AI*Masters* Capstone_Project

Finance: Fraud Detection Problem

Problem Statement

Finance Industry is the biggest consumer of Data Scientists. It faces constant attack by fraudsters, who try to trick the system. Correctly identifying fraudulent transactions is often compared with finding needle in a haystack because of the low event rate. It is important that credit card companies are able to recognize fraudulent credit card transactions so that the customers are not charged for items that they did not purchase. You are required to try various techniques such as supervised models with oversampling, unsupervised anomaly detection, and heuristics to get good accuracy at fraud detection.

Project Task: Week 1

Exploratory Data Analysis (EDA):

1. Perform an EDA on the Dataset. a) Check all the latent features and parameters with their mean and standard deviation. Value are close to 0 centered (mean)with unit standard deviation b) Find if there is any connection between Time, Amount, and the transaction being fraudulent.
2. Check the class count for each class. It's a class Imbalance problem.
3. Use techniques like undersampling or oversampling before running Naïve Bayes, Logistic Regression or SVM. a. Oversampling or undersampling can be used to tackle the class imbalance problem b. Oversampling increases the prior probability of imbalanced class and in case of other classifiers, error gets multiplied as the low-proportionate class is mimicked multiple times.
4. Following are the matrices for evaluating the model performance: Precision, Recall, F1-Score, AUC-ROC curve. Use F1 Score as the evaluation criteria for this project.

In [5]:
```
#importing the libs
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns

from matplotlib import figure
import matplotlib.gridspec as gridspec
from matplotlib.pylab import rcParams
rcParams['figure.figsize'] = 15,5

from sklearn import preprocessing
```

In [7]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

In [8]:
```
# import data
train_df=pd.read_csv('/content/drive/My Drive/Capstone_Project/train_data.csv')
val_df=pd.read_csv('/content/drive/My Drive/Capstone_Project/test_data_hidden.csv')
test_df=pd.read_csv('/content/drive/My Drive/Capstone_Project/test_data.csv')
```

In [ ]:
```
'''# import data

train_df=pd.read_csv('Financial/train_data.csv')
val_df=pd.read_csv('Financial/test_data_hidden.csv')
test_df=pd.read_csv('Financial/test_data.csv')'''
```

In [4]:
```
train_df.head(10)
```

Out[4]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14
0	38355.0	1.043949	0.318555	1.045810	2.805989	-0.561113	-0.367956	0.032736	-0.042333	-0.322674	0.499167	-0.572665	0.346009	-0.047407	-0.098964	-0.66
1	22555.0	-1.665159	0.808440	1.805627	1.903416	-0.821627	0.934790	-0.824802	0.975890	1.747469	-0.658751	1.281502	-1.430087	0.372028	1.403024	-2.73
2	2431.0	-0.324096	0.601836	0.865329	-2.138000	0.294663	-1.251553	1.072114	-0.334896	1.071268	-1.109522	-1.016020	-0.654945	-1.473470	0.317345	1.06
3	86773.0	-0.258270	1.217501	-0.585348	-0.875347	1.222481	-0.311027	1.073860	-0.161408	0.200665	0.154307	0.882673	0.547890	0.269484	-1.253302	-0.88
4	127202.0	2.142162	-0.494988	-1.936511	-0.818288	-0.025213	-1.027245	-0.151627	-0.305750	-0.869482	0.428729	1.136666	0.273476	0.697123	-1.222134	-0.93
5	37590.0	-6.341667	1.192815	-3.686579	-2.754006	-5.007164	3.988118	1.693606	-13.577522	2.557965	-0.931438	-1.189333	0.762725	-0.517857	0.067279	-0.09
6	56739.0	-0.463928	0.204745	2.795734	1.546200	-0.720374	1.108212	-0.581133	0.544075	1.099843	-0.653523	-1.420838	0.427211	-0.436201	-1.055012	-1.22
7	912.0	-1.394619	0.554224	-0.617805	-0.313706	2.157413	3.537534	-0.567305	1.380888	-0.112291	0.107269	-0.637728	0.099510	-0.062533	0.254824	0.31
8	171058.0	-2.121785	-1.518485	2.667942	-2.458839	-1.414952	0.807935	-1.870160	0.516477	-0.553359	0.645799	-0.514941	0.618199	1.461221	-2.116306	-3.24
9	79450.0	-2.254788	-0.955967	0.590596	0.114744	-5.876531	3.364858	6.365904	-1.252960	0.243849	-1.637022	-0.626434	0.105457	0.859541	-1.306715	-0.72

In [ ]:
```
val_df.head(10)
```

Out[ ]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	V22	V23	V24	V25	
0	113050.0	0.114697	0.796303	-0.149553	-0.823011	0.878763	-0.553152	0.939259	-0.108502	0.111137	...	-0.335776	-0.807853	-0.055940	-1.025281	-0.369557	0
1	26667.0	-0.039318	0.495784	-0.810884	0.546693	1.986257	4.386342	-1.344891	-1.743736	-0.563103	...	-1.377003	-0.072200	-0.197573	1.014807	1.011293	-0
2	159519.0	2.275706	-1.531508	-1.021969	-1.602152	-1.220329	-0.462376	-1.196485	-0.147058	-0.950224	...	-0.193271	-0.103533	0.150945	-0.811083	-0.197913	-0
3	137545.0	1.940137	-0.357671	-1.210551	0.382523	0.050823	-0.171322	-0.109124	-0.002115	0.869258	...	0.157994	0.650355	0.034206	0.739535	0.223605	-0
4	63369.0	1.081395	-0.502615	1.075887	-0.543359	-1.472946	-1.065484	-0.443231	-0.143374	1.659826	...	0.224157	0.821209	-0.137223	0.986259	0.563228	-0
5	55069.0	0.441380	-2.217230	0.802581	-0.127056	-1.867945	0.495430	-0.741205	0.214230	-0.198782	...	0.346116	0.232975	-0.316073	0.288840	0.103051	-0
6	135629.0	1.937007	0.394490	-0.860965	3.720728	0.458475	0.159445	0.017991	0.024848	-0.615042	...	0.258103	0.737337	0.030587	0.633156	0.198230	0
7	33643.0	-0.552654	-0.279974	2.626373	0.535665	-1.350645	0.523387	0.124452	0.076345	-0.800457	...	-0.094506	0.261415	0.152325	0.322421	-0.217550	-0
8	80729.0	-2.760629	2.206112	-0.193100	0.764237	-0.718603	-0.920526	0.228957	0.507112	0.084184	...	0.037991	0.463003	0.083789	0.412720	0.093874	-0
9	2473.0	-0.287085	0.061850	1.389693	-0.844605	-0.756236	-0.702512	0.256420	-0.056059	-1.814368	...	-0.187208	-0.212449	0.064802	0.547049	-0.537486	1

10 rows × 31 columns

In [ ]:
```
test_df.head(10)
```

Out[ ]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14	
0	113050.0	0.114697	0.796303	-0.149553	-0.823011	0.878763	-0.553152	0.939259	-0.108502	0.111137	-0.390521	-1.949546	-0.494436	-0.353696	0.158729	-0.267
1	26667.0	-0.039318	0.495784	-0.810884	0.546693	1.986257	4.386342	-1.344891	-1.743736	-0.563103	-0.616315	-0.587786	0.317419	-0.408521	0.719639	0.226
2	159519.0	2.275706	-1.531508	-1.021969	-1.602152	-1.220329	-0.462376	-1.196485	-0.147058	-0.950224	1.560463	-1.753256	-1.331010	-0.061941	-0.405532	0.048
3	137545.0	1.940137	-0.357671	-1.210551	0.382523	0.050823	-0.171322	-0.109124	-0.002115	0.869258	-0.001965	0.607629	1.048673	-0.514821	0.329538	-1.041
4	63369.0	1.081395	-0.502615	1.075887	-0.543359	-1.472946	-1.065484	-0.443231	-0.143374	1.659826	-1.131238	0.173132	1.430172	0.915609	-0.336588	1.140
5	55069.0	0.441380	-2.217230	0.802581	-0.127056	-1.867945	0.495430	-0.741205	0.214230	-0.198782	0.311865	1.308096	0.644987	0.029716	-0.594013	-1.096
6	135629.0	1.937007	0.394490	-0.860965	3.720728	0.458475	0.159445	0.017991	0.024848	-0.615042	1.511407	-1.706707	-1.172083	-1.492230	0.453003	-0.626
7	33643.0	-0.552654	-0.279974	2.626373	0.535665	-1.350645	0.523387	0.124452	0.076345	-0.800457	0.498082	-0.691389	-1.059067	-1.193405	-0.315771	1.034
8	80729.0	-2.760629	2.206112	-0.193100	0.764237	-0.718603	-0.920526	0.228957	0.507112	0.084184	1.200311	-0.516928	0.668461	1.020972	0.317697	0.999
9	2473.0	-0.287085	0.061850	1.389693	-0.844605	-0.756236	-0.702512	0.256420	-0.056059	-1.814368	0.581364	1.146370	-0.112688	-0.462959	0.453037	0.331

In [ ]:
```
train_df.describe()
```

Out[ ]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	
count	227845.000000	227845.000000	227845.000000	227845.000000	227845.000000	227845.000000	227845.000000	227845.000000	227845.000000	227845.000000	227845.0
mean	94752.853076	-0.003321	-0.001652	0.001066	-0.000374	0.000877	0.000770	-0.000035	0.001625	-0.000391	-0.0
std	47500.410602	1.963028	1.661178	1.516107	1.415061	1.367074	1.325341	1.220384	1.192648	1.097367	1.0
min	0.000000	-56.407510	-72.715728	-32.965346	-5.683171	-42.147898	-26.160506	-43.557242	-73.216718	-13.434066	-24.5
25%	54182.000000	-0.922851	-0.598040	-0.889246	-0.848884	-0.690811	-0.767803	-0.554761	-0.207838	-0.643365	-0.5
50%	84607.000000	0.012663	0.066665	0.182170	-0.019309	-0.055243	-0.273025	0.040409	0.022928	-0.050932	-0.0
75%	139340.000000	1.314821	0.804401	1.029449	0.744822	0.610852	0.400298	0.570631	0.327854	0.596671	0.4
max	172792.000000	2.454930	22.057729	9.382558	16.875344	34.801666	22.529298	36.877368	20.007208	15.594995	23.7

In [ ]:
```
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 227845 entries, 0 to 227844
Data columns (total 31 columns):
 #   Column  Non-Null Count   Dtype  
---  ------  --------------   -----  
 0   Time    227845 non-null  float64
 1   V1      227845 non-null  float64
 2   V2      227845 non-null  float64
 3   V3      227845 non-null  float64
 4   V4      227845 non-null  float64
 5   V5      227845 non-null  float64
 6   V6      227845 non-null  float64
 7   V7      227845 non-null  float64
 8   V8      227845 non-null  float64
 9   V9      227845 non-null  float64
 10  V10     227845 non-null  float64
 11  V11     227845 non-null  float64
 12  V12     227845 non-null  float64
 13  V13     227845 non-null  float64
 14  V14     227845 non-null  float64
 15  V15     227845 non-null  float64
 16  V16     227845 non-null  float64
 17  V17     227845 non-null  float64
 18  V18     227845 non-null  float64
 19  V19     227845 non-null  float64
 20  V20     227845 non-null  float64
 21  V21     227845 non-null  float64
 22  V22     227845 non-null  float64
 23  V23     227845 non-null  float64
 24  V24     227845 non-null  float64
 25  V25     227845 non-null  float64
 26  V26     227845 non-null  float64
 27  V27     227845 non-null  float64
 28  V28     227845 non-null  float64
 29  Amount  227845 non-null  float64
 30  Class   227845 non-null  int64  
dtypes: float64(30), int64(1)
memory usage: 53.9 MB
```

In [ ]:
```
val_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 56962 entries, 0 to 56961
Data columns (total 31 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   Time    56962 non-null  float64
 1   V1      56962 non-null  float64
 2   V2      56962 non-null  float64
 3   V3      56962 non-null  float64
 4   V4      56962 non-null  float64
 5   V5      56962 non-null  float64
 6   V6      56962 non-null  float64
 7   V7      56962 non-null  float64
 8   V8      56962 non-null  float64
 9   V9      56962 non-null  float64
 10  V10     56962 non-null  float64
 11  V11     56962 non-null  float64
 12  V12     56962 non-null  float64
 13  V13     56962 non-null  float64
 14  V14     56962 non-null  float64
 15  V15     56962 non-null  float64
 16  V16     56962 non-null  float64
 17  V17     56962 non-null  float64
 18  V18     56962 non-null  float64
 19  V19     56962 non-null  float64
 20  V20     56962 non-null  float64
 21  V21     56962 non-null  float64
 22  V22     56962 non-null  float64
 23  V23     56962 non-null  float64
 24  V24     56962 non-null  float64
 25  V25     56962 non-null  float64
 26  V26     56962 non-null  float64
 27  V27     56962 non-null  float64
 28  V28     56962 non-null  float64
 29  Amount  56962 non-null  float64
 30  Class   56962 non-null  int64  
dtypes: float64(30), int64(1)
memory usage: 13.5 MB
```

In [ ]:
```
test_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 56962 entries, 0 to 56961
Data columns (total 30 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   Time    56962 non-null  float64
 1   V1      56962 non-null  float64
 2   V2      56962 non-null  float64
 3   V3      56962 non-null  float64
 4   V4      56962 non-null  float64
 5   V5      56962 non-null  float64
 6   V6      56962 non-null  float64
 7   V7      56962 non-null  float64
 8   V8      56962 non-null  float64
 9   V9      56962 non-null  float64
 10  V10     56962 non-null  float64
 11  V11     56962 non-null  float64
 12  V12     56962 non-null  float64
 13  V13     56962 non-null  float64
 14  V14     56962 non-null  float64
 15  V15     56962 non-null  float64
 16  V16     56962 non-null  float64
 17  V17     56962 non-null  float64
 18  V18     56962 non-null  float64
 19  V19     56962 non-null  float64
 20  V20     56962 non-null  float64
 21  V21     56962 non-null  float64
 22  V22     56962 non-null  float64
 23  V23     56962 non-null  float64
 24  V24     56962 non-null  float64
 25  V25     56962 non-null  float64
 26  V26     56962 non-null  float64
 27  V27     56962 non-null  float64
 28  V28     56962 non-null  float64
 29  Amount  56962 non-null  float64
dtypes: float64(30)
memory usage: 13.0 MB
```

We shall merge the train and validation data and form a new data set on which we shall perform the EDA

In [9]:
```
frames=[train_df,val_df]
merge_df=pd.concat(frames)
```

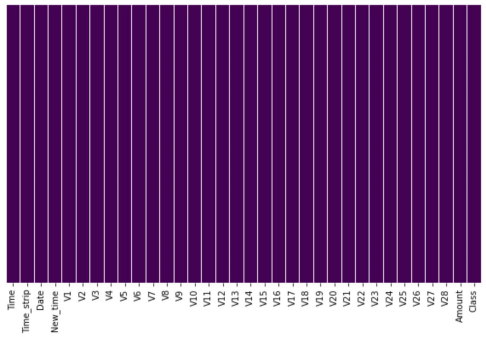
In [ ]:
```
merge_df
```

Out[ ]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	V22	V23	V24	V2
0	38355.0	1.043949	0.318555	1.045810	2.805989	-0.561113	-0.367956	0.032736	-0.042333	-0.322674	...	-0.240105	-0.680315	0.085328	0.684812	0.3186
1	22555.0	-1.665159	0.808440	1.805627	1.903416	-0.821627	0.934790	-0.824802	0.975890	1.747469	...	-0.335332	-0.510994	0.035839	0.147565	-0.5293
2	2431.0	-0.324096	0.601836	0.865329	-2.138000	0.294663	-1.251553	1.072114	-0.334896	1.071268	...	0.012220	0.352856	-0.341505	-0.145791	0.0941
3	86773.0	-0.258270	1.217501	-0.585348	-0.875347	1.222481	-0.311027	1.073860	-0.161408	0.200665	...	-0.424626	-0.781158	0.019316	0.178614	-0.3156
4	127202.0	2.142162	-0.494988	-1.936511	-0.818288	-0.025213	-1.027245	-0.151627	-0.305750	-0.869482	...	0.010115	0.021722	0.079463	-0.480899	0.0238
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
56957	136579.0	2.030797	-0.825073	-0.729555	-0.519187	-0.639893	-0.169482	-0.619049	-0.017902	-0.578643	...	-0.790167	-1.825357	0.600083	0.702623	-0.7826
56958	150070.0	-0.263947	1.119700	-0.639394	-0.880567	1.194120	-0.310693	0.962087	-0.088880	0.386664	...	-0.448081	-0.893010	0.004678	0.062555	-0.3475
56959	138634.0	2.206867	-0.748559	-1.443015	-1.101542	-0.332197	-0.646931	-0.536272	-0.129437	-0.712381	...	0.471336	1.314052	0.038930	0.747315	0.1580
56960	53907.0	1.430579	-0.842354	0.415998	-1.328439	-1.284654	-0.888110	-0.653237	-0.238164	-2.220845	...	-0.577415	-1.323989	0.336843	0.329714	-0.0074
56961	66373.0	-7.792712	5.599937	0.258943	0.061360	-2.586555	4.770837	-8.221863	-20.298380	2.028566	...	12.641459	-4.187308	2.655058	0.350225	0.4626

284807 rows × 31 columns

In [ ]:
```
#checking if there is any NULL data points
plt.figure(figsize=(10,6))
plt.style.use('seaborn-deep')
sns.heatmap(merge_df.isnull(),cbar=False,yticklabels=False,cmap="viridis")
plt.show()
```



There isn't any empty data points

In [ ]:
```
```

lets extract the time using the Date_time method

In [10]:
```
import datetime
# Lets strip the time  from the Time column and convert into 24hrs format. we shall inshiate the date 1/SEP/2013 for easing of understand
ing
merge_df.insert(1,'Time_strip',pd.to_datetime(merge_df.Time, unit='s',origin=pd.Timestamp('2013-09-01')))
merge_df.insert(2,'Date',merge_df['Time_strip'].dt.date)
merge_df.insert(3,'New_time',merge_df['Time_strip'].dt.time)
```

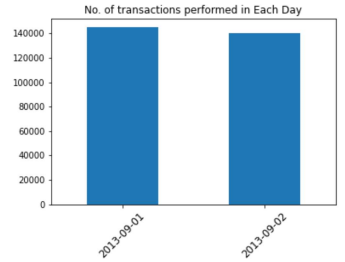
In [ ]:
```
merge_df
```

Out[ ]:

	Time	Time_strip	Date	New_time	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	
0	38355.0	2013-09-01 10:39:15	2013-09-01	10:39:15	1.043949	0.318555	1.045810	2.805989	-0.561113	-0.367956	0.032736	-0.042333	-0.322674	0.499167	-0.572665	0.3
1	22555.0	2013-09-01 06:15:55	2013-09-01	06:15:55	-1.665159	0.808440	1.805627	1.903416	-0.821627	0.934790	-0.824802	0.975890	1.747469	-0.658751	1.281502	-1.4
2	2431.0	2013-09-01 00:40:31	2013-09-01	00:40:31	-0.324096	0.601836	0.865329	-2.138000	0.294663	-1.251553	1.072114	-0.334896	1.071268	-1.109522	-1.016020	-0.6
3	86773.0	2013-09-02 00:06:13	2013-09-02	00:06:13	-0.258270	1.217501	-0.585348	-0.875347	1.222481	-0.311027	1.073860	-0.161408	0.200665	0.154307	0.882673	0.5
4	127202.0	2013-09-02 11:20:02	2013-09-02	11:20:02	2.142162	-0.494988	-1.936511	-0.818288	-0.025213	-1.027245	-0.151627	-0.305750	-0.869482	0.428729	1.136666	0.2
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
56957	136579.0	2013-09-02 13:56:19	2013-09-02	13:56:19	2.030797	-0.825073	-0.729555	-0.519187	-0.639893	-0.169482	-0.619049	-0.017902	-0.578643	0.915645	0.828552	1.2
56958	150070.0	2013-09-02 17:41:10	2013-09-02	17:41:10	-0.263947	1.119700	-0.639394	-0.880567	1.194120	-0.310693	0.962087	-0.088880	0.386664	0.195362	0.608261	-0.0
56959	138634.0	2013-09-02 14:30:34	2013-09-02	14:30:34	2.206867	-0.748559	-1.443015	-1.101542	-0.332197	-0.646931	-0.536272	-0.129437	-0.712381	1.057616	1.024802	-0.3
56960	53907.0	2013-09-01 14:58:27	2013-09-01	14:58:27	1.430579	-0.842354	0.415998	-1.328439	-1.284654	-0.888110	-0.653237	-0.238164	-2.220845	1.350845	0.323684	-0.1
56961	66373.0	2013-09-01 18:26:13	2013-09-01	18:26:13	-7.792712	5.599937	0.258943	0.061360	-2.586555	4.770837	-8.221863	-20.298380	2.028566	-0.030694	-1.062381	2.3

284807 rows × 34 columns

In [ ]:
```
# Lets Cross Check if we have correctly extracted Time by verifiying what Satement Suggest that We have Data of @ days of Transactions
merge_df.Date.value_counts().plot(kind='bar')
plt.title('No. of transactions performed in Each Day')
plt.xticks(fontsize=12,rotation=45)
plt.show()
```



In [ ]:
```
merge_df.New_time.describe()
```

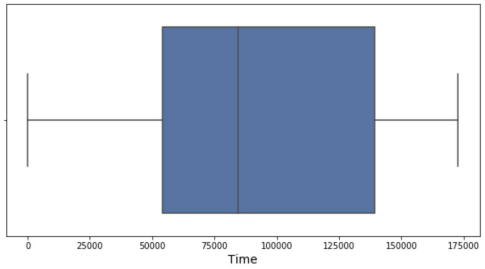
Out[ ]:
```
count       284807
unique       74698
top       21:19:12
freq            39
Name: New_time, dtype: object
```

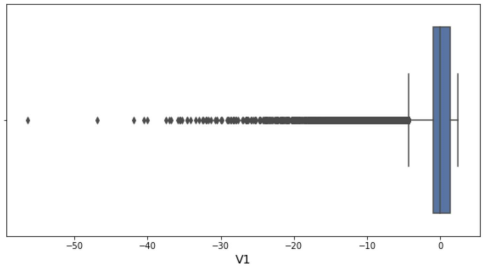
Cheking the outliers in the data

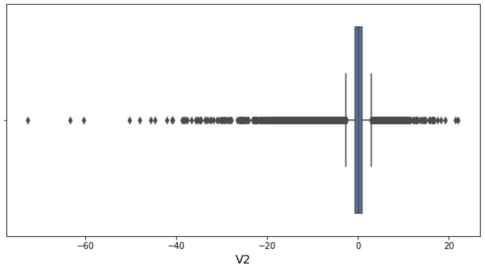
In [ ]:
```
Columns=list(merge_df.columns)
for n in range(0,3):
    Columns.pop(1)
print(Columns)
```

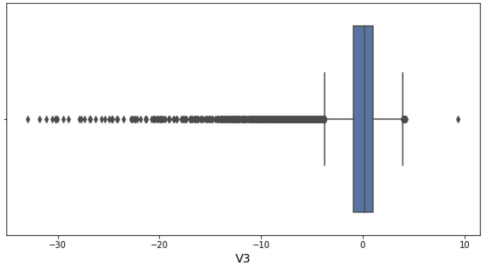
```
['Time', 'V1', 'V2', 'V3', 'V4', 'V5', 'V6', 'V7', 'V8', 'V9', 'V10', 'V11', 'V12', 'V13', 'V14', 'V15', 'V16', 'V17', 'V18', 'V19', 'V2
0', 'V21', 'V22', 'V23', 'V24', 'V25', 'V26', 'V27', 'V28', 'Amount', 'Class']
```

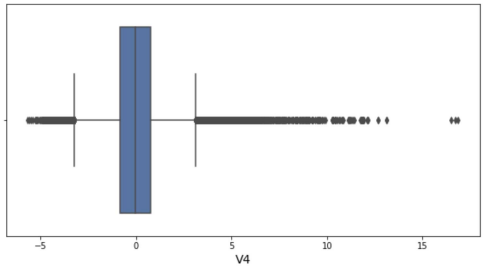
In [ ]:
```
for column in Columns:
    plt.figure(figsize=(10,5))
    sns.boxplot([column],data=train_df)
    plt.xlabel(column,fontsize=14)
    plt.show()
```

