In [1]:

```
# Libraries

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import datetime
import math
import matplotlib # For versioning

# Print Versions for sharing Projects

print(f"Pandas Version : Pandas {pd.__version__}")
print(f"Numpy Version : Numpy {np.__version__}")
print(f"Matplotlib Version : Matplotlib {matplotlib.__version__}")
print(f"Seaborn Version : Seaborn {sns.__version__}")

# Magic Functions for In-Notebook Display

%matplotlib inline
```

```
Pandas Version : Pandas 0.24.2
Numpy Version : Numpy 1.16.4
Matplotlib Version : Matplotlib 3.1.0
Seaborn Version : Seaborn 0.9.0
```

In [2]:

```
df = pd.read_csv('creditcard.csv')
```

In [3]:

```

# Create a new cell - Esc+B
# Delete a new cell - Esc+X
# Creating a Markdown Cell - Esc+M

```

In [4]:

```
dir(pd.set_option.__setattr__)
```

Out[4]:

```
['__call__',
 '__class__',
 '__delattr__',
 '__dir__',
 '__doc__',
 '__eq__',
 '__format__',
 '__ge__',
 '__getattribute__',
 '__gt__',
 '__hash__',
 '__init__',
 '__init_subclass__',
 '__le__',
 '__lt__',
 '__name__',
 '__ne__',
 '__new__',
 '__objclass__',
 '__qualname__',
 '__reduce__',
 '__reduce_ex__',
 '__repr__',
 '__self__',
 '__setattr__',
 '__sizeof__',
 '__str__',
 '__subclasshook__',
 '__text_signature__']
```

In [5]:

```
#pd.set_option('display.max_rows' , 500)-To see 500 rows
df.head()
```

Out[5]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533

5 rows × 31 columns

In [6]:

```
df.tail()
```

Out[6]:

	Time	V1	V2	V3	V4	V5	V6	V7
284802	172786.0	-11.881118	10.071785	-9.834783	-2.066656	-5.364473	-2.606837	-4.918215
284803	172787.0	-0.732789	-0.055080	2.035030	-0.738589	0.868229	1.058415	0.024330
284804	172788.0	1.919565	-0.301254	-3.249640	-0.557828	2.630515	3.031260	-0.296827
284805	172788.0	-0.240440	0.530483	0.702510	0.689799	-0.377961	0.623708	-0.686180
284806	172792.0	-0.533413	-0.189733	0.703337	-0.506271	-0.012546	-0.649617	1.577006

5 rows × 31 columns

In [7]:

```
df.shape
```

Out[7]:

```
(284807, 31)
```

In [8]:

```
df.Class.unique()
```

Out[8]:

```
array([0, 1], dtype=int64)
```

In [9]:

```
df.Time.dtype
```

Out[9]:

```
dtype('float64')
```

In [10]:

```
# Amount column is not normalised !! > To be fixed later ( Pre processing task 2 )
# Normalising or Scaling means modifying values such that => Mean = 0 , Std Dev = 1
```

In [11]:

```
df.Class.unique()
# 0  - Genuine Class
# 1 - Fraud Class
```

Out[11]:

```
array([0, 1], dtype=int64)
```

In [12]:

```
# Better Design
print(f"Rows : {df.shape[0]}") # Also the length of the dataset
print(f"Columns : {df.shape[1]}")
```

```
Rows : 284807
Columns : 31
```

In [13]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 284807 entries, 0 to 284806
Data columns (total 31 columns):
Time      284807 non-null float64
V1        284807 non-null float64
V2        284807 non-null float64
V3        284807 non-null float64
V4        284807 non-null float64
V5        284807 non-null float64
V6        284807 non-null float64
V7        284807 non-null float64
V8        284807 non-null float64
V9        284807 non-null float64
V10       284807 non-null float64
V11       284807 non-null float64
V12       284807 non-null float64
V13       284807 non-null float64
V14       284807 non-null float64
V15       284807 non-null float64
V16       284807 non-null float64
V17       284807 non-null float64
V18       284807 non-null float64
V19       284807 non-null float64
V20       284807 non-null float64
V21       284807 non-null float64
V22       284807 non-null float64
V23       284807 non-null float64
V24       284807 non-null float64
V25       284807 non-null float64
V26       284807 non-null float64
V27       284807 non-null float64
V28       284807 non-null float64
Amount    284807 non-null float64
Class     284807 non-null int64
dtypes: float64(30), int64(1)
memory usage: 67.4 MB
```

In [14]:

```
# All data types are float64 ,except 1 : Class
# 28 columns have Sequential Names and values that don't make any logical sense - > V1 , V2
# 3 columns : TIME , AMOUNT and CLASS which can be analysed for various INSIGHTS !
# Memory Usage : 64 MB , not so Harsh !!
# Column names are not lower_case , must fix this : Standardisation ( Data Pre Processing T
# Null values currently don't exist in any column , no missing values !
```

In [15]:

```
df.describe() # Use df['col_name'] for column analysis
```

Out[15]:

	Time	V1	V2	V3	V4	V
count	284807.000000	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+0
mean	94813.859575	3.919560e-15	5.688174e-16	-8.769071e-15	2.782312e-15	-1.552563e-1
std	47488.145955	1.958696e+00	1.651309e+00	1.516255e+00	1.415869e+00	1.380247e+0
min	0.000000	-5.640751e+01	-7.271573e+01	-4.832559e+01	-5.683171e+00	-1.137433e+0
25%	54201.500000	-9.203734e-01	-5.985499e-01	-8.903648e-01	-8.486401e-01	-6.915971e-0
50%	84692.000000	1.810880e-02	6.548556e-02	1.798463e-01	-1.984653e-02	-5.433583e-0
75%	139320.500000	1.315642e+00	8.037239e-01	1.027196e+00	7.433413e-01	6.119264e-0
max	172792.000000	2.454930e+00	2.205773e+01	9.382558e+00	1.687534e+01	3.480167e+0

8 rows × 31 columns

In [16]:

```
df['Class'].quantile(0.999)
```

Out[16]:

```
1.0
```

In [17]:

```
df[['Amount' , 'Class' , 'Time']].describe()
```

Out[17]:

	Amount	Class	Time
count	284807.000000	284807.000000	284807.000000
mean	88.349619	0.001727	94813.859575
std	250.120109	0.041527	47488.145955
min	0.000000	0.000000	0.000000
25%	5.600000	0.000000	54201.500000
50%	22.000000	0.000000	84692.000000
75%	77.165000	0.000000	139320.500000
max	25691.160000	1.000000	172792.000000

In [18]:

```
#Observations -
#Time column is not in standard measures , probably in seconds , but max of time is not equ
#Amount Min is 0 , must observe that for some errors or outliers
#Unscaled amount with high possible skewness , based on min , max and mean
#Class Imbalance Issue surely Exists - Let's discuss this further
```

In [19]:

```
df.head(2)
```

Out[19]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0

2 rows × 31 columns

In [20]:

```
df[['Amount' , 'Class' , 'Time']].describe()   #include = 'all' for categorical
```

Out[20]:

	Amount	Class	Time
count	284807.000000	284807.000000	284807.000000
mean	88.349619	0.001727	94813.859575
std	250.120109	0.041527	47488.145955
min	0.000000	0.000000	0.000000
25%	5.600000	0.000000	54201.500000
50%	22.000000	0.000000	84692.000000
75%	77.165000	0.000000	139320.500000
max	25691.160000	1.000000	172792.000000

In [21]:

```
# Since the time column is not in any standard sense , Datetime format or Timestamp format
# And as it starts from 0 , the dataset must have a starting and ending point, let's find w
```

In [22]:

```
# Important to know the time span of the data -
print(df['Time'].min() / (60*60))
print(df['Time'].max() / (60*60)) # ~ 48 hours , so 2 days ! , better picture
```

```
0.0
47.99777777777778
```

In [23]:

```
df['Time'].max()
```

Out[23]:

```
172792.0
```

In [24]:

```
print(df.isnull().any().sum()) # 3 ways
print('\n')
print(df.isnull().sum())
print('\n')
print(df.isnull().values.any()) # df['col_name']
```

```
0


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


False
```

In [25]:

```
print(len(df.drop_duplicates())) # Length of dataframe > Length after drop_duplicates()
print(len(df[df.duplicated()]))  # 1081 duplicate values , remove them !
# Quality Wise : Duplicates / Total Length = 1081/284807 = 0.00379  = 0.38 %
```

```
283726
1081
```

In [26]:

```
len(df)
```

Out[26]:

```
284807
```

In [27]:

```
df.duplicated().value_counts()
```

Out[27]:

```
False    283726
True       1081
dtype: int64
```

In [28]:

```
# Removing the Duplicate Values
df.drop_duplicates(inplace = True)
print(len(df))  # some data reduced
```

```
283726
```

In [29]:

```
df.tail()
```

Out[29]:

	Time	V1	V2	V3	V4	V5	V6	V7
284802	172786.0	-11.881118	10.071785	-9.834783	-2.066656	-5.364473	-2.606837	-4.918215
284803	172787.0	-0.732789	-0.055080	2.035030	-0.738589	0.868229	1.058415	0.024330
284804	172788.0	1.919565	-0.301254	-3.249640	-0.557828	2.630515	3.031260	-0.296827
284805	172788.0	-0.240440	0.530483	0.702510	0.689799	-0.377961	0.623708	-0.686180
284806	172792.0	-0.533413	-0.189733	0.703337	-0.506271	-0.012546	-0.649617	1.577006

5 rows × 31 columns

In [30]:

```
df.reset_index(drop = True , inplace = True)
```

In [31]:

```
df.tail()
```

Out[31]:

	Time	V1	V2	V3	V4	V5	V6	V7
283721	172786.0	-11.881118	10.071785	-9.834783	-2.066656	-5.364473	-2.606837	-4.918215
283722	172787.0	-0.732789	-0.055080	2.035030	-0.738589	0.868229	1.058415	0.024330
283723	172788.0	1.919565	-0.301254	-3.249640	-0.557828	2.630515	3.031260	-0.296827
283724	172788.0	-0.240440	0.530483	0.702510	0.689799	-0.377961	0.623708	-0.686180
283725	172792.0	-0.533413	-0.189733	0.703337	-0.506271	-0.012546	-0.649617	1.577006

5 rows × 31 columns

In [32]:

```
df.columns
```

Out[32]:

```
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', 'Amount',
       'Class'],
      dtype='object')
```

In [33]:

```
# Converting all column names to lower case # Task -3
df.columns = df.columns.str.lower() # .upper()
```

In [34]:

```
df.columns
```

Out[34]:

```
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', 'amount',
       'class'],
      dtype='object')
```

In [35]:

