Import Data & Libraries

Data source: https://www.kaggle.com/datasets/kartik2112/fraud-detection Took a sample of 50,000 from the "test" dataset, using: df_sample, df_sample_95 = train_test_split(df, test_size=0.95, stratify=df['is_fraud'], random_state=42). Our dataset is the 5% sample.

In [336…

```
#library imports
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import lightgbm as lgb
import warnings
warnings.filterwarnings("ignore", category=FutureWarning)

from xgboost import XGBClassifier
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from imblearn.over_sampling import SMOTE
from catboost import CatBoostClassifier
```

In [337…

```
#import data
df = pd.read_csv("fraud.csv")
df.head()
```

Out[337…

	Unnamed: 0	trans_date_trans_time	cc_num	merchant	category
0	417308	2020-12-01 05:38:34	348789608637806	fraud_Berge LLC	gas_transport
1	22343	2020-06-29 02:05:06	2291163933867244	fraud_Bins, Balistreri and Beatty	shopping_pos
2	540530	2020-12-28 15:48:07	372509258176510	fraud_Bradtke, Torp and Bahringer	personal_care
3	492286	2020-12-17 23:47:28	571365235126	fraud_Prosacco, Kreiger and Kovacek	home
4	17203	2020-06-27 11:52:35	4225990116481262579	fraud_Bernier, Volkman and Hoeger	misc_net

Exploratory Data Analysis

Basic Data Information

In [340…

```
#get shape
df.shape
```

Out[340…

```
(27785, 23)
```

In [341…

```
#are there duplicates?
df.duplicated().sum()
```

Out[341…

```
0
```

In [342…

```
#get datatypes
df.dtypes
```

Out[342…
```
Unnamed: 0                 int64
trans_date_trans_time     object
cc_num                     int64
merchant                  object
category                  object
amt                      float64
first                     object
last                      object
gender                    object
street                    object
city                      object
state                     object
zip                        int64
lat                      float64
long                     float64
city_pop                   int64
job                       object
dob                       object
trans_num                 object
unix_time                  int64
merch_lat                float64
merch_long               float64
is_fraud                   int64
dtype: object
```

In [343…
```
# is there class imbalance?
df['is_fraud'].value_counts()
```

Out[343…
```
is_fraud
0    27678
1      107
Name: count, dtype: int64
```

In [344…
```
sns.countplot(x='is_fraud', data=df)
plt.title('Target Class Distribution of is_fraud')
plt.show()
```

In [345…

```
#percentage of binary class
print("percentage of each class", df['is_fraud'].value_counts()/len(df)*100)
```

```
percentage of each class is_fraud
0   99.615
1    0.385
Name: count, dtype: float64
```

Data Quality Report

Continuous Features

In [348…

```
# identify continuous features
conf = df.select_dtypes(include=['float64', 'int64']).columns.tolist()
conf
```

Out[348…

```
['Unnamed: 0',
 'cc_num',
 'amt',
 'zip',
 'lat',
 'long',
 'city_pop',
 'unix_time',
 'merch_lat',
 'merch_long',
 'is_fraud']
```

In [349…

```
#identify any columns to filter out from the "continuous features"
conf_exclude = ['Unnamed: 0', 'cc_num'] #excluding unamned as that is just the row
filter_conf = [x for x in conf if x not in conf_exclude]
filter_conf
```

Out[349…

```
['amt',
 'zip',
 'lat',
 'long',
 'city_pop',
 'unix_time',
 'merch_lat',
 'merch_long',
 'is_fraud']
```

In [350…

```
#get summary stats on continuous
pd.set_option('display.float_format', '{:.2f}'.format)
df[filter_conf].describe()
```

Out[350…

	amt	zip	lat	long	city_pop	unix_time	merch_lat	mercl
count	27785.00	27785.00	27785.00	27785.00	27785.00	27785.00	27785.00	27
mean	68.28	48733.84	38.53	-90.17	86906.27	1380671597.50	38.53	
std	136.20	26895.98	5.03	13.64	290698.32	5194009.36	5.07	
min	1.00	1257.00	20.03	-165.67	23.00	1371816893.00	19.03	-
25%	9.52	26041.00	34.67	-96.79	743.00	1376061884.00	34.78	
50%	47.23	48174.00	39.37	-87.46	2456.00	1380691607.00	39.40	
75%	82.90	72011.00	41.89	-80.16	20328.00	1385862997.00	41.96	
max	8517.38	99783.00	65.69	-67.95	2906700.00	1388534055.00	66.67	

In [351…

```
pd.options.display.float_format = '{:.3f}'.format

data_quality_conf = pd.DataFrame({
    'Feature': filter_conf,
    'Count': df[filter_conf].count().values,
    'Missing Values': df[filter_conf].isnull().sum().values,
```

```
    'Cardinality': df[filter_conf].nunique().values,
    'Min': df[filter_conf].min().values,
    '1st Quartile': df[filter_conf].quantile(0.25).values,
    'Mean': df[filter_conf].mean().values,
    'Median': df[filter_conf].median().values,
    '3rd Quartile': df[filter_conf].quantile(0.75).values,
    'Max': df[filter_conf].max().values,
    'Standard Deviation': df[filter_conf].std().values,
})
print("Data Quality Report - Continuous Features")
data_quality_conf
```

```
Data Quality Report - Continuous Features
```

Out[351…

	Feature	Count	Missing Values	Cardinality	Min	1st Quartile	Mea
0	amt	27785	0	12365	1.000	9.520	68.28
1	zip	27785	0	900	1257.000	26041.000	48733.83
2	lat	27785	0	898	20.027	34.669	38.53
3	long	27785	0	899	-165.672	-96.787	-90.17
4	city_pop	27785	0	825	23.000	743.000	86906.26
5	unix_time	27785	0	27758	1371816893.000	1376061884.000	1380671597.49
6	merch_lat	27785	0	27767	19.027	34.776	38.53
7	merch_long	27785	0	27774	-166.670	-96.856	-90.17
8	is_fraud	27785	0	2	0.000	0.000	0.00

Categorical Features

In [353…

```
#identify any categorical features
catf = df.select_dtypes(include=['object']).columns.tolist()
catf
```

Out[353…

```
['trans_date_trans_time',
 'merchant',
 'category',
 'first',
 'last',
 'gender',
 'street',
 'city',
 'state',
 'job',
 'dob',
 'trans_num']
```

In [354…

```
#identify any columns to filter out from the "categorical features"
catf_exclude = ['trans_num'] #excluding transaction number as that is an ID
```

```
filter_catf = [x for x in catf if x not in catf_exclude]
filter_catf
```

Out[354…

```
['trans_date_trans_time',
 'merchant',
 'category',
 'first',
 'last',
 'gender',
 'street',
 'city',
 'state',
 'job',
 'dob']
```

In [355…

```
#create lists to store modes & frequencies
modes = []
mode_freqs = []
second_modes = []
second_mode_freqs = []
mode_percentages = []
second_mode_percentages = []
```

In [356…

```
# Calculate mode and frequency for each categorical feature
for feature in filter_catf:
    count = df[feature].count()
    mode = df[feature].mode().iloc[0]
    mode_freq = df[feature].value_counts().iloc[0]
    modes.append(mode)
    mode_freqs.append(mode_freq)
    mode_percentages.append((mode_freq / count) * 100 if count > 0 else 0)

    # Calculate second mode and its frequency
    if len(df[feature].value_counts()) > 1:
        second_mode = df[feature].value_counts().index[1]
        second_mode_freq = df[feature].value_counts().iloc[1]
    else:
        second_mode = None
        second_mode_freq = 0

    second_modes.append(second_mode)
    second_mode_freqs.append(second_mode_freq)
    second_mode_percentages.append((second_mode_freq / count) * 100 if count > 0 el
```

In [357…

```
#build quality report table
data_quality_catf = pd.DataFrame({
    'Feature': filter_catf,
    'Count': df[filter_catf].count().values,
    'Missing Values': df[filter_catf].isnull().sum().values,
    'Cardinality': df[filter_catf].nunique().values,
    'Mode':modes,
    'Mode Frequency':mode_freqs,
    'Mode %': mode_percentages,
    '2nd Mode':second_modes,
    '2nd Mode Frequency': second_mode_freqs,
```

```
    '2nd Mode %': second_mode_percentages,
})
print("Data Quality Report - Categorical Features")
data_quality_catf
```

Data Quality Report - Categorical Features

Out[357…

	Feature	Count	Missing Values	Cardinality	Mode	Mode Frequency	Mode %
0	trans_date_trans_time	27785	0	27758	2020-06-21 19:09:47	2	0.007
1	merchant	27785	0	693	fraud_Dickinson Ltd	84	0.302
2	category	27785	0	14	gas_transport	2820	10.149
3	first	27785	0	339	Christopher	573	2.062
4	last	27785	0	465	Smith	638	2.296
5	gender	27785	0	2	F	15252	54.893
6	street	27785	0	911	6983 Carrillo Isle	86	0.310
7	city	27785	0	839	Birmingham	140	0.504
8	state	27785	0	50	TX	2006	7.220
9	job	27785	0	476	Film/video editor	206	0.741
10	dob	27785	0	897	1977-03-23	124	0.446

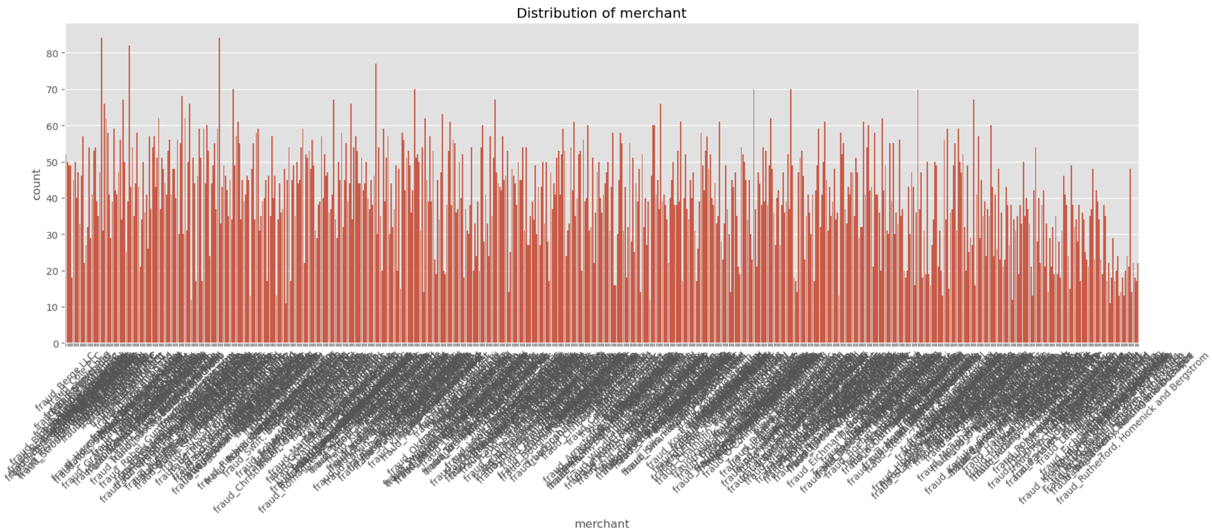
Univariate Analysis

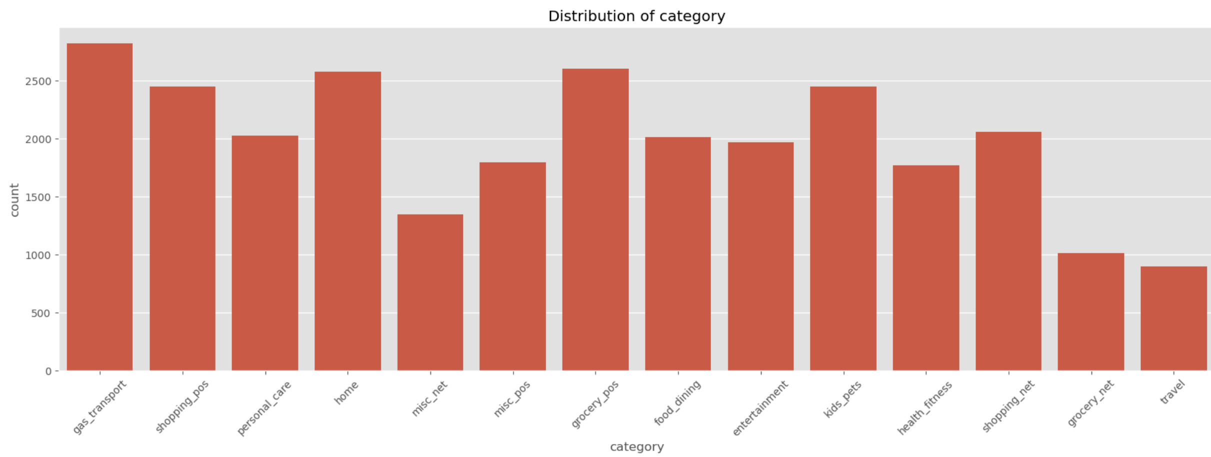
In [359…

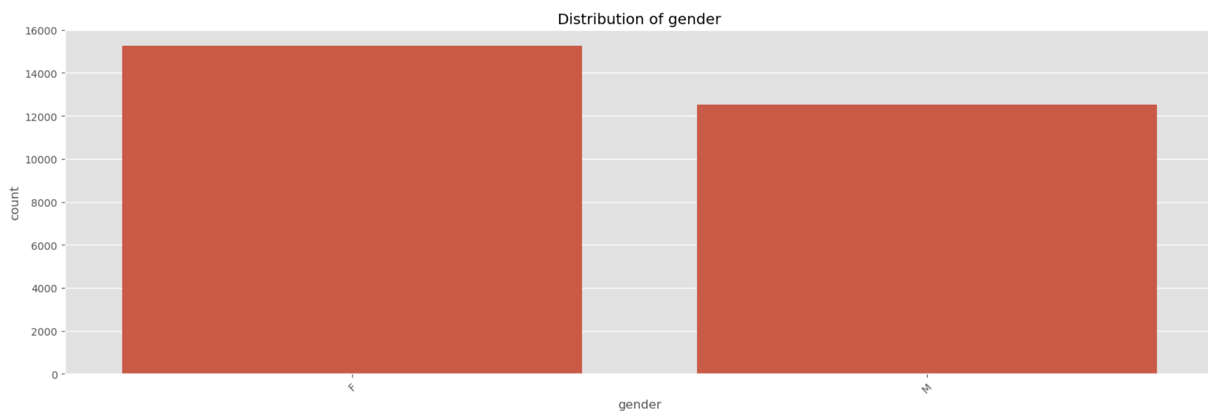
```
filter_catf2 = ['merchant','category', 'gender', 'job']
```

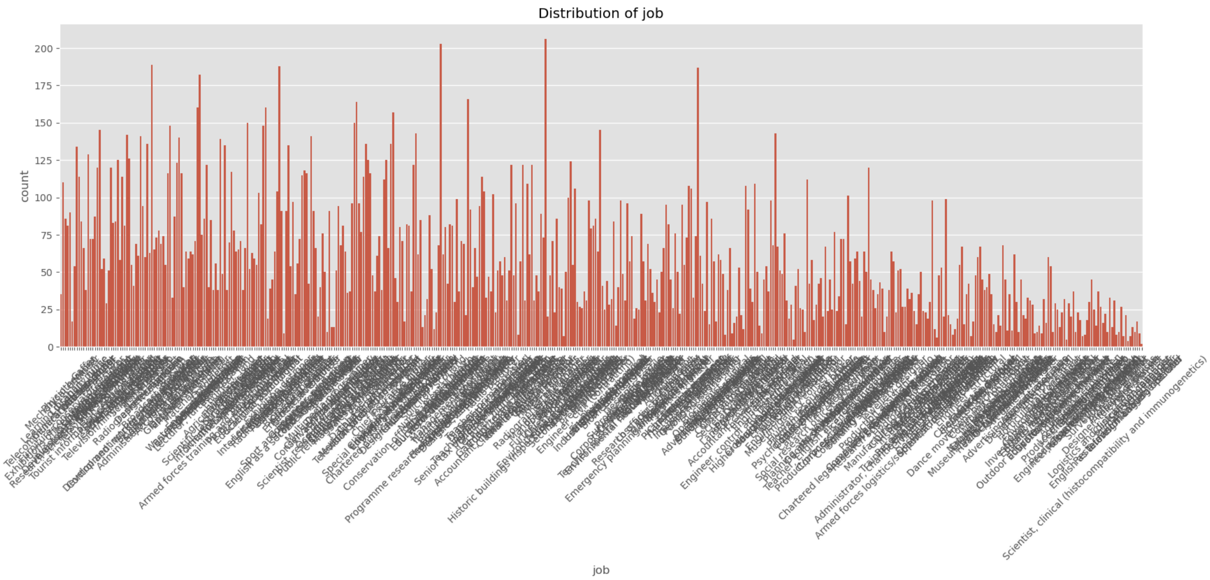
In [360…

```
#plot the categorical variables
plt.style.use('ggplot')

for column in filter_catf2:
    plt.figure(figsize=(20, 6))
    sns.countplot(x=column, data=df)
    plt.title(f'Distribution of {column}')
    plt.xticks(rotation =45)
    plt.show()
```


Distribution of merchant
count
merchant
fraud_Rutherford, Homenick and Bergstrom

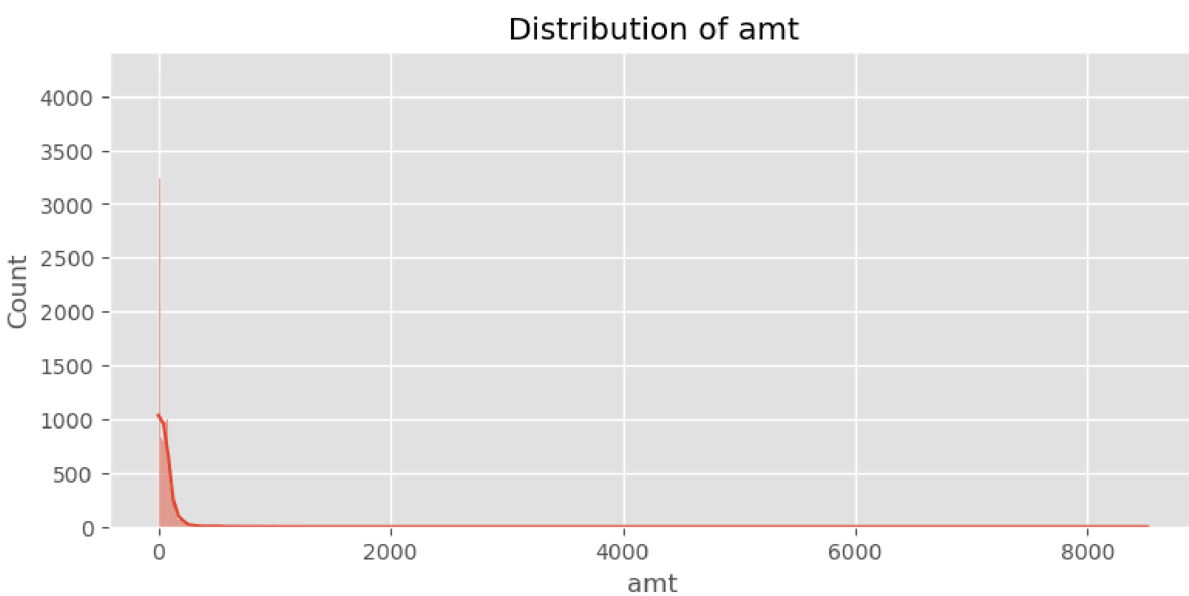

Distribution of category
count
category
gas_transport
shopping_pos
personal_care
home
misc_net
misc_pos
grocery_pos
food_dining
entertainment
kids_pets
health_fitness
shopping_net
grocery_net
travel