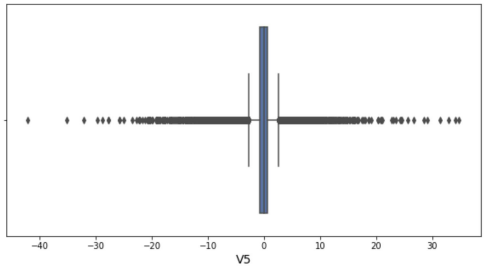


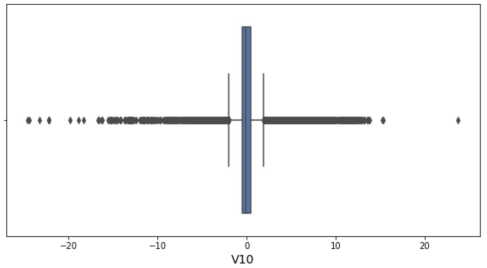


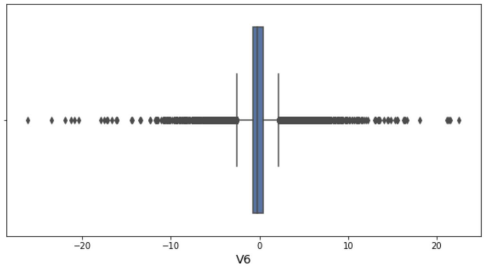


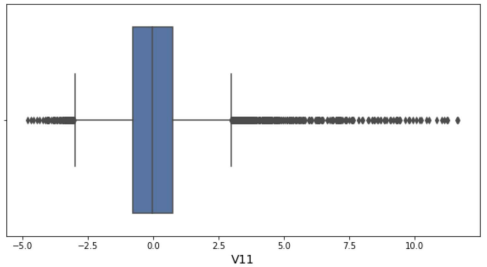


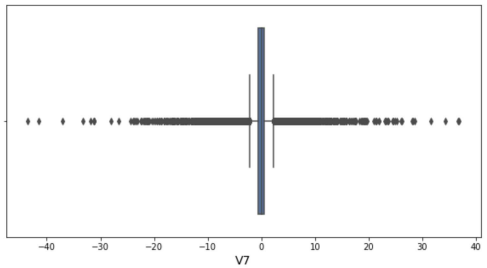


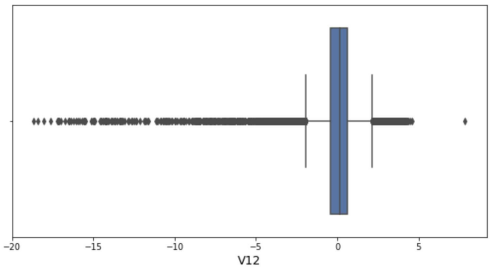

−40
−30
−20
−10
0
10
20
30
V5

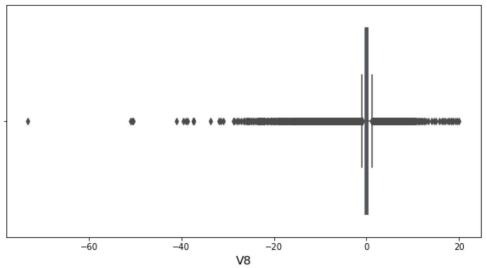

−20
−10
0
10
20
V10

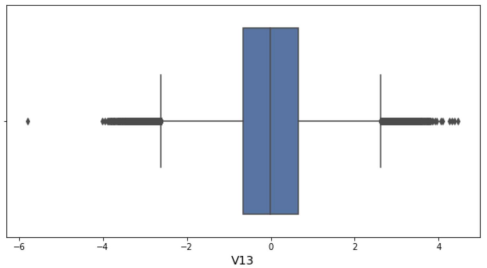

−20
−10
0
10
20
V6

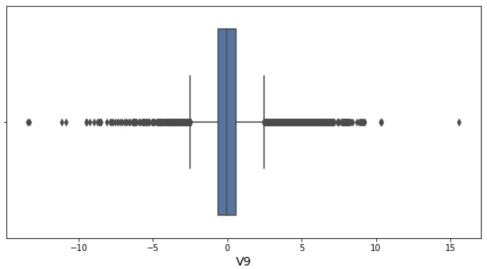

−5.0
−2.5
0.0
2.5
5.0
7.5
10.0
V11

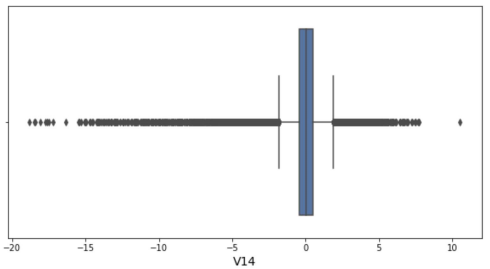

−40
−30
−20
−10
0
10
20
30
40
V7

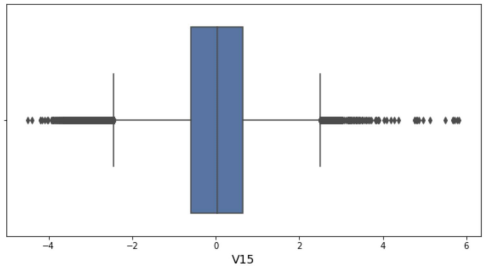

−20
−15
−10
−5
0
5
V12

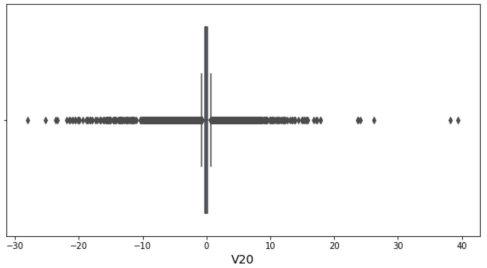

−60
−40
−20
0
20
V8

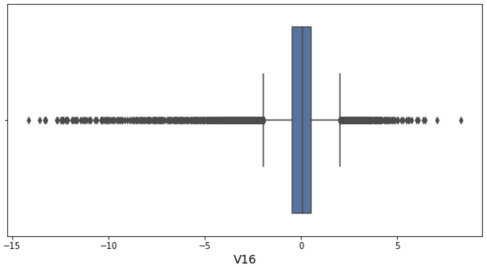

−6
−4
−2
0
2
4
V13

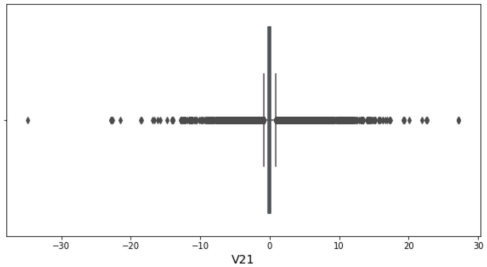

−10
−5
0
5
10
15
V9

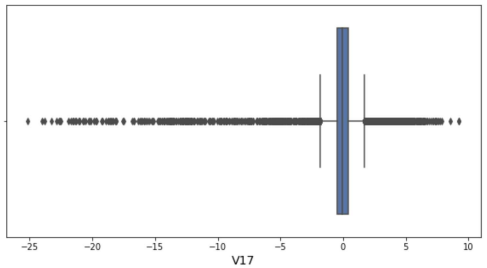

−20
−15
−10
−5
0
5
10
V14

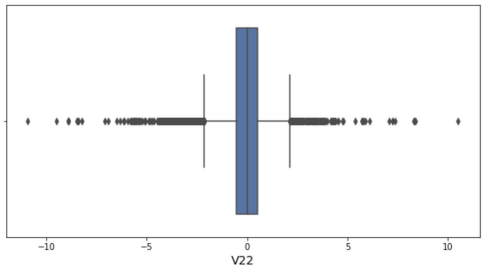

−4
−2
0
2
4
6
V15

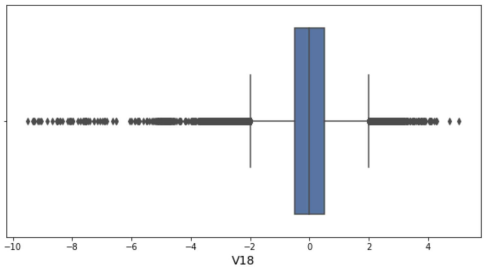

−30
−20
−10
0
10
20
30
40
V20

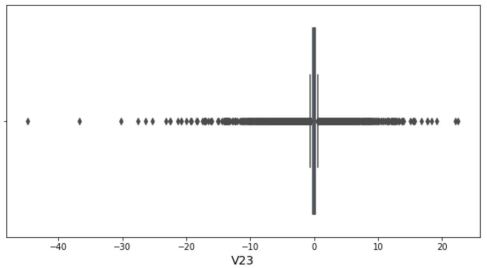

−15
−10
−5
0
5
V16

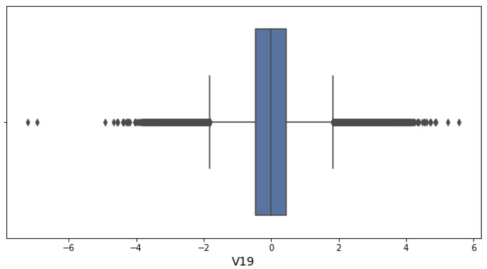

−30
−20
−10
0
10
20
30
V21

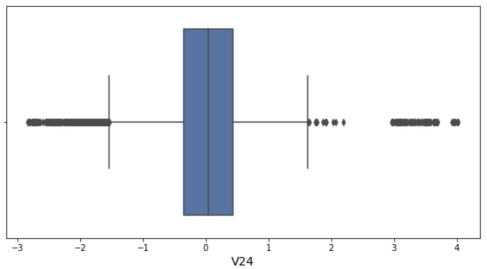

−25
−20
−15
−10
−5
0
5
10
V17

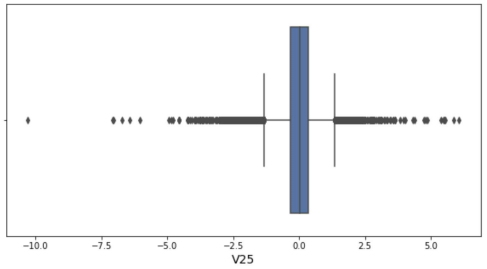

−10
−5
0
5
10
V22

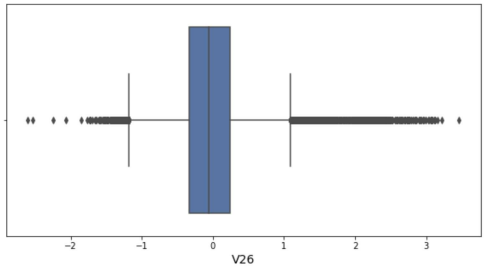

−10
−8
−6
−4
−2
0
2
4
V18

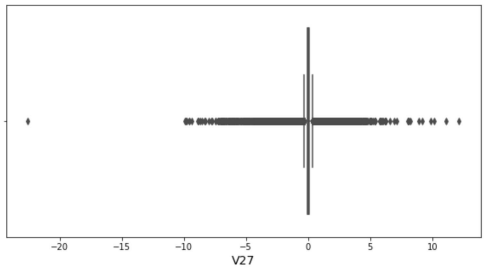

−40
−30
−20
−10
0
10
20
V23

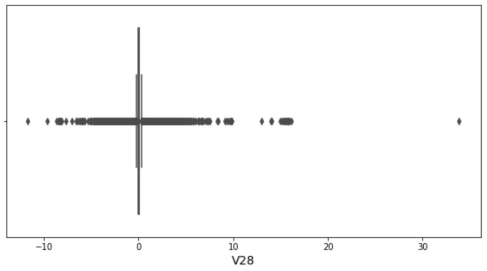

−6
−4
−2
0
2
4
6
V19

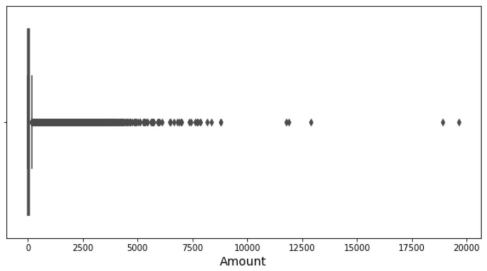

−3
−2
−1
0
1
2
3
4
V24

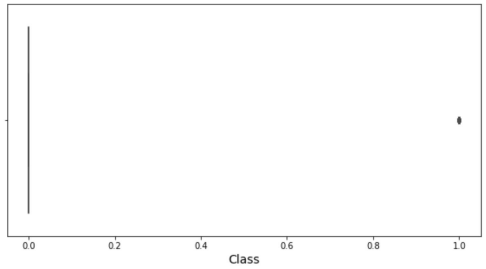












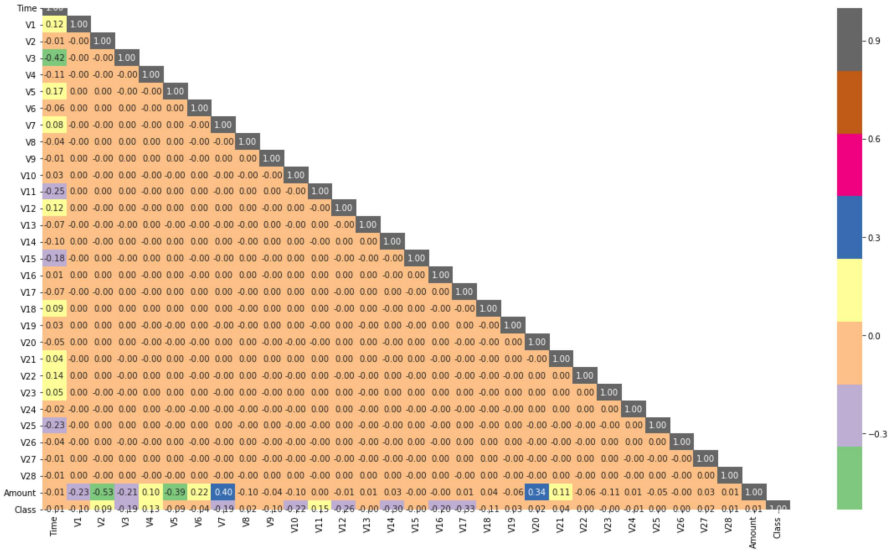
We oberve that we have large number of outliers we shall counter this by droping Columns which effect the prediction of the models

lets see the present data's features correlations b/w them*

In [ ]:
```
corr=merge_df.corr()
```

In [ ]:
```
# masking
m=np.ones_like(corr)
m[np.diag_indices_from(m)]=0
m[np.tril_indices_from(m)]=0
```

In [ ]:
```
plt.figure(figsize=(20,11))
sns.heatmap(corr,annot=True,cmap='Accent',mask=m,fmt='.2f')
plt.show()
```



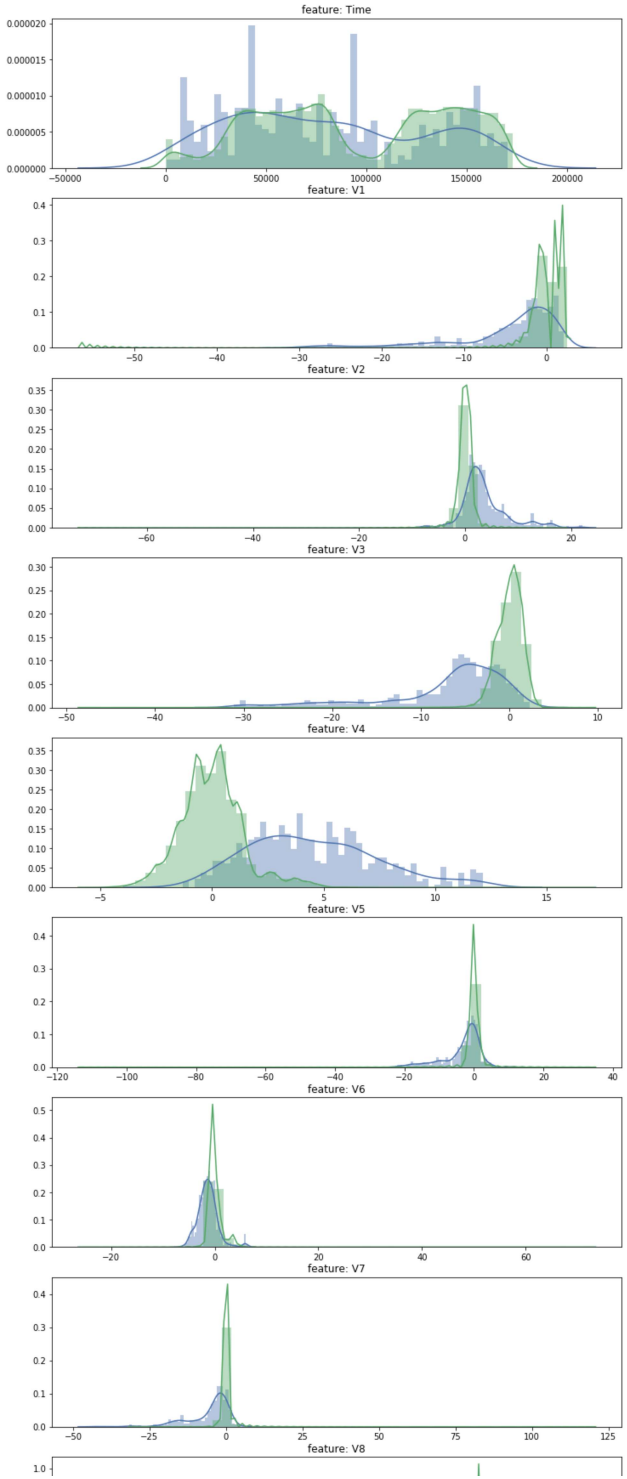
We observe that **V1,V2,V3,V5** show neagative corelation with Amount and **V10,V12,V14,V16,V17** Show NEGATIVE corr with Class

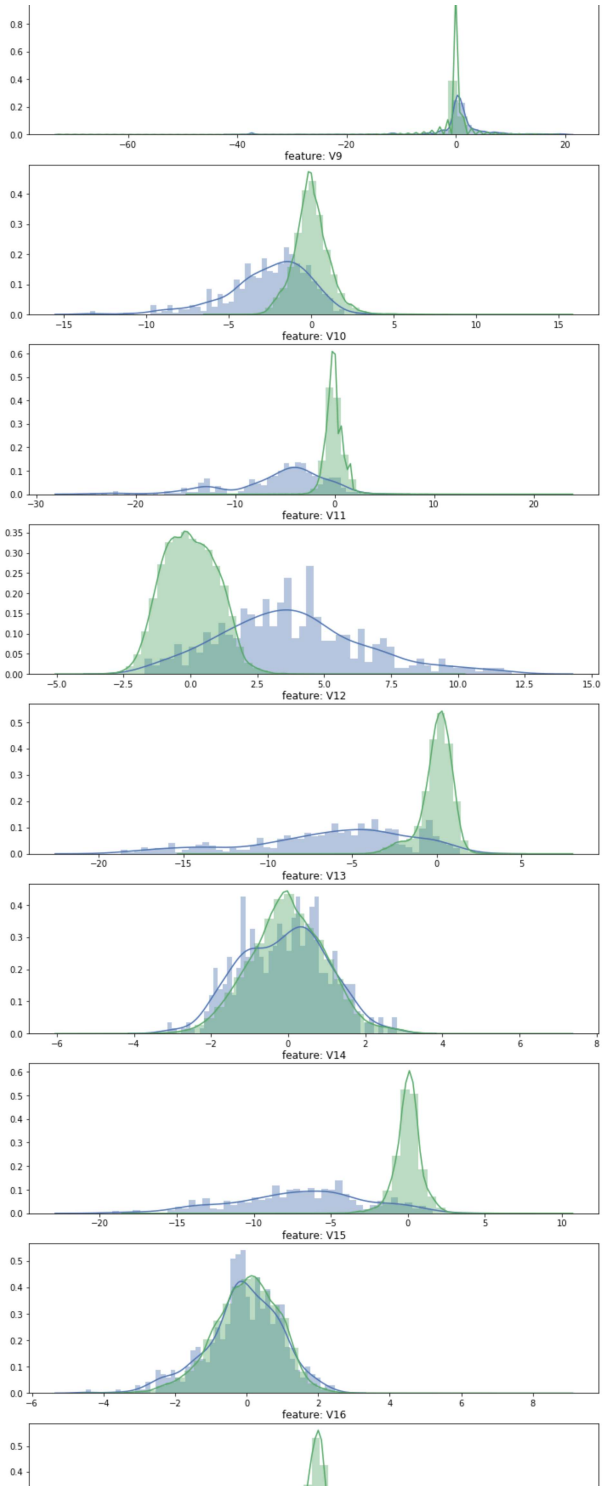
Lets check the Variance of each columns

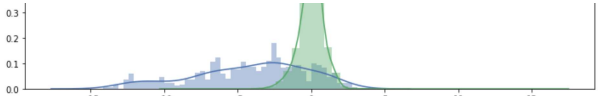
In [ ]:

```
plt.figure(figsize=(12,30*4))
gs = gridspec.GridSpec(31, 1)

for i, cn in enumerate(Columns):
    ax = plt.subplot(gs[i])
    sns.distplot(merge_df[cn][merge_df.Class == 1], bins=50)
    sns.distplot(merge_df[cn][merge_df.Class == 0], bins=50)
    ax.set_xlabel('')
    ax.set_title('feature: ' + str(cn))
plt.show()
```

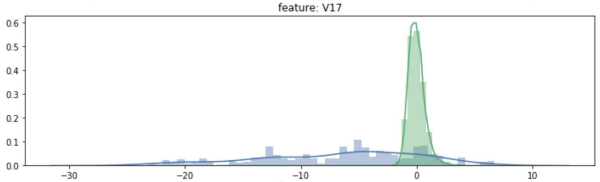
```
C:\Users\abhil\Anaconda3\lib\site-packages\statsmodels\nonparametric\kde.py:487: RuntimeWarning: invalid value encountered in true_divide
  binned = fast_linbin(X, a, b, gridsize) / (delta * nobs)
C:\Users\abhil\Anaconda3\lib\site-packages\statsmodels\nonparametric\kdetools.py:34: RuntimeWarning: invalid value encountered in double_
scalars
  FAC1 = 2*(np.pi*bw/RANGE)**2
```


feature: Time
feature: V1
feature: V2
feature: V3
feature: V4
feature: V5
feature: V6
feature: V7
feature: V8

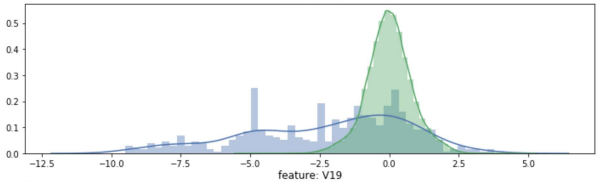

feature: V9
feature: V10
feature: V11
feature: V12
feature: V13
feature: V14
feature: V15
feature: V16



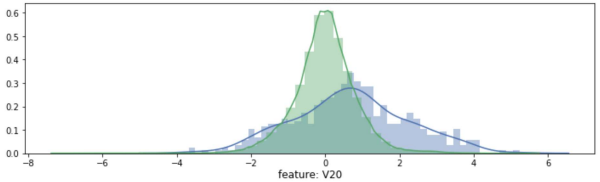
feature: V17



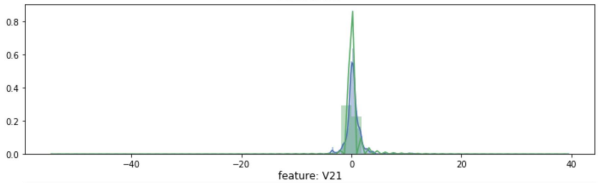
feature: V18



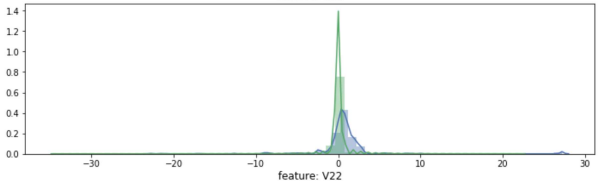
feature: V19



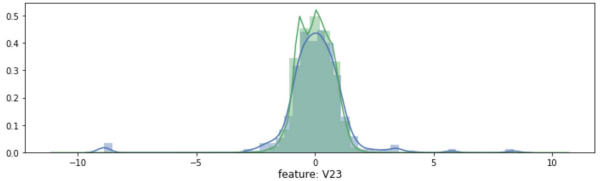
feature: V20



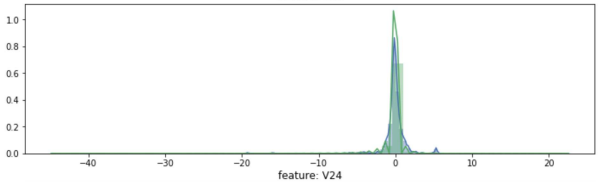
feature: V21



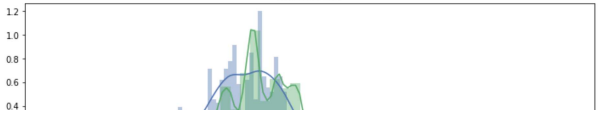
feature: V22

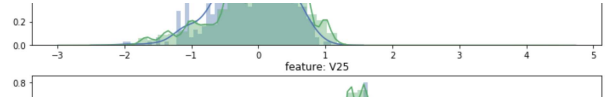


feature: V23

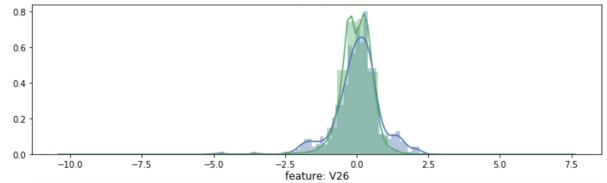


feature: V24

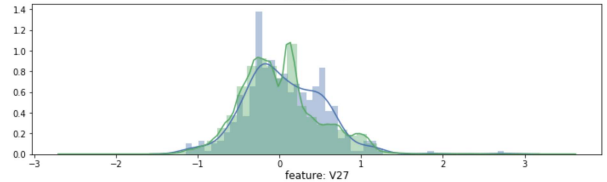




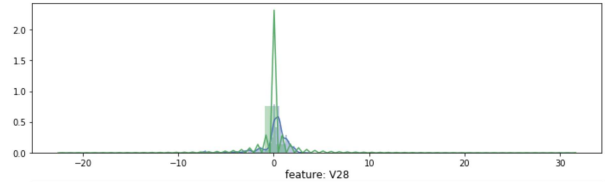
feature: V25



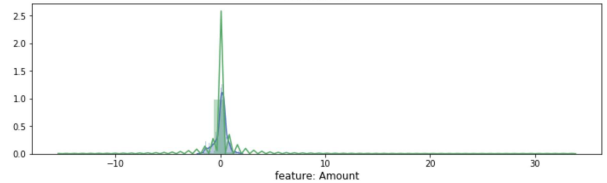
feature: V26



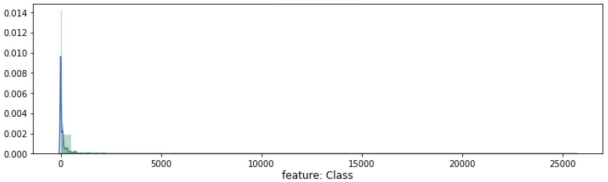
feature: V27



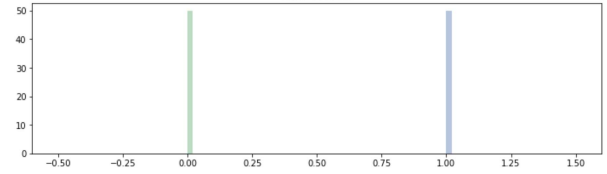
feature: V28



feature: Amount



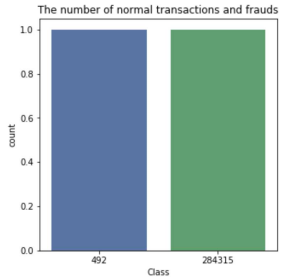
feature: Class



This dataset is very clean and doesn't contain any NAs, so the cleaning we did in this section is to drop some variables which have Zero or very low variance, normalize the Amount variable which is the only variable that has not been normalized yet, and resampling the dataset.

