Capstone Project - Credit Card Fraud Detection

The problem statement chosen for this project is to predict fraudulent credit card transactions with the help of machine learning models.

In this project, you will analyse customer-level data which has been collected and analysed during a research collaboration of Worldline and the Machine Learning Group.

The dataset is taken from the Kaggle website and it has a total of 2,84,807 transactions, out of which 492 are fraudulent. Since the dataset is highly imbalanced, so it needs to be handled before model building.

Business Problem Overview ¶

For many banks, retaining high profitable customers is the number one business goal. Banking fraud, however, poses a significant threat to this goal for different banks. In terms of substantial financial losses, trust and credibility, this is a concerning issue to both banks and customers alike.

It has been estimated by Nilson report that by 2020 the banking frauds would account to $30 billion worldwide. With the rise in digital payment channels, the number of fraudulent transactions is also increasing with new and different ways.

In the banking industry, credit card fraud detection using machine learning is not just a trend but a necessity for them to put proactive monitoring and fraud prevention mechanisms in place. Machine learning is helping these institutions to reduce time-consuming manual reviews, costly chargebacks and fees, and denials of legitimate transactions.

Data Overview

In [1]:
```
import pandas as pd
import numpy as np
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
#data = '/content/drive/My Drive/Colab Notebooks/Capstone/creditcard.csv'
## reading Demographic data file
data = pd.read_csv("creditcard.csv")
data.head(4)
```

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	0.
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.

4 rows × 31 columns

In [3]:
```
#creditcard_df overview
print(data.dtypes)
```

```
Time      float64
V1        float64
V2        float64
V3        float64
V4        float64
V5        float64
V6        float64
V7        float64
V8        float64
V9        float64
V10       float64
V11       float64
V12       float64
V13       float64
V14       float64
V15       float64
V16       float64
V17       float64
V18       float64
V19       float64
V20       float64
V21       float64
V22       float64
V23       float64
V24       float64
V25       float64
V26       float64
V27       float64
V28       float64
Amount    float64
Class       int64
dtype: object
```

In [4]:
```
# lets check the shape of the data set
data.shape
```

Out[4]:
```
(284807, 31)
```

In [35]:
```
#Checking Null value
data.isnull().sum()
```

Out[35]:
```
Time      0
V1        0
V2        0
V3        0
V4        0
V5        0
V6        0
V7        0
V8        0
V9        0
V10       0
V11       0
V12       0
V13       0
V14       0
V15       0
V16       0
V17       0
V18       0
V19       0
V20       0
V21       0
V22       0
V23       0
V24       0
V25       0
V26       0
V27       0
V28       0
Amount    0
Class     0
dtype: int64
```

In [36]:
```
## checking duplicate data and removing the duplicates
data.duplicated(subset=None, keep='first').count()
```

Out[36]:
```
284807
```

In [37]:
```
## checking number of unique entries across each variable
data.nunique()
```

Out[37]:
```
Time      124592
V1        275663
V2        275663
V3        275663
V4        275663
V5        275663
V6        275663
V7        275663
V8        275663
V9        275663
V10       275663
V11       275663
V12       275663
V13       275663
V14       275663
V15       275663
V16       275663
V17       275663
V18       275663
V19       275663
V20       275663
V21       275663
V22       275663
V23       275663
V24       275663
V25       275663
V26       275663
V27       275663
V28       275663
Amount     32767
Class          2
dtype: int64
```

In [38]:
```
## describing demographic data
data.describe(percentiles=[0.10,.25,.5,.75,.90,.95])
```

Out[38]:

	Time	V1	V2	V3	V4	V5
count	284807.000000	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05
mean	94813.859575	3.919560e-15	5.688174e-16	-8.769071e-15	2.782312e-15	-1.552563e-15
std	47488.145955	1.958696e+00	1.651309e+00	1.516255e+00	1.415869e+00	1.380247e+00
min	0.000000	-5.640751e+01	-7.271573e+01	-4.832559e+01	-5.683171e+00	-1.137433e+02
10%	35027.000000	-1.893272e+00	-1.359862e+00	-1.802587e+00	-1.656329e+00	-1.302171e+00
25%	54201.500000	-9.203734e-01	-5.985499e-01	-8.903648e-01	-8.486401e-01	-6.915971e-01
50%	84692.000000	1.810880e-02	6.548556e-02	1.798463e-01	-1.984653e-02	-5.433583e-02
75%	139320.500000	1.315642e+00	8.037239e-01	1.027196e+00	7.433413e-01	6.119264e-01
90%	157640.400000	2.015409e+00	1.326635e+00	1.676173e+00	1.482807e+00	1.407893e+00
95%	164143.400000	2.081223e+00	1.808585e+00	2.062635e+00	2.566501e+00	2.098960e+00
max	172792.000000	2.454930e+00	2.205773e+01	9.382558e+00	1.687534e+01	3.480167e+01

11 rows × 31 columns

Exploratory Data Analysis

In [39]:

```
import pandas_profiling as pf
pf.ProfileReport(data)
```

Out[39]:

Overview

Dataset info

Number of variables	31
Number of observations	284807
Total Missing (%)	0.0%
Total size in memory	67.4 MiB
Average record size in memory	248.0 B

Variables types

Numeric	30
Categorical	0
Boolean	1
Date	0
Text (Unique)	0
Rejected	0
Unsupported	0

Warnings

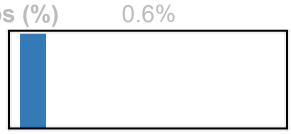
- Dataset has 1081 duplicate rows Warning

Variables

Amount
Numeric

Distinct count	32767
Unique (%)	11.5%
Missing (%)	0.0%
Missing (n)	0
Infinite (%)	0.0%
Infinite (n)	0

Mean	88.35
Minimum	0
Maximum	25691
Zeros (%)	0.6%



Toggle details

Class
Boolean

Distinct count	2
Unique (%)	0.0%
Missing (%)	0.0%
Missing (n)	0

Mean	0.0017275

0 284315

1	492

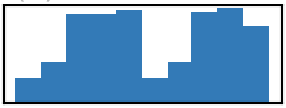
Toggle details

Time

Numeric

Distinct count	124592
Unique (%)	43.7%
Missing (%)	0.0%
Missing (n)	0
Infinite (%)	0.0%
Infinite (n)	0

Mean	94814
Minimum	0
Maximum	172790
Zeros (%)	0.0%



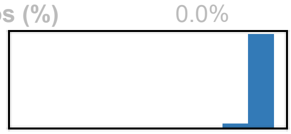
Toggle details

V1

Numeric

Distinct count	275663
Unique (%)	96.8%
Missing (%)	0.0%
Missing (n)	0
Infinite (%)	0.0%
Infinite (n)	0

Mean	3.9196e-15
Minimum	-56.408
Maximum	2.4549
Zeros (%)	0.0%



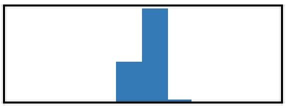
Toggle details

V10

Numeric

Distinct count	275663
Unique (%)	96.8%
Missing (%)	0.0%
Missing (n)	0
Infinite (%)	0.0%
Infinite (n)	0

Mean	1.7686e-15
Minimum	-24.588
Maximum	23.745
Zeros (%)	0.0%

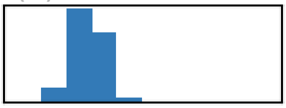


Toggle details

V11

Numeric

Distinct count	275663
Unique (%)	96.8%
Missing (%)	0.0%
Missing (n)	0
Infinite (%)	0.0%
Infinite (n)	0
Mean	9.1703e-16
Minimum	-4.7975
Maximum	12.019
Zeros (%)	0.0%

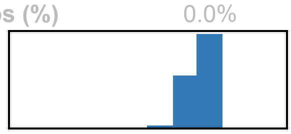


Toggle details

V12

Numeric

Distinct count	275663
Unique (%)	96.8%
Missing (%)	0.0%
Missing (n)	0
Infinite (%)	0.0%
Infinite (n)	0
Mean	-1.8107e-15
Minimum	-18.684
Maximum	7.8484
Zeros (%)	0.0%

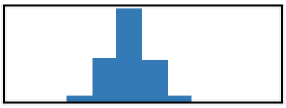


Toggle details

V13

Numeric

Distinct count	275663
Unique (%)	96.8%
Missing (%)	0.0%
Missing (n)	0
Infinite (%)	0.0%
Infinite (n)	0
Mean	1.6934e-15
Minimum	-5.7919
Maximum	7.1269
Zeros (%)	0.0%



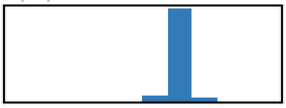
Toggle details

V14

Numeric

Distinct count	275663
Unique (%)	96.8%
Missing (%)	0.0%
Missing (n)	0
Infinite (%)	0.0%
Infinite (n)	0

Mean	1.479e-15
Minimum	-19.214
Maximum	10.527
Zeros (%)	0.0%



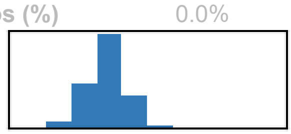
Toggle details

V15

Numeric

Distinct count	275663
Unique (%)	96.8%
Missing (%)	0.0%
Missing (n)	0
Infinite (%)	0.0%
Infinite (n)	0

Mean	3.4823e-15
Minimum	-4.4989
Maximum	8.8777
Zeros (%)	0.0%



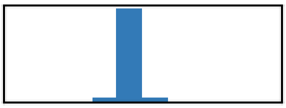
Toggle details

V16

Numeric

Distinct count	275663
Unique (%)	96.8%
Missing (%)	0.0%
Missing (n)	0
Infinite (%)	0.0%
Infinite (n)	0

Mean	1.392e-15
Minimum	-14.13
Maximum	17.315
Zeros (%)	0.0%

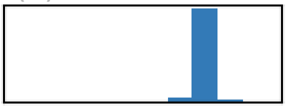


Toggle details

V17

Numeric

Distinct count	275663
Unique (%)	96.8%
Missing (%)	0.0%
Missing (n)	0
Infinite (%)	0.0%
Infinite (n)	0
Mean	-7.5285e-16
Minimum	-25.163
Maximum	9.2535
Zeros (%)	0.0%

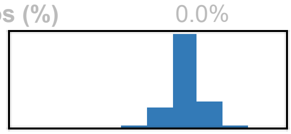


Toggle details

V18

Numeric

Distinct count	275663
Unique (%)	96.8%
Missing (%)	0.0%
Missing (n)	0
Infinite (%)	0.0%
Infinite (n)	0
Mean	4.3288e-16
Minimum	-9.4987
Maximum	5.0411
Zeros (%)	0.0%

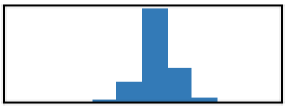


Toggle details

V19

Numeric

Distinct count	275663
Unique (%)	96.8%
Missing (%)	0.0%
Missing (n)	0
Infinite (%)	0.0%
Infinite (n)	0
Mean	9.0497e-16
Minimum	-7.2135
Maximum	5.592
Zeros (%)	0.0%

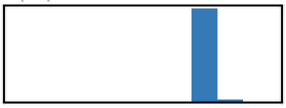


Toggle details

V2

Numeric

Distinct count	275663
Unique (%)	96.8%
Missing (%)	0.0%
Missing (n)	0
Infinite (%)	0.0%
Infinite (n)	0
Mean	5.6882e-16
Minimum	-72.716
Maximum	22.058
Zeros (%)	0.0%

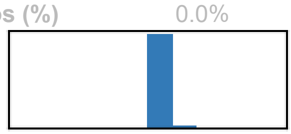


Toggle details

V20

Numeric

Distinct count	275663
Unique (%)	96.8%
Missing (%)	0.0%
Missing (n)	0
Infinite (%)	0.0%
Infinite (n)	0
Mean	5.0855e-16
Minimum	-54.498
Maximum	39.421
Zeros (%)	0.0%

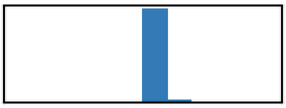


Toggle details

V21

Numeric

Distinct count	275663
Unique (%)	96.8%
Missing (%)	0.0%
Missing (n)	0
Infinite (%)	0.0%
Infinite (n)	0
Mean	1.5373e-16
Minimum	-34.83
Maximum	27.203
Zeros (%)	0.0%



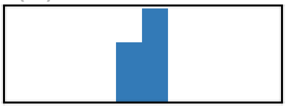
Toggle details

V22

Numeric

Distinct count	275663
Unique (%)	96.8%
Missing (%)	0.0%
Missing (n)	0
Infinite (%)	0.0%
Infinite (n)	0

Mean	7.9599e-16
Minimum	-10.933
Maximum	10.503
Zeros (%)	0.0%



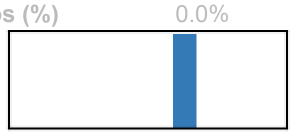
Toggle details

V23

Numeric

Distinct count	275663
Unique (%)	96.8%
Missing (%)	0.0%
Missing (n)	0
Infinite (%)	0.0%
Infinite (n)	0

Mean	5.3676e-16
Minimum	-44.808
Maximum	22.528
Zeros (%)	0.0%



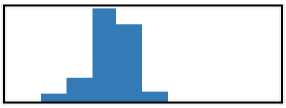
Toggle details

V24

Numeric

Distinct count	275663
Unique (%)	96.8%
Missing (%)	0.0%
Missing (n)	0
Infinite (%)	0.0%
Infinite (n)	0

Mean	4.4581e-15
Minimum	-2.8366
Maximum	4.5845
Zeros (%)	0.0%



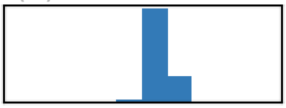
Toggle details

V25

Numeric

Distinct count	275663
Unique (%)	96.8%
Missing (%)	0.0%
Missing (n)	0
Infinite (%)	0.0%
Infinite (n)	0

Mean	1.453e-15
Minimum	-10.295
Maximum	7.5196
Zeros (%)	0.0%



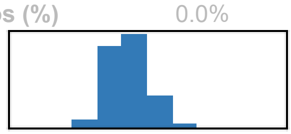
Toggle details

V26

Numeric

Distinct count	275663
Unique (%)	96.8%
Missing (%)	0.0%
Missing (n)	0
Infinite (%)	0.0%
Infinite (n)	0

Mean	1.6991e-15
Minimum	-2.6046
Maximum	3.5173
Zeros (%)	0.0%



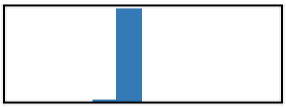
Toggle details

V27

Numeric

Distinct count	275663
Unique (%)	96.8%
Missing (%)	0.0%
Missing (n)	0
Infinite (%)	0.0%
Infinite (n)	0

Mean	-3.6602e-16
Minimum	-22.566
Maximum	31.612
Zeros (%)	0.0%

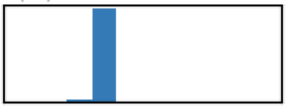


Toggle details

V28

Numeric

Distinct count	275663
Unique (%)	96.8%
Missing (%)	0.0%
Missing (n)	0
Infinite (%)	0.0%
Infinite (n)	0
Mean	-1.206e-16
Minimum	-15.43
Maximum	33.848
Zeros (%)	0.0%