```
#Let's understand the depth of the data using the three logically named columns : TIME , AM
```

In [36]:

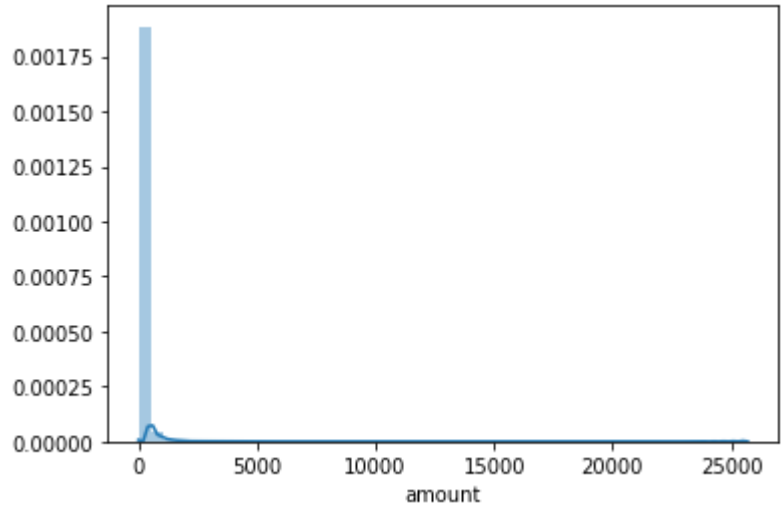
```
#Amount column
```

In [37]:

```
import warnings
warnings.filterwarnings('ignore') # USE this!
```

In [38]:

```
plt.figsize = (20,20)
sns.distplot(df['amount'])
plt.show()
```



In [39]:

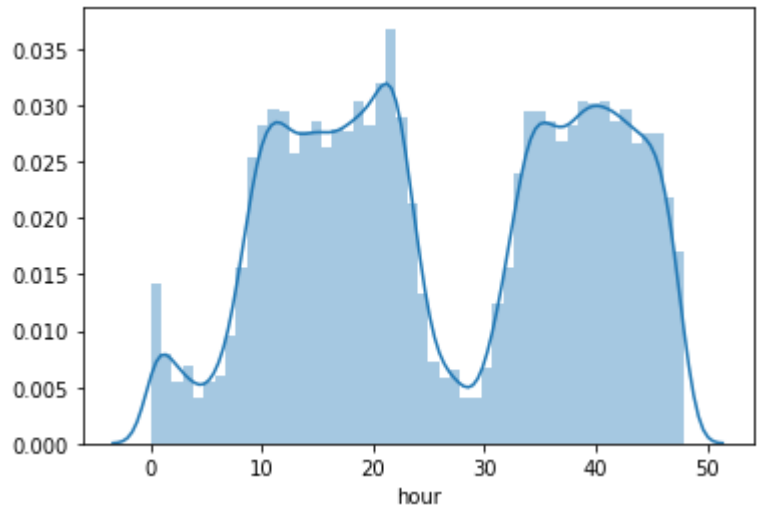
```
##Observation for the Amount Column:
#Data Set with respect to Amount is highly skewed, lots of small value / amount transaction
```

In [40]:

```
df['hour'] = df['time']/(60*60) # We should use the %24 hours
```

In [41]:

```
# Time plots
plt.figsize = (20,20)
sns.distplot(df['hour'])
plt.show()
```

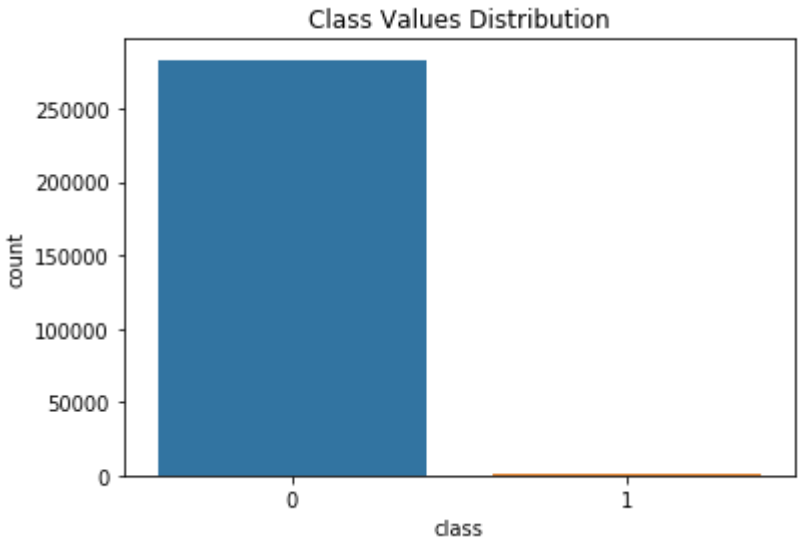


In [42]:

```
#Observation for Time:
#We can see during the night time there are less transactions happening hence that ridge in
```

In [43]:

```
#Class Plot
plt.figsize = (20,20)
sns.countplot(df['class']) # Highly Skewed , Imbalanced Data
plt.title('Class Values Distribution')
plt.show()
```



In [44]:

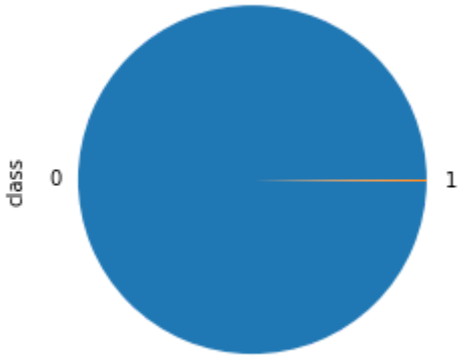
```
#We can see there's a huge imbalance in the Class coloumn.The no. of fraud transactions are
```

In [45]:

```
df['class'].value_counts().plot(kind = 'pie') # Different Style
# Plot the same pie chart with percnetages as legends !
# plt.legend( loc = 'right', labels=['%s, %1.1f %%' % (l, s) for l, s in zip(labels, sizes)
```

Out[45]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x29c0ad48198>
```

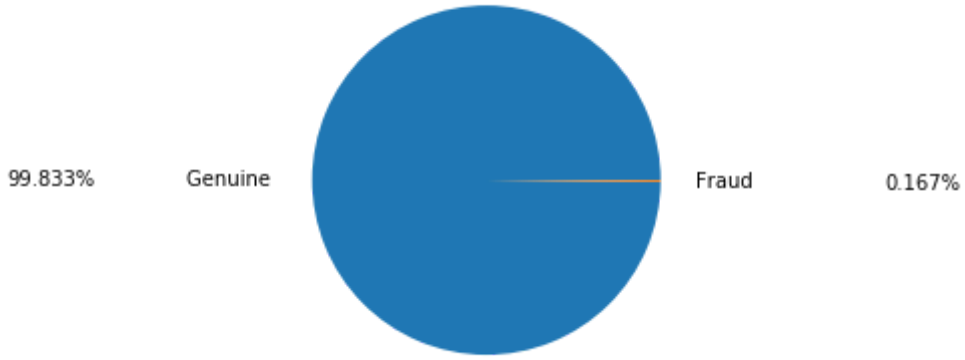


In [46]:

```
labels = ['Genuine ','Fraud ']
plt.pie(df['class'].value_counts(), labels=labels, autopct='%0.3f%%' , pctdistance=2.5, lab
```

Out[46]:

```
([<matplotlib.patches.Wedge at 0x29c0bcee0f0>,
  <matplotlib.patches.Wedge at 0x29c0bcee7f0>],
 [Text(-1.1999835424914616, 0.006284723513625731, 'Genuine '),
  Text(1.1999835428684147, -0.006284651539043478, 'Fraud ')],
 [Text(-2.499965713523878, 0.013093173986720275, '99.833%'),
  Text(2.4999657143091976, -0.013093024039673912, '0.167%')])
```



In [47]:

```
df['class'].value_counts()
# Class 0 is Legitimate , Genuine Transactions
# Class 1 represents Fraudulent Transactions
```

Out[47]:

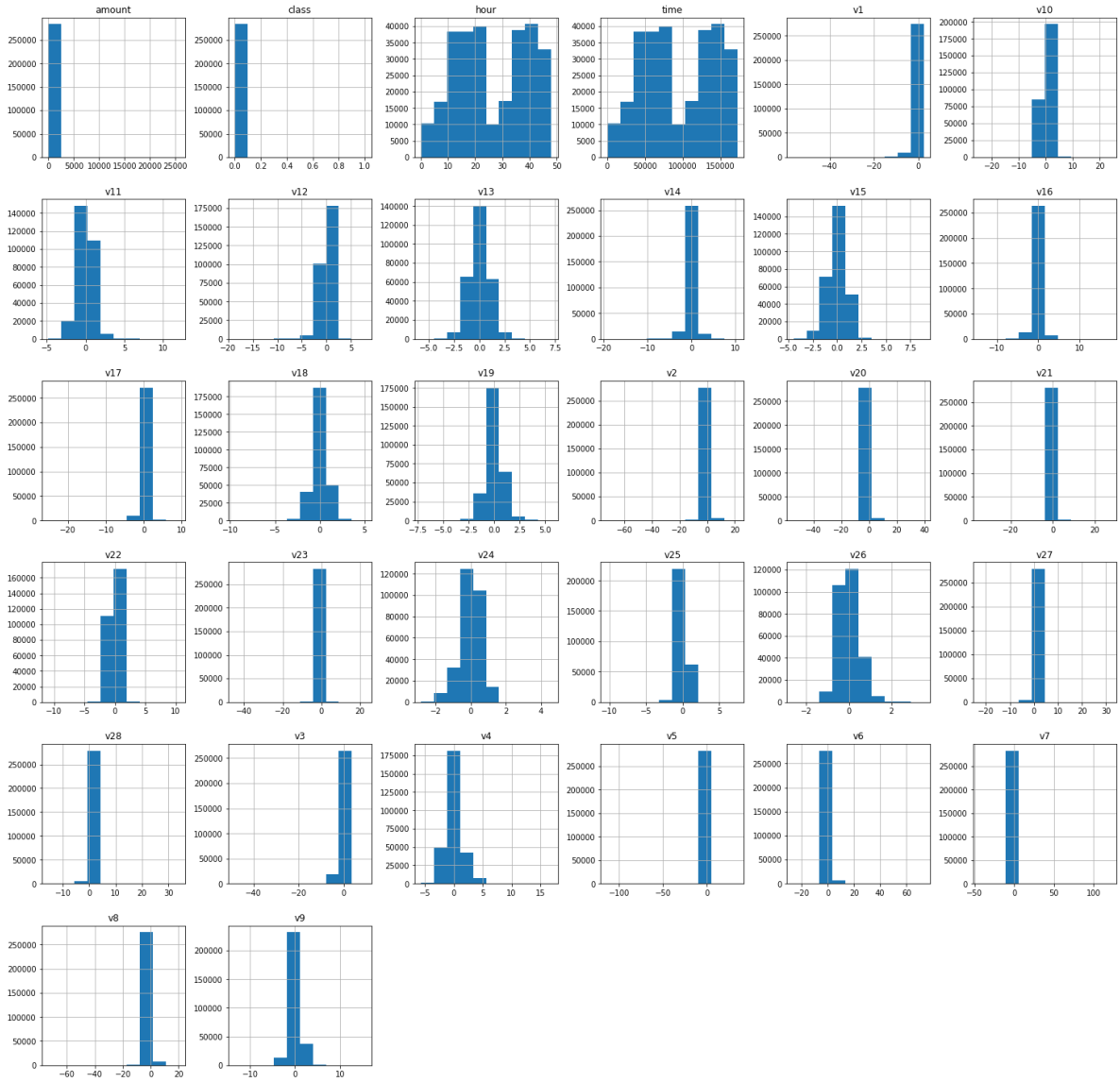
```
0    283253
1       473
Name: class, dtype: int64
```