In [35]:
```
## Through above observation we shall drop features we don't find important in model builing and prediction
merge_df=merge_df.drop(['V2','V3','V5','V6','V7','V8','V21','V27','V28'],axis=1)

train_df=train_df.drop(['V2','V3','V5','V6','V7','V8','V21','V27','V28'],axis=1)

val_df=val_df.drop(['V2','V3','V5','V6','V7','V8','V21','V27','V28'],axis=1)

test_df=test_df.drop(['V2','V3','V5','V6','V7','V8','V21','V27','V28'],axis=1)
```

In [ ]:
```
# Checking thge balance of the data
plt.figure(figsize=(5,5))
sns.countplot(merge_df['Class'].value_counts())
plt.title('The number of normal transactions and frauds')
plt.xlabel('Class')
plt.show()
```



We can observe that the diffwrence b/w the classes is very large, this is classisc case of imblance data

In [ ]:
```
# Extrating the fraud and non_fraudulnte data

fraud=merge_df.loc[merge_df.Class==1]
non_fraud=merge_df.loc[merge_df.Class==0]
```

In [ ]:
```
fraud.Amount.describe()
```

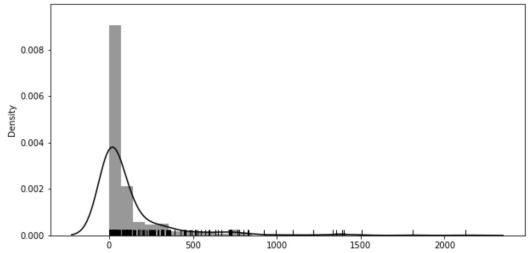
Out[ ]:
```
count     492.000000
mean      122.211321
std       256.683288
min         0.000000
25%         1.000000
50%         9.250000
75%       105.890000
max      2125.870000
Name: Amount, dtype: float64
```

In [ ]:
```
non_fraud.Amount.describe()
```

Out[ ]:
```
count    284315.000000
mean         88.291022
std         250.105092
min           0.000000
25%           5.650000
50%          22.000000
75%          77.050000
max       25691.160000
Name: Amount, dtype: float64
```

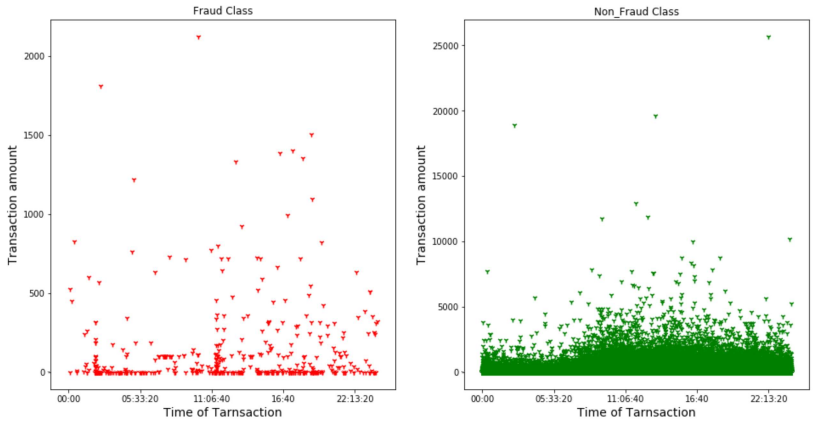
In [ ]:
```
# Fraudulate amount overview
plt.figure(figsize=(10,5))
sns.distplot(fraud.Amount.values, bins=30, rug=True,kde=True,color='Black')
plt.show()
```

```
/usr/local/lib/python3.6/dist-packages/seaborn/distributions.py:2551: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
/usr/local/lib/python3.6/dist-packages/seaborn/distributions.py:2055: FutureWarning: The `axis` variable is no longer used and will be removed. Instead, assign variables directly to `x` or `y`.
  warnings.warn(msg, FutureWarning)
```



We observe that the large numbers of the faruds amount is below 100 , That is the faruds are carried out with small amount rather than big amount, as they may rise alrams

In [ ]:
```
# The time around which trasactions taking place
fig,(ax1,ax2)=plt.subplots(ncols=2,nrows=1,figsize=(16,8),sharex=True)


ax1.scatter(y='Amount',x=fraud.New_time.values,data=fraud,marker='1',c='r')
ax1.set_title('Fraud Class')
ax1.set_xlabel('Time of Tarnsaction', fontsize=14)
ax1.set_ylabel('Transaction amount', fontsize=14)

ax2.scatter(y='Amount',x=non_fraud.New_time.values,data=non_fraud,marker='1',c='g')
ax2.set_title('Non_Fraud Class')
ax2.set_xlabel('Time of Tarnsaction', fontsize=14)
ax2.set_ylabel('Transaction amount', fontsize=14)
plt.show()
```



From the above plots

1. Most of the fraud transations is carried at small amount of 1EURs to be acuurate .
2. we can say that significant number of the frauds happen and increases around 11'o Clock and even the amount during this slightly high.
3. We can also Observe that most of the Higher Amount Frauds happen b/w range 11'o to 8'o clock in the evening with strong numbers of transaction around 4'o clock to 6'o clock
4. We also observe that there is a strong number of frauds happening in late hours of the night b/w Midnight to early Morning,This transation are carried with less amount range

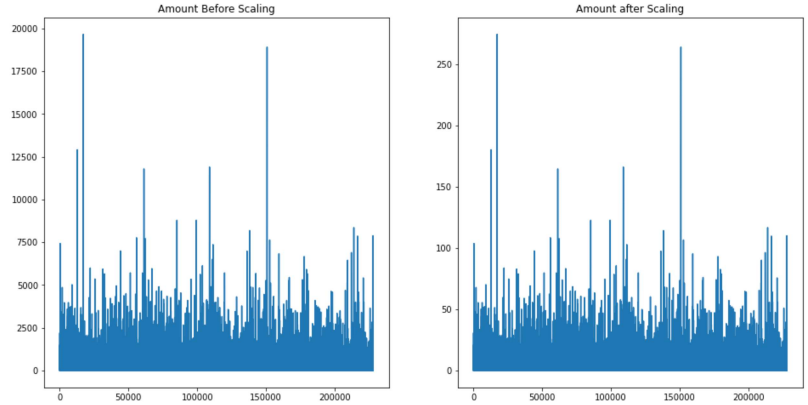
In [ ]:
```
```

We shall use method of under sampling and over sampling to tackel the class imbalance and We shall also Scale the Amount features has it shows large spread of data with less variance

In [ ]:
```
from imblearn.under_sampling import ClusterCentroids
from imblearn.over_sampling import RandomOverSampler
from collections import Counter
from sklearn.model_selection import train_test_split

from sklearn.preprocessing import RobustScaler,StandardScaler
from sklearn.decomposition import PCA
```

In [12]:
```
# Scaling the model using Robust Scaler over Min_Max sience the data contains large no of outliers
scaler=RobustScaler()
train_df['Amount_Stand'] = scaler.fit_transform(train_df['Amount'].values.reshape(-1,1))
val_df['Amount_Stand'] = scaler.fit_transform(val_df['Amount'].values.reshape(-1,1))
test_df['Amount_Stand'] = scaler.fit_transform(test_df['Amount'].values.reshape(-1,1))
```

In [9]:
```
fig,(ax1,ax2)=plt.subplots(1,2,figsize=(16,8),sharex=True)
ax1.plot(train_df.Amount)
ax1.set_title('Amount Before Scaling')

ax2.plot(train_df.Amount_Stand)
ax2.set_title('Amount after Scaling')
plt.show()
```



We can observe that Amount after Standersing, has decrese the range of the amount Spread without affecting its values importance

Data Preparartion and tackling the imbalanced problem

In [36]:
```
X = train_df.drop(['Class','Amount'],axis=1)
y = train_df['Class']
```

In [37]:
```
X.shape
```

Out[37]: (227845, 21)

In [ ]:
```
#Under Sampling the majority class to balance the data
cc = ClusterCentroids(random_state=5)
X_resampled, y_resampled = cc.fit_resample(X,y)
```

In [ ]:
```
print(sorted(Counter(y_resampled).items()))
```

```
[(0, 394), (1, 394)]
```

In [ ]:
```
# Over Sampling the classes in data
Ros=RandomOverSampler()
X_ovr_sampled, y_ovr_sampled = Ros.fit_resample(X,y)
```

In [ ]:
```
print(sorted(Counter(y_ovr_sampled).items()))
```

```
[(0, 227451), (1, 227451)]
```

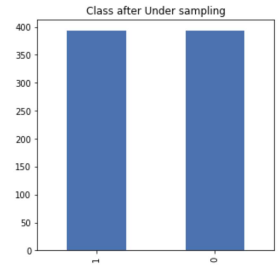
In [ ]:
```
print('Before: Under_Sampling',y.value_counts(),sep='\n')
print()
print('After: Under_Sampling',y_resampled.unique(),sep='\n')
```

```
Before: Under_Sampling
0    227451
1       394
Name: Class, dtype: int64

After: Under_Sampling
[0 1]
```

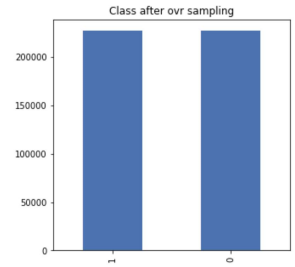
In [ ]:
```
print('Before: Over_Sampling',y.value_counts(),sep='\n')
print()
print('After: Over_Sampling',y_ovr_sampled.value_counts(),sep='\n')
```

```
Before: Over_Sampling
0    227451
1       394
Name: Class, dtype: int64

After: Over_Sampling
1    227451
0    227451
Name: Class, dtype: int64
```

In [ ]:
```
plt.figure(figsize=(5,5))
y_resampled.value_counts().plot(kind='bar')
plt.title('Class after Under sampling')
plt.show()
```



In [ ]:
```
plt.figure(figsize=(5,5))
y_ovr_sampled.value_counts().plot(kind='bar')
plt.title('Class after ovr sampling')
plt.show()
```



creating validation data split

In [43]:
```
X_val = val_df.drop(['Class','Amount'],axis=1)
y_val = val_df['Class']

X_val.shape
```

Out[43]: (56962, 21)

In [ ]:
```
# PCA # Optional
pca=PCA()

X_train_pca=pca.fit_transform(X_train)
X_val_pca=pca.fit_transform(X_val)

explained_variance = pca.explained_variance_ratio_
explained_variance
```

Out[ ]:
```
array([9.99999898e-01, 7.84510445e-08, 8.83250564e-09, 5.52393305e-09,
       4.08812626e-09, 9.95060323e-10, 8.04145015e-10, 7.48835062e-10,
       6.95104890e-10, 4.29617219e-10, 3.93738238e-10, 2.88893428e-10,
       1.82723579e-10, 1.72642855e-10, 1.24198103e-10, 1.00142464e-10,
       7.64906867e-11, 7.56572229e-11, 5.76875786e-11, 4.30090801e-11,
       3.63755031e-11, 1.97709912e-11, 1.57161618e-11, 1.37089710e-11])
```

Week 2

Modeling Techniques: Try out models like Naive Bayes, Logistic Regression or SVM. Find out which one performs the best Use different Tree-based classifiers like Random Forest and XGBoost.

Machine Learning model buildng and training

***Train the Models* : First we shall trainthe model on under Sampled data and Predict the result and Even train on over sampled data and predict and Compare the models over Accuracy and F1 Score**

In [15]:
```
from sklearn.naive_bayes import BernoulliNB
from sklearn.linear_model import LogisticRegression
from sklearn.linear_model import SGDClassifier
```

In [17]:
```
# Train the models on under Sampled data
# Train Logistic Regression model
Log_clf=LogisticRegression(solver='liblinear')
Log_clf.fit(X_resampled,y_resampled)


# Train Navie Bayes
NB_clf=BernoulliNB(fit_prior=True)
NB_clf.fit(X_resampled,y_resampled)

#Train SVM based SGD classifier
SGD_clf=SGDClassifier(loss='modified_huber',
                      random_state=5)

SGD_clf.fit(X_resampled,y_resampled)
```

Evaluate the models : We shall use Repeated k Flod of evaluate our model

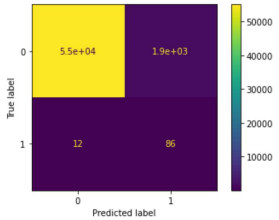
In [18]:
```
import sklearn
from sklearn.model_selection import cross_val_score,RepeatedStratifiedKFold
from sklearn.metrics import accuracy_score,roc_curve,confusion_matrix,classification_report

cv = RepeatedStratifiedKFold(n_splits=5, n_repeats=3, random_state=1)
```

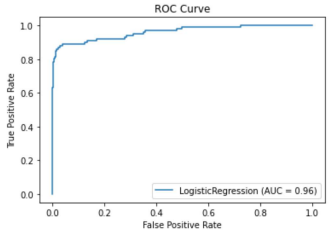
In [28]:
```
moodel_list=[('Logistic Regression Classifier ',Log_clf),('Navie Base BernoulliNB',NB_clf),
             ('SGD Classifer',SGD_clf)]

models=[m for m in moodel_list]
print(models)
```

```
[('Logistic Regression Classifier ', LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=None, solver='liblinear', tol=0.0001, verbose=0,
                   warm_start=False)), ('Navie Base BernoulliNB', BernoulliNB(alpha=1.0, binarize=0.0, class_prior=None, fit_prior=Tru
e)), ('SGD Classifer', SGDClassifier(alpha=0.0001, average=False, class_weight=None,
              early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=True,
              l1_ratio=0.15, learning_rate='optimal', loss='modified_huber',
              max_iter=1000, n_iter_no_change=5, n_jobs=None, penalty='l2',
              power_t=0.5, random_state=5, shuffle=True, tol=0.001,
              validation_fraction=0.1, verbose=0, warm_start=False))]
```

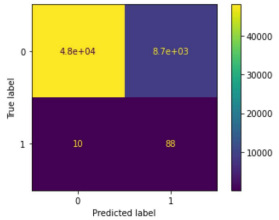
In [29]:
```
print('================ *Model Evaluation Results* ================','\n')

for i,v in models:
    pred=v.predict(X_val)
    scores=cross_val_score(v,X_resampled,y_resampled,cv=cv)
    accu=accuracy_score(y_val,pred)
    con_matrix=confusion_matrix(y_val,pred)
    clf_rep=classification_report(y_val,pred,zero_division=0)

    print('===== {} ====='.format(i))

    print ("Cross Validation Mean Score: ", '{}%'.format(np.round(scores.mean(), 3) * 100))
    print()
    print ("Model Accuracy: ", '{}%'.format(np.round(accu, 3) * 100))
    print()
    print("Classification Report:" "\n", clf_rep)
    print()
    print("Confusion Matrix:")
    sklearn.metrics.plot_confusion_matrix(v,X_val,y_val)
    print()

    sklearn.metrics.plot_roc_curve(v,X_val,y_val)
    plt.title('ROC Curve')
    plt.show()
```

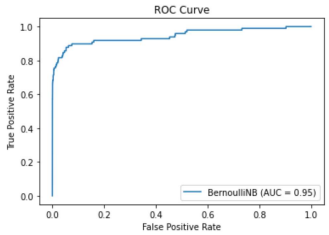
```
================ *Model Evaluation Results* =================

===== Logistic Regression Classifier  =====
Cross Validation Mean Score:  96.2%

Model Accuracy:  96.7%

Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.97      0.98     56864
           1       0.04      0.88      0.08        98

    accuracy                           0.97     56962
   macro avg       0.52      0.92      0.53     56962
weighted avg       1.00      0.97      0.98     56962


Confusion Matrix:
```



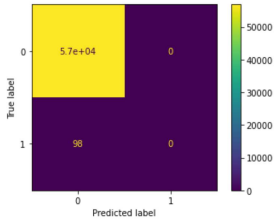


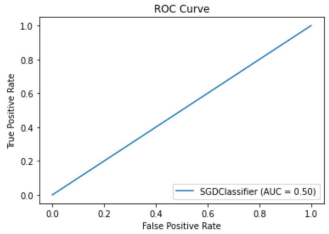

```
===== Navie Base BernoulliNB =====
Cross Validation Mean Score:  94.3%

Model Accuracy:  84.7%

Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.85      0.92     56864
           1       0.01      0.90      0.02        98

    accuracy                           0.85     56962
   macro avg       0.50      0.87      0.47     56962
weighted avg       1.00      0.85      0.92     56962


Confusion Matrix:
```






```
===== SGD Classifer =====
Cross Validation Mean Score:  50.0%

Model Accuracy:  99.8%

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56864
           1       0.00      0.00      0.00        98

    accuracy                           1.00     56962
   macro avg       0.50      0.50      0.50     56962
weighted avg       1.00      1.00      1.00     56962


Confusion Matrix:
```





Above is the Evalulation of the models using the under sampled data points.

1. We obverve that the LOGISTIC Regression and the Navie Based have good Cross Validation score.

```
Models prediction Accuracy : Logistics Classifier   -          95 %
                             Navie Based Classifier -          72 %
                             Stochastic Gradient Descent (SGD)-  99 %
```

F1 score :

	Logistics Classifier	Navie Based	SGD
class 0:	0.97	0.84	1
class 1 :	0.08	0.02	0

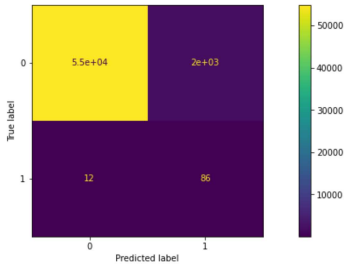
In [ ]:

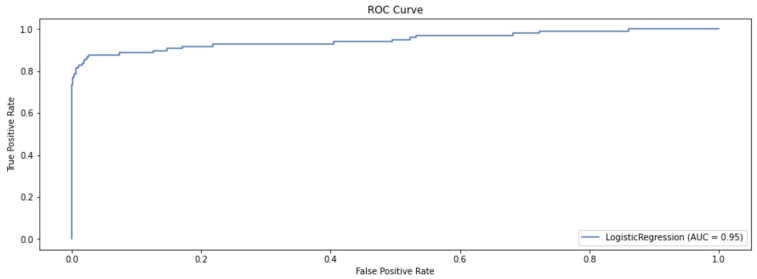
In [ ]:
```
# Training the model on over Sampled data
Log_clf.fit(X_ovr_sampled, y_ovr_sampled)
NB_clf.fit(X_ovr_sampled, y_ovr_sampled)
SGD_clf.fit(X_ovr_sampled, y_ovr_sampled)
```

Out[ ]:
```
SGDClassifier(alpha=0.0001, average=False, class_weight=None,
              early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=True,
              l1_ratio=0.15, learning_rate='optimal', loss='modified_huber',
              max_iter=1000, n_iter_no_change=5, n_jobs=None, penalty='l2',
              power_t=0.5, random_state=5, shuffle=True, tol=0.001,
              validation_fraction=0.1, verbose=0, warm_start=False)
```

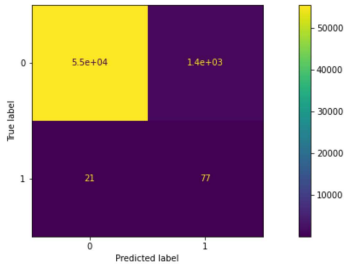
In [ ]:
```
print('================ *Model Evaluation Results for Over Sampling* ================','\n')

for i,v in models:
    pred=v.predict(X_val)
    scores=cross_val_score(v,X_ovr_sampled,y_ovr_sampled,cv=10)
    accu=accuracy_score(y_val,pred)
    con_matrix=confusion_matrix(y_val,pred)
    clf_rep=classification_report(y_val,pred)

    print('===== {} ====='.format(i))

    print ("Cross Validation Mean Score: ", '{}%'.format(np.round(scores.mean(), 3) * 100))
    print()
    print ("Model Accuracy: ", '{}%'.format(np.round(accu, 3) * 100))
    print()
    print("Classification Report:" "\n", clf_rep)
    print()
    print("Confusion Matrix:")
    sklearn.metrics.plot_confusion_matrix(v,X_val,y_val)
    print()

    sklearn.metrics.plot_roc_curve(v,X_val,y_val)
    plt.title('ROC Curve')
    plt.show()
```

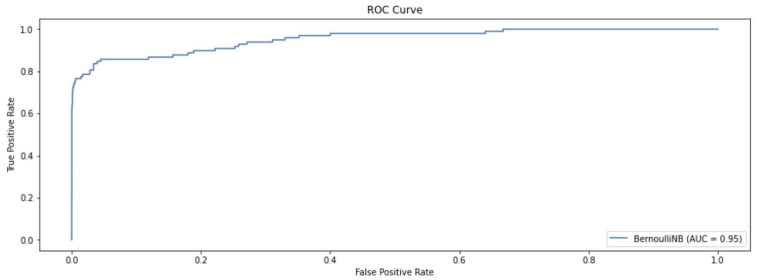
```
================ *Model Evaluation Results for Over Sampling* =================

===== Logistic Regression Classifier  =====
Cross Validation Mean Score:  93.30000000000001%

Model Accuracy:  96.5%

Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.97      0.98     56864
           1       0.04      0.88      0.08        98

    accuracy                           0.97     56962
   macro avg       0.52      0.92      0.53     56962
weighted avg       1.00      0.97      0.98     56962


Confusion Matrix:
```



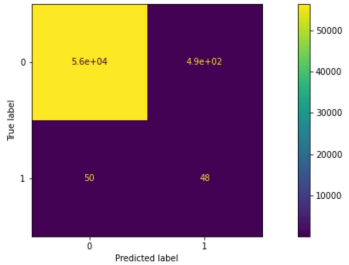


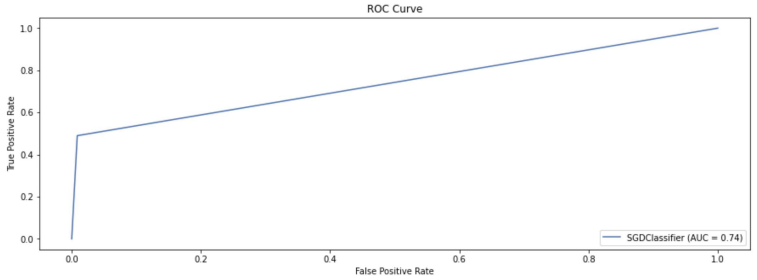

```
===== Navie Base BernoulliNB =====
Cross Validation Mean Score:  91.2%

Model Accuracy:  97.5%

Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.98      0.99     56864
           1       0.05      0.79      0.10        98

    accuracy                           0.98     56962
   macro avg       0.53      0.88      0.54     56962
weighted avg       1.00      0.98      0.99     56962


Confusion Matrix:
```






```
===== SGD Classifer =====
Cross Validation Mean Score:  71.5%

Model Accuracy:  99.1%

Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.99      1.00     56864
           1       0.09      0.49      0.15        98

    accuracy                           0.99     56962
   macro avg       0.54      0.74      0.57     56962
weighted avg       1.00      0.99      0.99     56962


Confusion Matrix:
```





Above is the Evalulation of the models using the Over sampled data points.