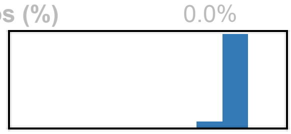


Toggle details

V3

Numeric

Distinct count	275663
Unique (%)	96.8%
Missing (%)	0.0%
Missing (n)	0
Infinite (%)	0.0%
Infinite (n)	0
Mean	-8.7691e-15
Minimum	-48.326
Maximum	9.3826
Zeros (%)	0.0%

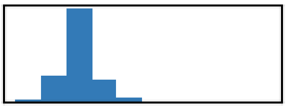


Toggle details

V4

Numeric

Distinct count	275663
Unique (%)	96.8%
Missing (%)	0.0%
Missing (n)	0
Infinite (%)	0.0%
Infinite (n)	0
Mean	2.7823e-15
Minimum	-5.6832
Maximum	16.875
Zeros (%)	0.0%

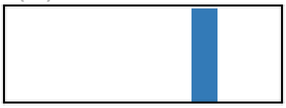


Toggle details

V5

Numeric

Distinct count	275663
Unique (%)	96.8%
Missing (%)	0.0%
Missing (n)	0
Infinite (%)	0.0%
Infinite (n)	0
Mean	-1.5526e-15
Minimum	-113.74
Maximum	34.802
Zeros (%)	0.0%

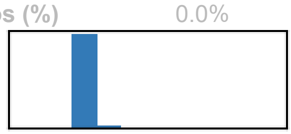


Toggle details

V6

Numeric

Distinct count	275663
Unique (%)	96.8%
Missing (%)	0.0%
Missing (n)	0
Infinite (%)	0.0%
Infinite (n)	0
Mean	2.0107e-15
Minimum	-26.161
Maximum	73.302
Zeros (%)	0.0%

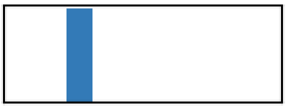


Toggle details

V7

Numeric

Distinct count	275663
Unique (%)	96.8%
Missing (%)	0.0%
Missing (n)	0
Infinite (%)	0.0%
Infinite (n)	0
Mean	-1.6942e-15
Minimum	-43.557
Maximum	120.59
Zeros (%)	0.0%

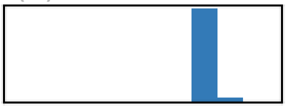


Toggle details

V8

Numeric

Distinct count	275663
Unique (%)	96.8%
Missing (%)	0.0%
Missing (n)	0
Infinite (%)	0.0%
Infinite (n)	0
Mean	-1.927e-16
Minimum	-73.217
Maximum	20.007
Zeros (%)	0.0%

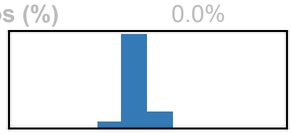


Toggle details

V9

Numeric

Distinct count	275663
Unique (%)	96.8%
Missing (%)	0.0%
Missing (n)	0
Infinite (%)	0.0%
Infinite (n)	0
Mean	-3.137e-15
Minimum	-13.434
Maximum	15.595
Zeros (%)	0.0%



Toggle details

Correlations

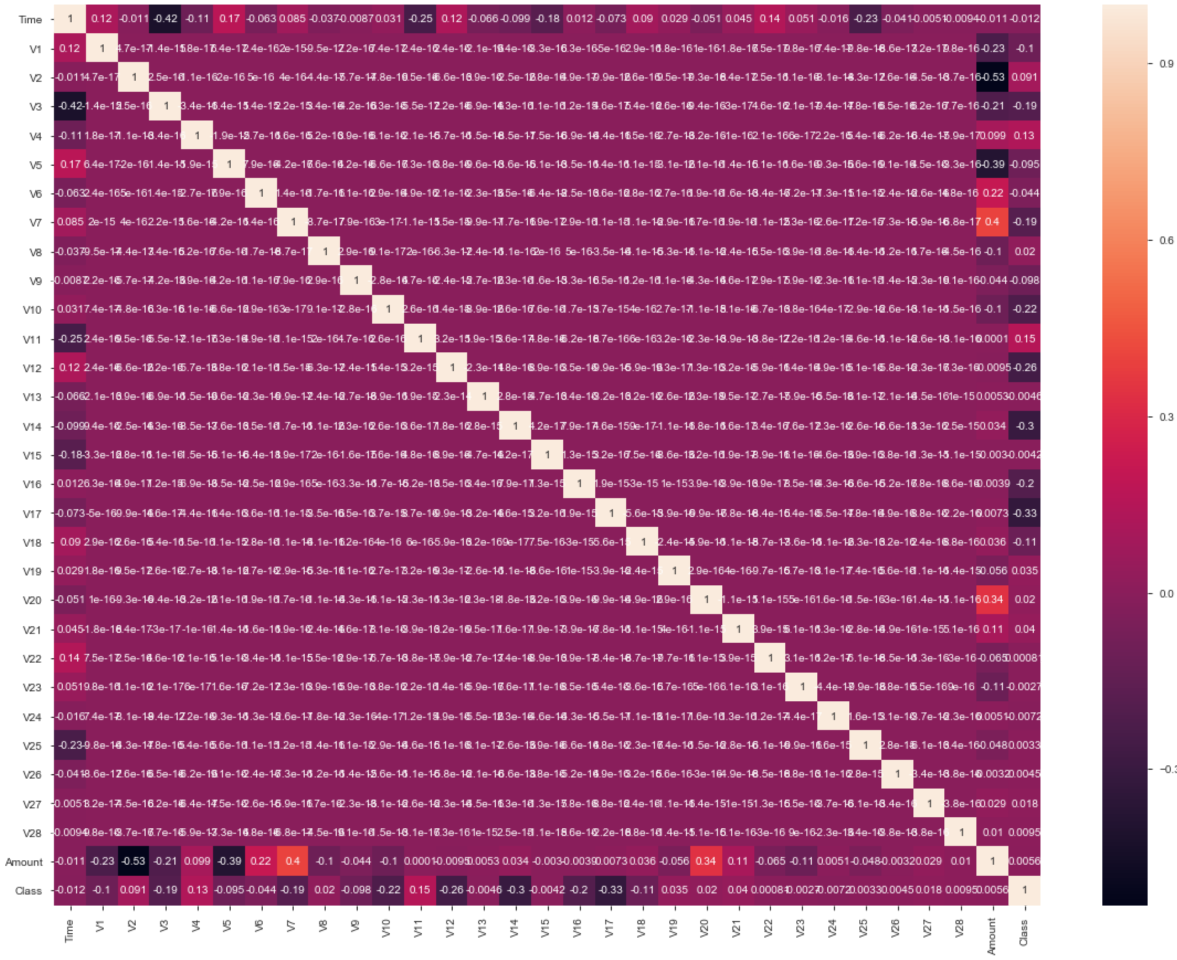
Sample

Time	V1	V2	V3	V4	V5	V6	V7

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

In [40]:
```
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [41]:
```
plt.figure(figsize = (20,15))
sns.heatmap(data.corr(), annot = True)
plt.show()
```

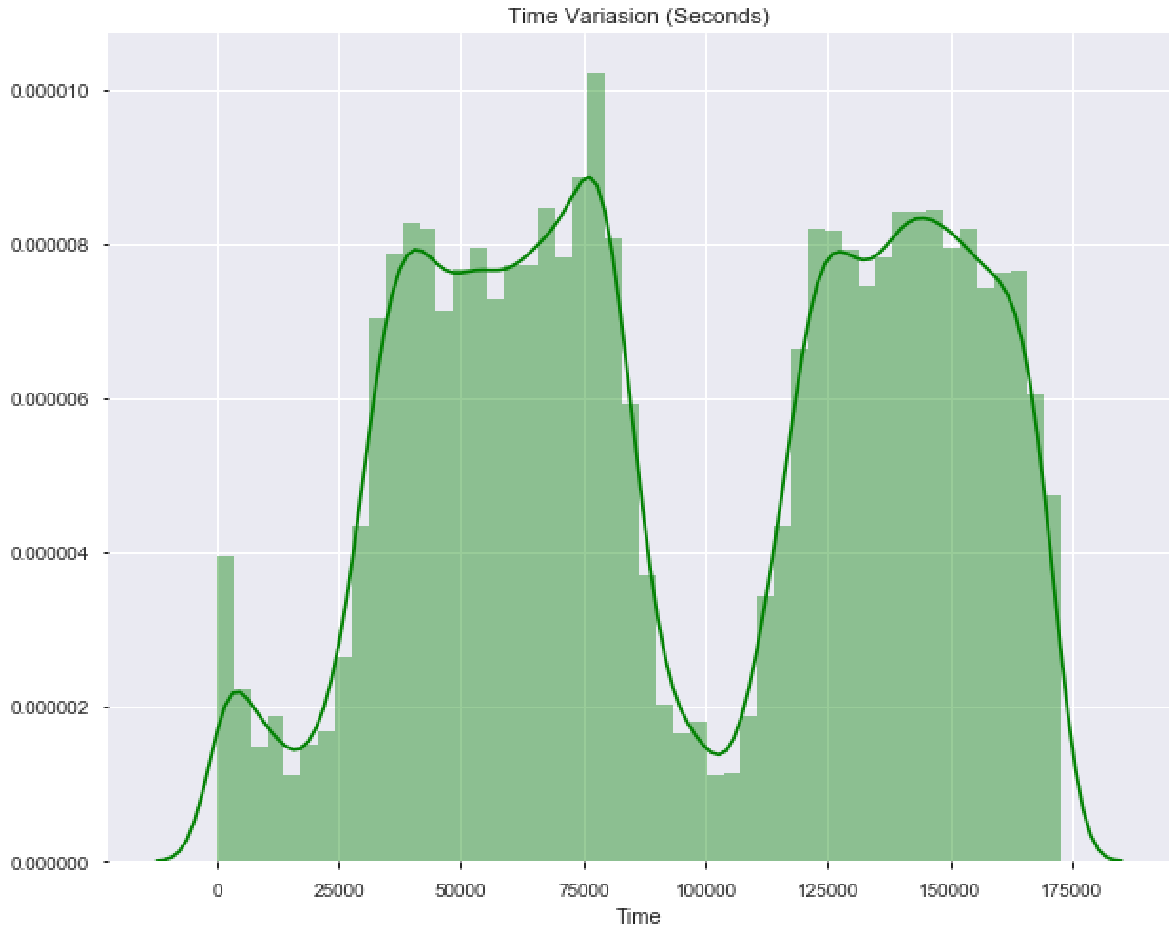


In [42]:
```
#plot the distribution plot of time

plt.figure(figsize=(10,8), )
plt.title('Time Variasion (Seconds)')

sns.distplot(data['Time'],color='green')
```

Out[42]: <matplotlib.axes._subplots.AxesSubplot at 0x2240e316588>

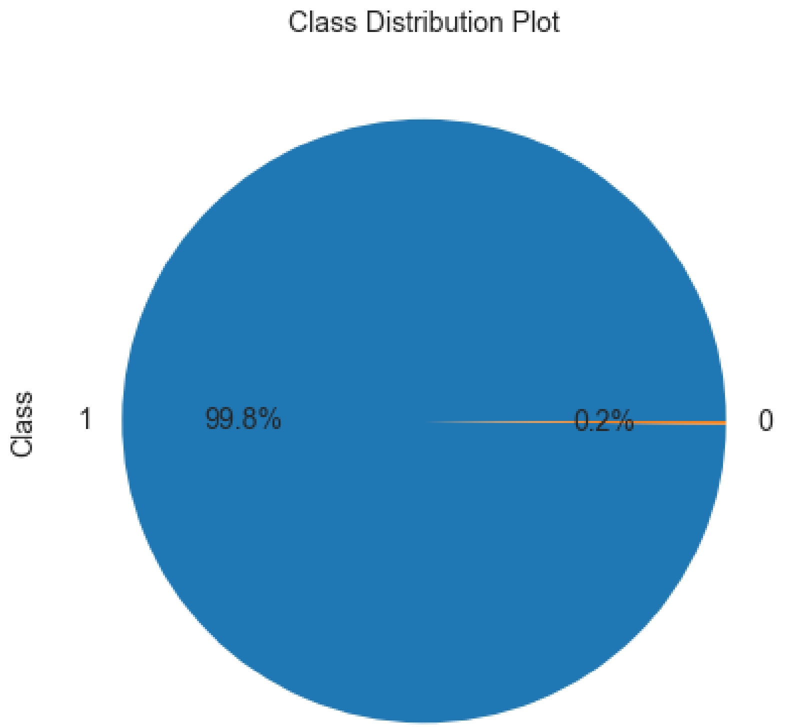


In [43]:
```
# lets create a copy of the demographic dataset to perform EDA
data1 = pd.DataFrame(data).copy()
```

In [44]:
```
#Tag Churners and Remove Attributes of The Churn Phase
# Checking the churn distribution
axis = (data1['Class'].value_counts()*100.0 /len(data1)).plot.pie(autopct='%.1
f%%', labels = ['1', '0'],figsize =(7,7), fontsize = 14 )
axis.set_ylabel('Class',fontsize = 14)
axis.set_title('Class Distribution Plot', fontsize = 14)

#Checking the class Rate
check = (sum(data1['Class'])/len(data1['Class'].index))*100
print(check)
```

```
0.1727485630620034
```



From this dataset we derive there are only 492 fraudulent transactions.

That's only 0.173% data is frund of all of the transactions in this dataset

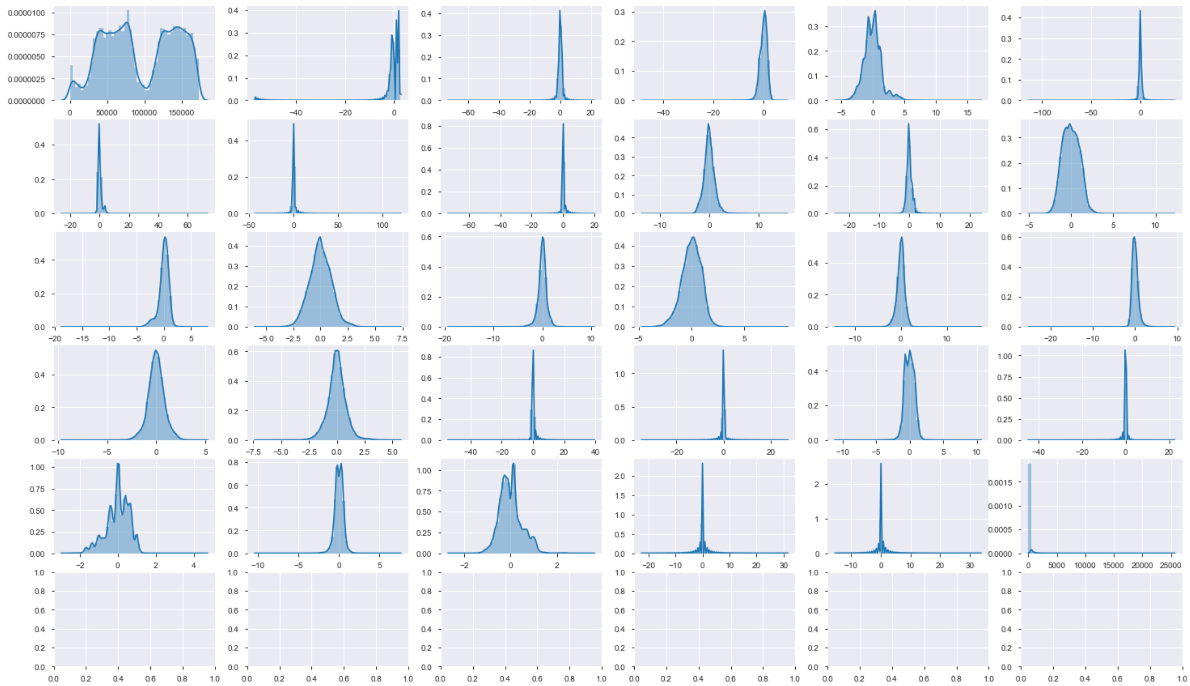
Splitting the data into train & test data

In [45]:
```
from sklearn.metrics import precision_score, recall_score
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import train_test_split
```

In [46]:
```
# Putting feature variable to X
X = data1.drop(['Class'],axis=1)
# Putting response variable to y
y = data1['Class']
# Please note, we do not need data scaling here as the data is already scaled
# Splitting the data into train and test
X_train, X_test, y_train, y_test = train_test_split(X,y, train_size=0.7,test_s
ize=0.3,random_state=100)
# lets save all the variable except the target variable
data3 = data1.drop(['Class'],1).columns
```

In [47]:
```
# Ploting the histogram variables from the credit dataset to cross check the s
kewness
fig, axes = plt.subplots(nrows=6, ncols=6,figsize=(25,15))

for i, column in enumerate(X.columns):
    sns.distplot(X[column],ax=axes[i//6,i%6])
```



In [48]:
```
# Checking th train data set
X_train.head()
```

Out[48]:

	Time	V1	V2	V3	V4	V5	V6	V7	
7610	10529.0	1.160485	0.010653	0.731921	-0.083757	-0.204162	0.309873	-0.503116	0.⋅
190214	128741.0	2.054237	-0.078678	-1.233161	0.183785	0.187539	-0.605905	0.102048	-0.⋅
130590	79387.0	1.434517	-1.560173	-0.783968	-2.432927	0.578638	3.528638	-1.814737	0.8
247916	153735.0	-0.112311	1.235492	-0.312905	-0.502613	0.699869	-1.028247	0.964615	-0.⋅
55518	46986.0	1.123477	-0.093882	0.988880	0.533433	-0.769281	-0.068741	-0.575773	0.2

5 rows × 30 columns

In [49]:
```
# Checking th test data set
X_test.head()
```

Out[49]:

	Time	V1	V2	V3	V4	V5	V6	V7	
49089	43906.0	1.229452	-0.235478	-0.627166	0.419877	1.797014	4.069574	-0.896223	1.0
154704	102638.0	2.016893	-0.088751	-2.989257	-0.142575	2.675427	3.332289	-0.652336	0.7
67247	52429.0	0.535093	-1.469185	0.868279	0.385462	-1.439135	0.368118	-0.499370	0.3
251657	155444.0	2.128486	-0.117215	-1.513910	0.166456	0.359070	-0.540072	0.116023	-0.2
201903	134084.0	0.558593	1.587908	-2.368767	5.124413	2.171788	-0.500419	1.059829	-0.2

5 rows × 30 columns

In [50]:
```
print("Before OverSampling, counts of label '1' in Train Data Set: {}".format(
sum(y_train==1)))
print("Before OverSampling, counts of label '0' in Train Data Set: {} \n".form
at(sum(y_train==0)))

print("Before OverSampling, counts of label '1' in Test Data Set: {}".format(s
um(y_test==1)))
print("Before OverSampling, counts of label '0' in Test Data Set: {} \n".forma
t(sum(y_test==0)))
```

```
Before OverSampling, counts of label '1' in Train Data Set: 350
Before OverSampling, counts of label '0' in Train Data Set: 199014

Before OverSampling, counts of label '1' in Test Data Set: 142
Before OverSampling, counts of label '0' in Test Data Set: 85301
```

Model development with imbalance dataset

Logistic Regression with RFE

In [51]:
```
from sklearn.linear_model import LogisticRegression
import statsmodels.api as sm

import sklearn.metrics as metrics
from sklearn.metrics import confusion_matrix
from sklearn.metrics import precision_score, recall_score, precision_recall_cu
rve,f1_score, fbeta_score, accuracy_score
```

In [52]:
```
# Default logistic regression model
# class_weight="balanced" will take care of the class imbalance in the dataset
logm1 = sm.GLM(y_train,(sm.add_constant(X_train)), class_weight="balanced",fam
ily = sm.families.Binomial())
logm1.fit().summary()
```

Out[52]:

Generalized Linear Model Regression Results

Dep. Variable:	Class	**No. Observations:**	199364
Model:	GLM	**Df Residuals:**	199333
Model Family:	Binomial	**Df Model:**	30
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-725.80
Date:	Mon, 06 Apr 2020	**Deviance:**	1451.6
Time:	20:02:24	**Pearson chi2:**	5.75e+06
No. Iterations:	12	**Covariance Type:**	nonrobust

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	-8.2473	0.295	-27.946	0.000	-8.826	-7.669
Time	-6.096e-06	2.77e-06	-2.204	0.027	-1.15e-05	-6.76e-07
V1	0.2048	0.053	3.834	0.000	0.100	0.309
V2	-0.0747	0.067	-1.115	0.265	-0.206	0.057
V3	-0.0662	0.065	-1.014	0.311	-0.194	0.062
V4	0.6854	0.083	8.263	0.000	0.523	0.848
V5	0.0972	0.079	1.237	0.216	-0.057	0.251
V6	-0.1082	0.090	-1.201	0.230	-0.285	0.068
V7	-0.0986	0.082	-1.208	0.227	-0.259	0.061
V8	-0.2002	0.040	-4.957	0.000	-0.279	-0.121
V9	-0.4619	0.127	-3.638	0.000	-0.711	-0.213
V10	-0.8623	0.114	-7.551	0.000	-1.086	-0.638
V11	-0.1698	0.100	-1.689	0.091	-0.367	0.027
V12	0.0211	0.103	0.204	0.838	-0.181	0.223
V13	-0.3442	0.102	-3.385	0.001	-0.543	-0.145
V14	-0.6182	0.076	-8.103	0.000	-0.768	-0.469
V15	-0.2032	0.108	-1.890	0.059	-0.414	0.007
V16	-0.1570	0.139	-1.130	0.258	-0.429	0.115
V17	-0.1223	0.085	-1.447	0.148	-0.288	0.043
V18	0.0533	0.150	0.355	0.722	-0.241	0.347
V19	0.1266	0.118	1.076	0.282	-0.104	0.357
V20	-0.5751	0.108	-5.316	0.000	-0.787	-0.363
V21	0.3820	0.075	5.118	0.000	0.236	0.528
V22	0.5303	0.160	3.308	0.001	0.216	0.845
V23	-0.0574	0.072	-0.798	0.425	-0.198	0.084
V24	0.0919	0.182	0.506	0.613	-0.264	0.448
V25	-0.1094	0.166	-0.661	0.509	-0.434	0.215
V26	-0.0112	0.231	-0.049	0.961	-0.463	0.441
V27	-0.8578	0.167	-5.145	0.000	-1.185	-0.531
V28	-0.3664	0.116	-3.158	0.002	-0.594	-0.139

Amount	0.0009	0.000	1.960	0.050	1.04e-07	0.002

p-value of the feauture *V26* is high, lets drop it and re create the model

In [53]:
```
df_col = data3.drop('V26', 1)
X_train_sm = sm.add_constant(X_train[df_col])
# class_weight="balanced" will take care of the class imbalance in the dataset
logm1 = sm.GLM(y_train,X_train_sm, class_weight="balanced",family = sm.familie
s.Binomial())
res = logm1.fit()
res.summary()
```

Out[53]:

Generalized Linear Model Regression Results

Dep. Variable:	Class	**No. Observations:**	199364
Model:	GLM	**Df Residuals:**	199334
Model Family:	Binomial	**Df Model:**	29
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-725.80
Date:	Mon, 06 Apr 2020	**Deviance:**	1451.6
Time:	20:02:45	**Pearson chi2:**	5.72e+06
No. Iterations:	12	**Covariance Type:**	nonrobust

	coef	std err	z	P>|z|	[0.025	0.975]
const	-8.2465	0.295	-27.982	0.000	-8.824	-7.669
Time	-6.104e-06	2.76e-06	-2.211	0.027	-1.15e-05	-6.94e-07
V1	0.2045	0.053	3.855	0.000	0.101	0.308
V2	-0.0742	0.066	-1.120	0.263	-0.204	0.056
V3	-0.0663	0.065	-1.016	0.309	-0.194	0.062
V4	0.6857	0.083	8.286	0.000	0.524	0.848
V5	0.0976	0.078	1.244	0.214	-0.056	0.251
V6	-0.1086	0.090	-1.211	0.226	-0.284	0.067
V7	-0.0980	0.080	-1.217	0.224	-0.256	0.060
V8	-0.2003	0.040	-4.964	0.000	-0.279	-0.121
V9	-0.4606	0.124	-3.709	0.000	-0.704	-0.217
V10	-0.8627	0.114	-7.567	0.000	-1.086	-0.639
V11	-0.1696	0.100	-1.689	0.091	-0.366	0.027
V12	0.0221	0.101	0.218	0.828	-0.177	0.221
V13	-0.3443	0.102	-3.389	0.001	-0.544	-0.145
V14	-0.6179	0.076	-8.123	0.000	-0.767	-0.469
V15	-0.2029	0.107	-1.891	0.059	-0.413	0.007
V16	-0.1576	0.138	-1.139	0.255	-0.429	0.114
V17	-0.1231	0.083	-1.484	0.138	-0.286	0.039
V18	0.0540	0.149	0.362	0.717	-0.238	0.347
V19	0.1256	0.116	1.084	0.278	-0.102	0.353
V20	-0.5746	0.108	-5.330	0.000	-0.786	-0.363
V21	0.3817	0.074	5.125	0.000	0.236	0.528
V22	0.5297	0.160	3.313	0.001	0.216	0.843
V23	-0.0575	0.072	-0.799	0.424	-0.198	0.084
V24	0.0917	0.182	0.505	0.614	-0.264	0.447
V25	-0.1105	0.164	-0.673	0.501	-0.432	0.211
V27	-0.8579	0.167	-5.143	0.000	-1.185	-0.531
V28	-0.3662	0.116	-3.157	0.002	-0.594	-0.139
Amount	0.0009	0.000	1.960	0.050	8.53e-08	0.002

p-value of the feauture *V12* is high, lets drop it and re create the model

In [54]:
```
df_col = df_col.drop('V12', 1)
X_train_sm = sm.add_constant(X_train[df_col])
# class_weight="balanced" will take care of the class imbalance in the dataset
logm1 = sm.GLM(y_train,X_train_sm, class_weight="balanced",family = sm.familie
s.Binomial())
res = logm1.fit()
res.summary()
```

Out[54]:

Generalized Linear Model Regression Results

Dep. Variable:	Class	**No. Observations:**	199364
Model:	GLM	**Df Residuals:**	199335
Model Family:	Binomial	**Df Model:**	28
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-725.82
Date:	Mon, 06 Apr 2020	**Deviance:**	1451.6
Time:	20:02:55	**Pearson chi2:**	6.02e+06
No. Iterations:	12	**Covariance Type:**	nonrobust

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	-8.2438	0.294	-28.047	0.000	-8.820	-7.668
Time	-6.014e-06	2.73e-06	-2.205	0.027	-1.14e-05	-6.69e-07
V1	0.2034	0.053	3.857	0.000	0.100	0.307
V2	-0.0774	0.064	-1.209	0.227	-0.203	0.048
V3	-0.0643	0.064	-0.998	0.318	-0.190	0.062
V4	0.6796	0.077	8.831	0.000	0.529	0.830
V5	0.0935	0.076	1.233	0.218	-0.055	0.242
V6	-0.1081	0.090	-1.208	0.227	-0.284	0.067
V7	-0.1001	0.080	-1.258	0.208	-0.256	0.056
V8	-0.2007	0.040	-4.974	0.000	-0.280	-0.122
V9	-0.4624	0.123	-3.763	0.000	-0.703	-0.222
V10	-0.8558	0.109	-7.843	0.000	-1.070	-0.642
V11	-0.1689	0.100	-1.685	0.092	-0.365	0.028
V13	-0.3407	0.100	-3.410	0.001	-0.536	-0.145
V14	-0.6140	0.074	-8.347	0.000	-0.758	-0.470
V15	-0.2050	0.107	-1.919	0.055	-0.414	0.004
V16	-0.1538	0.136	-1.128	0.259	-0.421	0.113
V17	-0.1157	0.075	-1.533	0.125	-0.264	0.032
V18	0.0514	0.148	0.348	0.728	-0.238	0.341
V19	0.1252	0.116	1.084	0.278	-0.101	0.352
V20	-0.5711	0.107	-5.353	0.000	-0.780	-0.362
V21	0.3805	0.074	5.127	0.000	0.235	0.526
V22	0.5292	0.160	3.316	0.001	0.216	0.842
V23	-0.0586	0.072	-0.817	0.414	-0.199	0.082
V24	0.0922	0.181	0.508	0.612	-0.263	0.448
V25	-0.1067	0.163	-0.653	0.514	-0.427	0.214
V27	-0.8530	0.166	-5.140	0.000	-1.178	-0.528
V28	-0.3652	0.116	-3.138	0.002	-0.593	-0.137
Amount	0.0009	0.000	1.954	0.051	-2.67e-06	0.002

p-value of the feauture *V18* is high, lets drop it and re create the model

In [55]:

```
df_col = df_col.drop('V18', 1)
X_train_sm = sm.add_constant(X_train[df_col])
# class_weight="balanced" will take care of the class imbalance in the dataset
logm1 = sm.GLM(y_train,X_train_sm, class_weight="balanced",family = sm.familie
s.Binomial())
res = logm1.fit()
res.summary()
```

Out[55]:

Generalized Linear Model Regression Results

Dep. Variable:	Class	**No. Observations:**	199364
Model:	GLM	**Df Residuals:**	199336
Model Family:	Binomial	**Df Model:**	27
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-725.88
Date:	Mon, 06 Apr 2020	**Deviance:**	1451.8
Time:	20:03:44	**Pearson chi2:**	6.05e+06
No. Iterations:	12	**Covariance Type:**	nonrobust

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	-8.2556	0.293	-28.215	0.000	-8.829	-7.682
Time	-5.91e-06	2.71e-06	-2.178	0.029	-1.12e-05	-5.91e-07
V1	0.2037	0.053	3.858	0.000	0.100	0.307
V2	-0.0742	0.064	-1.162	0.245	-0.199	0.051
V3	-0.0636	0.065	-0.985	0.325	-0.190	0.063
V4	0.6811	0.077	8.848	0.000	0.530	0.832
V5	0.0976	0.075	1.294	0.196	-0.050	0.245
V6	-0.1098	0.090	-1.226	0.220	-0.285	0.066
V7	-0.0995	0.080	-1.247	0.212	-0.256	0.057
V8	-0.2005	0.040	-4.970	0.000	-0.280	-0.121
V9	-0.4595	0.123	-3.725	0.000	-0.701	-0.218
V10	-0.8590	0.109	-7.866	0.000	-1.073	-0.645
V11	-0.1629	0.099	-1.649	0.099	-0.357	0.031
V13	-0.3428	0.100	-3.431	0.001	-0.539	-0.147
V14	-0.6164	0.073	-8.430	0.000	-0.760	-0.473
V15	-0.2055	0.107	-1.925	0.054	-0.415	0.004
V16	-0.1317	0.122	-1.076	0.282	-0.372	0.108
V17	-0.1050	0.069	-1.525	0.127	-0.240	0.030
V19	0.1353	0.112	1.209	0.227	-0.084	0.355
V20	-0.5660	0.106	-5.340	0.000	-0.774	-0.358
V21	0.3838	0.074	5.213	0.000	0.239	0.528
V22	0.5337	0.159	3.365	0.001	0.223	0.845
V23	-0.0565	0.072	-0.789	0.430	-0.197	0.084
V24	0.0892	0.181	0.492	0.622	-0.266	0.445
V25	-0.1055	0.164	-0.645	0.519	-0.426	0.215
V27	-0.8539	0.166	-5.141	0.000	-1.179	-0.528
V28	-0.3646	0.116	-3.132	0.002	-0.593	-0.136
Amount	0.0009	0.000	1.997	0.046	1.71e-05	0.002

p-value of the feauture *V24* is high, lets drop it and re create the model

In [56]:
```
df_col = df_col.drop('V24', 1)
X_train_sm = sm.add_constant(X_train[df_col])
# class_weight="balanced" will take care of the class imbalance in the dataset
logm1 = sm.GLM(y_train,X_train_sm, class_weight="balanced",family = sm.familie
s.Binomial())
res = logm1.fit()
res.summary()
```

Out[56]:

Generalized Linear Model Regression Results

Dep. Variable:	Class	**No. Observations:**	199364
Model:	GLM	**Df Residuals:**	199337
Model Family:	Binomial	**Df Model:**	26
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-726.00
Date:	Mon, 06 Apr 2020	**Deviance:**	1452.0
Time:	20:03:54	**Pearson chi2:**	5.92e+06
No. Iterations:	12	**Covariance Type:**	nonrobust

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	-8.2511	0.293	-28.196	0.000	-8.825	-7.678
Time	-5.929e-06	2.72e-06	-2.182	0.029	-1.13e-05	-6.03e-07
V1	0.2035	0.053	3.848	0.000	0.100	0.307
V2	-0.0736	0.064	-1.145	0.252	-0.199	0.052
V3	-0.0605	0.065	-0.932	0.351	-0.188	0.067
V4	0.6821	0.077	8.848	0.000	0.531	0.833
V5	0.0919	0.076	1.210	0.226	-0.057	0.241
V6	-0.1200	0.090	-1.339	0.181	-0.296	0.056
V7	-0.0995	0.080	-1.240	0.215	-0.257	0.058
V8	-0.2022	0.040	-4.996	0.000	-0.282	-0.123
V9	-0.4576	0.123	-3.719	0.000	-0.699	-0.216
V10	-0.8537	0.109	-7.862	0.000	-1.066	-0.641
V11	-0.1631	0.098	-1.657	0.097	-0.356	0.030
V13	-0.3403	0.100	-3.416	0.001	-0.536	-0.145
V14	-0.6121	0.072	-8.444	0.000	-0.754	-0.470
V15	-0.2088	0.107	-1.960	0.050	-0.418	8.7e-06
V16	-0.1379	0.121	-1.140	0.254	-0.375	0.099
V17	-0.1050	0.069	-1.530	0.126	-0.239	0.029
V19	0.1368	0.111	1.231	0.218	-0.081	0.355
V20	-0.5695	0.106	-5.358	0.000	-0.778	-0.361
V21	0.3819	0.073	5.200	0.000	0.238	0.526
V22	0.5326	0.158	3.361	0.001	0.222	0.843
V23	-0.0582	0.072	-0.809	0.418	-0.199	0.083
V25	-0.1086	0.163	-0.664	0.506	-0.429	0.212
V27	-0.8519	0.166	-5.123	0.000	-1.178	-0.526
V28	-0.3640	0.117	-3.113	0.002	-0.593	-0.135
Amount	0.0009	0.000	1.996	0.046	1.73e-05	0.002

p-value of the feauture *V25* is high, lets drop it and re create the model

In [57]:

```
df_col = df_col.drop('V25', 1)
X_train_sm = sm.add_constant(X_train[df_col])
# class_weight="balanced" will take care of the class imbalance in the dataset
logm1 = sm.GLM(y_train,X_train_sm, class_weight="balanced",family = sm.familie
s.Binomial())
res = logm1.fit()
res.summary()
```

Out[57]:

Generalized Linear Model Regression Results

Dep. Variable:	Class	**No. Observations:**	199364
Model:	GLM	**Df Residuals:**	199338
Model Family:	Binomial	**Df Model:**	25
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-726.22
Date:	Mon, 06 Apr 2020	**Deviance:**	1452.4
Time:	20:04:03	**Pearson chi2:**	5.90e+06
No. Iterations:	12	**Covariance Type:**	nonrobust

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	-8.2954	0.286	-29.029	0.000	-8.855	-7.735
Time	-5.606e-06	2.68e-06	-2.093	0.036	-1.09e-05	-3.57e-07
V1	0.2053	0.053	3.871	0.000	0.101	0.309
V2	-0.0709	0.066	-1.077	0.281	-0.200	0.058
V3	-0.0548	0.064	-0.850	0.395	-0.181	0.072
V4	0.6861	0.077	8.884	0.000	0.535	0.837
V5	0.0935	0.076	1.223	0.221	-0.056	0.243
V6	-0.1176	0.090	-1.313	0.189	-0.293	0.058
V7	-0.1037	0.081	-1.274	0.202	-0.263	0.056
V8	-0.2032	0.041	-4.984	0.000	-0.283	-0.123
V9	-0.4526	0.123	-3.674	0.000	-0.694	-0.211
V10	-0.8537	0.109	-7.829	0.000	-1.067	-0.640
V11	-0.1608	0.098	-1.636	0.102	-0.353	0.032
V13	-0.3398	0.100	-3.409	0.001	-0.535	-0.144
V14	-0.6113	0.073	-8.420	0.000	-0.754	-0.469
V15	-0.2002	0.106	-1.893	0.058	-0.408	0.007
V16	-0.1386	0.121	-1.143	0.253	-0.376	0.099
V17	-0.1047	0.069	-1.522	0.128	-0.239	0.030
V19	0.1414	0.111	1.271	0.204	-0.077	0.359
V20	-0.5653	0.108	-5.259	0.000	-0.776	-0.355
V21	0.3837	0.074	5.200	0.000	0.239	0.528
V22	0.5419	0.160	3.396	0.001	0.229	0.855
V23	-0.0780	0.066	-1.180	0.238	-0.208	0.052
V27	-0.8582	0.168	-5.121	0.000	-1.187	-0.530
V28	-0.3761	0.115	-3.266	0.001	-0.602	-0.150
Amount	0.0010	0.000	2.002	0.045	2.07e-05	0.002

p-value of the feauture *V3* is high, lets drop it and re create the model

In [58]:
```
df_col = df_col.drop('V3', 1)
X_train_sm = sm.add_constant(X_train[df_col])
# class_weight="balanced" will take care of the class imbalance in the dataset
logm1 = sm.GLM(y_train,X_train_sm, class_weight="balanced",family = sm.familie
s.Binomial())
res = logm1.fit()
res.summary()
```

Out[58]:

Generalized Linear Model Regression Results

Dep. Variable:	Class	**No. Observations:**	199364
Model:	GLM	**Df Residuals:**	199339
Model Family:	Binomial	**Df Model:**	24
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-726.58
Date:	Mon, 06 Apr 2020	**Deviance:**	1453.2
Time:	20:04:12	**Pearson chi2:**	6.00e+06
No. Iterations:	12	**Covariance Type:**	nonrobust

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	-8.4107	0.253	-33.215	0.000	-8.907	-7.914
Time	-4.476e-06	2.32e-06	-1.925	0.054	-9.03e-06	8.06e-08
V1	0.1940	0.052	3.746	0.000	0.092	0.295
V2	-0.0580	0.067	-0.861	0.390	-0.190	0.074
V4	0.6941	0.077	8.980	0.000	0.543	0.846
V5	0.0739	0.076	0.974	0.330	-0.075	0.223
V6	-0.1370	0.090	-1.524	0.127	-0.313	0.039
V7	-0.1203	0.081	-1.491	0.136	-0.279	0.038
V8	-0.1966	0.042	-4.735	0.000	-0.278	-0.115
V9	-0.4506	0.123	-3.666	0.000	-0.691	-0.210
V10	-0.8691	0.107	-8.089	0.000	-1.080	-0.658
V11	-0.1384	0.095	-1.462	0.144	-0.324	0.047
V13	-0.3333	0.099	-3.350	0.001	-0.528	-0.138
V14	-0.6146	0.072	-8.484	0.000	-0.757	-0.473
V15	-0.1859	0.104	-1.788	0.074	-0.390	0.018
V16	-0.1342	0.121	-1.110	0.267	-0.371	0.103
V17	-0.0959	0.068	-1.416	0.157	-0.229	0.037
V19	0.1278	0.110	1.165	0.244	-0.087	0.343
V20	-0.5800	0.106	-5.478	0.000	-0.788	-0.372
V21	0.3730	0.073	5.117	0.000	0.230	0.516
V22	0.5242	0.158	3.318	0.001	0.215	0.834
V23	-0.0731	0.069	-1.066	0.286	-0.207	0.061
V27	-0.8679	0.165	-5.270	0.000	-1.191	-0.545
V28	-0.3814	0.118	-3.245	0.001	-0.612	-0.151
Amount	0.0011	0.001	2.109	0.035	7.66e-05	0.002

p-value of the feauture *V2* is high, lets drop it and re create the model

In [59]:
```
df_col = df_col.drop('V2', 1)
X_train_sm = sm.add_constant(X_train[df_col])
# class_weight="balanced" will take care of the class imbalance in the dataset
logm1 = sm.GLM(y_train,X_train_sm, class_weight="balanced",family = sm.familie
s.Binomial())
res = logm1.fit()
res.summary()
```

Out[59]:

Generalized Linear Model Regression Results

Dep. Variable:	Class	**No. Observations:**	199364
Model:	GLM	**Df Residuals:**	199340
Model Family:	Binomial	**Df Model:**	23
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-726.91
Date:	Mon, 06 Apr 2020	**Deviance:**	1453.8
Time:	20:04:17	**Pearson chi2:**	5.72e+06
No. Iterations:	12	**Covariance Type:**	nonrobust

	coef	std err	z	P>|z|	[0.025	0.975]
const	-8.4232	0.254	-33.116	0.000	-8.922	-7.925
Time	-4.66e-06	2.34e-06	-1.993	0.046	-9.24e-06	-7.76e-08
V1	0.1906	0.055	3.478	0.001	0.083	0.298
V4	0.6964	0.082	8.543	0.000	0.537	0.856
V5	0.1193	0.054	2.199	0.028	0.013	0.226
V6	-0.1490	0.088	-1.691	0.091	-0.322	0.024
V7	-0.1215	0.087	-1.392	0.164	-0.293	0.050
V8	-0.1891	0.041	-4.594	0.000	-0.270	-0.108
V9	-0.4069	0.114	-3.565	0.000	-0.631	-0.183
V10	-0.8612	0.111	-7.773	0.000	-1.078	-0.644
V11	-0.1436	0.095	-1.511	0.131	-0.330	0.043
V13	-0.3365	0.099	-3.395	0.001	-0.531	-0.142
V14	-0.6044	0.073	-8.280	0.000	-0.748	-0.461
V15	-0.1843	0.105	-1.763	0.078	-0.389	0.021
V16	-0.1278	0.123	-1.039	0.299	-0.369	0.113
V17	-0.1105	0.066	-1.673	0.094	-0.240	0.019
V19	0.1392	0.110	1.268	0.205	-0.076	0.354
V20	-0.5928	0.107	-5.561	0.000	-0.802	-0.384
V21	0.3581	0.071	5.066	0.000	0.220	0.497
V22	0.5306	0.159	3.344	0.001	0.220	0.842
V23	-0.0504	0.070	-0.718	0.473	-0.188	0.087
V27	-0.8467	0.164	-5.168	0.000	-1.168	-0.526
V28	-0.3661	0.123	-2.980	0.003	-0.607	-0.125
Amount	0.0014	0.000	3.031	0.002	0.000	0.002

p-value of the feauture *V23* is high, lets drop it and re create the model

In [60]:

```
df_col = df_col.drop('V23', 1)
X_train_sm = sm.add_constant(X_train[df_col])
# class_weight="balanced" will take care of the class imbalance in the dataset
logm1 = sm.GLM(y_train,X_train_sm, class_weight="balanced",family = sm.familie
s.Binomial())
res = logm1.fit()
res.summary()
```

Out[60]:

Generalized Linear Model Regression Results

Dep. Variable:	Class	**No. Observations:**	199364
Model:	GLM	**Df Residuals:**	199341
Model Family:	Binomial	**Df Model:**	22
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-727.16
Date:	Mon, 06 Apr 2020	**Deviance:**	1454.3
Time:	20:04:37	**Pearson chi2:**	5.90e+06
No. Iterations:	12	**Covariance Type:**	nonrobust

	coef	std err	z	P>|z|	[0.025	0.975]
const	-8.4197	0.254	-33.096	0.000	-8.918	-7.921
Time	-4.691e-06	2.34e-06	-2.003	0.045	-9.28e-06	-1e-07
V1	0.2073	0.050	4.131	0.000	0.109	0.306
V4	0.6819	0.079	8.664	0.000	0.528	0.836
V5	0.1191	0.054	2.191	0.028	0.013	0.226
V6	-0.1477	0.087	-1.688	0.091	-0.319	0.024
V7	-0.1475	0.081	-1.830	0.067	-0.305	0.010
V8	-0.1827	0.040	-4.601	0.000	-0.261	-0.105
V9	-0.4238	0.111	-3.813	0.000	-0.642	-0.206
V10	-0.8547	0.109	-7.808	0.000	-1.069	-0.640
V11	-0.1464	0.095	-1.540	0.124	-0.333	0.040
V13	-0.3367	0.099	-3.393	0.001	-0.531	-0.142
V14	-0.6106	0.073	-8.400	0.000	-0.753	-0.468
V15	-0.1845	0.105	-1.764	0.078	-0.389	0.021
V16	-0.1374	0.121	-1.140	0.254	-0.374	0.099
V17	-0.1047	0.065	-1.607	0.108	-0.232	0.023
V19	0.1305	0.109	1.200	0.230	-0.083	0.343
V20	-0.6125	0.103	-5.939	0.000	-0.815	-0.410
V21	0.3525	0.069	5.087	0.000	0.217	0.488
V22	0.5157	0.157	3.291	0.001	0.209	0.823
V27	-0.8739	0.157	-5.570	0.000	-1.181	-0.566
V28	-0.3742	0.119	-3.134	0.002	-0.608	-0.140
Amount	0.0015	0.000	3.709	0.000	0.001	0.002

p-value of the feauture *V16* is high, lets drop it and re create the model

In [61]:
```
df_col = df_col.drop('V16', 1)
X_train_sm = sm.add_constant(X_train[df_col])
# class_weight="balanced" will take care of the class imbalance in the dataset
logm1 = sm.GLM(y_train,X_train_sm, class_weight="balanced",family = sm.familie
s.Binomial())
res = logm1.fit()
res.summary()
```

Out[61]:

Generalized Linear Model Regression Results

Dep. Variable:	Class	**No. Observations:**	199364
Model:	GLM	**Df Residuals:**	199342
Model Family:	Binomial	**Df Model:**	21
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-727.80
Date:	Mon, 06 Apr 2020	**Deviance:**	1455.6
Time:	20:04:42	**Pearson chi2:**	5.42e+06
No. Iterations:	12	**Covariance Type:**	nonrobust

	coef	std err	z	P>|z|	[0.025	0.975]
const	-8.4006	0.252	-33.295	0.000	-8.895	-7.906
Time	-4.973e-06	2.32e-06	-2.143	0.032	-9.52e-06	-4.26e-07
V1	0.2124	0.049	4.318	0.000	0.116	0.309
V4	0.6858	0.079	8.729	0.000	0.532	0.840
V5	0.1207	0.054	2.226	0.026	0.014	0.227
V6	-0.1475	0.088	-1.675	0.094	-0.320	0.025
V7	-0.1507	0.079	-1.902	0.057	-0.306	0.005
V8	-0.1806	0.039	-4.573	0.000	-0.258	-0.103
V9	-0.4096	0.111	-3.704	0.000	-0.626	-0.193
V10	-0.8804	0.107	-8.261	0.000	-1.089	-0.672
V11	-0.1451	0.095	-1.529	0.126	-0.331	0.041
V13	-0.3368	0.099	-3.395	0.001	-0.531	-0.142
V14	-0.6156	0.072	-8.538	0.000	-0.757	-0.474
V15	-0.1808	0.105	-1.724	0.085	-0.386	0.025
V17	-0.1542	0.048	-3.192	0.001	-0.249	-0.060
V19	0.1825	0.099	1.836	0.066	-0.012	0.377
V20	-0.5962	0.100	-5.950	0.000	-0.793	-0.400
V21	0.3747	0.066	5.657	0.000	0.245	0.505
V22	0.5364	0.155	3.462	0.001	0.233	0.840
V27	-0.8948	0.152	-5.877	0.000	-1.193	-0.596
V28	-0.3888	0.116	-3.361	0.001	-0.615	-0.162
Amount	0.0015	0.000	3.676	0.000	0.001	0.002

p-value of the feauture *V11* is high, lets drop it and re create the model

In [62]:
```
df_col = df_col.drop('V11', 1)
X_train_sm = sm.add_constant(X_train[df_col])
# class_weight="balanced" will take care of the class imbalance in the dataset
logm1 = sm.GLM(y_train,X_train_sm, class_weight="balanced",family = sm.familie
s.Binomial())
res = logm1.fit()
res.summary()
```

Out[62]:

Generalized Linear Model Regression Results

Dep. Variable:	Class	**No. Observations:**	199364
Model:	GLM	**Df Residuals:**	199343
Model Family:	Binomial	**Df Model:**	20
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-728.97
Date:	Mon, 06 Apr 2020	**Deviance:**	1457.9
Time:	20:04:47	**Pearson chi2:**	6.76e+06
No. Iterations:	12	**Covariance Type:**	nonrobust

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	-8.4392	0.252	-33.473	0.000	-8.933	-7.945
Time	-4.013e-06	2.23e-06	-1.796	0.073	-8.39e-06	3.67e-07
V1	0.2035	0.049	4.139	0.000	0.107	0.300
V4	0.6896	0.079	8.719	0.000	0.535	0.845
V5	0.1170	0.054	2.171	0.030	0.011	0.223
V6	-0.1357	0.087	-1.561	0.119	-0.306	0.035
V7	-0.1369	0.080	-1.719	0.086	-0.293	0.019
V8	-0.1794	0.039	-4.573	0.000	-0.256	-0.102
V9	-0.3753	0.109	-3.437	0.001	-0.589	-0.161
V10	-0.8566	0.107	-8.031	0.000	-1.066	-0.648
V13	-0.3309	0.099	-3.348	0.001	-0.525	-0.137
V14	-0.5642	0.064	-8.778	0.000	-0.690	-0.438
V15	-0.1818	0.105	-1.731	0.084	-0.388	0.024
V17	-0.1473	0.049	-3.038	0.002	-0.242	-0.052
V19	0.1661	0.099	1.677	0.094	-0.028	0.360
V20	-0.5630	0.101	-5.571	0.000	-0.761	-0.365
V21	0.3666	0.066	5.548	0.000	0.237	0.496
V22	0.5250	0.154	3.400	0.001	0.222	0.828
V27	-0.8506	0.155	-5.486	0.000	-1.154	-0.547
V28	-0.3733	0.116	-3.208	0.001	-0.601	-0.145
Amount	0.0014	0.000	3.388	0.001	0.001	0.002

p-value of the feauture *V6* is high, lets drop it and re create the model

In [63]:
```
df_col = df_col.drop('V6', 1)
X_train_sm = sm.add_constant(X_train[df_col])
# class_weight="balanced" will take care of the class imbalance in the dataset
logm1 = sm.GLM(y_train,X_train_sm, class_weight="balanced",family = sm.familie
s.Binomial())
res = logm1.fit()
res.summary()
```

Out[63]:

Generalized Linear Model Regression Results

Dep. Variable:	Class	**No. Observations:**	199364
Model:	GLM	**Df Residuals:**	199344
Model Family:	Binomial	**Df Model:**	19
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-730.31
Date:	Mon, 06 Apr 2020	**Deviance:**	1460.6
Time:	20:04:52	**Pearson chi2:**	6.78e+06
No. Iterations:	12	**Covariance Type:**	nonrobust

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	-8.4636	0.252	-33.575	0.000	-8.958	-7.970
Time	-3.561e-06	2.2e-06	-1.618	0.106	-7.87e-06	7.52e-07
V1	0.1874	0.048	3.914	0.000	0.094	0.281
V4	0.6848	0.079	8.669	0.000	0.530	0.840
V5	0.1658	0.043	3.837	0.000	0.081	0.250
V7	-0.1513	0.078	-1.935	0.053	-0.305	0.002
V8	-0.1451	0.031	-4.633	0.000	-0.207	-0.084
V9	-0.3541	0.109	-3.244	0.001	-0.568	-0.140
V10	-0.8773	0.107	-8.206	0.000	-1.087	-0.668
V13	-0.3325	0.099	-3.342	0.001	-0.527	-0.137
V14	-0.5753	0.064	-8.938	0.000	-0.701	-0.449
V15	-0.1434	0.101	-1.426	0.154	-0.340	0.054
V17	-0.1550	0.048	-3.231	0.001	-0.249	-0.061
V19	0.1522	0.097	1.575	0.115	-0.037	0.342
V20	-0.5454	0.100	-5.470	0.000	-0.741	-0.350
V21	0.3615	0.065	5.529	0.000	0.233	0.490
V22	0.4965	0.152	3.266	0.001	0.199	0.794
V27	-0.8379	0.156	-5.379	0.000	-1.143	-0.533
V28	-0.3772	0.122	-3.084	0.002	-0.617	-0.137
Amount	0.0013	0.000	3.193	0.001	0.001	0.002

p-value of the feauture *V15* is high, lets drop it and re create the model

In [64]:
```
df_col = df_col.drop('V15', 1)
X_train_sm = sm.add_constant(X_train[df_col])
# class_weight="balanced" will take care of the class imbalance in the dataset
logm1 = sm.GLM(y_train,X_train_sm, class_weight="balanced",family = sm.families.Binomial())
res = logm1.fit()
res.summary()
```

Out[64]:

Generalized Linear Model Regression Results

Dep. Variable:	Class	**No. Observations:**	199364
Model:	GLM	**Df Residuals:**	199345
Model Family:	Binomial	**Df Model:**	18
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-731.31
Date:	Mon, 06 Apr 2020	**Deviance:**	1462.6
Time:	20:04:56	**Pearson chi2:**	6.47e+06
No. Iterations:	12	**Covariance Type:**	nonrobust

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	-8.5156	0.251	-33.985	0.000	-9.007	-8.024
Time	-2.906e-06	2.15e-06	-1.352	0.176	-7.12e-06	1.31e-06
V1	0.1892	0.048	3.967	0.000	0.096	0.283
V4	0.7018	0.080	8.823	0.000	0.546	0.858
V5	0.1613	0.043	3.764	0.000	0.077	0.245
V7	-0.1474	0.078	-1.890	0.059	-0.300	0.005
V8	-0.1488	0.032	-4.707	0.000	-0.211	-0.087
V9	-0.3386	0.110	-3.081	0.002	-0.554	-0.123
V10	-0.8832	0.108	-8.163	0.000	-1.095	-0.671
V13	-0.3339	0.100	-3.352	0.001	-0.529	-0.139
V14	-0.5630	0.064	-8.735	0.000	-0.689	-0.437
V17	-0.1637	0.048	-3.413	0.001	-0.258	-0.070
V19	0.1243	0.095	1.311	0.190	-0.062	0.310
V20	-0.5334	0.100	-5.339	0.000	-0.729	-0.338
V21	0.3655	0.065	5.597	0.000	0.238	0.494
V22	0.4899	0.152	3.229	0.001	0.193	0.787
V27	-0.8269	0.157	-5.258	0.000	-1.135	-0.519
V28	-0.3688	0.118	-3.123	0.002	-0.600	-0.137
Amount	0.0012	0.000	3.047	0.002	0.000	0.002

p-value of the feauture *V19* is high, lets drop it and re create the model

In [65]:
```python
df_col = df_col.drop('V19', 1)
X_train_sm = sm.add_constant(X_train[df_col])
# class_weight="balanced" will take care of the class imbalance in the dataset
logm1 = sm.GLM(y_train,X_train_sm, class_weight="balanced",family = sm.families.Binomial())
res = logm1.fit()
res.summary()
```

Out[65]:

Generalized Linear Model Regression Results

Dep. Variable:	Class	**No. Observations:**	199364
Model:	GLM	**Df Residuals:**	199346
Model Family:	Binomial	**Df Model:**	17
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-732.17
Date:	Mon, 06 Apr 2020	**Deviance:**	1464.3
Time:	20:05:01	**Pearson chi2:**	6.64e+06
No. Iterations:	12	**Covariance Type:**	nonrobust

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	-8.5239	0.251	-33.965	0.000	-9.016	-8.032
Time	-2.867e-06	2.15e-06	-1.335	0.182	-7.08e-06	1.34e-06
V1	0.1823	0.047	3.893	0.000	0.090	0.274
V4	0.7025	0.080	8.835	0.000	0.547	0.858
V5	0.1619	0.043	3.801	0.000	0.078	0.245
V7	-0.1389	0.077	-1.809	0.070	-0.289	0.012
V8	-0.1500	0.031	-4.889	0.000	-0.210	-0.090
V9	-0.3230	0.110	-2.942	0.003	-0.538	-0.108
V10	-0.8845	0.109	-8.103	0.000	-1.098	-0.671
V13	-0.3253	0.099	-3.273	0.001	-0.520	-0.131
V14	-0.5591	0.065	-8.635	0.000	-0.686	-0.432
V17	-0.1860	0.045	-4.123	0.000	-0.274	-0.098
V20	-0.5345	0.100	-5.333	0.000	-0.731	-0.338
V21	0.3700	0.065	5.718	0.000	0.243	0.497
V22	0.5110	0.151	3.373	0.001	0.214	0.808
V27	-0.8062	0.159	-5.063	0.000	-1.118	-0.494
V28	-0.3714	0.124	-3.000	0.003	-0.614	-0.129
Amount	0.0012	0.000	2.949	0.003	0.000	0.002

p-value of the feauture *TIME* is high, lets drop it and re create the model

In [66]:
```python
df_col = df_col.drop('Time', 1)
X_train_sm = sm.add_constant(X_train[df_col])
# class_weight="balanced" will take care of the class imbalance in the dataset
logm1 = sm.GLM(y_train,X_train_sm, class_weight="balanced",family = sm.familie
s.Binomial())
res = logm1.fit()
res.summary()
```

Out[66]:

Generalized Linear Model Regression Results

Dep. Variable:	Class	**No. Observations:**	199364
Model:	GLM	**Df Residuals:**	199347
Model Family:	Binomial	**Df Model:**	16
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-733.06
Date:	Mon, 06 Apr 2020	**Deviance:**	1466.1
Time:	20:05:47	**Pearson chi2:**	5.55e+06
No. Iterations:	12	**Covariance Type:**	nonrobust

	coef	std err	z	P>|z|	[0.025	0.975]
const	-8.7852	0.166	-52.961	0.000	-9.110	-8.460
V1	0.1762	0.046	3.834	0.000	0.086	0.266
V4	0.7064	0.079	8.918	0.000	0.551	0.862
V5	0.1512	0.042	3.584	0.000	0.069	0.234
V7	-0.1303	0.076	-1.725	0.084	-0.278	0.018
V8	-0.1513	0.031	-4.958	0.000	-0.211	-0.091
V9	-0.2978	0.108	-2.764	0.006	-0.509	-0.087
V10	-0.8851	0.109	-8.093	0.000	-1.099	-0.671
V13	-0.3211	0.099	-3.231	0.001	-0.516	-0.126
V14	-0.5566	0.065	-8.602	0.000	-0.683	-0.430
V17	-0.1906	0.045	-4.217	0.000	-0.279	-0.102
V20	-0.5182	0.099	-5.235	0.000	-0.712	-0.324
V21	0.3566	0.063	5.637	0.000	0.233	0.481
V22	0.4725	0.146	3.233	0.001	0.186	0.759
V27	-0.7885	0.159	-4.960	0.000	-1.100	-0.477
V28	-0.3702	0.126	-2.942	0.003	-0.617	-0.124
Amount	0.0011	0.000	2.808	0.005	0.000	0.002

p-value of the feauture *V7* is high, lets drop it and re create the model

In [67]:
```
df_col = df_col.drop('V7', 1)
X_train_sm = sm.add_constant(X_train[df_col])
# class_weight="balanced" will take care of the class imbalance in the dataset
logm1 = sm.GLM(y_train,X_train_sm, class_weight="balanced",family = sm.familie
s.Binomial())
res = logm1.fit()
res.summary()
```

Out[67]:

Generalized Linear Model Regression Results

Dep. Variable:	Class	**No. Observations:**	199364
Model:	GLM	**Df Residuals:**	199348
Model Family:	Binomial	**Df Model:**	15
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-734.63
Date:	Mon, 06 Apr 2020	**Deviance:**	1469.3
Time:	20:05:51	**Pearson chi2:**	6.86e+06
No. Iterations:	12	**Covariance Type:**	nonrobust

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	-8.7403	0.164	-53.277	0.000	-9.062	-8.419
V1	0.1235	0.033	3.713	0.000	0.058	0.189
V4	0.7443	0.077	9.710	0.000	0.594	0.895
V5	0.1363	0.045	3.037	0.002	0.048	0.224
V8	-0.1729	0.030	-5.677	0.000	-0.233	-0.113
V9	-0.2275	0.102	-2.240	0.025	-0.427	-0.028
V10	-0.9086	0.111	-8.155	0.000	-1.127	-0.690
V13	-0.3369	0.099	-3.412	0.001	-0.530	-0.143
V14	-0.5465	0.066	-8.294	0.000	-0.676	-0.417
V17	-0.2236	0.042	-5.341	0.000	-0.306	-0.142
V20	-0.4018	0.078	-5.173	0.000	-0.554	-0.250
V21	0.3540	0.065	5.474	0.000	0.227	0.481
V22	0.4138	0.141	2.932	0.003	0.137	0.690
V27	-0.6779	0.157	-4.331	0.000	-0.985	-0.371
V28	-0.3248	0.114	-2.860	0.004	-0.547	-0.102
Amount	0.0005	0.000	2.414	0.016	8.47e-05	0.001

p-values looks good now, lets check VIF

In [68]:
```
vif = pd.DataFrame()
vif['Features'] = X_train[df_col].columns
vif['VIF'] = [variance_inflation_factor(X_train[df_col].values, i) for i in ra
nge(X_train[df_col].shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

Out[68]:

	Features	VIF
14	Amount	1.51
9	V20	1.19
2	V5	1.18
0	V1	1.07
10	V21	1.02
1	V4	1.01
3	V8	1.01
5	V10	1.01
11	V22	1.01
4	V9	1.00
6	V13	1.00
7	V14	1.00
8	V17	1.00
12	V27	1.00
13	V28	1.00

In [69]:
```
# VIF also Looks good , lets make predictions now on the train set
y_train_pred = res.predict(X_train_sm)
y_train_pred[:10]
```

Out[69]:
```
7610      0.000029
190214    0.000127
130590    0.000012
247916    0.000142
55518     0.000246
147392    0.000029
5549      0.000071
182927    0.000174
177760    0.000288
266732    0.000378
dtype: float64
```

In [70]:
```
# reshape the dataframe to get an array
y_train_pred = y_train_pred.values.reshape(-1)
y_train_pred[:10]
```

Out[70]:
```
array([2.93003752e-05, 1.26508019e-04, 1.24898233e-05, 1.41927065e-04,
       2.46264845e-04, 2.88407101e-05, 7.14548782e-05, 1.73571732e-04,
       2.87660597e-04, 3.77650172e-04])
```

In [71]:
```
# Create a dataframe with the actual performance tag and the predicted probabi
lities
y_train_pred_final = pd.DataFrame({'Class':y_train.values, 'probability':y_tra
in_pred})
#y_train_pred_final['Application ID'] = y_train.index
y_train_pred_final.head()
```

Out[71]:

	Class	probability
0	0	0.000029
1	0	0.000127
2	0	0.000012
3	0	0.000142
4	0	0.000246

In [72]:
```
## making the predictions based on the probability with the cut-off value as
 0.1
## this cut-off value will be tuned later
y_train_pred_final['predicted'] = y_train_pred_final["probability"].map(lambda
x: 1 if x > 0.1 else 0)
# Let's see the head
y_train_pred_final.head()
```

Out[72]:

	Class	probability	predicted
0	0	0.000029	0
1	0	0.000127	0
2	0	0.000012	0
3	0	0.000142	0
4	0	0.000246	0

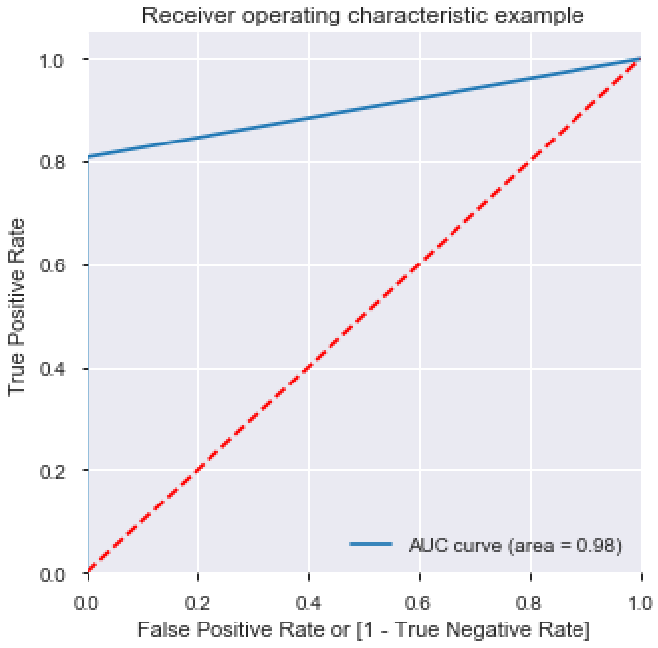
In [73]:
```
# lets check the confusion metrics, accuracy, sensitivity, specificity, precis
ion and recall of the model built
from sklearn import metrics

confusion = metrics.confusion_matrix(y_train_pred_final["Class"],y_train_pred_
final["predicted"])
print("Confusion Metrics:\n",confusion)
TP = confusion[1,1] # true positive
TN = confusion[0,0] # true negatives
FP = confusion[0,1] # false positives
FN = confusion[1,0] # false negatives
print("\nAccuracy:{}".format(round((TP+TN)/(TP+TN+FP+FN),3)))
print("Recall/Sensitivity:",recall_score(y_train_pred_final["Class"],y_train_p
red_final["predicted"]))
print("Precision:",precision_score(y_train_pred_final["Class"],y_train_pred_fi
nal["predicted"]))
print("Specificity:{}".format(round(TN/float(TN+FP),3)))
print("AUC:", metrics.roc_auc_score(y_train_pred_final["Class"], y_train_pred_
final["probability"]))
```

```
Confusion Metrics:
 [[198956     58]
 [    67    283]]

Accuracy:0.999
Recall/Sensitivity: 0.8085714285714286
Precision: 0.8299120234604106
Specificity:1.0
AUC: 0.9799494364359148
```

In [74]:
```
## using roc_cuve from the matrics
fpr, tpr, thresholds = metrics.roc_curve( y_train_pred_final["Class"], y_train
_pred_final.predicted, drop_intermediate = False )
auc_score = metrics.roc_auc_score( y_train_pred_final["Class"], y_train_pred_f
inal["probability"] )
plt.figure(figsize=(5, 5))
plt.plot( fpr, tpr, label='AUC curve (area = %0.2f)' % auc_score )
plt.plot([0, 1], [0, 1], 'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate or [1 - True Negative Rate]')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic example')
plt.legend(loc="lower right")
plt.show()
```



K Nearest Neighbors

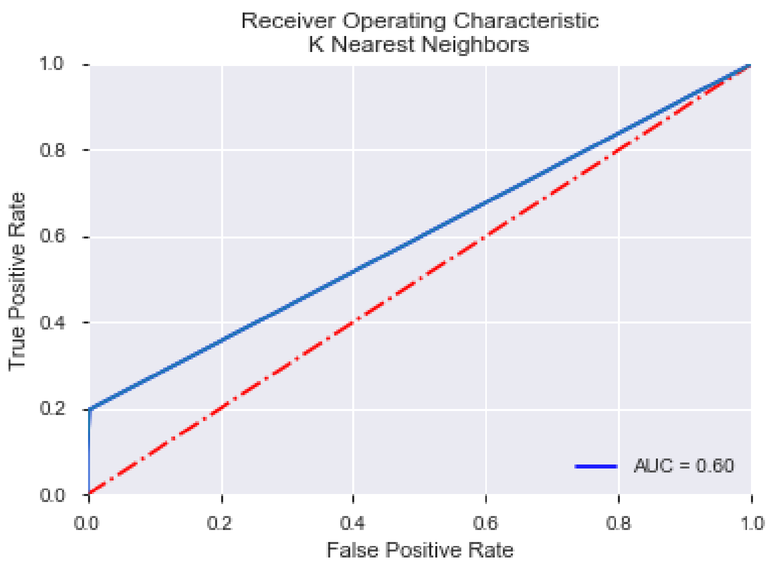
In [75]:
```
#K Nearest Neighbors
from sklearn.neighbors import KNeighborsClassifier
```

In [76]:
```
knn=KNeighborsClassifier(n_neighbors=5)
knn.fit(X_train,y_train)
y_knn=knn.predict(X_test)
y_knn_prob=knn.predict_proba(X_test)[:,1]
```

In [77]:
```
#metrics evaluation
print("Confusion Matrix:\n",metrics.confusion_matrix(y_test,y_knn))
print("Accuracy:\n",metrics.accuracy_score(y_test,y_knn))
print("Precision:\n",metrics.precision_score(y_test,y_knn))
print("Recall:\n",metrics.recall_score(y_test,y_knn))
print("AUC:\n",metrics.roc_auc_score(y_test,y_knn_prob))
auc=metrics.roc_auc_score(y_test,y_knn_prob)
```

```
Confusion Matrix:
 [[85301     0]
 [  132    10]]
Accuracy:
 0.9984551104244935
Precision:
 1.0
Recall:
 0.07042253521126761
AUC:
 0.5972707088122574
```

In [78]:
```
#plotting the AUC curve
fpr,tpr,thresholds=metrics.roc_curve(y_test,y_knn_prob)
plt.plot(fpr,tpr,'b', label='AUC = %0.2f'% auc)
plt.plot([0,1],[0,1],'r-.')
plt.plot(fpr,tpr)
#plt.title('K Nearest Neighbors')
plt.xlim([0.0,1.0])
plt.ylim([0.0,1.0])
plt.title('Receiver Operating Characteristic\nK Nearest Neighbors')
plt.legend(loc='lower right')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



Decision Tree Model

In [79]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report, confusion_matrix, accuracy_
score
```

In [80]:
```python
# lets create a decision tree with default hyper parameters.
dt_model = DecisionTreeClassifier(class_weight='balanced',max_depth=5)
dt_model.fit(X_train, y_train)
```

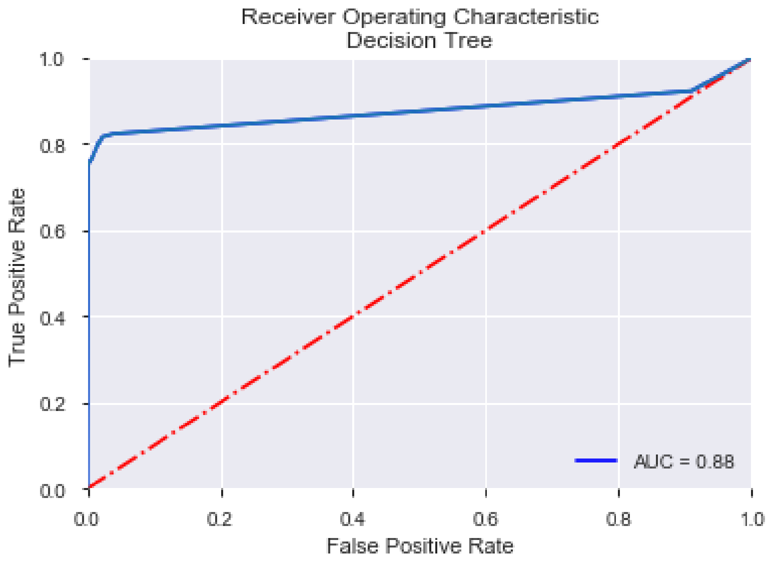
Out[80]:
```
DecisionTreeClassifier(ccp_alpha=0.0, class_weight='balanced', criterion='gin
i',
                       max_depth=5, max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort='deprecated',
                       random_state=None, splitter='best')
```

In [81]:
```python
# predictions on the training dataset
y_train_pred= dt_model.predict(X_train)
y_dt=dt_model.predict(X_test)
y_dt_prob=dt_model.predict_proba(X_test)[:,1]
```

In [82]:
```python
#metrics evaluation
print("Confusion Matrix:\n",metrics.confusion_matrix(y_test,y_dt))
print("Accuracy:\n",metrics.accuracy_score(y_test,y_dt))
print("Precision:\n",metrics.precision_score(y_test,y_dt))
print("Recall:\n",metrics.recall_score(y_test,y_dt))
print("AUC:\n",metrics.roc_auc_score(y_test,y_dt_prob))
auc=metrics.roc_auc_score(y_test,y_dt_prob)
```

```
Confusion Matrix:
 [[83295  2006]
 [   26   116]]
Accuracy:
 0.9762180635043245
Precision:
 0.05466540999057493
Recall:
 0.8169014084507042
AUC:
 0.8778875996863468
```

In [83]:
```
#plotting the AUC curve
fpr,tpr,thresholds=metrics.roc_curve(y_test,y_dt_prob)
plt.plot(fpr,tpr,'b', label='AUC = %0.2f'% auc)
plt.plot([0,1],[0,1],'r-.')
plt.plot(fpr,tpr)
plt.xlim([0.0,1.0])
plt.ylim([0.0,1.0])
plt.title('Receiver Operating Characteristic\nDecision Tree')
plt.legend(loc='lower right')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



Random Forest

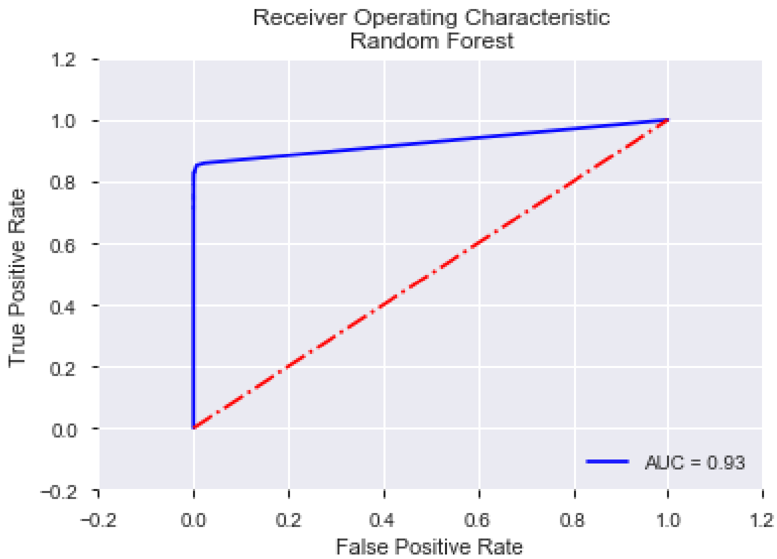
In [84]:
```
from sklearn.ensemble import RandomForestClassifier
```

In [85]:
```
rf=RandomForestClassifier(random_state=3)
rf.fit(X_train,y_train)
y_rf=rf.predict(X_test)
y_rf_prob=rf.predict_proba(X_test)[:,1]
```

In [86]:
```
#Performance metrics evaluation
print("Confusion Matrix:\n",metrics.confusion_matrix(y_test,y_rf))
print("Accuracy:\n",metrics.accuracy_score(y_test,y_rf))
print("Precision:\n",metrics.precision_score(y_test,y_rf))
print("Recall:\n",metrics.recall_score(y_test,y_rf))
print("AUC:\n",metrics.roc_auc_score(y_test,y_rf_prob))
auc=metrics.roc_auc_score(y_test,y_rf_prob)
```

```
Confusion Matrix:
 [[85284    17]
 [   35   107]]
Accuracy:
 0.9993914071369217
Precision:
 0.8629032258064516
Recall:
 0.7535211267605634
AUC:
 0.9277379968961611
```

In [87]:
```
## using roc_cuve from the matrics
#plotting the AUC curve
fpr,tpr,thresholds=metrics.roc_curve(y_test,y_rf_prob, drop_intermediate = Fal
se)
plt.plot(fpr,tpr,'b', label='AUC = %0.2f'% auc)
plt.plot([0,1],[0,1],'r-.')
plt.xlim([-0.2,1.2])
plt.ylim([-0.2,1.2])
plt.title('Receiver Operating Characteristic\nRandom Forest')
plt.legend(loc='lower right')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



Model building with balancing Classes

Till now we have check the model with imbalance data set, Now we develop balance data set by SMOTE

In [88]:
```
# Creating seperate class variable
cls_val = data1['Class']
```

In [89]:
```
#dropping the target variable from the data set
data1.drop('Class',axis=1,inplace=True)
data1.shape
```

Out[89]: (284807, 30)

In [90]:
```
#converting them to numpy arrays
X=np.array(data1)
y=np.array(cls_val)
X.shape
y.shape
```

Out[90]: (284807,)

In [91]:
```
#splitting the data set into train and test (70:30)
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.30,random_state
=1)
print(X_train.shape,X_test.shape,y_train.shape,y_test.shape)
```

```
(199364, 30) (85443, 30) (199364,) (85443,)
```

In [92]:
```
#splitting the data set into train and test (80:20)
#from sklearn.model_selection import train_test_split
#X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.20,random_stat
e=1)
#print(X_train.shape,X_test.shape,y_train.shape,y_test.shape)
```

In [93]:
```
#applyting SMOTE to oversample the minority class
from imblearn.over_sampling import SMOTE
sm=SMOTE(random_state=2)
X_sm,y_sm=sm.fit_sample(X_train,y_train)
print(X_sm.shape,y_sm.shape)
```

```
(398014, 30) (398014,)
```

In [94]:
```
print("After OverSampling, counts of label '1' in Test Data Set: {}".format(su
m(y_sm==1)))
print("After OverSampling, counts of label '0' in Test Data Set: {} \n".format
(sum(y_sm==0)))
```

```
After OverSampling, counts of label '1' in Test Data Set: 199007
After OverSampling, counts of label '0' in Test Data Set: 199007
```

Logistic Regression

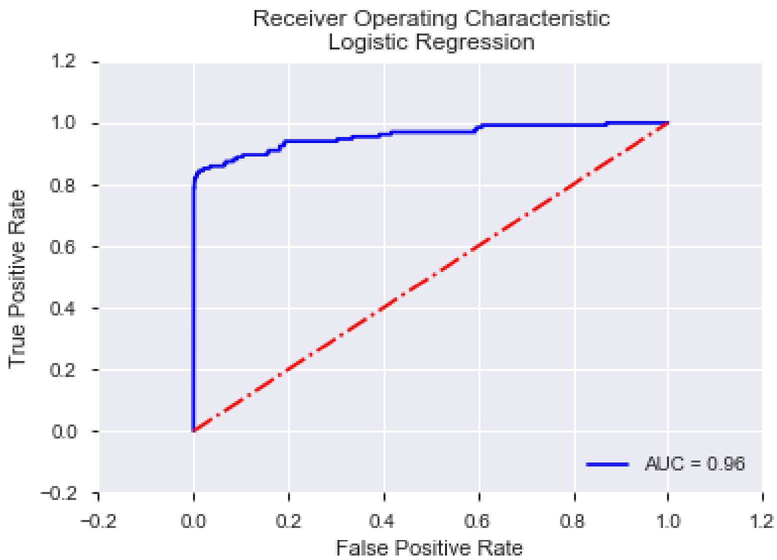
In [95]:
```
from sklearn.linear_model import LogisticRegression
import matplotlib.pyplot as plt
from sklearn import metrics
```

In [96]:
```
#Logistic Regression
logreg=LogisticRegression()
logreg.fit(X_sm,y_sm)
y_logreg=logreg.predict(X_test)
y_logreg_prob=logreg.predict_proba(X_test)[:,1]
```

In [97]:
```
#Performance metrics evaluation
print("Confusion Matrix:\n",metrics.confusion_matrix(y_test,y_logreg))
print("Accuracy:\n",metrics.accuracy_score(y_test,y_logreg))
print("Precision:\n",metrics.precision_score(y_test,y_logreg))
print("Recall:\n",metrics.recall_score(y_test,y_logreg))
print("AUC:\n",metrics.roc_auc_score(y_test,y_logreg_prob))
auc=metrics.roc_auc_score(y_test,y_logreg_prob)
```

```
Confusion Matrix:
 [[83875  1433]
 [   21   114]]
Accuracy:
 0.982982807251618
Precision:
 0.07369101486748546
Recall:
 0.8444444444444444
AUC:
 0.9578111296930165
```

In [98]:
```
#plotting the AUC curve
fpr,tpr,thresholds=metrics.roc_curve(y_test,y_logreg_prob)
plt.plot(fpr,tpr,'b', label='AUC = %0.2f'% auc)
plt.plot([0,1],[0,1],'r-.')
plt.xlim([-0.2,1.2])
plt.ylim([-0.2,1.2])
plt.title('Receiver Operating Characteristic\nLogistic Regression')
plt.legend(loc='lower right')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



K Nearest Neighbors

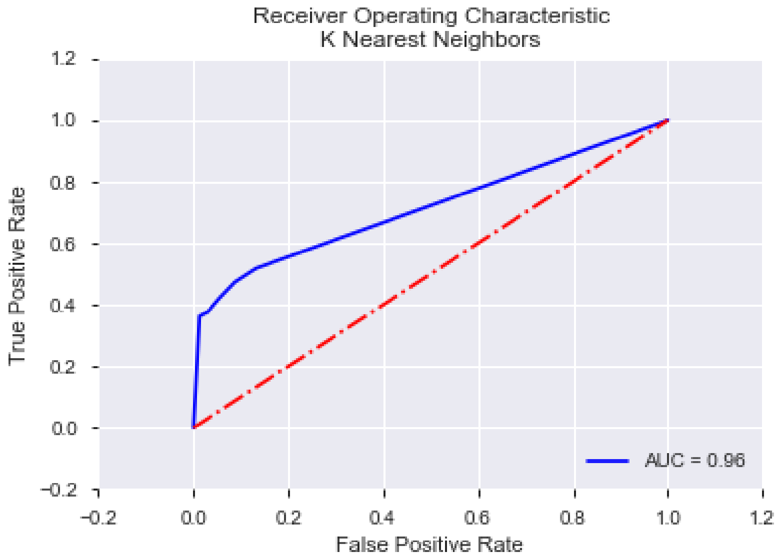
In [99]:
```
#K Nearest Neighbors
from sklearn.neighbors import KNeighborsClassifier
```

In [100]:
```
knn=KNeighborsClassifier(n_neighbors=5)
knn.fit(X_sm,y_sm)
y_knn=knn.predict(X_test)
y_knn_prob=knn.predict_proba(X_test)[:,1]
```

In [101]:
```
# Matrics Performance Evaluation
print("Confusion Matrix:\n",metrics.confusion_matrix(y_test,y_knn))
print("Accuracy:\n",metrics.accuracy_score(y_test,y_knn))
print("Precision:\n",metrics.precision_score(y_test,y_knn))
print("Recall:\n",metrics.recall_score(y_test,y_knn))
print("AUC:\n",metrics.roc_auc_score(y_test,y_knn_prob))
```

```
Confusion Matrix:
 [[80590  4718]
 [   78    57]]
Accuracy:
 0.9438690120899313
Precision:
 0.011937172774869111
Recall:
 0.4222222222222222
AUC:
 0.7143800937431078
```

In [102]:
```
#plotting the AUC curve
fpr,tpr,thresholds=metrics.roc_curve(y_test,y_knn_prob)
plt.plot(fpr,tpr,'b', label='AUC = %0.2f'% auc)
plt.plot([0,1],[0,1],'r-.')
plt.xlim([-0.2,1.2])
plt.ylim([-0.2,1.2])
plt.title('Receiver Operating Characteristic\nK Nearest Neighbors')
plt.legend(loc='lower right')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



Decision Tree

In [103]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report, confusion_matrix, accuracy_
score
```

In [104]:
```
# lets create a decision tree with default hyper parameters.
dt_model = DecisionTreeClassifier(class_weight='balanced',max_depth=5)
dt_model.fit(X_sm,y_sm)
```

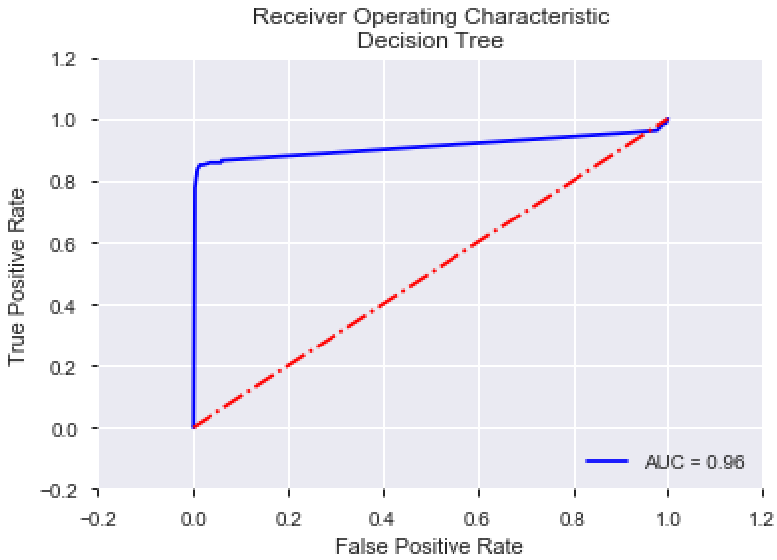
Out[104]:
```
DecisionTreeClassifier(ccp_alpha=0.0, class_weight='balanced', criterion='gin
i',
                       max_depth=5, max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort='deprecated',
                       random_state=None, splitter='best')
```

In [105]:
```
# predictions on the training dataset
#y_train_pred= dt_model.predict(X_train)
y_dt=dt_model.predict(X_test)
y_dt_prob=dt_model.predict_proba(X_test)[:,1]
```

In [106]:
```
#Metrics evaluation
print("Confusion Matrix:\n",metrics.confusion_matrix(y_test,y_dt))
print("Accuracy:\n",metrics.accuracy_score(y_test,y_dt))
print("Precision:\n",metrics.precision_score(y_test,y_dt))
print("Recall:\n",metrics.recall_score(y_test,y_dt))
print("AUC:\n",metrics.roc_auc_score(y_test,y_dt_prob))
```

```
Confusion Matrix:
 [[84145  1163]
 [   20   115]]
Accuracy:
 0.9861545123649684
Precision:
 0.08998435054773082
Recall:
 0.8518518518518519
AUC:
 0.9102880803155105
```

In [107]:
```
#plotting the AUC curve
fpr,tpr,thresholds=metrics.roc_curve(y_test,y_dt_prob)
plt.plot(fpr,tpr,'b', label='AUC = %0.2f'% auc)
plt.plot([0,1],[0,1],'r-.')
plt.xlim([-0.2,1.2])
plt.ylim([-0.2,1.2])
plt.title('Receiver Operating Characteristic\nDecision Tree')
plt.legend(loc='lower right')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



Hyperparameter Tuning for DecisionTree Classifier

In [108]:
```
# Let's tune hyper parameters for DecisionTree Classifier
# GridSearchCV to find optimal max_depth
from sklearn.model_selection import KFold
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import RandomizedSearchCV
```

In [109]:
```python
# Create the parameter grid
param_grid = {
    'max_depth': range(3, 15, 5),
    'min_samples_leaf': range(10, 150, 50),
    'min_samples_split': range(50, 150, 50),
    'criterion': ["entropy", "gini"]
}

n_folds = 5

# Instantiate the grid search model
dtree = DecisionTreeClassifier(class_weight='balanced',#criterion = "gini",
                               random_state = 101)
grid_search = RandomizedSearchCV(estimator = dtree, param_distributions = para
m_grid,scoring='roc_auc',
                          cv = n_folds, verbose = 1,n_jobs=-1)

# Fit the grid search to the data
grid_search.fit(X_sm,y_sm)
```

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

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  42 tasks      | elapsed:  7.2min
[Parallel(n_jobs=-1)]: Done  50 out of  50 | elapsed:  9.0min finished
```

Out[109]:
```
RandomizedSearchCV(cv=5, error_score=nan,
                   estimator=DecisionTreeClassifier(ccp_alpha=0.0,
                                                    class_weight='balanced',
                                                    criterion='gini',
                                                    max_depth=None,
                                                    max_features=None,
                                                    max_leaf_nodes=None,
                                                    min_impurity_decrease=0.0,
                                                    min_impurity_split=None,
                                                    min_samples_leaf=1,
                                                    min_samples_split=2,
                                                    min_weight_fraction_leaf=
0.0,
                                                    presort='deprecated',
                                                    random_state=101,
                                                    splitter='best'),
                   iid='deprecated', n_iter=10, n_jobs=-1,
                   param_distributions={'criterion': ['entropy', 'gini'],
                                        'max_depth': range(3, 15, 5),
                                        'min_samples_leaf': range(10, 150, 5
0),
                                        'min_samples_split': range(50, 150, 5
0)},
                   pre_dispatch='2*n_jobs', random_state=None, refit=True,
                   return_train_score=False, scoring='roc_auc', verbose=1)
```

In [110]:
```
# cv results
cv_results = pd.DataFrame(grid_search.cv_results_)
cv_results
```

Out[110]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_min_samples_split	parar
0	24.026006	3.091412	0.112514	0.015244	50	
1	25.179380	0.405345	0.102513	0.013543	100	
2	65.011925	0.485211	0.112678	0.012687	50	
3	42.120822	0.179860	0.116011	0.017145	100	
4	24.796445	0.410433	0.103652	0.018528	100	
5	59.517178	1.849481	0.108420	0.011012	50	
6	65.459065	2.957018	0.107234	0.014629	50	
7	16.695753	0.113246	0.103911	0.007405	100	
8	16.817425	0.131938	0.106230	0.011720	100	
9	60.691331	8.836754	0.083572	0.016719	50	

In [111]:
```
# printing the optimal accuracy score and hyperparameters
print("best accuracy", grid_search.best_score_)
print(grid_search.best_estimator_)
```

```
best accuracy 0.9993366485904097
DecisionTreeClassifier(ccp_alpha=0.0, class_weight='balanced',
                       criterion='entropy', max_depth=13, max_features=None,
                       max_leaf_nodes=None, min_impurity_decrease=0.0,
                       min_impurity_split=None, min_samples_leaf=60,
                       min_samples_split=50, min_weight_fraction_leaf=0.0,
                       presort='deprecated', random_state=101, splitter='bes
t')
```

In [112]:
```
# model with optimal hyperparameters
clf_gini_df = DecisionTreeClassifier(class_weight='balanced',
                                     criterion = "entropy",
                                    random_state = 101,
                                    max_depth=13,
                                    min_samples_leaf=10,
                                    min_samples_split=100)
clf_gini_df.fit(X_sm,y_sm)
```

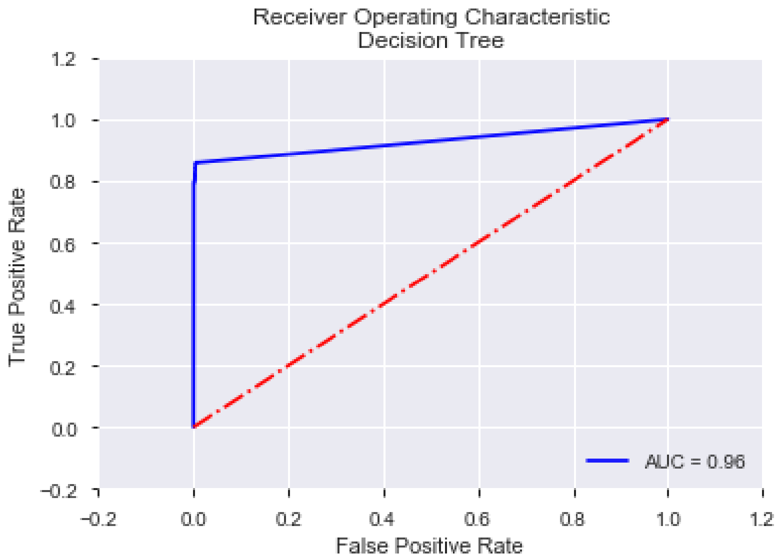
Out[112]:
```
DecisionTreeClassifier(ccp_alpha=0.0, class_weight='balanced',
                       criterion='entropy', max_depth=13, max_features=None,
                       max_leaf_nodes=None, min_impurity_decrease=0.0,
                       min_impurity_split=None, min_samples_leaf=10,
                       min_samples_split=100, min_weight_fraction_leaf=0.0,
                       presort='deprecated', random_state=101, splitter='bes
t')
```

In [113]:
```
# predictions on the training dataset
#y_train_pred= clf_gini_df.predict(X_train)
y_dt=clf_gini_df.predict(X_test)
y_dt_prob=clf_gini_df.predict_proba(X_test)[:,1]
```

In [114]:
```
#Metrics evaluation
print("Confusion Matrix:\n",metrics.confusion_matrix(y_test,y_dt))
print("Accuracy:\n",metrics.accuracy_score(y_test,y_dt))
print("Precision:\n",metrics.precision_score(y_test,y_dt))
print("Recall:\n",metrics.recall_score(y_test,y_dt))
print("AUC:\n",metrics.roc_auc_score(y_test,y_dt_prob))
```

```
Confusion Matrix:
 [[84950   358]
 [   20   115]]
Accuracy:
 0.9955759980337769
Precision:
 0.24312896405919662
Recall:
 0.8518518518518519
AUC:
 0.928406349801764
```

```
In [115]: #plotting the AUC curve
fpr,tpr,thresholds=metrics.roc_curve(y_test,y_dt_prob)
plt.plot(fpr,tpr,'b', label='AUC = %0.2f'% auc)
plt.plot([0,1],[0,1],'r-.')
plt.xlim([-0.2,1.2])
plt.ylim([-0.2,1.2])
plt.title('Receiver Operating Characteristic\nDecision Tree')
plt.legend(loc='lower right')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



Here we easily understand, AUC is good 96% but the gap between Precision 16% and Recall 78%, is much high.

Random Forest

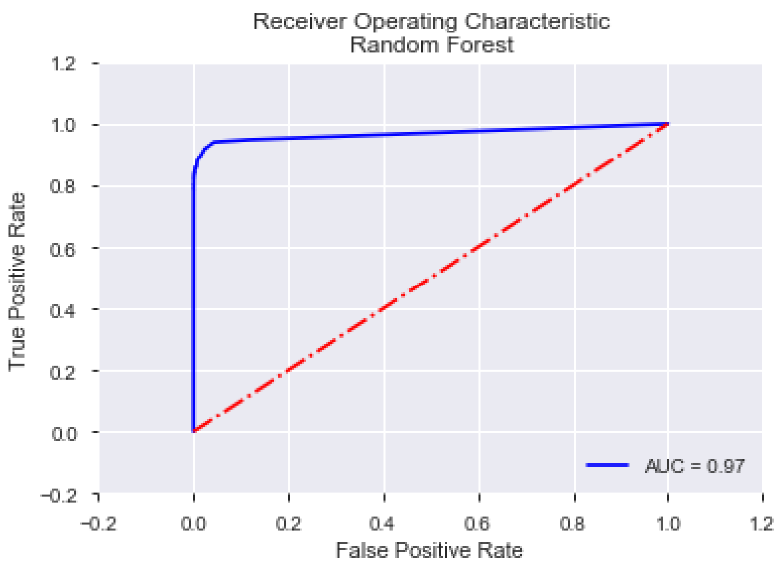
```
In [116]: #Random Forest
from sklearn.ensemble import RandomForestClassifier
```

```
In [117]: rf=RandomForestClassifier(random_state=3)
rf.fit(X_sm,y_sm)
y_rf=rf.predict(X_test)
y_rf_prob=rf.predict_proba(X_test)[:,1]
```

In [118]:
```
#Performance metrics evaluation
print("Confusion Matrix:\n",metrics.confusion_matrix(y_test,y_rf))
print("Accuracy:\n",metrics.accuracy_score(y_test,y_rf))
print("Precision:\n",metrics.precision_score(y_test,y_rf))
print("Recall:\n",metrics.recall_score(y_test,y_rf))
print("AUC:\n",metrics.roc_auc_score(y_test,y_rf_prob))
auc=metrics.roc_auc_score(y_test,y_rf_prob)
```

```
Confusion Matrix:
 [[85291    17]
 [   27   108]]
Accuracy:
 0.9994850368081645
Precision:
 0.864
Recall:
 0.8
AUC:
 0.9689061770074102
```

In [119]:
```
#plotting the AUC curve
fpr,tpr,thresholds=metrics.roc_curve(y_test,y_rf_prob)
plt.plot(fpr,tpr,'b', label='AUC = %0.2f'% auc)
plt.plot([0,1],[0,1],'r-.')
plt.xlim([-0.2,1.2])
plt.ylim([-0.2,1.2])
plt.title('Receiver Operating Characteristic\nRandom Forest')
plt.legend(loc='lower right')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



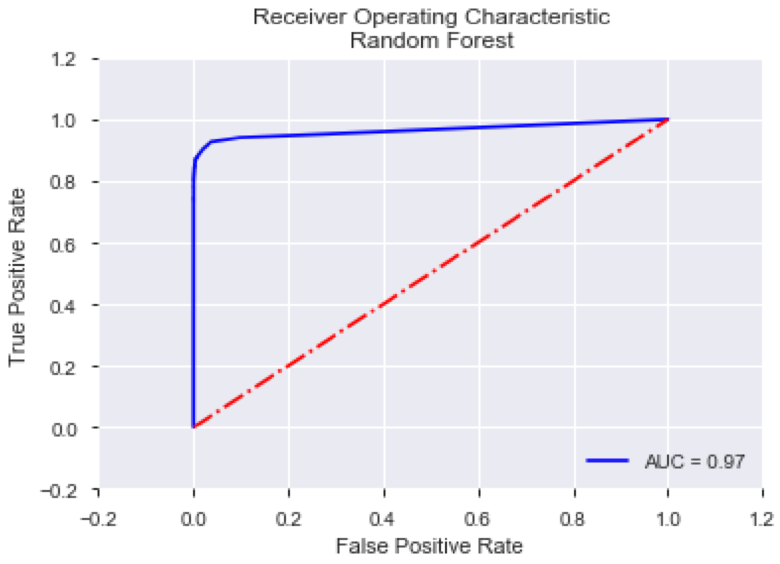
Random Forest by using criterion='entropy'

In [120]:
```
#Random Forest
from sklearn.ensemble import RandomForestClassifier
# By using criterion='entropy'
rf=RandomForestClassifier(criterion='entropy',random_state=3)
rf.fit(X_sm,y_sm)
y_rf=rf.predict(X_test)
y_rf_prob=rf.predict_proba(X_test)[:,1]
```

In [121]:
```
#Performance metrics evaluation
print("Confusion Matrix:\n",metrics.confusion_matrix(y_test,y_rf))
print("Accuracy:\n",metrics.accuracy_score(y_test,y_rf))
print("Precision:\n",metrics.precision_score(y_test,y_rf))
print("Recall:\n",metrics.recall_score(y_test,y_rf))
print("AUC:\n",metrics.roc_auc_score(y_test,y_rf_prob))
auc=metrics.roc_auc_score(y_test,y_rf_prob)
```

```
Confusion Matrix:
 [[85289    19]
 [   26   109]]
Accuracy:
 0.9994733330992591
Precision:
 0.8515625
Recall:
 0.8074074074074075
AUC:
 0.965297770692341
```

In [122]:
```
#plotting the AUC curve
fpr,tpr,thresholds=metrics.roc_curve(y_test,y_rf_prob)
plt.plot(fpr,tpr,'b', label='AUC = %0.2f'% auc)
plt.plot([0,1],[0,1],'r-.')
plt.xlim([-0.2,1.2])
plt.ylim([-0.2,1.2])
plt.title('Receiver Operating Characteristic\nRandom Forest')
plt.legend(loc='lower right')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



XGBoost

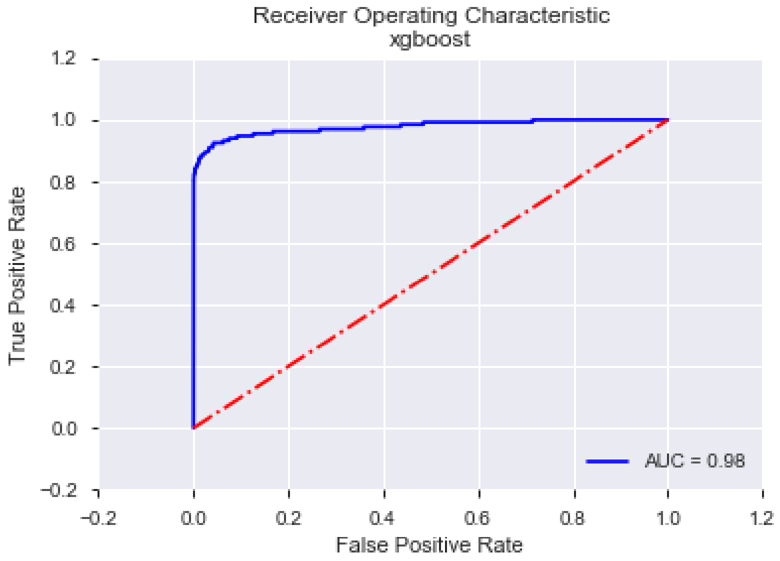
In [123]:
```
# import xgboost
from xgboost import XGBClassifier
```

In [124]:
```
# XGBoost CV model
xgc = XGBClassifier()
xgc.fit(X_sm,y_sm)
y_xg=xgc.predict(X_test)
y_xg_prob=xgc.predict_proba(X_test)[:,1]
```

In [125]:
```
#Performance metrics evaluation
print("Confusion Matrix:\n",metrics.confusion_matrix(y_test,y_xg))
print("Accuracy:\n",metrics.accuracy_score(y_test,y_xg))
print("Precision:\n",metrics.precision_score(y_test,y_xg))
print("Recall:\n",metrics.recall_score(y_test,y_xg))
print("AUC:\n",metrics.roc_auc_score(y_test,y_xg_prob))
auc=metrics.roc_auc_score(y_test,y_xg_prob)
```

```
Confusion Matrix:
 [[84908   400]
 [   21   114]]
Accuracy:
 0.9950727385508468
Precision:
 0.22178988326848248
Recall:
 0.8444444444444444
AUC:
 0.9774115232126204
```

In [126]:
```
#plotting the AUC curve
fpr,tpr,thresholds=metrics.roc_curve(y_test,y_xg_prob)
plt.plot(fpr,tpr,'b', label='AUC = %0.2f'% auc)
plt.plot([0,1],[0,1],'r-.')
plt.xlim([-0.2,1.2])
plt.ylim([-0.2,1.2])
plt.title('Receiver Operating Characteristic\nxgboost')
plt.legend(loc='lower right')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



Naive Bayes

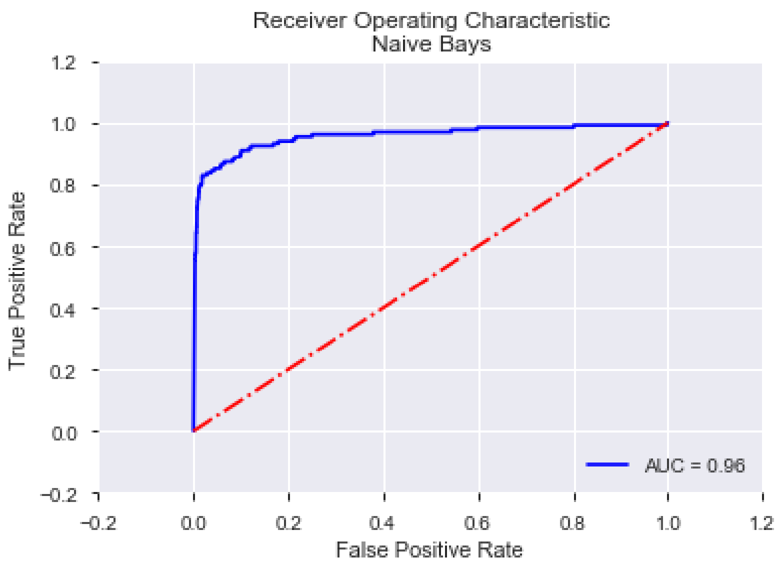
In [127]:
```
# import Gaussian Naive Bays
from sklearn.naive_bayes import GaussianNB
```

In [128]:
```
# XGBoost  model
gnb = GaussianNB()
gnb.fit(X_sm,y_sm)
y_gnb=gnb.predict(X_test)
y_gnb_prob=gnb.predict_proba(X_test)[:,1]
```

In [129]:
```
#Performance metrics evaluation
print("Confusion Matrix:\n",metrics.confusion_matrix(y_test,y_gnb))
print("Accuracy:\n",metrics.accuracy_score(y_test,y_gnb))
print("Precision:\n",metrics.precision_score(y_test,y_gnb))
print("Recall:\n",metrics.recall_score(y_test,y_gnb))
print("AUC:\n",metrics.roc_auc_score(y_test,y_gnb_prob))
auc=metrics.roc_auc_score(y_test,y_gnb_prob)
```

```
Confusion Matrix:
 [[84694   614]
 [   37    98]]
Accuracy:
 0.9923808855026158
Precision:
 0.13764044943820225
Recall:
 0.725925925925926
AUC:
 0.9574081888894099
```

In [130]:
```
#plotting the AUC curve
fpr,tpr,thresholds=metrics.roc_curve(y_test,y_gnb_prob)
plt.plot(fpr,tpr,'b', label='AUC = %0.2f'% auc)
plt.plot([0,1],[0,1],'r-.')
plt.xlim([-0.2,1.2])
plt.ylim([-0.2,1.2])
plt.title('Receiver Operating Characteristic\nNaive Bays')
plt.legend(loc='lower right')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



Recommendation for Final Model Selection on Balancing Data

Below is the overall Summary of the various model performances on various parameters

Model Name	Accuracy	Precision	Recall	AUC
Logistic Regression	98%	7%	84%	96%
K Nearest Neighbors	94%	1%	42%	71%
Decision Tree	99%	24%	86%	93%
Random Forest	99%	86%	80%	97%
XGBoost	99%	22%	84%	98%
Naive Bayes	99%	14%	73%	96%

So here we can consider Random Forest model is best model comparatively other. As it is good recall and

```
In [ ]:
```