In [48]:

```
#Visualising Data with Histogram Plots:
```

In [49]:

```
df.hist(figsize = (25,25))
plt.show()
```



In [50]:

```
df.corr()
```

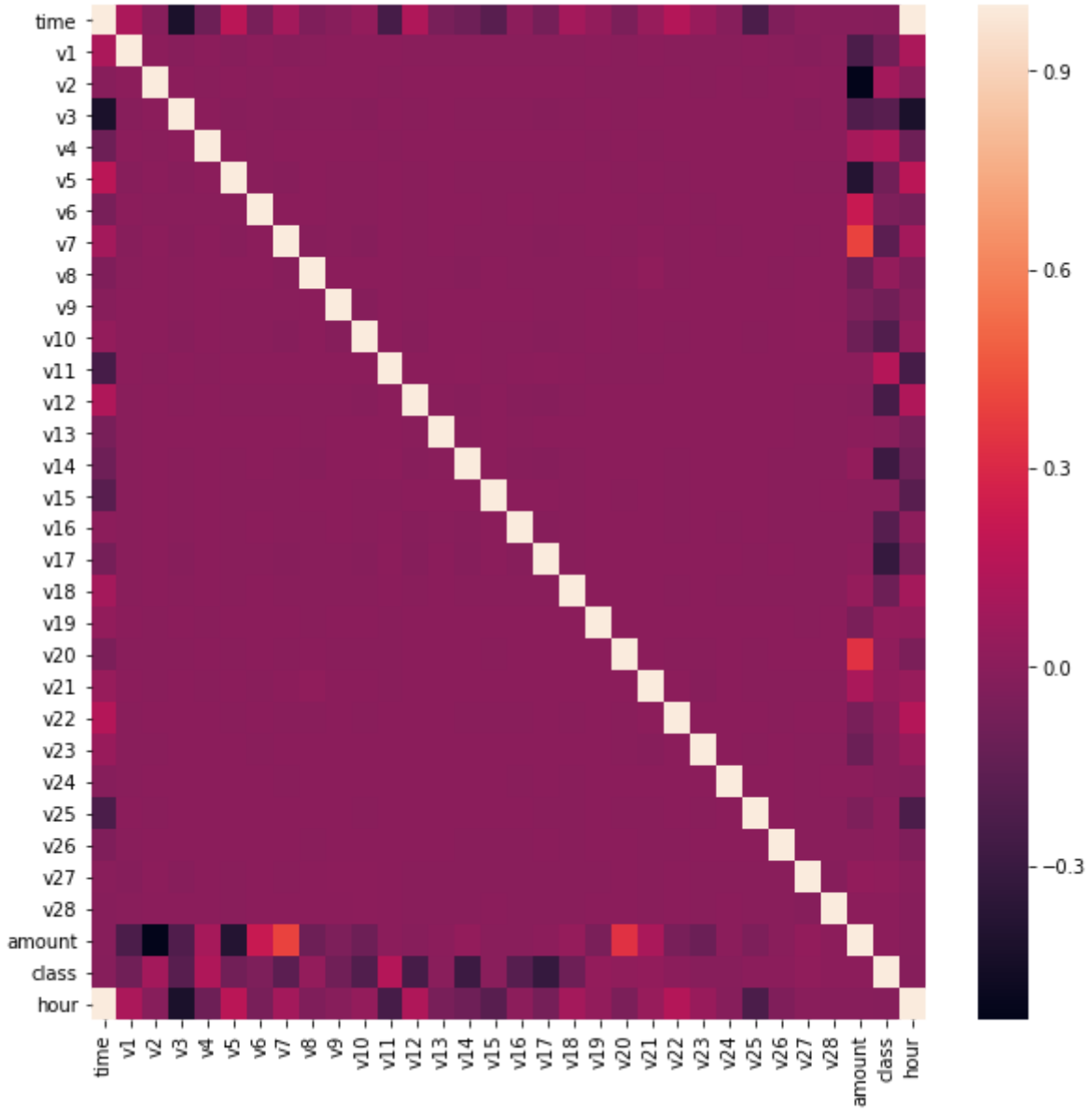
Out[50]:

	time	v1	v2	v3	v4	v5	v6	v7
time	1.000000	0.117927	-0.010556	-0.422054	-0.105845	0.173223	-0.063279	0.085335
v1	0.117927	1.000000	0.006875	-0.008112	0.002257	-0.007036	0.000413	-0.009173
v2	-0.010556	0.006875	1.000000	0.005278	-0.001495	0.005210	-0.000594	0.007425
v3	-0.422054	-0.008112	0.005278	1.000000	0.002829	-0.006879	-0.001511	-0.011721
v4	-0.105845	0.002257	-0.001495	0.002829	1.000000	0.001744	-0.000880	0.004657
v5	0.173223	-0.007036	0.005210	-0.006879	0.001744	1.000000	-0.000938	-0.008709
v6	-0.063279	0.000413	-0.000594	-0.001511	-0.000880	-0.000938	1.000000	0.000436
v7	0.085335	-0.009173	0.007425	-0.011721	0.004657	-0.008709	0.000436	1.000000
v8	-0.038203	-0.001168	0.002899	-0.001815	0.000890	0.001430	0.003036	-0.006419
v9	-0.007861	0.001828	-0.000274	-0.003579	0.002154	-0.001213	-0.000734	-0.004921
v10	0.031068	0.000815	0.000620	-0.009632	0.002753	-0.006050	-0.002180	-0.013617
v11	-0.248536	0.001028	-0.000633	0.002339	-0.001223	0.000411	-0.000211	0.002454
v12	0.125500	-0.001524	0.002266	-0.005900	0.003366	-0.002342	-0.001185	-0.006153
v13	-0.065958	-0.000568	0.000680	0.000113	0.000177	0.000019	0.000397	-0.000170
v14	-0.100316	-0.002663	0.002711	-0.003027	0.002801	-0.001000	0.000184	-0.003816
v15	-0.184392	-0.000602	0.001538	-0.001230	0.000572	-0.001171	-0.000470	-0.001394
v16	0.011286	-0.003345	0.004013	-0.004430	0.003346	-0.002373	0.000122	-0.005944
v17	-0.073819	-0.003491	0.003244	-0.008159	0.003655	-0.004466	-0.001716	-0.008794
v18	0.090305	-0.003535	0.002477	-0.003495	0.002325	-0.002685	0.000541	-0.004279
v19	0.029537	0.000919	-0.000358	-0.000016	-0.000560	0.000436	0.000106	0.000846
v20	-0.051022	-0.001393	-0.001287	-0.002269	0.000318	-0.001185	-0.000181	-0.001192
v21	0.045913	0.002818	-0.004897	0.003500	-0.001034	0.001622	-0.002134	0.009010
v22	0.143727	-0.001436	0.001237	-0.000275	0.000115	-0.000559	0.001104	-0.002280
v23	0.051474	-0.001330	-0.003855	0.000449	0.000732	0.001183	-0.000755	0.003303
v24	-0.015954	-0.000723	0.000701	-0.000072	-0.000120	0.000198	0.001202	-0.000384
v25	-0.233262	-0.000222	-0.001569	0.000425	0.000162	0.000069	0.000697	-0.000072
v26	-0.041818	-0.000684	0.000253	-0.000094	0.000777	0.000390	-0.000028	0.000624
v27	-0.005171	-0.015706	0.007555	-0.007051	0.001322	-0.005798	0.000289	-0.004537
v28	-0.009305	-0.004861	0.001611	-0.000134	0.000231	-0.000820	0.000925	0.001657
amount	-0.010559	-0.230105	-0.533428	-0.212410	0.099514	-0.387685	0.216389	0.400408
class	-0.012359	-0.094486	0.084624	-0.182322	0.129326	-0.087812	-0.043915	-0.172347
hour	1.000000	0.117927	-0.010556	-0.422054	-0.105845	0.173223	-0.063279	0.085335

32 rows × 32 columns

In [51]:

```
# Plotting a Correlation Plot to observe any correlations or patterns between the columns i

corr_matrix = df.corr()
plot = plt.figure(figsize = (10,10))
sns.heatmap(corr_matrix) # seaborn Library
plt.show()
```



In [ ]:

```
# Finally let's also plot a box plot for observing if columns have some outliers , or a par
for col in df.columns:
    plt.figure()
    df[col].plot(kind = 'box')
```

In [53]:

```
# Class - Genuine , Fraud
# df['class'].map({'0':'Genuine' , '1':'Fraud'})

# df['col_name'] = df['col_name'].replace(np.nan , 'replace_value')
```

In [54]:

```
pd.set_option('display.max_rows' , 500)
df.head()
```

Out[54]:

	time	v1	v2	v3	v4	v5	v6	v7	v8	
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	

5 rows × 32 columns

In [55]:

```
#After Observation we now fix the problems that we observed , also help in better visualisa
#First we create we create , modify and handle columns and then visualise again¶
#1. Handling the TIME column
#2. Scaling and Binning the AMOUNT column
#3. Solving the Imbalance of the CLASS columns
```

In [56]:

```
# Handle the time columns - Convert from seconds to Hours
# Bin the Amount columns : pd.cut()
# Solving the Imbalance - imblearn python library ( Undersampling , Over Sampling and SMOTE
```

In [57]:

```
### Processing the Time Column

df['hour'] = df['time']/(60*60)%24   # 2 days of data

import math
df['hour'] = df['hour'].apply(lambda x : math.floor(x))
```

