Mishra530Week12-FinalProject

June 3, 2023

[1]:
```
# DSC 530,Spring 2023 - T301 Data Exploration and Analytics(2235-1)
# Assignment: Week 12 - 12.2 Assignment: Term Project
# Author by:  Debabrata Mishra
# Date: 2023-06-03

# Term Project: Credit Card Fraud Detection EDA
```

1 Credit Card Fraud Detection (Transactional) EDA

1.1 Overview

Credit card fraud is a growing concern for financial institutions, merchants, and consumers alike. With the increasing use of credit cards for online transactions, the opportunity for fraudsters to commit fraudulent activities has increased dramatically. Due to the technological innovation and the emergence of a new Payment techniques, we do see huge increase in BOT attacks, Account takeover, new account fraud, cloned cards, cards-not-present schemes and mobile payments. Such widespread acceptance of cashless transactions leads fraudsters to carry out fraudulent attacks regularly and change their tactics to avoid detection.

1.2 Identifying business problems

Impact to business and individual customers due to financial loss

Inconvience to customers

Compliance and legal issues

Impact the expantation of existing business or start of new business

Cost of chargebacks

1.3 What I intend to analyze

The objectives of my analysis are as follows

Dataset Overview: I will explore the dataset to determine the number of instances (observations) and features (variables) it contains.

Target Variable Distribution: I will investigate the distribution of the target variable to understand the proportion of fraud and non-fraud instances in the dataset.

Missing Values: I will identify if there are any missing values in the dataset and quantify their extent. Additionally, I will examine the distribution of missing values across features.

Feature Correlation: I will assess the correlation between different features in the dataset to identify potential relationships or dependencies among variables.

Geographical Patterns: I will explore if there are any geographical patterns in the occurrence of fraud transactions, which could indicate specific regions with higher or lower fraud rates.

Transaction Behavior Differences: I will compare the transaction behavior between fraud and non-fraud instances, focusing on variables such as transaction amount and transaction frequency, to identify any notable differences.

Relationship with Target Variable: I will examine the relationships between the target variable (fraud vs. non-fraud) and other features in the dataset to determine if any variables are particularly informative for fraud detection.

Outliers: I will identify and analyze any outliers present in the dataset, quantifying their frequency and distribution across variables.

2 Analysis, Code and Relevant results

[2]:
```
# Imports

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
from sklearn.metrics import roc_auc_score,roc_curve,precision_score

import statsmodels.api as sm
from scipy.stats import norm, lognorm

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
import warnings
from matplotlib import rcParams
from matplotlib import rcParams

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

# Suppress warning messages
warnings.filterwarnings('ignore')
warnings.simplefilter('ignore')

rcParams['figure.figsize'] = 11.7,8.27
rcParams.update({'font.size': 8})
```

[3]:
```
# Read and Load the dataset
data = pd.read_csv('ds_fraud_txn.csv')
data.shape
```

[3]:
```
(1296675, 23)
```

[4]:
```
# Check the data
data.head()
```

[4]:
```
   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
```

[5]:
```python
# Overview of the structure and characteristics
data.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
```

[6]:
```
# Modification activities

# Rename and data elements formatting
data.rename(columns = {'Unnamed: 0':'id', 'cc_num':'accountNumber', 'amt':
 ↪'amount'}, inplace = True)
data['trans_date_trans_time'] = pd.
 ↪to_datetime(data['trans_date_trans_time'],errors='coerce')

# Categories of date and time
data['year']=data['trans_date_trans_time'].dt.year
data['month']=data['trans_date_trans_time'].dt.strftime('%b')
data['month']=data['trans_date_trans_time'].dt.month
data['day']=data['trans_date_trans_time'].dt.day
data['hour']=data['trans_date_trans_time'].dt.hour
data['weekday']=data['trans_date_trans_time'].dt.strftime('%a')
data['dayofYear']=data['trans_date_trans_time'].dt.dayofyear

data['trans_date_trans_time']=pd.to_datetime(data['trans_date_trans_time'])
data['txn_date']=data['trans_date_trans_time'].dt.strftime('%Y-%m-%d')
data['txn_date']=pd.to_datetime(data['txn_date'])
data['dob']=pd.to_datetime(data['dob'])

# Create a variable age of customer on day of transaction

data["age"] =data["txn_date"]-data["dob"]
data["age"] =data["age"].astype('timedelta64[Y]')
```

[7]:
```
# check the data after modification
data.head()
```

[7]:
```
   id trans_date_trans_time      accountNumber  \
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  amount      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  year  month  day  hour weekday  dayofYear   txn_date   age
0         0  2019      1    1     0     Tue          1 2019-01-01  30.0
1         0  2019      1    1     0     Tue          1 2019-01-01  40.0
2         0  2019      1    1     0     Tue          1 2019-01-01  56.0
3         0  2019      1    1     0     Tue          1 2019-01-01  51.0
4         0  2019      1    1     0     Tue          1 2019-01-01  32.0
```

[8]:
```
# Overview of the structure and characteristics
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1296675 entries, 0 to 1296674
Data columns (total 31 columns):
 #   Column                 Non-Null Count    Dtype
---  ------                 --------------    -----
 0   id                     1296675 non-null  int64
 1   trans_date_trans_time  1296675 non-null  datetime64[ns]
 2   accountNumber          1296675 non-null  int64
 3   merchant               1296675 non-null  object
 4   category               1296675 non-null  object
```

```
 5   amount                  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  datetime64[ns]
 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
 23  year                    1296675 non-null  int64
 24  month                   1296675 non-null  int64
 25  day                     1296675 non-null  int64
 26  hour                    1296675 non-null  int64
 27  weekday                 1296675 non-null  object
 28  dayofYear               1296675 non-null  int64
 29  txn_date                1296675 non-null  datetime64[ns]
 30  age                     1296675 non-null  float64
dtypes: datetime64[ns](3), float64(6), int64(11), object(11)
memory usage: 306.7+ MB
```

[9]:

```
# Get the count and peercentage of Confirmed Fraud and Not-Fraud records
Num_of_Fraud = round(data['is_fraud'].value_counts()[1]/len(data)*100,3)
Num_of_NonFraud = round(data['is_fraud'].value_counts()[0]/len(data)*100,3)

print("Number of Confirmed Fraud Records            :",data['is_fraud'].
 ↪value_counts()[1])
print("Number of Non-Fraud Records                  :",data['is_fraud'].
 ↪value_counts()[0])
print("\n")
print("Percentage of Confirmed Fraud Records        :", Num_of_Fraud,"%")
print("Percentage of Not-Fraud Records              :",Num_of_NonFraud,"%")
```

```
Number of Confirmed Fraud Records            : 7506
Number of Non-Fraud Records                  : 1289169


Percentage of Confirmed Fraud Records        : 0.579 %
Percentage of Not-Fraud Records              : 99.421 %
```

```
[10]: # Lets shuffle the data before creating the subsamples
data = data.sample(frac=1)

# amount of fraud classes
fraud_df = data.loc[data['is_fraud'] == 1]
non_fraud_df = data.loc[data['is_fraud'] == 0]
normal_distributed_df = pd.concat([fraud_df])

# Shuffle dataframe rows for a sub sample of confirmed fraud data
subsample_analysis_df = normal_distributed_df.sample(frac=1, random_state=42)
```

3 Describing the Variables

```
[11]: # 1. Describing some of the Variables
variable_descriptions = {
    'amount': 'The amount of the transaction',
    'is_fraud': 'Status of the transaction , 0: Not-Fraud , 1: Confirmed Fraud',
    'city': 'The city where merchant is regustered/located  or city where the␣
 ↪transaction occured',
    'state': 'The state where merchant is regustered/located  or state where␣
 ↪the transaction occured',
    'day': 'The state where merchant is regustered/located  or state where the␣
 ↪transaction occured',
    'age': 'The age of the customer at time of transaction',
    'Category': 'The merchant/business category and type of transaction occured␣
 ↪like POS vs Ecomm',
    'weekday': 'day of the week when transaction occured',
    'trans_date_trans_time': 'Local date and time when transaction occured '
}

# Print variable descriptions
for var, desc in variable_descriptions.items():
    print(f"{var}","     :",f"{desc}")
```

```
amount      : The amount of the transaction
is_fraud      : Status of the transaction , 0: Not-Fraud , 1: Confirmed Fraud
city      : The city where merchant is regustered/located  or city where the
transaction occured
state      : The state where merchant is regustered/located  or state where the
transaction occured
day      : The state where merchant is regustered/located  or state where the
transaction occured
age      : The age of the customer at time of transaction
Category      : The merchant/business category and type of transaction occured
like POS vs Ecomm
weekday      : day of the week when transaction occured
trans_date_trans_time      : Local date and time when transaction occured
```

4 Descriptive Characteristics

[12]:
```
# Descriptive Characteristics
data.describe()
```

[12]:
```
                 id  accountNumber        amount           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          year         month           day          hour  \
count  1.296675e+06  1.296675e+06  1.296675e+06  1.296675e+06  1.296675e+06
mean   5.788652e-03  2.019287e+03  6.142150e+00  1.558798e+01  1.280486e+01
std    7.586269e-02  4.522452e-01  3.417703e+00  8.829121e+00  6.817824e+00
min    0.000000e+00  2.019000e+03  1.000000e+00  1.000000e+00  0.000000e+00
25%    0.000000e+00  2.019000e+03  3.000000e+00  8.000000e+00  7.000000e+00
50%    0.000000e+00  2.019000e+03  6.000000e+00  1.500000e+01  1.400000e+01
75%    0.000000e+00  2.020000e+03  9.000000e+00  2.300000e+01  1.900000e+01
max    1.000000e+00  2.020000e+03  1.200000e+01  3.100000e+01  2.300000e+01

          dayofYear           age
count  1.296675e+06  1.296675e+06
mean   1.713139e+02  4.549592e+01
std    1.043757e+02  1.739739e+01
min    1.000000e+00  1.300000e+01
25%    8.700000e+01  3.200000e+01
50%    1.550000e+02  4.300000e+01
75%    2.550000e+02  5.700000e+01
max    3.650000e+02  9.500000e+01
```

[13]:
```
# Descriptive Characteristics - Confirmed Fraud data
fraud_df.describe()
```

[13]:

```
                 id  accountNumber       amount           zip          lat  \
count  7.506000e+03   7.506000e+03  7506.000000   7506.000000  7506.000000
mean   6.249497e+05   4.003577e+17   531.320092  48038.714229    38.663609
std    4.010560e+05   1.276871e+18   390.560070  27265.558212     5.172289
min    2.449000e+03   6.041621e+10     1.060000   1330.000000    20.027100
25%    2.398565e+05   1.800429e+14   245.662500  24927.000000    35.056100
50%    6.381620e+05   3.528041e+15   396.505000  46290.000000    39.433600
75%    9.849215e+05   4.651007e+15   900.875000  71107.000000    42.073175
max    1.295733e+06   4.992346e+18  1376.040000  99783.000000    66.693300

              long      city_pop     unix_time    merch_lat   merch_long  \
count  7506.000000  7.506000e+03  7.506000e+03  7506.000000  7506.000000
mean    -89.916041  9.727676e+04  1.348389e+09    38.653901   -89.915808
std      14.278221  3.265815e+05  1.383020e+07     5.218387    14.298685
min    -165.672300  2.300000e+01  1.325466e+09    19.425114  -166.550779
25%     -96.701000  7.465000e+02  1.335744e+09    35.114671   -96.671038
50%     -86.691900  2.623000e+03  1.348872e+09    39.427008   -86.813044
75%     -79.941600  2.143700e+04  1.360021e+09    41.986902   -79.907096
max     -68.556500  2.906700e+06  1.371787e+09    67.510267   -67.569238

       is_fraud         year        month          day         hour  \
count    7506.0  7506.000000  7506.000000  7506.000000  7506.000000
mean        1.0  2019.304556     5.586331    16.033173    14.037836
std         0.0     0.460250     3.454753     8.709623     9.702306
min         1.0  2019.000000     1.000000     1.000000     0.000000
25%         1.0  2019.000000     3.000000     9.000000     2.000000
50%         1.0  2019.000000     5.000000    16.000000    22.000000
75%         1.0  2020.000000     8.000000    23.000000    23.000000
max         1.0  2020.000000    12.000000    31.000000    23.000000

         dayofYear          age
count  7506.000000  7506.000000
mean    154.934186    48.288836
std     105.508070    18.849917
min       1.000000    14.000000
25%      67.000000    32.000000
50%     135.000000    47.000000
75%     243.000000    60.000000
max     365.000000    93.000000
```

5 Plot Histogram

5.1 Plot Histogram for each variable of full dataset

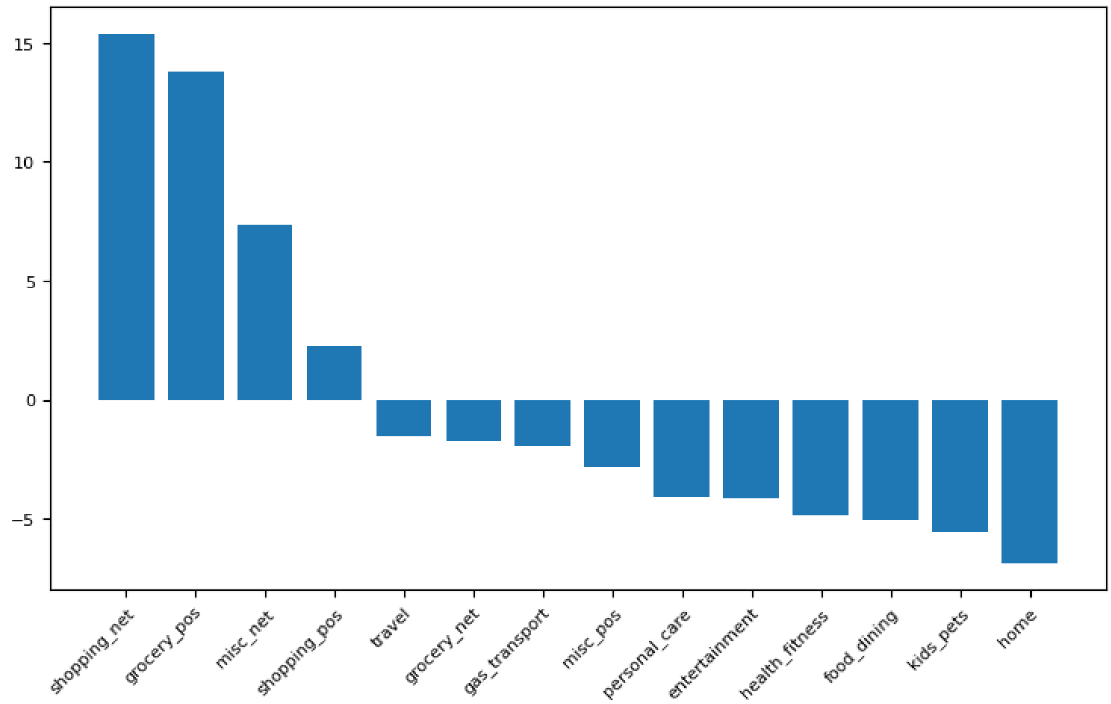
[14]:
```python
#plot histogram of each variable
data.hist(figsize=(20,20),facecolor='blue',density=True,alpha=0.5)
plt.show()
```

[15]:
```python
#plot histogram of each variabale of confirmed fraud data
fraud_df.hist(figsize=(20,20),facecolor='orange',density=True,alpha=0.5)
plt.show()
```

5.2 Plot Histogram for selected variables

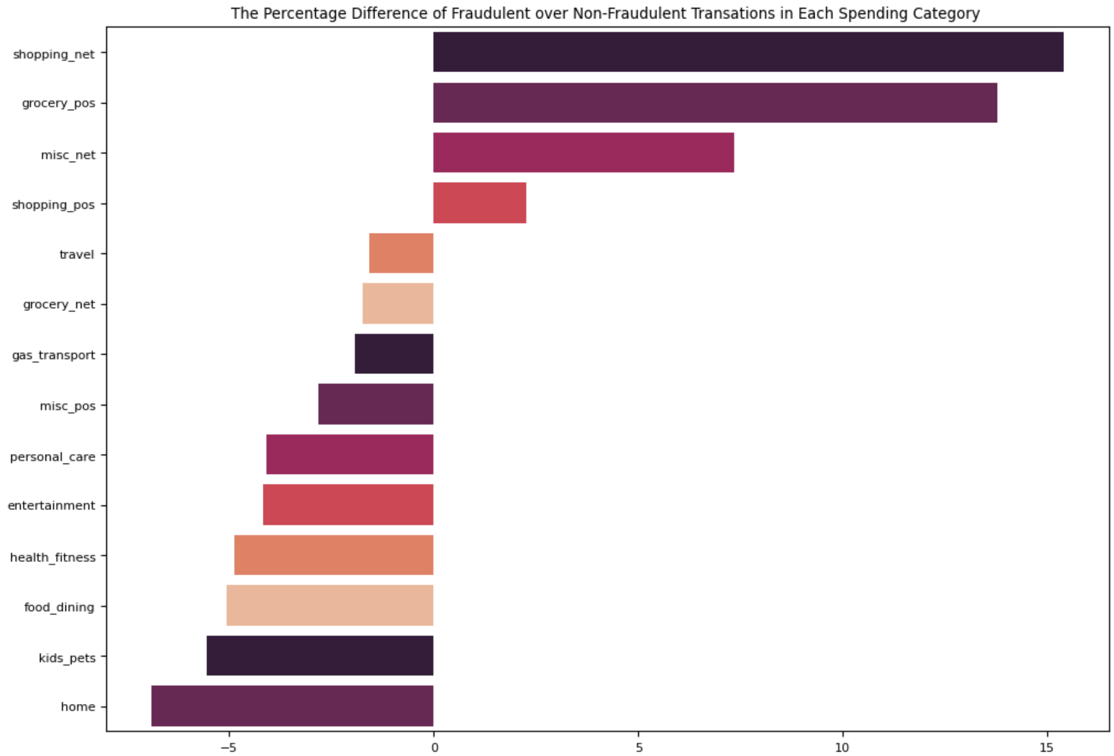
[16]:
```
#  Category -  Fraud Vs Not-Fraud ( 0- Not-Fraud , 1 - Fraud)
x = data[data['is_fraud']== 1]['category']
y = data[data['is_fraud']== 0]['category']



a1 = x.value_counts(normalize=True)
a2 = y.value_counts(normalize=True)
z = (a1 - a2)*100
z = z.sort_values(ascending=False)

cat = z.index
```

```
freq = z.values
positions = range(len(cat))

plt.figure(figsize=(9,5))
plt.bar(positions, freq  )
plt.xticks(positions,cat, rotation=45, ha="right",rotation_mode='anchor',␣
 ↪wrap=True)

plt.show()
```

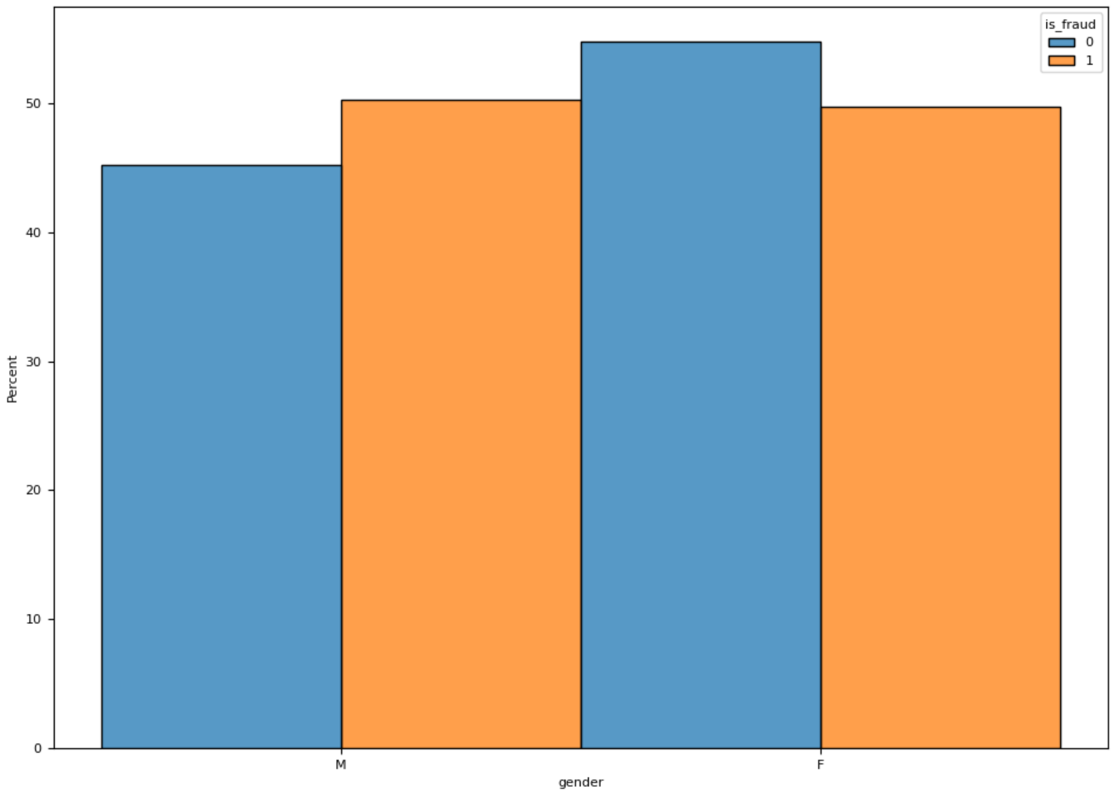


[17]:
```
#  Category -  Fraud Vs Not-Fraud ( 0- Not-Fraud , 1 - Fraud)
color = sns.color_palette("rocket")
ax = sns.barplot(y=cat, x = freq,palette=color)
plt.title('The Percentage Difference of Fraudulent over Non-Fraudulent␣
 ↪Transations in Each Spending Category ')
```

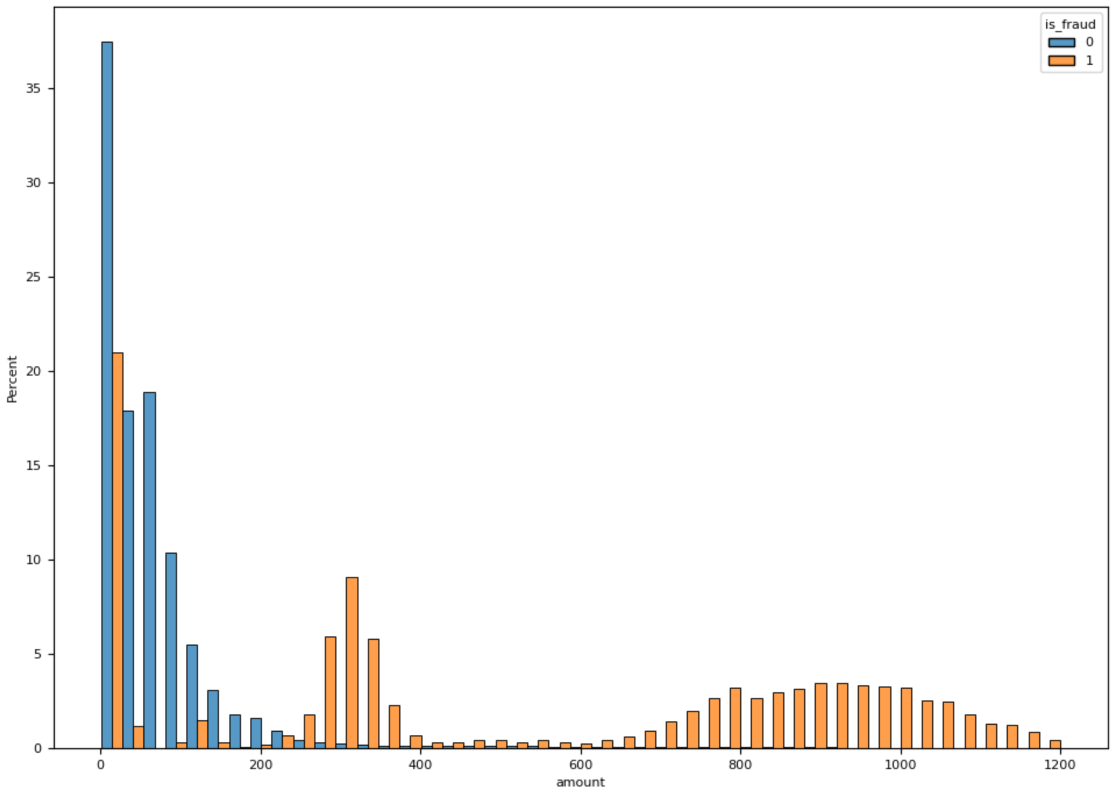
[17]:
```
Text(0.5, 1.0, 'The Percentage Difference of Fraudulent over Non-Fraudulent
Transations in Each Spending Category ')
```



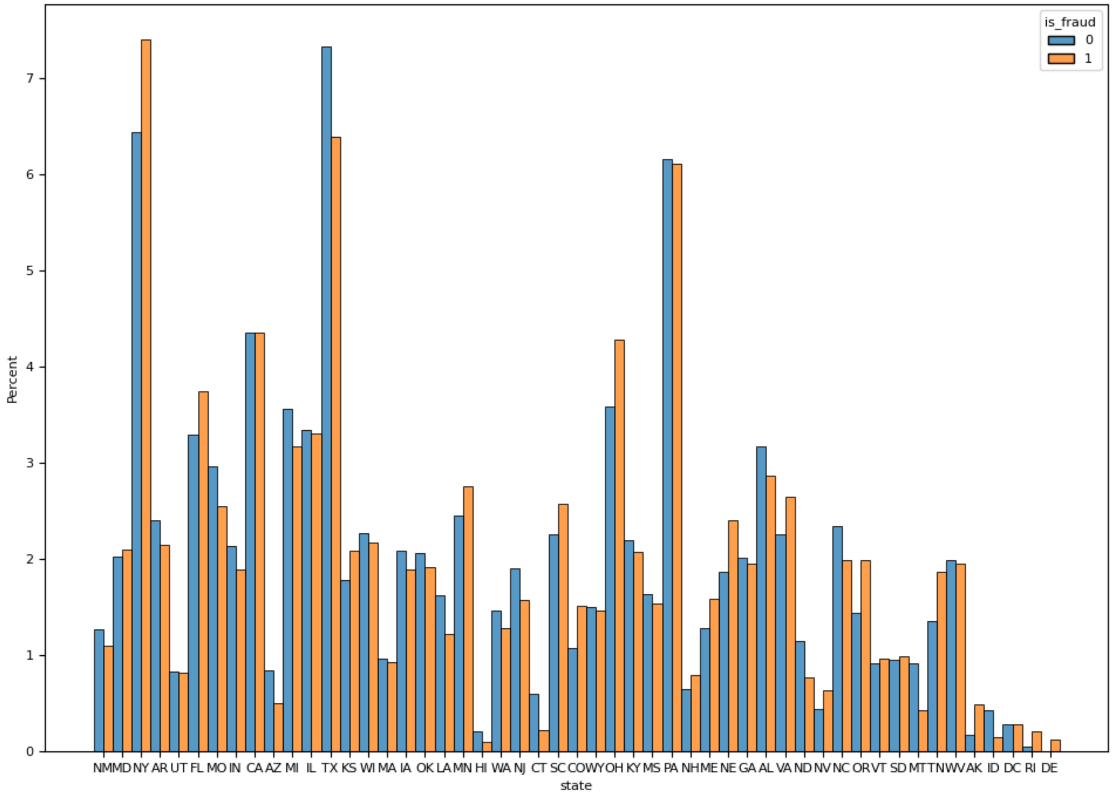

```
[18]: #  Gender - Fraud Vs Not-Fraud ( 0- Not-Fraud , 1 - Fraud)
ax = sns.histplot(x='gender',␣
 ↪data=data,stat='percent',hue='is_fraud',multiple='dodge', common_norm=False)
```



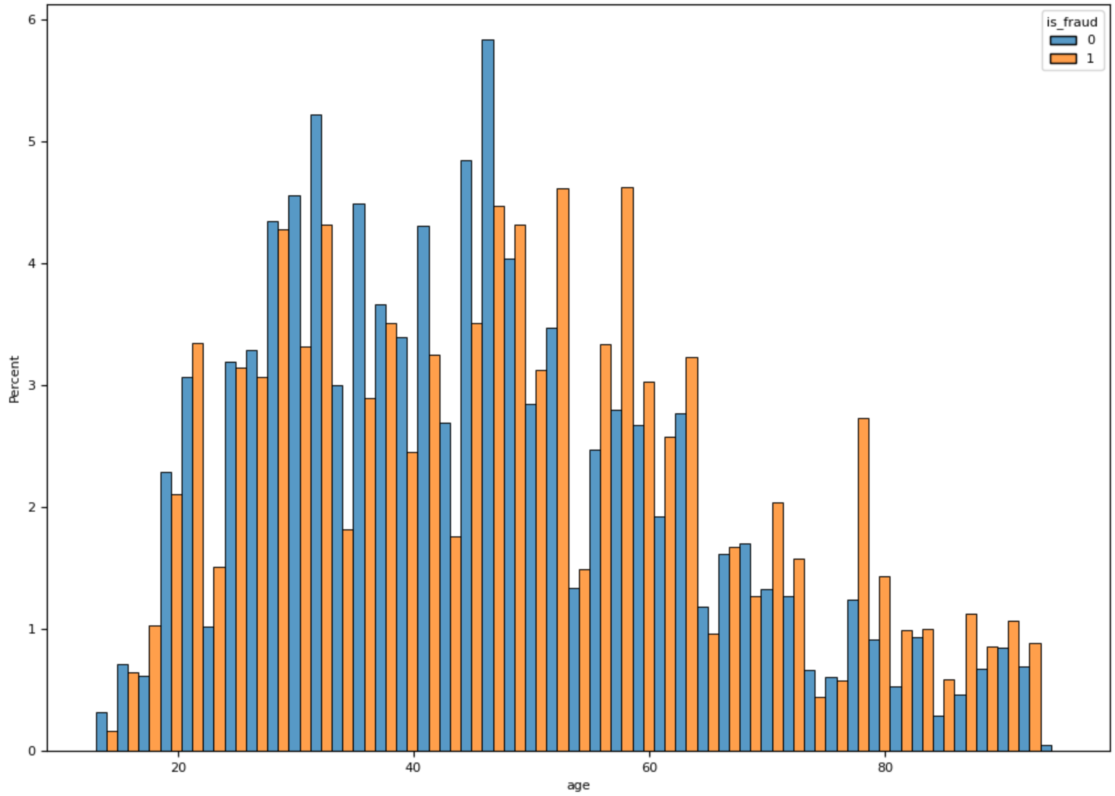
[19]:
```
# Amount - Fraud Vs Not-Fraud ( 0- Not-Fraud , 1 - Fraud)
ax=sns.histplot(x='amount',data=data[data.
 ↪amount<=1200],hue='is_fraud',stat='percent',multiple='dodge'
                ,common_norm=False,bins=45)
```



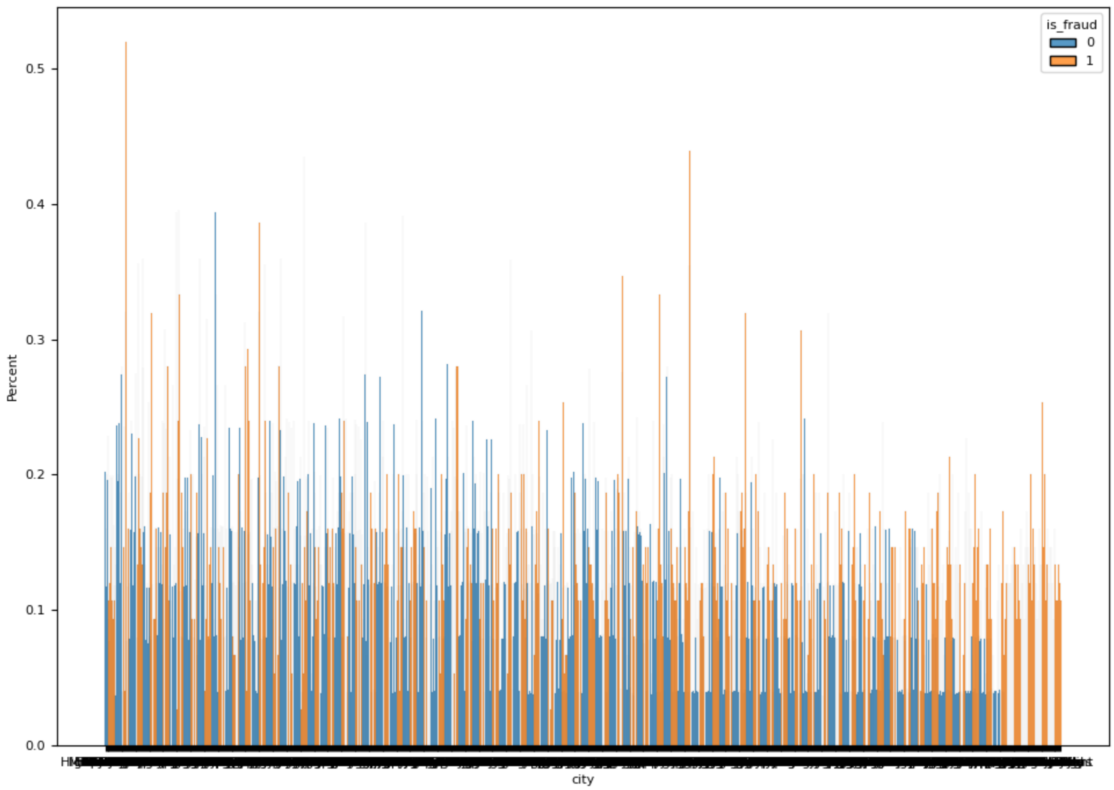
[20]:
```
# State- Fraud Vs Not-Fraud ( 0- Not-Fraud , 1 - Fraud)
ax=sns.
 ↪histplot(x='state',data=data,hue='is_fraud',stat='percent',multiple='dodge'
                 ,common_norm=False,bins=45)
```



[21]:
```
# age- Fraud Vs Not-Fraud ( 0- Not-Fraud , 1 - Fraud)
ax=sns.histplot(x='age',data=data,hue='is_fraud',stat='percent',multiple='dodge'
                 ,common_norm=False,bins=45)
```

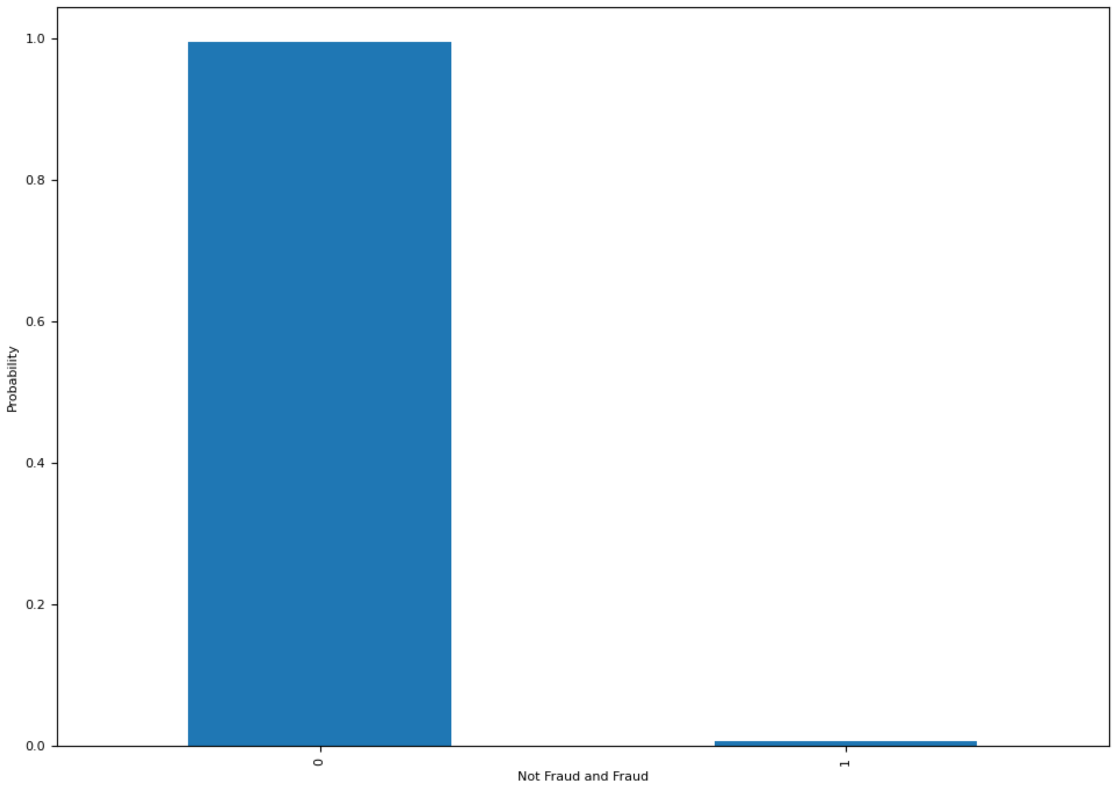


[22]:
```
# City- Fraud Vs Not-Fraud ( 0- Not-Fraud , 1 - Fraud)
ax=sns.
↪histplot(x='city',data=data,hue='is_fraud',stat='percent',multiple='dodge'
                    ,common_norm=False,bins=45)
```

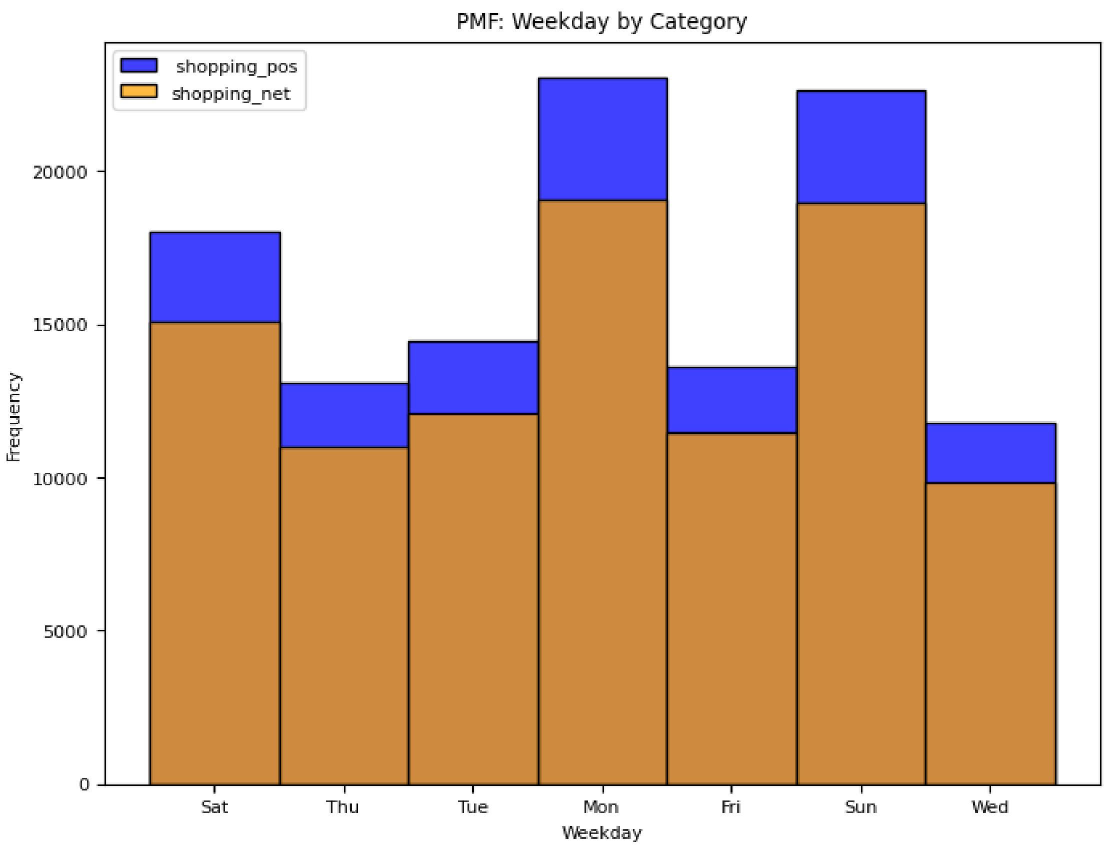


6 Probability Mass Function (PMF)

[23]:
```
# Create a new dataframe containing only the "is fraud" column
class_df = data[["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()
```



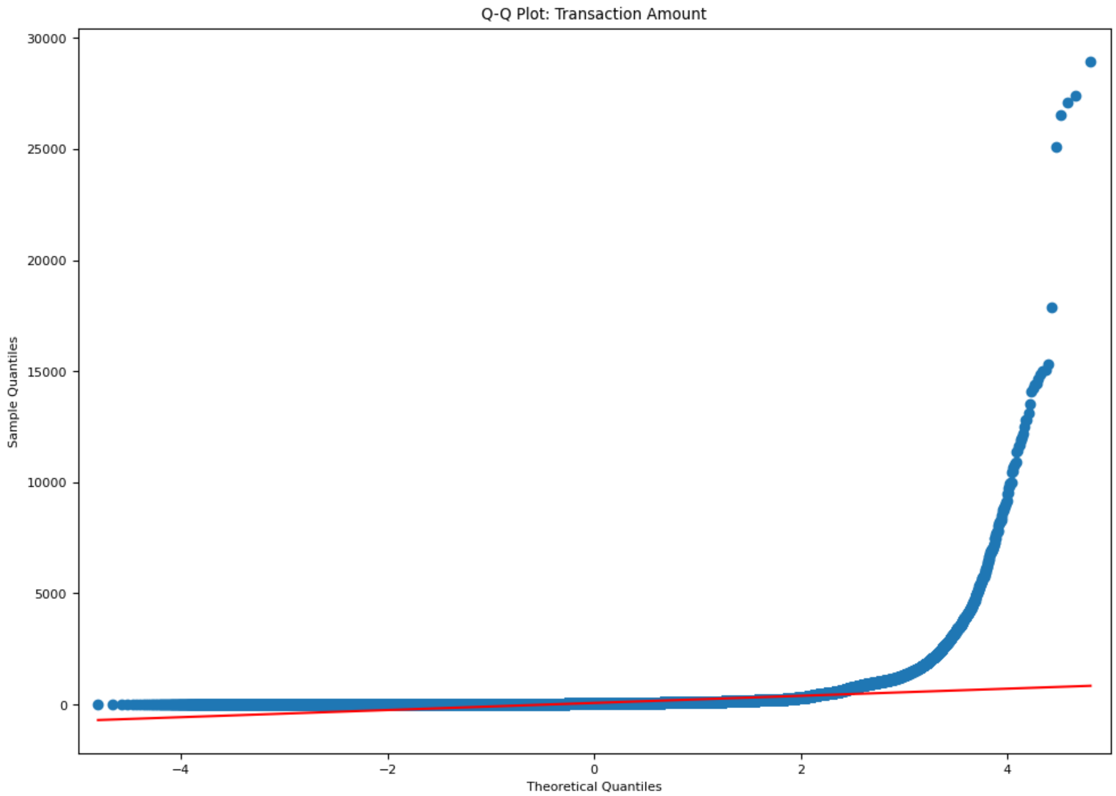
[24]:
```
# PMF for Weekday by Category
scenario_1 = data[data['category'] == 'shopping_pos']
scenario_2 = data[data['category'] == 'shopping_net']

plt.figure(figsize=(8, 6))
sns.histplot(scenario_1['weekday'], kde=False, color='blue', label='␣
↪shopping_pos')
sns.histplot(scenario_2['weekday'], kde=False, color='orange',␣
↪label='shopping_net')
plt.title('PMF: Weekday by Category')
plt.xlabel('Weekday')
plt.ylabel('Frequency')
plt.legend()
plt.show()
```



7 Cumulative Distribution Function (CDF)

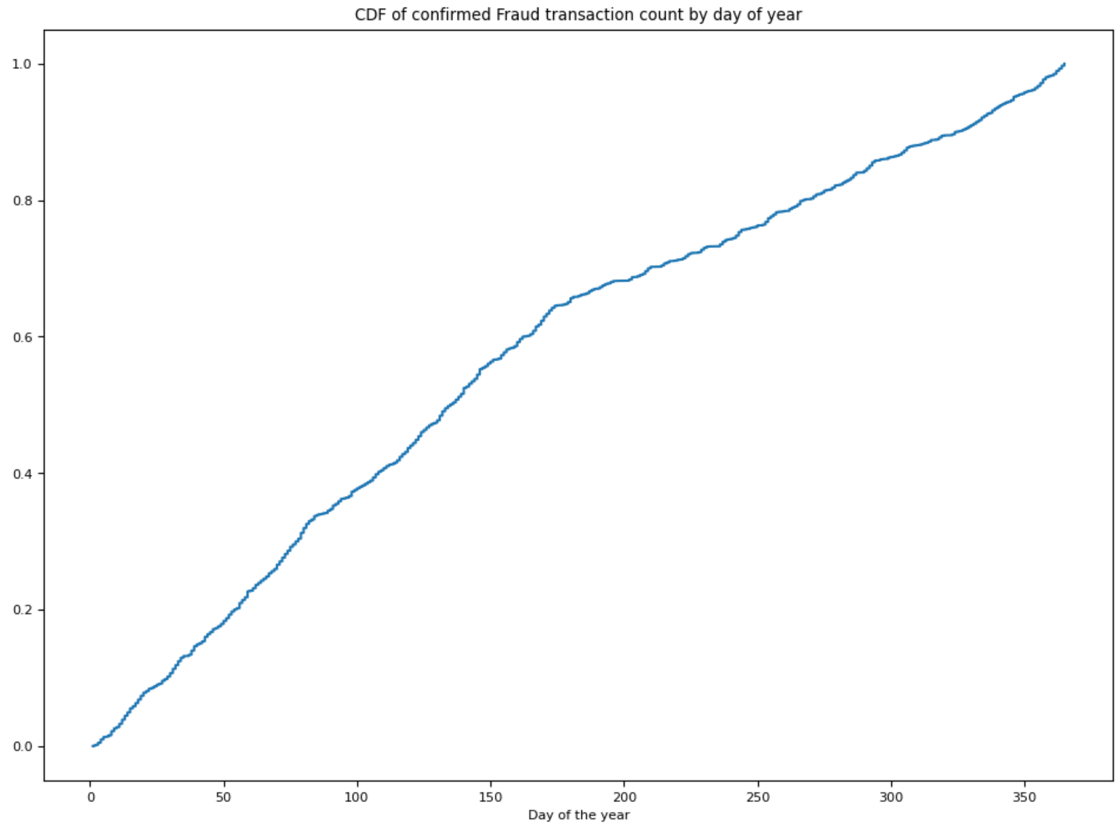
[25]:
```
# Cumulative Distribution Function (CDF)
plt.figure(figsize=(8, 6))
sm.qqplot(data['amount'], line='s')
plt.title('Q-Q Plot: Transaction Amount')
plt.xlabel('Theoretical Quantiles')
plt.ylabel('Sample Quantiles')
plt.show()
```

```
<Figure size 800x600 with 0 Axes>
```



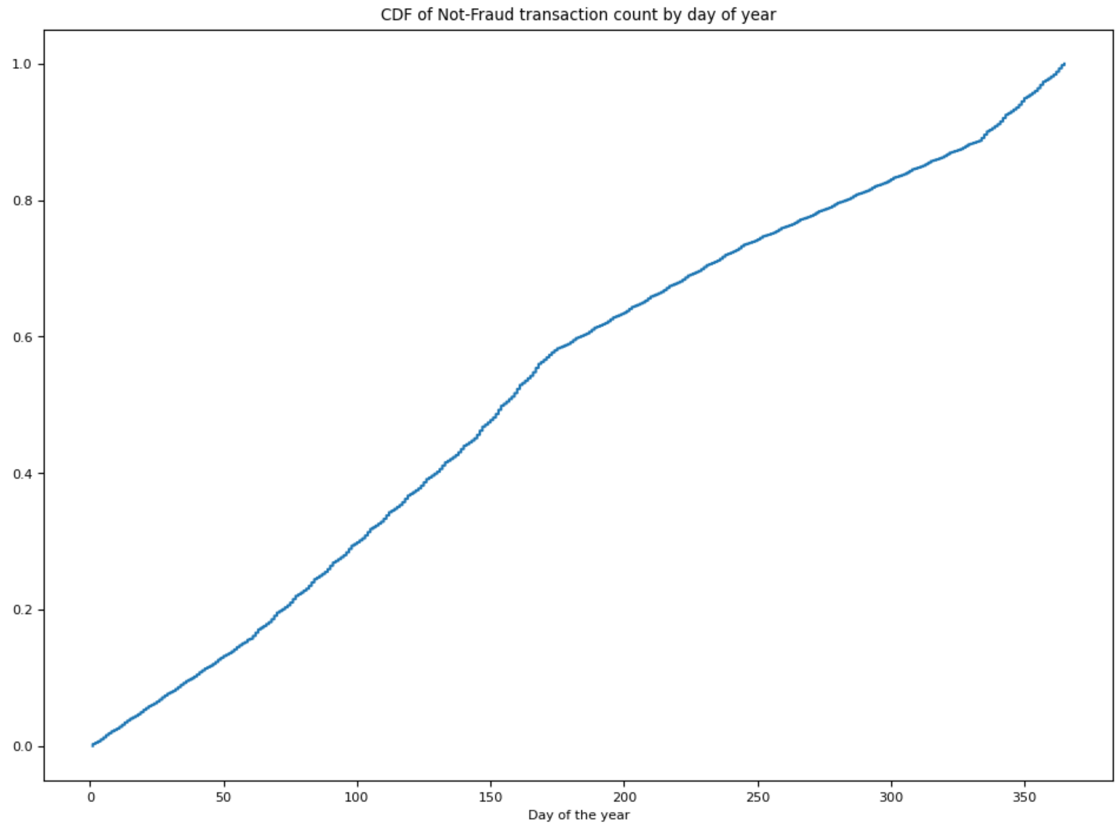
[26]:
```python
# CDF of confirmed Fraud transaction count by day of year
data_cdf_plot = fraud_df.dayofYear
x = np.sort(data_cdf_plot)
y = np.arange(len(x))/float(len(x)-1)

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

[26]: [<matplotlib.lines.Line2D at 0x19dc9125c10>]



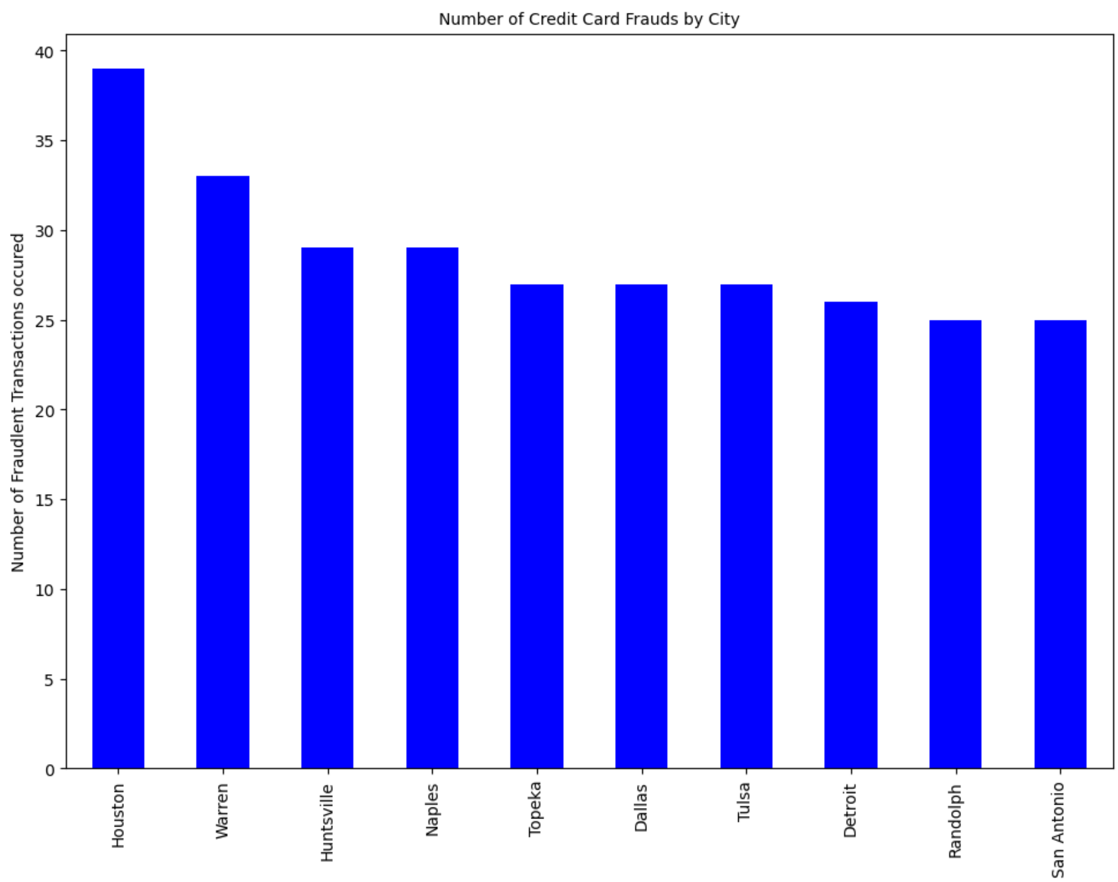
[27]:
```
# CDF of Not-Fraud transaction count by day of year
data_cdf_plot_nf = non_fraud_df.dayofYear
x = np.sort(data_cdf_plot_nf)
y = np.arange(len(x))/float(len(x)-1)

# plotting
plt.xlabel('Day of the year')
plt.title('CDF of Not-Fraud transaction count by day of year')
plt.plot(x, y)
```

[27]: [<matplotlib.lines.Line2D at 0x19dc7d71b20>]



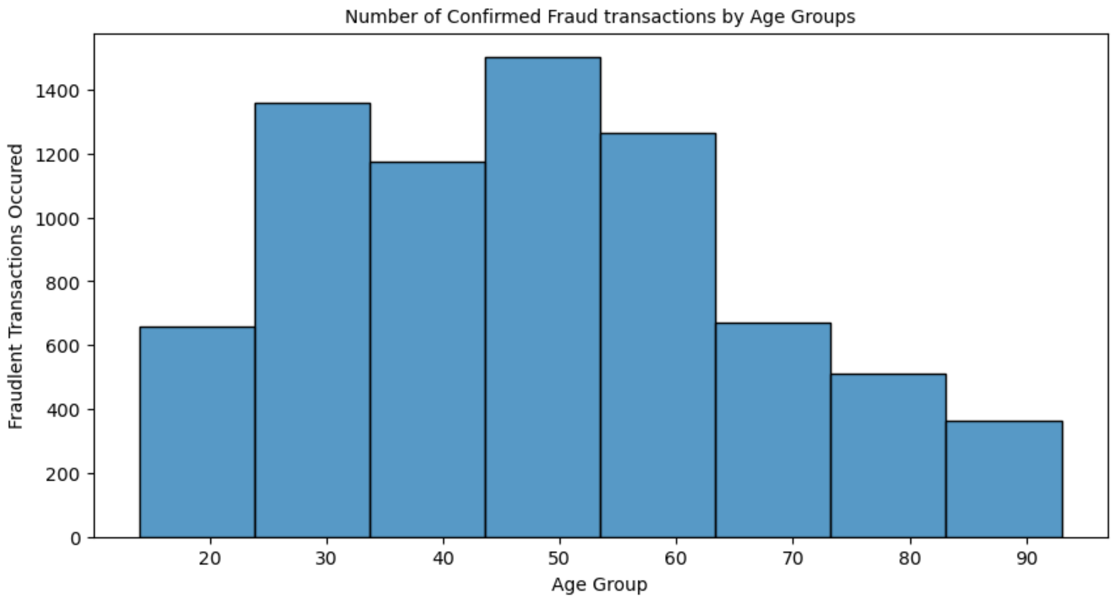
8 Analytical Distribution

[28]:
```
# Confirmed Fraud Transactions occurence by City
plt.rcParams.update({'font.size': 10})
fraud_df.city.value_counts(sort=True,ascending=False).head(10).
  ↪plot(kind="bar",color='blue')
plt.ylabel('Number of Fraudlent Transactions occured', fontsize=10)
plt.title("Number of Credit Card Frauds by City", fontsize=10)
plt.show()
```

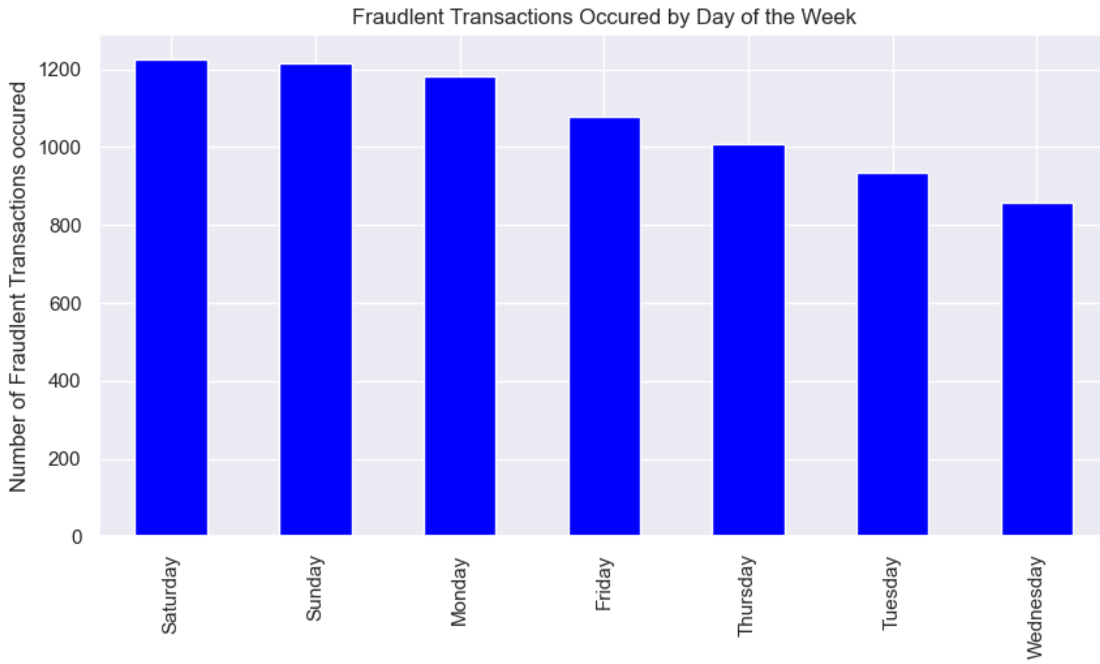


[29]:
```
# Confirmed Fraud Transactions occurence by Age Group
plt.figure(figsize=(10,5))
plt.title("Number of Confirmed Fraud transactions by Age Groups", fontsize=10)
plt.ylabel('Fraudlent Transactions Occured', fontsize=10)
plt.xlabel('Age Group', fontsize=10)
sns.histplot(fraud_df.age, bins=8, kde=False)
```

[29]:
```
<AxesSubplot:title={'center':'Number of Confirmed Fraud transactions by Age
Groups'}, xlabel='Age Group', ylabel='Fraudlent Transactions Occured'>
```

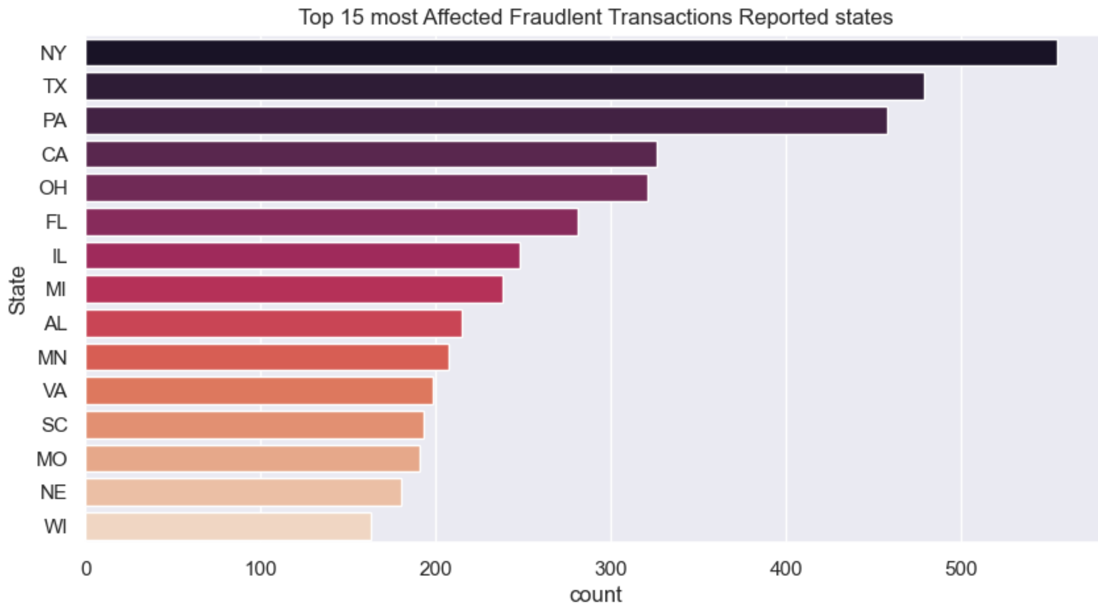


[30]:
```
#Fraudlent Transactions occurence by day of week
plt.rcParams.update({'font.size': 10})
sns.set_style('white')
sns.set(rc={'figure.figsize':(10,5)})

fraud_df.trans_date_trans_time.dt.day_name().
 ↪value_counts(sort=True,ascending=False).head(10).
 ↪plot(kind="bar",color='blue')
plt.ylabel('Number of Fraudlent Transactions occured')
plt.title('Fraudlent Transactions Occured by Day of the Week')
plt.show()
```



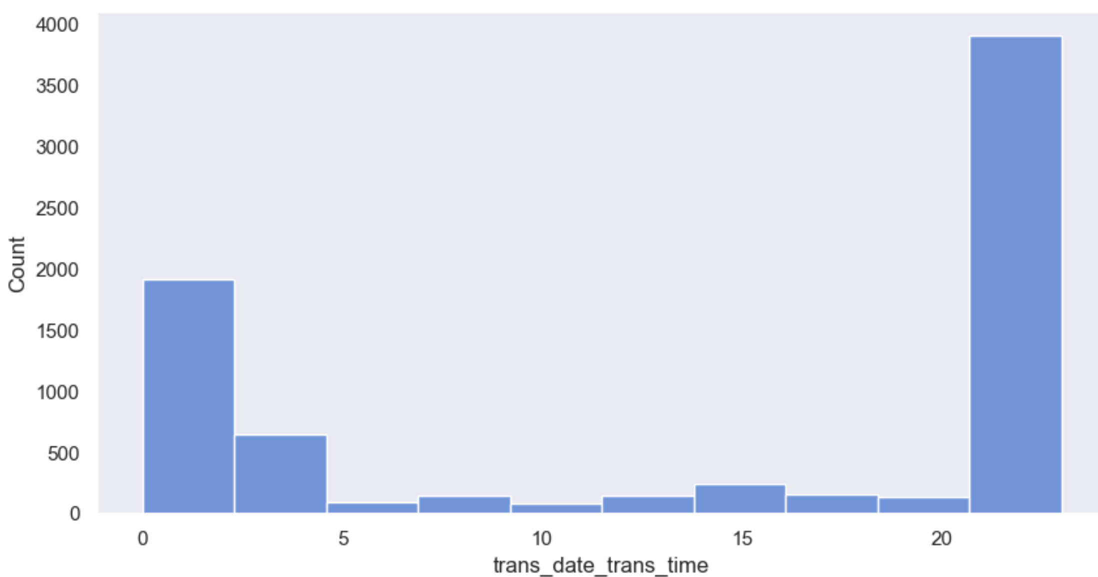
[31]:

```
# 15 most Affected Fraudlent Transactions Occured states.
state_count15=fraud_df["state"].value_counts().sort_values(ascending=False)[:15]
sns.set_style('white')
sns.set(rc={'figure.figsize':(10,5)})
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)
```



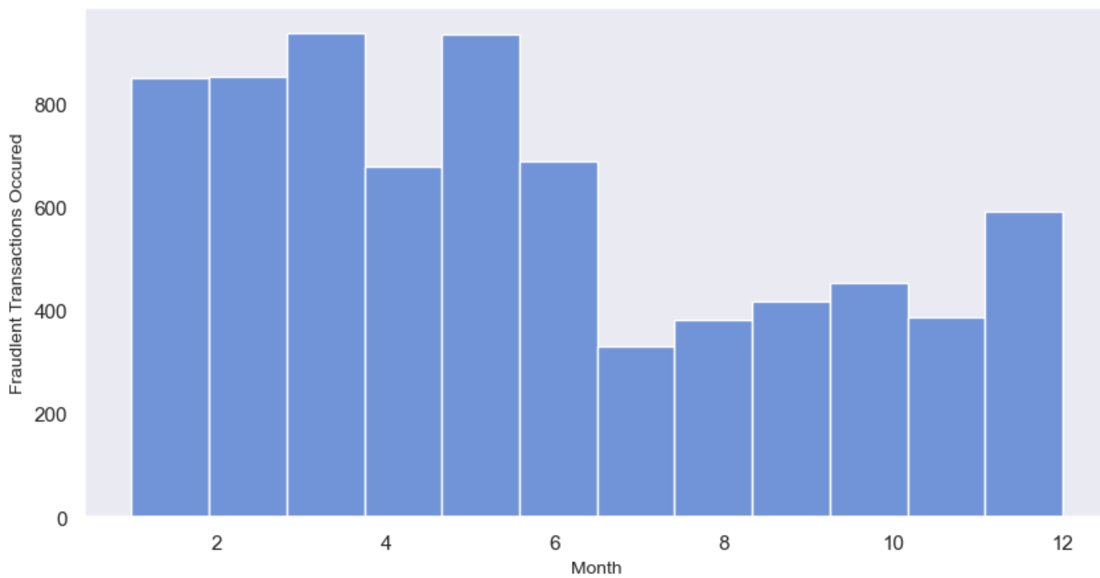

```
<Figure size 1000x500 with 0 Axes>
```

[32]:
```python
# Time Based analysis
fraud_df['trans_dte_trans_time']= pd.to_datetime(fraud_df.trans_date_trans_time)
hr = fraud_df.trans_date_trans_time.dt.hour
sns.set_style('white')
sns.set(rc={'figure.figsize':(10,5)})
sns.set(color_codes=True)
sns.set(style="dark", palette="muted")
sns.histplot(hr,bins=10);
```

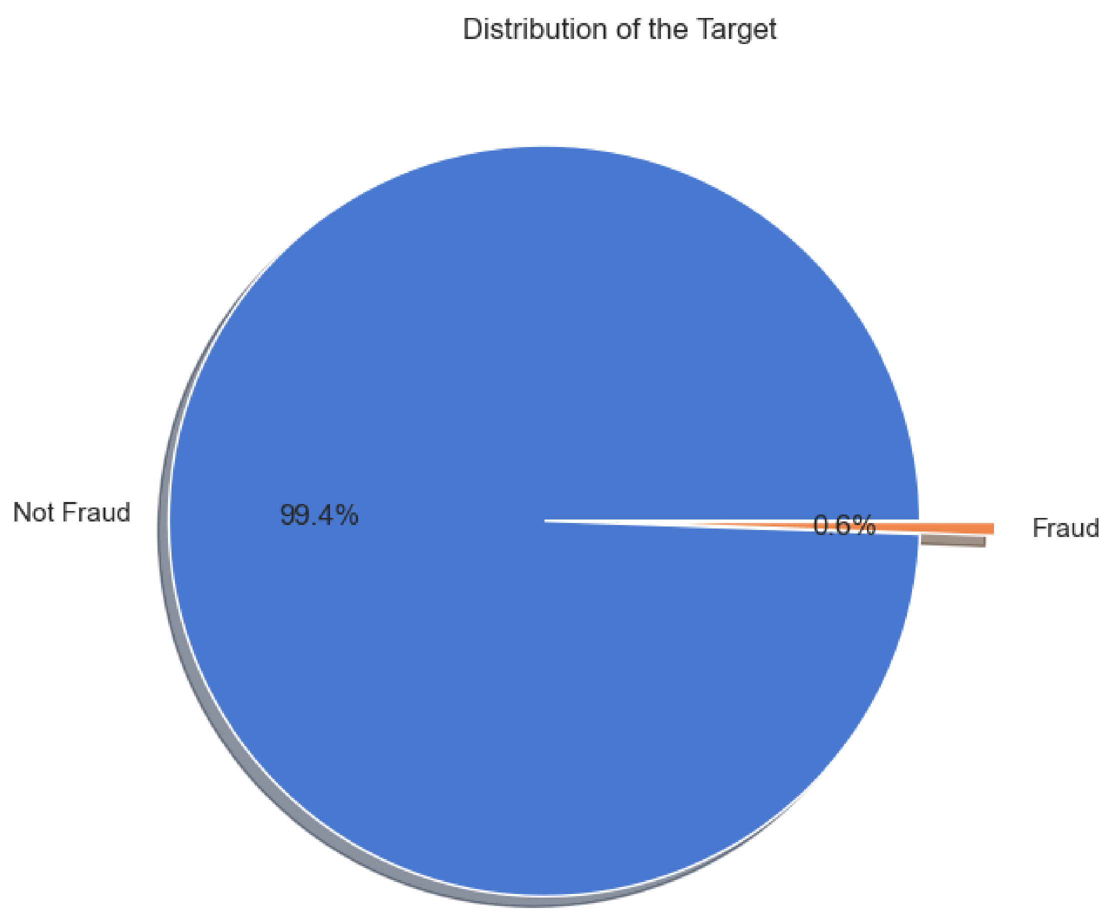


[33]:
```
plt.figure(figsize=(10,5))
plt.ylabel('Fraudlent Transactions Occured', fontsize=10)
plt.xlabel('Month', fontsize=10)

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

[33]:
```
<AxesSubplot:xlabel='Month', ylabel='Fraudlent Transactions Occured'>
```

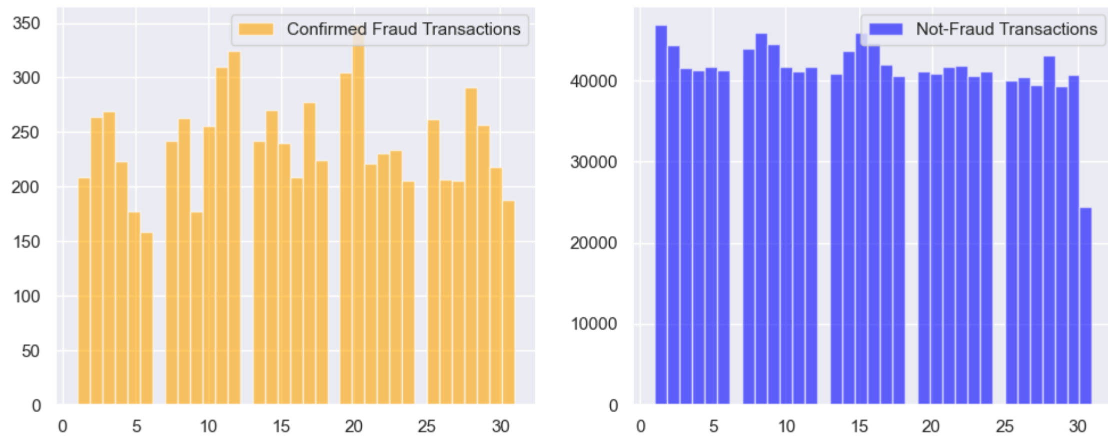


[34]:
```
# Check is_fraud variables that has 0 value for Genuine transactions and 1␣
↪for␣Fraud
plt.figure(figsize = [7,7])
plot_var = data['is_fraud'].value_counts(normalize = True)
plt.pie(plot_var,
autopct='%1.1f%%',
labels = ['Not Fraud','Fraud'],
explode = [0.2, 0],
shadow = True) # plotting the pie chart
plt.title('Distribution of the Target');
```

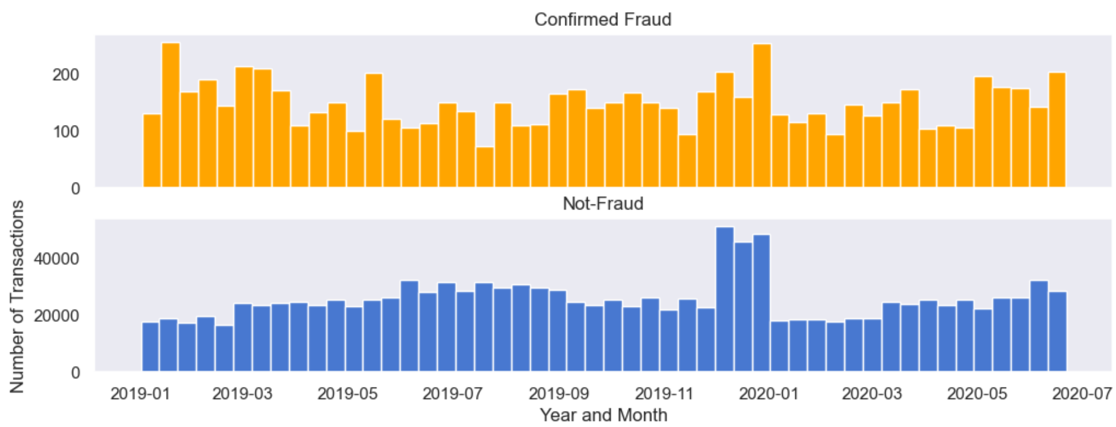


[35]:
```
plt.figure(figsize=(12, 10))
plt.subplot(2, 2, 1)
data[data.is_fraud == 1].day.hist(bins=35, color='orange', alpha=0.
↪6,label="Confirmed Fraud Transactions")
plt.legend()
plt.subplot(2, 2, 2)
data[data.is_fraud == 0].day.hist(bins=35, color='blue', alpha=0.6,␣
↪label="Not-Fraud Transactions")
plt.legend()
```

[35]:
```
<matplotlib.legend.Legend at 0x19dc942f070>
```



[36]:
```
# now checking Time value in case of confirmed Fraud and Not-Fraud 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(data.trans_date_trans_time[data.is_fraud == 1], bins =␣
↪bins,color='orange')
axis_1.set_title('Confirmed Fraud')
axis_2.hist(data.trans_date_trans_time[data.is_fraud == 0], bins = bins)
axis_2.set_title('Not-Fraud')
plt.xlabel('Year and Month')
plt.ylabel('Number of Transactions')
plt.show()
```

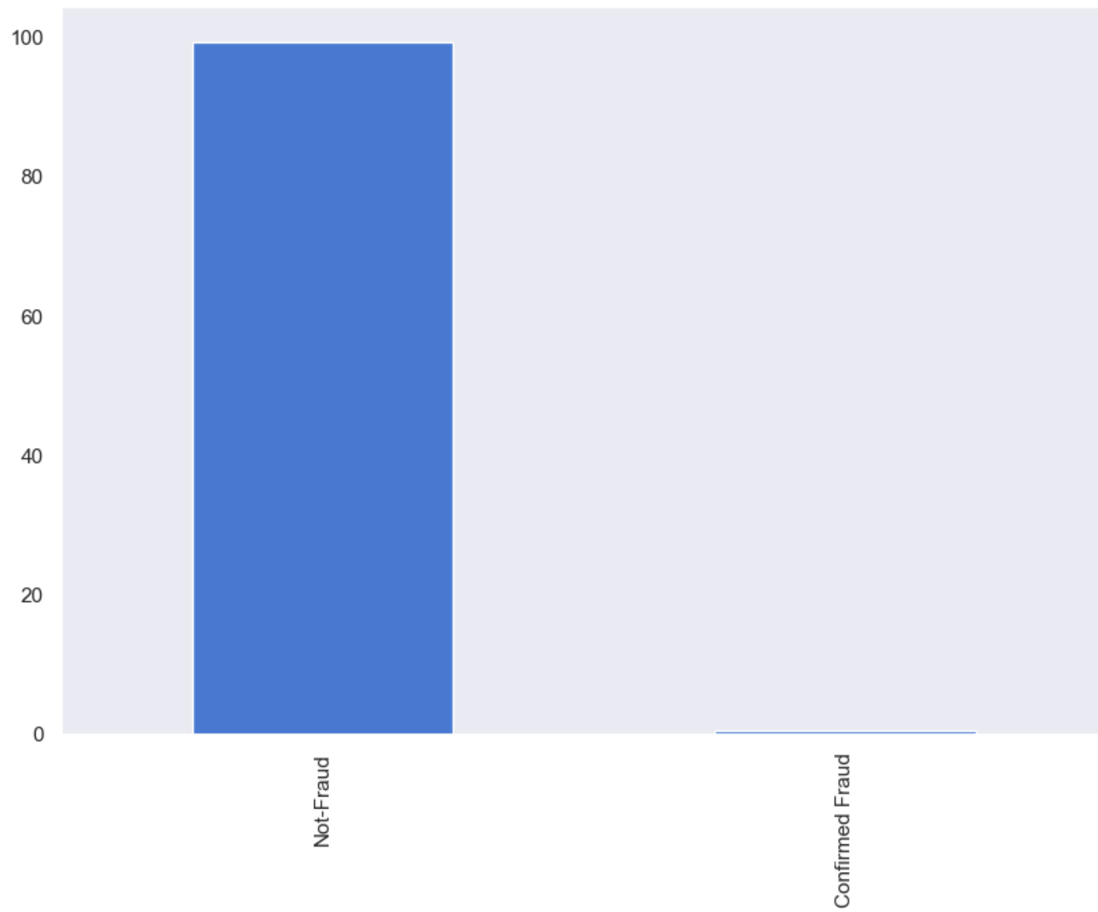


[37]:
```
# Inspect the Target variable
v1 = data['is_fraud'].value_counts().rename('count') # count of classes
```

```
v2 = (data['is_fraud'].value_counts(normalize = True)*100).
 ↪rename('distribution') # normalisation of the classes

tem = pd.concat([v1,v2], axis = 1)
tem.index = ['Not-Fraud','Confirmed Fraud']
tem['distribution'].plot(kind = 'bar', figsize = [10,7]);
tem
```

[37]:

	count	distribution
Not-Fraud	1289169	99.421135
Confirmed Fraud	7506	0.578865

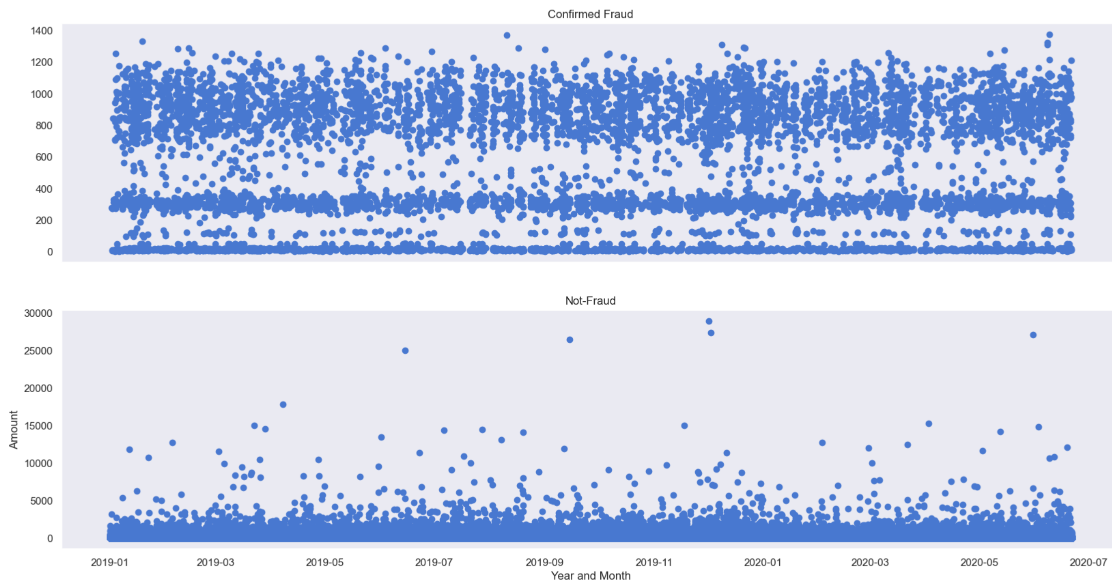


9 Scatter Plot

[38]:

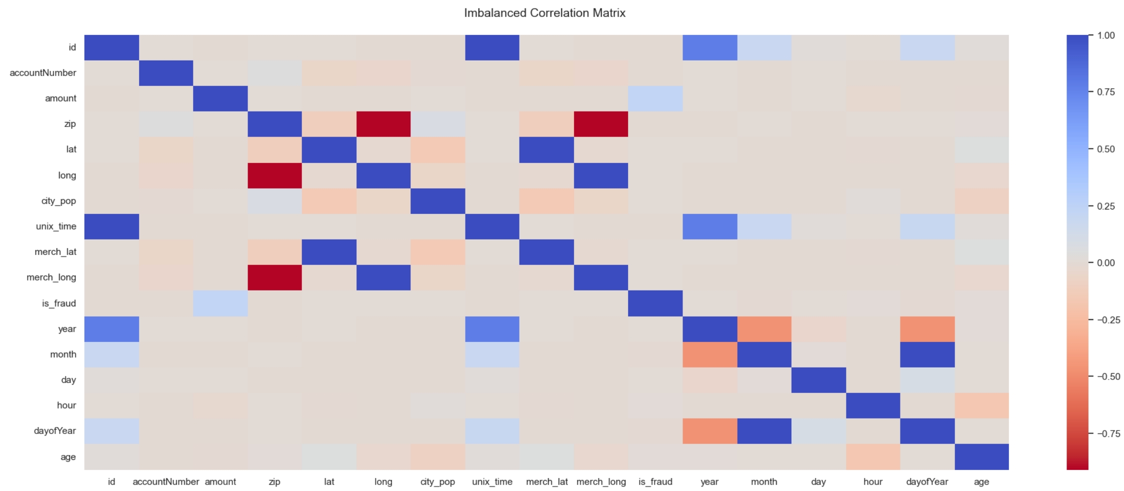
```
# checking Date and TIme vs Amount feature. scatter plot
fig, (axis_1, axis_2) = plt.subplots(2, 1, sharex=True, figsize=(20,10))
```

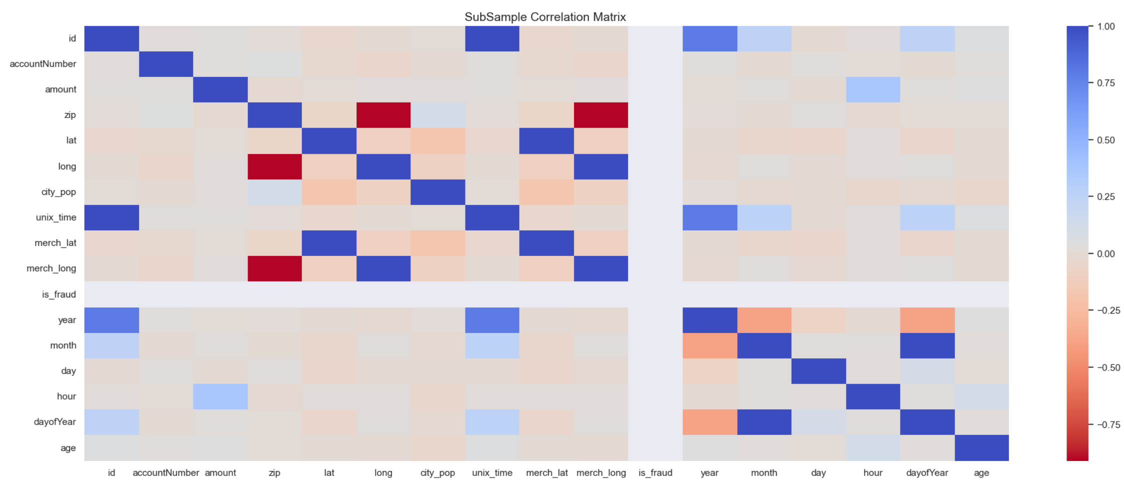
```
axis_1.scatter(data.trans_date_trans_time[data.is_fraud == 1], data.amount[data.
    ↪is_fraud == 1])
axis_1.set_title('Confirmed Fraud')

axis_2.scatter(data.trans_date_trans_time[data.is_fraud == 0], data.amount[data.
    ↪is_fraud == 0])
axis_2.set_title('Not-Fraud')

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



10 Imbalanced Correlation, Covariance and Pearson's correlation

[39]:
```
# Imbalanced Correlation
f, (ax1, ax2) = plt.subplots(2, 1, figsize=(24,20))
corr = data.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 = subsample_analysis_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()
```

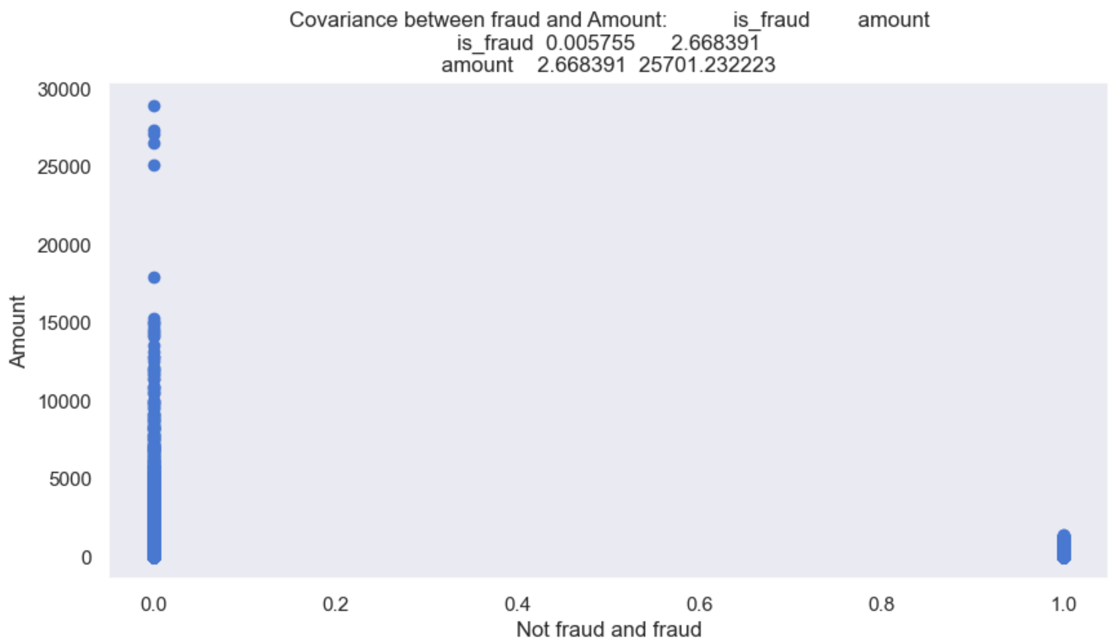




[40]:
```
# Covariance

np.cov(data.amount[data.is_fraud == 1])
print("Covariance between Confirmed Fraud Transactions and Amount: ",data.
    ↪amount.cov(data.is_fraud == 1))

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

# Calculate the covariance
covariance = is_fraud_amount.cov()
print(covariance)

# Create a scatter plot
plt.scatter(data["is_fraud"], data["amount"])
plt.xlabel("Not fraud and fraud")
```

```
plt.ylabel("Amount")
plt.title(f"Covariance between fraud and Amount: {covariance}")
plt.show()
```

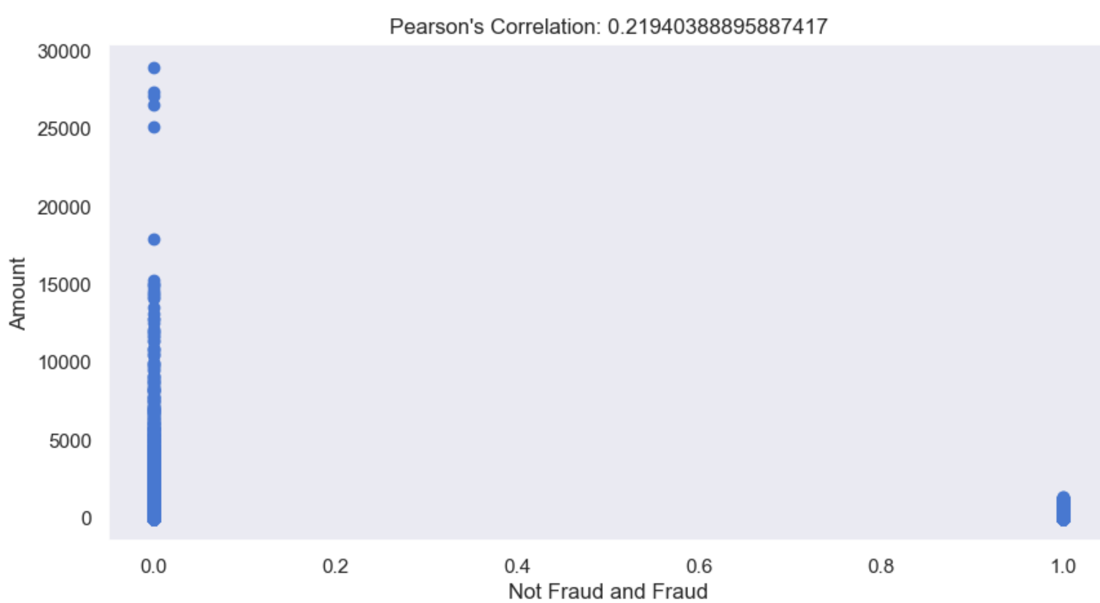
```
Covariance between Confirmed Fraud Transactions and Amount:  2.6683913904857643
          is_fraud        amount
is_fraud  0.005755      2.668391
amount    2.668391  25701.232223
```



[41]:
```
# Pearson’s correlation

# Drop any missing data
data.dropna(inplace=True)

# Calculate Pearson's correlation coefficient

corr_matrix = data.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 = data["is_fraud"].corr(data["amount"], method="pearson")
print("Pearson's correlation coefficient between Not-Fraud, Confirmed Fraud and␣
↪Amount:", correlation)
```

```python
# Create a scatter plot
plt.scatter(data["is_fraud"], data["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
age              0.012250
day              0.003848
year             0.003004
city_pop         0.002136
lat              0.001894
merch_lat        0.001741
merch_long       0.001721
long             0.001721
accountNumber   -0.000981
zip             -0.002162
id              -0.004767
unix_time       -0.005078
dayofYear       -0.011974
month           -0.012409
Name: is_fraud, dtype: float64
Pearson's correlation coefficient between Not-Fraud, Confirmed Fraud and Amount:
0.21940388895887417
```



11 Hypothesis Test

[42]:
```
import scipy.stats as stats
# Extract the transaction amount for fraudulent and non-fraudulent transactions
fraudulent_amounts = data.loc[data['is_fraud'] == 1, 'amount']
non_fraudulent_amounts = data.loc[data['is_fraud'] == 0, 'amount']

# Perform the two-sample t-test
t_stat, p_value = stats.ttest_ind(fraudulent_amounts, non_fraudulent_amounts,␣
↪equal_var=False)

# Interpret the results
alpha = 0.05  # significance level

if p_value < alpha:
    print("Reject the null hypothesis. There is a significant difference in␣
↪mean transaction amounts between fraudulent and non-fraudulent transactions.
↪")
else:
    print("Fail to reject the null hypothesis. There is not enough evidence to␣
↪support a significant difference in mean transaction amounts between␣
↪fraudulent and non-fraudulent transactions.")
```

```
Reject the null hypothesis. There is a significant difference in mean
transaction amounts between fraudulent and non-fraudulent transactions.
```

12 Regression Analysis

[43]:
```
x=data.iloc[:,:-1]
y=data.iloc[:,len(data.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,)
```

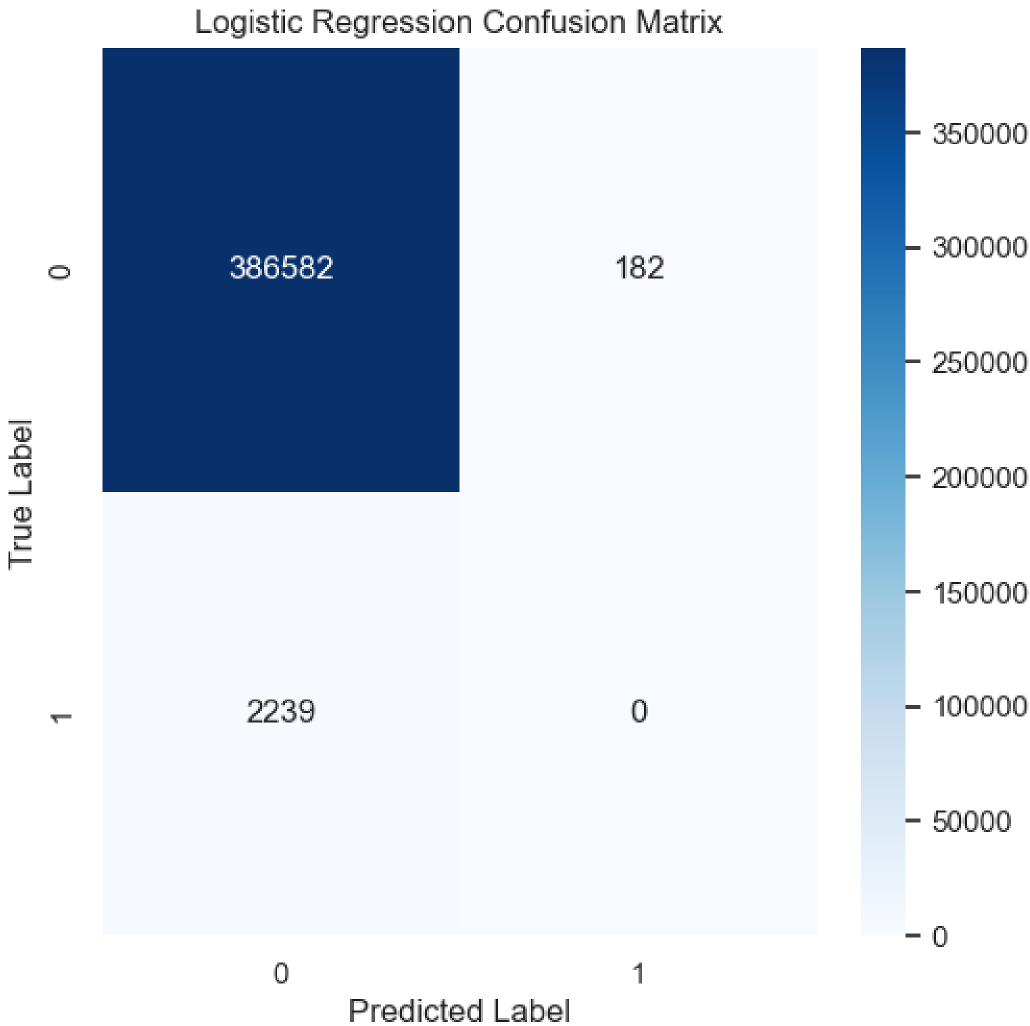
[44]:
```
num = int(len(x) * 0.2)
xtrain = x[:-num]
ytrain = y[:-num]
xtest = x[-num:]
ytest = y[-num:]
print("# train:", len(xtrain))
print("# test:", len(xtest))
```

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

[45]:

```
# Separate the features and labels
X = data.drop('is_fraud', axis=1)
y = data['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    386764
           1       0.00      0.00      0.00      2239

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



13 Conclusion

1.What do you feel was missed during the analysis?

Ans:

May be some anomalous patterns and outliers, Behavious Analysis were missed during my analysis

2.Were there any variables you felt could have helped in the analysis?

Ans:

PosEntryMode, Secure/NonSecure data for ecomm transactions, CAVV Validation results and BIN numbers are not present in transactional information . Simillarly the customer-related variables (e.g., customer demographics, spending behavior), and additional external variables that might provide context (e.g., location, IP address, device information) are not present. The analysis would have been much better with these variables.

3.Were there any assumptions made you felt were incorrect?

Ans:

There could be some dependencies or autorelations present in data which I might not have considered

4.What challenges did you face, what did you not fully understand?

Ans:

Class Imbalance: Thedatasets often exhibit a significant class imbalance, with a majority of instances being non-fraudulent and only a small portion being fraudulent. This class imbalance has an impact on the analysis and required special handling.