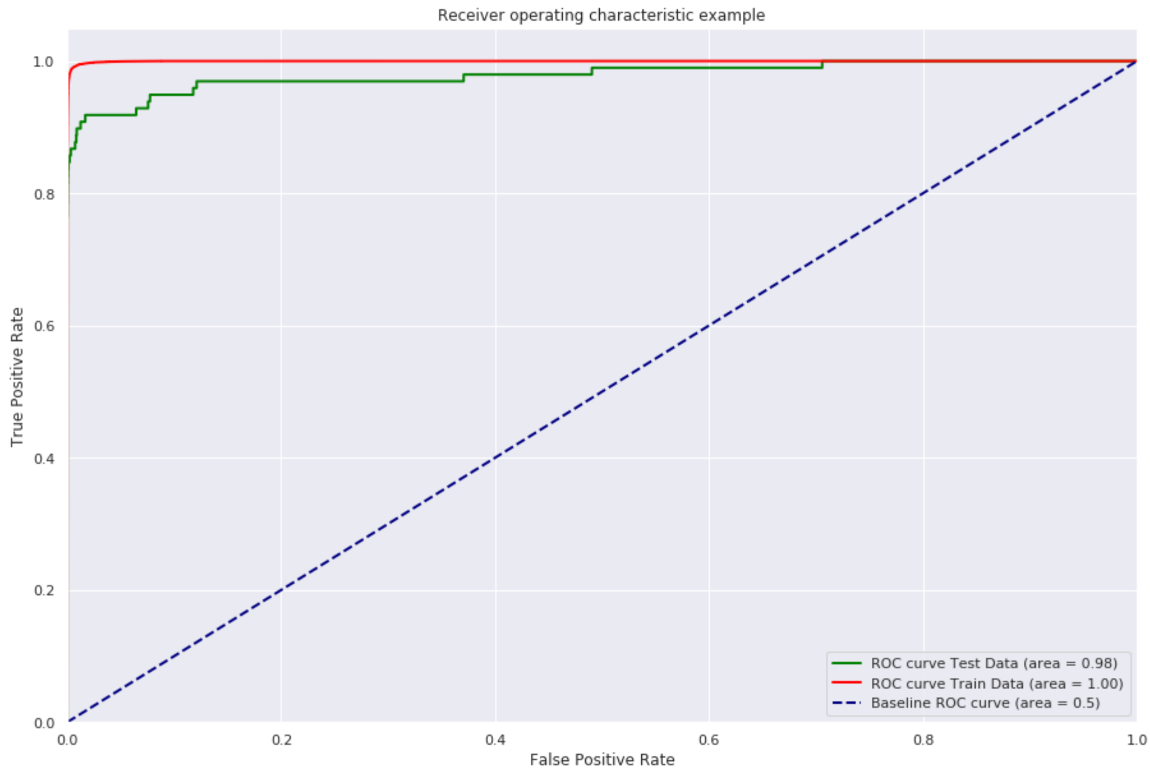
```
rf_grid_results, trained_model =  model_report(rsearch_cv, X_train, y_train, X_test, y_
test, class_labels=y_train)
```

```
Training the model...
Training completed...


Training Time (HH:MM:SS.ms) -- 0:03:24.267284


Predicting test data...
Predicting test data completed...


Testing Time(HH:MM:SS:ms) -- 0:00:00.446870


---------------------
|      F1 Score      |
---------------------

    0.9978406657069625


---------------------
|      Accuracy      |
---------------------

    0.9978406657069625


---------------------
|      Recall        |
---------------------

    0.8571428571428571


---------------------
|      ROC AUC       |
---------------------

    0.9787046501211627


-------------------------
| Classifiction Report  |
-------------------------
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56864
           1       0.44      0.86      0.58        98

   micro avg       1.00      1.00      1.00     56962
   macro avg       0.72      0.93      0.79     56962
weighted avg       1.00      1.00      1.00     56962
```



In [41]:

```
#Calibrate the model
from sklearn.calibration import CalibratedClassifierCV
sig_clf = CalibratedClassifierCV(trained_model, method="sigmoid")
sig_clf.fit(X_train, y_train)

#Plot the ROC curve
plot_roc_curve(sig_clf, X_train, y_train, X_test, y_test)
```



6. XGBoost Classifier

In [42]:

```
from xgboost import XGBClassifier

st=dt.now()
tuned_parameters = {'learning_rate':[0.1,0.01,0.001,0.0001],
                    'n_estimators':[10,25,50,100,250,500,750,1000,1500,2000,3000],
                    'subsample':[0.6,0.7,0.8],
                    'min_child_weight':[3,5,7,9],
                    'max_depth': [3,4,5,6,7,9],
                    'colsample_bytree':[0.6,0.7,0.8],
                    'gamma':[0,0.5,1]}

model = XGBClassifier(random_state=state)
rsearch_cv = RandomizedSearchCV(estimator=model,
                                param_distributions=tuned_parameters,
                                cv=5, scoring='roc_auc',
                                n_jobs=-1,
                                verbose=5,
                                random_state=state)
rsearch_cv.fit(X_train, y_train)

print("Time taken to complete random search: ",dt.now()-st)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent worker
s.
[Parallel(n_jobs=-1)]: Done   2 tasks      | elapsed:   53.2s
[Parallel(n_jobs=-1)]: Done  46 out of  50 | elapsed: 227.1min remaining:
19.8min
[Parallel(n_jobs=-1)]: Done  50 out of  50 | elapsed: 233.4min finished

Time taken to complete random search:  4:17:40.461677
```

In [43]:

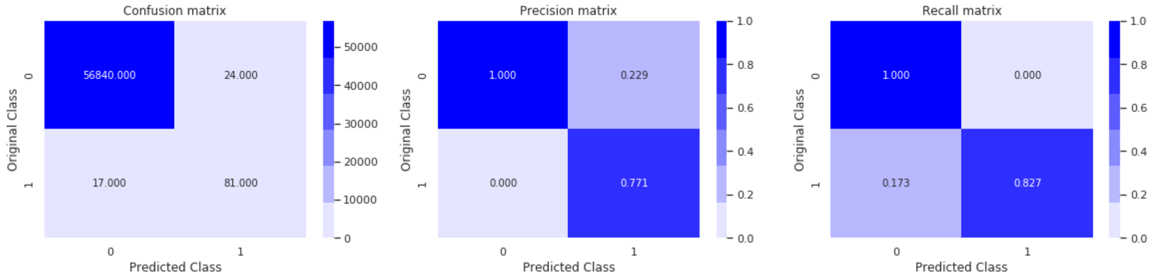
```
print_grid_search_attributes(rsearch_cv)
```

```
--------------------------
|      Best Estimator     |
--------------------------

        XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=
1,
       colsample_bytree=0.8, gamma=1, learning_rate=0.1, max_delta_step=0,
       max_depth=7, min_child_weight=3, missing=None, n_estimators=750,
       n_jobs=1, nthread=None, objective='binary:logistic',
       random_state=48, reg_alpha=0, reg_lambda=1, scale_pos_weight=1,
       seed=None, silent=True, subsample=0.6)

--------------------------
|     Best parameters     |
--------------------------
        Parameters of best estimator :

        {'subsample': 0.6, 'n_estimators': 750, 'min_child_weight': 3, 'ma
x_depth': 7, 'learning_rate': 0.1, 'gamma': 1, 'colsample_bytree': 0.8}

---------------------------------
|   No of CrossValidation sets   |
--------------------------------

        Total numbre of cross validation sets: 5

--------------------------
|       Best Score        |
--------------------------

        Average Cross Validate scores of best estimator :

        0.9999929931773612
```

In [53]:

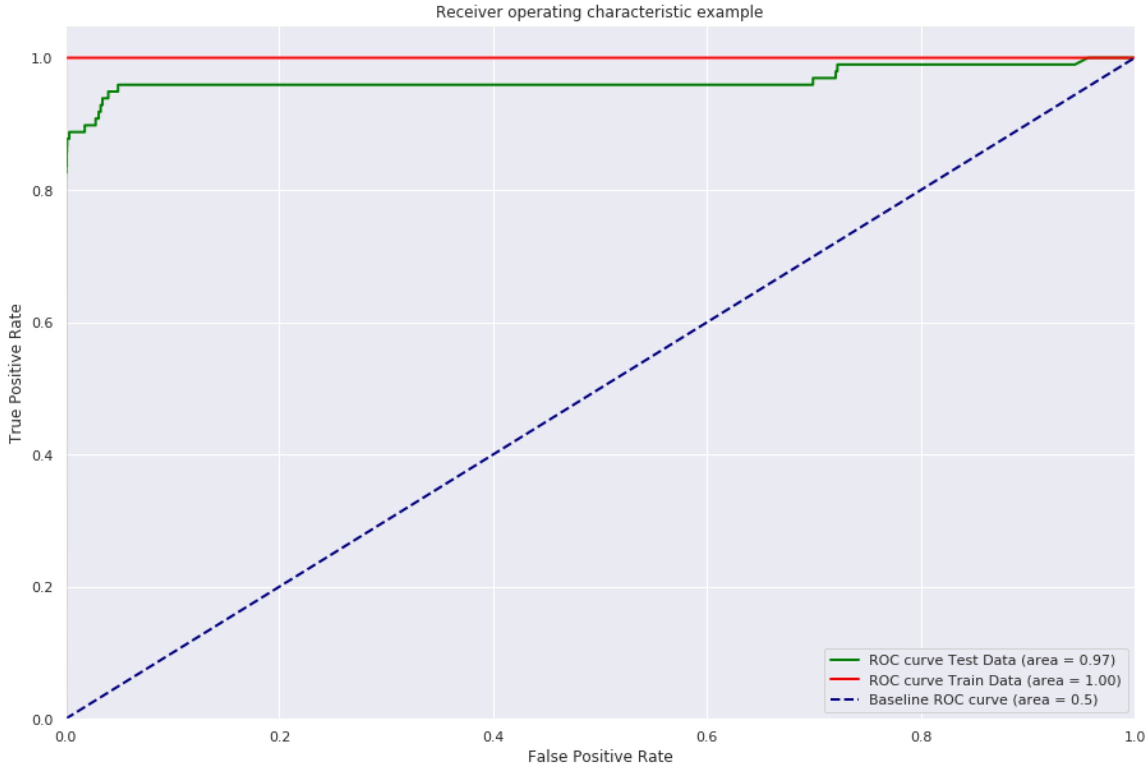
```
xgb_grid_results, trained_model =  model_report(rsearch_cv, X_train, y_train, X_test.va
lues, y_test, class_labels=y_train)
```

```
Training the model...
Training completed...


Training Time (HH:MM:SS.ms) -- 0:24:39.380942


Predicting test data...
Predicting test data completed...


Testing Time(HH:MM:SS:ms) -- 0:00:02.056257


---------------------
|      F1 Score      |
---------------------

    0.9992802219023208


---------------------
|      Accuracy      |
---------------------

    0.9992802219023208


---------------------
|      Recall        |
---------------------

    0.826530612244898


---------------------
|      ROC AUC       |
---------------------

    0.9659689283704478


-------------------------
| Classifiction Report  |
-------------------------
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56864
           1       0.77      0.83      0.80        98

   micro avg       1.00      1.00      1.00     56962
   macro avg       0.89      0.91      0.90     56962
weighted avg       1.00      1.00      1.00     56962
```



In [54]:

```
#Calibrate the model
from sklearn.calibration import CalibratedClassifierCV
sig_clf = CalibratedClassifierCV(trained_model, method="sigmoid")
sig_clf.fit(X_train, y_train)

#Plot the ROC curve
plot_roc_curve(sig_clf, X_train, y_train, X_test, y_test)
```



In [ ]:

```
### Use pretty table to display all the metrics for undersampled data
```

In [ ]:

```

```

In [ ]:

```

```

In [ ]:

```

```

In [55]:

```
print('\n                               Accuracy        Recall      ROC-AUC')
print('                             ----------      --------    --------')

print('Logistic Regression         : {:.04}%         {:.04}%       {:.04}'.format(log_r
eg_grid_results['Accuracy'] * 100,
                                                                             log_r
eg_grid_results['Recall'] * 100,
                                                                             log_r
eg_grid_results['ROC-AUC']))
print('KNN Classifier              : {:.04}%         {:.04}%       {:.04}'.format(knn_g
rid_results['Accuracy'] * 100,
                                                                             knn_g
rid_results['Recall'] * 100,
                                                                             knn_g
rid_results['ROC-AUC']))
print('Decision Trees Classifier   : {:.04}%         {:.04}%       {:.04}'.format(dt_gr
id_results['Accuracy'] * 100,
                                                                             dt_gr
id_results['Recall'] * 100,
                                                                             dt_gr
id_results['ROC-AUC']))

print('Random Forest Classifier    : {:.04}%          {:.04}%       {:.04}'.format(rf_g
rid_results['Accuracy'] * 100,
                                                                             rf_gr
id_results['Recall'] * 100,
                                                                             rf_gr
id_results['ROC-AUC']))
print('XGBoost Classifier          : {:.04}%         {:.04}%       {:.04}'.format(xgb_g
rid_results['Accuracy'] * 100,
                                                                             xgb_g
rid_results['Recall'] * 100,
                                                                             xgb_g
rid_results['ROC-AUC']))
```

```
                             Accuracy        Recall      ROC-AUC
                            ----------      --------    --------
Logistic Regression         : 97.42%         90.82%       0.975
KNN Classifier              : 99.65%         85.71%       0.9326
Decision Trees Classifier   : 98.47%         81.63%       0.9513
Random Forest Classifier    : 99.78%          85.71%       0.9787
XGBoost Classifier          : 99.93%         82.65%       0.966
```

In [ ]: