subramanian530Week12_CreditCardFraud_EDA_FinalProject

March 4, 2023

1 Final Project: CreditCard Fraud Detection EDA

2 Bellevue University

3 DSC 530 Data Exploration and Analysis

Background

My final project will focus on CreditCard Fraud Detection Exploratory Data Analysis. The question I intend to analyze is, How many instances and features are there in the dataset?.What is the distribution of the target variable (fraud vs. non-fraud)?Are there any missing values in the dataset? If so, how many and what is their distribution?.What is the correlation between different features in the dataset?.Are there any geographical patterns in the occurrence of fraud transactions?.Is there any difference in the transaction behavior (e.g., transaction amount, transaction frequency) between fraud and non-fraud transactions?.Are there any relationships between the target variable and the other features in the dataset?.Are there any outliers in the dataset? If so, how many and what is their distribution?

Analysis

Import the essential packages (Tried a few different methods from different packages throughout the analysis)

Dataset https://www.kaggle.com/datasets/kartik2112/fraud-detection

[2]:
```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import seaborn as sns
import matplotlib.pyplot as plt
import sklearn
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression

%matplotlib inline
import seaborn as sns
import matplotlib.pyplot as plt
import matplotlib.gridspec as gridspec

from sklearn.linear_model     import LogisticRegression
```

```
from sklearn.ensemble         import RandomForestClassifier
from sklearn.model_selection  import train_test_split,StratifiedShuffleSplit
from sklearn.metrics          import␣
 ↪classification_report,confusion_matrix,auc,roc_auc_score,roc_curve,precision_score,recall_s


from sklearn.impute import SimpleImputer
from sklearn.metrics import precision_score,accuracy_score,confusion_matrix
from sklearn.model_selection import cross_val_score
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import  Pipeline
from sklearn.ensemble import RandomForestClassifier
```

[3]:
```
from sklearn import preprocessing
from sklearn.utils import resample
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
pd.options.mode.chained_assignment = None
pd.options.display.max_columns = 999
```

[4]:
```
import warnings
warnings.filterwarnings('ignore')
warnings.simplefilter('ignore')

from matplotlib import rcParams
rcParams['figure.figsize'] = 11.7,8.27

from matplotlib import rcParams
rcParams.update({'font.size': 8})
```

[5]:
```
df = pd.read_csv('fraudTrain.csv')
df.shape # Approximately around 2.8 million records and 22 variables
```

[5]:
```
(1296675, 23)
```

[6]:
```
df.head()
```

[6]:
```
   Unnamed: 0 trans_date_trans_time            cc_num  \
0           0   2019-01-01 00:00:18  2703186189652095
1           1   2019-01-01 00:00:44      630423337322
2           2   2019-01-01 00:00:51    38859492057661
3           3   2019-01-01 00:01:16  3534093764340240
4           4   2019-01-01 00:03:06   375534208663984

                            merchant       category     amt      first  \
0          fraud_Rippin, Kub and Mann       misc_net    4.97   Jennifer
1     fraud_Heller, Gutmann and Zieme    grocery_pos  107.23  Stephanie
```

```
2                fraud_Lind-Buckridge  entertainment  220.11     Edward
3  fraud_Kutch, Hermiston and Farrell  gas_transport   45.00     Jeremy
4                 fraud_Keeling-Crist       misc_pos   41.96      Tyler

      last gender                        street            city state    zip  \
0    Banks      F                561 Perry Cove  Moravian Falls    NC  28654
1     Gill      F  43039 Riley Greens Suite 393          Orient    WA  99160
2  Sanchez      M      594 White Dale Suite 530     Malad City    ID  83252
3    White      M   9443 Cynthia Court Apt. 038         Boulder    MT  59632
4   Garcia      M              408 Bradley Rest        Doe Hill    VA  24433

       lat      long  city_pop                                job         dob  \
0  36.0788  -81.1781      3495          Psychologist, counselling  1988-03-09
1  48.8878 -118.2105       149  Special educational needs teacher  1978-06-21
2  42.1808 -112.2620      4154        Nature conservation officer  1962-01-19
3  46.2306 -112.1138      1939                    Patent attorney  1967-01-12
4  38.4207  -79.4629        99     Dance movement psychotherapist  1986-03-28

                          trans_num   unix_time  merch_lat  merch_long  \
0  0b242abb623afc578575680df30655b9  1325376018  36.011293  -82.048315
1  1f76529f8574734946361c461b024d99  1325376044  49.159047 -118.186462
2  a1a22d70485983eac12b5b88dad1cf95  1325376051  43.150704 -112.154481
3  6b849c168bdad6f867558c3793159a81  1325376076  47.034331 -112.561071
4  a41d7549acf90789359a9aa5346dcb46  1325376186  38.674999  -78.632459

   is_fraud
0         0
1         0
2         0
3         0
4         0
```

[7]:
```
df.describe()
```

[7]:
```
         Unnamed: 0        cc_num           amt           zip           lat  \
count  1.296675e+06  1.296675e+06  1.296675e+06  1.296675e+06  1.296675e+06
mean   6.483370e+05  4.171920e+17  7.035104e+01  4.880067e+04  3.853762e+01
std    3.743180e+05  1.308806e+18  1.603160e+02  2.689322e+04  5.075808e+00
min    0.000000e+00  6.041621e+10  1.000000e+00  1.257000e+03  2.002710e+01
25%    3.241685e+05  1.800429e+14  9.650000e+00  2.623700e+04  3.462050e+01
50%    6.483370e+05  3.521417e+15  4.752000e+01  4.817400e+04  3.935430e+01
75%    9.725055e+05  4.642255e+15  8.314000e+01  7.204200e+04  4.194040e+01
max    1.296674e+06  4.992346e+18  2.894890e+04  9.978300e+04  6.669330e+01

               long      city_pop     unix_time     merch_lat    merch_long  \
count  1.296675e+06  1.296675e+06  1.296675e+06  1.296675e+06  1.296675e+06
mean  -9.022634e+01  8.882444e+04  1.349244e+09  3.853734e+01 -9.022646e+01
```

```
std    1.375908e+01  3.019564e+05  1.284128e+07  5.109788e+00  1.377109e+01
min   -1.656723e+02  2.300000e+01  1.325376e+09  1.902779e+01 -1.666712e+02
25%   -9.679800e+01  7.430000e+02  1.338751e+09  3.473357e+01 -9.689728e+01
50%   -8.747690e+01  2.456000e+03  1.349250e+09  3.936568e+01 -8.743839e+01
75%   -8.015800e+01  2.032800e+04  1.359385e+09  4.195716e+01 -8.023680e+01
max   -6.795030e+01  2.906700e+06  1.371817e+09  6.751027e+01 -6.695090e+01

           is_fraud
count  1.296675e+06
mean   5.788652e-03
std    7.586269e-02
min    0.000000e+00
25%    0.000000e+00
50%    0.000000e+00
75%    0.000000e+00
max    1.000000e+00
```

[8]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1296675 entries, 0 to 1296674
Data columns (total 23 columns):
 #   Column                 Non-Null Count    Dtype
---  ------                 --------------    -----
 0   Unnamed: 0             1296675 non-null  int64
 1   trans_date_trans_time  1296675 non-null  object
 2   cc_num                 1296675 non-null  int64
 3   merchant               1296675 non-null  object
 4   category               1296675 non-null  object
 5   amt                    1296675 non-null  float64
 6   first                  1296675 non-null  object
 7   last                   1296675 non-null  object
 8   gender                 1296675 non-null  object
 9   street                 1296675 non-null  object
 10  city                   1296675 non-null  object
 11  state                  1296675 non-null  object
 12  zip                    1296675 non-null  int64
 13  lat                    1296675 non-null  float64
 14  long                   1296675 non-null  float64
 15  city_pop               1296675 non-null  int64
 16  job                    1296675 non-null  object
 17  dob                    1296675 non-null  object
 18  trans_num              1296675 non-null  object
 19  unix_time              1296675 non-null  int64
 20  merch_lat              1296675 non-null  float64
 21  merch_long             1296675 non-null  float64
 22  is_fraud               1296675 non-null  int64
dtypes: float64(5), int64(6), object(12)
```

```
memory usage: 227.5+ MB
```

[9]:
```
df.rename(columns = {'unnamed':'ID', 'CC_num':'CreditCard_Num', 'amt':
  ↪'Amount'}, inplace = True)

df['trans_date_trans_time'] = pd.to_datetime(df['trans_date_trans_time'],
  ↪errors='coerce')


# Categories of date and time
df['Year']=df['trans_date_trans_time'].dt.year
df['Month']=df['trans_date_trans_time'].dt.strftime('%b')
df['Month']=df['trans_date_trans_time'].dt.month
df['Day']=df['trans_date_trans_time'].dt.day
df['Hour']=df['trans_date_trans_time'].dt.hour
df['Weekday']=df['trans_date_trans_time'].dt.strftime('%a')
df['DayofYear']=df['trans_date_trans_time'].dt.dayofyear
```

[10]:
```
Num_of_Fraud = round(df['is_fraud'].value_counts()[1]/len(df)*100,3)
Num_of_NonFraud = round(df['is_fraud'].value_counts()[0]/len(df)*100,3)


print("Number of Fraud Values :\t\t  \t   ",df['is_fraud'].value_counts()[1])
print("Number of Non Fraud Values :\t\t        ",df['is_fraud'].
  ↪value_counts()[0])
print("\n")
print("Percentage of Fraud transactions :  \t\t ", Num_of_Fraud)
print("Percentage of Normal(Non-Fraud) transactions :  ",Num_of_NonFraud)
```

```
Number of Fraud Values :                           7506
Number of Non Fraud Values :                    1289169


Percentage of Fraud transactions :                 0.579
Percentage of Normal(Non-Fraud) transactions :   99.421
```

[11]:
```
# Lets shuffle the data before creating the subsamples

df = df.sample(frac=1)

# amount of fraud classes
fraud_df = df.loc[df['is_fraud'] == 1]
non_fraud_df = df.loc[df['is_fraud'] == 0]

normal_distributed_df = pd.concat([fraud_df])

# Shuffle dataframe rows
new_df = normal_distributed_df.sample(frac=1, random_state=42)
```

```
new_df.head()
```

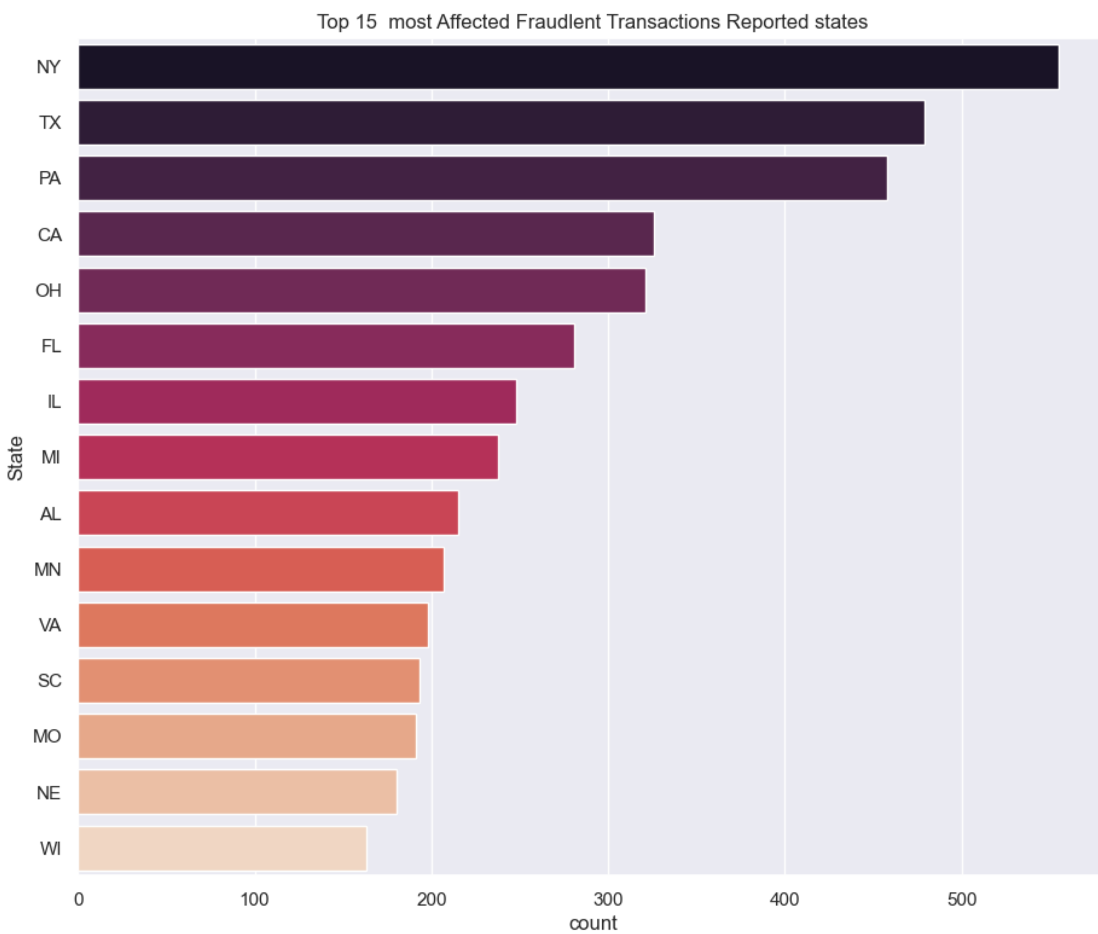
[11]:

```
         Unnamed: 0 trans_date_trans_time            cc_num  \
1065820     1065820   2020-03-17 23:36:02   213154573301411
521397       521397   2019-08-12 18:39:18  4294040533480516
1202397     1202397   2020-05-17 22:01:45    30103132002433
146235       146235   2019-03-20 00:49:42    30131826429364
133786       133786   2019-03-14 22:03:59     4383521454815

                                      merchant       category  Amount  \
1065820                   fraud_Heathcote LLC   shopping_net  980.76
521397                      fraud_Abshire PLC  entertainment  413.75
1202397  fraud_Medhurst, Cartwright and Ebert  personal_care   21.00
146235    fraud_Greenholt, Jacobi and Gleason  gas_transport    8.47
133786    fraud_Mosciski, Ziemann and Farrell   shopping_net  964.32

               first       last gender                      street  \
1065820  Christopher   Sheppard      M           39218 Baker Shoals
521397          Gail     Weaver      F             979 Stewart Lake
1202397    Stephanie  Middleton      F  99736 Rose Shoals Apt. 504
146235       Brianna      Foley      F          57256 Raymond Ports
133786          John  Robertson      M  209 Austin Stream Apt. 231

                 city state    zip      lat     long  city_pop  \
1065820       Bristow    IN  47515  38.1981 -86.6821       965
521397    New Ellenton    SC  29809  33.4130 -81.6900      2206
1202397     Morrisdale    PA  16858  41.0001 -78.2357      3688
146235       Knoxville    TN  37932  35.9335 -84.1481    391389
133786    Indianapolis    IN  46290  39.9347 -86.1633    910148

                                job         dob  \
1065820      Horticultural therapist  1982-02-10
521397          Biomedical scientist  1986-12-31
1202397           Dispensing optician  1987-10-26
146235   Designer, industrial/product  1994-04-22
133786             Academic librarian  1987-09-22

                                trans_num   unix_time  merch_lat  merch_long  \
1065820  525ee8f4a93966291e2d24554c749ea7  1363563362  37.749660  -87.437968
521397   4bc7f75bcea48a3979f8925a891a6aa6  1344796758  33.367925  -81.736367
1202397  0417c1d680e0db41bb7d788db9378771  1368828105  41.489279  -78.305863
146235   b08c79be5c560452ba32d08f29b2f46f  1332204582  35.565623  -84.992306
133786   cebec3a646f32a2563ecc6498e8c0b41  1331762639  40.183257  -85.921964

         is_fraud  Year  Month  Day  Hour Weekday  DayofYear
1065820         1  2020      3   17    23     Tue         77
```

521397	1	2019	8	12	18	Mon	224
1202397	1	2020	5	17	22	Sun	138
146235	1	2019	3	20	0	Wed	79
133786	1	2019	3	14	22	Thu	73

4 Descriptive Statistical Analysis

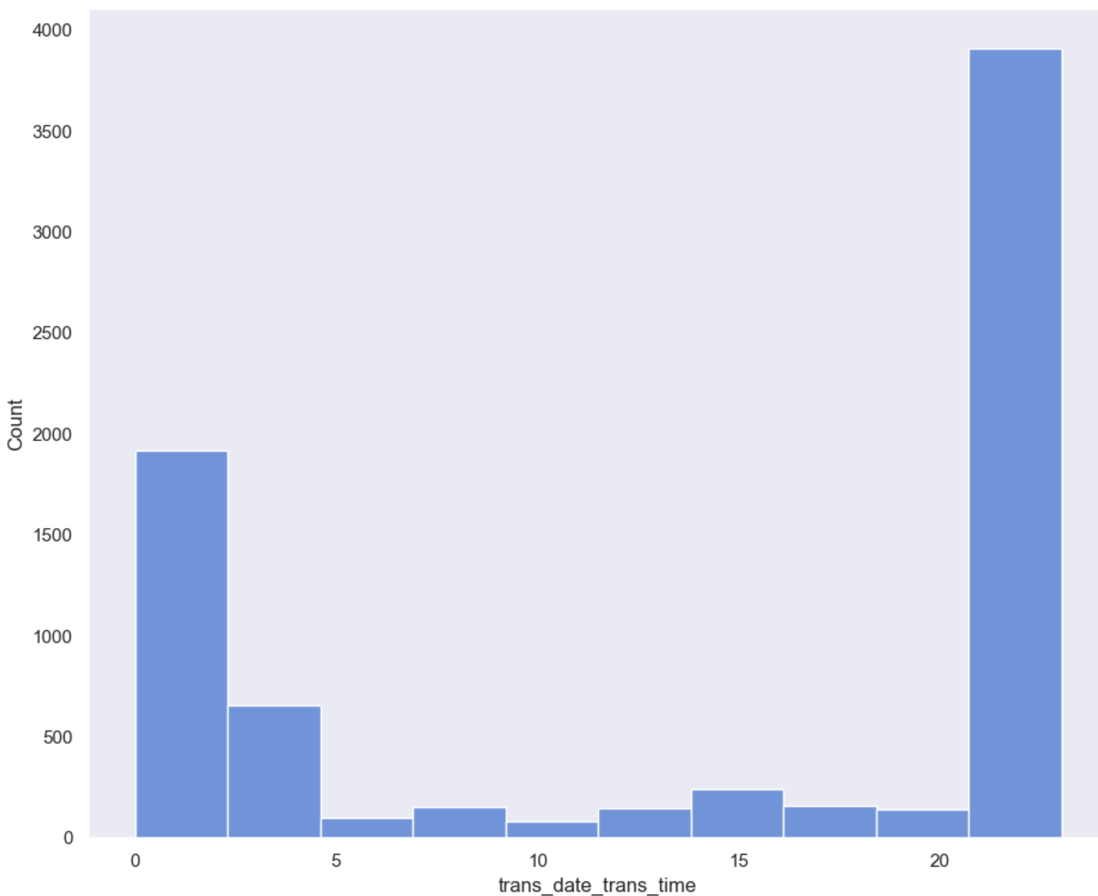
[12]:
```
# 15 most Affected Fraudlent Transactions Occured states
state_count15=new_df["state"].value_counts().sort_values(ascending=False)[:15]
sns.set_style('white')
sns.set(rc={'figure.figsize':(11,9)})
sns.barplot(x=state_count15.values,y=state_count15.index, palette='rocket')
plt.xlabel('count')
plt.ylabel('State')
plt.title("Top 15  most Affected Fraudlent Transactions Reported states")
plt.show()
plt.savefig('states_plot.jpg', bbox_inches='tight', dpi=150)
```



<Figure size 1100x900 with 0 Axes>

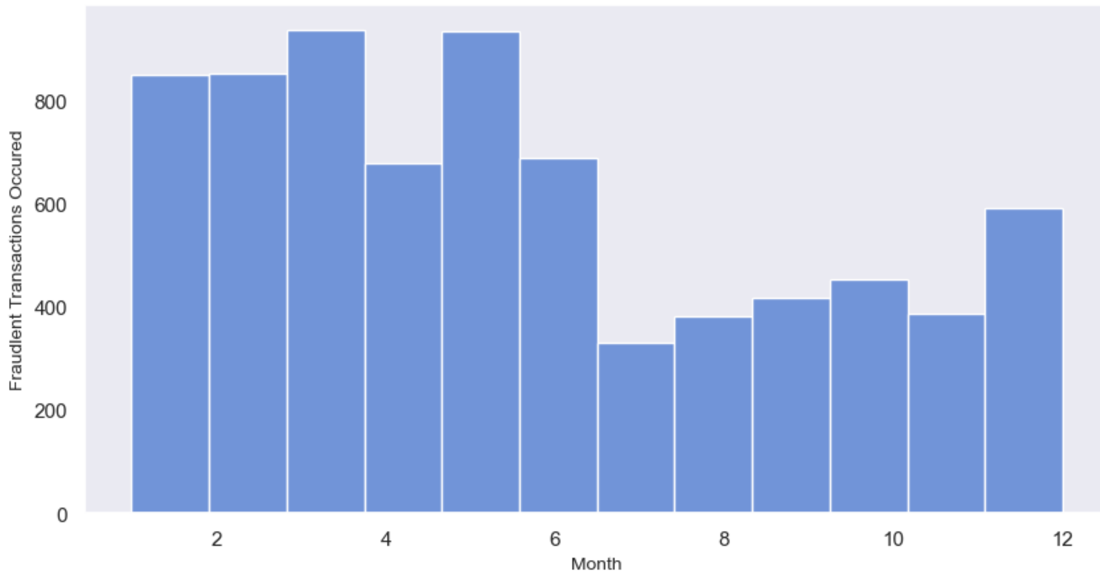
5 Time Based analysis

[13]:
```
new_df['trans_dte_trans_time']= pd.to_datetime(new_df.trans_date_trans_time)
hr = new_df.trans_date_trans_time.dt.hour
sns.set(color_codes=True)
sns.set(style="dark", palette="muted")
sns.histplot(hr,bins=10);
```

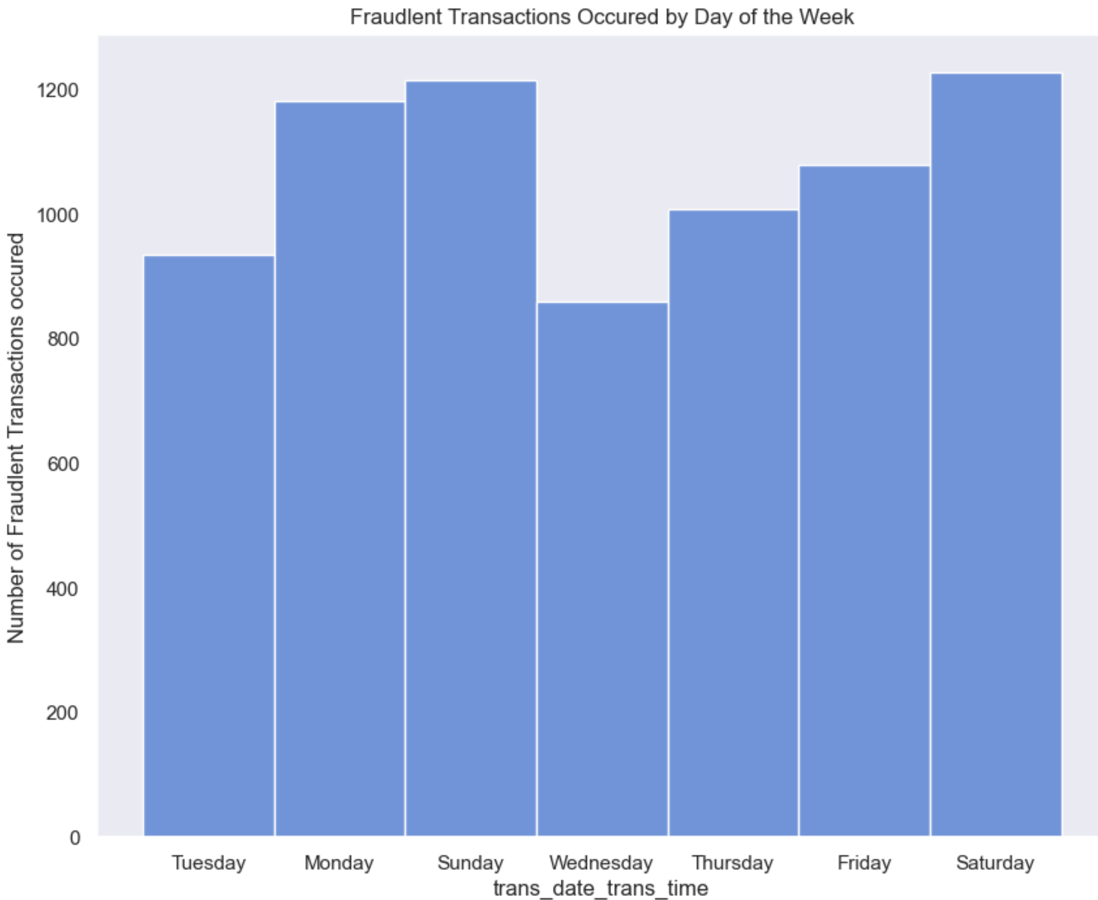


[14]:
```
plt.figure(figsize=(10,5))
plt.ylabel('Fraudlent Transactions Occured', fontsize=10)
plt.xlabel('Month', fontsize=10)

# Number of Fraudelent transactions by week
sns.histplot(new_df.Month, bins=12, kde=False)
```

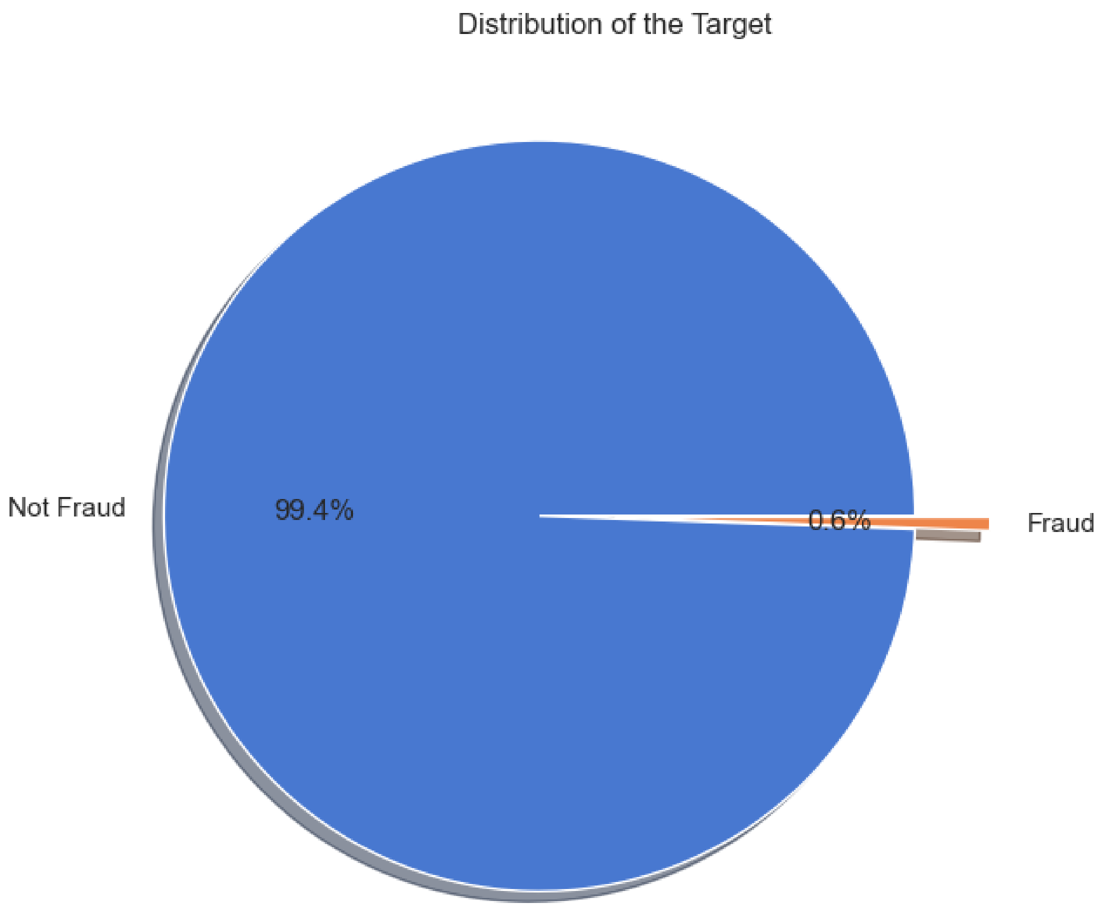
[14]: <AxesSubplot:xlabel='Month', ylabel='Fraudlent Transactions Occured'>



[15]:
```
#Fraudlent Transactions occurence by day of week
days = new_df.trans_date_trans_time.dt.day_name()
fig, axs = plt.subplots(figsize=(10,8))
sns.histplot(days,kde=False);
plt.ylabel('Number of Fraudlent Transactions occured')
plt.title('Fraudlent Transactions Occured by Day of the Week')
plt.show();
```

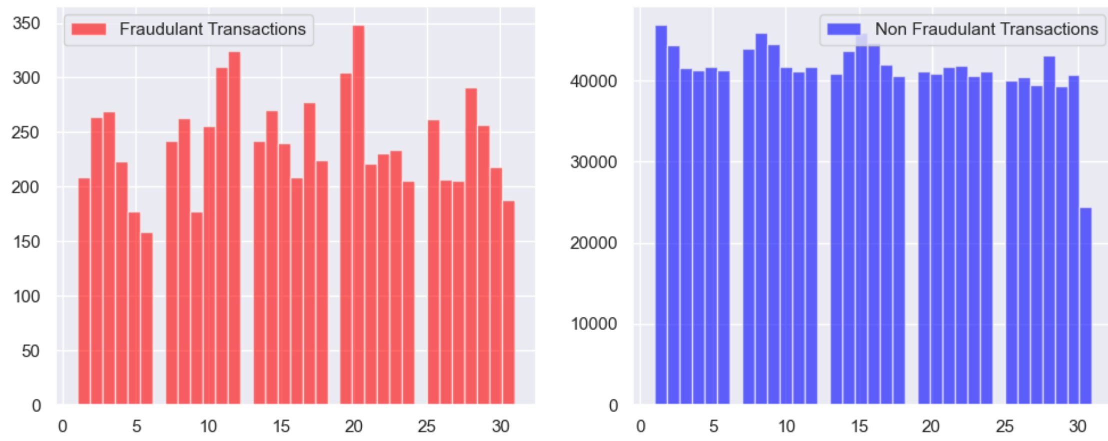


[16]:
```
# Check is_fraud variables that has 0 value for Genuine transactions and 1 for␣
↪Fraud

plt.figure(figsize = [7,7])
plot_var = df['is_fraud'].value_counts(normalize = True)
plt.pie(plot_var,
        autopct='%1.1f%%',
        labels = ['Not Fraud','Fraud'],
        explode = [0.2, 0],
        shadow = True) # plotting the pie chart
plt.title('Distribution of the Target');
```

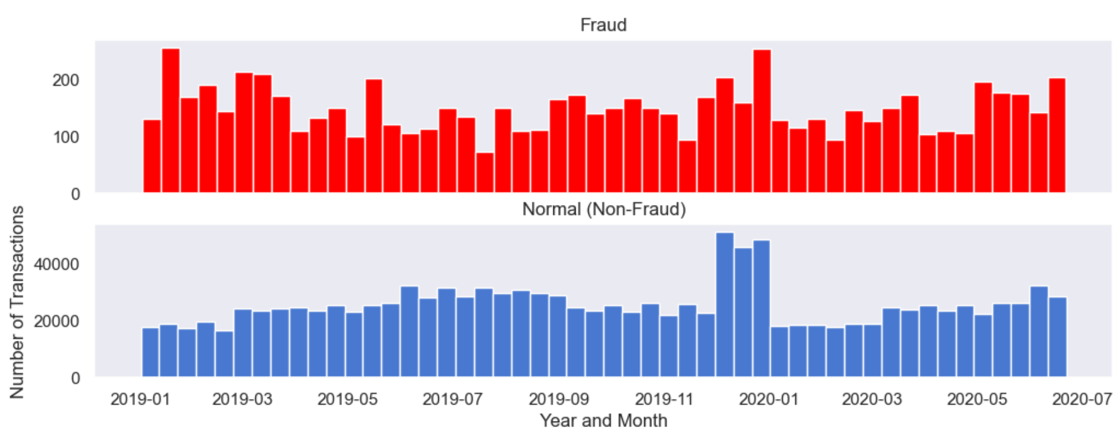


[17]:
```
plt.figure(figsize=(12, 10))

plt.subplot(2, 2, 1)
df[df.is_fraud == 1].Day.hist(bins=35, color='red', alpha=0.6,␣
    ↪label="Fraudulant Transactions")
plt.legend()

plt.subplot(2, 2, 2)
df[df.is_fraud == 0].Day.hist(bins=35, color='blue', alpha=0.6, label="Non␣
    ↪Fraudulant Transactions")
plt.legend()
```

[17]:
```
<matplotlib.legend.Legend at 0x2161e015520>
```



[18]:
```python
# now checking Time value in case of Fraud and Normal Transaction compared␣
↪according to Number of transactions.

fig, (axis_1, axis_2) = plt.subplots(2, 1, sharex=True, figsize=(12,4))
bins = 50

axis_1.hist(df.trans_date_trans_time[df.is_fraud == 1], bins = bins,␣
↪color='red')
axis_1.set_title('Fraud')

axis_2.hist(df.trans_date_trans_time[df.is_fraud == 0], bins = bins)
axis_2.set_title('Normal (Non-Fraud)')

plt.xlabel('Year and Month')
plt.ylabel('Number of Transactions')
plt.show()
```

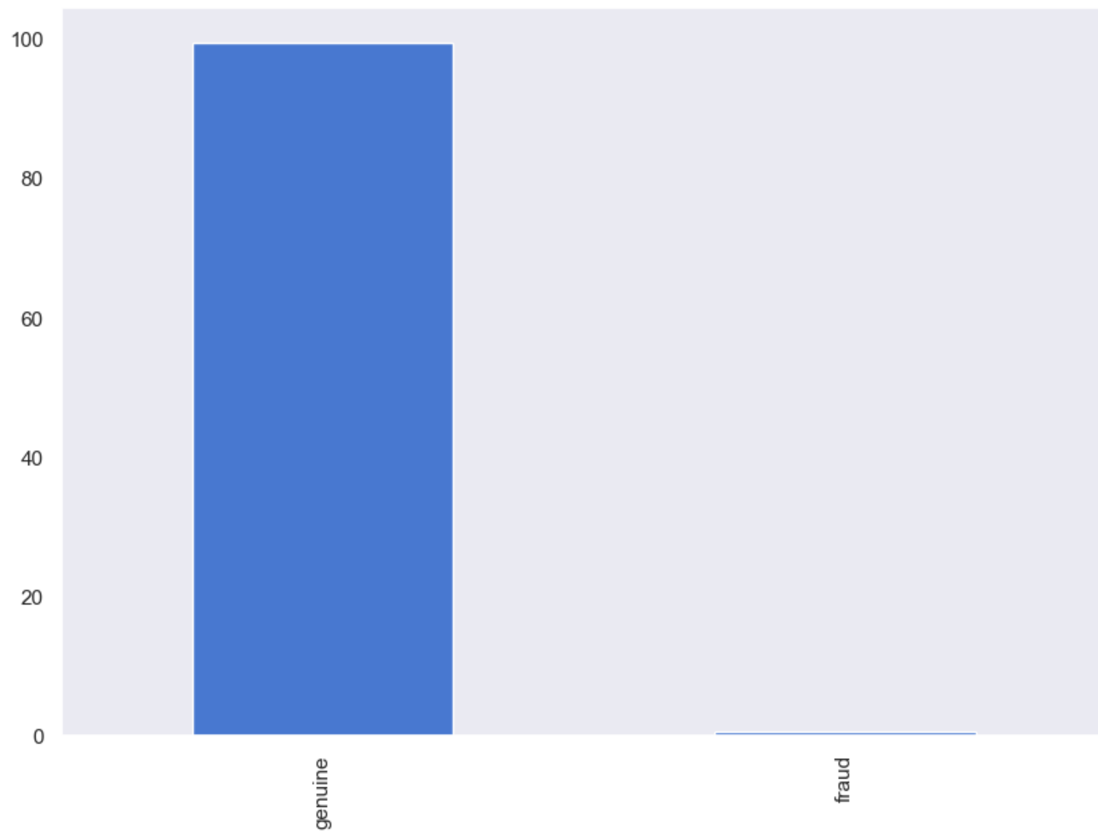


6 Inspect the Target variable

[19]:
```
a = df['is_fraud'].value_counts().rename('count') # count of classes
b = (df['is_fraud'].value_counts(normalize = True)*100).rename('distribution')␣
↪# normalisation of the classes
tem = pd.concat([a,b], axis = 1)
tem.index = ['genuine','fraud']
tem['distribution'].plot(kind = 'bar', figsize = [10,7]);
tem
```

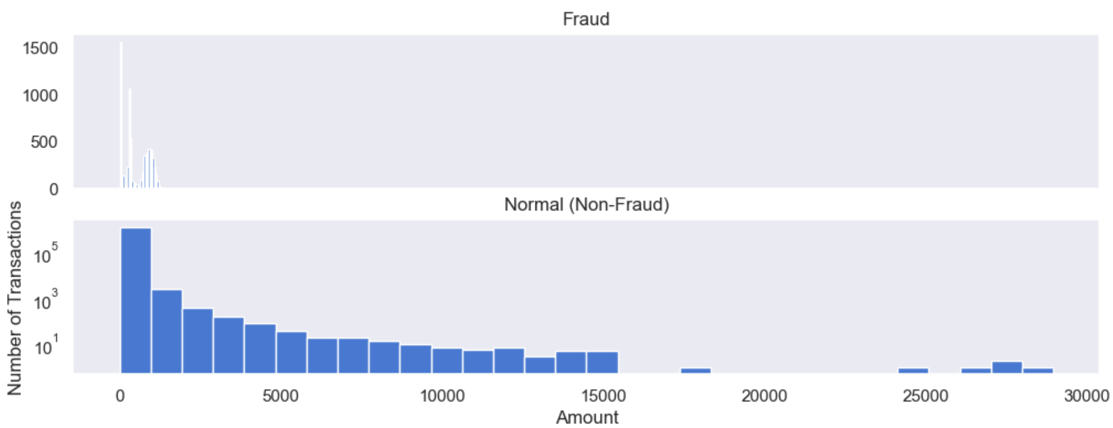
[19]:

	count	distribution
genuine	1289169	99.421135
fraud	7506	0.578865



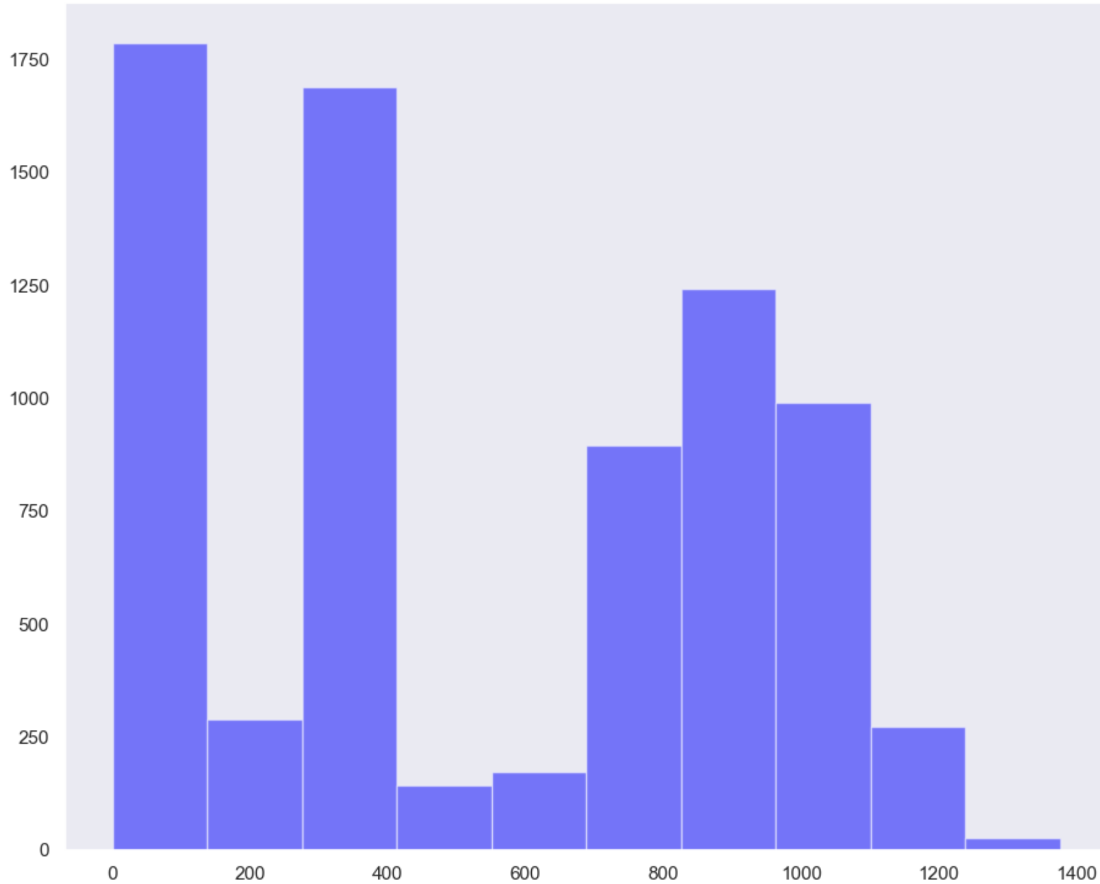
[20]:
```
# now checking Amount in case of Fraud and Normal Transaction compared␣
↪according to Number of transactions.

fig, (axis_1, axis_2) = plt.subplots(2, 1, sharex=True, figsize=(12,4))

bins = 30
```

```
axis_1.hist(df.Amount[df.is_fraud == 1], bins = bins)
axis_1.set_title('Fraud')

axis_2.hist(df.Amount[df.is_fraud == 0], bins = bins)
axis_2.set_title('Normal (Non-Fraud)')

plt.xlabel('Amount')
plt.ylabel('Number of Transactions')
plt.yscale("log")
plt.show()

# we can see here that fraud transactions are of smaller amount. but this cant␣
↪be used solely because normal transactions
# too have a lot of transactions of smaller amount.
```



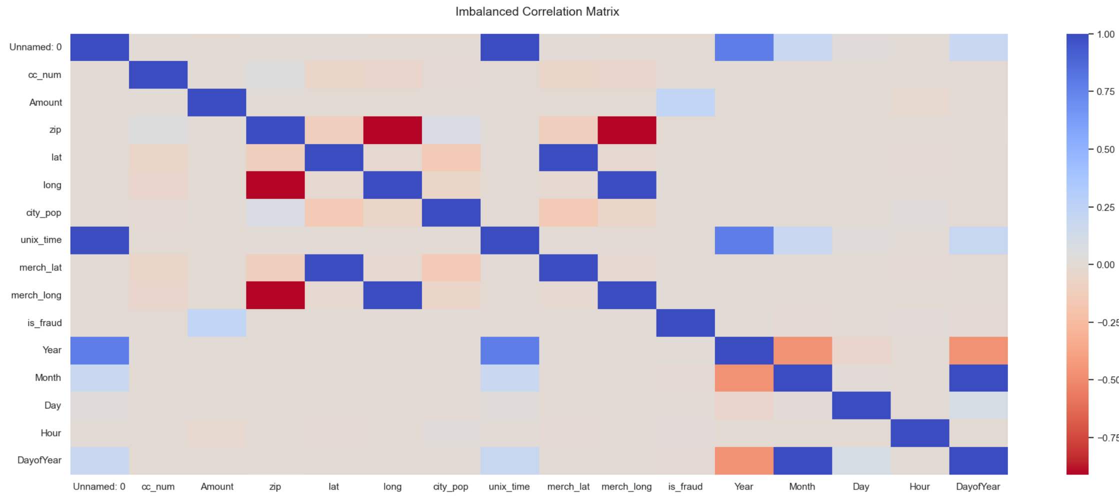
[21]:
```
# Fraud data looks interesting , lets look into it a bit more
# lets see the transaction amount in case Fraud at a smaller scale.

print(df.Amount[df.is_fraud == 1 ].describe())
plt.hist(df.Amount[df.is_fraud == 1 ], 10, facecolor='blue', alpha=0.5)
plt.show()
```

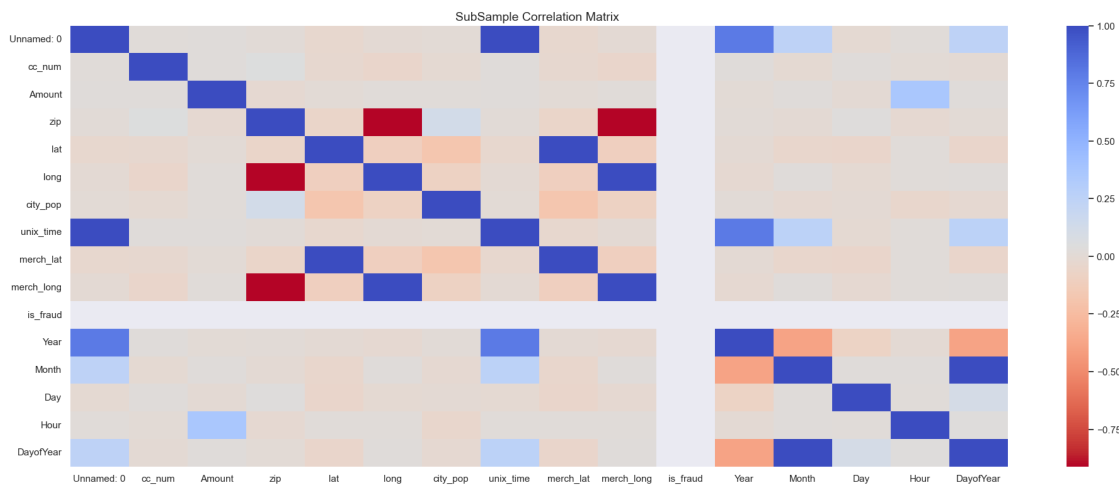
```
count    7506.000000
mean      531.320092
std       390.560070
min         1.060000
25%       245.662500
50%       396.505000
75%       900.875000
max      1376.040000
Name: Amount, dtype: float64
```



7 Imbalanced Correlation

[22]:
```
# Entire DataFrame
# Make sure we use the subsample in our correlation

f, (ax1, ax2) = plt.subplots(2, 1, figsize=(24,20))

corr = df.corr()
sns.heatmap(corr, cmap='coolwarm_r', annot_kws={'size':20}, ax=ax1)
ax1.set_title("Imbalanced Correlation Matrix \n ", fontsize=14)

sub_sample_corr = new_df.corr()
sns.heatmap(sub_sample_corr, cmap='coolwarm_r', annot_kws={'size':20}, ax=ax2)
ax2.set_title('SubSample Correlation Matrix ', fontsize=14)
plt.show()
```



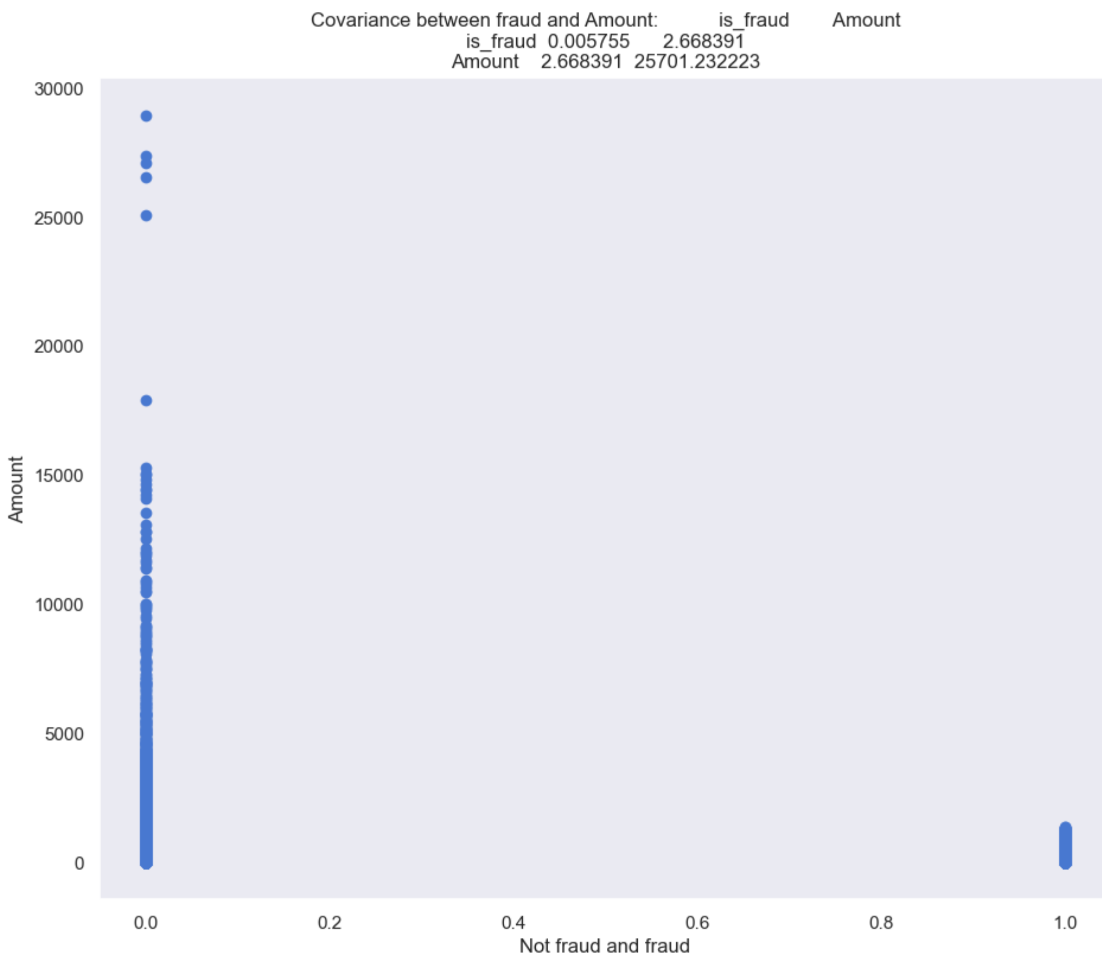


8 Covariance

[23]:
```python
#np.cov(df.is_fraud,df.amount)
np.cov(df.Amount[df.is_fraud == 1])
print("Covariance between Fraud Transactions and Amount: ",df.Amount.cov(df.
 ↪is_fraud == 1))

# Select the "Class" and "Amount" columns
is_fraud_amount = df[["is_fraud", "Amount"]]

# Calculate the covariance
covariance = is_fraud_amount.cov()

print(covariance)
```

```python
# Create a scatter plot
plt.scatter(df["is_fraud"], df["Amount"])
plt.xlabel("Not fraud and fraud")
plt.ylabel("Amount")
plt.title(f"Covariance between fraud and Amount: {covariance}")
plt.show()
```

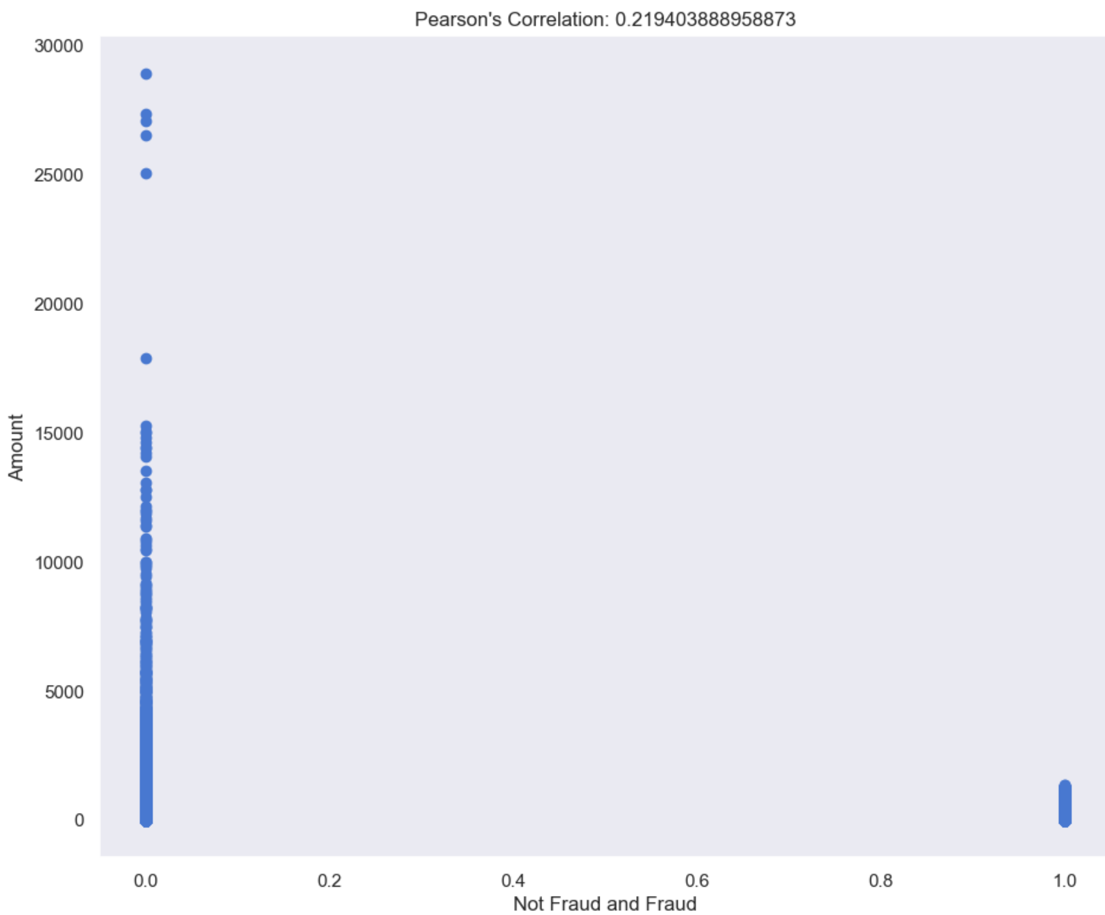
```
Covariance between Fraud Transactions and Amount:  2.668391390485763
          is_fraud        Amount
is_fraud  0.005755      2.668391
Amount    2.668391  25701.232223
```



9 Pearson's correlation

[24]:
```python
# Drop any missing data
df.dropna(inplace=True)

# Calculate Pearson's correlation coefficient
corr_matrix = df.corr(method='pearson')
fraud_corr = corr_matrix['is_fraud'].sort_values(ascending=False)

# Print the correlation values for each feature in descending order
print(fraud_corr)

# Calculate Pearson's correlation coefficient
correlation = df["is_fraud"].corr(df["Amount"], method="pearson")
print("Pearson's correlation coefficient between Not fraud, Fraud and Amount:␣
↪", correlation)

# Create a scatter plot
plt.scatter(df["is_fraud"], df["Amount"])
plt.xlabel("Not Fraud and Fraud")
plt.ylabel("Amount")
plt.title(f"Pearson's Correlation: {correlation}")
plt.show()
```

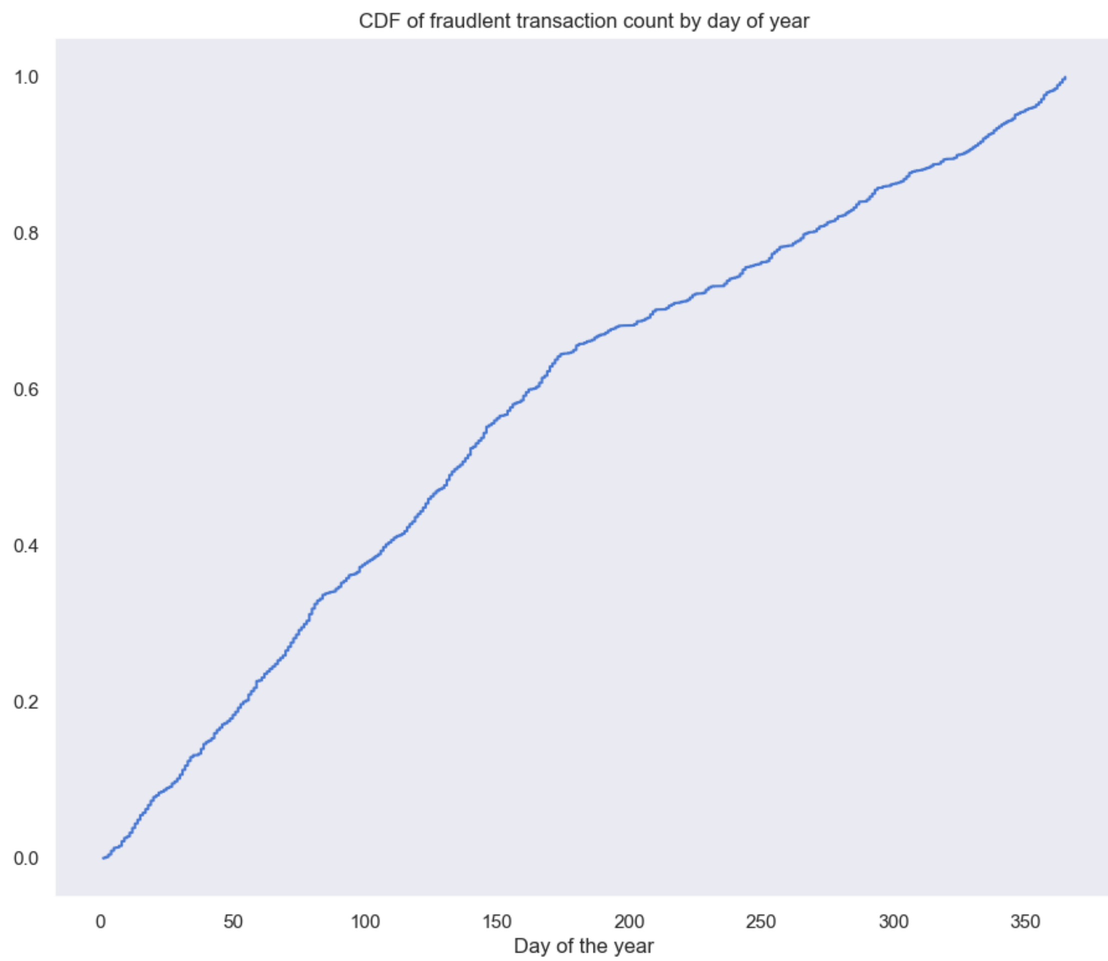
```
is_fraud       1.000000
Amount         0.219404
Hour           0.013799
Day            0.003848
Year           0.003004
city_pop       0.002136
lat            0.001894
merch_lat      0.001741
merch_long     0.001721
long           0.001721
cc_num        -0.000981
zip           -0.002162
Unnamed: 0    -0.004767
unix_time     -0.005078
DayofYear     -0.011974
Month         -0.012409
Name: is_fraud, dtype: float64
Pearson's correlation coefficient between Not fraud, Fraud and Amount:
0.219403888958873
```



10 Cumulative Distribution Function

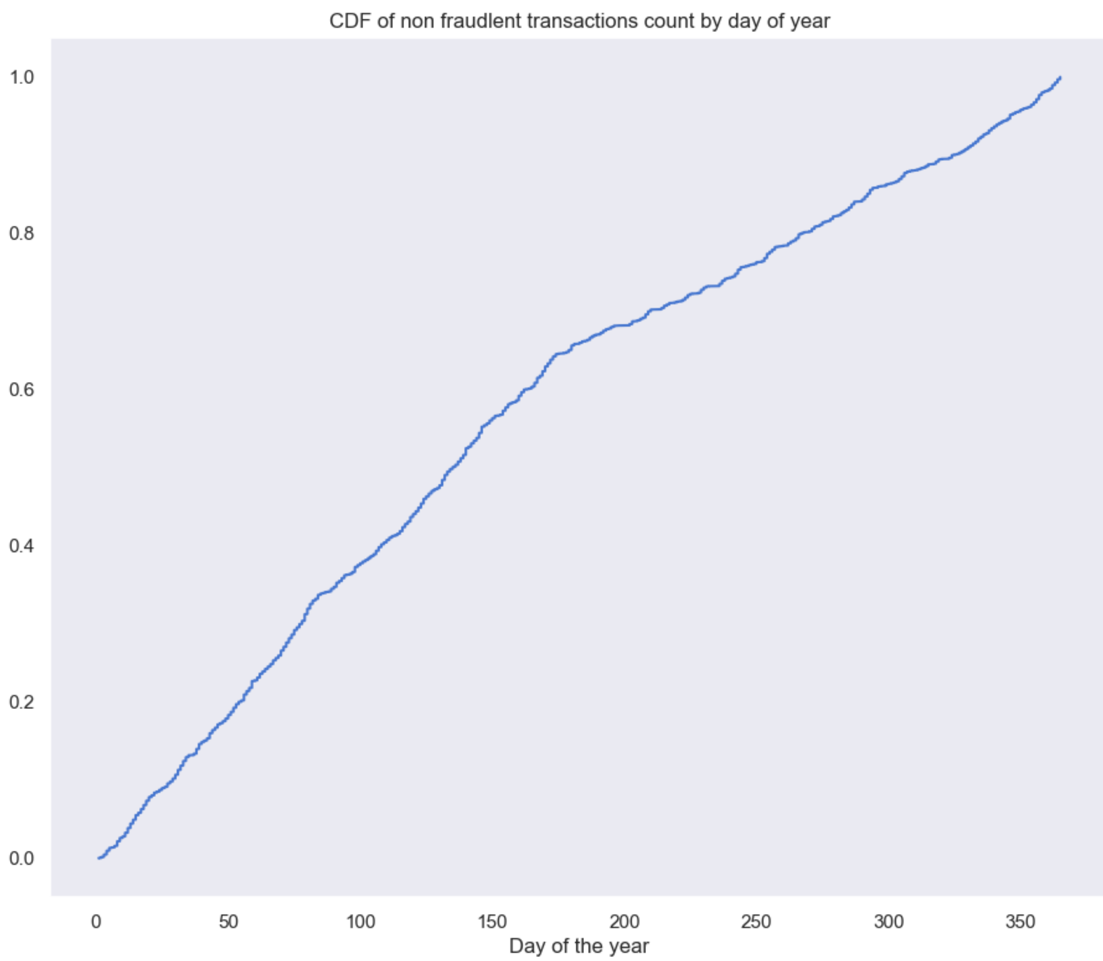
[25]:
```
data = new_df.DayofYear
# sort the data in ascending order
x = np.sort(data)
# get the cdf values of y
y = np.arange(len(x))/float(len(x)-1)

# plotting
plt.xlabel('Day of the year')
plt.title('CDF of fraudlent transaction count by day of year')
plt.plot(x, y)
```

[25]: [<matplotlib.lines.Line2D at 0x21601441700>]

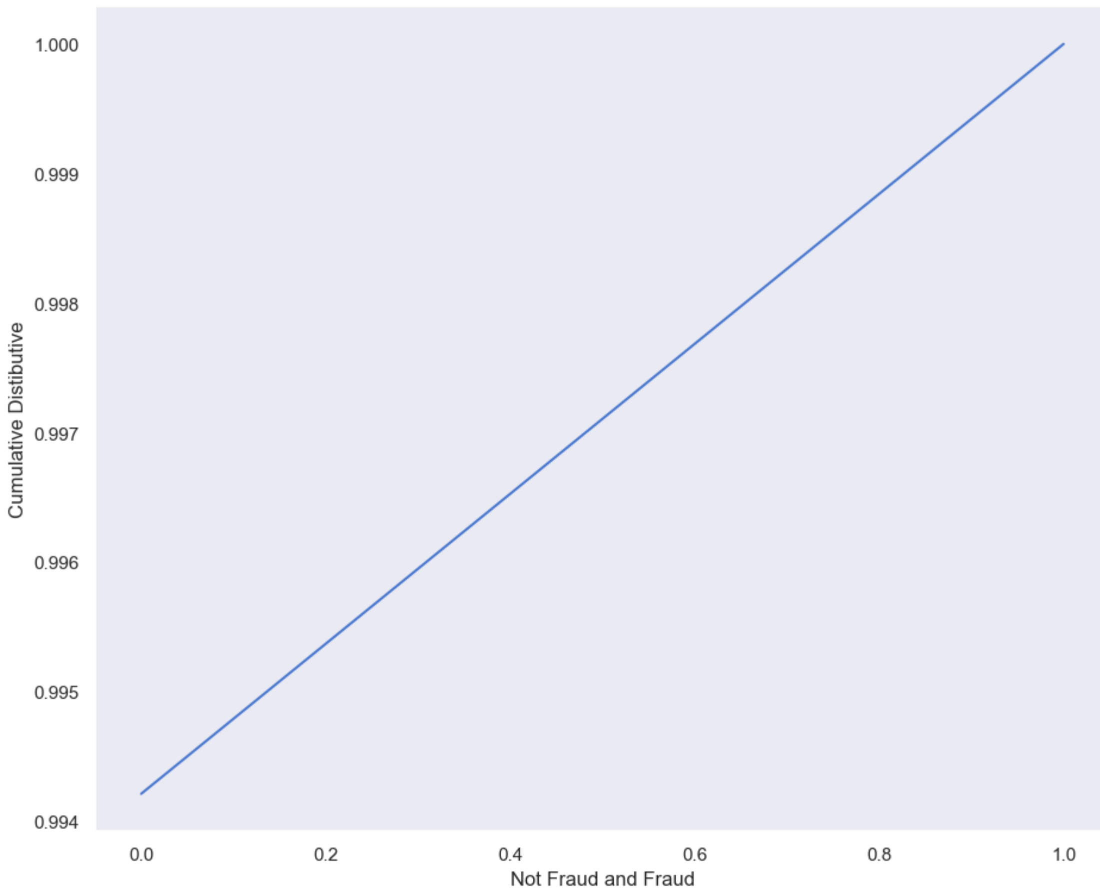


[26]:
```
# data = df.DayofYear
# sort the data in ascending order
x = np.sort(data)
# get the cdf values of y
y = np.arange(len(x))/float(len(x)-1)

# plotting
plt.xlabel('Day of the year')
plt.title('CDF of non fraudlent transactions count by day of year')
plt.plot(x, y)
```

[26]: [<matplotlib.lines.Line2D at 0x2160149e970>]

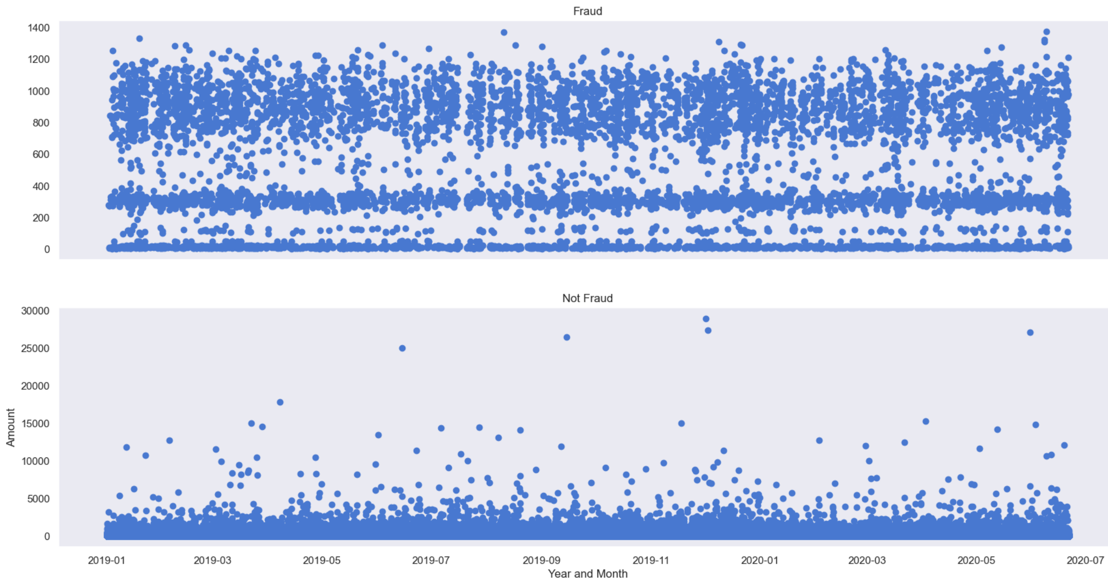


[27]:
```
# Create a new dataframe containing only the "is_fraud" column
#class_df = df[["Class"]]

# Calculate the CDF
cdf = df["is_fraud"].value_counts(normalize=True).sort_index().cumsum()

# Plot the CDF
cdf.plot()
plt.xlabel("Not Fraud and Fraud")
plt.ylabel("Cumulative Distibutive")
plt.show()
```



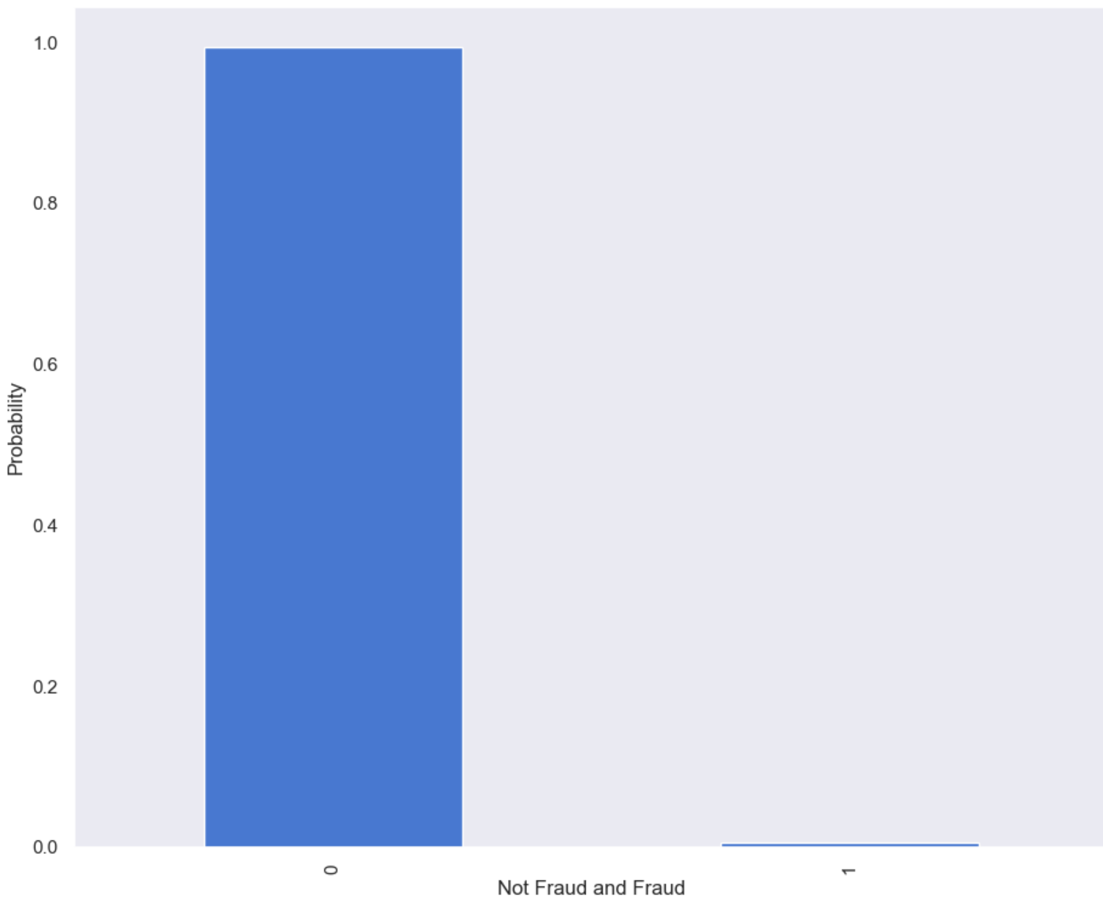
11 Scatter Plot

[28]:
```
# checking Date and TIme vs Amount feature. scatter plot

fig, (axis_1, axis_2) = plt.subplots(2, 1, sharex=True, figsize=(20,10))

axis_1.scatter(df.trans_date_trans_time[df.is_fraud == 1], df.Amount[df.
 ↪is_fraud == 1])
axis_1.set_title('Fraud')

axis_2.scatter(df.trans_date_trans_time[df.is_fraud == 0], df.Amount[df.
 ↪is_fraud == 0])
axis_2.set_title('Not Fraud')

plt.xlabel('Year and Month')
plt.ylabel('Amount')
plt.show()
```



12 Probability Mass Function

[29]:
```
# Create a new dataframe containing only the "is fraud" column
class_df = df[["is_fraud"]]

# Calculate the probability mass function
pmf = class_df["is_fraud"].value_counts(normalize=True)

# Plot the probability mass function
pmf.plot(kind="bar")
plt.xlabel("Not Fraud and Fraud")
plt.ylabel("Probability")
plt.show()
```

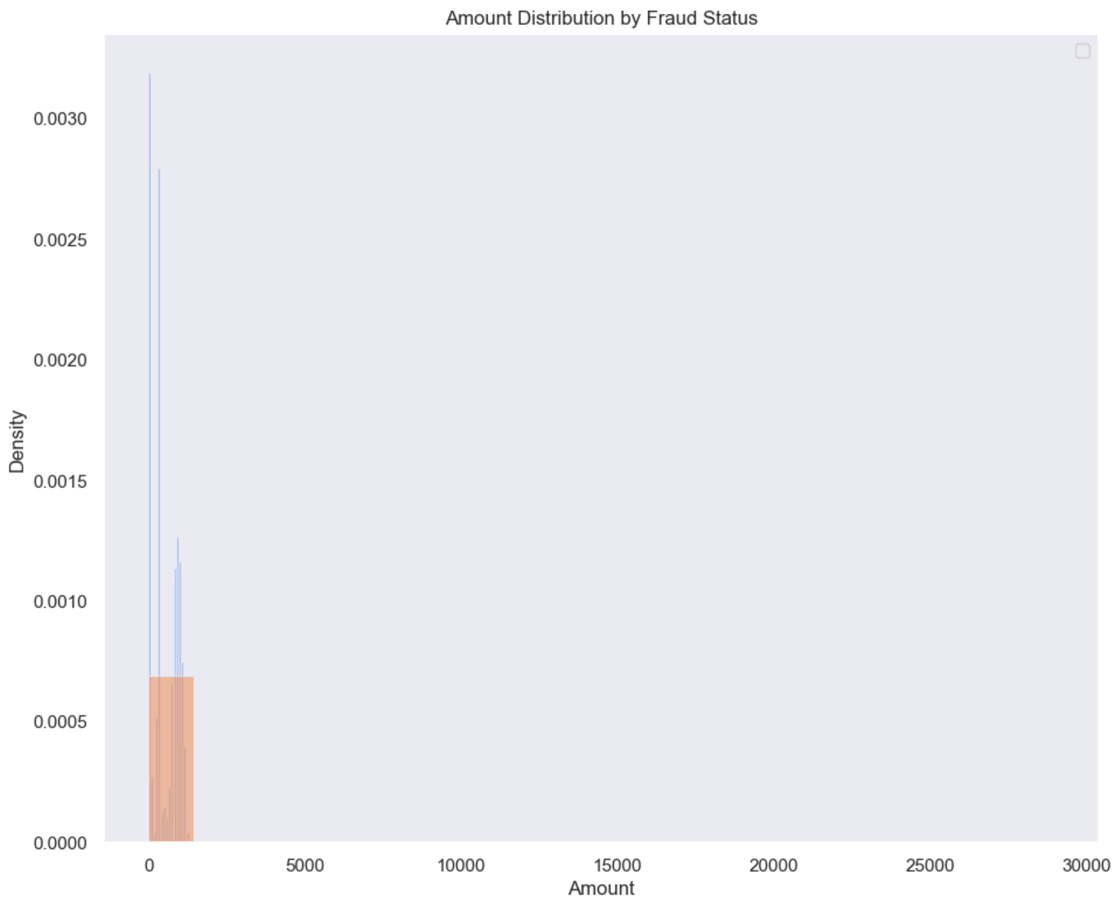


13 Normal Distribution

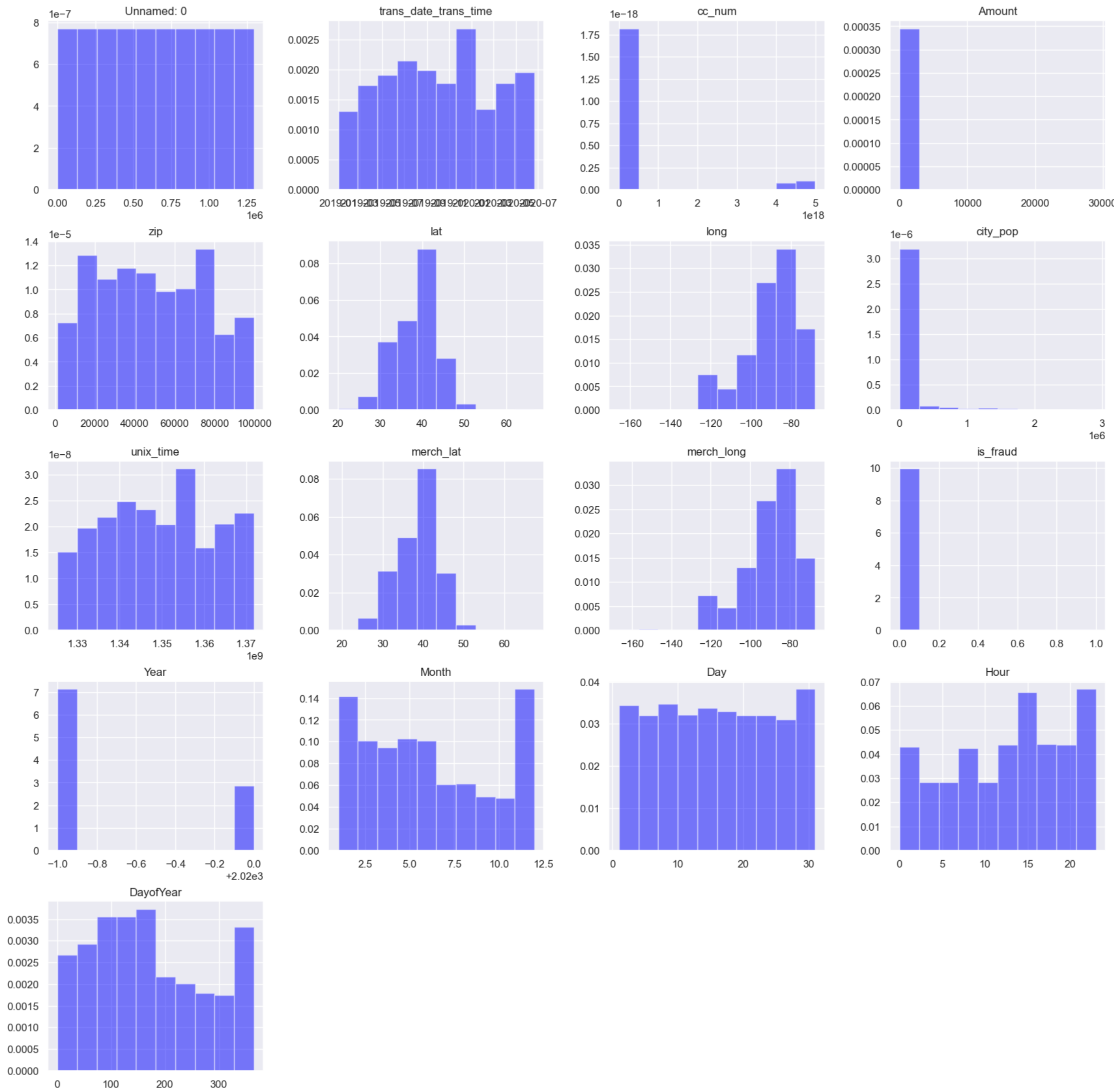
[30]:
```
# Separate the data by fraud and not fraud
fraud_data = df[df['is_fraud'] == 1]
not_fraud_data = df[df['is_fraud'] == 0]

# Calculate the mean and standard deviation for amount for fraud and not fraud
fraud_amount_mean = np.mean(df['Amount'])
fraud_amount_std = np.std(df['Amount'])
not_fraud_amount_mean = np.mean(df['Amount'])
not_fraud_amount_std = np.std(df['Amount'])

# Create normal distribution plots for amount for fraud and not fraud
plt.hist(fraud_data['Amount'], bins=20, density=True, alpha=0.5)
plt.hist(not_fraud_data['Amount'], bins=20, density=True, alpha=0.5)
plt.legend()
plt.title('Amount Distribution by Fraud Status')
plt.xlabel('Amount')
```

```
plt.ylabel('Density')
plt.show()
```

```
No artists with labels found to put in legend.  Note that artists whose label
start with an underscore are ignored when legend() is called with no argument.
```



[31]:
```
#plot histogram of each parameter
df.hist(figsize=(20,20),
         facecolor='blue',
       density=True,
       alpha=0.5)
plt.show()
```



[32]:
```
x=df.iloc[:,:-1]
y=df.iloc[:,len(df.columns)-1]
ncols  = ['zip','lat','city_pop','is_fraud', 'Amount']
x= x[ncols]
print("x.shape:", x.shape)
print("y.shape:", y.shape)
```

```
x.shape: (1296675, 5)
y.shape: (1296675,)
```

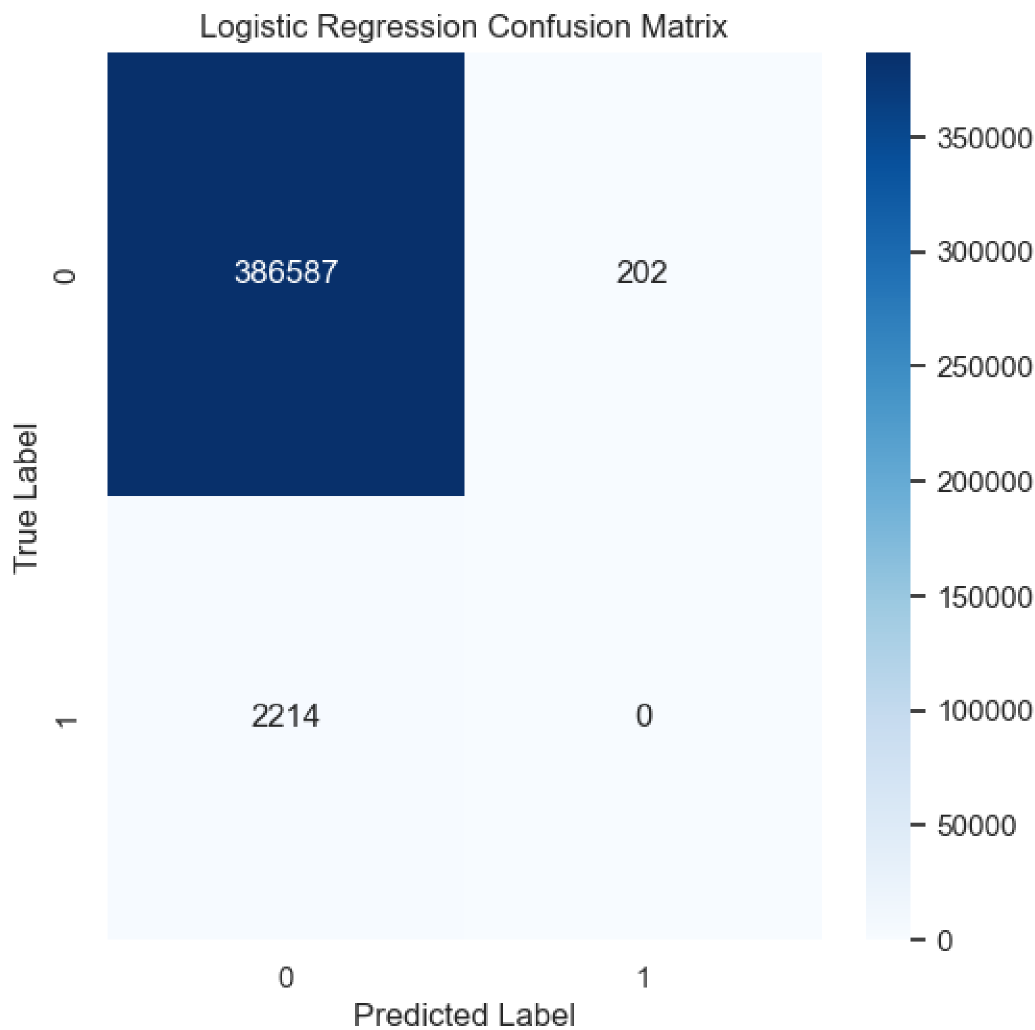
[33]:
```
num = int(len(x) * 0.2)
xtrain = x[:-num]
ytrain = y[:-num]
xtest = x[-num:]
```

```
ytest = y[-num:]

print("# train:", len(xtrain))
print("# test:", len(xtest))
```

```
# train: 1037340
# test: 259335
```

[34]:
```
# Separate the features and labels
X = df.drop('is_fraud', axis=1)
y = df['is_fraud']

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.3,␣
↪random_state=42)

# Fit a logistic regression model on the training data
lr = LogisticRegression()
lr.fit(X_train, y_train)

# Predict the labels of the test data
y_pred = lr.predict(X_test)

# Print the classification report
print(classification_report(y_test, y_pred))


# Plot the logistic regression confusion matrix
plt.figure(figsize=(6, 6))
cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True, cmap="Blues", fmt="d")
plt.title('Logistic Regression Confusion Matrix')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```

```
              precision    recall  f1-score   support

           0       0.99      1.00      1.00    386789
           1       0.00      0.00      0.00      2214

    accuracy                           0.99    389003
   macro avg       0.50      0.50      0.50    389003
weighted avg       0.99      0.99      0.99    389003
```


Logistic Regression Confusion Matrix
386587
202
2214
0
True Label
0
1
0
1
Predicted Label
350000
300000
250000
200000
150000
100000
50000
0

```
[ ]:
```