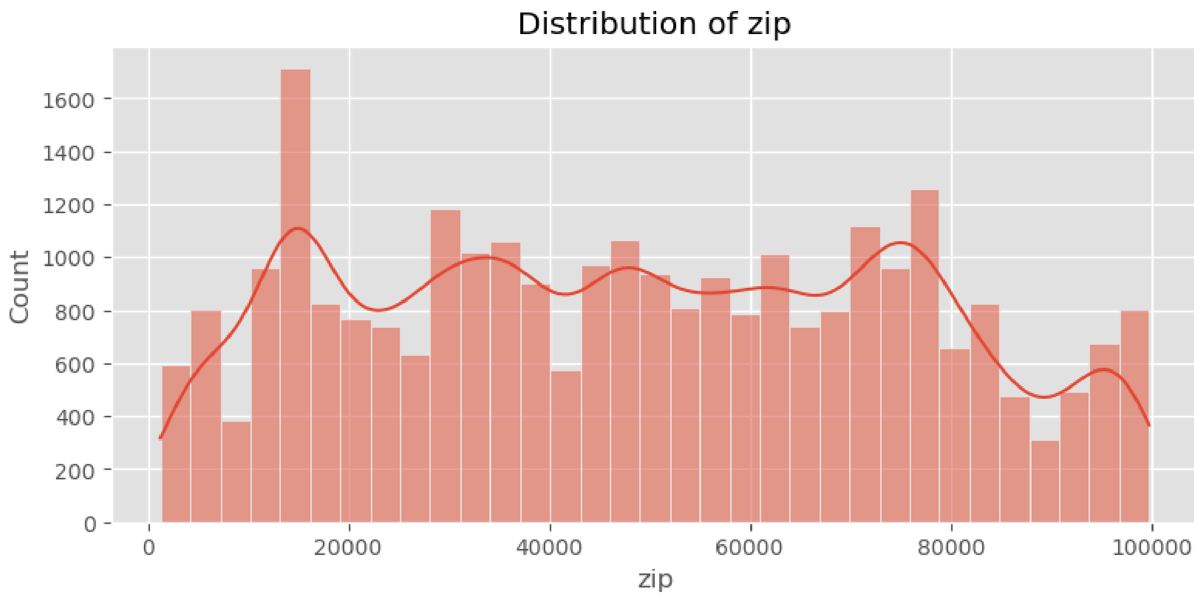

Distribution of gender
count
gender
F
M

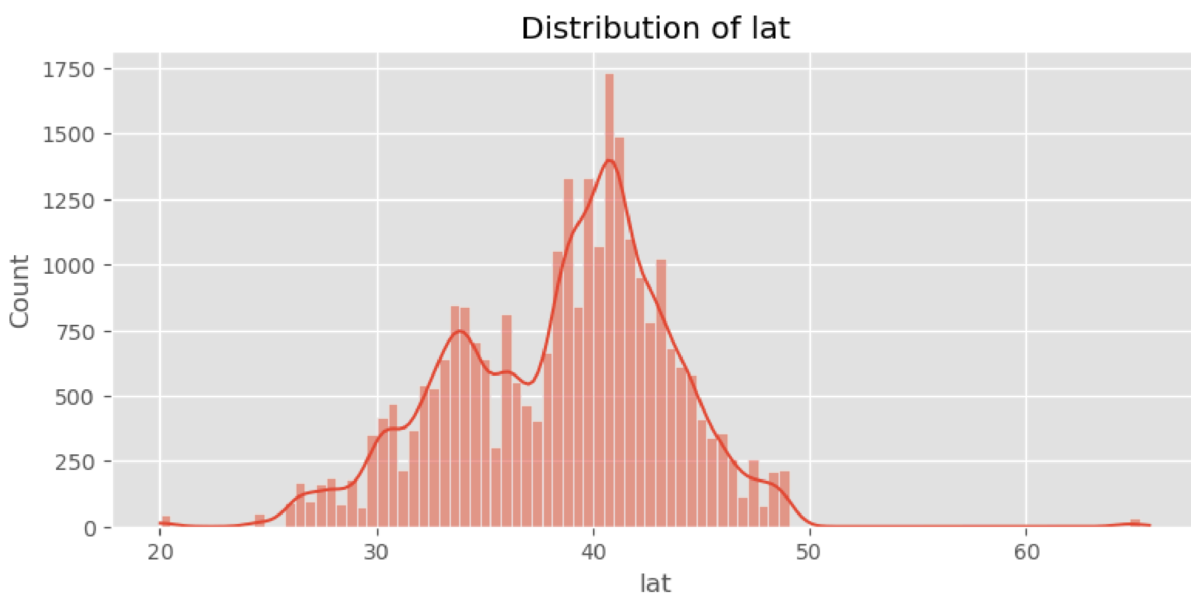


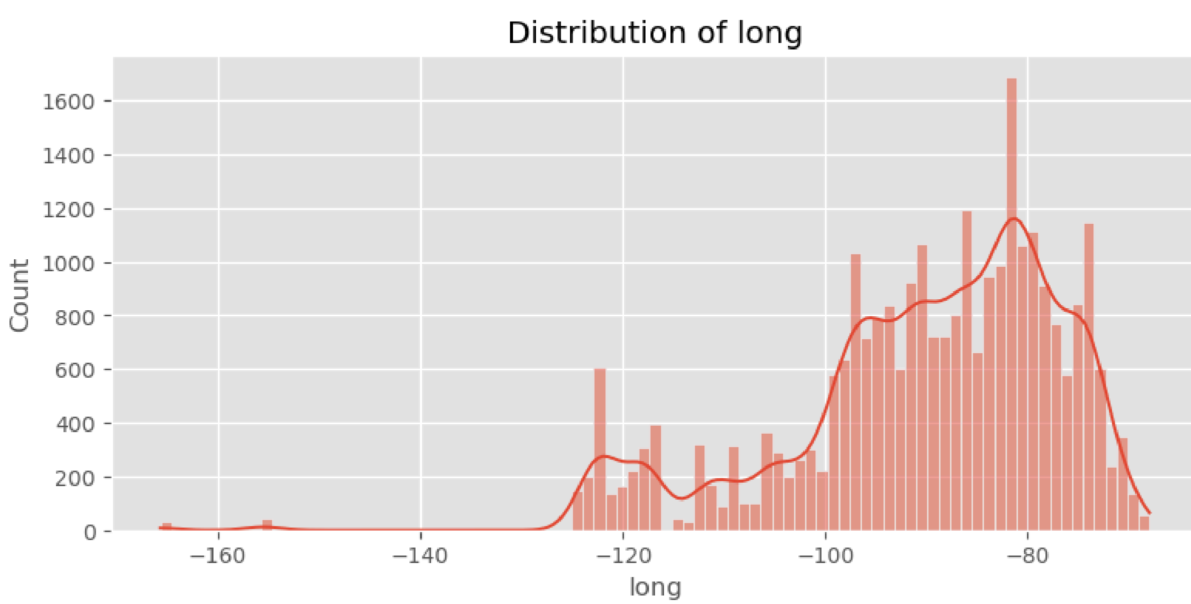
In [361…

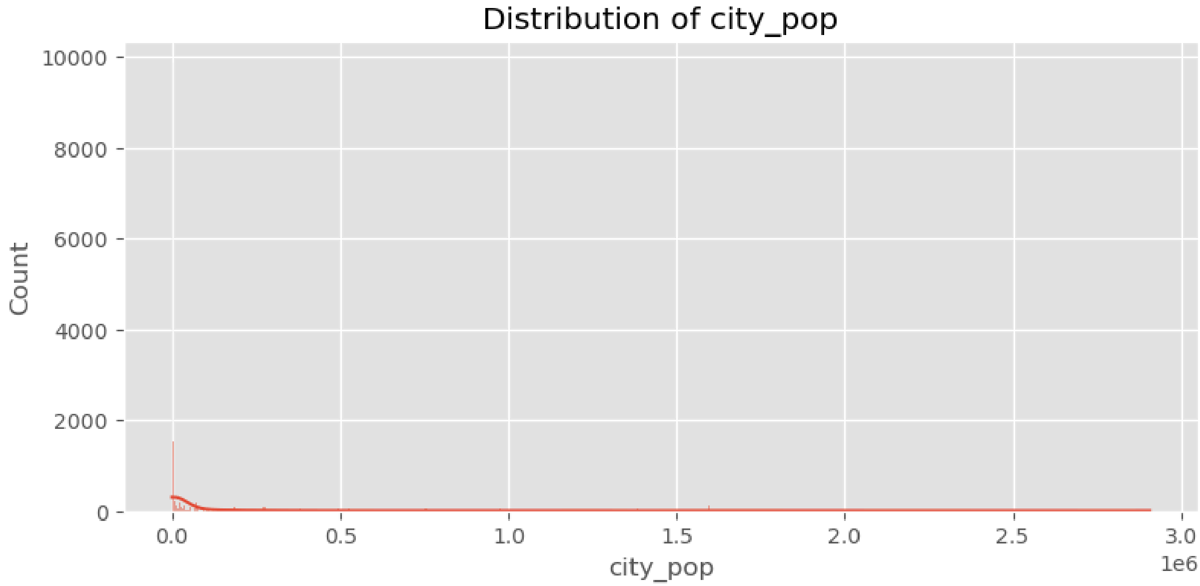
```
#plot histograms for numerical variables
plt.style.use('ggplot')
for column in filter_conf:
    plt.figure(figsize=(20, 4))
    plt.subplot(1, 2, 1)
    sns.histplot(df[column], kde = True)
    plt.title(f'Distribution of {column}')
    plt.show()
```

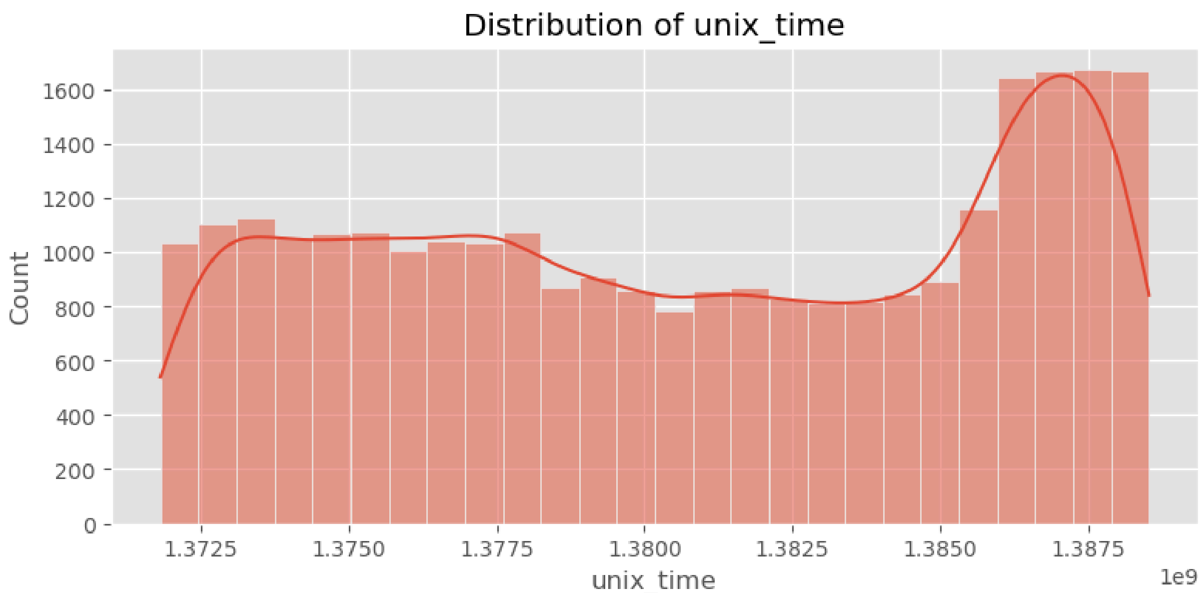


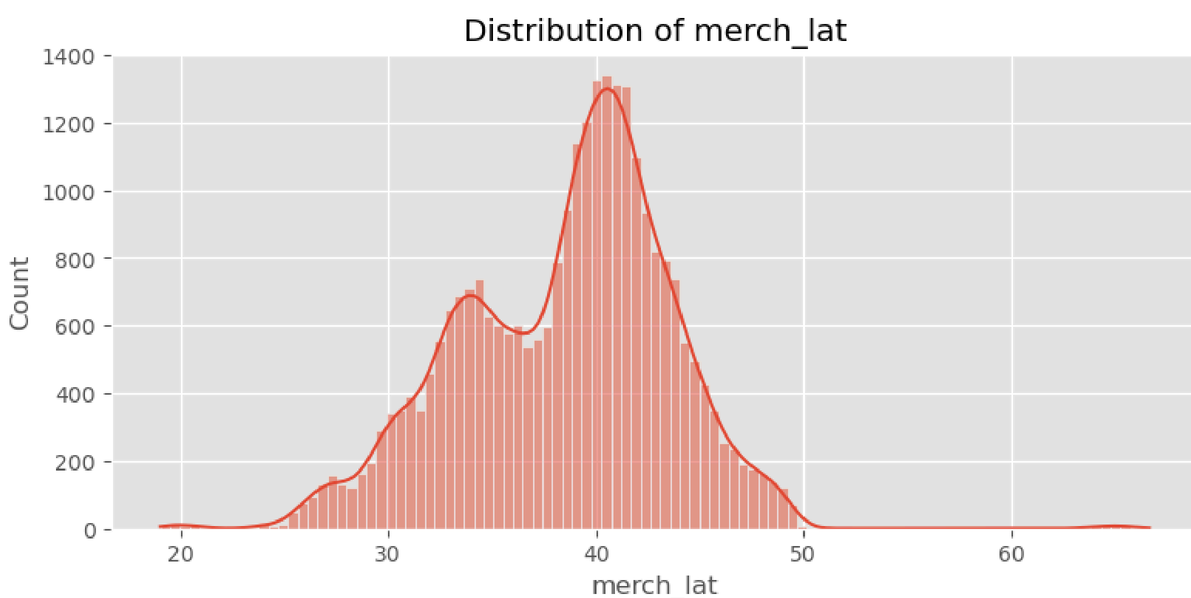

Distribution of zip
Count
zip
0
200
400
600
800
1000
1200
1400
1600
0
20000
40000
60000
80000
100000

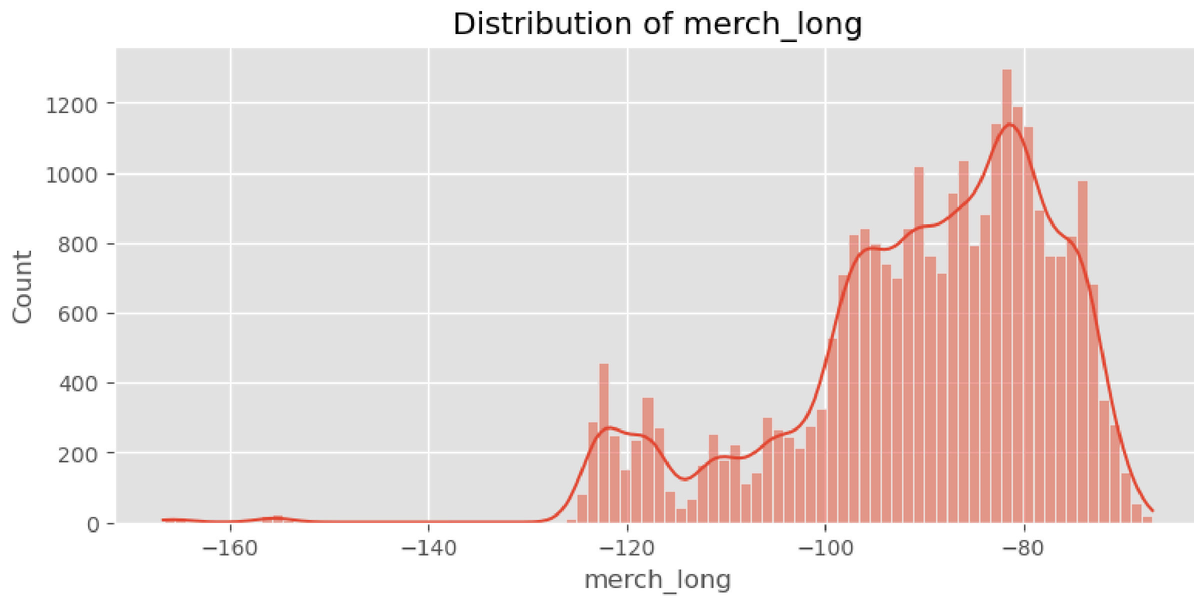

Distribution of lat
Count
lat
0
250
500
750
1000
1250
1500
1750
20
30
40
50
60

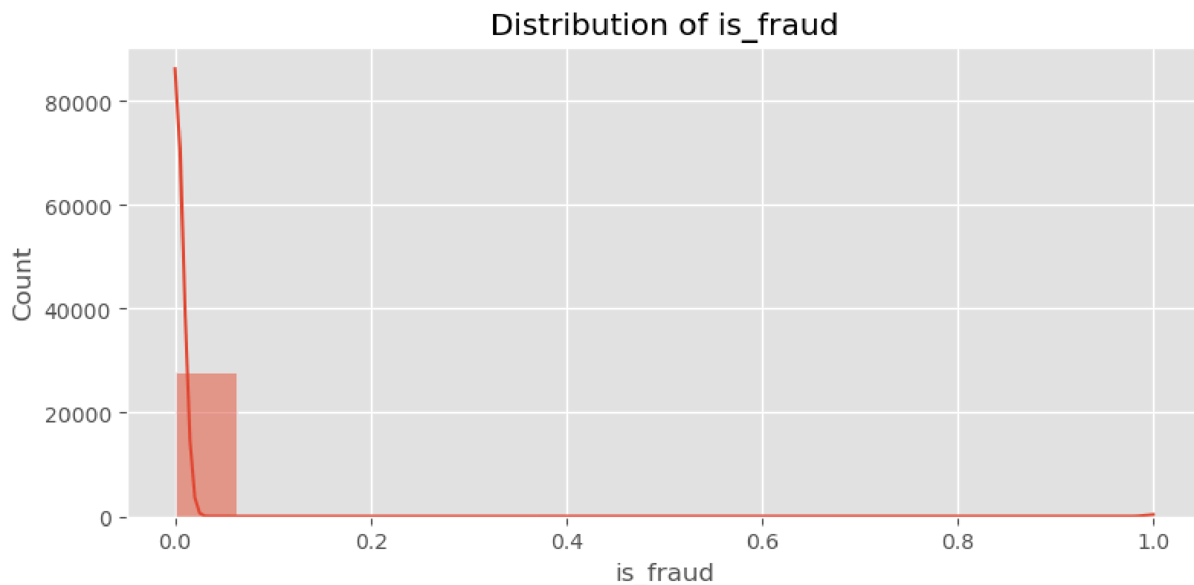

Distribution of long
Count
long
0
200
400
600
800
1000
1200
1400
1600
−160
−140
−120
−100
−80


Distribution of city_pop
Count
city_pop
1e6


Distribution of unix_time
Count
unix_time
1e9

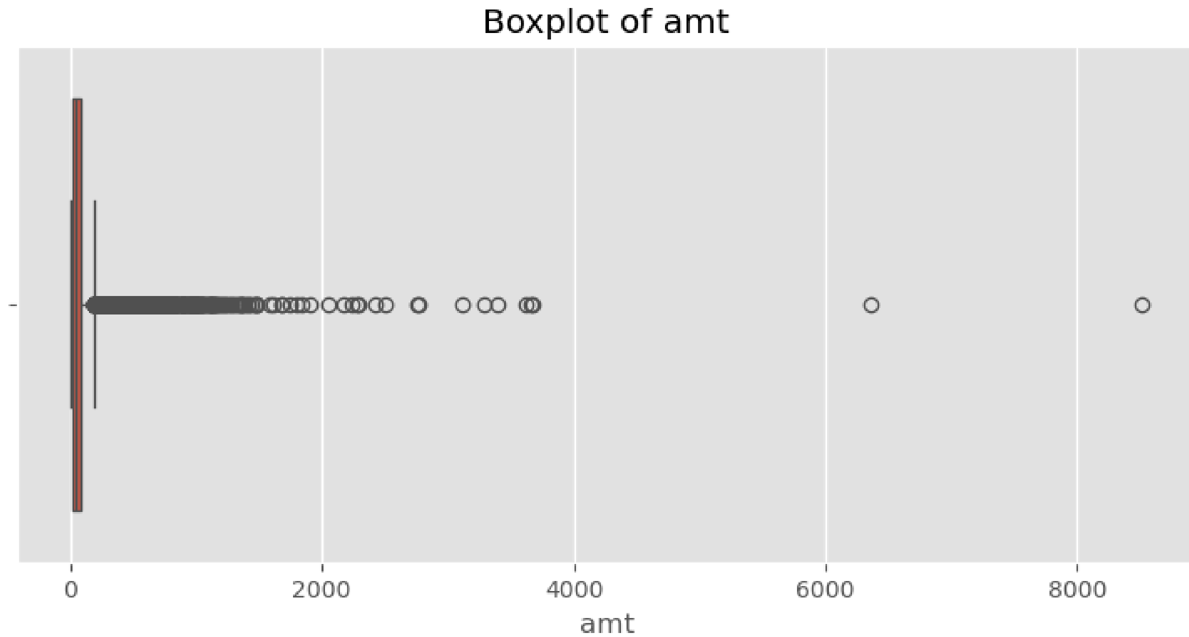

Distribution of merch_lat
Count
merch_lat

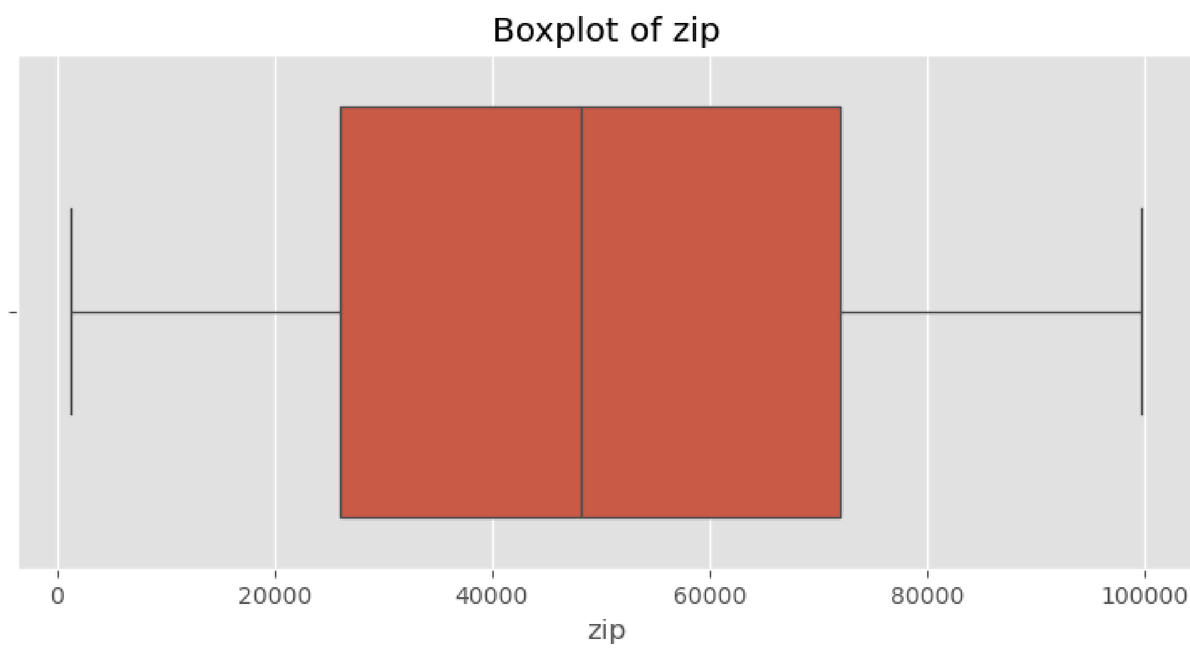


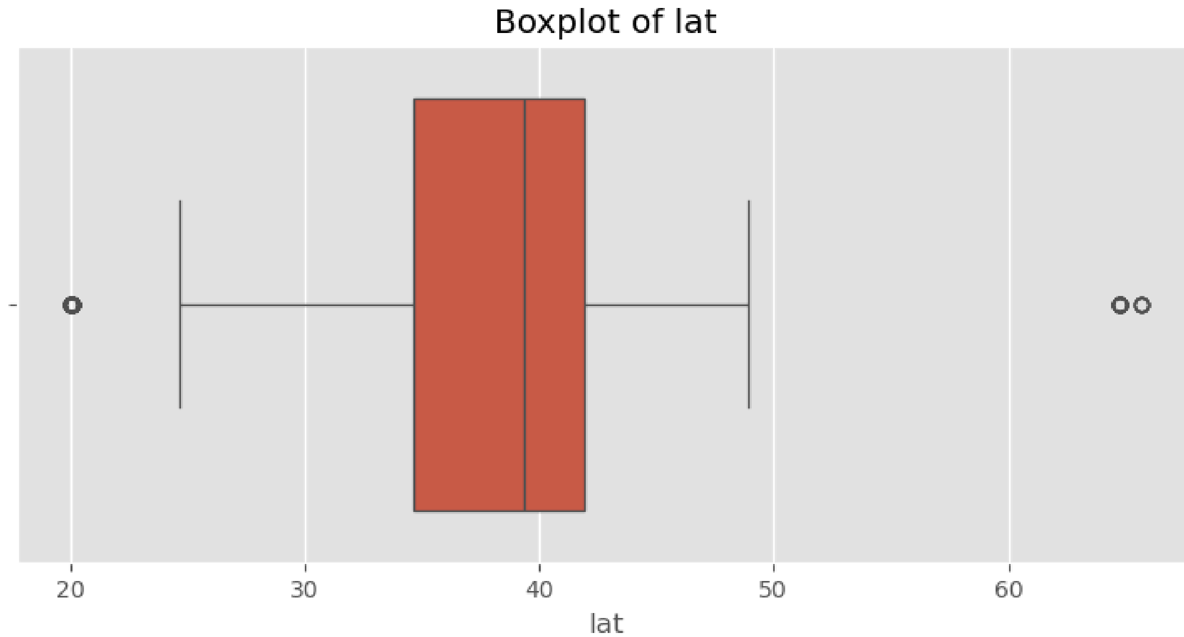


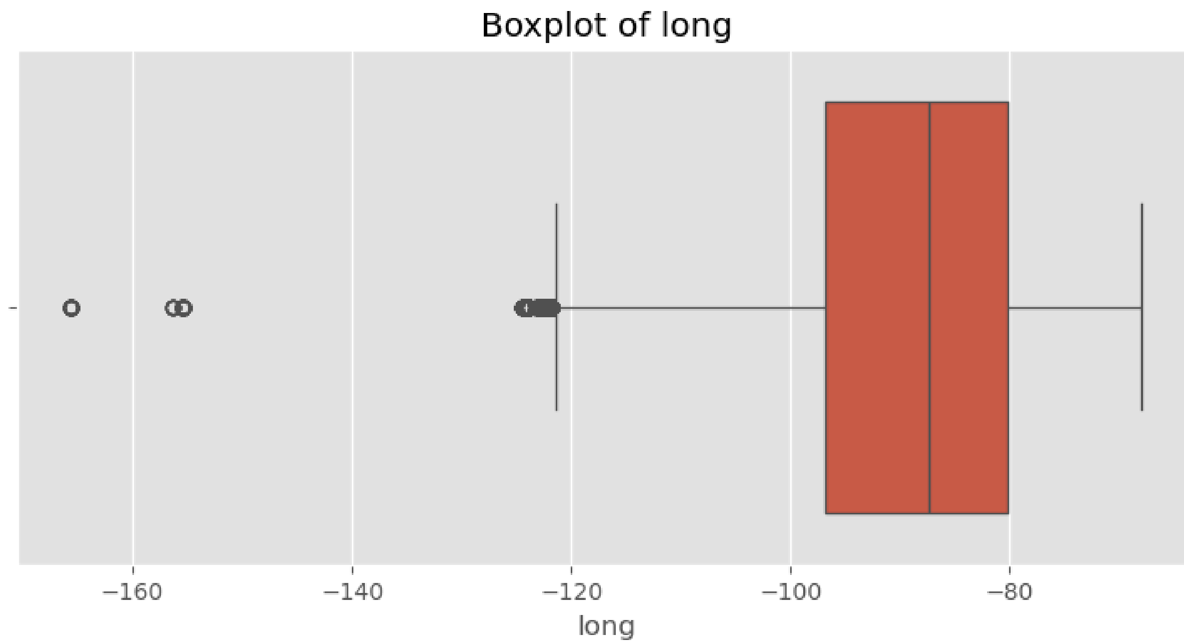
In [362…

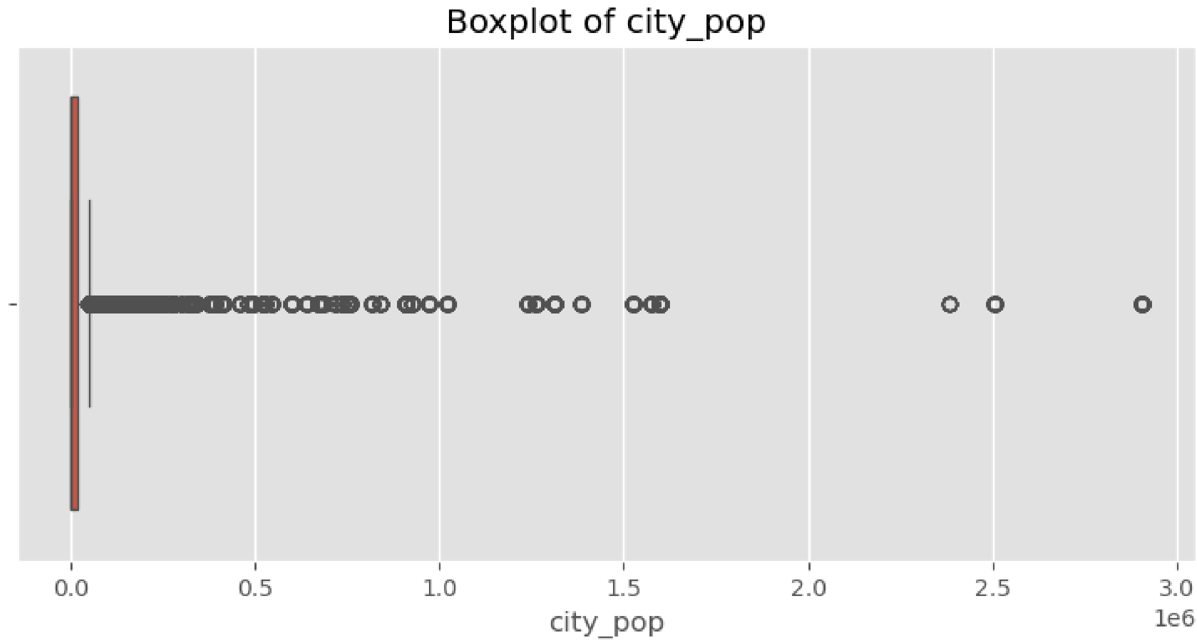
```
#plot boxplots of all continuous features
plt.style.use('ggplot')
for column in filter_conf:
    plt.figure(figsize=(20, 4))
    plt.subplot(1, 2, 1)
    sns.boxplot(x=df[column])
    plt.title(f'Boxplot of {column}')
    plt.show()
```

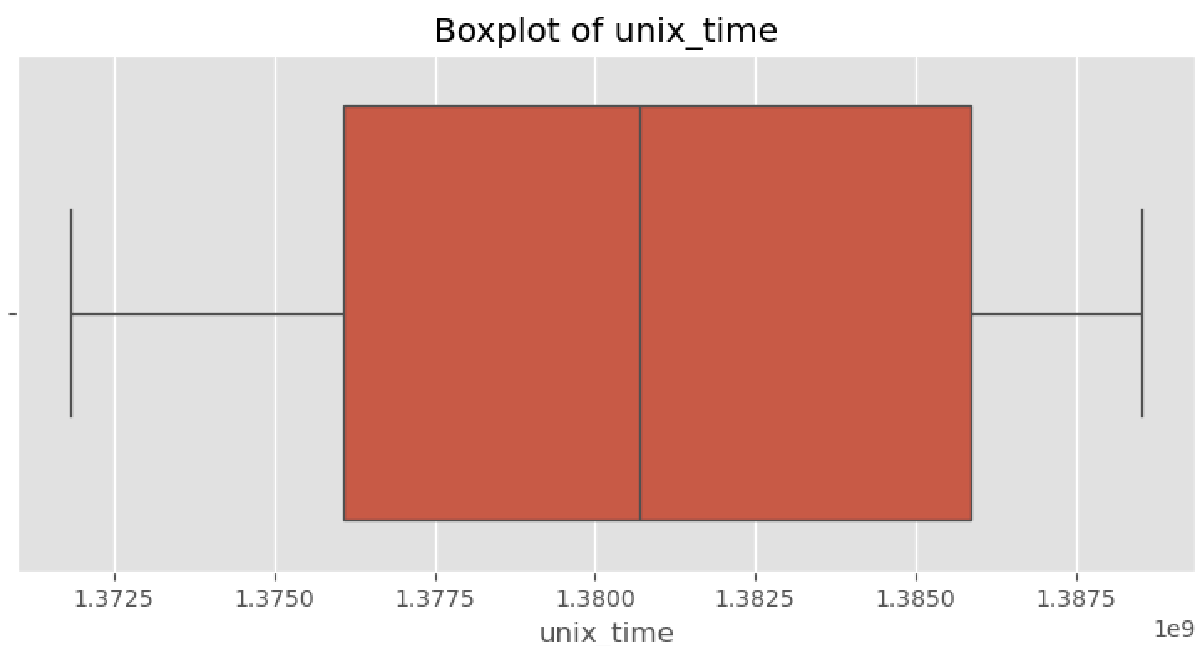

Boxplot of amt
0
2000
4000
6000
8000
amt

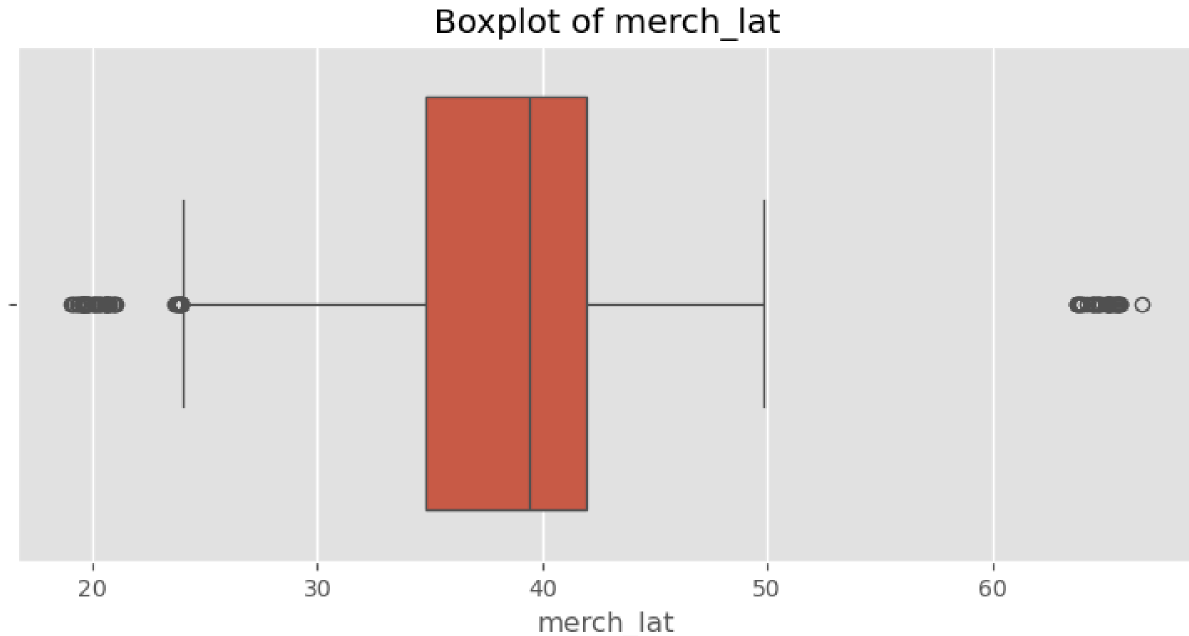

Boxplot of zip
0
20000
40000
60000
80000
100000
zip

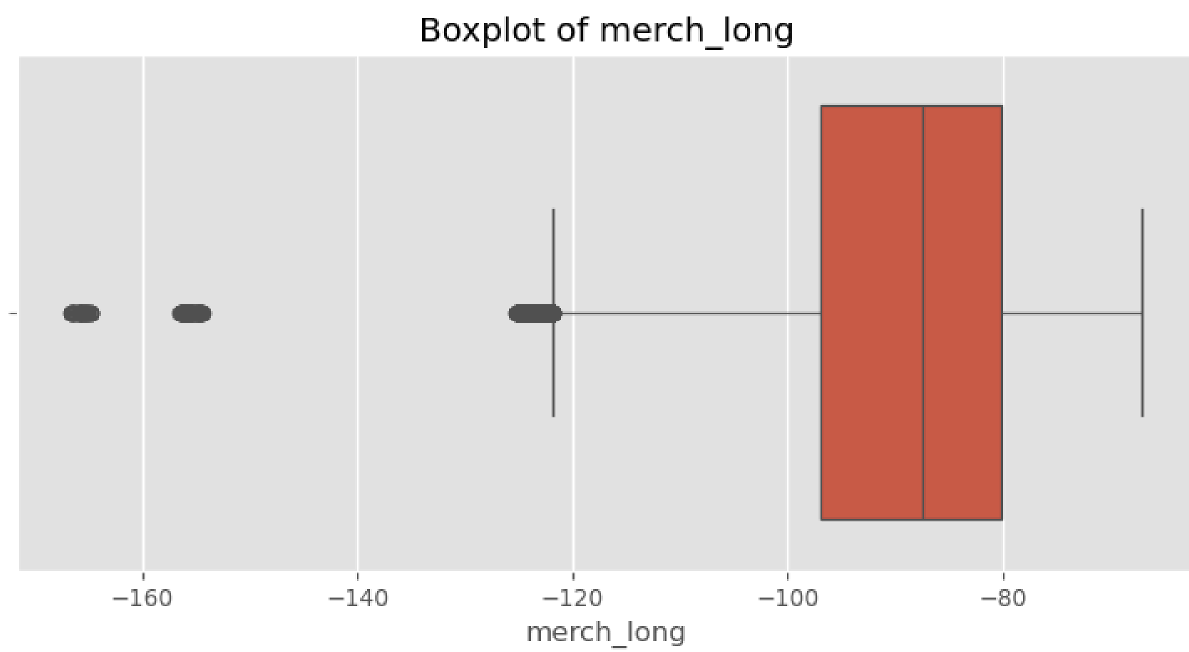

Boxplot of lat
20
30
40
50
60
lat

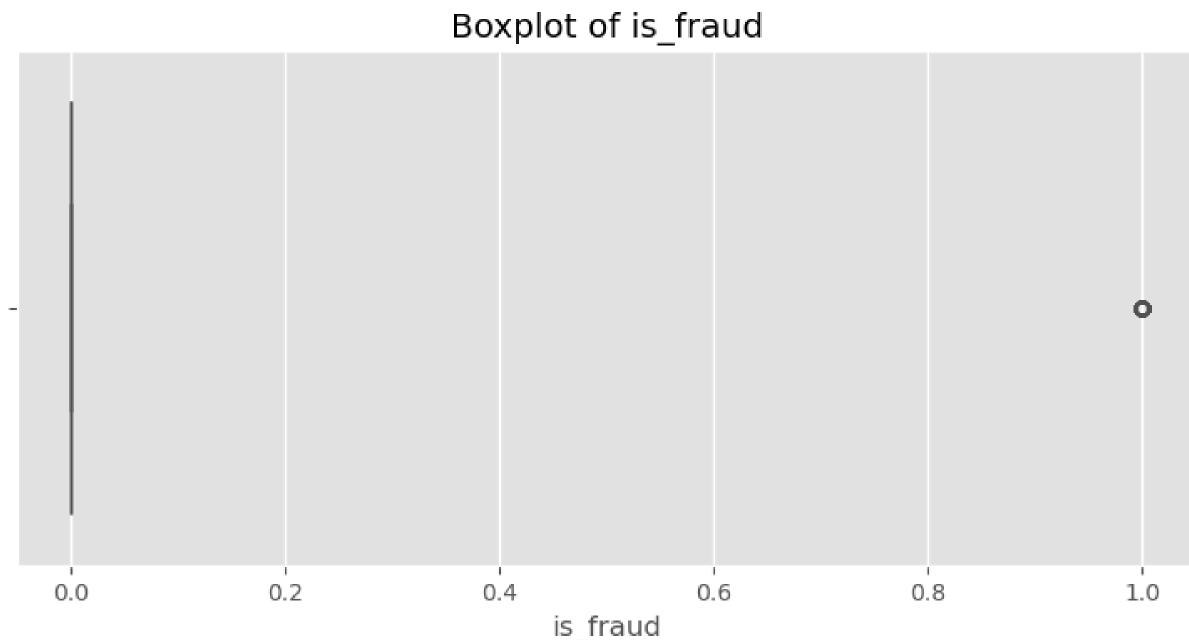

Boxplot of long
−160
−140
−120
−100
−80
long


Boxplot of city_pop
0.0
0.5
1.0
1.5
2.0
2.5
3.0
1e6
city_pop


Boxplot of unix_time
1.3725
1.3750
1.3775
1.3800
1.3825
1.3850
1.3875
1e9
unix_time


Boxplot of merch_lat
20
30
40
50
60
merch_lat


Boxplot of merch_long
−160
−140
−120
−100
−80
merch_long



Multivariate Analysis

Correlations

In [365…

```
#correlations
corr_matrix = df[filter_conf].corr()
corr_matrix
```

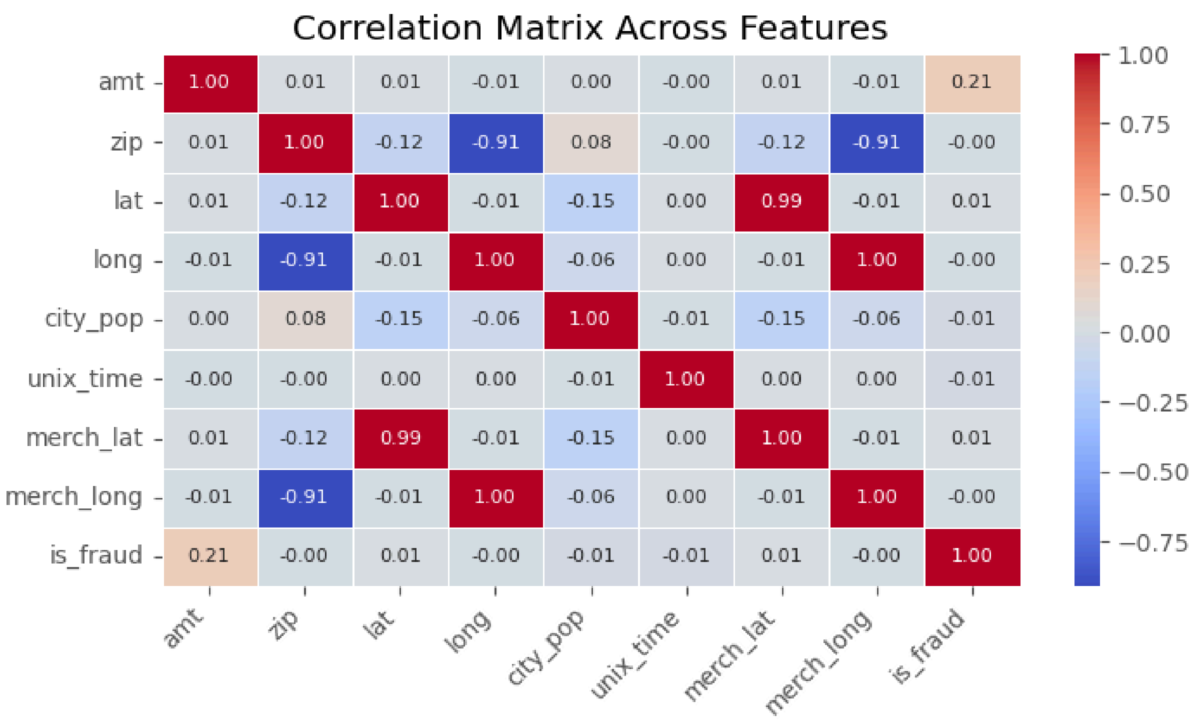
Out[365…

	amt	zip	lat	long	city_pop	unix_time	merch_lat	merch_long	is_f
amt	1.000	0.008	0.006	-0.008	0.003	-0.002	0.007	-0.008	
zip	0.008	1.000	-0.122	-0.912	0.080	-0.003	-0.121	-0.911	-
lat	0.006	-0.122	1.000	-0.007	-0.147	0.002	0.993	-0.006	
long	-0.008	-0.912	-0.007	1.000	-0.059	0.001	-0.007	0.999	-
city_pop	0.003	0.080	-0.147	-0.059	1.000	-0.007	-0.146	-0.059	-
unix_time	-0.002	-0.003	0.002	0.001	-0.007	1.000	0.001	0.001	-
merch_lat	0.007	-0.121	0.993	-0.007	-0.146	0.001	1.000	-0.007	
merch_long	-0.008	-0.911	-0.006	0.999	-0.059	0.001	-0.007	1.000	-
is_fraud	0.206	-0.002	0.014	-0.003	-0.010	-0.010	0.015	-0.003	

In [366…

```
# Create a heatmap
plt.figure(figsize=(8, 4))
heatmap = sns.heatmap(corr_matrix, annot=True, fmt=".2f", cmap='coolwarm', linewidt

# Rotate the x and y labels for better readability
```

```
plt.xticks(rotation=45, ha='right')
plt.yticks(rotation=0)

# Show the heatmap
plt.title("Correlation Matrix Across Features")
plt.show()
```



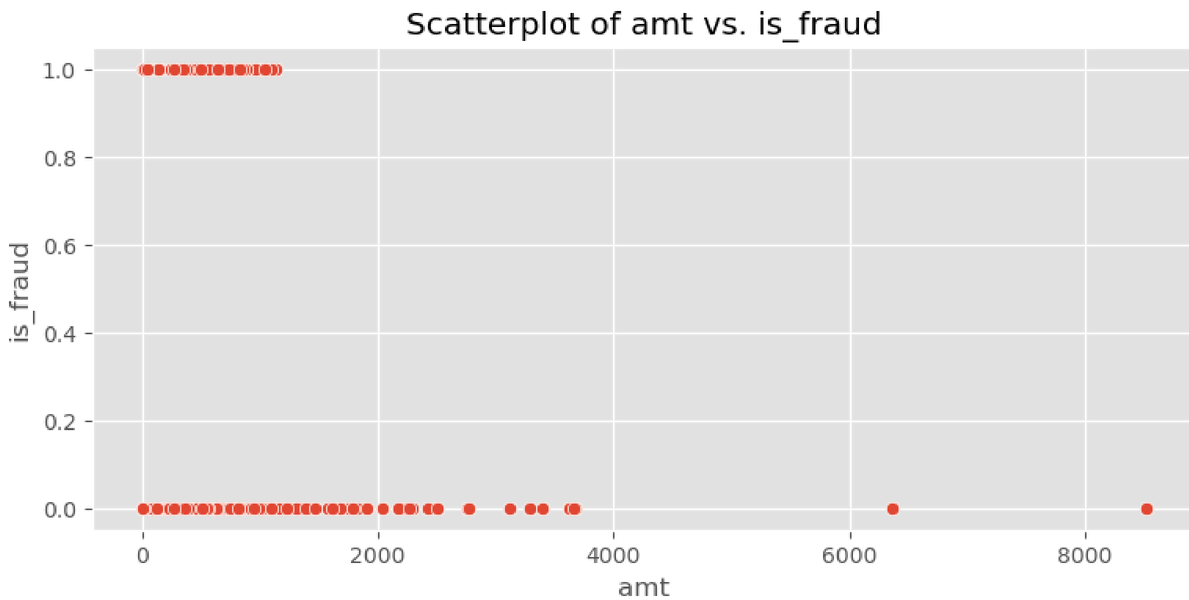
In [367…

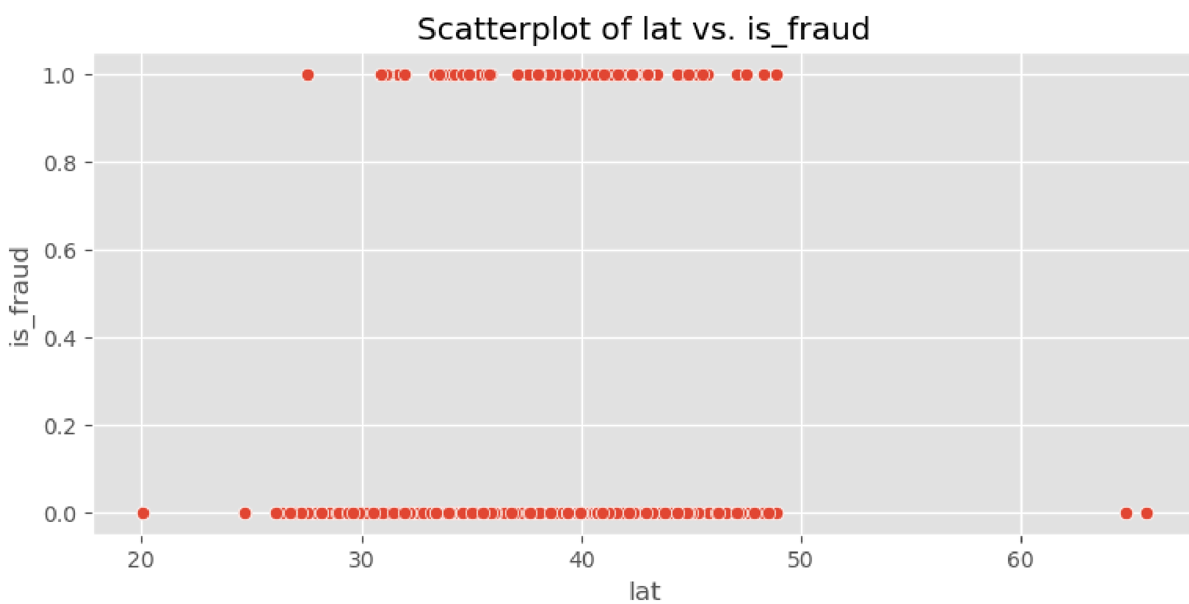
```
#identify most highly correlated items to the target variable
target_column = 'is_fraud'
corr_with_target = corr_matrix[target_column].abs() #get the absolute value of feat
threshold = .01 #set the threshold for correlation
high_corr = corr_with_target[corr_with_target > threshold].index.tolist() #gets the
print(high_corr)
```

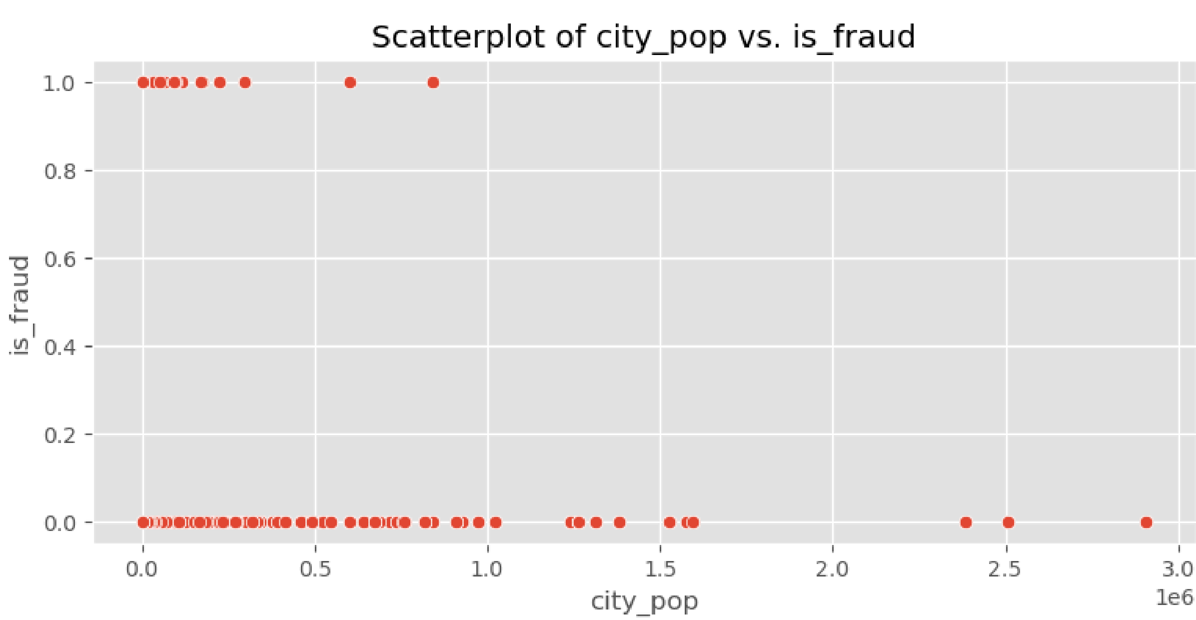
```
['amt', 'lat', 'city_pop', 'merch_lat', 'is_fraud']
```

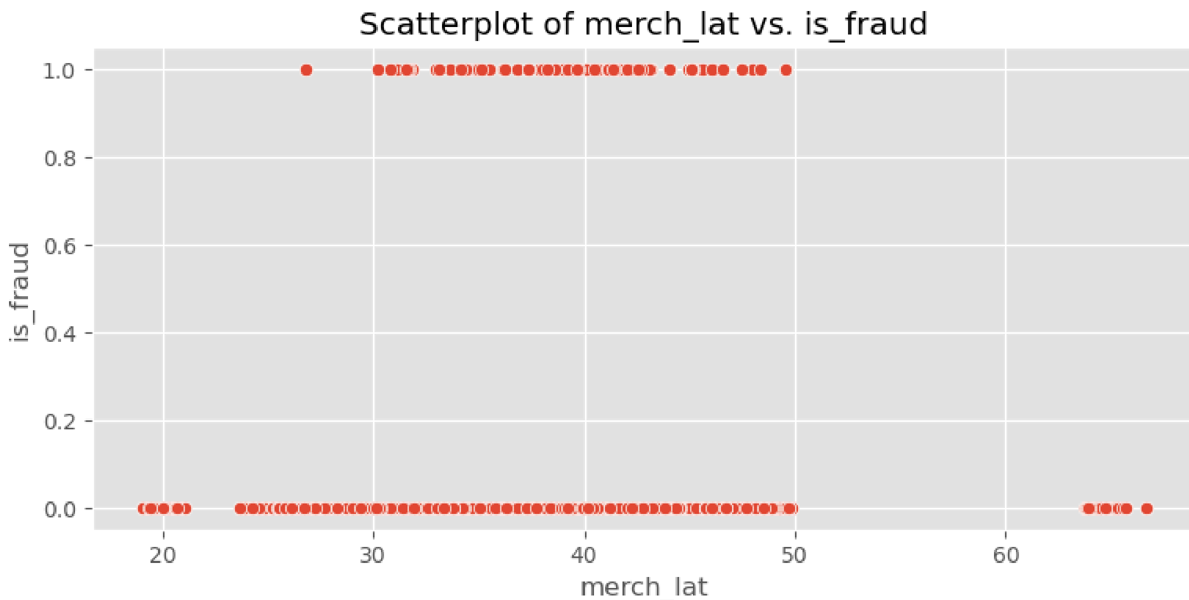
In [368…

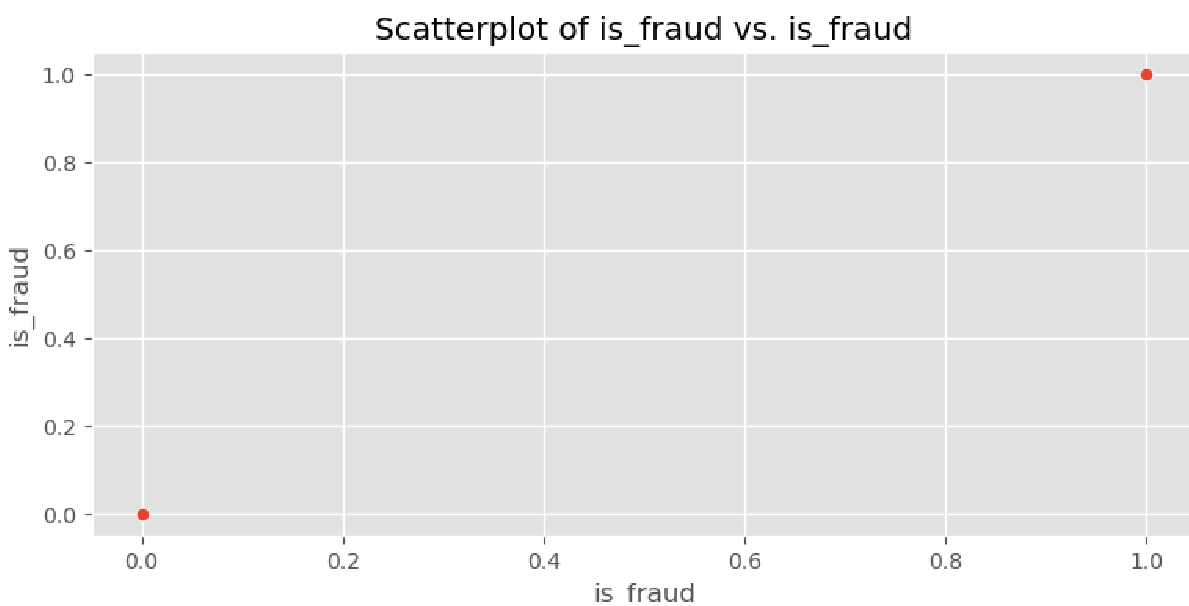
```
#plot scatterplots for threshold meeting the correlation
plt.style.use('ggplot')
for column in high_corr:
    plt.figure(figsize=(20, 4))
    plt.subplot(1, 2, 1)
    sns.scatterplot(x=df[column], y=df['is_fraud'])
    plt.title(f'Scatterplot of {column} vs. is_fraud')
    plt.show()
```


Scatterplot of amt vs. is_fraud
is_fraud
1.0
0.8
0.6
0.4
0.2
0.0
0
2000
4000
6000
8000
amt


Scatterplot of lat vs. is_fraud
is_fraud
1.0
0.8
0.6
0.4
0.2
0.0
20
30
40
50
60
lat

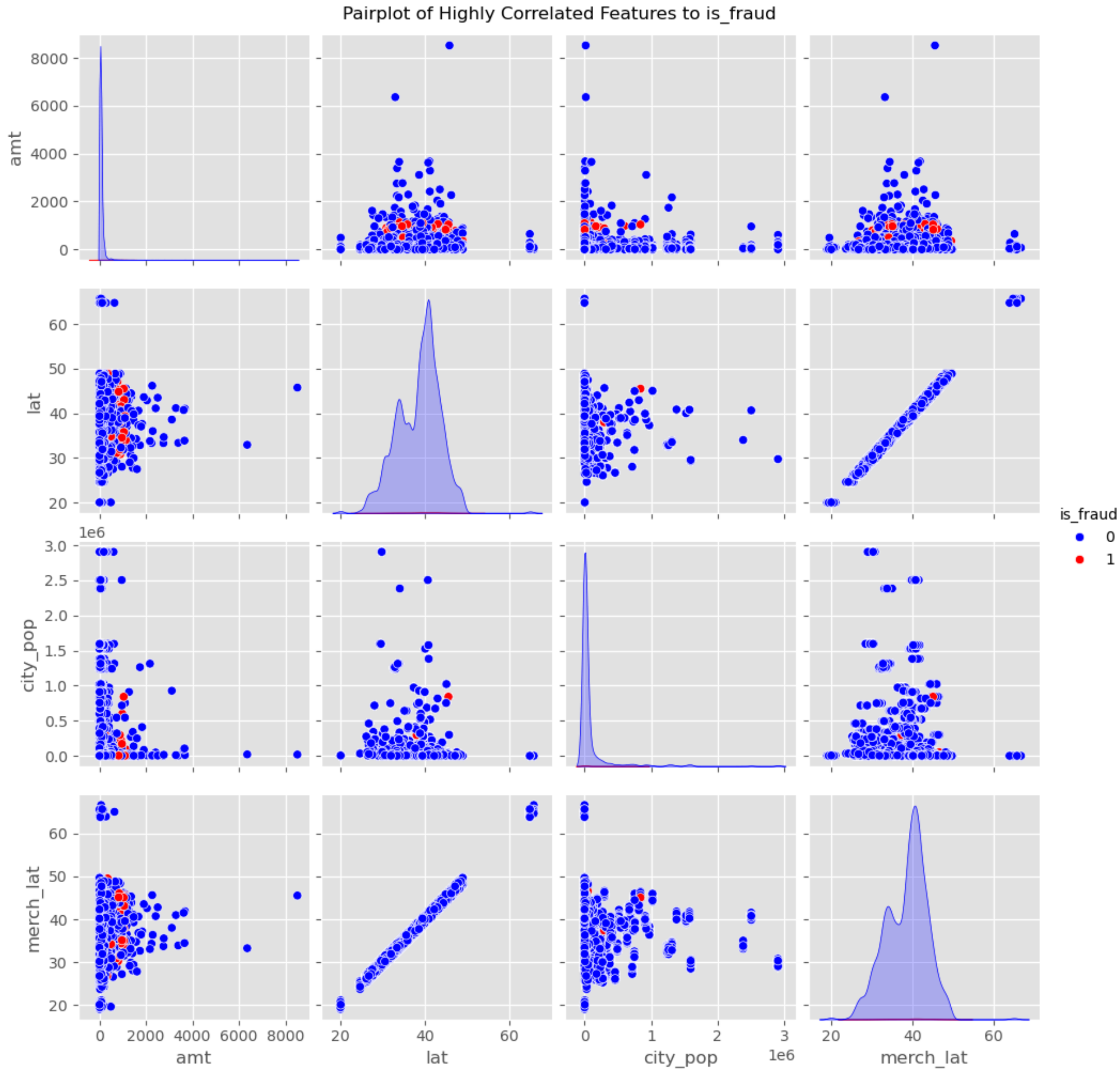

Scatterplot of city_pop vs. is_fraud
is_fraud
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.5
1.0
1.5
2.0
2.5
3.0
1e6
city_pop





In [369…

```
sns.pairplot(df[high_corr], hue='is_fraud', palette={1: 'red', 0: 'blue'})
plt.suptitle("Pairplot of Highly Correlated Features to is_fraud",y= 1.01) #ensures
plt.show()
```



Data Pre-Processing

In [371…
```
df1 = df.copy()
```

In [372…
```
df1.head()
```

Out[372…

	Unnamed: 0	trans_date_trans_time	cc_num	merchant	category
0	417308	2020-12-01 05:38:34	348789608637806	fraud_Berge LLC	gas_transport
1	22343	2020-06-29 02:05:06	2291163933867244	fraud_Bins, Balistreri and Beatty	shopping_pos
2	540530	2020-12-28 15:48:07	372509258176510	fraud_Bradtke, Torp and Bahringer	personal_care
3	492286	2020-12-17 23:47:28	571365235126	fraud_Prosacco, Kreiger and Kovacek	home
4	17203	2020-06-27 11:52:35	4225990116481262579	fraud_Bernier, Volkman and Hoeger	misc_net

Feature Transformation - Distance

In [374…

```
import math
#haversine formula calculates the difference between two points. Tutorial here:
#https://www.geeksforgeeks.org/haversine-formula-to-find-distance-between-two-point

#create haversine function
def haversine(lat1, lon1, lat2, lon2):
    # distance between latitudes and longitudes
    dLat = (lat2 - lat1) * math.pi / 180.0
    dLon = (lon2 - lon1) * math.pi / 180.0

    # convert to radians
    lat1 = lat1 * math.pi / 180.0
    lat2 = lat2 * math.pi / 180.0

    # apply formula
    a = (pow(math.sin(dLat / 2), 2) +
         pow(math.sin(dLon / 2), 2) *
         math.cos(lat1) * math.cos(lat2))
    rad = 6371  # Earth’s radius in kilometers
    c = 2 * math.asin(math.sqrt(a))
    return rad * c

df1['distance_km'] = df1.apply(lambda row: haversine(row['lat'], row['long'], row['
                                                      row['merch_long']), axis=1)
```

```
# Display the updated dataframe with the distance column
print(df1[['lat', 'long', 'merch_lat', 'merch_long', 'distance_km']])
```

```
          lat     long  merch_lat  merch_long  distance_km
0      40.454  -98.654     40.000     -99.040       60.200
1      33.966  -80.936     33.547     -80.976       46.722
2      42.915  -83.484     43.651     -84.041       93.483
3      44.599  -86.214     44.948     -85.290       82.612
4      20.083 -155.488     19.658    -156.016       72.611
...       ...      ...        ...         ...          ...
27780  31.957  -98.966     31.894     -99.870       85.625
27781  39.372  -77.823     40.371     -77.906      111.349
27782  39.935  -86.163     39.986     -86.364       18.056
27783  42.189  -74.923     42.298     -74.987       13.216
27784  39.406  -75.321     40.162     -75.233       84.435

[27785 rows x 5 columns]
```

In [375…

```
df1.head()
```

Out[375…

	Unnamed: 0	trans_date_trans_time	cc_num	merchant	category
0	417308	2020-12-01 05:38:34	348789608637806	fraud_Berge LLC	gas_transport
1	22343	2020-06-29 02:05:06	2291163933867244	fraud_Bins, Balistreri and Beatty	shopping_pos
2	540530	2020-12-28 15:48:07	372509258176510	fraud_Bradtke, Torp and Bahringer	personal_care
3	492286	2020-12-17 23:47:28	571365235126	fraud_Prosacco, Kreiger and Kovacek	home
4	17203	2020-06-27 11:52:35	4225990116481262579	fraud_Bernier, Volkman and Hoeger	misc_net

DOB Transformation

Transform DOB to be the following generation numbers:

- Silent Generation: Born before 1945 : 0
- Baby Boomers: 1946–1964 : 1
- Generation X: 1965–1980 : 2
- Millennials (Gen Y): 1981–1996 : 3

- Generation Z (Gen Z): 1997–2012 : 4
- Generation Alpha: 2013 and later : 5

In [378…

```
# Convert 'DOB' column to datetime format
df1['dob'] = pd.to_datetime(df1['dob'], format='%Y-%m-%d')

# Function to categorize generations into numerical format
def categorize_generation(dob):
    if dob < pd.Timestamp('1945-01-01'):
        return 0  # Silent Generation
    elif dob < pd.Timestamp('1965-01-01'):
        return 1  # Baby Boomers
    elif dob < pd.Timestamp('1981-01-01'):
        return 2  # Generation X
    elif dob < pd.Timestamp('1997-01-01'):
        return 3  # Millennials
    elif dob < pd.Timestamp('2013-01-01'):
        return 4  # Generation Z
    else:
        return 5  # Generation Alpha

# Apply the function to create a new column for generations in numerical format
df1['Generation_Numeric'] = df1['dob'].apply(categorize_generation)

# Drop the original 'DOB' column
df1.drop(columns=['dob'], inplace=True)

# Display the updated DataFrame
df1.head()
```

Out[378…

	Unnamed: 0	trans_date_trans_time	cc_num	merchant	category	
0	417308	2020-12-01 05:38:34	348789608637806	fraud_Berge LLC	gas_transport	5
1	22343	2020-06-29 02:05:06	2291163933867244	fraud_Bins, Balistreri and Beatty	shopping_pos	3
2	540530	2020-12-28 15:48:07	372509258176510	fraud_Bradtke, Torp and Bahringer	personal_care	
3	492286	2020-12-17 23:47:28	571365235126	fraud_Prosacco, Kreiger and Kovacek	home	2
4	17203	2020-06-27 11:52:35	4225990116481262579	fraud_Bernier, Volkman and Hoeger	misc_net	

City Population Transformation

Transforming city_pop to

https://www.oecd.org/en/data/indicators/urban-population-by-city-size.html?oecdcontrol-38c744bfa4-var1=USA%7COAVG

- large metropolitan areas if they have a population of 1.5 million or more;
- metropolitan areas if their population is between 500 000 and 1.5 million;
- medium-size urban areas if their population is between 200 000 and 500 000;
- small urban areas if their population is between 50 000 and 200 000.

In [381…

```python
# Define a function to categorize city populations based on OECD standards
def categorize_city_pop_oecd(city_pop):
    if city_pop >= 1500000:
        return 'Large Metropolitan Area'
    elif 500000 <= city_pop < 1500000:
        return 'Metropolitan Area'
    elif 200000 <= city_pop < 500000:
        return 'Medium-Size Urban Area'
    elif 50000 <= city_pop < 200000:
        return 'Small Urban Area'
    else:
        return 'Rural Area'

# Apply the function to the city_pop column in df1
df1['city_pop_category'] = df1['city_pop'].apply(categorize_city_pop_oecd)

# Display the updated dataframe with the new column
print(df1[['city_pop', 'city_pop_category']].head())
```

```
   city_pop       city_pop_category
0       331              Rural Area
1    333497  Medium-Size Urban Area
2      6951              Rural Area
3       372              Rural Area
4      4878              Rural Area
```

In [382…

```python
df1.head()
```

Out[382…

	Unnamed: 0	trans_date_trans_time	cc_num	merchant	category
0	417308	2020-12-01 05:38:34	348789608637806	fraud_Berge LLC	gas_transport
1	22343	2020-06-29 02:05:06	2291163933867244	fraud_Bins, Balistreri and Beatty	shopping_pos
2	540530	2020-12-28 15:48:07	372509258176510	fraud_Bradtke, Torp and Bahringer	personal_care
3	492286	2020-12-17 23:47:28	571365235126	fraud_Prosacco, Kreiger and Kovacek	home
4	17203	2020-06-27 11:52:35	4225990116481262579	fraud_Bernier, Volkman and Hoeger	misc_net

Transforming Date/Time Features

In [384…

```
df1['trans_date_trans_time'] = pd.to_datetime(df1['trans_date_trans_time'])

# Extract temporal features
df1['day_of_week'] = df1['trans_date_trans_time'].dt.dayofweek
df1['hour_of_day'] = df1['trans_date_trans_time'].dt.hour
df1['month'] = df1['trans_date_trans_time'].dt.month
df1['quarter'] = df1['trans_date_trans_time'].dt.quarter

def categorize_time_of_day(hour):
    if 5 <= hour < 12:
        return 'morning'
    elif 12 <= hour < 17:
        return 'noon'
    elif 17 <= hour < 21:
        return 'evening'
    else:
        return 'night'

df1['time_of_day'] = df1['hour_of_day'].apply(categorize_time_of_day)
df1['is_weekend'] = df1['day_of_week'].apply(lambda x: 1 if x >= 5 else 0)

# Display the updated DataFrame with new features
features_to_display = ['trans_date_trans_time', 'day_of_week', 'hour_of_day', 'mont

# Display only the selected features (without rolling_avg)
df1[features_to_display].head()
```

Out[384…

	trans_date_trans_time	day_of_week	hour_of_day	month	quarter	time_of_day	is_weeke
0	2020-12-01 05:38:34	1	5	12	4	morning	
1	2020-06-29 02:05:06	0	2	6	2	night	
2	2020-12-28 15:48:07	0	15	12	4	noon	
3	2020-12-17 23:47:28	3	23	12	4	night	
4	2020-06-27 11:52:35	5	11	6	2	morning	

Drop Unnecessary Columns

Dropping the following columns:

- Dropping the following due to being unique identifiers, thus not appropriate for prediction: cc_num, Unnamed: 0, first, last, merchant, trans_num
- Dropping the following due to redundancy after feature transformation: trans_date_trans_time, merch_lat, merch_long, city, state, zip, lat, long, unix_time, street, city_pop
- Dropping the following due to high-cardinality / curse of dimensionality: job. Cardinality is 476.

In [387…

```
df2 = df1.copy()  # Create a copy of df1

# Drop the specified columns
columns_to_drop = [
    'trans_date_trans_time',
    'merch_lat',
    'merch_long',
    'merchant',
    'cc_num',
    'Unnamed: 0',
    'first',
    'last',
    'city',
    'state',
    'zip',
    'lat',
    'long',
    'trans_num',
    'unix_time',
    'job',
    'street',
    'city_pop'
]

df2.drop(columns=columns_to_drop, inplace=True, errors='ignore')  # Drop columns an
```

```
# Display the updated DataFrame df2
df2.head()
```

Out[387…

	category	amt	gender	is_fraud	distance_km	Generation_Numeric	city_pop_cate
0	gas_transport	50.420	F	0	60.200	1	Rural
1	shopping_pos	39.470	M	0	46.722	2	Medium Urban
2	personal_care	8.160	F	0	93.483	3	Rural
3	home	25.480	F	0	82.612	3	Rural
4	misc_net	5.710	M	0	72.611	2	Rural

Data Analysis - Transformed Data

In [389…

```
#fraud only
df_fraud = df2[df2['is_fraud'] == 1]
#not fraud only
df_safe = df2[df2['is_fraud'] == 0]
```

In [390…

```
df2_cont = df2.select_dtypes(include=['float64', 'int64']).columns.tolist()
print(f"The continous variables are: {df2_cont}")
df2_cat = df2.select_dtypes(include=['object']).columns.tolist()
print(f"The categorical variables are: {df2_cat}")
```

```
The continous variables are: ['amt', 'is_fraud', 'distance_km', 'Generation_Numeri
c', 'is_weekend']
The categorical variables are: ['category', 'gender', 'city_pop_category', 'time_of_
day']
```

Amount

In [392…

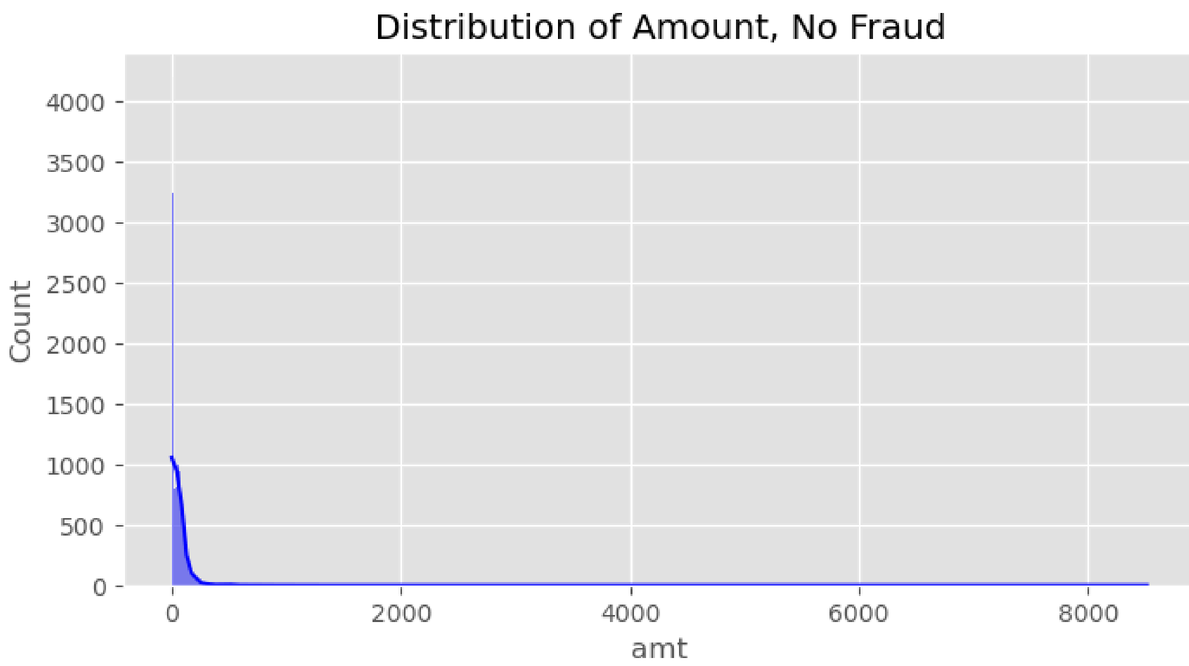
```
df_safe['amt'].describe()
```

Out[392…

```
count    27678.000
mean        66.542
std        131.295
min          1.000
25%          9.490
50%         47.070
75%         82.510
max       8517.380
Name: amt, dtype: float64
```

In [393…

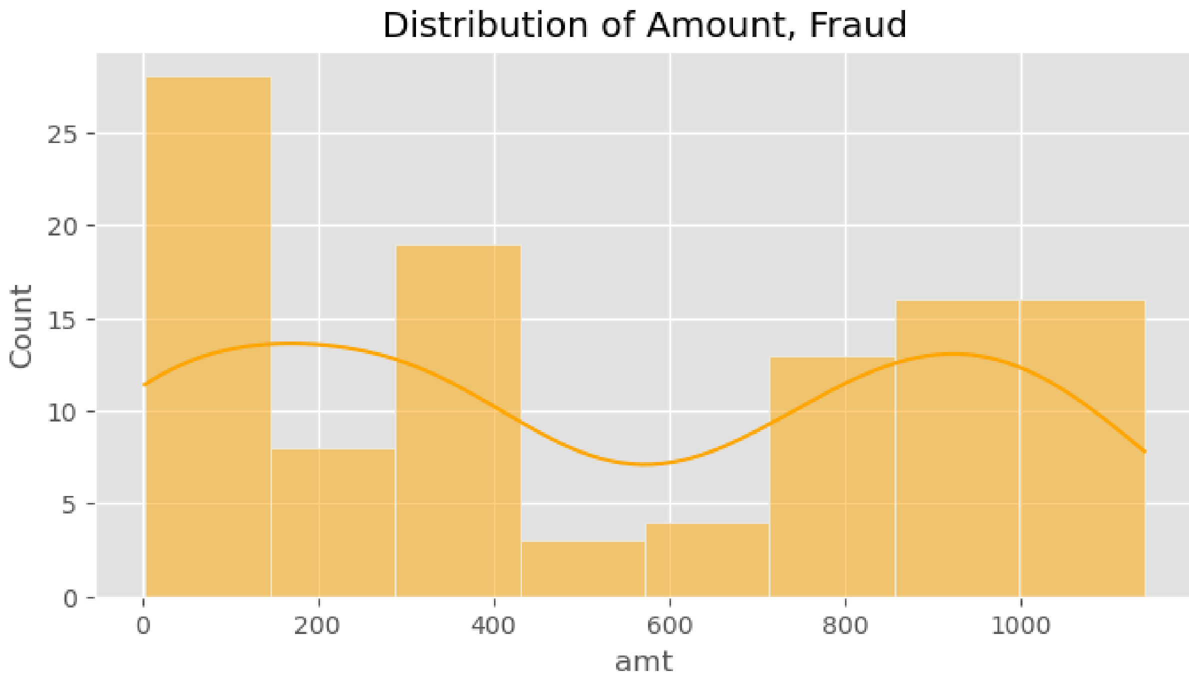
```
plt.figure(figsize=(8, 4))
sns.histplot(df_safe['amt'], kde=True, color='blue')
plt.title(f'Distribution of Amount, No Fraud')
plt.show()
```



In [394...
```
df_fraud['amt'].describe()
```

Out[394...
```
count     107.000
mean      519.221
std       393.892
min         3.150
25%       138.295
50%       378.560
75%       900.815
max      1139.970
Name: amt, dtype: float64
```

In [395...
```
plt.figure(figsize=(8, 4))
sns.histplot(df_fraud['amt'], kde=True, color = "orange")
plt.title(f'Distribution of Amount, Fraud')
plt.show()
```



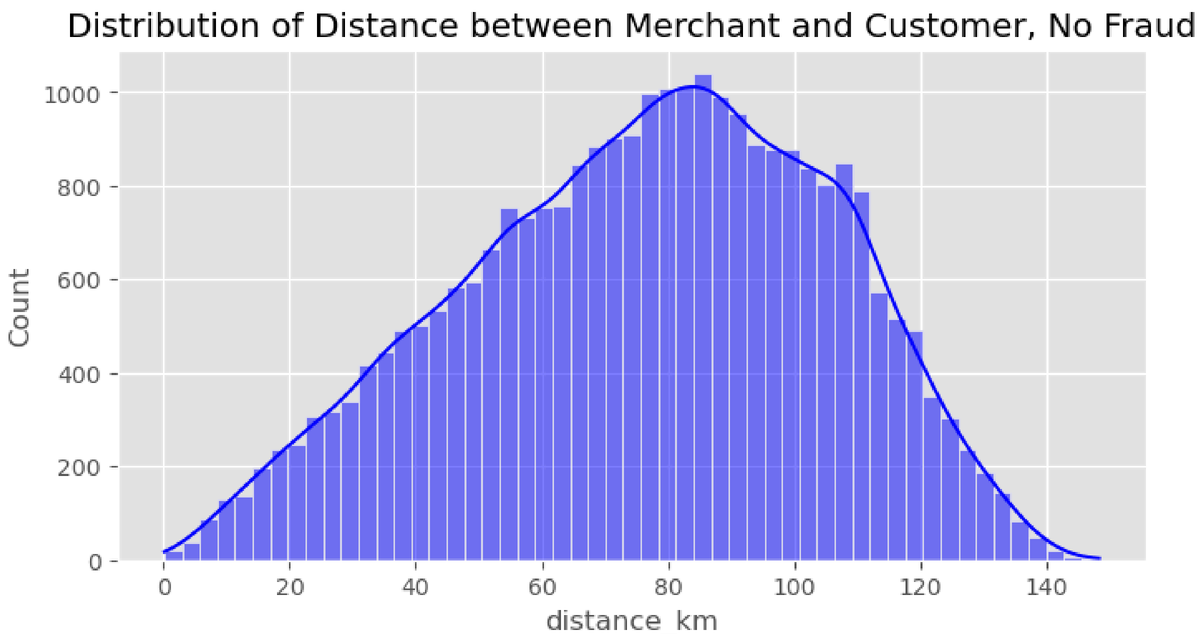
Average fraud transaction is 519.22 in comparison to non-fraud average of 66.54. The majority of non-fraud transactions are under $47 while fraud is higher amounts

Distance_KM

In [398…
```
df_safe['distance_km'].describe()
```

Out[398…
```
count    27678.000
mean        76.418
std         28.925
min          0.148
25%         55.700
50%         78.556
75%         98.668
max        148.395
Name: distance_km, dtype: float64
```

In [399…
```
plt.figure(figsize=(8, 4))
sns.histplot(df_safe['distance_km'], kde=True, color='blue')
plt.title(f'Distribution of Distance between Merchant and Customer, No Fraud')
plt.show()
```



In [400…

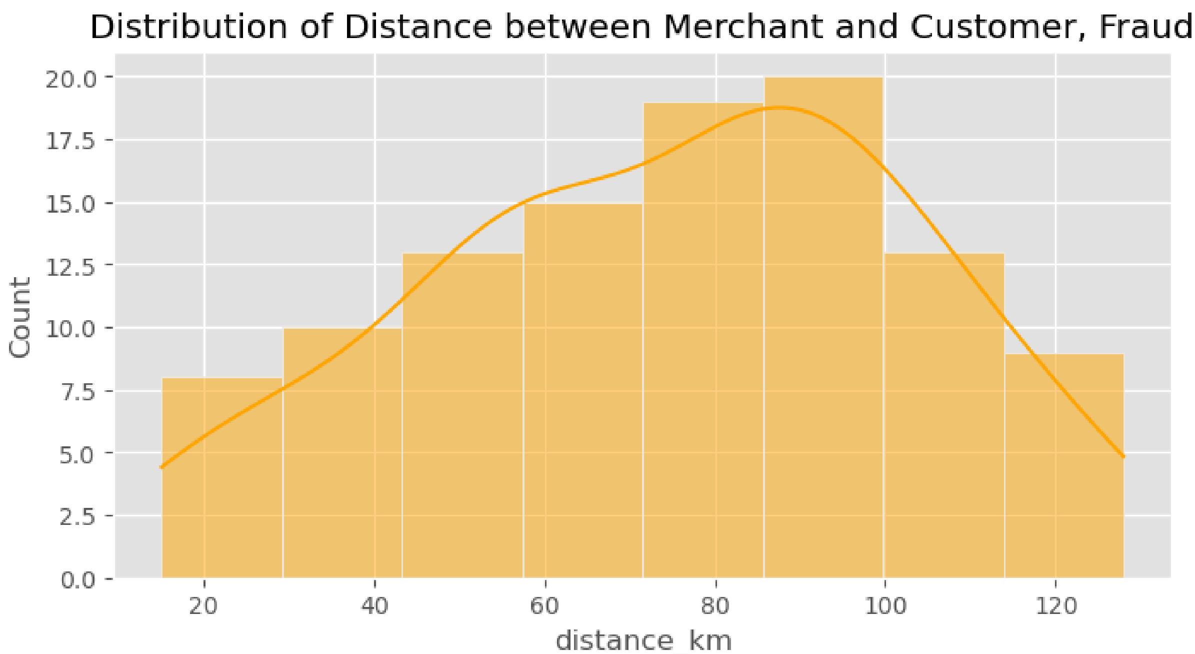
```
df_fraud['distance_km'].describe()
```

Out[400…

```
count    107.000
mean      74.704
std       28.697
min       15.061
25%       54.903
50%       77.960
75%       96.390
max      127.969
Name: distance_km, dtype: float64
```

In [401…

```
plt.figure(figsize=(8, 4))
sns.histplot(df_fraud['distance_km'], kde=True, color = "orange")
plt.title(f'Distribution of Distance between Merchant and Customer, Fraud')
plt.show()
```



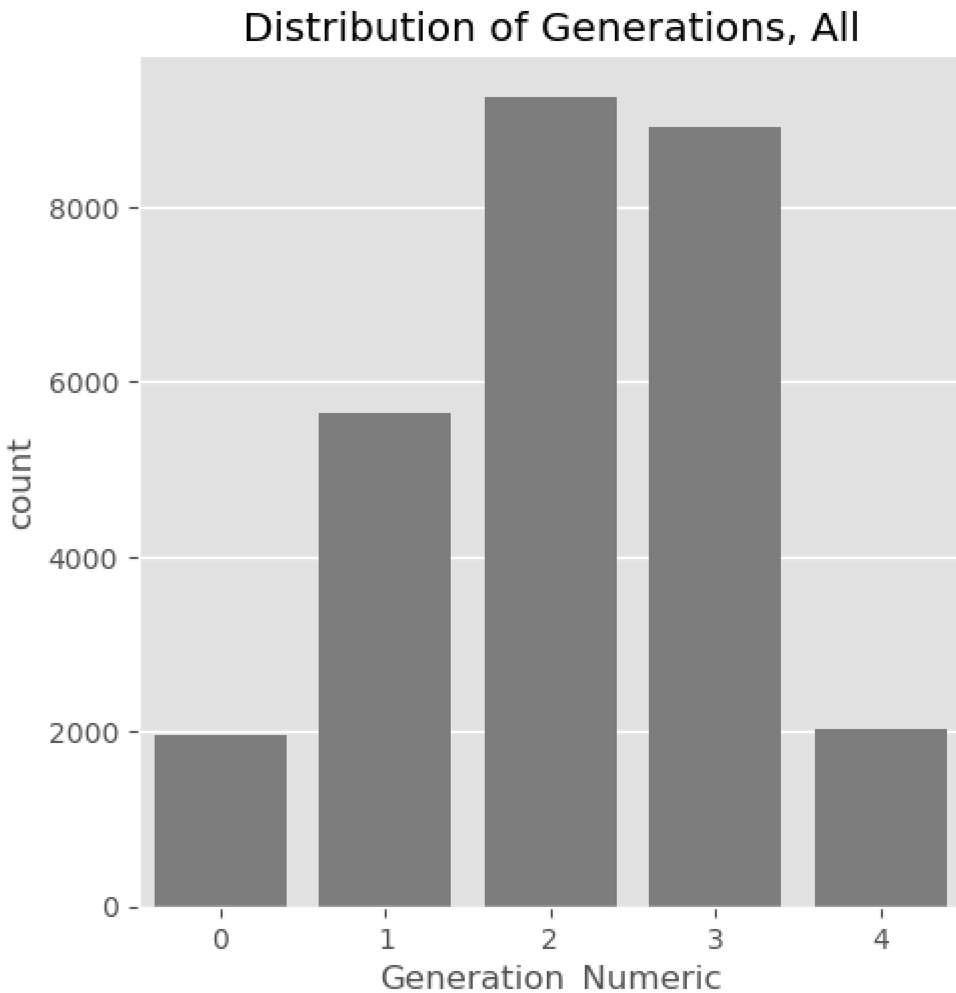
The distribution of distance for non-fraud appears to be somewhat normally distributed. Fraud seems concentrated at lower distances and a right-skew with a concentration at the 70-90 range.

Generations

In [404…

```
plt.figure(figsize=(8, 4))
sns.catplot(data = df2, x = "Generation_Numeric", kind ="count", color = 'grey')
plt.title(f'Distribution of Generations, All')
plt.show()
```

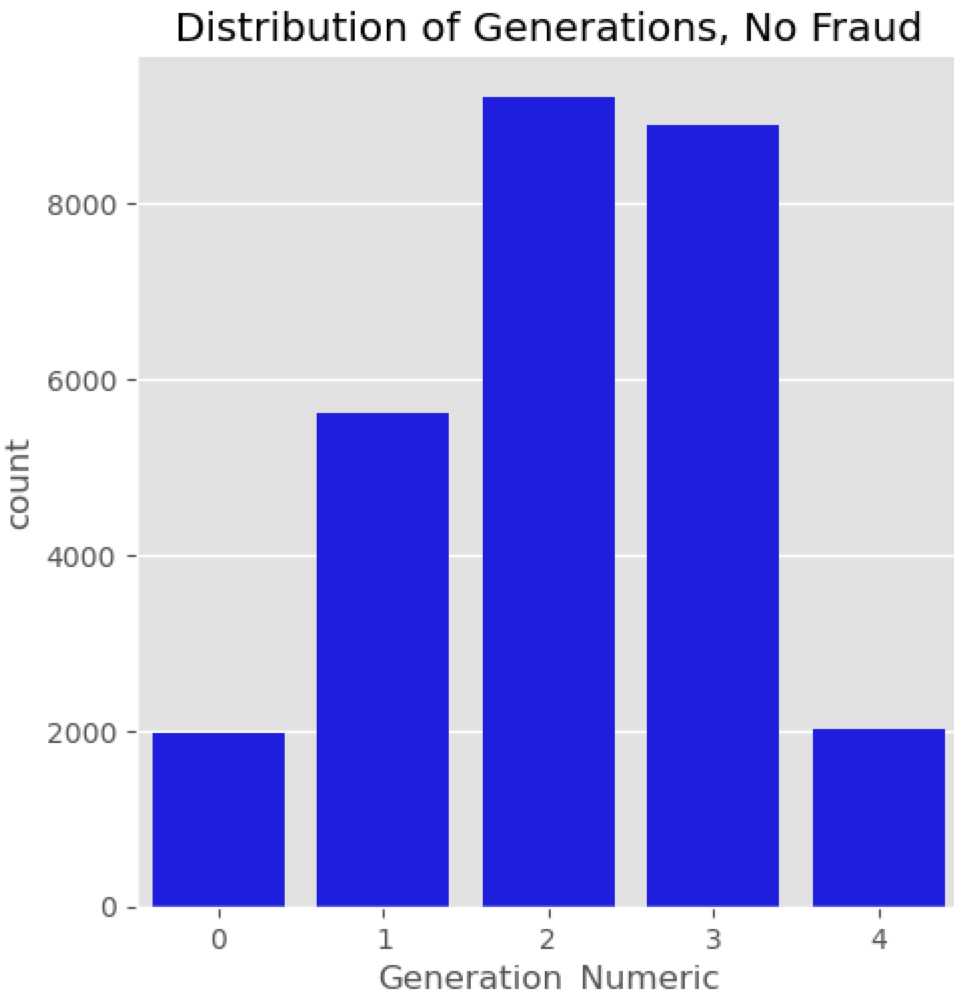
```
<Figure size 800x400 with 0 Axes>
```



In [405…

```
plt.figure(figsize=(8, 4))
sns.catplot(data = df_safe, x = "Generation_Numeric", kind ="count", color = 'blue'
plt.title(f'Distribution of Generations, No Fraud')
plt.show()
```

```
<Figure size 800x400 with 0 Axes>
```



In [406…

```
plt.figure(figsize=(8, 4))
sns.catplot(data = df_fraud, x = "Generation_Numeric", kind ="count", color = 'oran
plt.title(f'Distribution of Generations, Fraud')
plt.show()
```

<Figure size 800x400 with 0 Axes>

In [407…

```
#get original generation counts
o0 = df2[df2['Generation_Numeric'] == 0].shape[0]
o1 = df2[df2['Generation_Numeric'] == 1].shape[0]
o2 = df2[df2['Generation_Numeric'] == 2].shape[0]
o3 = df2[df2['Generation_Numeric'] == 3].shape[0]
o4 = df2[df2['Generation_Numeric'] == 4].shape[0]
o5 = df2[df2['Generation_Numeric'] == 5].shape[0]
#get fraud generation counts
f0 = df_fraud[df_fraud['Generation_Numeric'] == 0].shape[0]
f1 = df_fraud[df_fraud['Generation_Numeric'] == 1].shape[0]
f2 = df_fraud[df_fraud['Generation_Numeric'] == 2].shape[0]
f3 = df_fraud[df_fraud['Generation_Numeric'] == 3].shape[0]
f4 = df_fraud[df_fraud['Generation_Numeric'] == 4].shape[0]
f5 = df_fraud[df_fraud['Generation_Numeric'] == 5].shape[0]
#get fraud %
fp0 = (f0 / o0 * 100) if o0 != 0 else 0
fp1 = (f1 / o1 * 100) if o1 != 0 else 0
fp2 = (f2 / o2 * 100) if o2 != 0 else 0
fp3 = (f3 / o3 * 100) if o3 != 0 else 0
fp4 = (f4 / o4 * 100) if o4 != 0 else 0
fp5 = (f5 / o5 * 100) if o5 != 0 else 0


gen_fraud = pd.DataFrame({
    'Generation ID': ['0', '1', '2', '3', '4', '5'],
```

```
    'Generation': ["Silent", "Baby Boomer", "Gen X", "Millennial", "Gen Z", "Gen Al
    'Total Count': [o0, o1, o2, o3, o4, o5],
    'Total Fraud': [f0, f1, f2, f3, f4, f5],
    'Percent Fraud': [fp0, fp1, fp2, fp3, fp4, fp5]
})

gen_fraud
```

Out[407…

	Generation ID	Generation	Total Count	Total Fraud	Percent Fraud
0	0	Silent	1968	8	0.407
1	1	Baby Boomer	5640	28	0.496
2	2	Gen X	9251	40	0.432
3	3	Millennial	8912	23	0.258
4	4	Gen Z	2014	8	0.397
5	5	Gen Alpha	0	0	0.000

The distribution of generations in the original dataset is 33% Generation X closely followed by 32% millennial generation and 20% baby boomer. Among the fraudulet transactions the generations most hit was Gen X at 37%, followed by baby boomers (26%) and then millennials (28%). However when looking at the likelihood of fraud within the generations themselves you see an interesting story. Millennials are the least likely generation to experience fraud. The Silent Generation, Baby Boomers, Gen X and Gen Z alre are within 40-50%. This points to educational opportunities

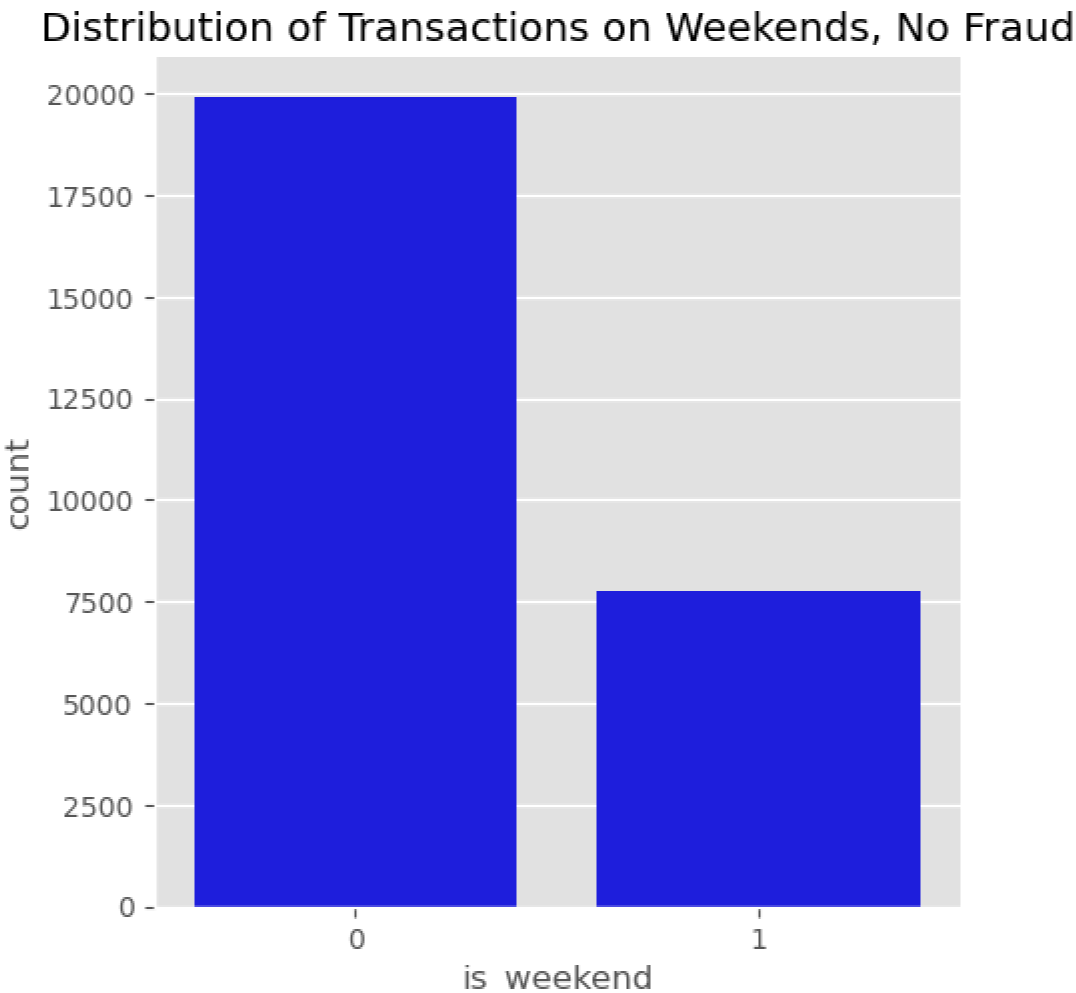
Time

Is Weekend

In [411…

```
plt.figure(figsize=(8, 4))
sns.catplot(data = df_safe, x = "is_weekend", kind ="count", color = 'blue')
plt.title(f'Distribution of Transactions on Weekends, No Fraud')
plt.show()
```

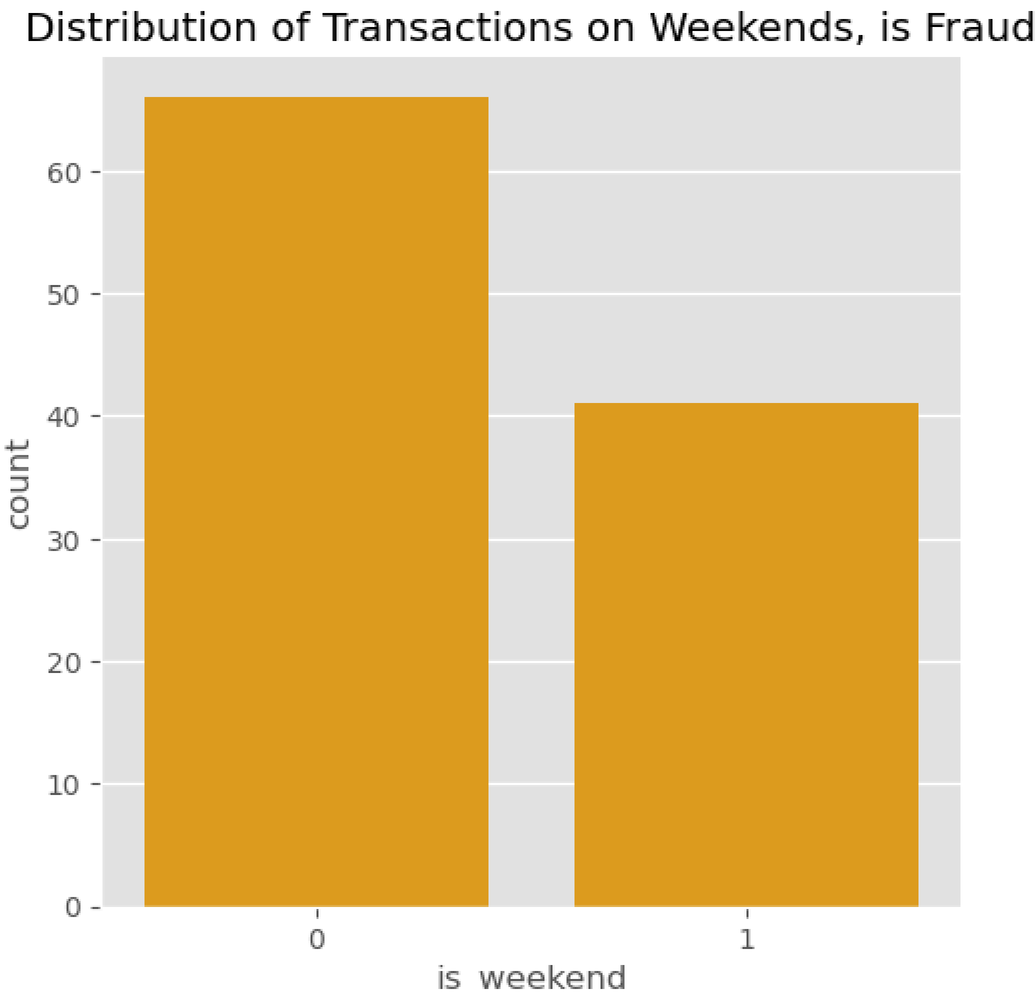
```
<Figure size 800x400 with 0 Axes>
```



In [412…

```
plt.figure(figsize=(8, 4))
sns.catplot(data = df_fraud, x = "is_weekend", kind ="count", color = 'orange')
plt.title(f'Distribution of Transactions on Weekends, is Fraud')
plt.show()
```

```
<Figure size 800x400 with 0 Axes>
```

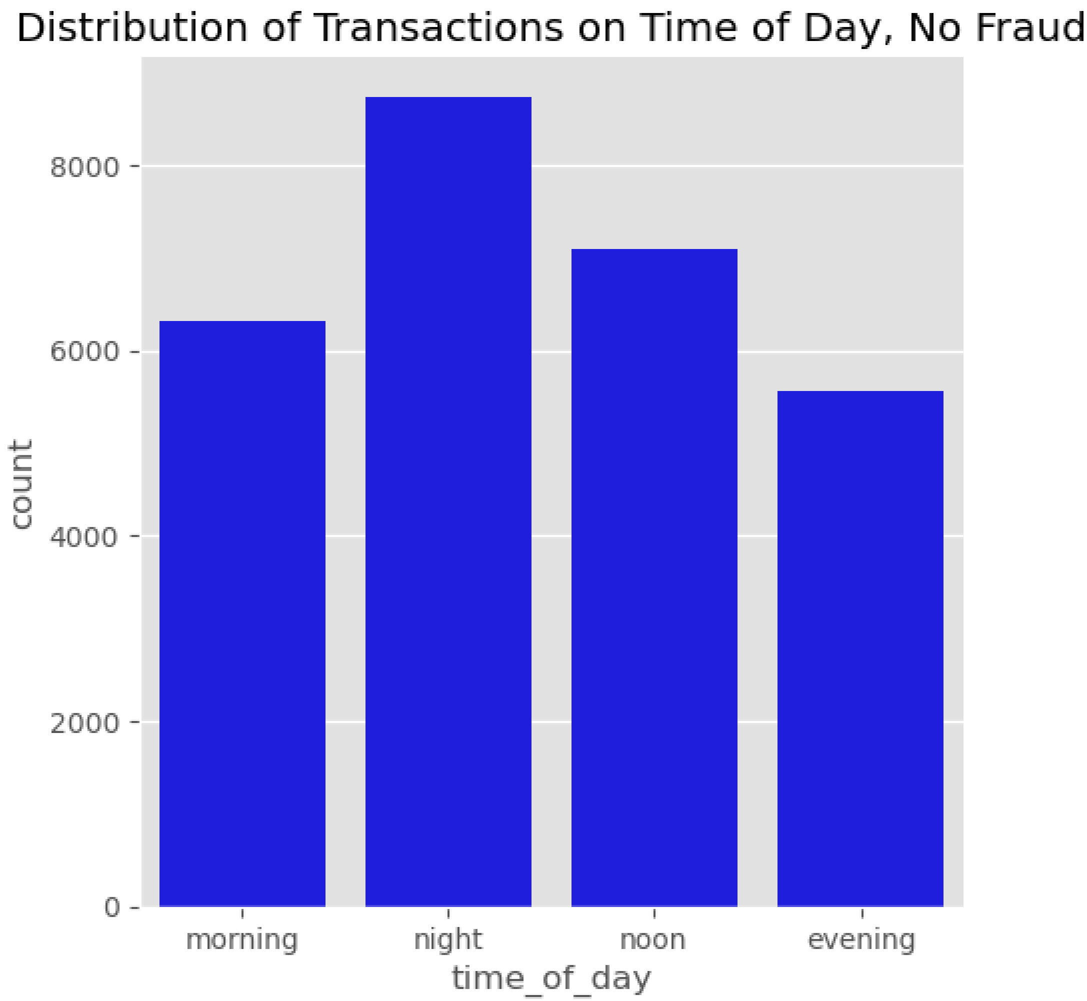


Time of Day

In [414…

```
plt.figure(figsize=(8, 4))
sns.catplot(data = df_safe, x = "time_of_day", kind ="count", color = 'blue')
plt.title(f'Distribution of Transactions on Time of Day, No Fraud')
plt.show()
```

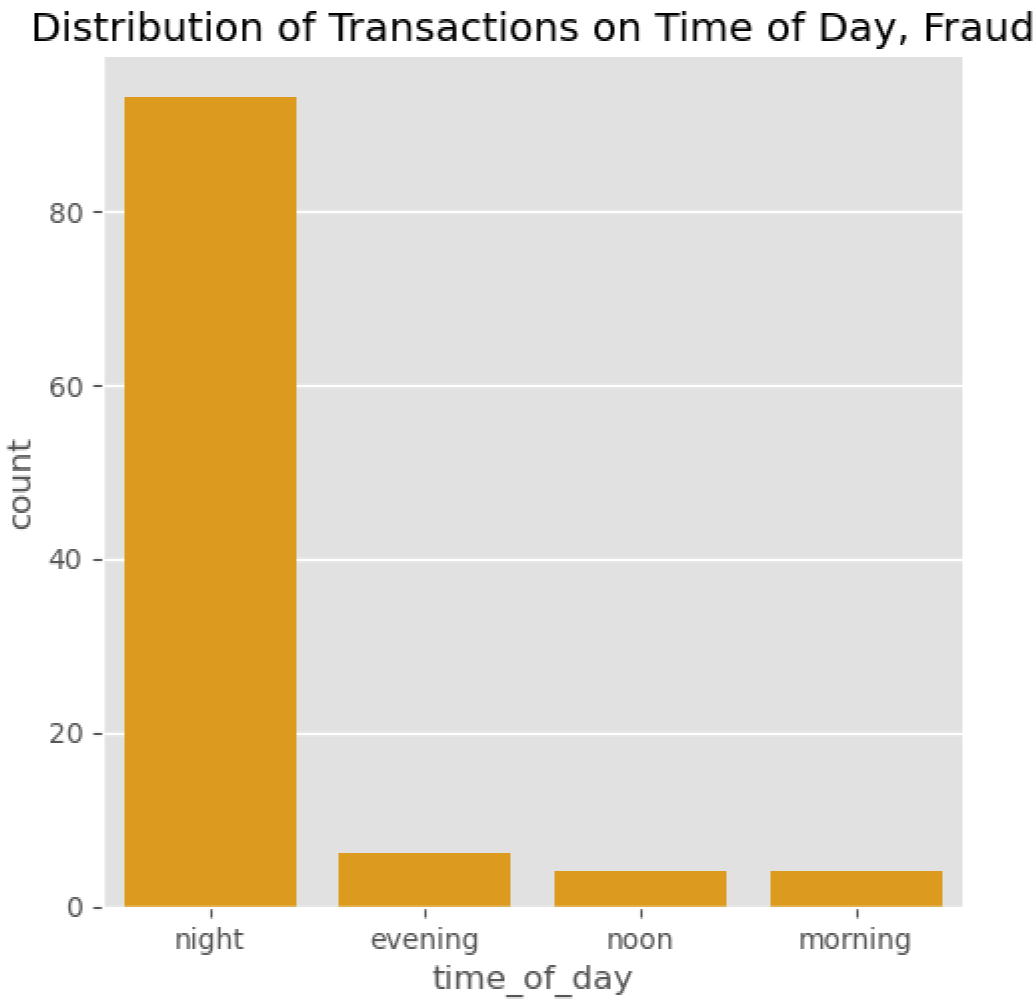
```
<Figure size 800x400 with 0 Axes>
```



In [415…

```
plt.figure(figsize=(8, 4))
sns.catplot(data = df_fraud, x = "time_of_day", kind ="count", color = 'orange')
plt.title(f'Distribution of Transactions on Time of Day, Fraud')
plt.show()
```

```
<Figure size 800x400 with 0 Axes>
```



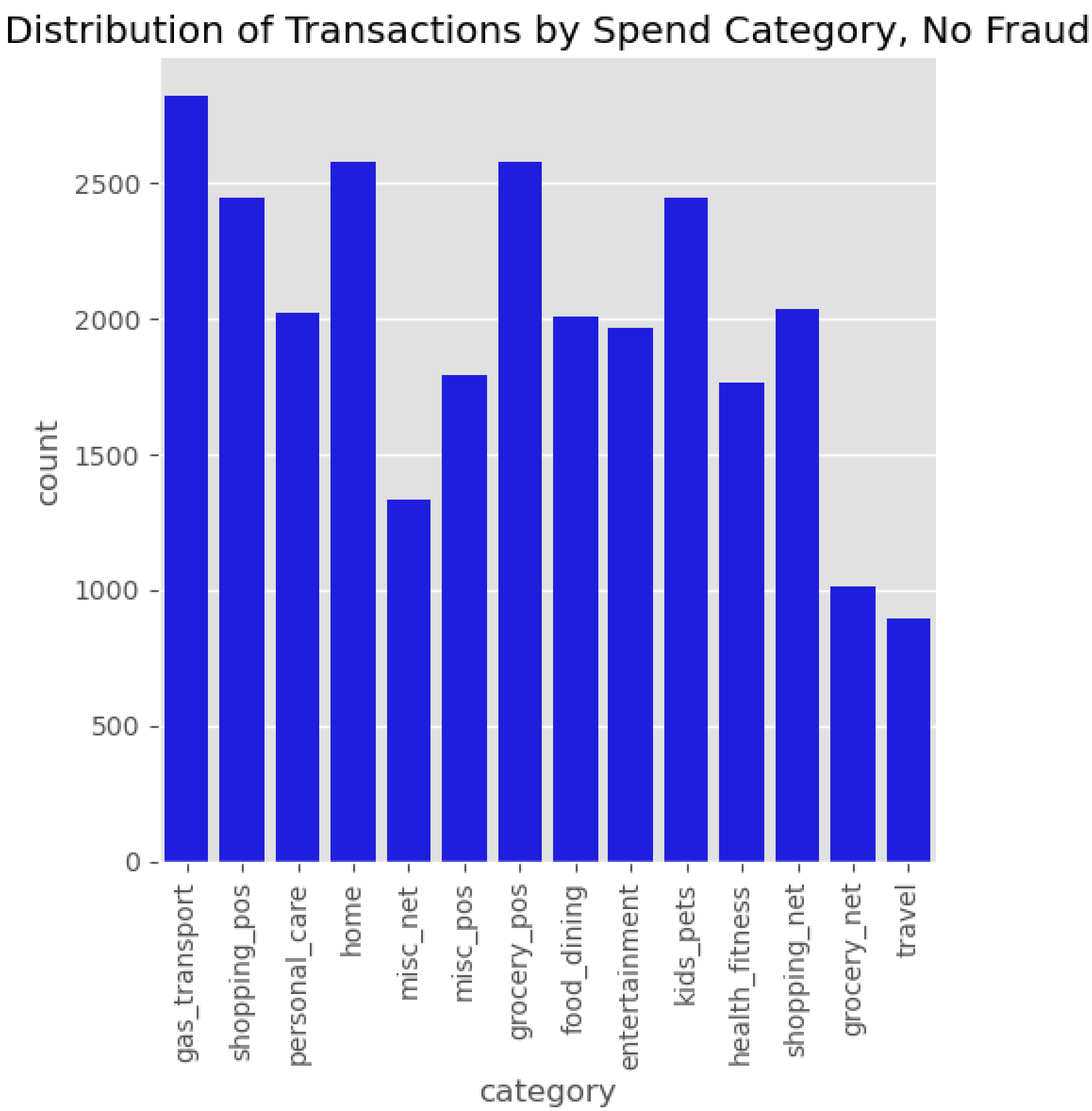
A high distribution of fraud occurs at night.

Spend Category

In [418…

```
plt.figure(figsize=(8, 4))
sns.catplot(data = df_safe, x = "category", kind ="count", color = 'blue')
plt.title(f'Distribution of Transactions by Spend Category, No Fraud')
plt.xticks(rotation=90)
plt.show()
```

```
<Figure size 800x400 with 0 Axes>
```



In [419…

```
df_safe['category'].value_counts()
```

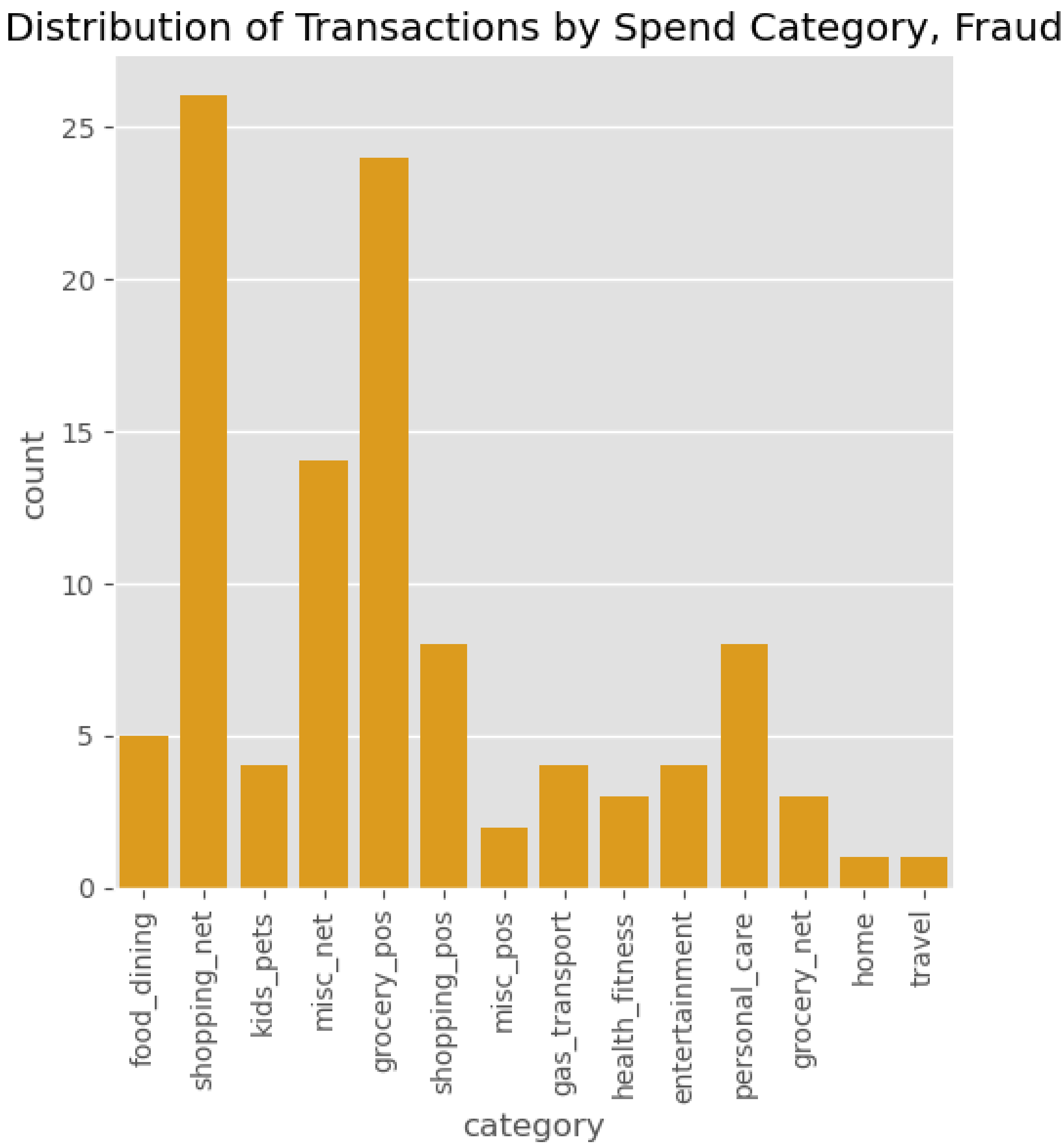
Out[419…

```
category
gas_transport     2816
home              2578
grocery_pos       2577
kids_pets         2446
shopping_pos      2441
shopping_net      2033
personal_care     2018
food_dining       2008
entertainment     1964
misc_pos          1793
health_fitness    1766
misc_net          1335
grocery_net       1009
travel             894
Name: count, dtype: int64
```

In [420…

```
plt.figure(figsize=(8, 4))
sns.catplot(data = df_fraud, x = "category", kind ="count", color = 'orange')
plt.title(f'Distribution of Transactions by Spend Category, Fraud')
plt.xticks(rotation = 90)
plt.show()
```

```
<Figure size 800x400 with 0 Axes>
```



In [421…

```
df_fraud['category'].value_counts()
```

Out[421…

```
category
shopping_net      26
grocery_pos       24
misc_net          14
shopping_pos       8
personal_care      8
food_dining        5
kids_pets          4
gas_transport      4
entertainment      4
health_fitness     3
grocery_net        3
misc_pos           2
home               1
travel             1
Name: count, dtype: int64
```

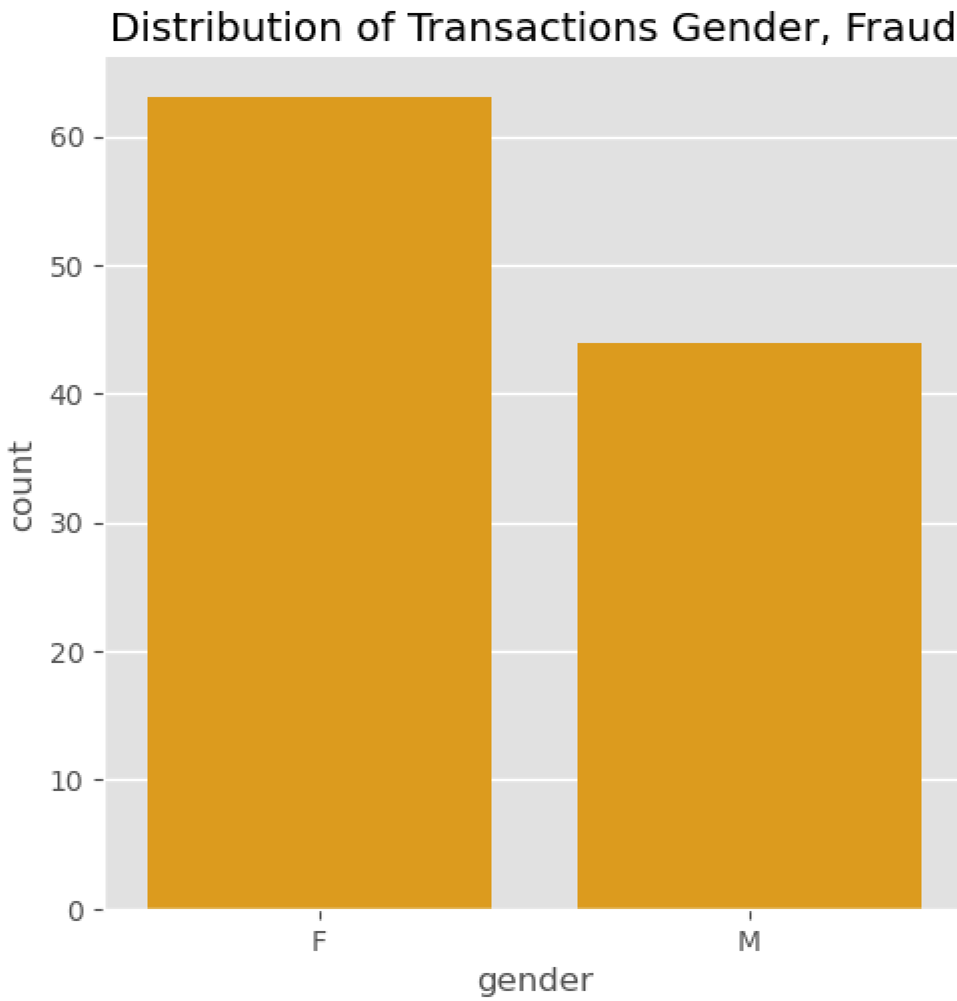
The bigest categories of fraud are online shopping, misc online and grocery.

Gender

In [424…

```
plt.figure(figsize=(8, 4))
sns.catplot(data = df_fraud, x = "gender", kind ="count", color = 'orange')
plt.title(f'Distribution of Transactions Gender, Fraud')
plt.show()
```

```
<Figure size 800x400 with 0 Axes>
```



In [425…

```
female_total = df2[df2['gender'] == 'F'].shape[0]
male_total = df2[df2['gender'] == 'M'].shape[0]
female_fraud = df_fraud[df_fraud['gender'] == 'F'].shape[0]
male_fraud = df_fraud[df_fraud['gender'] == 'M'].shape[0]
female_fraud_percent = (female_fraud/female_total)*100 if female_total != 0 else 0
male_fraud_percent = (male_fraud/male_total)*100 if male_total != 0 else 0

mf_fraud = pd.DataFrame({
    'Gender': ["F", "M"],
    'Total Count': [female_total, male_total],
    'Fraud Count': [female_fraud, male_fraud],
    'Fraud %': [female_fraud_percent, male_fraud_percent]
})

mf_fraud
```

Out[425…

	Gender	Total Count	Fraud Count	Fraud %
0	F	15252	63	0.413
1	M	12533	44	0.351

There is a slightly higher likelihood of fraud occuring among women vs men.

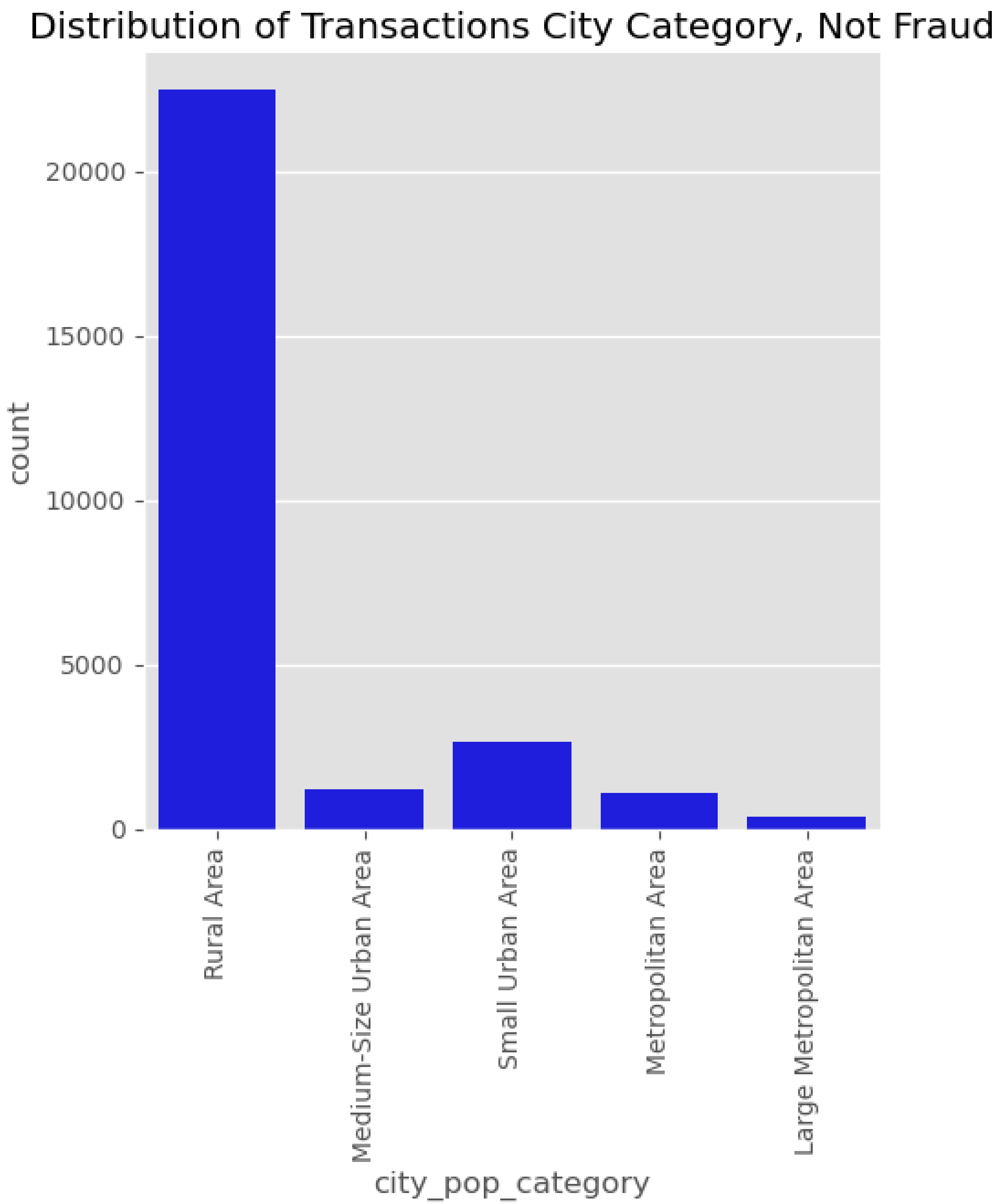
City Population

In [ ]:

In [428…

```
plt.figure(figsize=(8, 4))
sns.catplot(data = df_safe, x = "city_pop_category", kind ="count", color = 'blue')
plt.title(f'Distribution of Transactions City Category, Not Fraud')
plt.xticks(rotation = 90)
plt.show()
```

<Figure size 800x400 with 0 Axes>

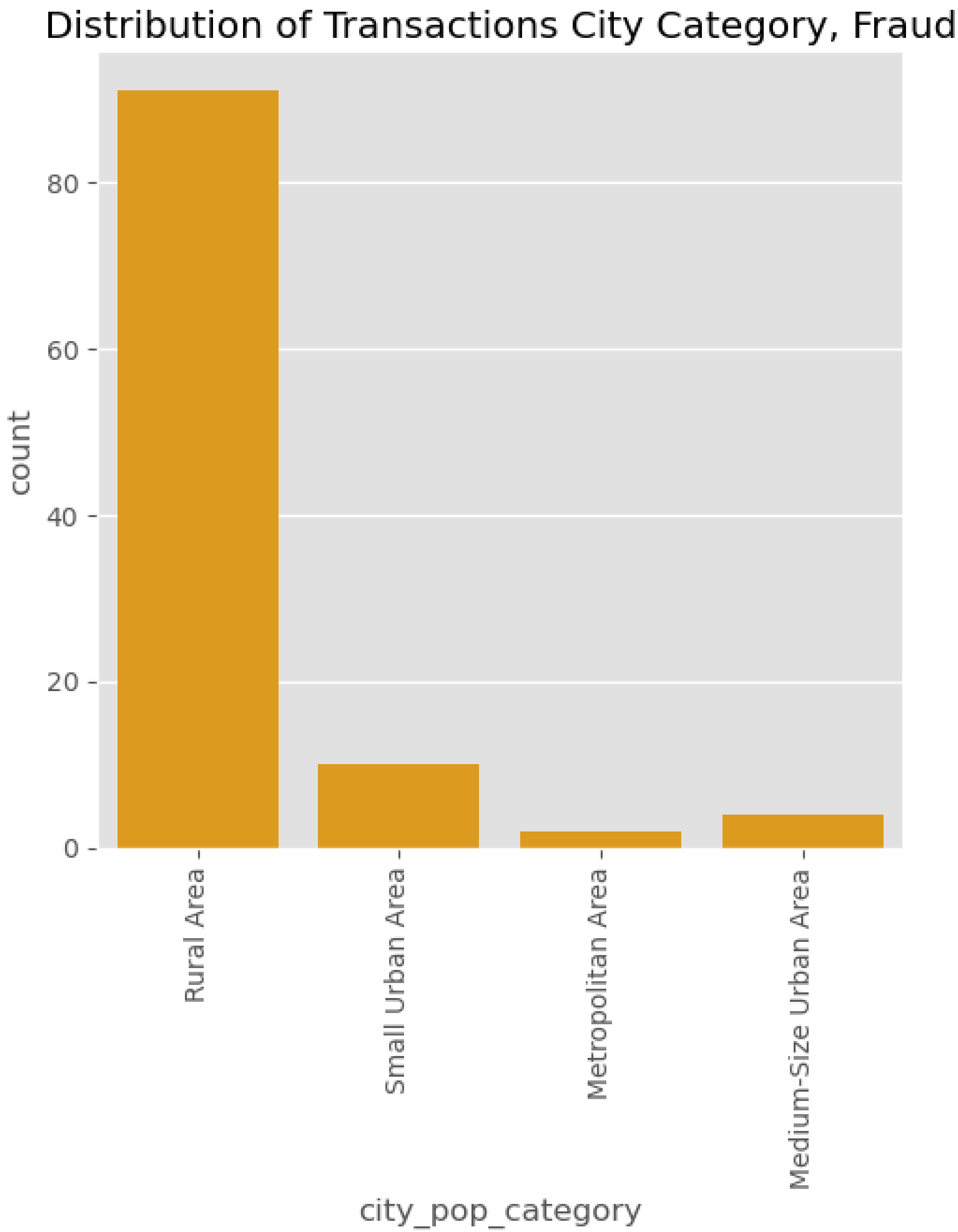


In [429…

```
plt.figure(figsize=(8, 4))
sns.catplot(data = df_fraud, x = "city_pop_category", kind ="count", color = 'orang
```

```
plt.title(f'Distribution of Transactions City Category, Fraud')
plt.xticks(rotation = 90)
plt.show()
```

<Figure size 800x400 with 0 Axes>



In [430…

```
df_fraud['city_pop_category'].value_counts()
```

Out[430…

```
city_pop_category
Rural Area                91
Small Urban Area          10
Medium-Size Urban Area     4
Metropolitan Area          2
Name: count, dtype: int64
```

In [431…

```
r_total = df2[df2['city_pop_category'] == 'Rural Area'].shape[0]
su_total = df2[df2['city_pop_category'] == 'Small Urban Area'].shape[0]
```

```
med_total = df2[df2['city_pop_category'] == 'Medium-Size Urban Area'].shape[0]
metro_total = df2[df2['city_pop_category'] == 'Metropolitan Area'].shape[0]

r_fraud = df_fraud[df_fraud['city_pop_category'] == 'Rural Area'].shape[0]
su_fraud = df_fraud[df_fraud['city_pop_category'] == 'Small Urban Area'].shape[0]
med_fraud = df_fraud[df_fraud['city_pop_category'] == 'Medium-Size Urban Area'].sha
metro_fraud = df_fraud[df_fraud['city_pop_category'] == 'Metropolitan Area'].shape[


r_per = (r_fraud/r_total)*100
su_per = (su_fraud/su_total)*100
med_per = (med_fraud/med_total)*100
metro_per = (metro_fraud/metro_total)*100

city_fraud = pd.DataFrame({
    'City Pop Category': ["Rural Area", "Small Urban Area", "Medium-Size Urban Area
    'Total Count': [r_total, su_total,med_total, metro_total],
    'Fraud Count': [r_fraud, su_fraud, med_fraud, metro_fraud],
    'Fraud %': [r_per, su_per,med_per, metro_per]
})

city_fraud
```

Out[431…

	City Pop Category	Total Count	Fraud Count	Fraud %
0	Rural Area	22559	91	0.403
1	Small Urban Area	2626	10	0.381
2	Medium-Size Urban Area	1174	4	0.341
3	Metropolitan Area	1080	2	0.185

Majority of the dataset is in rural areas, but the proportion of fraud seems somewhat evenly distributed between rural, small urban and medium sized urban.There is not much representation of metro.

Prep Data for Modeling

Convert Catagorical to Dummy Variables

https://www.geeksforgeeks.org/python-pandas-get_dummies-method/

In [435…

```
# Displaying all columns in the dataset df1 along with their data types
all_columns_info = df2.dtypes
print(all_columns_info)
```

```
category                 object
amt                     float64
gender                   object
is_fraud                  int64
distance_km             float64
Generation_Numeric        int64
city_pop_category        object
day_of_week               int32
hour_of_day               int32
month                     int32
quarter                   int32
time_of_day              object
is_weekend                int64
dtype: object
```

In [436…

```
# One-hot encoding for the specified categorical column
df3 = pd.get_dummies(df2,
                     columns=['category', 'city_pop_category', 'gender', 'time_of_d
                     prefix=['category', 'city_pop_category', 'gender', 'time_of_da
                     drop_first=True)  # Dropping the first category to avoid multi

# Convert any boolean columns in df3 to integers
bool_cols = df3.select_dtypes(include=[bool]).columns  # Find any boolean columns
df3[bool_cols] = df3[bool_cols].astype(int)  # Convert them to integers

# Verify the data types in the new DataFrame
print(df3.dtypes)

# Display the first few rows of the resulting DataFrame
df3.head()
```

```
amt                                              float64
is_fraud                                           int64
distance_km                                      float64
Generation_Numeric                                 int64
day_of_week                                        int32
hour_of_day                                        int32
month                                              int32
quarter                                            int32
is_weekend                                         int64
category_food_dining                               int32
category_gas_transport                             int32
category_grocery_net                               int32
category_grocery_pos                               int32
category_health_fitness                            int32
category_home                                      int32
category_kids_pets                                 int32
category_misc_net                                  int32
category_misc_pos                                  int32
category_personal_care                             int32
category_shopping_net                              int32
category_shopping_pos                              int32
category_travel                                    int32
city_pop_category_Medium-Size Urban Area           int32
city_pop_category_Metropolitan Area                int32
city_pop_category_Rural Area                       int32
city_pop_category_Small Urban Area                 int32
gender_M                                           int32
time_of_day_morning                                int32
time_of_day_night                                  int32
time_of_day_noon                                   int32
dtype: object
```

Out[436…

	amt	is_fraud	distance_km	Generation_Numeric	day_of_week	hour_of_day	month
0	50.420	0	60.200	1	1	5	12
1	39.470	0	46.722	2	0	2	6
2	8.160	0	93.483	3	0	15	12
3	25.480	0	82.612	3	3	23	12
4	5.710	0	72.611	2	5	11	6

Handling imbalanced dataset (target variable) by using SMOTE library

https://www.geeksforgeeks.org/smote-for-imbalanced-classification-with-python/#smote-synthetic-minority-oversampling-technique

In [438…

```
# Separate features and target variable
X = df3.drop('is_fraud', axis=1)  # Drop the target variable
y = df3['is_fraud']                # Target variable
```

```
# Convert categorical variables to numeric using one-hot encoding
X = pd.get_dummies(X, drop_first=True)

# Check for missing values and handle them
if X.isnull().sum().any():
    print("Missing values detected in features.")
    X.fillna(X.mean(), inplace=True)  # Fill NaN values with mean for numeric featu

# Ensure target variable is of integer type
y = y.astype(int)

# Split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta

# Apply SMOTE
smote = SMOTE(random_state=42)
X_resampled, y_resampled = smote.fit_resample(X_train, y_train)

# Scale the features
scaler = StandardScaler()
X_resampled = scaler.fit_transform(X_resampled)
X_test = scaler.transform(X_test)  # Apply the same transformation to the test set

# Check class distribution
print("Before SMOTE:")
print(y_train.value_counts())
print("\nAfter SMOTE:")
print(pd.Series(y_resampled).value_counts())
```

```
Before SMOTE:
is_fraud
0    22142
1       86
Name: count, dtype: int64

After SMOTE:
is_fraud
0    22142
1    22142
Name: count, dtype: int64
```

Normalization

In [440…

```
# Set the option to display all columns
pd.set_option('display.max_columns', None)

# Display the first 5 rows of the dataframe with all columns visible
pd.DataFrame(X_resampled).head()
```

Out[440…

	0	1	2	3	4	5	6	7	8	9	10	11
0	-0.477	1.492	-0.922	1.653	-0.339	-0.657	-0.501	2.011	-0.247	-0.250	-0.137	2.452
1	-0.593	0.626	-0.922	-0.950	-0.087	0.478	1.208	-0.497	-0.247	-0.250	-0.137	-0.408
2	-0.648	1.660	0.110	1.133	-0.718	1.613	1.208	2.011	-0.247	-0.250	7.308	-0.408
3	-0.321	0.455	1.142	1.653	-1.728	1.613	1.208	2.011	-0.247	-0.250	-0.137	2.452
4	-0.649	1.778	0.110	-0.950	0.923	-0.657	-0.501	-0.497	4.056	-0.250	-0.137	-0.408

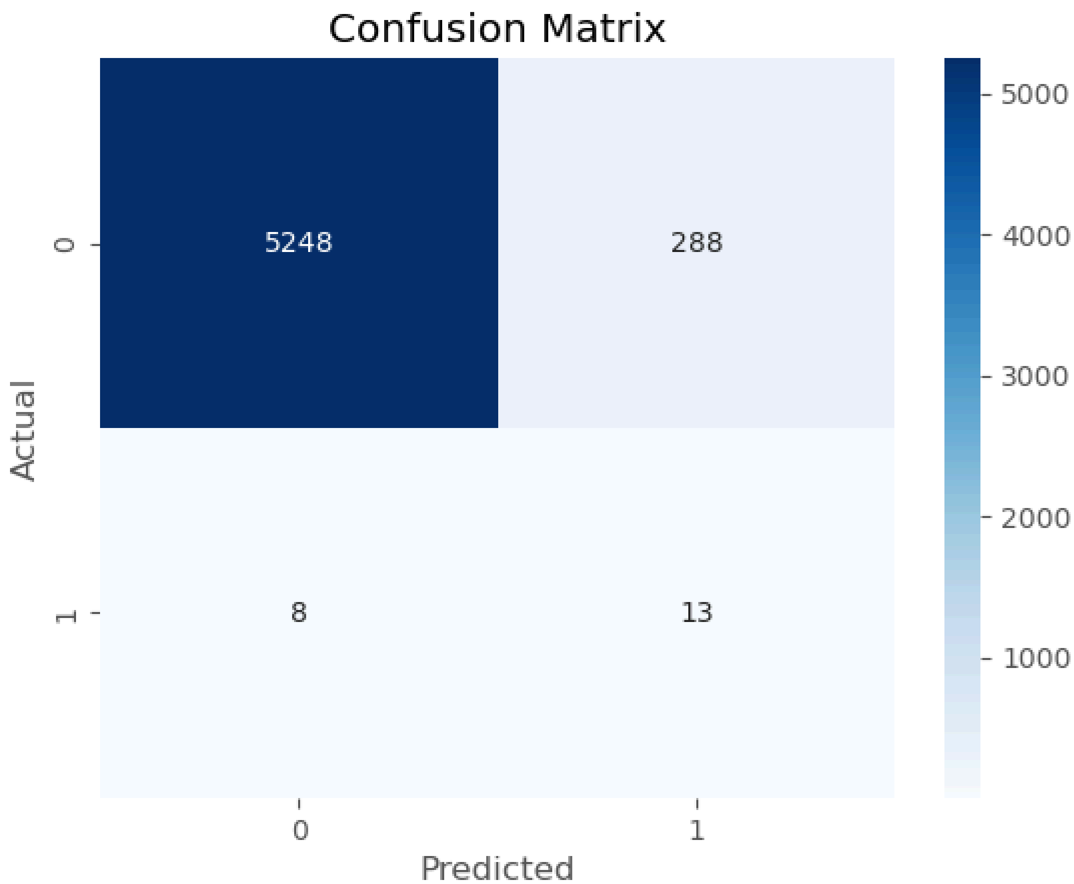
Data Modeling

Logistic Regression

In [443…

```
# Logistic Regression with class_weight='balanced'
model = LogisticRegression(class_weight='balanced', max_iter=1000, random_state=42)
model.fit(X_resampled, y_resampled)

# Predictions on the test set
y_pred = model.predict(X_test)

# Confusion Matrix and Classification Report
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred))

print("\nClassification Report:")
print(classification_report(y_test, y_pred))

# Visualizing the Confusion Matrix

cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title('Confusion Matrix')
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.show()
```

```
Confusion Matrix:
[[5248  288]
 [   8   13]]

Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.95      0.97      5536
           1       0.04      0.62      0.08        21

    accuracy                           0.95      5557
   macro avg       0.52      0.78      0.53      5557
weighted avg       0.99      0.95      0.97      5557
```



High Accuracy: The model has a high accuracy (95%) primarily due to the correct prediction of non-fraud cases, which dominate the dataset. However, the model struggles to correctly identify fraud cases, as indicated by the very low precision (0.04) for class 1 (fraud).

Precision vs. Recall for Fraud: The recall for fraud cases (0.62) is better than the precision (0.04), meaning that while the model captures a decent portion of actual fraud cases, it misclassifies many non-fraud cases as fraud, leading to a low precision.

XGBoost

In [446…

```
# Calculate scale_pos_weight (ratio of negative to positive examples)
neg, pos = np.bincount(y_train)  # For X_resampled and y_resampled use for SMOTE
scale_pos_weight = neg / pos

# XGBoost Classifier
xgb_model = XGBClassifier(scale_pos_weight=scale_pos_weight, eval_metric='logloss')
xgb_model.fit(X_resampled, y_resampled)

# Predictions
y_pred = xgb_model.predict(X_test)

# Evaluation
print("XGBoost Confusion Matrix:")
print(confusion_matrix(y_test, y_pred))
print("\nXGBoost Classification Report:")
print(classification_report(y_test, y_pred))
```

```
XGBoost Confusion Matrix:
[[5501   35]
 [   6   15]]

XGBoost Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.99      1.00      5536
           1       0.30      0.71      0.42        21

    accuracy                           0.99      5557
   macro avg       0.65      0.85      0.71      5557
weighted avg       1.00      0.99      0.99      5557
```

High Overall Accuracy: The accuracy is significantly high (99%), indicating that the model performs very well on the dataset.

Improved Fraud Detection: Compared to Logistic Regression, XGBoost shows a significant improvement in fraud detection (class 1). The recall for fraud cases is now 0.71 (71%), meaning the model captures more actual fraud cases than the Logistic Regression model.

Precision for Fraud Cases: Although precision is still relatively low for fraud cases (0.30), it is an improvement over the Logistic Regression model. This shows that while the model predicts more fraud cases, some of the predictions are still incorrect (false positives).

Balanced Performance: XGBoost strikes a good balance between precision and recall for both classes, which is crucial for fraud detection, where false negatives (missed fraud cases) are more costly than false positives.

Fraud Detection using XGBoost and Deep Learning : https://medium.com/@f2005636/fraud-detection-using-xgboost-and-deep-learning-c8e1ce6c5c32

LightGBM

In [450…

```
# LightGBM Dataset
lgb_train = lgb.Dataset(X_resampled, label=y_resampled)

# LightGBM Parameters
lgb_params = {
    'objective': 'binary',
    'is_unbalance': True,  # Handles class imbalance
    'metric': 'binary_logloss',
    'boosting_type': 'gbdt'
}

# Train the model
lgb_model = lgb.train(lgb_params, lgb_train, num_boost_round=100)

# Predictions
y_pred = (lgb_model.predict(X_test) > 0.5).astype(int)

# Evaluation
print("LightGBM Confusion Matrix:")
print(confusion_matrix(y_test, y_pred))
print("\nLightGBM Classification Report:")
print(classification_report(y_test, y_pred))
```

```
[LightGBM] [Info] Number of positive: 22142, number of negative: 22142
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of testing wa
s 0.002841 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 627
[LightGBM] [Info] Number of data points in the train set: 44284, number of used feat
ures: 29
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
LightGBM Confusion Matrix:
[[5514   22]
 [   6   15]]

LightGBM Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      5536
           1       0.41      0.71      0.52        21

    accuracy                           0.99      5557
   macro avg       0.70      0.86      0.76      5557
weighted avg       1.00      0.99      1.00      5557
```

Fighting Fraud at the Speed of LightGBM : https://feedzai.com/blog/lightgbm/

Strong Non-Fraud Detection: The model performs perfectly on class 0 (non-fraud), achieving a precision, recall, and F1-score of 1.00.

Fraud Detection Performance: LightGBM shows a moderate improvement in fraud detection compared to Logistic Regression and XGBoost. The recall remains consistent with XGBoost (0.71), but the precision has increased to 0.41, meaning more fraud cases are correctly identified as fraud without too many false positives.

Balanced Performance: With a higher F1-score for fraud (0.52) compared to XGBoost (0.42), LightGBM provides better overall balance in fraud detection while maintaining high accuracy across both classes.

CatBoost

In [454…

```
# CatBoost Classifier
catboost_model = CatBoostClassifier(iterations=1000, depth=6, learning_rate=0.1, sc
catboost_model.fit(X_resampled, y_resampled)

# Predictions
y_pred = catboost_model.predict(X_test)

# Evaluation
print("CatBoost Confusion Matrix:")
print(confusion_matrix(y_test, y_pred))
print("\nCatBoost Classification Report:")
print(classification_report(y_test, y_pred))
```

```
CatBoost Confusion Matrix:
[[4554  982]
 [   3   18]]

CatBoost Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.82      0.90      5536
           1       0.02      0.86      0.04        21

    accuracy                           0.82      5557
   macro avg       0.51      0.84      0.47      5557
weighted avg       1.00      0.82      0.90      5557
```

CatBoost for Fraud Detection in Financial Transactions https://ieeexplore.ieee.org/document/9342475

High Recall for Fraud Detection: The model performs very well in identifying actual fraud cases, with a recall of 0.86. This means 86% of the actual fraud cases were successfully detected.

Low Precision for Fraud: The precision for fraud is very low (0.02), indicating that the model predicts many non-fraud cases as fraud, resulting in a large number of false positives.

Performance on Non-Fraud Cases: The model achieves perfect precision for non-fraud cases (1.00) but only captures 82% of the actual non-fraud cases (recall of 0.82).

** In this specific fraud detection case, LightGBM is the best-performing model as it has the least amount of false negatives. Prioritizing recall, the model is correctly identifying approximately 86% of actual fraud cases.**