In [58]:

```
#Scale the Amount Column
# StandardScaler RobustScaler
```

In [59]:

```
from sklearn.preprocessing import StandardScaler # importing a class from a module of a lib

ss = StandardScaler() # object of the class StandardScaler ()
```

In [60]:

```
# fit - > amount column
# transform - > StandardScaler

# predict - > test data ( prediction )
```

In [61]:

```
df['amount'].values.reshape(-1 , 1)
```

Out[61]:

```
array([[149.62],
       [  2.69],
       [378.66],
       ...,
       [ 67.88],
       [ 10.  ],
       [217.  ]])
```

In [62]:

```
ss.fit_transform(df['amount'].values.reshape(-1,1))
```

Out[62]:

```
array([[ 0.24419951],
       [-0.34258399],
       [ 1.15889967],
       ...,
       [-0.0822395 ],
       [-0.31339058],
       [ 0.51329005]])
```

In [63]:

```
df['amount_scaled'] = ss.fit_transform(df['amount'].values.reshape(-1,1))
```

In [64]:

```
df.head()
```

Out[64]:

	time	v1	v2	v3	v4	v5	v6	v7	v8	
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	

5 rows × 33 columns

In [65]:

```
#Visualising Again
```

In [66]:

```
# Let's see if we find any particular pattern between time ( in hours ) and Fraud vs Legit

# matplotlib.pyplot as plt

plt.figure(figsize=(10,10)) # tuple of the figure size
# seaborn as sns

sns.distplot(df[df['class'] == 0]["hour"], color='g') # Genuine - green

sns.distplot(df[df['class'] == 1]["hour"], color='r') # Frauduletn - Red

plt.title('Fraud vs Legit Transactions by Hours', fontsize=10)
plt.xlim([0,25])
plt.show()
```

In [67]:

```
# with a very small confidence we may say that Fraud transactions are more frequent towards
# But thats not significant enough
```

In [68]:

```
# Observing patterns in No of Legit Transactions vs Time (Hour) to observe more

legit_hour_count = df[df['class']==0].groupby(['hour'] , as_index = False)['hour'].size().r
```

In [69]:

```
legit_hour_count
```

Out[69]:

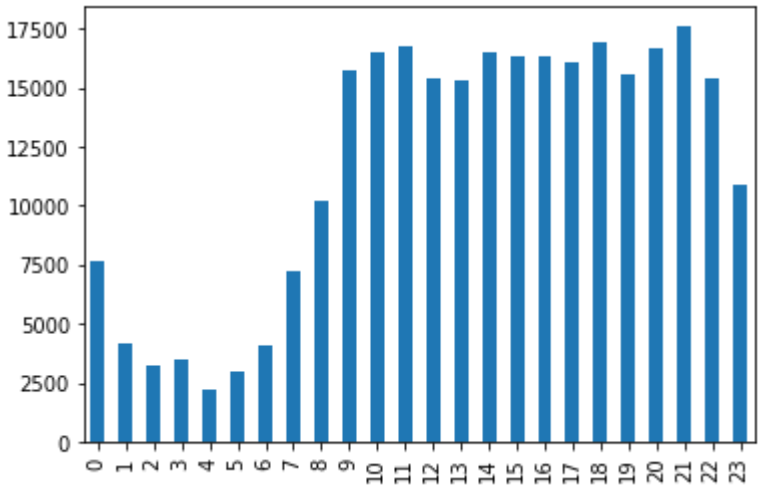
	hour	Count
0	0	7641
1	1	4198
2	2	3260
3	3	3470
4	4	2181
5	5	2977
6	6	4073
7	7	7210
8	8	10223
9	9	15751
10	10	16540
11	11	16728
12	12	15361
13	13	15306
14	14	16497
15	15	16348
16	16	16374
17	17	16102
18	18	16931
19	19	15547
20	20	16687
21	21	17613
22	22	15369
23	23	10866

In [70]:

```
legit_hour_count['Count'].plot(kind = 'bar')
```

Out[70]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x29c0d3fff28>
```



In [71]:

```
pd.DataFrame(df[df['class']==1].hour.value_counts().rename_axis('hour').reset_index(name =
```

Out[71]:

	hour	Count
23	0	6
18	1	10
1	2	48
11	3	17
7	4	23
17	5	11
21	6	9
5	7	23
19	8	9
15	9	16
22	10	8
0	11	53
13	12	17
14	13	17
6	14	23
4	15	26
8	16	22
3	17	28
2	18	28
9	19	19
10	20	18
16	21	16
20	22	9
12	23	17

In [72]:

```
fraud_hour_count = df[df['class']==1].groupby(['hour'] , as_index = False)['hour'].size().r
```

In [73]:

```
fraud_hour_count.head()
```

Out[73]:

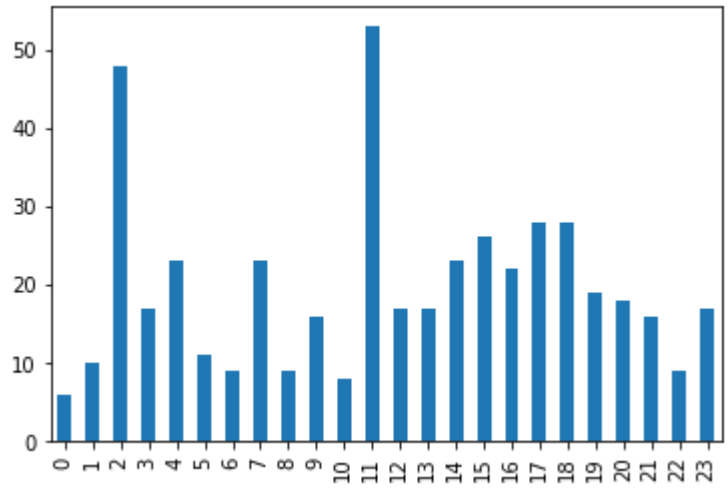
	hour	Count
0	0	6
1	1	10
2	2	48
3	3	17
4	4	23

In [74]:

```
fraud_hour_count['Count'].plot(kind = 'bar')
```

Out[74]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x29c0d4db320>
```

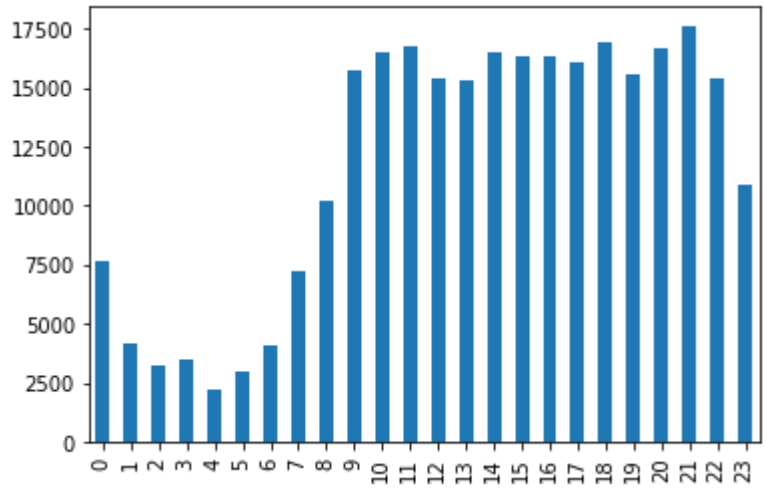


In [75]:

```
legit_hour_count['Count'].plot(kind = 'bar')
```

Out[75]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x29c0d4eafd0>
```



###############

###############Let's Discuss Next Steps -¶

####1 Classification Models

#Logistic Regression

#XG Boost

#SVM 's

#Decision Trees

#####2 Class Imbalance Solutions

#Under Sampling

#Over Sampling

#SMOTE

####3 Metrics

#Accuracy Score

#Confusion Matrix

#ROC_AUC

#F1 Score

#Under Sampling and Over Sampling

#Synthetic Minority OverSampling Technique

#1.As in the above analysis we found that time variable doesn't make any senseto when a fraud transaction is happening

#so we remove that variable from our dataset.

#2.We remove amount coloumn as we have amount_scaled coloumn.

#3. We remove hour coloumn as also it doesn't make any sense.

#4.Class is our dependent variable.

In [76]:

```
df.head()
```

Out[76]:

	time	v1	v2	v3	v4	v5	v6	v7	v8	
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	

5 rows × 33 columns

In [77]:

```
y = df['class'].values

X = df.drop(columns = ['time' , 'amount' , 'hour' , 'class'])
```

In [78]:

```
X.head()
```

Out[78]:

	v1	v2	v3	v4	v5	v6	v7	v8	
0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.3637
1	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.2554
2	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.5146
3	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.3870
4	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.8177

5 rows × 29 columns

In [79]:

```
from sklearn.linear_model import LogisticRegression # Importing Classifier Step
from sklearn.model_selection import train_test_split
```

In [80]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=0) #


logreg = LogisticRegression() # () towards the end
logreg.fit(X_train, y_train )
```

Out[80]:

```
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='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```

In [81]:

```
y_pred = logreg.predict(X_test)

from sklearn.metrics import accuracy_score


print(accuracy_score(y_pred , y_test))
```

```
0.9991541154632393
```

In [82]:

```
#Class Imbalance
```

In [83]:

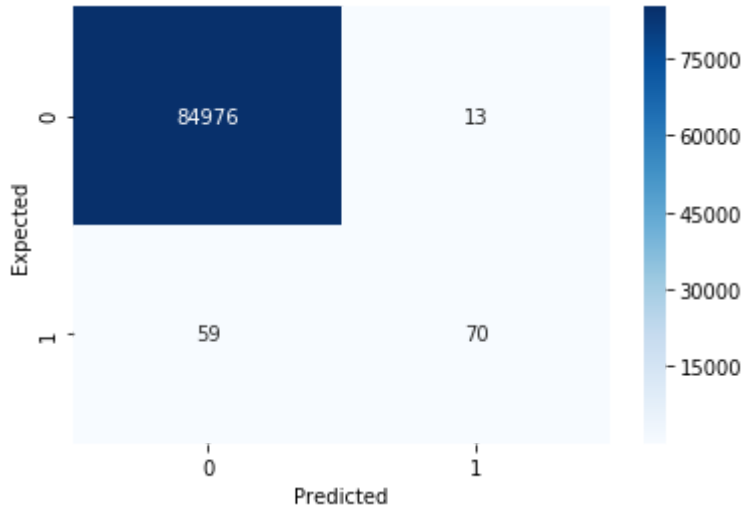
```
from sklearn.metrics import confusion_matrix
cnf_matrix = confusion_matrix(y_test , y_pred)

cnf_matrix
```

Out[83]:

```
array([[84976,    13],
       [   59,    70]], dtype=int64)
```

In [84]:

```
sns.heatmap(pd.DataFrame(cnf_matrix), annot = True, cmap = 'Blues', fmt = 'd')
plt.xlabel('Predicted')
plt.ylabel('Expected')
plt.show()
```



#Understanding the Confusion Matrix Plot

#Why and When ? -

#Every problem is different and derives a different set of values for a particular business use case , thus every model must be evaluated differently.

#Let's get to know the terminology and Structure first -

#A confusion matrix is defined into four parts : { TRUE , FALSE } (Actual) ,{POSITIVE , NEGATIVE} (Predicted) Positive and Negative is what you predict , True and False is what you are told

#Which brings us to 4 relations : True Positive , True Negative , False Positive , False Negative

#Predicted - Rows and Actual as C olumns

#Accuracy , Precision and Recall

#Accuracy - > The most used and classic classification metric : Suited for binary classification problems.

#Accuracy = (TP + TN) / (TP + TN + FP + FN)

#Basically Rightly predicted results amongst all the results , used when the classes are balanced

#Precision - > What proportion of predicted positives are truly positive ? Used when we need to predict the positive thoroughly, sure about it !

#Precision = (TP) / (TP + FP)

#Recall - > What proportion of actual positives is correctly classified ? choice when we want to capture as many positives as possible

#Recall = TP / (TP + FN)

#F1 Score

#Harmonic mean of Precision and RecallF1 = 2*(precision * recall) / (precision + recall) It basically maintains a balance between the precision and recall for your classifier

What is an ROC_AUC Curve ?

It is an evaluation metric that helps identify the strength of the model to distinguish between two outcomes. It defines if a model can create a clear boundary between the postive and the negative class.

Let's talk about some definitions first:

Sensitivity The sensitivity of a model is defined by the proportion of actual positives that are classified as Psitives , i.e = TP / (TP + FN)

Specificity The specificity of a model is defined by the proportion of actual negatives that are classified as Negatives , i.e = TN / (TN + FP)

As we can see that both are independent of each other and lie in teo different quadrants , we can understand that they are inversely related to each other. Thus as Sensitivity goes up , Specificity goes down and vice versa.

ROC CURVE It is a plot between Sesitivity and (1 - Specificity) , which intuitively is a plot between True Positive Rate and False Positive Rate. It depicts if a model can clearly identify each class or not

Higher the area under the curve , better the model and it's ability to seperate the positive and negative class

In [85]:

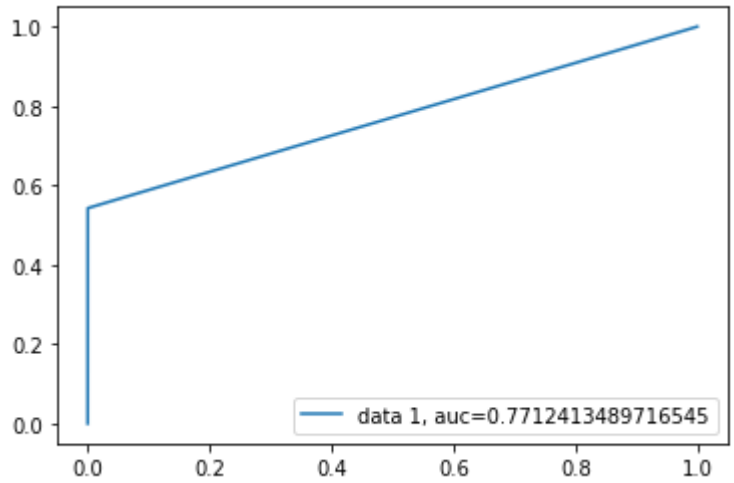
```
from sklearn.metrics import roc_auc_score
roc_auc_score(y_test , y_pred)

# Accuracy - 99%
# Accuracy Stage 1 - 62%
# Accuracy Stage 2 - 52%
```

Out[85]:

```
0.7712413489716545
```

In [88]:

```
from sklearn.metrics import roc_curve

y_pred_proba = logreg.predict_proba(X_test)[::,1]

fpr, tpr, _ = roc_curve(y_test,  y_pred)

auc = roc_auc_score(y_test, y_pred)

plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
plt.legend(loc=4)
plt.show()
```



In [87]:

```
#Let's Fix the class Imbalance and apply some sampling techniques
```

```
  File "<ipython-input-87-9236f58b2ae9>", line 1
    Let's Fix the class Imbalance and apply some sampling techniques
                                                                    ^
SyntaxError: EOL while scanning string literal
```

In [ ]:

```
# the imblearn library
!pip install imblearn
```

In [ ]:

```
from sklearn.metrics import precision_score, recall_score, f1_score, roc_auc_score, accurac
```

In [90]:

```
!pip install imblearn
from imblearn.over_sampling import SMOTE
from imblearn.under_sampling import RandomUnderSampler
```

```
Requirement already satisfied: imblearn in c:\users\lenovo\anaconda3\lib\sit
e-packages (0.0)
Requirement already satisfied: imbalanced-learn in c:\users\lenovo\anaconda3
\lib\site-packages (from imblearn) (0.6.1)
Requirement already satisfied: scikit-learn>=0.22 in c:\users\lenovo\anacond
a3\lib\site-packages (from imbalanced-learn->imblearn) (0.22)
Requirement already satisfied: numpy>=1.11 in c:\users\lenovo\anaconda3\lib
\site-packages (from imbalanced-learn->imblearn) (1.16.4)
Requirement already satisfied: joblib>=0.11 in c:\users\lenovo\anaconda3\lib
\site-packages (from imbalanced-learn->imblearn) (0.13.2)
Requirement already satisfied: scipy>=0.17 in c:\users\lenovo\anaconda3\lib
\site-packages (from imbalanced-learn->imblearn) (1.2.1)
```

In [94]:

```
from collections import Counter
from sklearn.datasets import make_classification

#X, y = make_classification(n_classes=2) #, class_sep=2,weights=[0.1, 0.9], n_informative=3
print('Original dataset shape %s' % Counter(y))

rus = RandomUnderSampler(random_state=42)
X_res, y_res = rus.fit_resample(X, y)
print('Resampled dataset shape %s' % Counter(y_res))
```

```
Original dataset shape Counter({0: 283253, 1: 473})
Resampled dataset shape Counter({0: 473, 1: 473})
```

In [95]:

```
X_train, X_test, y_train, y_test = train_test_split(X_res, y_res, test_size=0.3, random_sta
logreg = LogisticRegression()
logreg.fit(X_train, y_train)
```

Out[95]:

```
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='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```

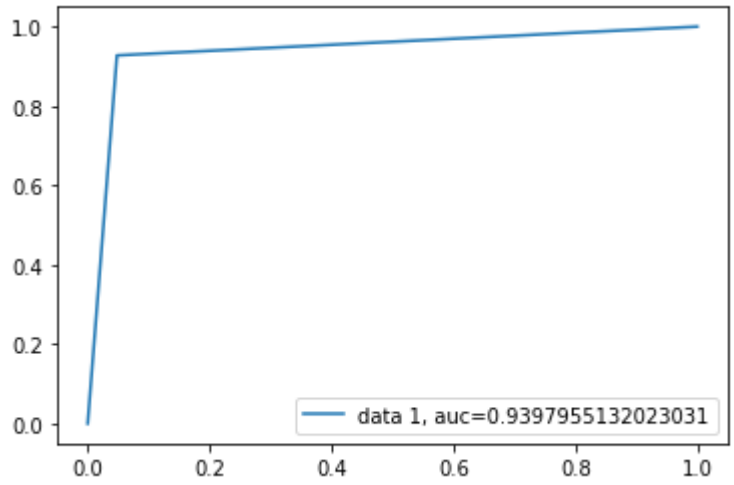
In [96]:

```
y_pred = logreg.predict(X_test)

from sklearn.metrics import accuracy_score
print(accuracy_score(y_pred , y_test))  # Accuracy is surely reducedd , let's look at the r
```

```
0.9401408450704225
```

In [97]:

```
y_pred_proba = logreg.predict_proba(X_test)[::,1]
fpr, tpr, _ = roc_curve(y_test,  y_pred)
auc = roc_auc_score(y_test, y_pred)
plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
plt.legend(loc=4)
plt.show()
```



Let's try Oversampling

In [98]:

```
from imblearn.over_sampling import RandomOverSampler
```

In [99]:

```
print('Original dataset shape %s' % Counter(y))
random_state = 42
rus = RandomOverSampler(random_state=random_state)
X_res, y_res = rus.fit_resample(X, y)
print('Resampled dataset shape %s' % Counter(y_res))
```

```
Original dataset shape Counter({0: 283253, 1: 473})
Resampled dataset shape Counter({0: 283253, 1: 283253})
```

In [100]:

```
X_train, X_test, y_train, y_test = train_test_split(X_res, y_res, test_size=0.3, random_sta
logreg = LogisticRegression()
logreg.fit(X_train, y_train)
```

Out[100]:

```
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='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```

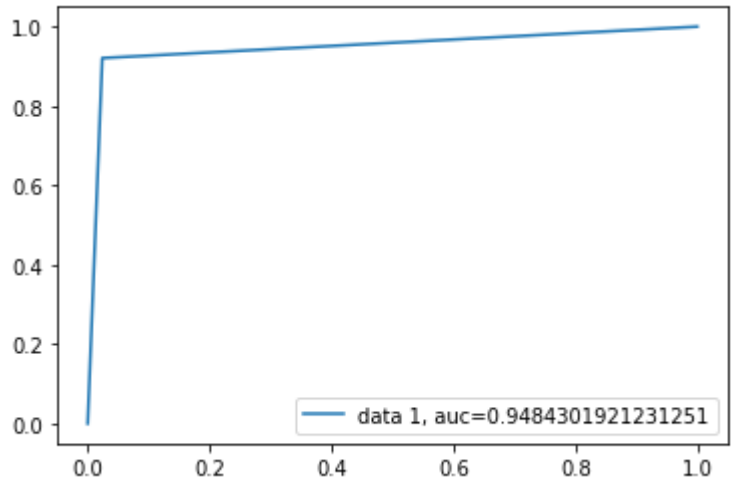
In [101]:

```
y_pred = logreg.predict(X_test)

from sklearn.metrics import accuracy_score
print(accuracy_score(y_pred , y_test))  # Accuracy is surely reducedd , let's look at the r
```

```
0.9483501223874976
```

In [102]:

```
y_pred_proba = logreg.predict_proba(X_test)[::,1]
fpr, tpr, _ = roc_curve(y_test,  y_pred)
auc = roc_auc_score(y_test, y_pred)
plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
plt.legend(loc=4)
plt.show()
```



In [ ]:

```
# SMOTE Sampling.
```

In [103]:

```
from imblearn.over_sampling import SMOTE
```

In [104]:

```
print('Original dataset shape %s' % Counter(y))

rus = SMOTE(random_state=42)
X_res, y_res = rus.fit_resample(X, y)
print('Resampled dataset shape %s' % Counter(y_res))
```

```
Original dataset shape Counter({0: 283253, 1: 473})
Resampled dataset shape Counter({0: 283253, 1: 283253})
```

In [105]:

```
X_train, X_test, y_train, y_test = train_test_split(X_res, y_res, test_size=0.3, random_sta
logreg = LogisticRegression()
logreg.fit(X_train, y_train)
```

Out[105]:

```
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='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```

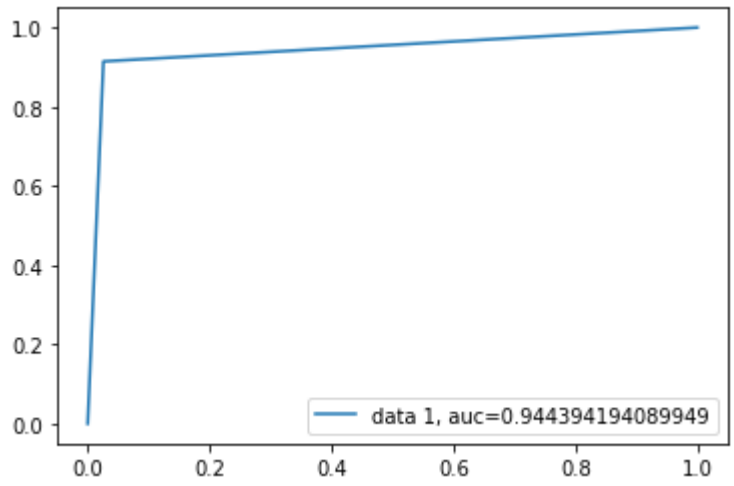
In [106]:

```
y_pred = logreg.predict(X_test)

from sklearn.metrics import accuracy_score
print(accuracy_score(y_pred , y_test))  # Accuracy is surely reducedd , let's look at the r
```

```
0.9443078045565807
```

In [107]:

```
y_pred_proba = logreg.predict_proba(X_test)[::,1]
fpr, tpr, _ = roc_curve(y_test,  y_pred)
auc = roc_auc_score(y_test, y_pred)
plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
plt.legend(loc=4)
plt.show()
```



In [110]:

```
len(y)
```

Out[110]:

```
283726
```

In [ ]:

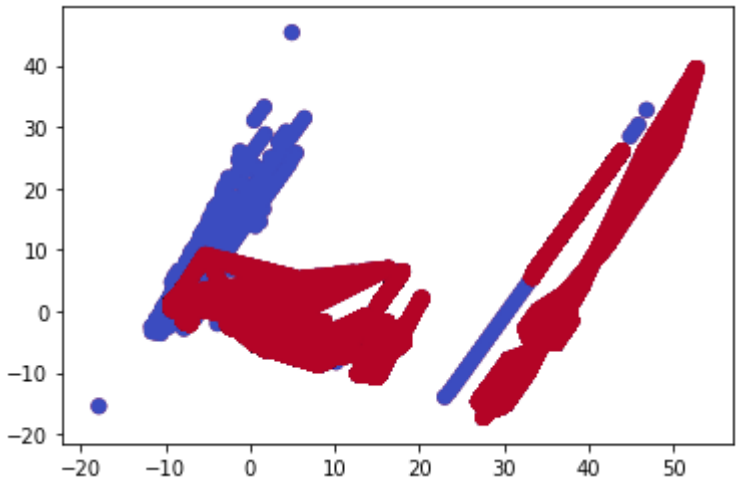
```
#Principal Component Analysis
```

In [112]:

```
from sklearn.decomposition import PCA # SVD , t-SNE , Linear Discrimant Analysis
X_reduced_pca = PCA(n_components=2, random_state=42).fit_transform(X_res)
```

In [113]:

```
plt.scatter(X_reduced_pca[:,0], X_reduced_pca[:,1], c=(y_res== 0), cmap='coolwarm', label='
plt.scatter(X_reduced_pca[:,0], X_reduced_pca[:,1], c=(y_res == 1), cmap='coolwarm', label=
plt.show()
```



In [ ]:

```
# let's now try either different models , first by creating multiple datsets for undersampl
```

In [ ]:

```
#Undersampled Data
```

In [114]:

```
rus = RandomUnderSampler(random_state=42)
X_under, y_under = rus.fit_resample(X, y)
print('Resampled dataset shape %s' % Counter(y_under))
```

```
Resampled dataset shape Counter({0: 473, 1: 473})
```

In [ ]:

```
#Oversampled Data
```

In [115]:

```
rus = RandomOverSampler(random_state=42)
X_over, y_over = rus.fit_resample(X, y)
print('Resampled dataset shape %s' % Counter(y_over))
```

```
Resampled dataset shape Counter({0: 283253, 1: 283253})
```

In [ ]:

```
#SMOTE Data
```

In [116]:

```
rus = SMOTE(random_state=42)
X_smote, y_smote = rus.fit_resample(X, y)
print('Resampled dataset shape %s' % Counter(y_smote))
```

```
Resampled dataset shape Counter({0: 283253, 1: 283253})
```

#Now applying different models and evaluating the dataset

In [118]:

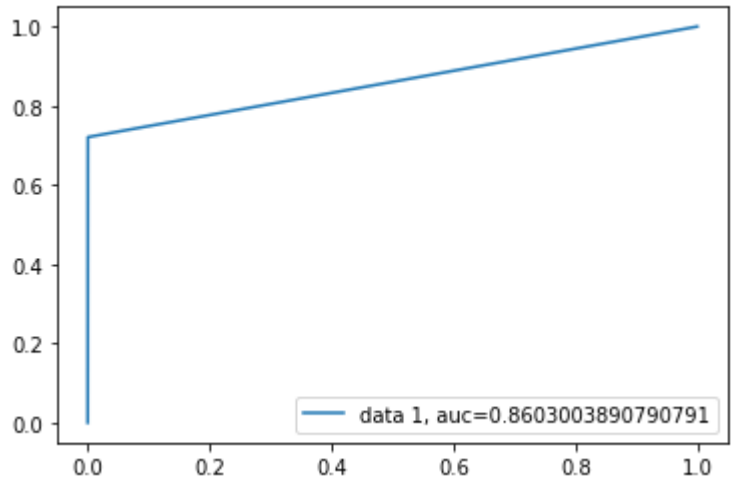
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
```

#Classifier 2 - Decision Tree Classifier

In [119]:

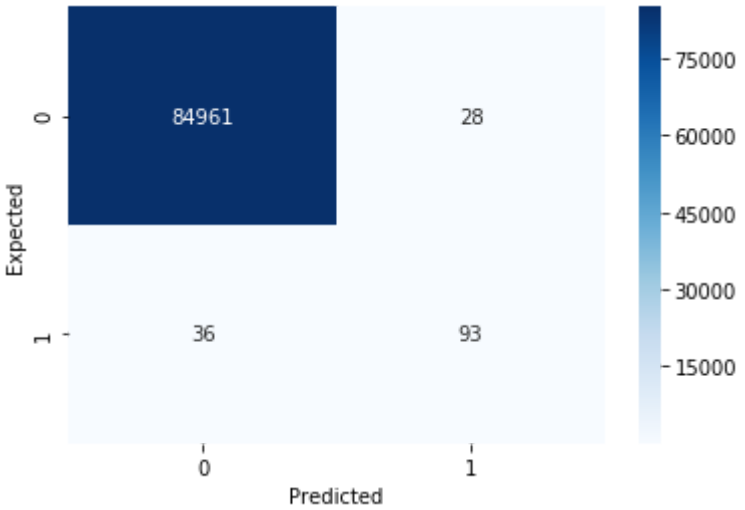
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=0)
dte = DecisionTreeClassifier()
dte.fit( X_train, y_train )

y_pred = dte.predict(X_test)

print(accuracy_score(y_pred , y_test))

y_pred_proba = dte.predict_proba(X_test)[::,1]
fpr, tpr, _ = roc_curve(y_test,  y_pred)
auc = roc_auc_score(y_test, y_pred)
plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
plt.legend(loc=4)
plt.show()
```

```
0.9992481026339904
```



In [120]:

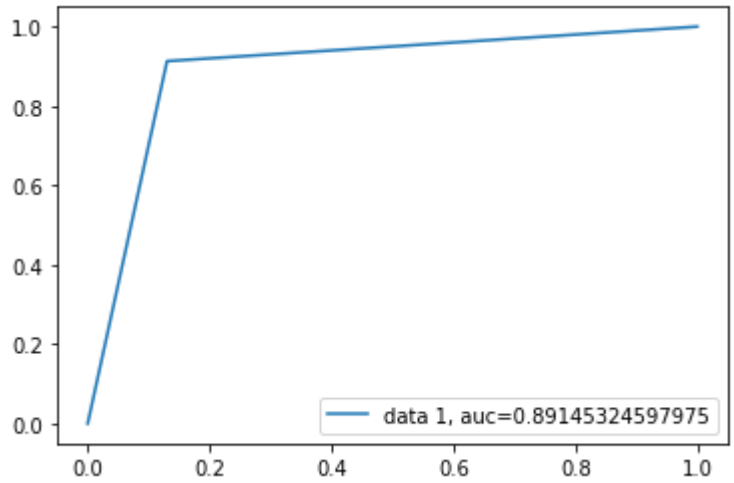
```
cnf_matrix = confusion_matrix(y_test , y_pred)
sns.heatmap(pd.DataFrame(cnf_matrix), annot = True, cmap = 'Blues', fmt = 'd')
plt.xlabel('Predicted')
plt.ylabel('Expected')
plt.show()
```



In [121]:

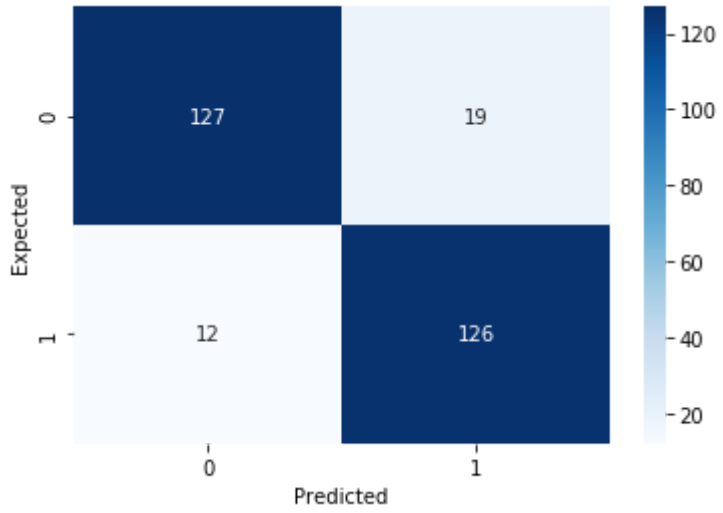
```
# Undersampled data with Decision Tree Classifiers

X_train, X_test, y_train, y_test = train_test_split(X_under, y_under, test_size=0.3, random
dte = DecisionTreeClassifier()
dte.fit(X_train, y_train)

y_pred = dte.predict(X_test)
print(accuracy_score(y_pred , y_test))

y_pred_proba = dte.predict_proba(X_test)[::,1]
fpr, tpr, _ = roc_curve(y_test,  y_pred)
auc = roc_auc_score(y_test, y_pred)
plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
plt.legend(loc=4)
plt.show()
```

```
0.8908450704225352
```



In [122]:

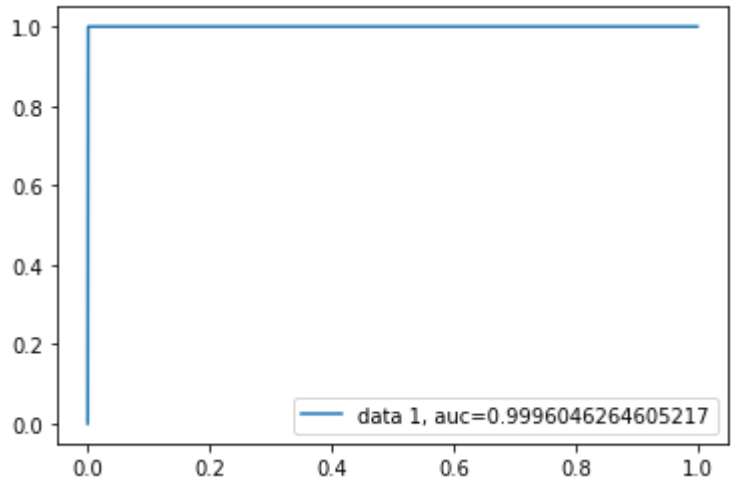
```
cnf_matrix = confusion_matrix(y_test , y_pred)
sns.heatmap(pd.DataFrame(cnf_matrix), annot = True, cmap = 'Blues', fmt = 'd')
plt.xlabel('Predicted')
plt.ylabel('Expected')
plt.show()
```



In [123]:

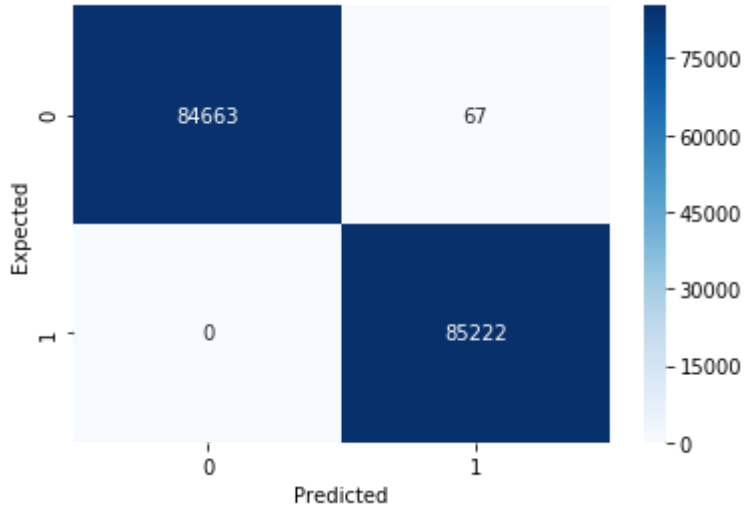
```
# Oversampled data with Decision Tree Classifiers # Best model after Classifier - DTE

X_train, X_test, y_train, y_test = train_test_split(X_over, y_over, test_size=0.3, random_s
dte = DecisionTreeClassifier()
dte.fit(X_train, y_train)

y_pred = dte.predict(X_test)
print(accuracy_score(y_pred , y_test))

y_pred_proba = dte.predict_proba(X_test)[::,1]
fpr, tpr, _ = roc_curve(y_test,  y_pred)
auc = roc_auc_score(y_test, y_pred)
plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
plt.legend(loc=4)
plt.show()
```

```
0.9996057710412352
```



In [124]:

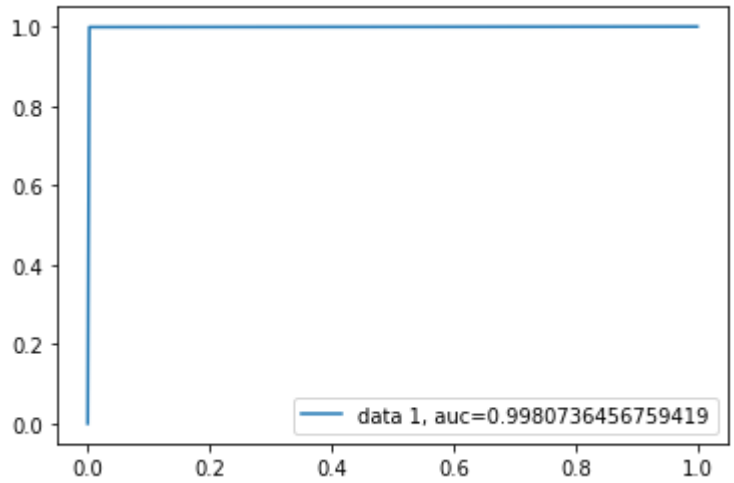
```
cnf_matrix = confusion_matrix(y_test , y_pred)
sns.heatmap(pd.DataFrame(cnf_matrix), annot = True, cmap = 'Blues', fmt = 'd')
plt.xlabel('Predicted')
plt.ylabel('Expected')
plt.show()
```



In [125]:

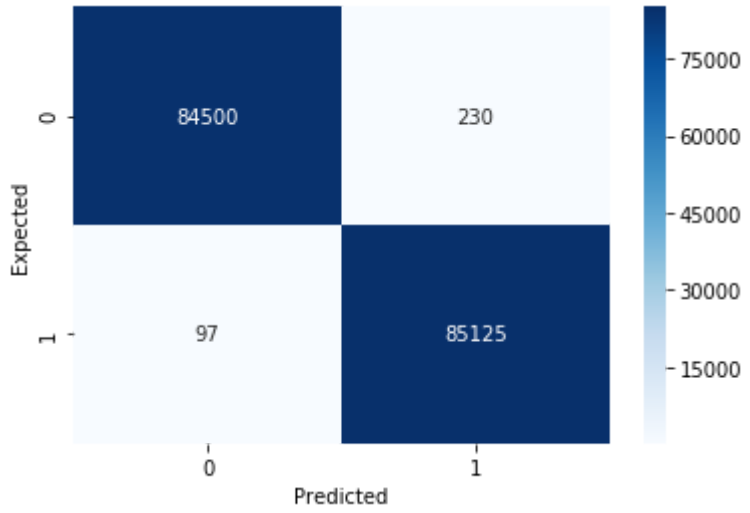
```
# SMOTE data with Decision Tree Classifiers

X_train, X_test, y_train, y_test = train_test_split(X_smote, y_smote, test_size=0.3, random
dte = DecisionTreeClassifier()
dte.fit(X_train, y_train)

y_pred = dte.predict(X_test)
print(accuracy_score(y_pred , y_test))

y_pred_proba = dte.predict_proba(X_test)[::,1]
fpr, tpr, _ = roc_curve(y_test,  y_pred)
auc = roc_auc_score(y_test, y_pred)
plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
plt.legend(loc=4)
plt.show()
```

```
0.9980759273206552
```



In [126]:

```
cnf_matrix = confusion_matrix(y_test , y_pred)
sns.heatmap(pd.DataFrame(cnf_matrix), annot = True, cmap = 'Blues', fmt = 'd')
plt.xlabel('Predicted')
plt.ylabel('Expected')
plt.show()
```

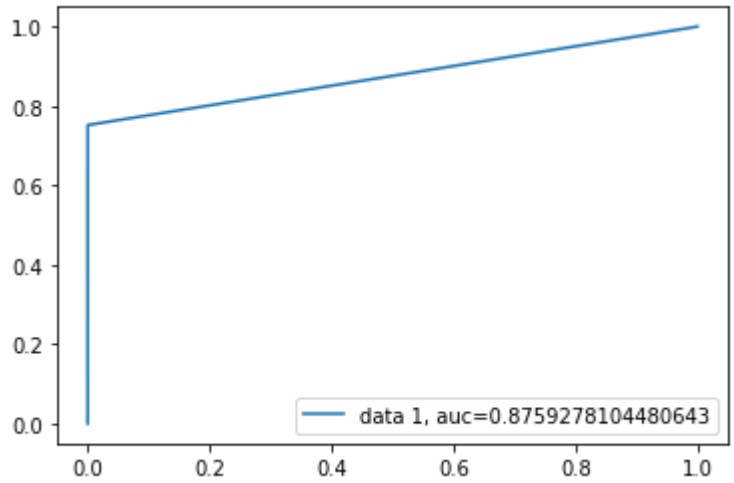


Classifier - 3 Random Forest Classifier

In [127]:

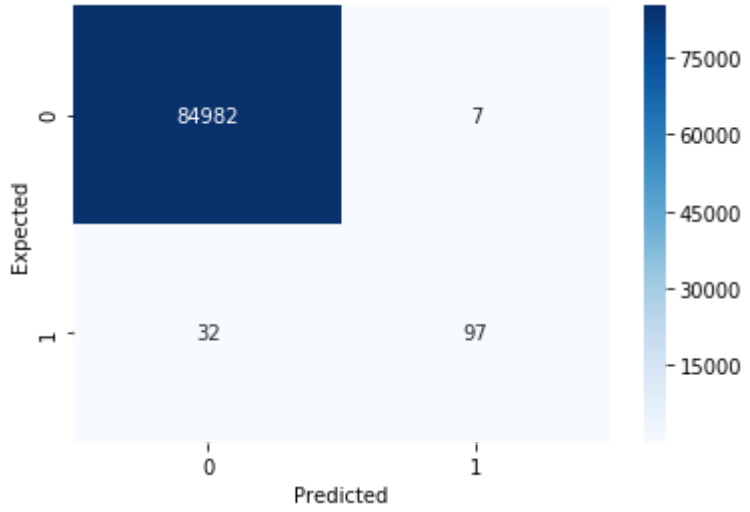
```
# Raw Data

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=0)
rfc = RandomForestClassifier()
rfc.fit( X_train, y_train )

y_pred = rfc.predict(X_test)

print(accuracy_score(y_pred , y_test))

y_pred_proba = rfc.predict_proba(X_test)[::,1]
fpr, tpr, _ = roc_curve(y_test,  y_pred)
auc = roc_auc_score(y_test, y_pred)
plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
plt.legend(loc=4)
plt.show()
```

```
0.9995418125425879
```



In [128]:

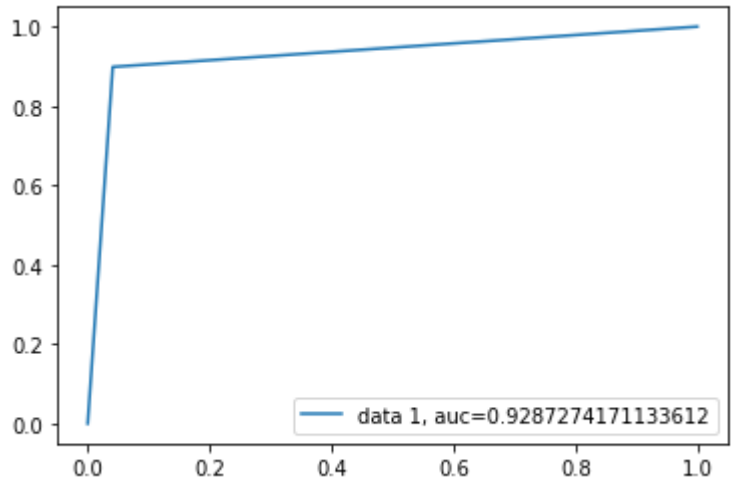
```
cnf_matrix = confusion_matrix(y_test , y_pred)
sns.heatmap(pd.DataFrame(cnf_matrix), annot = True, cmap = 'Blues', fmt = 'd')
plt.xlabel('Predicted')
plt.ylabel('Expected')
plt.show()
```



In [129]:

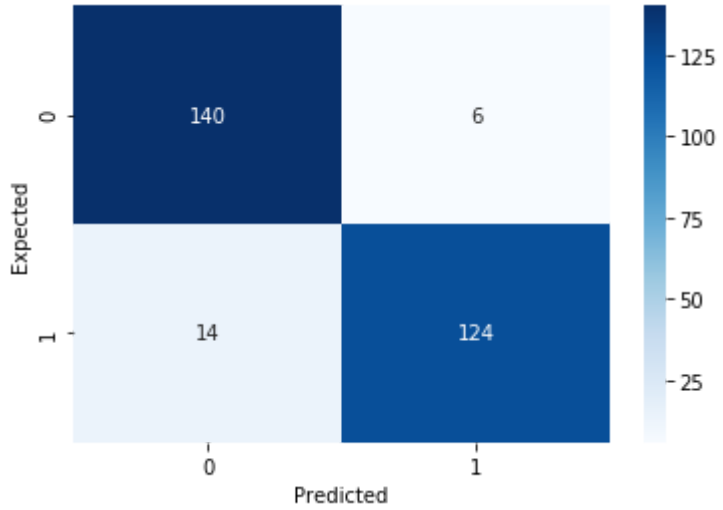
```
# Undersampled
X_train, X_test, y_train, y_test = train_test_split(X_under, y_under, test_size=0.3, random
rfc = RandomForestClassifier()
rfc.fit( X_train, y_train )

y_pred = rfc.predict(X_test)

print(accuracy_score(y_pred , y_test))

y_pred_proba = rfc.predict_proba(X_test)[::,1]
fpr, tpr, _ = roc_curve(y_test,  y_pred)
auc = roc_auc_score(y_test, y_pred)
plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
plt.legend(loc=4)
plt.show()
```

```
0.9295774647887324
```



In [130]:

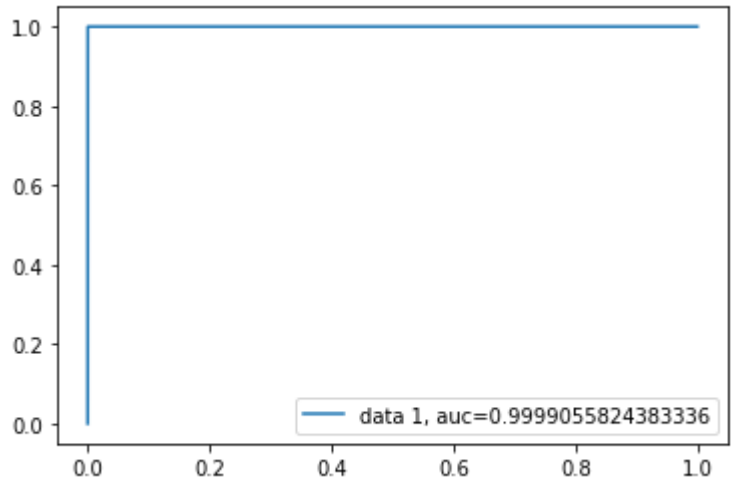
```
cnf_matrix = confusion_matrix(y_test , y_pred)
sns.heatmap(pd.DataFrame(cnf_matrix), annot = True, cmap = 'Blues', fmt = 'd')
plt.xlabel('Predicted')
plt.ylabel('Expected')
plt.show()
```



In [131]:

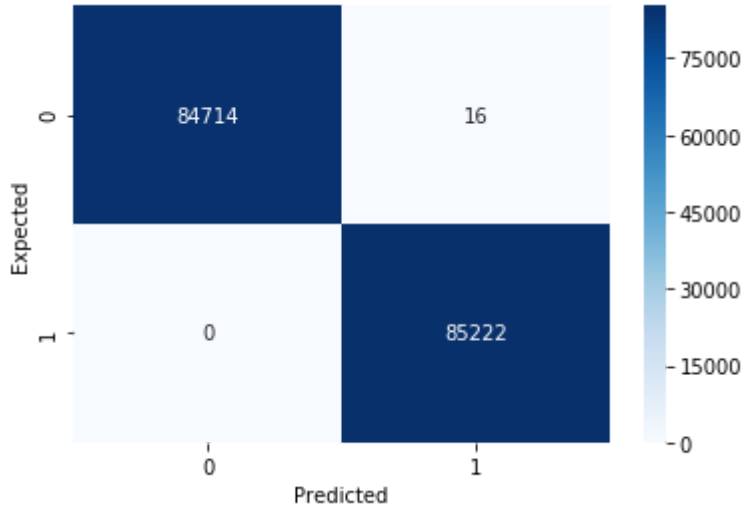
```
# Oversampled Data
X_train, X_test, y_train, y_test = train_test_split(X_over, y_over, test_size=0.3, random_s
rfc = RandomForestClassifier()
rfc.fit( X_train, y_train )

y_pred = rfc.predict(X_test)

print(accuracy_score(y_pred , y_test))

y_pred_proba = rfc.predict_proba(X_test)[::,1]
fpr, tpr, _ = roc_curve(y_test,  y_pred)
auc = roc_auc_score(y_test, y_pred)
plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
plt.legend(loc=4)
plt.show()
```

```
0.9999058557710412
```



In [132]:

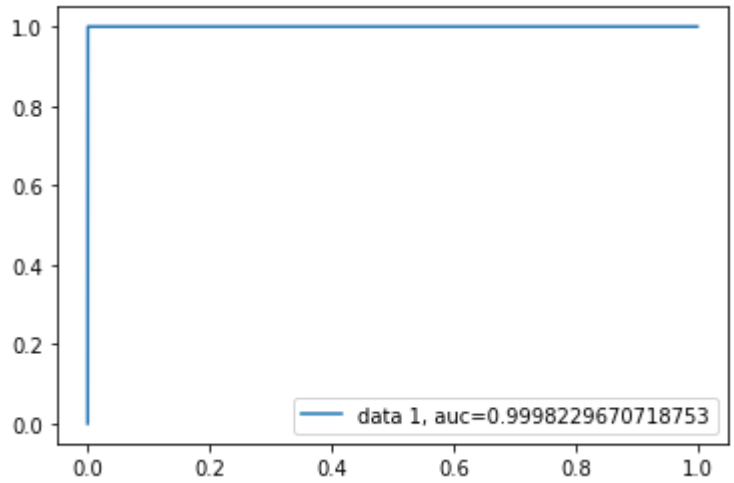
```
cnf_matrix = confusion_matrix(y_test , y_pred)
sns.heatmap(pd.DataFrame(cnf_matrix), annot = True, cmap = 'Blues', fmt = 'd')
plt.xlabel('Predicted')
plt.ylabel('Expected')
plt.show()
```



In [133]:

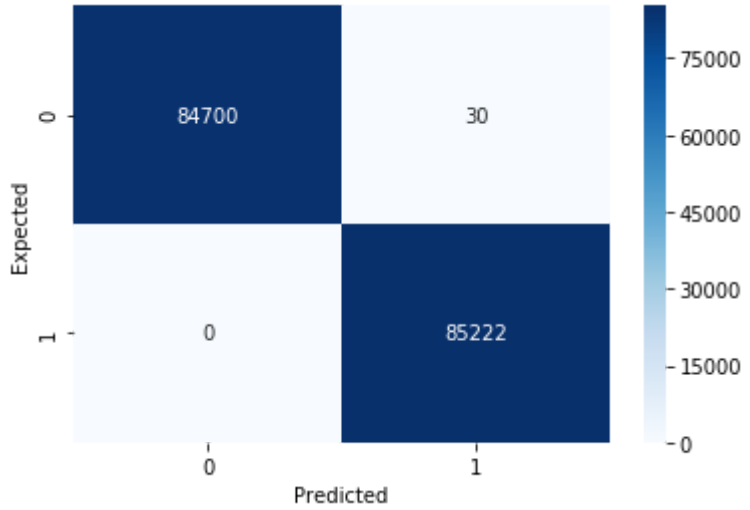
```
# Smote Data
X_train, X_test, y_train, y_test = train_test_split(X_smote, y_smote, test_size=0.3, random
rfc = RandomForestClassifier()
rfc.fit( X_train, y_train )

y_pred = rfc.predict(X_test)

print(accuracy_score(y_pred , y_test))

y_pred_proba = rfc.predict_proba(X_test)[::,1]
fpr, tpr, _ = roc_curve(y_test,  y_pred)
auc = roc_auc_score(y_test, y_pred)
plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
plt.legend(loc=4)
plt.show()
```

```
0.9998234795707023
```



In [134]:

```
cnf_matrix = confusion_matrix(y_test , y_pred)
sns.heatmap(pd.DataFrame(cnf_matrix), annot = True, cmap = 'Blues', fmt = 'd')
plt.xlabel('Predicted')
plt.ylabel('Expected')
plt.show()
```



In [ ]:

```
##here we see that we achieve the maximum accuracy with oversampled Random forest classifie
```

In [ ]:

```

```