1. We obverve that the LOGISTIC Regression and the Navie Based have good Cross Validation score.

```
Models prediction Accuracy : Logistics Classifier   -            96  %
                             Navie Based Classifier -            97 %
                             Stochastic Gradient Descent (SGD)-  99 %
```

F1 score :

	Logistics Classifier	Navie Based	SGD
class 0:	0.97	0.99	1
class 1 :	0.05	0.10	0.15

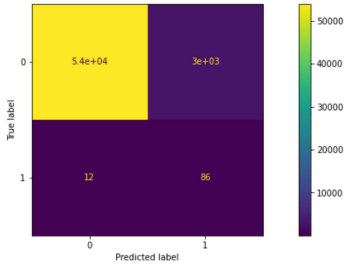
Test the model using the actual test data

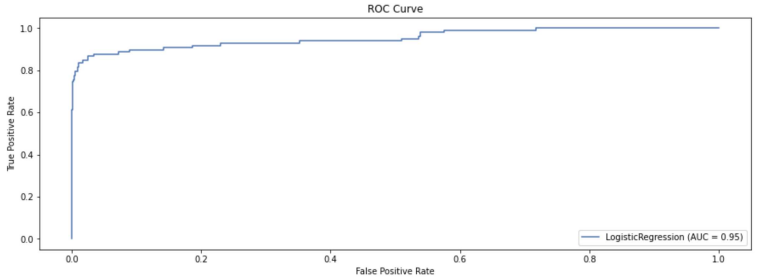
In [51]:
```
X_test=test_df.drop(['Amount'],axis=1)
X_test.shape
```

Out[51]:
```
(56962, 21)
```

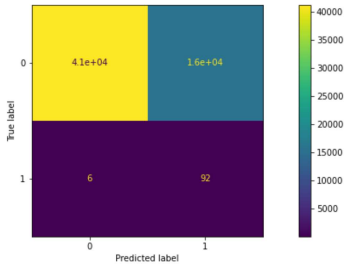
In [ ]:
```
print('================ *Result for Model Trained on Under Sampled Data * ================','\n')
classdict = {'normal':0, 'fraudulent':1}
for i,v in models:
    pred=v.predict(X_test)
    accu=accuracy_score(y_val,pred)
    con_matrix=confusion_matrix(y_val,pred)
    clf_rep=classification_report(y_val,pred)

    print('===== {} ====='.format(i))

    print()
    print ("Model Accuracy: ", '{}%'.format(np.round(accu, 3) * 100))
    print()
    print("Classification Report:" "\n", clf_rep)
    print()
    print("Confusion Matrix:")
    sklearn.metrics.plot_confusion_matrix(v,X_test,y_val)
    print()


    sklearn.metrics.plot_roc_curve(v,X=X_test,y=y_val)
    plt.title('ROC Curve')
    plt.show()
```

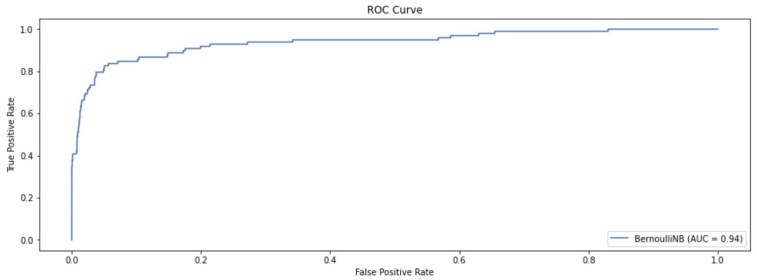
```
================ *Result for Model Trained on Under Sampled Data * =================

===== Logistic Regression Classifier  =====

Model Accuracy:  94.8%

Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.95      0.97     56864
           1       0.03      0.88      0.05        98

    accuracy                           0.95     56962
   macro avg       0.51      0.91      0.51     56962
weighted avg       1.00      0.95      0.97     56962


Confusion Matrix:
```



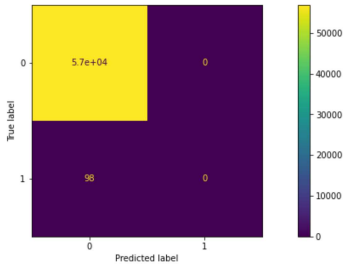


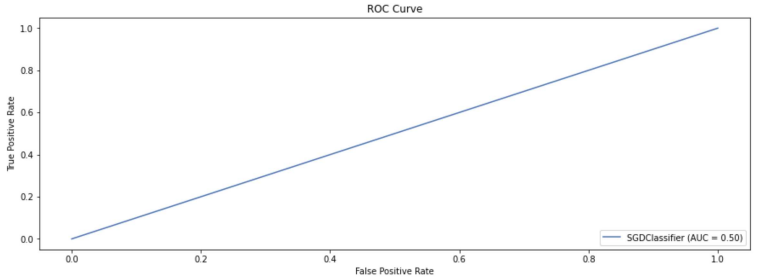

```
===== Navie Base BernoulliNB =====

Model Accuracy:  72.39999999999999%

Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.72      0.84     56864
           1       0.01      0.94      0.01        98

    accuracy                           0.72     56962
   macro avg       0.50      0.83      0.43     56962
weighted avg       1.00      0.72      0.84     56962


Confusion Matrix:
```






```
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/_classification.py:1272: UndefinedMetricWarning: Precision and F-score are ill-def
ined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))

===== SGD Classifer =====

Model Accuracy:  99.8%

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56864
           1       0.00      0.00      0.00        98

    accuracy                           1.00     56962
   macro avg       0.50      0.50      0.50     56962
weighted avg       1.00      1.00      1.00     56962


Confusion Matrix:
```

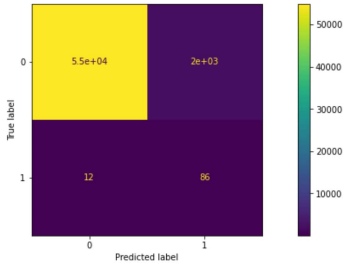


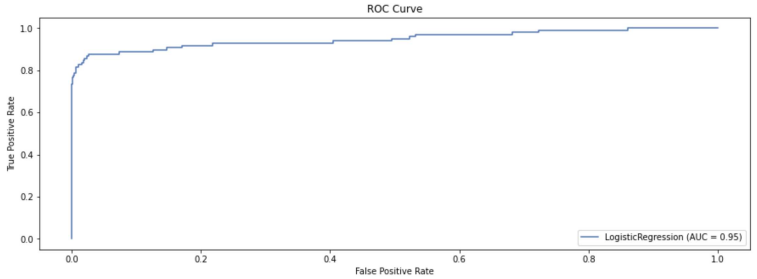


In [ ]:

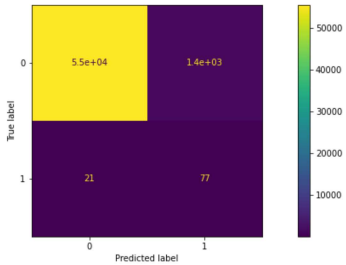
```
print('================ *Result for Model Trained on Over Sampled Data * =================','\n')
classdict = {'normal':0, 'fraudulent':1}
for i,v in models:
    pred=v.predict(X_test)
    accu=accuracy_score(y_val,pred)
    con_matrix=confusion_matrix(y_val,pred)
    clf_rep=classification_report(y_val,pred)

    print('===== {} ====='.format(i))

    print()
    print ("Model Accuracy: ", '{}%'.format(np.round(accu, 3) * 100))
    print()
    print("Classification Report:" "\n", clf_rep)
    print()
    print("Confusion Matrix:")
    sklearn.metrics.plot_confusion_matrix(v,X_test,y_val)
    print()


    sklearn.metrics.plot_roc_curve(v,X=X_test,y=y_val)
    plt.title('ROC Curve')
    plt.show()
```

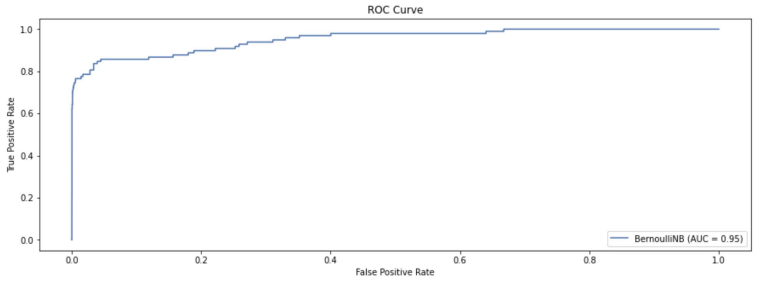
```
================ *Result for Model Trained on Over Sampled Data * =================

===== Logistic Regression Classifier  =====

Model Accuracy:  96.5%

Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.97      0.98     56864
           1       0.04      0.88      0.08        98

    accuracy                           0.97     56962
   macro avg       0.52      0.92      0.53     56962
weighted avg       1.00      0.97      0.98     56962


Confusion Matrix:
```



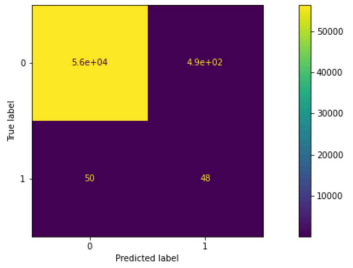


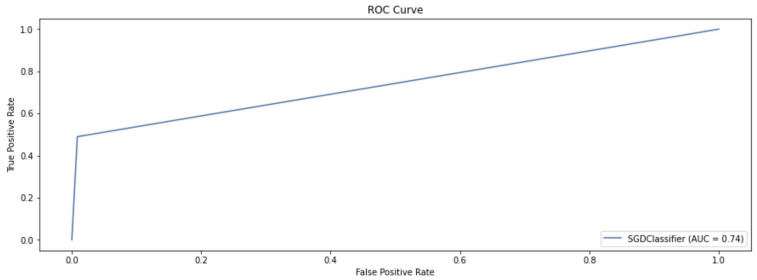

```
===== Navie Base BernoulliNB =====

Model Accuracy:  97.5%

Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.98      0.99     56864
           1       0.05      0.79      0.10        98

    accuracy                           0.98     56962
   macro avg       0.53      0.88      0.54     56962
weighted avg       1.00      0.98      0.99     56962


Confusion Matrix:
```






```
===== SGD Classifer =====

Model Accuracy:  99.1%

Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.99      1.00     56864
           1       0.09      0.49      0.15        98

    accuracy                           0.99     56962
   macro avg       0.54      0.74      0.57     56962
weighted avg       1.00      0.99      0.99     56962


Confusion Matrix:
```





Below Tabel Shows the Comparision of All three models build, Trained and Evaluated on

1. Under Sampled Data Set
2. Over Sampled Data Set

Classifier Models Accuracy and F1 Score comparision on Under Sampled and Over Sample of Imblance Class Data Set

Sampling Tech	Model	Logistics Regression	Navie Based Clf	SVM Based SGD Classifier
Under Sample	Evaluation Accuracy	95%	72%	99%
	F1 Score			
	Class 0 : Non Fraud	0.97	0.84	1
	Class 1 : Fraud	0.05	0.01	0
Over Sampling	Evalution Accuracy	96%	97%	99%
	F1 Score			
	Class 0 : Non Fraud	0.97	0.99	1
	Class 1 : Fraud	0.05	0.1	0.15

From Above Comparision we can Conlude following

1. The Models Have Good Accuracy score , But show poor F1 score in the Minoerity class prediction but Excel in prediction of Dominat class,they fail in Prediction of the Smaller Class
2. Logistics Regression Model Dosen't show any defference in Acuuracy for both Smapling Technices and F1 Score remains same in both the method for both classes.
3. Navie Based Bernoulli Classifier Show siginficant imporvement in Accuracy and Slight improvment of 10% in F1 Score for both the classes
4. SGD model has the best accuracy yet have the worst F1 score. This model fail to predict the fraud class in unders sampled tech. But shows better performance in Over sampling tech.

Using the random forest classifier along with class imblance correction features

We shall use class weight age to counter the class imbalance problem.

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

In [20]:
```
#split the data with out sampling the data
Rf_X,Rf_y=X,y
```

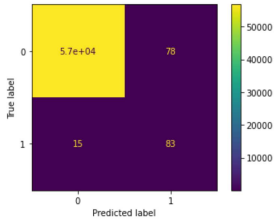
In [ ]:
```
# Train RandomForest Classifier
RF_clf=RandomForestClassifier(criterion='entropy',max_depth=5,class_weight='balanced_subsample')
RF_clf.fit(Rf_X,Rf_y)
```

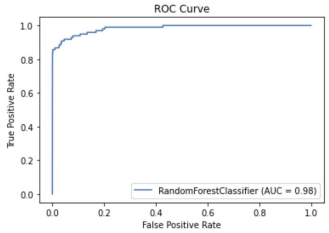
Out[ ]:
```
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0,
                       class_weight='balanced_subsample', criterion='entropy',
                       max_depth=5, max_features='auto', max_leaf_nodes=None,
                       max_samples=None, min_impurity_decrease=0.0,
                       min_impurity_split=None, min_samples_leaf=1,
                       min_samples_split=2, min_weight_fraction_leaf=0.0,
                       n_estimators=100, n_jobs=None, oob_score=False,
                       random_state=None, verbose=0, warm_start=False)
```

In [ ]:

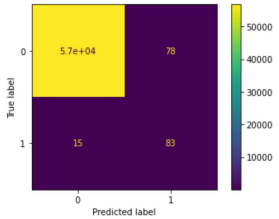
```
print('================ * RF Model Evaluation Results* =================','\n')

pred=RF_clf.predict(X_val)
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)
scores=cross_val_score(RF_clf,Rf_X,Rf_y,cv=cv)
accu=accuracy_score(y_val,pred)
con_matrix=confusion_matrix(y_val,pred)
clf_rep=classification_report(y_val,pred)

print('=====Random Forest Classifier =====')

print ("Cross Validation Mean Score: ", '{}%'.format(np.round(scores.mean(), 3) * 100))
print()
print ("Model Accuracy: ", '{}%'.format(np.round(accu, 3) * 100))
print()
print("Classification Report:" "\n", clf_rep)
print()
print("Confusion Matrix:")
sklearn.metrics.plot_confusion_matrix(RF_clf,X_val,y_val)
print()

sklearn.metrics.plot_roc_curve(RF_clf,X_val,y_val)
plt.title('ROC Curve')
plt.show()

print('==================Test Result of the Model=================')
pred=RF_clf.predict(X_test)
accu=accuracy_score(y_val,pred)
con_matrix=confusion_matrix(y_val,pred)
clf_rep=classification_report(y_val,pred)



print()
print ("Model Accuracy: ", '{}%'.format(np.round(accu, 3) * 100))
print()
print("Classification Report:" "\n", clf_rep)
print()
print("Confusion Matrix:")
sklearn.metrics.plot_confusion_matrix(RF_clf,X_test,y_val)
print()


sklearn.metrics.plot_roc_curve(RF_clf,X=X_test,y=y_val)
plt.title('ROC Curve')
plt.show()
```

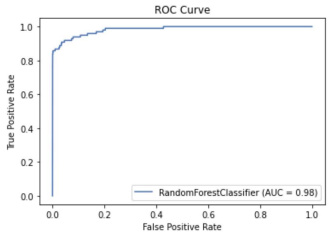
```
================ * RF Model Evaluation Results* =================

=====Random Forest Classifier =====
Cross Validation Mean Score:  99.9%

Model Accuracy:  99.8%

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56864
           1       0.52      0.85      0.64        98

    accuracy                           1.00     56962
   macro avg       0.76      0.92      0.82     56962
weighted avg       1.00      1.00      1.00     56962


Confusion Matrix:
```






```
==================Test Result of the Model=================

Model Accuracy:  99.8%

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56864
           1       0.52      0.85      0.64        98

    accuracy                           1.00     56962
   macro avg       0.76      0.92      0.82     56962
weighted avg       1.00      1.00      1.00     56962


Confusion Matrix:
```





Above is the Evalulation of the Ensembled based Random forest alogo without any Pre prossecing of the data to counter the IMblance in the calss . The model Uses the funcion of Class weightage : where both the class are assigned particular weightage. I used 'balanced_subsample' method where . Data is subsampled randomly and both class are assigned Weigate to tackel the imblance.

1. We obverve that the .

```
Models prediction Accuracy : Random Forest   -       98.3  %
```

F1 score :

```
              Random Forest Classifier

class 0:       0.99              |

class 1 :      0.64              |
```

In [ ]:

Using XG Boost Classifier

The XGBoost classifier has the method of wegihtage to deal with the class imblance in the data, We shall use this method to tackel the class imbalance in our data. Insted of Standardising the data through Under Sampling or Over Sampling .

In [19]:
```
from xgboost.sklearn import XGBClassifier
from collections import Counter
```

In [20]:
```
X_gb_train,y_gb_train=X,y
```

In [21]:
```
X_gb_train.shape,y_gb_train.shape
```

Out[21]:
```
((227845, 30), (227845,))
```

In [32]:
```
# count examples in each class
counter = Counter(y)
# estimate scale_pos_weight value
weight = counter[1] / counter[0]
print('Weightage sholud be given to majority class during classification is :',weight)
```

```
Weightage sholud be given to majority class during classification is : 0.0017322412299792043
```

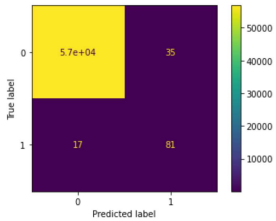
In [33]:
```
# define model
XGB_clf = XGBClassifier(scale_pos_weight=1/0.001732,max_depth=5)
```

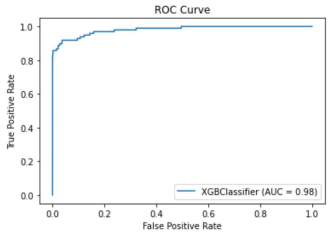
In [34]:
```
XGB_clf.fit(X_gb_train,y_gb_train)
```

Out[34]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0,
              learning_rate=0.1, max_delta_step=0, max_depth=5,
              min_child_weight=1, missing=None, n_estimators=100, n_jobs=1,
              nthread=None, objective='binary:logistic', random_state=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=577.3672055427252,
              seed=None, silent=None, subsample=1, verbosity=1)
```

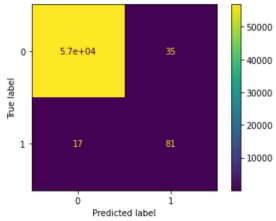
In [35]:
```
print("================Model Evalution================")
y_pred=XGB_clf.predict(X_val)
scores = cross_val_score(XGB_clf, X_gb_train, y_gb_train, scoring='roc_auc', cv=cv, n_jobs=-1)
accu=accuracy_score(y_val,y_pred)
con_matrix=confusion_matrix(y_val,y_pred)
clf_rep=classification_report(y_val,y_pred)


print ("Cross Validation Mean Score: ", '{}%'.format(np.round(scores.mean(), 3) * 100))
print()
print ("Model Accuracy: ", '{}%'.format(np.round(accu, 3) * 100))
print()
print("Classification Report:" "\n", clf_rep)
print()
print("Confusion Matrix:")
sklearn.metrics.plot_confusion_matrix(XGB_clf,X_val,y_val)
print()


sklearn.metrics.plot_roc_curve(XGB_clf,X=X_test,y=y_val)
plt.title('ROC Curve')
plt.show()


print('==================Test Result of the Model================')
pred=XGB_clf.predict(X_test)
accu=accuracy_score(y_val,pred)
con_matrix=confusion_matrix(y_val,pred)
clf_rep=classification_report(y_val,pred)



print()
print ("Model Accuracy: ", '{}%'.format(np.round(accu, 3) * 100))
print()
print("Classification Report:" "\n", clf_rep)
print()
print("Confusion Matrix:")
sklearn.metrics.plot_confusion_matrix(XGB_clf,X_test,y_val)
print()


sklearn.metrics.plot_roc_curve(XGB_clf,X=X_test,y=y_val)
plt.title('ROC Curve')
plt.show()
```

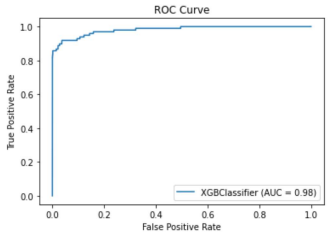
```
=================Model Evalution=================
Cross Validation Mean Score:  97.6%

Model Accuracy:  99.9%

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56864
           1       0.70      0.83      0.76        98

    accuracy                           1.00     56962
   macro avg       0.85      0.91      0.88     56962
weighted avg       1.00      1.00      1.00     56962


Confusion Matrix:
```






```
==================Test Result of the Model=================

Model Accuracy:  99.9%

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56864
           1       0.70      0.83      0.76        98

    accuracy                           1.00     56962
   macro avg       0.85      0.91      0.88     56962
weighted avg       1.00      1.00      1.00     56962


Confusion Matrix:
```





The Above Evalution shows that the Boosted Gradient classifier anlong with Class Imbalance correction method through is Best performing Classifier till now.

The Model has a high Accuracy and Cross Val Score.

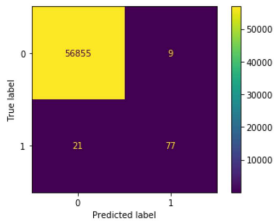
F1 Score of Class 1 (fraud) : is 0.76 which is a decent score

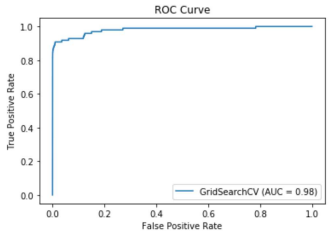
We shall fine tune the model by tuning the HyperParameters using GridSearchCV if we can imporve the preformance of the model.

```
In [22]: from sklearn.model_selection import GridSearchCV

In [23]: para={'learning_rate':[0.01,0.1,0.2],'max_depth': [5,7,10]}

In [24]: para
Out[24]: {'learning_rate': [0.01, 0.1, 0.2], 'max_depth': [5, 7, 10]}

In [38]: grid=GridSearchCV(XGB_clf,param_grid=para,scoring='roc_auc',cv=cv)

In [ ]:  grid_result=grid.fit(X_gb_train,y_gb_train)

In [ ]: grid_result.best_params_

In [ ]: grid_result.best_estimator_
```

In [ ]:
```
y_pred=grid_result.predict(X_test)

accu=accuracy_score(y_val,y_pred)
con_matrix=confusion_matrix(y_val,y_pred)
clf_rep=classification_report(y_val,y_pred)

print ("Model Accuracy: ", '{}%'.format(np.round(accu, 3) * 100))
print()
print("Classification Report:" "\n", clf_rep)
print()
print("Confusion Matrix:")
sklearn.metrics.plot_confusion_matrix(grid_result,X_test,y_val)
print()

sklearn.metrics.plot_roc_curve(grid_result,X=X_test,y=y_val)
plt.title('ROC Curve')
plt.show()
```

```
Model Accuracy:  99.9%

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56864
           1       0.90      0.79      0.84        98

    accuracy                           1.00     56962
   macro avg       0.95      0.89      0.92     56962
weighted avg       1.00      1.00      1.00     56962


Confusion Matrix:
```





Through Use of GridSearchCV we are able to increase the F1 Score of the XGBoost Classifier from 0.76 to 0.84 an large impovement model performance .

The Best Parameters extracted from the Grid is :

```
Learning Rate - 0.1
Max Depth     -  10
Weight -     1/0.001
```

Lets try one more model from Ensembled Learning method along with Deision Tree classifer Algo .

We Shall Try the AdaBoost Classifer as the Base Classifier and over it we shall run the Deision tree Classifier which take care of the Class imbalance problem with the class weightage technic.

In [25]:
```
from sklearn.ensemble import AdaBoostClassifier
from sklearn.tree import DecisionTreeClassifier
```

In [ ]:
```
```

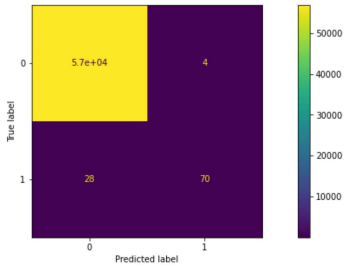
In [26]:
```
DT=DecisionTreeClassifier(max_depth=5,class_weight='balanced')

ESL_clf=AdaBoostClassifier(base_estimator=DT,random_state=42)
```

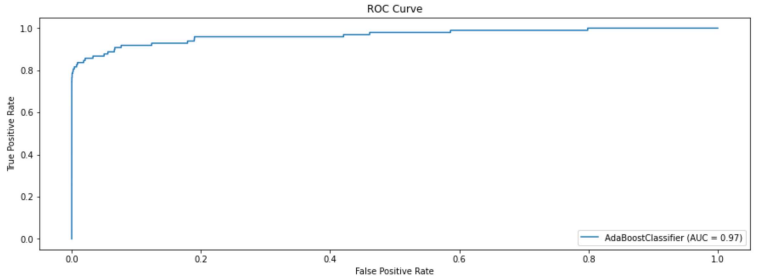
In [27]:
```
ESL_clf.fit(X,y)
```

Out[27]:
```
AdaBoostClassifier(algorithm='SAMME.R',
                   base_estimator=DecisionTreeClassifier(ccp_alpha=0.0,
                                                         class_weight='balanced',
                                                         criterion='gini',
                                                         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'),
                   learning_rate=1.0, n_estimators=50, random_state=42)
```

In [30]:
```
print('=================Test Result of the model==============')
pred=ESL_clf.predict(X_test)
accu=accuracy_score(y_val,pred)
con_matrix=confusion_matrix(y_val,pred)
clf_rep=classification_report(y_val,pred)


print()
print ("Model Accuracy: ", '{}%'.format(np.round(accu, 3) * 100))
print()
print("Classification Report:" "\n", clf_rep)
print()
print("Confusion Matrix:")
sklearn.metrics.plot_confusion_matrix(ESL_clf,X_test,y_val)
print()


sklearn.metrics.plot_roc_curve(ESL_clf,X=X_test,y=y_val)
plt.title('ROC Curve')
plt.show()
```

```
=================Test Result of the model==============

Model Accuracy:  99.9%

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56864
           1       0.95      0.71      0.81        98

    accuracy                           1.00     56962
   macro avg       0.97      0.86      0.91     56962
weighted avg       1.00      1.00      1.00     56962


Confusion Matrix:
```





In [ ]:
```
```

We can observe that Ensembeled based AdaBoost algorithm along with Tree Based Decision Tree algorithm shows a Better results which has Good accuracy rate and a Better F1 Score for the Fraud Points (Class1).

Project Task: Week 3

Applying ANN:

Use ANN (Artificial Neural Network) to identify fradulent and non-fradulent. a) Fine-tune number of layers b) Number of Neurons in each layers c) Experiment in batch-size d) Experiment with number of epochs. Check the observations in loss and accuracy e) Play with different Learning Rate variants of Gradient Descent like Adam, SGD, RMS-prop f) Find out which activation performs best for this use case and why? g) Check Confusion Matrix, Precision, Recall and F1-Score

1. Try out Dropout for ANN. How is it performed? Compare model performance with the traditional ML based prediction models from above.
2. Find the best setting of neural net that can be best classified as fraudulent and non-fraudulent transactions. Use techniques like Grid Search, Cross-Validation and Random search.

Anomaly Detection:

1. Implement anomaly detection algorithms. a) Assume that the data is coming from a single or a combination of multivariate Gaussian b) Formalize a scoring criterion, which gives a scoring probability for the given data point whether it belongs to the multivariate Gaussian or Normal Distribution fitted in a)

In [31]:
```
from keras.models import Sequential,Model,load_model
from keras.layers import Dense,Dropout,BatchNormalization,Flatten
import tensorflow as tf

#importing the libs
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
```

In [32]:
```
from keras.wrappers.scikit_learn import KerasClassifier
import sklearn
cv = RepeatedStratifiedKFold(n_splits=5, n_repeats=3, random_state=1)
```

In [45]:
```
X_val.shape
```

Out[45]: (56962, 21)

Here, I will define our classifier builder object. I will use ANN with 3 hidden layers with 24,32,24 nodes each respectively . My activation function will be relu(x, alpha=0.0, max_value=None), random weights of layers will be "uniformly" distirbuted, output node will have sigmoid activation function, because classification is binary.For compiling of model I will use adam optimizer, binary cross entropy loss function.

In [44]:
```
# build a Simple ANN Model

model = Sequential()
model.add(Dense(24, input_dim=21, activation='relu', kernel_initializer='he_uniform'))
model.add(BatchNormalization())

model.add(Dense(units=32,activation='relu'))
model.add(BatchNormalization())

model.add(Dense(units=24,activation='relu'))
model.add(BatchNormalization())

model.add(Dense(1, activation='sigmoid'))
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
```

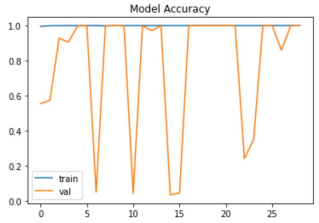
In [46]:
```
# simple early stopping : This tech is used to stop learning of the model if there isn't imporvment in model scores.
es = tf.keras.callbacks.EarlyStopping(monitor='val_loss', mode='auto',patience=10,restore_best_weights=True, verbose=1)

# fit the data
history=model.fit(X,y,validation_data=(X_val,y_val),epochs=50,batch_size=100,callbacks=[es])
```

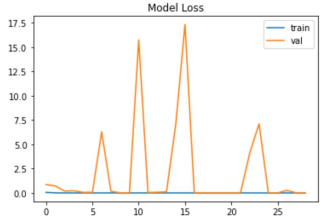
```
Epoch 1/50
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0565 - accuracy: 0.9946 - val_loss: 0.8631 - val_accuracy: 0.5541
Epoch 2/50
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0104 - accuracy: 0.9984 - val_loss: 0.7200 - val_accuracy: 0.5730
Epoch 3/50
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0052 - accuracy: 0.9990 - val_loss: 0.1943 - val_accuracy: 0.9276
Epoch 4/50
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0038 - accuracy: 0.9992 - val_loss: 0.2303 - val_accuracy: 0.9050
Epoch 5/50
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0037 - accuracy: 0.9992 - val_loss: 0.0600 - val_accuracy: 0.9974
Epoch 6/50
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0039 - accuracy: 0.9992 - val_loss: 0.0666 - val_accuracy: 0.9982
Epoch 7/50
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0045 - accuracy: 0.9991 - val_loss: 6.2730 - val_accuracy: 0.0492
Epoch 8/50
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0090 - accuracy: 0.9982 - val_loss: 0.1827 - val_accuracy: 0.9982
Epoch 9/50
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0041 - accuracy: 0.9992 - val_loss: 0.0046 - val_accuracy: 0.9991
Epoch 10/50
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0036 - accuracy: 0.9993 - val_loss: 0.0105 - val_accuracy: 0.9986
Epoch 11/50
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0037 - accuracy: 0.9992 - val_loss: 15.7249 - val_accuracy: 0.0423
Epoch 12/50
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0034 - accuracy: 0.9993 - val_loss: 0.0500 - val_accuracy: 0.9984
Epoch 13/50
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0033 - accuracy: 0.9993 - val_loss: 0.0719 - val_accuracy: 0.9702
Epoch 14/50
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0034 - accuracy: 0.9994 - val_loss: 0.1251 - val_accuracy: 0.9983
Epoch 15/50
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0035 - accuracy: 0.9993 - val_loss: 7.0586 - val_accuracy: 0.0337
Epoch 16/50
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0035 - accuracy: 0.9992 - val_loss: 17.3156 - val_accuracy: 0.0436
Epoch 17/50
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0034 - accuracy: 0.9993 - val_loss: 0.0219 - val_accuracy: 0.9985
Epoch 18/50
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0033 - accuracy: 0.9993 - val_loss: 0.0196 - val_accuracy: 0.9989
Epoch 19/50
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0034 - accuracy: 0.9994 - val_loss: 0.0044 - val_accuracy: 0.9993
Epoch 20/50
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0032 - accuracy: 0.9993 - val_loss: 0.0101 - val_accuracy: 0.9991
Epoch 21/50
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0032 - accuracy: 0.9994 - val_loss: 0.0044 - val_accuracy: 0.9992
Epoch 22/50
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0032 - accuracy: 0.9994 - val_loss: 0.0257 - val_accuracy: 0.9989
Epoch 23/50
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0032 - accuracy: 0.9994 - val_loss: 4.1436 - val_accuracy: 0.2412
Epoch 24/50
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0032 - accuracy: 0.9994 - val_loss: 7.1050 - val_accuracy: 0.3476
Epoch 25/50
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0034 - accuracy: 0.9993 - val_loss: 0.0077 - val_accuracy: 0.9990
Epoch 26/50
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0032 - accuracy: 0.9994 - val_loss: 0.0044 - val_accuracy: 0.9992
Epoch 27/50
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0032 - accuracy: 0.9993 - val_loss: 0.2740 - val_accuracy: 0.8596
Epoch 28/50
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0034 - accuracy: 0.9993 - val_loss: 0.0119 - val_accuracy: 0.9990
Epoch 29/50
2263/2279 [============================>.] - ETA: 0s - loss: 0.0030 - accuracy: 0.9994Restoring model weights from the end of the best epoch.
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0030 - accuracy: 0.9994 - val_loss: 0.0088 - val_accuracy: 0.9990
Epoch 00029: early stopping
```

In [48]:
```
# Model Learning accuracy
_, train_acc = model.evaluate(X, y, verbose=0)
_, val_acc = model.evaluate(X_val, y_val, verbose=0)
print('Train: %.3f, Validation: %.3f' % (train_acc, val_acc))
```

```
Train: 0.999, Validation: 0.999
```

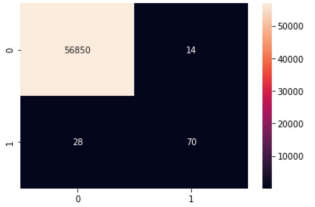
In [49]:
```
# Model learning accuracy

plt.plot(history.history['accuracy'], label='train')
plt.plot(history.history['val_accuracy'], label='val')
plt.title("Model Accuracy")
plt.legend()
plt.show()

plt.plot(history.history['loss'], label='train')
plt.plot(history.history['val_loss'], label='val')
plt.title('Model Loss')
plt.legend()
plt.show()
```

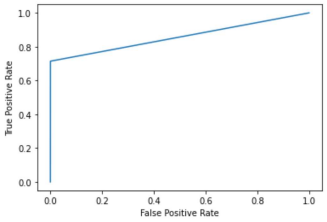




In [52]:
```
y_pred=(model.predict(X_test)>0.5).astype('int32')
accu=accuracy_score(y_val,y_pred)
con_matrix=confusion_matrix(y_val,y_pred)
clf_rep=classification_report(y_val,y_pred,zero_division=0)

print ("Model Accuracy: ", '{}%'.format(np.round(accu, 3) * 100))
print()
print("Classification Report:" "\n", clf_rep)
print()
sns.heatmap(con_matrix,annot=True, fmt="d")
plt.show()
# calculate roc curve
fpr, tpr, thresholds = roc_curve(y_val, y_pred)
plt.plot(fpr,tpr)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.show()
```

```
Model Accuracy:  99.9%

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56864
           1       0.83      0.71      0.77        98

    accuracy                           1.00     56962
   macro avg       0.92      0.86      0.88     56962
weighted avg       1.00      1.00      1.00     56962
```





The simple ANN model show a Better performance compared to many of the ML model.

The even though Model Accuracy is very high it has a good F1 Score of 0.77 for Fraud Class predtiction

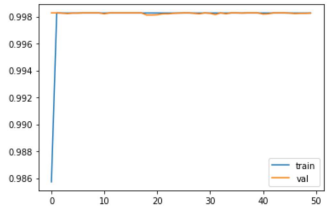
Trying Drop Out function and its effects on the model.

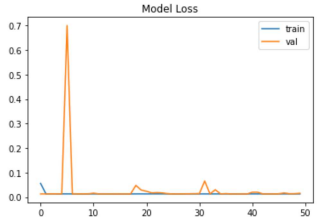
In [57]:
```
model_1 = Sequential()
model_1.add(Dense(24, input_dim=21, activation='relu', kernel_initializer='he_uniform'))
model_1.add(Dropout(0.1))
model_1.add(BatchNormalization())

model_1.add(Dense(units=32,activation='relu'))
model_1.add(Dropout(0.1))
model_1.add(BatchNormalization())


model_1.add(Dense(units=24,activation='relu'))
model_1.add(Dropout(0.1))
model_1.add(BatchNormalization())


model_1.add(Dense(1, activation='sigmoid'))
model_1.compile(loss='binary_crossentropy', optimizer='adam', metrics=['acc'])
```

In [58]:
```
# fit the data
history_drop=model_1.fit(X,y,validation_data=(X_val,y_val),epochs=50,batch_size=100)
```

```
Epoch 1/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0557 - acc: 0.9857 - val_loss: 0.0127 - val_acc: 0.9983
Epoch 2/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0133 - acc: 0.9983 - val_loss: 0.0127 - val_acc: 0.9983
Epoch 3/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0130 - acc: 0.9983 - val_loss: 0.0131 - val_acc: 0.9983
Epoch 4/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0130 - acc: 0.9983 - val_loss: 0.0131 - val_acc: 0.9982
Epoch 5/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0129 - acc: 0.9983 - val_loss: 0.0130 - val_acc: 0.9983
Epoch 6/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0129 - acc: 0.9983 - val_loss: 0.7004 - val_acc: 0.9983
Epoch 7/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0128 - acc: 0.9983 - val_loss: 0.0130 - val_acc: 0.9983
Epoch 8/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0129 - acc: 0.9983 - val_loss: 0.0128 - val_acc: 0.9983
Epoch 9/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0127 - acc: 0.9983 - val_loss: 0.0132 - val_acc: 0.9983
Epoch 10/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0127 - acc: 0.9983 - val_loss: 0.0128 - val_acc: 0.9983
Epoch 11/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0128 - acc: 0.9983 - val_loss: 0.0159 - val_acc: 0.9982
Epoch 12/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0127 - acc: 0.9983 - val_loss: 0.0126 - val_acc: 0.9983
Epoch 13/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0127 - acc: 0.9983 - val_loss: 0.0127 - val_acc: 0.9983
Epoch 14/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0127 - acc: 0.9983 - val_loss: 0.0127 - val_acc: 0.9983
Epoch 15/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0126 - acc: 0.9983 - val_loss: 0.0126 - val_acc: 0.9983
Epoch 16/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0127 - acc: 0.9983 - val_loss: 0.0126 - val_acc: 0.9983
Epoch 17/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0127 - acc: 0.9983 - val_loss: 0.0127 - val_acc: 0.9983
Epoch 18/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0126 - acc: 0.9983 - val_loss: 0.0126 - val_acc: 0.9983
Epoch 19/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0128 - acc: 0.9983 - val_loss: 0.0475 - val_acc: 0.9981
Epoch 20/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0128 - acc: 0.9983 - val_loss: 0.0286 - val_acc: 0.9981
Epoch 21/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0128 - acc: 0.9983 - val_loss: 0.0236 - val_acc: 0.9981
Epoch 22/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0128 - acc: 0.9983 - val_loss: 0.0170 - val_acc: 0.9982
Epoch 23/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0128 - acc: 0.9983 - val_loss: 0.0181 - val_acc: 0.9982
Epoch 24/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0128 - acc: 0.9983 - val_loss: 0.0169 - val_acc: 0.9982
Epoch 25/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0128 - acc: 0.9983 - val_loss: 0.0138 - val_acc: 0.9983
Epoch 26/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0128 - acc: 0.9983 - val_loss: 0.0127 - val_acc: 0.9983
Epoch 27/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0128 - acc: 0.9983 - val_loss: 0.0129 - val_acc: 0.9983
Epoch 28/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0128 - acc: 0.9983 - val_loss: 0.0130 - val_acc: 0.9982
Epoch 29/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0128 - acc: 0.9983 - val_loss: 0.0133 - val_acc: 0.9982
Epoch 30/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0128 - acc: 0.9983 - val_loss: 0.0137 - val_acc: 0.9983
Epoch 31/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0128 - acc: 0.9983 - val_loss: 0.0140 - val_acc: 0.9982
Epoch 32/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0128 - acc: 0.9983 - val_loss: 0.0654 - val_acc: 0.9982
Epoch 33/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0128 - acc: 0.9983 - val_loss: 0.0127 - val_acc: 0.9983
Epoch 34/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0128 - acc: 0.9983 - val_loss: 0.0298 - val_acc: 0.9982
Epoch 35/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0128 - acc: 0.9983 - val_loss: 0.0128 - val_acc: 0.9983
Epoch 36/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0128 - acc: 0.9983 - val_loss: 0.0140 - val_acc: 0.9983
Epoch 37/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0128 - acc: 0.9983 - val_loss: 0.0128 - val_acc: 0.9983
Epoch 38/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0128 - acc: 0.9983 - val_loss: 0.0127 - val_acc: 0.9983
Epoch 39/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0128 - acc: 0.9983 - val_loss: 0.0127 - val_acc: 0.9983
Epoch 40/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0128 - acc: 0.9983 - val_loss: 0.0127 - val_acc: 0.9983
Epoch 41/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0128 - acc: 0.9983 - val_loss: 0.0196 - val_acc: 0.9982
Epoch 42/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0128 - acc: 0.9983 - val_loss: 0.0197 - val_acc: 0.9982
Epoch 43/50
2279/2279 [==============================] - 7s 3ms/step - loss: 0.0128 - acc: 0.9983 - val_loss: 0.0128 - val_acc: 0.9983
Epoch 44/50
2279/2279 [==============================] - 6s 3ms/step - loss: 0.0128 - acc: 0.9983 - val_loss: 0.0127 - val_acc: 0.9983
Epoch 45/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0128 - acc: 0.9983 - val_loss: 0.0128 - val_acc: 0.9983
Epoch 46/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0128 - acc: 0.9983 - val_loss: 0.0132 - val_acc: 0.9983
Epoch 47/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0127 - acc: 0.9983 - val_loss: 0.0168 - val_acc: 0.9982
Epoch 48/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0128 - acc: 0.9983 - val_loss: 0.0135 - val_acc: 0.9982
Epoch 49/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0128 - acc: 0.9983 - val_loss: 0.0136 - val_acc: 0.9982
Epoch 50/50
2279/2279 [==============================] - 5s 2ms/step - loss: 0.0127 - acc: 0.9983 - val_loss: 0.0154 - val_acc: 0.9983
```

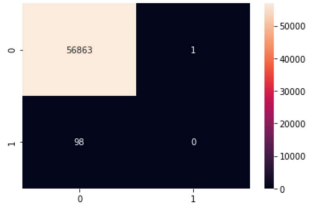
In [59]:
```
plt.plot(history_drop.history['acc'], label='train')
plt.plot(history_drop.history['val_acc'], label='val')
plt.legend()
plt.show()

plt.plot(history_drop.history['loss'], label='train')
plt.plot(history_drop.history['val_loss'], label='val')
plt.title('Model Loss')
plt.legend()
plt.show()
```

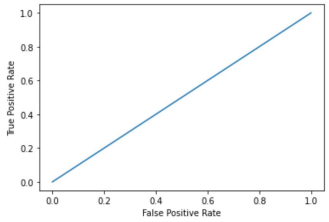




In [61]:
```
y_pred=(model_1.predict(X_test)>0.5).astype('int32')
accu=accuracy_score(y_val,y_pred)
con_matrix=confusion_matrix(y_val,y_pred)
clf_rep=classification_report(y_val,y_pred,zero_division=0)

print ("Model Accuracy: ", '{}%'.format(np.round(accu, 3) * 100))
print()
print("Classification Report:" "\n", clf_rep)
print()
sns.heatmap(con_matrix,annot=True, fmt="d")
plt.show()
# calculate roc curve
fpr, tpr, thresholds = roc_curve(y_val, y_pred)
plt.plot(fpr,tpr)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.show()
```

```
Model Accuracy:  99.8%

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56864
           1       0.00      0.00      0.00        98

    accuracy                           1.00     56962
   macro avg       0.50      0.50      0.50     56962
weighted avg       1.00      1.00      1.00     56962
```





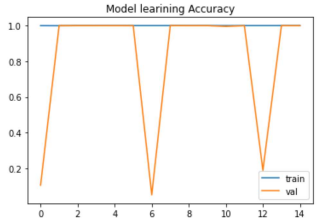
The Useage of the dropout Layer doesn't Help much infact the model F1 Score fall drastically when compared to model without Dropout layer

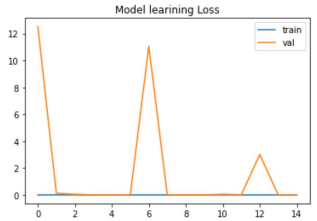
Trying the model with deffirent Epochs and Batch Size there effects

In [62]:
```
history_epoch_1=model.fit(X,y,validation_data=(X_val,y_val),epochs=75,batch_size=100,callbacks=[es])
```

```
Epoch 1/75
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0040 - accuracy: 0.9991 - val_loss: 12.5298 - val_accuracy: 0.1065
Epoch 2/75
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0056 - accuracy: 0.9987 - val_loss: 0.1325 - val_accuracy: 0.9991
Epoch 3/75
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0033 - accuracy: 0.9993 - val_loss: 0.0501 - val_accuracy: 0.9992
Epoch 4/75
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0033 - accuracy: 0.9993 - val_loss: 0.0058 - val_accuracy: 0.9992
Epoch 5/75
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0031 - accuracy: 0.9994 - val_loss: 0.0038 - val_accuracy: 0.9992
Epoch 6/75
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0032 - accuracy: 0.9994 - val_loss: 0.0155 - val_accuracy: 0.9988
Epoch 7/75
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0032 - accuracy: 0.9994 - val_loss: 11.0647 - val_accuracy: 0.0527
Epoch 8/75
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0032 - accuracy: 0.9994 - val_loss: 0.0040 - val_accuracy: 0.9993
Epoch 9/75
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0032 - accuracy: 0.9994 - val_loss: 0.0042 - val_accuracy: 0.9992
Epoch 10/75
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0031 - accuracy: 0.9994 - val_loss: 0.0045 - val_accuracy: 0.9992
Epoch 11/75
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0031 - accuracy: 0.9994 - val_loss: 0.0548 - val_accuracy: 0.9949
Epoch 12/75
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0033 - accuracy: 0.9994 - val_loss: 0.0130 - val_accuracy: 0.9989
Epoch 13/75
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0033 - accuracy: 0.9994 - val_loss: 3.0077 - val_accuracy: 0.1898
Epoch 14/75
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0031 - accuracy: 0.9994 - val_loss: 0.0057 - val_accuracy: 0.9990
Epoch 15/75
2274/2279 [============================>.] - ETA: 0s - loss: 0.0032 - accuracy: 0.9994Restoring model weights from the end of the best ep
och.
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0032 - accuracy: 0.9994 - val_loss: 0.0116 - val_accuracy: 0.9990
Epoch 00015: early stopping
```

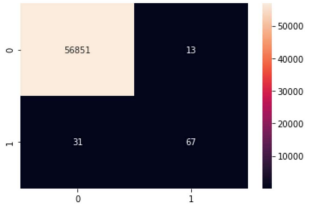
In [63]:
```
plt.plot(history_epoch_1.history['accuracy'], label='train')
plt.plot(history_epoch_1.history['val_accuracy'], label='val')
plt.title('Model learining Accuracy')
plt.legend()
plt.show()

plt.plot(history_epoch_1.history['loss'], label='train')
plt.plot(history_epoch_1.history['val_loss'], label='val')
plt.title('Model learining Loss')
plt.legend()
plt.show()
```

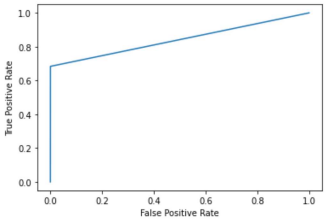




In [64]:
```
y_pred_1=(model.predict(X_test)>0.5).astype('int32')
accu=accuracy_score(y_val,y_pred_1)
con_matrix=confusion_matrix(y_val,y_pred_1)
clf_rep=classification_report(y_val,y_pred_1,zero_division=0)

print ("Model Accuracy: ", '{}%'.format(np.round(accu, 3) * 100))
print()
print("Classification Report:" "\n", clf_rep)
print()
sns.heatmap(con_matrix,annot=True, fmt="d")
plt.show()
# calculate roc curve
fpr, tpr, thresholds = roc_curve(y_val, y_pred_1)
plt.plot(fpr,tpr)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.show()
```

```
Model Accuracy:  99.9%

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56864
           1       0.84      0.68      0.75        98

    accuracy                           1.00     56962
   macro avg       0.92      0.84      0.88     56962
weighted avg       1.00      1.00      1.00     56962
```

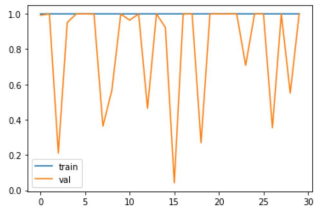


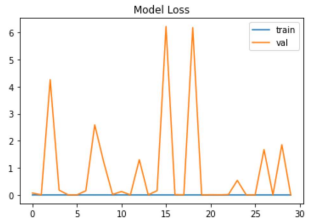


In [65]:
```
# Decrease in  no of epochs
history_epoch_2=model.fit(X,y,validation_data=(X_val,y_val),epochs=30,batch_size=100)
```

```
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0033 - accuracy: 0.9994 - val_loss: 0.0735 - val_accuracy: 0.9920
Epoch 2/30
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0032 - accuracy: 0.9994 - val_loss: 0.0078 - val_accuracy: 0.9991
Epoch 3/30
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0032 - accuracy: 0.9993 - val_loss: 4.2545 - val_accuracy: 0.2103
Epoch 4/30
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0032 - accuracy: 0.9994 - val_loss: 0.1814 - val_accuracy: 0.9507
Epoch 5/30
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0032 - accuracy: 0.9994 - val_loss: 0.0091 - val_accuracy: 0.9991
Epoch 6/30
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0031 - accuracy: 0.9994 - val_loss: 0.0054 - val_accuracy: 0.9992
Epoch 7/30
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0032 - accuracy: 0.9994 - val_loss: 0.1565 - val_accuracy: 0.9985
Epoch 8/30
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0031 - accuracy: 0.9994 - val_loss: 2.5865 - val_accuracy: 0.3633
Epoch 9/30
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0032 - accuracy: 0.9993 - val_loss: 1.2237 - val_accuracy: 0.5660
Epoch 10/30
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0031 - accuracy: 0.9994 - val_loss: 0.0207 - val_accuracy: 0.9989
Epoch 11/30
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0032 - accuracy: 0.9993 - val_loss: 0.1298 - val_accuracy: 0.9638
Epoch 12/30
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0031 - accuracy: 0.9993 - val_loss: 0.0046 - val_accuracy: 0.9992
Epoch 13/30
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0031 - accuracy: 0.9994 - val_loss: 1.3034 - val_accuracy: 0.4644
Epoch 14/30
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0031 - accuracy: 0.9994 - val_loss: 0.0056 - val_accuracy: 0.9992
Epoch 15/30
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0031 - accuracy: 0.9994 - val_loss: 0.1612 - val_accuracy: 0.9229
Epoch 16/30
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0031 - accuracy: 0.9994 - val_loss: 6.2142 - val_accuracy: 0.0419
Epoch 17/30
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0031 - accuracy: 0.9994 - val_loss: 0.0149 - val_accuracy: 0.9989
Epoch 18/30
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0031 - accuracy: 0.9994 - val_loss: 0.0081 - val_accuracy: 0.9991
Epoch 19/30
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0031 - accuracy: 0.9994 - val_loss: 6.1729 - val_accuracy: 0.2691
Epoch 20/30
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0031 - accuracy: 0.9994 - val_loss: 0.0038 - val_accuracy: 0.9993
Epoch 21/30
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0030 - accuracy: 0.9994 - val_loss: 0.0112 - val_accuracy: 0.9990
Epoch 22/30
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0031 - accuracy: 0.9994 - val_loss: 0.0074 - val_accuracy: 0.9990
Epoch 23/30
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0030 - accuracy: 0.9994 - val_loss: 0.0164 - val_accuracy: 0.9993
Epoch 24/30
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0031 - accuracy: 0.9994 - val_loss: 0.5403 - val_accuracy: 0.7079
Epoch 25/30
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0031 - accuracy: 0.9994 - val_loss: 0.0047 - val_accuracy: 0.9992
Epoch 26/30
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0031 - accuracy: 0.9994 - val_loss: 0.0035 - val_accuracy: 0.9993
Epoch 27/30
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0030 - accuracy: 0.9994 - val_loss: 1.6761 - val_accuracy: 0.3541
Epoch 28/30
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0030 - accuracy: 0.9994 - val_loss: 0.0037 - val_accuracy: 0.9993
Epoch 29/30
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0030 - accuracy: 0.9994 - val_loss: 1.8553 - val_accuracy: 0.5509
Epoch 30/30
2279/2279 [==============================] - 4s 2ms/step - loss: 0.0030 - accuracy: 0.9994 - val_loss: 0.0038 - val_accuracy: 0.9993
```

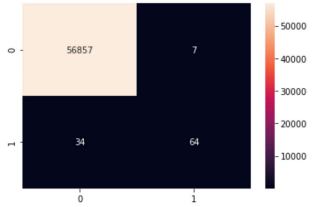
In [66]:
```
plt.plot(history_epoch_2.history['accuracy'], label='train')
plt.plot(history_epoch_2.history['val_accuracy'], label='val')
plt.legend()
plt.show()

plt.plot(history_epoch_2.history['loss'], label='train')
plt.plot(history_epoch_2.history['val_loss'], label='val')
plt.title('Model Loss')
plt.legend()
plt.show()
```

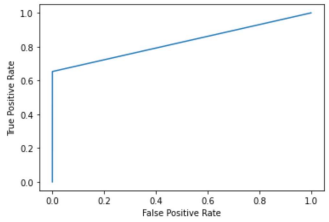




In [67]:
```
y_pred_1=(model.predict(X_test)>0.5).astype('int32')
accu=accuracy_score(y_val,y_pred_1)
con_matrix=confusion_matrix(y_val,y_pred_1)
clf_rep=classification_report(y_val,y_pred_1,zero_division=0)

print ("Model Accuracy: ", '{}%'.format(np.round(accu, 3) * 100))
print()
print("Classification Report:" "\n", clf_rep)
print()
sns.heatmap(con_matrix,annot=True, fmt="d")
plt.show()
# calculate roc curve
fpr, tpr, thresholds = roc_curve(y_val, y_pred_1)
plt.plot(fpr,tpr)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.show()
```

```
Model Accuracy:  99.9%

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56864
           1       0.90      0.65      0.76        98

    accuracy                           1.00     56962
   macro avg       0.95      0.83      0.88     56962
weighted avg       1.00      1.00      1.00     56962
```





The Change in the Epochs Nos doesn't Change much in the model Performance even if we increases or Decrease the numbers

Epochs No.	F1 Score
50	0.77
75	0.75
30	0.76

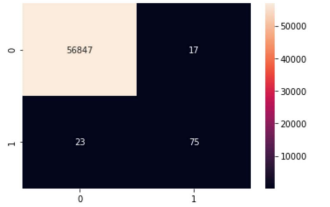
In [ ]:

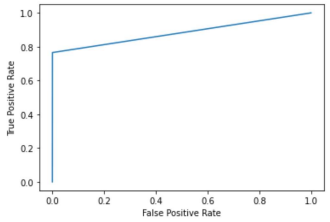
In [68]:
```
# Change in Batch size
history_batch_1=model.fit(X,y,validation_data=(X_val,y_val),epochs=50,batch_size=50,callbacks=[es])
```

```
Epoch 1/50
4557/4557 [==============================] - 7s 2ms/step - loss: 0.0032 - accuracy: 0.9994 - val_loss: 0.0040 - val_accuracy: 0.9993
Epoch 2/50
4557/4557 [==============================] - 8s 2ms/step - loss: 0.0031 - accuracy: 0.9994 - val_loss: 0.0050 - val_accuracy: 0.9991
Epoch 3/50
4557/4557 [==============================] - 7s 2ms/step - loss: 0.0031 - accuracy: 0.9994 - val_loss: 8.6368 - val_accuracy: 0.1323
Epoch 4/50
4557/4557 [==============================] - 7s 2ms/step - loss: 0.0031 - accuracy: 0.9994 - val_loss: 0.0037 - val_accuracy: 0.9992
Epoch 5/50
4557/4557 [==============================] - 8s 2ms/step - loss: 0.0031 - accuracy: 0.9994 - val_loss: 0.0083 - val_accuracy: 0.9991
Epoch 6/50
4557/4557 [==============================] - 8s 2ms/step - loss: 0.0032 - accuracy: 0.9994 - val_loss: 0.0119 - val_accuracy: 0.9989
Epoch 7/50
4557/4557 [==============================] - 8s 2ms/step - loss: 0.0032 - accuracy: 0.9994 - val_loss: 0.0265 - val_accuracy: 0.9983
Epoch 8/50
4557/4557 [==============================] - 7s 2ms/step - loss: 0.0031 - accuracy: 0.9994 - val_loss: 0.0042 - val_accuracy: 0.9993
Epoch 9/50
4557/4557 [==============================] - 8s 2ms/step - loss: 0.0032 - accuracy: 0.9994 - val_loss: 0.0034 - val_accuracy: 0.9993
Epoch 10/50
4557/4557 [==============================] - 7s 2ms/step - loss: 0.0031 - accuracy: 0.9994 - val_loss: 0.0058 - val_accuracy: 0.9992
Epoch 11/50
4557/4557 [==============================] - 8s 2ms/step - loss: 0.0032 - accuracy: 0.9993 - val_loss: 0.0109 - val_accuracy: 0.9991
Epoch 12/50
4557/4557 [==============================] - 8s 2ms/step - loss: 0.0031 - accuracy: 0.9994 - val_loss: 0.0131 - val_accuracy: 0.9989
Epoch 13/50
4557/4557 [==============================] - 8s 2ms/step - loss: 0.0031 - accuracy: 0.9994 - val_loss: 0.0662 - val_accuracy: 0.9986
Epoch 14/50
4557/4557 [==============================] - 8s 2ms/step - loss: 0.0031 - accuracy: 0.9994 - val_loss: 0.0102 - val_accuracy: 0.9989
Epoch 15/50
4557/4557 [==============================] - 8s 2ms/step - loss: 0.0032 - accuracy: 0.9994 - val_loss: 0.0102 - val_accuracy: 0.9992
Epoch 16/50
4557/4557 [==============================] - 8s 2ms/step - loss: 0.0031 - accuracy: 0.9994 - val_loss: 0.0151 - val_accuracy: 0.9987
Epoch 17/50
4557/4557 [==============================] - 8s 2ms/step - loss: 0.0031 - accuracy: 0.9994 - val_loss: 3.0666 - val_accuracy: 0.0959
Epoch 18/50
4557/4557 [==============================] - 7s 2ms/step - loss: 0.0031 - accuracy: 0.9994 - val_loss: 0.0045 - val_accuracy: 0.9992
Epoch 19/50
4550/4557 [============================>.] - ETA: 0s - loss: 0.0031 - accuracy: 0.9994Restoring model weights from the end of the best epoch.
4557/4557 [==============================] - 7s 2ms/step - loss: 0.0031 - accuracy: 0.9994 - val_loss: 0.3812 - val_accuracy: 0.7924
Epoch 00019: early stopping
```

In [69]:
```
y_pred_1=(model.predict(X_test)>0.5).astype('int32')
accu=accuracy_score(y_val,y_pred_1)
con_matrix=confusion_matrix(y_val,y_pred_1)
clf_rep=classification_report(y_val,y_pred_1,zero_division=0)

print ("Model Accuracy: ", '{}%'.format(np.round(accu, 3) * 100))
print()
print("Classification Report:" "\n", clf_rep)
print()
sns.heatmap(con_matrix,annot=True, fmt="d")
plt.show()
# calculate roc curve
fpr, tpr, thresholds = roc_curve(y_val, y_pred_1)
plt.plot(fpr,tpr)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.show()
```

```
Model Accuracy:  99.9%

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56864
           1       0.82      0.77      0.79        98

    accuracy                           1.00     56962
   macro avg       0.91      0.88      0.89     56962
weighted avg       1.00      1.00      1.00     56962
```



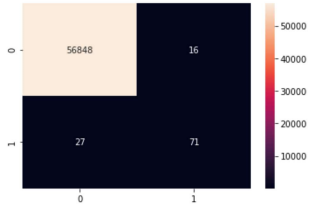


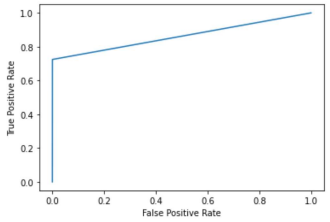
In [73]:
```
history_batch_1=model.fit(X,y,validation_data=(X_val,y_val),epochs=50,batch_size=30,callbacks=[es])
```

```
Epoch 1/50
7595/7595 [==============================] - 13s 2ms/step - loss: 0.0032 - accuracy: 0.9994 - val_loss: 0.0122 - val_accuracy: 0.9990
Epoch 2/50
7595/7595 [==============================] - 13s 2ms/step - loss: 0.0032 - accuracy: 0.9993 - val_loss: 0.0045 - val_accuracy: 0.9993
Epoch 3/50
7595/7595 [==============================] - 13s 2ms/step - loss: 0.0033 - accuracy: 0.9993 - val_loss: 0.0608 - val_accuracy: 0.9959
Epoch 4/50
7595/7595 [==============================] - 13s 2ms/step - loss: 0.0032 - accuracy: 0.9994 - val_loss: 0.6437 - val_accuracy: 0.5509
Epoch 5/50
7595/7595 [==============================] - 12s 2ms/step - loss: 0.0032 - accuracy: 0.9994 - val_loss: 0.1572 - val_accuracy: 0.9472
Epoch 6/50
7595/7595 [==============================] - 12s 2ms/step - loss: 0.0032 - accuracy: 0.9994 - val_loss: 12.4939 - val_accuracy: 0.0890
Epoch 7/50
7595/7595 [==============================] - 13s 2ms/step - loss: 0.0032 - accuracy: 0.9994 - val_loss: 0.0036 - val_accuracy: 0.9992
Epoch 8/50
7595/7595 [==============================] - 13s 2ms/step - loss: 0.0033 - accuracy: 0.9994 - val_loss: 0.0049 - val_accuracy: 0.9993
Epoch 9/50
7595/7595 [==============================] - 12s 2ms/step - loss: 0.0032 - accuracy: 0.9994 - val_loss: 10.2905 - val_accuracy: 0.0477
Epoch 10/50
7595/7595 [==============================] - 12s 2ms/step - loss: 0.0032 - accuracy: 0.9994 - val_loss: 0.5653 - val_accuracy: 0.8292
Epoch 11/50
7595/7595 [==============================] - 13s 2ms/step - loss: 0.0033 - accuracy: 0.9994 - val_loss: 0.0036 - val_accuracy: 0.9993
Epoch 12/50
7595/7595 [==============================] - 13s 2ms/step - loss: 0.0032 - accuracy: 0.9994 - val_loss: 0.0041 - val_accuracy: 0.9993
Epoch 13/50
7595/7595 [==============================] - 13s 2ms/step - loss: 0.0032 - accuracy: 0.9993 - val_loss: 0.0392 - val_accuracy: 0.9982
Epoch 14/50
7595/7595 [==============================] - 12s 2ms/step - loss: 0.0031 - accuracy: 0.9994 - val_loss: 0.3858 - val_accuracy: 0.8315
Epoch 15/50
7595/7595 [==============================] - 13s 2ms/step - loss: 0.0032 - accuracy: 0.9994 - val_loss: 0.0051 - val_accuracy: 0.9992
Epoch 16/50
7595/7595 [==============================] - 13s 2ms/step - loss: 0.0033 - accuracy: 0.9993 - val_loss: 3.2088 - val_accuracy: 0.3872
Epoch 17/50
7582/7595 [============================>.] - ETA: 0s - loss: 0.0032 - accuracy: 0.9994Restoring model weights from the end of the best epoch.
7595/7595 [==============================] - 13s 2ms/step - loss: 0.0032 - accuracy: 0.9994 - val_loss: 0.0562 - val_accuracy: 0.9722
Epoch 00017: early stopping
```

In [74]:
```
y_pred_1=(model.predict(X_test)>0.5).astype('int32')
accu=accuracy_score(y_val,y_pred_1)
con_matrix=confusion_matrix(y_val,y_pred_1)
clf_rep=classification_report(y_val,y_pred_1,zero_division=0)

print ("Model Accuracy: ", '{}%'.format(np.round(accu, 3) * 100))
print()
print("Classification Report:" "\n", clf_rep)
print()
sns.heatmap(con_matrix,annot=True, fmt="d")
plt.show()
# calculate roc curve
fpr, tpr, thresholds = roc_curve(y_val, y_pred_1)
plt.plot(fpr,tpr)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.show()
```

```
Model Accuracy:  99.9%

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56864
           1       0.82      0.72      0.77        98

    accuracy                           1.00     56962
   macro avg       0.91      0.86      0.88     56962
weighted avg       1.00      1.00      1.00     56962
```



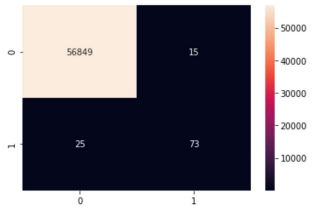


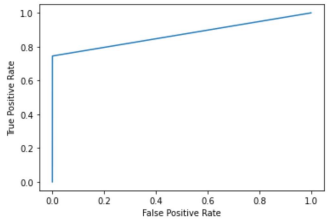
In [131]:
```
history_batch_2=model.fit(X,y,validation_data=(X_val,y_val),epochs=25,batch_size=150,callbacks=[es])
```

```
Epoch 1/25
1519/1519 [==============================] - 3s 2ms/step - loss: 0.0058 - accuracy: 0.9989 - val_loss: 2.7235 - val_accuracy: 0.3174
Epoch 2/25
1519/1519 [==============================] - 3s 2ms/step - loss: 0.0044 - accuracy: 0.9992 - val_loss: 0.0141 - val_accuracy: 0.9987
Epoch 3/25
1519/1519 [==============================] - 3s 2ms/step - loss: 0.0038 - accuracy: 0.9993 - val_loss: 9.8470 - val_accuracy: 0.2603
Epoch 4/25
1519/1519 [==============================] - 3s 2ms/step - loss: 0.0037 - accuracy: 0.9993 - val_loss: 4.1893 - val_accuracy: 0.5381
Epoch 5/25
1519/1519 [==============================] - 3s 2ms/step - loss: 0.0035 - accuracy: 0.9993 - val_loss: 0.0460 - val_accuracy: 0.9985
Epoch 6/25
1519/1519 [==============================] - 3s 2ms/step - loss: 0.0035 - accuracy: 0.9993 - val_loss: 7.0624 - val_accuracy: 0.2152
Epoch 7/25
1519/1519 [==============================] - 3s 2ms/step - loss: 0.0037 - accuracy: 0.9992 - val_loss: 17.2997 - val_accuracy: 0.0377
Epoch 8/25
1519/1519 [==============================] - 3s 2ms/step - loss: 0.0033 - accuracy: 0.9993 - val_loss: 0.0045 - val_accuracy: 0.9993
Epoch 9/25
1519/1519 [==============================] - 3s 2ms/step - loss: 0.0033 - accuracy: 0.9993 - val_loss: 0.0229 - val_accuracy: 0.9988
Epoch 10/25
1519/1519 [==============================] - 3s 2ms/step - loss: 0.0032 - accuracy: 0.9993 - val_loss: 0.0122 - val_accuracy: 0.9989
Epoch 11/25
1519/1519 [==============================] - 3s 2ms/step - loss: 0.0034 - accuracy: 0.9992 - val_loss: 0.0107 - val_accuracy: 0.9989
Epoch 12/25
1519/1519 [==============================] - 3s 2ms/step - loss: 0.0032 - accuracy: 0.9994 - val_loss: 0.0112 - val_accuracy: 0.9989
Epoch 13/25
1519/1519 [==============================] - 3s 2ms/step - loss: 0.0032 - accuracy: 0.9994 - val_loss: 0.0155 - val_accuracy: 0.9989
Epoch 14/25
1519/1519 [==============================] - 3s 2ms/step - loss: 0.0031 - accuracy: 0.9994 - val_loss: 3.3743 - val_accuracy: 0.2516
Epoch 15/25
1519/1519 [==============================] - 3s 2ms/step - loss: 0.0031 - accuracy: 0.9994 - val_loss: 0.0047 - val_accuracy: 0.9993
Epoch 16/25
1519/1519 [==============================] - 3s 2ms/step - loss: 0.0030 - accuracy: 0.9994 - val_loss: 0.0059 - val_accuracy: 0.9992
Epoch 17/25
1519/1519 [==============================] - 3s 2ms/step - loss: 0.0031 - accuracy: 0.9994 - val_loss: 0.0121 - val_accuracy: 0.9991
Epoch 18/25
1492/1519 [============================>.] - ETA: 0s - loss: 0.0032 - accuracy: 0.9993Restoring model weights from the end of the best ep
och.
1519/1519 [==============================] - 3s 2ms/step - loss: 0.0032 - accuracy: 0.9993 - val_loss: 0.0059 - val_accuracy: 0.9991
Epoch 00018: early stopping
```

In [132]:
```
y_pred_1=(model.predict(X_test)>0.5).astype('int32')
accu=accuracy_score(y_val,y_pred_1)
con_matrix=confusion_matrix(y_val,y_pred_1)
clf_rep=classification_report(y_val,y_pred_1,zero_division=0)

print ("Model Accuracy: ", '{}%'.format(np.round(accu, 3) * 100))
print()
print("Classification Report:" "\n", clf_rep)
print()
sns.heatmap(con_matrix,annot=True, fmt="d")
plt.show()
# calculate roc curve
fpr, tpr, thresholds = roc_curve(y_val, y_pred_1)
plt.plot(fpr,tpr)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.show()
```

```
Model Accuracy:  99.9%

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56864
           1       0.83      0.74      0.78        98

    accuracy                           1.00     56962
   macro avg       0.91      0.87      0.89     56962
weighted avg       1.00      1.00      1.00     56962
```





In [ ]:

The Change in the Batch Size Nos doesn't Change much in the model Performance even if we increases or Decrease the numbers

Batch Size	F1 Score
30	0.77
50	0.79
100	0.77
150	0.77

Using GridSearch_CV to find the best parameters for the model

In [75]:
```
def classifier(optimizer='adam',activation='sigmoid',learn_rate=0.01):
  model_CV = Sequential()
  model_CV.add(Dense(24, input_dim=21, activation='relu', kernel_initializer='he_uniform'))
  model_CV.add(BatchNormalization())

  model_CV.add(Dense(units=32,activation='relu'))
  model_CV.add(BatchNormalization())

  model_CV.add(Dense(units=24,activation='relu'))
  model_CV.add(BatchNormalization())

  model_CV.add(Dense(1, activation=activation))
  model_CV.compile(loss='binary_crossentropy', optimizer=optimizer, metrics=['accuracy'])
  return model_CV
```

In [76]:
```
keras_classifier=KerasClassifier(build_fn=classifier)
```

In [77]:
```
# define the grid search parameters
optimizer = ['SGD', 'Adagrad', 'Adam','Adamax']
learn_rate = [0.01,0.05, 0.1, 0.2]
activation = ['softmax', 'relu', 'sigmoid']
dropout_rate = [0.0, 0.1, 0.2, 0.3, 0.4, 0.5]
```

In [78]:
```
param_grid = dict(optimizer=optimizer,
                  learn_rate=learn_rate,
                  activation=activation)
```

In [124]:
```
grid = GridSearchCV(estimator=keras_classifier, param_grid=param_grid, n_jobs=-1)
grid_result = grid.fit(X,y)


# summarize results
print("Best: %f using %s" % (grid_result.best_score_, grid_result.best_params_))
means = grid_result.cv_results_['mean_test_score']
stds = grid_result.cv_results_['std_test_score']
params = grid_result.cv_results_['params']
for mean, stdev, param in zip(means, stds, params):
    print("%f (%f) with: %r" % (mean, stdev, param))
```

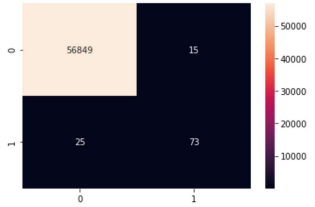
```
/usr/local/lib/python3.6/dist-packages/joblib/externals/loky/process_executor.py:691: UserWarning: A worker stopped while some jobs were given to the executor. This can be caused by a too short worker timeout or by a memory leak.
  "timeout or by a memory leak.", UserWarning

7121/7121 [==============================] - 9s 1ms/step - loss: 0.0308 - accuracy: 0.9972
Best: 0.998297 using {'activation': 'sigmoid', 'learn_rate': 0.1, 'optimizer': 'Adamax'}
0.001729 (0.000175) with: {'activation': 'softmax', 'learn_rate': 0.01, 'optimizer': 'SGD'}
0.001729 (0.000175) with: {'activation': 'softmax', 'learn_rate': 0.01, 'optimizer': 'Adagrad'}
0.001729 (0.000175) with: {'activation': 'softmax', 'learn_rate': 0.01, 'optimizer': 'Adam'}
0.001729 (0.000175) with: {'activation': 'softmax', 'learn_rate': 0.01, 'optimizer': 'Adamax'}
0.001729 (0.000175) with: {'activation': 'softmax', 'learn_rate': 0.05, 'optimizer': 'SGD'}
0.001729 (0.000175) with: {'activation': 'softmax', 'learn_rate': 0.05, 'optimizer': 'Adagrad'}
0.001729 (0.000175) with: {'activation': 'softmax', 'learn_rate': 0.05, 'optimizer': 'Adam'}
0.001729 (0.000175) with: {'activation': 'softmax', 'learn_rate': 0.05, 'optimizer': 'Adamax'}
0.001729 (0.000175) with: {'activation': 'softmax', 'learn_rate': 0.1, 'optimizer': 'SGD'}
0.001729 (0.000175) with: {'activation': 'softmax', 'learn_rate': 0.1, 'optimizer': 'Adagrad'}
0.001729 (0.000175) with: {'activation': 'softmax', 'learn_rate': 0.1, 'optimizer': 'Adam'}
0.001729 (0.000175) with: {'activation': 'softmax', 'learn_rate': 0.1, 'optimizer': 'Adamax'}
0.001729 (0.000175) with: {'activation': 'softmax', 'learn_rate': 0.2, 'optimizer': 'SGD'}
0.001729 (0.000175) with: {'activation': 'softmax', 'learn_rate': 0.2, 'optimizer': 'Adagrad'}
0.001729 (0.000175) with: {'activation': 'softmax', 'learn_rate': 0.2, 'optimizer': 'Adam'}
0.001729 (0.000175) with: {'activation': 'softmax', 'learn_rate': 0.2, 'optimizer': 'Adamax'}
0.998231 (0.000209) with: {'activation': 'relu', 'learn_rate': 0.01, 'optimizer': 'SGD'}
0.998218 (0.000193) with: {'activation': 'relu', 'learn_rate': 0.01, 'optimizer': 'Adagrad'}
0.998262 (0.000181) with: {'activation': 'relu', 'learn_rate': 0.01, 'optimizer': 'Adam'}
0.998165 (0.000187) with: {'activation': 'relu', 'learn_rate': 0.01, 'optimizer': 'Adamax'}
0.998240 (0.000174) with: {'activation': 'relu', 'learn_rate': 0.05, 'optimizer': 'SGD'}
0.998240 (0.000176) with: {'activation': 'relu', 'learn_rate': 0.05, 'optimizer': 'Adagrad'}
0.957686 (0.081040) with: {'activation': 'relu', 'learn_rate': 0.05, 'optimizer': 'Adam'}
0.998179 (0.000156) with: {'activation': 'relu', 'learn_rate': 0.05, 'optimizer': 'Adamax'}
0.998240 (0.000181) with: {'activation': 'relu', 'learn_rate': 0.1, 'optimizer': 'SGD'}
0.971630 (0.046430) with: {'activation': 'relu', 'learn_rate': 0.1, 'optimizer': 'Adagrad'}
0.998231 (0.000176) with: {'activation': 'relu', 'learn_rate': 0.1, 'optimizer': 'Adam'}
0.998293 (0.000134) with: {'activation': 'relu', 'learn_rate': 0.1, 'optimizer': 'Adamax'}
0.998249 (0.000179) with: {'activation': 'relu', 'learn_rate': 0.2, 'optimizer': 'SGD'}
0.998258 (0.000185) with: {'activation': 'relu', 'learn_rate': 0.2, 'optimizer': 'Adagrad'}
0.998222 (0.000185) with: {'activation': 'relu', 'learn_rate': 0.2, 'optimizer': 'Adam'}
0.998244 (0.000165) with: {'activation': 'relu', 'learn_rate': 0.2, 'optimizer': 'Adamax'}
0.998249 (0.000183) with: {'activation': 'sigmoid', 'learn_rate': 0.01, 'optimizer': 'SGD'}
0.998143 (0.000247) with: {'activation': 'sigmoid', 'learn_rate': 0.01, 'optimizer': 'Adagrad'}
0.830038 (0.336391) with: {'activation': 'sigmoid', 'learn_rate': 0.01, 'optimizer': 'Adam'}
0.810389 (0.359095) with: {'activation': 'sigmoid', 'learn_rate': 0.01, 'optimizer': 'Adamax'}
0.998258 (0.000177) with: {'activation': 'sigmoid', 'learn_rate': 0.05, 'optimizer': 'SGD'}
0.998157 (0.000230) with: {'activation': 'sigmoid', 'learn_rate': 0.05, 'optimizer': 'Adagrad'}
0.998244 (0.000197) with: {'activation': 'sigmoid', 'learn_rate': 0.05, 'optimizer': 'Adam'}
0.834997 (0.325398) with: {'activation': 'sigmoid', 'learn_rate': 0.05, 'optimizer': 'Adamax'}
0.998227 (0.000158) with: {'activation': 'sigmoid', 'learn_rate': 0.1, 'optimizer': 'SGD'}
0.998258 (0.000162) with: {'activation': 'sigmoid', 'learn_rate': 0.1, 'optimizer': 'Adagrad'}
0.998218 (0.000197) with: {'activation': 'sigmoid', 'learn_rate': 0.1, 'optimizer': 'Adam'}
0.998297 (0.000190) with: {'activation': 'sigmoid', 'learn_rate': 0.1, 'optimizer': 'Adamax'}
0.998227 (0.000199) with: {'activation': 'sigmoid', 'learn_rate': 0.2, 'optimizer': 'SGD'}
0.998266 (0.000171) with: {'activation': 'sigmoid', 'learn_rate': 0.2, 'optimizer': 'Adagrad'}
0.854225 (0.288115) with: {'activation': 'sigmoid', 'learn_rate': 0.2, 'optimizer': 'Adam'}
0.805052 (0.386353) with: {'activation': 'sigmoid', 'learn_rate': 0.2, 'optimizer': 'Adamax'}
```

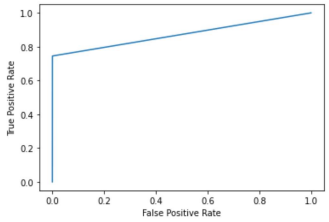
In [125]:
```
grid_result.best_params_
```

Out[125]:
```
{'activation': 'sigmoid', 'learn_rate': 0.1, 'optimizer': 'Adamax'}
```

In [133]:
```
y_pred_1=(grid.predict(X_test)>0.5).astype('int32')
accu=accuracy_score(y_val,y_pred_1)
con_matrix=confusion_matrix(y_val,y_pred_1)
clf_rep=classification_report(y_val,y_pred_1,zero_division=0)

print ("Model Accuracy: ", '{}%'.format(np.round(accu, 3) * 100))
print()
print("Classification Report:" "\n", clf_rep)
print()
sns.heatmap(con_matrix,annot=True, fmt="d")
plt.show()
# calculate roc curve
fpr, tpr, thresholds = roc_curve(y_val, y_pred_1)
plt.plot(fpr,tpr)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.show()
```

```
Model Accuracy:  99.9%

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56864
           1       0.83      0.74      0.78        98

    accuracy                           1.00     56962
   macro avg       0.91      0.87      0.89     56962
weighted avg       1.00      1.00      1.00     56962
```





In [ ]:

Anomaly Detection using the Inter Quartile Range method.

In [ ]:

In [79]:
```
# We shall use the Validation data sets for the steps
val_df=pd.read_csv('/content/drive/My Drive/Capstone_Project/test_data_hidden.csv')

val_df['Amount_Stand'] = scaler.fit_transform(val_df['Amount'].values.reshape(-1,1))
val_df=val_df.drop('Amount',axis=1)
```

In [80]:
```
test_df=pd.read_csv('/content/drive/My Drive/Capstone_Project/test_data.csv')

test_df['Amount_Stand'] = scaler.fit_transform(test_df['Amount'].values.reshape(-1,1))
test_df=test_df.drop('Amount',axis=1)
```

In [81]:
```
Q1 = val_df.quantile(0.25)
Q3 = val_df.quantile(0.75)

IQR = Q3 - Q1
print(IQR)
```

```
Time             84948.750000
V1                   2.228317
V2                   1.401371
V3                   1.910858
V4                   1.586305
V5                   1.309512
V6                   1.162945
V7                   1.120866
V8                   0.536095
V9                   1.241706
V10                  0.988180
V11                  1.496742
V12                  1.022559
V13                  1.316119
V14                  0.911374
V15                  1.224599
V16                  0.992674
V17                  0.887576
V18                  0.996978
V19                  0.914603
V20                  0.342839
V21                  0.415019
V22                  1.073514
V23                  0.310164
V24                  0.794256
V25                  0.664632
V26                  0.568052
V27                  0.160941
V28                  0.129834
Class                0.000000
Amount_Stand         1.000000
dtype: float64
```

In [83]:
```
col_name = 'Amount_Stand'
low  = Q1[col_name] - 1.5 * IQR[col_name]
high = Q3[col_name] + 1.5 * IQR[col_name]

low, high
```

Out[83]: (-1.7265423941016902, 2.27345760589831)

In [84]:
```
# Filtering Values between Q1-1.5IQR and Q3+1.5IQR
query_string = '{} < @low or {} > @high'.format(col_name, col_name)

outlier_arr1 = val_df.query(query_string).index
outlier_arr1
```

Out[84]:
```
Int64Index([    5,    17,    37,    40,    67,    72,    98,    99,   101,
              117,
            ...
            56812, 56825, 56847, 56852, 56859, 56877, 56902, 56918, 56937,
            56945],
           dtype='int64', length=6320)
```

In [85]:
```
# Find the Anomaly outliers
init = False

for col_name in list(val_df.columns):

    low  = Q1[col_name] - 1.5 * IQR[col_name]
    high = Q3[col_name] + 1.5 * IQR[col_name]

    query_string = '{} < @low or {} > @high'.format(col_name, col_name)

    outlier_arr_loop = val_df.query(query_string).index

    if not init:
        outlier_arr = outlier_arr_loop
        init = True

    outlier_arr = outlier_arr.union(outlier_arr_loop)
```

In [86]:
```
# Lets Extract the Anomaly Data Sets from the Validation Data
anomaly_df=val_df.iloc[outlier_arr]
anomaly_df
```

Out[86]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14
1	26667.0	-0.039318	0.495784	-0.810884	0.546693	1.986257	4.386342	-1.344891	-1.743736	-0.563103	-0.616315	-0.587786	0.317419	-0.408521	0.719639
5	55069.0	0.441380	-2.217230	0.802581	-0.127056	-1.867945	0.495430	-0.741205	0.214230	-0.198782	0.311865	1.308096	0.644987	0.029716	-0.594013
6	135629.0	1.937007	0.394490	-0.860965	3.720728	0.458475	0.159445	0.017991	0.024848	-0.615042	1.511407	-1.706707	-1.172083	-1.492230	0.453003
7	33643.0	-0.552654	-0.279974	2.626373	0.535665	-1.350645	0.523387	0.124452	0.076345	-0.800457	0.498082	-0.691389	-1.059067	-1.193405	-0.315771
8	80729.0	-2.760629	2.206112	-0.193100	0.764237	-0.718603	-0.920526	0.228957	0.507112	0.084184	1.200311	-0.516928	0.668461	1.020972	0.317697
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
56948	92437.0	2.076251	-1.002324	0.075623	-0.036659	-1.061289	0.504667	-1.393393	0.055859	1.904680	0.196185	-0.738811	-1.767448	2.918756	0.355505
56949	63981.0	-0.870892	0.432589	0.970395	1.529227	2.793893	4.226519	-0.357106	1.168700	-1.179056	0.287702	-0.693478	-0.360441	-0.115741	-0.030648
56953	157273.0	1.716127	0.008542	0.207395	3.814778	-0.434853	0.419651	-0.565365	0.254429	-0.485550	1.578050	0.284249	-0.014221	-0.892248	0.203525
56954	35641.0	-0.906365	0.103318	1.244399	0.676516	1.485228	0.205018	0.084021	0.107232	-0.887351	-0.195039	-1.114959	0.015297	1.407310	0.092644
56961	66373.0	-7.792712	5.599937	0.258943	0.061360	-2.586555	4.770837	-8.221863	-20.298380	2.028566	-0.030694	-1.062381	2.770191	-0.732390	0.095124

27588 rows × 31 columns

In [87]:
```
ano_count=anomaly_df['Class'].value_counts()
ano_count
```

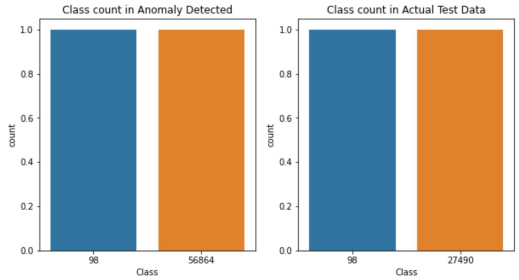
Out[87]:
```
0    27490
1       98
Name: Class, dtype: int64
```

In [89]:
```
true_count=val_df.Class.value_counts()
true_count
```

Out[89]:
```
0    56864
1       98
Name: Class, dtype: int64
```

From the above methodlogy we can observe that we have sucessfully extracted all the fraudulant data points. We have 98 fraud data points in our Orginal test data set. After using the IQR method we where able to extract all the 98 fraud values

In [90]:
```
fig,(ax1,ax2)=plt.subplots(1,2,figsize=(10,5))
sns.countplot(x=true_count,ax=ax1)
ax1.set_title('Class count in Anomaly Detected')
sns.countplot(x=ano_count,ax=ax2)
ax2.set_title('Class count in Actual Test Data')
plt.show()
```



In [ ]:

Project Task: Week 4

Inference and Observations:

Visualize the scores for Fraudulent and Non-Fraudulent transactions. Find out the threshold value for marking or reporting a transaction as fraudulent in your anomaly detection system. Can this score be used as an engineered feature in the models developed previously? Are there any incremental gains in F1-Score.

Determining the Threshold value and its affects on the model prediction

Using Z Score method

In [91]:
```
val_df=pd.read_csv('/content/drive/My Drive/Capstone_Project/test_data_hidden.csv')
val_df['Amount_Stand'] = scaler.fit_transform(val_df['Amount'].values.reshape(-1,1))
val_df=val_df.drop('Amount',axis=1)
```

In [92]:
```
from scipy import stats


z=np.abs(stats.zscore(val_df))
```

Setting the threshold at 3 and 4 for anomaly values. And checking there affects on the ML and ANN model

In [93]:
```
threshold = 3

result = np.where(z > threshold)
result
```

Out[93]:
```
(array([    1,    20,    23, ..., 56961, 56961, 56961]),
 array([ 6, 13, 12, ..., 21, 22, 23]))
```

In [94]:
```
threshold = 4

result_1 = np.where(z > threshold)
result_1
```

Out[94]:
```
(array([   29,    29,    40, ..., 56961, 56961, 56961]),
 array([ 7, 23,  5, ..., 21, 22, 23]))
```

In [95]:
```
print('Outliers at Threshold 3',(len(result[0]),len(result[1])))
print('Outliers at Threshold 4',(len(result_1[0]),len(result_1[1])))
```

```
Outliers at Threshold 3 (16633, 16633)
Outliers at Threshold 4 (7315, 7315)
```

In [96]:
```
outlier_3 = pd.DataFrame(data=result[0], columns=['ROWNUM'])
outlier_3['COLNUM'] = result[1]
outlier_3
```

Out[96]:

	ROWNUM	COLNUM
0	1	6
1	20	13
2	23	12
3	29	7
4	29	8
...	...	...
16628	56961	8
16629	56961	17
16630	56961	21
16631	56961	22
16632	56961	23

16633 rows × 2 columns

In [97]:
```
outlier_4 = pd.DataFrame(data=result_1[0], columns=['ROWNUM'])
outlier_4['COLNUM'] = result_1[1]
outlier_4
```

Out[97]:

	ROWNUM	COLNUM
0	29	7
1	29	23
2	40	5
3	40	6
4	40	8
...	...	...
7310	56961	7
7311	56961	8
7312	56961	21
7313	56961	22
7314	56961	23

7315 rows × 2 columns

In [98]:
```
outlier_3.COLNUM.value_counts()
```

Out[98]:
```
20    955
2     899
27    897
6     848
8     848
21    824
1     786
30    755
10    705
19    702
28    688
14    682
12    656
23    639
4     637
7     606
25    571
5     502
17    487
9     464
3     408
16    407
18    342
22    263
15    250
13    246
26    203
11    136
24    129
29     98
Name: COLNUM, dtype: int64
```

In [99]:
```
outlier_4.COLNUM.value_counts()
```

Out[99]:
```
8     579
27    536
20    524
21    503
30    482
10    455
2     444
23    403
1     376
28    373
7     335
5     247
14    240
9     208
17    199
3     189
6     162
25    161
19    122
26    111
12    110
22    106
16     99
29     98
4      84
18     68
11     57
24     30
15     11
13      3
Name: COLNUM, dtype: int64
```

In [100]:
```
columns =val_df.columns
columns
```

Out[100]:
```
Index(['Time', 'V1', 'V2', 'V3', 'V4', 'V5', 'V6', 'V7', 'V8', 'V9', 'V10',
       'V11', 'V12', 'V13', 'V14', 'V15', 'V16', 'V17', 'V18', 'V19', 'V20',
       'V21', 'V22', 'V23', 'V24', 'V25', 'V26', 'V27', 'V28', 'Class',
       'Amount_Stand'],
      dtype='object')
```

In [101]:
```
outlier_3['COLNAME'] = columns[outlier_3.COLNUM]
outlier_3.head(10)
```

Out[101]:

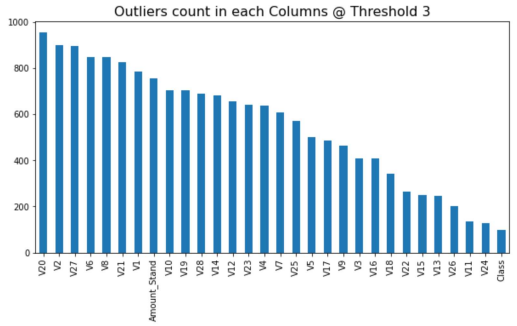
	ROWNUM	COLNUM	COLNAME
0	1	6	V6
1	20	13	V13
2	23	12	V12
3	29	7	V7
4	29	8	V8
5	29	21	V21
6	29	23	V23
7	29	25	V25
8	30	19	V19
9	30	25	V25

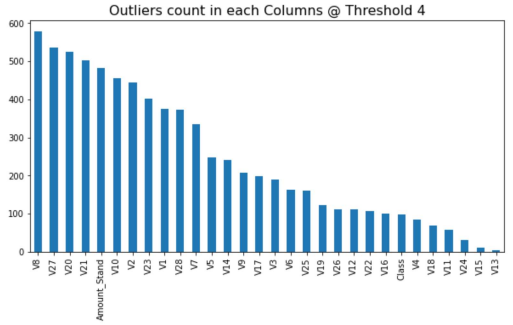
In [102]:
```
outlier_4['COLNAME'] = columns[outlier_4.COLNUM]
outlier_4.head(10)
```

Out[102]:

	ROWNUM	COLNUM	COLNAME
0	29	7	V7
1	29	23	V23
2	40	5	V5
3	40	6	V6
4	40	8	V8
5	40	10	V10
6	40	21	V21
7	40	22	V22
8	40	27	V27
9	40	28	V28

In [103]:
```
plt.figure(figsize=(10,5))
outlier_3.COLNAME.value_counts(sort=True).plot(kind='bar')
plt.title("Outliers count in each Columns @ Threshold 3",fontsize=16)
plt.show()

plt.figure(figsize=(10,5))
outlier_4.COLNAME.value_counts(sort=True).plot(kind='bar')
plt.title("Outliers count in each Columns @ Threshold 4",fontsize=16)
plt.show()
```





In [104]:
```
new_3df=val_df.drop(['V20','V2','V27','V6','V8','V1','V21','V10','V19'],axis=1)

test_3df=test_df.drop(['V20','V2','V27','V6','V8','V1','V21','V10','V19'],axis=1)
new_3df.shape
```

Out[104]:
```
(56962, 22)
```

In [105]:
```
new_3df.describe()
```

Out[105]:

	Time	V3	V4	V5	V7	V9	V11	V12	V13	V14	V15	569
count	56962.000000	56962.000000	56962.000000	56962.000000	56962.000000	56962.000000	56962.000000	56962.000000	56962.000000	56962.000000	56962.000000	
mean	95057.882360	-0.004263	0.001496	-0.003508	0.000141	0.001564	-0.008330	-0.000041	-0.000320	-0.003711	0.002949	
std	47438.688395	1.516853	1.419107	1.431731	1.301800	1.103688	1.015901	0.997691	0.994583	0.954667	0.912533	
min	2.000000	-48.325589	-5.560118	-113.743307	-28.215112	-9.481456	-4.009307	-18.553697	-3.848943	-19.214325	-4.092344	-1
25%	54286.250000	-0.893961	-0.847617	-0.694059	-0.551096	-0.642072	-0.768230	-0.405703	-0.648105	-0.423884	-0.575757	
50%	85226.500000	0.170910	-0.022094	-0.051828	0.039155	-0.052607	-0.043537	0.140321	-0.013682	0.046713	0.051535	
75%	139235.000000	1.016897	0.738688	0.615454	0.569769	0.599634	0.728512	0.616856	0.668013	0.487491	0.648842	
max	172785.000000	3.985446	15.304184	29.016124	120.589494	10.370658	12.018913	4.846452	7.126883	7.421944	8.877742	

The threshold of **4** is set and outliers are Anomoly are detected.

We shall drop columns which has outliers of count around and more of 350 data points from our training data sets. And then use them in our ML models and compare the changes. We observe outliers in Amount too but it is a important feature so we shall scale it has done before.

In [106]:
```
new_4df=val_df.drop(['V27','V8','V20','V21','V10','V2','V23','V7','V1'],axis=1)
test_4df=test_df.drop(['V27','V8','V20','V21','V10','V2','V23','V7','V1'],axis=1)

new_4df.shape
```

Out[106]: (56962, 22)

In [107]:
```
new_4df.describe()
```

Out[107]:

	Time	V3	V4	V5	V6	V9	V11	V12	V13	V14	V15	569
count	56962.000000	56962.000000	56962.000000	56962.000000	56962.000000	56962.000000	56962.000000	56962.000000	56962.000000	56962.000000	56962.000000	
mean	95057.882360	-0.004263	0.001496	-0.003508	-0.003079	0.001564	-0.008330	-0.000041	-0.000320	-0.003711	0.002949	
std	47438.688395	1.516853	1.419107	1.431731	1.359647	1.103688	1.015901	0.997691	0.994583	0.954667	0.912533	
min	2.000000	-48.325589	-5.560118	-113.743307	-20.054615	-9.481456	-4.009307	-18.553697	-3.848943	-19.214325	-4.092344	-1
25%	54286.250000	-0.893961	-0.847617	-0.694059	-0.770145	-0.642072	-0.768230	-0.405703	-0.648105	-0.423884	-0.575757	
50%	85226.500000	0.170910	-0.022094	-0.051828	-0.278939	-0.052607	-0.043537	0.140321	-0.013682	0.046713	0.051535	
75%	139235.000000	1.016897	0.738688	0.615454	0.392801	0.599634	0.728512	0.616856	0.668013	0.487491	0.648842	
max	172785.000000	3.985446	15.304184	29.016124	73.301626	10.370658	12.018913	4.846452	7.126883	7.421944	8.877742	

In [108]:
```
X3=new_3df.drop(['Class'],axis=1)
y3=new_3df['Class']

X4=new_4df.drop(['Class'],axis=1)
y4=new_4df['Class']
```

In [109]:
```
X_3train,X_3val,y_3train,y_3val=train_test_split(X3,y3,test_size=0.35,random_state=1)

X_4train,X_4val,y_4train,y_4val=train_test_split(X4,y4,test_size=0.35,random_state=1)
```

In [110]:
```
X_3train.shape,X_3val.shape
```

Out[110]: ((37025, 21), (19937, 21))

In [111]:
```
X_4train.shape,X_4val.shape
```

Out[111]: ((37025, 21), (19937, 21))

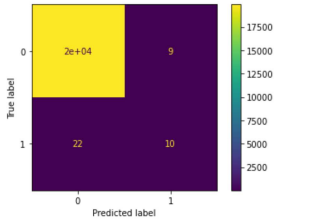
In [112]:
```
# Train Logistic Regression model
Log_clf.fit(X_3train,y_3train)

# Train Navie Bayes
NB_clf.fit(X_3train,y_3train)
```

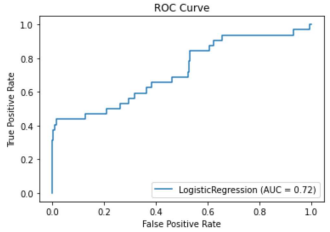
Out[112]: BernoulliNB(alpha=1.0, binarize=0.0, class_prior=None, fit_prior=True)

In [113]:
```
moodel_list=[('Logistic Regression Classifier ',Log_clf),
             ('Navie Base BernoulliNB',NB_clf)]
models=[m for m in moodel_list]
```

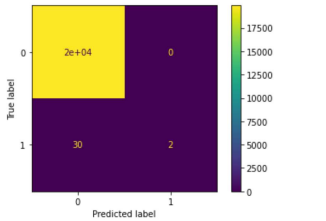
In [114]:
```
print('================ *Model Evaluation @ Threshold 3 Results* ================','\n')

for i,v in models:
    pred=v.predict(X_3val)
    accu=accuracy_score(y_3val,pred)
    con_matrix=confusion_matrix(y_3val,pred)
    clf_rep=classification_report(y_3val,pred,zero_division=0)

    print('===== {} ====='.format(i))

    print ("Model Accuracy: ", '{}%'.format(accu))
    print()
    print("Classification Report:" "\n", clf_rep)
    print()
    print("Confusion Matrix:")
    sklearn.metrics.plot_confusion_matrix(v,X_3val,y_3val)
    print()

    sklearn.metrics.plot_roc_curve(v,X_3val,y_3val)
    plt.title('ROC Curve')
    plt.show()
```

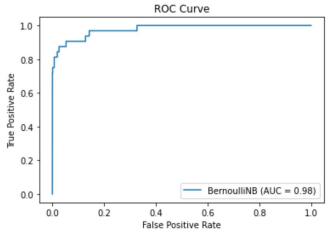
```
================ *Model Evaluation @ Threshold 3 Results* =================

===== Logistic Regression Classifier  =====
Model Accuracy:  0.9984451020715253%

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     19905
           1       0.53      0.31      0.39        32

    accuracy                           1.00     19937
   macro avg       0.76      0.66      0.70     19937
weighted avg       1.00      1.00      1.00     19937


Confusion Matrix:
```






```
===== Navie Base BernoulliNB =====
Model Accuracy:  0.9984952600692181%

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     19905
           1       1.00      0.06      0.12        32

    accuracy                           1.00     19937
   macro avg       1.00      0.53      0.56     19937
weighted avg       1.00      1.00      1.00     19937


Confusion Matrix:
```



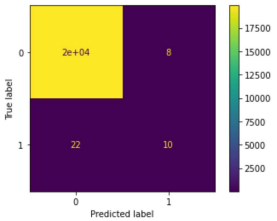


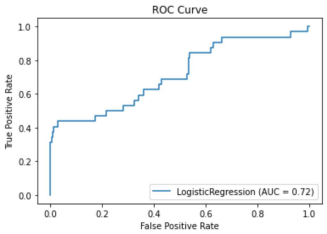
In [115]:
```
# Train Logistic Regression model
Log_clf.fit(X_4train,y_4train)


# Train Navie Bayes
NB_clf.fit(X_4train,y_4train)
```

Out[115]:
```
BernoulliNB(alpha=1.0, binarize=0.0, class_prior=None, fit_prior=True)
```

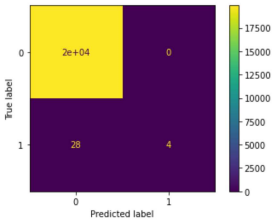
In [116]:
```
print('================ *Model Evaluation  @ Threshold 4 Results* ================','\n')

for i,v in models:
    pred=v.predict(X_4val)
    accu=accuracy_score(y_4val,pred)
    con_matrix=confusion_matrix(y_4val,pred)
    clf_rep=classification_report(y_4val,pred,zero_division=0)

    print('===== {} ====='.format(i))
    print ("Model Accuracy: ", accu)
    print()
    print("Classification Report:" "\n", clf_rep)
    print()
    print("Confusion Matrix:")
    sklearn.metrics.plot_confusion_matrix(v,X_4val,y_4val)
    print()

    sklearn.metrics.plot_roc_curve(v,X_4val,y_4val)
    plt.title('ROC Curve')
    plt.show()
```

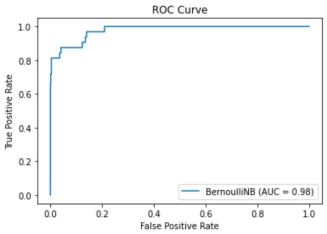
```
================ *Model Evaluation  @ Threshold 4 Results* ================

===== Logistic Regression Classifier  =====
Model Accuracy:  0.9984952600692181

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     19905
           1       0.56      0.31      0.40        32

    accuracy                           1.00     19937
   macro avg       0.78      0.66      0.70     19937
weighted avg       1.00      1.00      1.00     19937


Confusion Matrix:
```






```
===== Navie Base BernoulliNB =====
Model Accuracy:  0.9985955760646035

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     19905
           1       1.00      0.12      0.22        32

    accuracy                           1.00     19937
   macro avg       1.00      0.56      0.61     19937
weighted avg       1.00      1.00      1.00     19937


Confusion Matrix:
```





In [117]:
```
model = Sequential()
model.add(Dense(24, input_dim=21, activation='relu', kernel_initializer='he_uniform'))
model.add(BatchNormalization())

model.add(Dense(units=32,activation='relu'))
model.add(BatchNormalization())

model.add(Dense(units=24,activation='relu'))
model.add(BatchNormalization())

model.add(Dense(1, activation='sigmoid'))
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
```

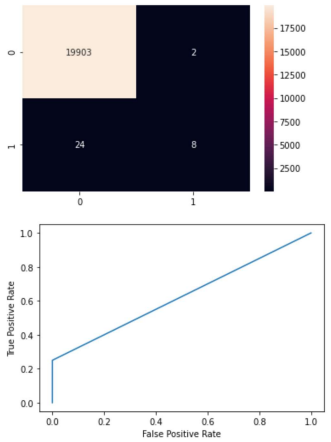
In [118]:
```
# fit the data
history3=model.fit(X_3train,y_3train,validation_data=(X_3val,y_3val),epochs=50,batch_size=50)
```

```
Epoch 1/50
741/741 [==============================] - 2s 2ms/step - loss: 0.1475 - accuracy: 0.9858 - val_loss: 0.0123 - val_accuracy: 0.9983
Epoch 2/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0153 - accuracy: 0.9981 - val_loss: 0.0642 - val_accuracy: 0.9859
Epoch 3/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0133 - accuracy: 0.9982 - val_loss: 0.0274 - val_accuracy: 0.9983
Epoch 4/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0132 - accuracy: 0.9982 - val_loss: 0.5589 - val_accuracy: 0.6990
Epoch 5/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0130 - accuracy: 0.9982 - val_loss: 0.0217 - val_accuracy: 0.9983
Epoch 6/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0127 - accuracy: 0.9982 - val_loss: 0.0198 - val_accuracy: 0.9983
Epoch 7/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0100 - accuracy: 0.9984 - val_loss: 0.0721 - val_accuracy: 0.9983
Epoch 8/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0074 - accuracy: 0.9986 - val_loss: 6.6146 - val_accuracy: 0.0369
Epoch 9/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0067 - accuracy: 0.9988 - val_loss: 0.0963 - val_accuracy: 0.9984
Epoch 10/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0064 - accuracy: 0.9988 - val_loss: 0.0697 - val_accuracy: 0.9987
Epoch 11/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0064 - accuracy: 0.9986 - val_loss: 0.1873 - val_accuracy: 0.9984
Epoch 12/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0058 - accuracy: 0.9987 - val_loss: 0.0135 - val_accuracy: 0.9985
Epoch 13/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0055 - accuracy: 0.9989 - val_loss: 0.0309 - val_accuracy: 0.9984
Epoch 14/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0055 - accuracy: 0.9989 - val_loss: 0.1137 - val_accuracy: 0.9983
Epoch 15/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0057 - accuracy: 0.9990 - val_loss: 0.9754 - val_accuracy: 0.5468
Epoch 16/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0059 - accuracy: 0.9989 - val_loss: 0.1529 - val_accuracy: 0.9843
Epoch 17/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0054 - accuracy: 0.9989 - val_loss: 0.0182 - val_accuracy: 0.9985
Epoch 18/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0061 - accuracy: 0.9989 - val_loss: 0.8753 - val_accuracy: 0.7264
Epoch 19/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0070 - accuracy: 0.9989 - val_loss: 2.0369 - val_accuracy: 0.9982
Epoch 20/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0054 - accuracy: 0.9990 - val_loss: 12.0677 - val_accuracy: 0.2654
Epoch 21/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0062 - accuracy: 0.9989 - val_loss: 1.5554 - val_accuracy: 0.9982
Epoch 22/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0050 - accuracy: 0.9990 - val_loss: 1.3819 - val_accuracy: 0.9981
Epoch 23/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0066 - accuracy: 0.9986 - val_loss: 0.8652 - val_accuracy: 0.9905
Epoch 24/50
741/741 [==============================] - 2s 2ms/step - loss: 0.0056 - accuracy: 0.9990 - val_loss: 2.2953 - val_accuracy: 0.5115
Epoch 25/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0044 - accuracy: 0.9993 - val_loss: 0.0433 - val_accuracy: 0.9992
Epoch 26/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0044 - accuracy: 0.9992 - val_loss: 7.3340 - val_accuracy: 0.4149
Epoch 27/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0047 - accuracy: 0.9991 - val_loss: 22.6352 - val_accuracy: 0.0057
Epoch 28/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0044 - accuracy: 0.9991 - val_loss: 8.4750 - val_accuracy: 0.2510
Epoch 29/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0043 - accuracy: 0.9990 - val_loss: 0.0295 - val_accuracy: 0.9986
Epoch 30/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0056 - accuracy: 0.9986 - val_loss: 19.7940 - val_accuracy: 0.0481
Epoch 31/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0046 - accuracy: 0.9991 - val_loss: 0.0360 - val_accuracy: 0.9985
Epoch 32/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0047 - accuracy: 0.9990 - val_loss: 0.0155 - val_accuracy: 0.9986
Epoch 33/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0051 - accuracy: 0.9990 - val_loss: 0.9963 - val_accuracy: 0.6990
Epoch 34/50
741/741 [==============================] - 2s 2ms/step - loss: 0.0046 - accuracy: 0.9991 - val_loss: 0.0215 - val_accuracy: 0.9985
Epoch 35/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0045 - accuracy: 0.9990 - val_loss: 0.0088 - val_accuracy: 0.9993
Epoch 36/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0046 - accuracy: 0.9990 - val_loss: 4.7799 - val_accuracy: 0.4807
Epoch 37/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0044 - accuracy: 0.9990 - val_loss: 0.0088 - val_accuracy: 0.9989
Epoch 38/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0047 - accuracy: 0.9991 - val_loss: 30.8042 - val_accuracy: 0.0365
Epoch 39/50
741/741 [==============================] - 2s 2ms/step - loss: 0.0045 - accuracy: 0.9991 - val_loss: 0.0137 - val_accuracy: 0.9987
Epoch 40/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0045 - accuracy: 0.9991 - val_loss: 47.0118 - val_accuracy: 0.0319
Epoch 41/50
741/741 [==============================] - 2s 2ms/step - loss: 0.0045 - accuracy: 0.9991 - val_loss: 0.0175 - val_accuracy: 0.9993
Epoch 42/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0046 - accuracy: 0.9990 - val_loss: 0.0334 - val_accuracy: 0.9984
Epoch 43/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0044 - accuracy: 0.9990 - val_loss: 0.0137 - val_accuracy: 0.9988
Epoch 44/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0047 - accuracy: 0.9991 - val_loss: 0.0059 - val_accuracy: 0.9991
Epoch 45/50
741/741 [==============================] - 2s 2ms/step - loss: 0.0047 - accuracy: 0.9991 - val_loss: 9.9291 - val_accuracy: 0.1293
Epoch 46/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0042 - accuracy: 0.9992 - val_loss: 18.8097 - val_accuracy: 0.0492
Epoch 47/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0043 - accuracy: 0.9990 - val_loss: 0.0200 - val_accuracy: 0.9987
Epoch 48/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0049 - accuracy: 0.9990 - val_loss: 0.0367 - val_accuracy: 0.9984
Epoch 49/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0046 - accuracy: 0.9989 - val_loss: 7.0024 - val_accuracy: 0.3140
Epoch 50/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0048 - accuracy: 0.9990 - val_loss: 0.0075 - val_accuracy: 0.9987
```

In [119]:

```
y_pred=(model.predict(X_3val)>0.5).astype('int32')
accu=accuracy_score(y_3val,y_pred)
con_matrix=confusion_matrix(y_3val,y_pred)
clf_rep=classification_report(y_3val,y_pred,zero_division=0)

print ("Model Accuracy: ", '{}%'.format(np.round(accu, 3) * 100))
print()
print("Classification Report:" "\n", clf_rep)
print()
sns.heatmap(con_matrix,annot=True, fmt="d")
plt.show()
# calculate roc curve
fpr, tpr, thresholds = roc_curve(y_3val, y_pred)
plt.plot(fpr,tpr)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.show()
```

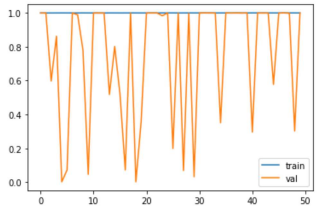
```
Model Accuracy:  99.9%

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     19905
           1       0.80      0.25      0.38        32

    accuracy                           1.00     19937
   macro avg       0.90      0.62      0.69     19937
weighted avg       1.00      1.00      1.00     19937
```



In [121]:
```
history4=model.fit(X_4train,y_4train,validation_data=(X_4val,y_4val),epochs=50,batch_size=50)
```

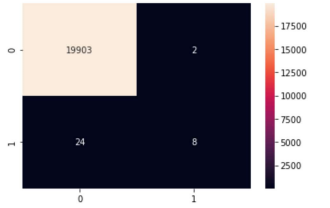
```
Epoch 1/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0046 - accuracy: 0.9990 - val_loss: 0.0081 - val_accuracy: 0.9987
Epoch 2/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0044 - accuracy: 0.9990 - val_loss: 0.0124 - val_accuracy: 0.9987
Epoch 3/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0043 - accuracy: 0.9990 - val_loss: 1.3250 - val_accuracy: 0.5972
Epoch 4/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0039 - accuracy: 0.9990 - val_loss: 0.3067 - val_accuracy: 0.8621
Epoch 5/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0041 - accuracy: 0.9992 - val_loss: 20.0669 - val_accuracy: 0.0024
Epoch 6/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0042 - accuracy: 0.9991 - val_loss: 6.7662 - val_accuracy: 0.0722
Epoch 7/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0042 - accuracy: 0.9991 - val_loss: 0.0110 - val_accuracy: 0.9988
Epoch 8/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0042 - accuracy: 0.9990 - val_loss: 0.0622 - val_accuracy: 0.9879
Epoch 9/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0042 - accuracy: 0.9992 - val_loss: 0.3941 - val_accuracy: 0.7815
Epoch 10/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0044 - accuracy: 0.9991 - val_loss: 13.2472 - val_accuracy: 0.0463
Epoch 11/50
741/741 [==============================] - 2s 2ms/step - loss: 0.0052 - accuracy: 0.9989 - val_loss: 0.0090 - val_accuracy: 0.9990
Epoch 12/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0050 - accuracy: 0.9988 - val_loss: 0.0117 - val_accuracy: 0.9987
Epoch 13/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0045 - accuracy: 0.9989 - val_loss: 0.0905 - val_accuracy: 0.9985
Epoch 14/50
741/741 [==============================] - 2s 2ms/step - loss: 0.0045 - accuracy: 0.9991 - val_loss: 3.3146 - val_accuracy: 0.5177
Epoch 15/50
741/741 [==============================] - 2s 2ms/step - loss: 0.0044 - accuracy: 0.9991 - val_loss: 0.3790 - val_accuracy: 0.8013
Epoch 16/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0043 - accuracy: 0.9990 - val_loss: 3.7885 - val_accuracy: 0.5198
Epoch 17/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0043 - accuracy: 0.9991 - val_loss: 22.1246 - val_accuracy: 0.0727
Epoch 18/50
741/741 [==============================] - 2s 2ms/step - loss: 0.0043 - accuracy: 0.9992 - val_loss: 0.0065 - val_accuracy: 0.9989
Epoch 19/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0043 - accuracy: 0.9991 - val_loss: 8.4129 - val_accuracy: 0.0022
Epoch 20/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0043 - accuracy: 0.9990 - val_loss: 8.6236 - val_accuracy: 0.3590
Epoch 21/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0038 - accuracy: 0.9991 - val_loss: 0.0644 - val_accuracy: 0.9985
Epoch 22/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0039 - accuracy: 0.9992 - val_loss: 0.0129 - val_accuracy: 0.9988
Epoch 23/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0039 - accuracy: 0.9991 - val_loss: 0.0150 - val_accuracy: 0.9989
Epoch 24/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0040 - accuracy: 0.9991 - val_loss: 0.1030 - val_accuracy: 0.9824
Epoch 25/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0037 - accuracy: 0.9992 - val_loss: 0.0046 - val_accuracy: 0.9994
Epoch 26/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0040 - accuracy: 0.9993 - val_loss: 12.4890 - val_accuracy: 0.1990
Epoch 27/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0043 - accuracy: 0.9990 - val_loss: 0.0705 - val_accuracy: 0.9985
Epoch 28/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0042 - accuracy: 0.9991 - val_loss: 24.8322 - val_accuracy: 0.0691
Epoch 29/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0039 - accuracy: 0.9992 - val_loss: 0.0279 - val_accuracy: 0.9970
Epoch 30/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0039 - accuracy: 0.9992 - val_loss: 29.9610 - val_accuracy: 0.0325
Epoch 31/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0038 - accuracy: 0.9992 - val_loss: 0.0248 - val_accuracy: 0.9987
Epoch 32/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0038 - accuracy: 0.9991 - val_loss: 0.0093 - val_accuracy: 0.9994
Epoch 33/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0039 - accuracy: 0.9992 - val_loss: 0.0129 - val_accuracy: 0.9988
Epoch 34/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0041 - accuracy: 0.9991 - val_loss: 0.0096 - val_accuracy: 0.9988
Epoch 35/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0040 - accuracy: 0.9991 - val_loss: 3.3579 - val_accuracy: 0.3510
Epoch 36/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0040 - accuracy: 0.9992 - val_loss: 0.0052 - val_accuracy: 0.9993
Epoch 37/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0042 - accuracy: 0.9991 - val_loss: 0.0211 - val_accuracy: 0.9986
Epoch 38/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0038 - accuracy: 0.9992 - val_loss: 0.0838 - val_accuracy: 0.9990
Epoch 39/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0040 - accuracy: 0.9990 - val_loss: 0.0631 - val_accuracy: 0.9985
Epoch 40/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0039 - accuracy: 0.9990 - val_loss: 0.0042 - val_accuracy: 0.9993
Epoch 41/50
741/741 [==============================] - 2s 2ms/step - loss: 0.0036 - accuracy: 0.9993 - val_loss: 3.9510 - val_accuracy: 0.2958
Epoch 42/50
741/741 [==============================] - 2s 2ms/step - loss: 0.0039 - accuracy: 0.9992 - val_loss: 0.0107 - val_accuracy: 0.9988
Epoch 43/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0038 - accuracy: 0.9992 - val_loss: 0.2744 - val_accuracy: 0.9985
Epoch 44/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0040 - accuracy: 0.9991 - val_loss: 0.0406 - val_accuracy: 0.9987
Epoch 45/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0040 - accuracy: 0.9992 - val_loss: 0.9187 - val_accuracy: 0.5773
Epoch 46/50
741/741 [==============================] - 2s 2ms/step - loss: 0.0040 - accuracy: 0.9991 - val_loss: 0.0080 - val_accuracy: 0.9989
Epoch 47/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0040 - accuracy: 0.9992 - val_loss: 0.0292 - val_accuracy: 0.9994
Epoch 48/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0038 - accuracy: 0.9992 - val_loss: 0.1661 - val_accuracy: 0.9976
Epoch 49/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0039 - accuracy: 0.9992 - val_loss: 1.8836 - val_accuracy: 0.3027
Epoch 50/50
741/741 [==============================] - 1s 2ms/step - loss: 0.0038 - accuracy: 0.9991 - val_loss: 0.0161 - val_accuracy: 0.9987
```

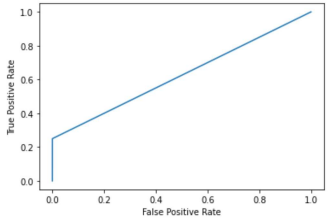
In [122]:
```
plt.plot(history4.history['accuracy'], label='train')
plt.plot(history4.history['val_accuracy'], label='val')
plt.legend()
plt.show()
```



In [123]:
```
y_pred=(model.predict(X_4val)>0.5).astype('int32')
accu=accuracy_score(y_4val,y_pred)
con_matrix=confusion_matrix(y_4val,y_pred)
clf_rep=classification_report(y_4val,y_pred,zero_division=0)

print ("Model Accuracy: ", '{}%'.format(np.round(accu, 3) * 100))
print()
print("Classification Report:" "\n", clf_rep)
print()
sns.heatmap(con_matrix,annot=True, fmt="d")
plt.show()
# calculate roc curve
fpr, tpr, thresholds = roc_curve(y_4val, y_pred)
plt.plot(fpr,tpr)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.show()
```

```
Model Accuracy:  99.9%

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     19905
           1       0.80      0.25      0.38        32

    accuracy                           1.00     19937
   macro avg       0.90      0.62      0.69     19937
weighted avg       1.00      1.00      1.00     19937
```





Model		Logistic Regression	Navie Based Model	ANN Model
Using Sampling Methos	F1 Score			
	Class 0	1	1	1
	Class 1	0.05	0.1	0.77
Z Score Method				
Threshold = 3	Class 0	1	1	1
	Class 1	0.39	0.12	0.38
Threshold = 4	Class 0	1	1	1
	Class 1	0.4	0.22	0.38

Above is the Compression of the models F1 Score of Best Score in Sampling Method and the Models When we process the Data Using Z Score method at Threshold **3 & 4**

1. We can say that the Machine Learning Models Perform Well we apply the Z sore Method but the ANN models underperform than Before.
2. When Comparision with Models at Thershold 3 and 4

- We Logistic Regression Model Doesn't Show much change but certainly better than the Sampling Data trained model.
- The Navie Based Classifier show large imporment in the model F1 score compored in previous method used

Hence I Would Suggest the Threshold Value to REmove the Outliers should Be 4

In [ ]:

Conclusion

After Various Methodolgy of Data Processing , Models Trainning and Tuning for the Fraud Detection in the highly Imblanced Data.

- The Data which we had obtained had large numbers of Outliers , Some of the Features were poorly distributre have even very low Variance.
- The EDA showed how the Fraud takes place through low amount but at a Large scale . We can say that the Since the Amount is low the Coustomer may Not Notice the fraud happened in there Account or may simple choose of ignore to rise the issues to the bank itself.
- After Training and Predcting the varoius ML model , We can observe that the Tree Based model which have the Class Ibmalnce Countering Fearuters Out Perform the Other type of ML Models.
- The Simple ANN models without much of Data processing of the Class outperform a some of the HyperTuned Machine Learing Model.
- The ANN models do work better then ML models but not much of increase in the Model Performance after various tuning methods.
- The Anomaly Detection using the Outliers Extraction Method works wells.
- The Threshold Of 4 can be used to in anamoly predicition.

In [ ]: