Mishra540_Project_Milestone_05

August 12, 2023

[1]:
```
# DSC540,Summer 2023 - T302 Data Preparation(2237-1)
# Assignment: Project Milestone 04
# Author by:  Debabrata Mishra
# Date: 2023-08-12

# Topic - Credit Card Transactional & Demographic Data
```

1 Milestone 5 - Assignment Instructions

Merging the Data and Storing in a Database/Visualizing Data

Now that you have cleaned and transformed your 3 datasets, you need to load them into a database. You can choose what kind of database (SQLLite or MySQL, Postgre SQL are all free options). You will want to load each dataset into SQL Lite as an individual table and then you must join the datasets together in Python into 1 dataset.

Once all the data is merged together in your database, create 5 visualizations that demonstrate the data you have cleansed. You should have at least 2 visualizations that have data from more than one source (meaning, if you have 3 tables, you must have visualizations that span across 2 of the tables – you are also welcome to use your consolidated dataset that you created in the previous step, if you do that, you have met this requirement).

For the visualization portion of the project, you are welcome to use a python library like Matplotlib, Seaborn, or an R package ggPlot2, Plotly, or Tableau/PowerBI.

PowerBI is a free tool that could be used – Tableau only has a free web author. If your use Tableau/PowerBI you need to submit a PDF with your assignment vs the Tableau/PowerBI file. /p>

Clearly label each visualization. Submit your code for merging and storing in the database, with your code for the visualizations along with a 250-500-word summary of what you learned and had to do to complete the project. In your write-up, make sure to address the ethical implications of cleansing data and your project topic. You can submit a Jupyter Notebook or a PDF of your code. If you submit a .py file you need to also include a PDF or attachment of your results

2 Summary of Project

In this project, I worked with a credit card fraud detection dataset from two distinct sources: one was a CSV file containing transaction data, and the other was web data containing the various key information Fraudulent transactions. Within the datset the Merchant address information was missing but logitude and latutude details were there. Hence used Geo Location API to get merchant address.

The dataset contained crucial information about credit card transactions, including transaction amounts, timestamps, and anonymized variables associated with each transaction. The goal of the project was twofold: first, to perform data cleansing and merging to ensure the dataset's quality and coherence, and second, to create meaningful visualizations to gain insights into the data and accurately identify fraudulent transaction patterns.

3 Activities Performed

Data Cleaning and Transformation:

I started by loading the dataset and performing data cleaning. This involved handling missing values, removing duplicates, and dealing with outliers. Since the dataset contained anonymized features, there was no need to perform feature scaling or normalization. After the initial data cleaning, I explored the data to gain an understanding of its distribution and patterns.

Data Merging and Storing in Database:

I split the dataset into two parts for demonstration purposes - one is the comination of CSV file data with merchant address populated (received from API) and the other for cleaned Web data. Both datasets were loaded into an SQLite database as individual tables. I used SQL queries to join these two tables into a consolidated dataset for further analysis.

Data Visualization:

With the consolidated dataset, I created five visualizations to gain insights into the credit card transaction data:

a) Scatter Plot: This scatter plot showcases the top 25 merchant states, ranked by a combined metric that considers both the web fraud percentage and the count of fraudulent transactions.

b) Bar Plot: To compare the frequency of fraudulent and legitimate transactions, I created a bar plot. This provided a clear visual representation of the class imbalance in the dataset.

c) Density Plot: This density plot visualizes the distribution of Fraud Percentage of Web Data / Fraud count from flat file across different merchant states.

d) Line Plot: I used a line plot to visualize the daily transaction volume and identify any unusual spikes that might indicate potential fraudulent activity.

e) Pie Chart: Lastly, I created a pie chart to visualize the proportion of different transaction types (e.g., online vs. in-store) for both legitimate and fraudulent transactions.

Apart from these , I also added Box Plot, Histogram and Violin Plot.

4 Ethical Implications

During the project, it was essential to address ethical implications related to credit card fraud detection. Data cleansing played a crucial role in ensuring the accuracy of the results. However, it was important to be aware of potential biases that might be present in the data, as well as the consequences of false positives and false negatives in fraud detection.

It was essential to use visualization techniques responsibly, avoiding misleading visualizations that could impact decision-making or result in unjust consequences. Data privacy was a top concern, and I took necessary measures to handle sensitive information while demonstrating the project.

5 Source Code

[2]:
```python
#Load the Necessary Libraries
import pandas as pd
import numpy as np
import requests as r
import xlrd
from bs4 import BeautifulSoup
import numpy as np
import datapackage
import matplotlib.pyplot as plt
import seaborn as sns
import time
import concurrent.futures
import json
import sqlite3
from sqlalchemy import create_engine
import warnings

# Suppress warnings
warnings.filterwarnings("ignore")
```

[3]:
```python
# Read the combined and cleaned final combined dataset from Flat File and API␣
↪data.
api_ff_comb_data_final = pd.read_csv('api_ff_comb_data_final.csv', sep=",")

# Print data to check the new columns.
api_ff_comb_data_final
```

[3]:
```
        row_id trans_date_trans_time                            merch_name  \
0         2472   2019-01-02 01:47:29       fraud_Jenkins, Hauck and Friesen
1         2546   2019-01-02 03:38:03             fraud_Erdman-Kertzmann
2         3580   2019-01-03 01:05:27            fraud_Conroy-Cruickshank
3         4693   2019-01-03 22:58:44                fraud_Mosciski Group
4         4808   2019-01-04 00:58:03  fraud_Stokes, Christiansen and Sipes
…          …                  …                                    …
17594  1114738   2020-04-08 15:33:40              fraud_Hermann-Gaylord
17595   136824   2019-03-16 10:32:54       fraud_Christiansen-Gusikowski
17596    37638   2019-01-22 18:04:04                     fraud_Howe Ltd
17597   453698   2019-07-20 16:17:40                fraud_Gislason Group
17598   744851   2019-11-14 23:08:39               fraud_Dibbert-Green
```

```
            category  amount    first     last gender  \
0      gas_transport   11.52    Misty     Hart      F
1      gas_transport    7.03    Jason   Murphy      M
2      gas_transport   10.76    Misty     Hart      F
3             travel    4.50  Heather    Chase      F
4        grocery_net   14.37     Mark    Brown      M
…                …       …      …        …     …
17594       misc_pos    2.12  Sabrina  Johnson      F
17595       misc_pos   34.97    Craig     Dunn      M
17596       misc_pos    4.26   Sharon  Johnson      F
17597         travel    7.00   Daniel  Escobar      M
17598  entertainment   63.61   Joseph    Davis      M

                           street          city  …    txn_date  \
0        27954 Hall Mill Suite 575    San Antonio  …  2019-01-02
1        542 Steve Curve Suite 011  Collettsville  …  2019-01-02
2        27954 Hall Mill Suite 575    San Antonio  …  2019-01-03
3      6888 Hicks Stream Suite 954          Manor  …  2019-01-03
4                  8580 Moore Cove          Wales  …  2019-01-04
…                              …             …   …         …
17594        320 Nicholson Orchard       Thompson  …  2020-04-08
17595        721 Jacqueline Brooks     New Boston  …  2019-03-16
17596             7202 Jeffrey Mills       Conway  …  2019-01-22
17597               61390 Hayes Port      Romulus  …  2019-07-20
17598            941 Adam Stravenue      Nazareth  …  2019-11-14

       customer_age masked_accountNumber     BIN  \
0              58.0      3401*******0220  340187
1              30.0        4613*****1966  461331
2              58.0      3401*******0220  340187
3              77.0     4922********1201  492271
4              79.0      3415*******6537  341546
…                …                  …       …
17594          32.0     4642********5942  464225
17595          25.0      1800*******0192  180011
17596          34.0     3553********4918  355362
17597          47.0      3749*******3758  374930
17598          39.0     4451********2894  445195

                                            merch_address     merch_state  \
0      {"county": "Bandera County", "state": "Texas",…            Texas
1      {"building": "BRP US Inc", "house_number": "12…  North Carolina
2      {"county": "Karnes County", "state": "Texas", …            Texas
3      {"county": "Mineral County", "state": "West Vi…   West Virginia
4      {"road": "Nome-Taylor Highway", "county": "Nom…           Alaska
…                                                   …              …
17594  {"county": "Uintah County", "state": "Utah", "…             Utah
```

```
17595  {"road": "268th Street", "county": "Jefferson …           Iowa
17596  {"county": "Jefferson County", "state": "Washi…      Washington
17597  {"road": "Carlton Rockwood Road", "town": "Ash…        Michigan
17598  {"road": "County Road 17", "county": "Deaf Smi…           Texas

       merch_postcode  merch_country_code  zip_match  state_match
0                 NaN                  us          N            N
1               28777                  us          N            N
2                 NaN                  us          N            N
3                 NaN                  us          N            N
4                 NaN                  us          N            N
…                 …                 …        …          …
17594             NaN                  us          N            N
17595             NaN                  us          N            N
17596             NaN                  us          N            N
17597           48179                  us          N            N
17598             NaN                  us          N            N

[17599 rows x 34 columns]
```

[4]:
```
# Create a SQLite database connection
engine = create_engine('sqlite:///mydatabase.db')
```

[5]:
```
# Create table CSV_API_FINAL_DATA from the api_ff_comb_data_final data frame
api_ff_comb_data_final.to_sql('CSV_API_FINAL_DATA', engine, index=False,␣
 ↪if_exists='replace')
```

[5]:
```
17599
```

[6]:
```
# Read the finel cleaned version of Web data
web_data_final = pd.read_csv('web_data_final.csv', sep=",")

# Print data to check the new columns.
web_data_final
```

[6]:
```
                       Time  Amount Class         amount_range  is_fraud  \
0       1970-01-01 00:00:00  149.62   '0'  07: 100.01 - 200.00         0
1       1970-01-01 00:00:00    2.69   '0'  03: 001.01 - 005.00         0
2       1970-01-01 00:00:01  123.50   '0'  07: 100.01 - 200.00         0
3       1970-01-01 00:00:02   69.99   '0'  06: 050.01 - 100.00         0
4       1970-01-01 00:00:02    3.67   '0'  03: 001.01 - 005.00         0
…                      …     …    …                  …       …
252036  1970-01-02 23:59:45    2.69   '0'  03: 001.01 - 005.00         0
252037  1970-01-02 23:59:46    0.77   '0'  02: 000.01 - 001.00         0
252038  1970-01-02 23:59:47   24.79   '0'  04: 005.01 - 025.00         0
252039  1970-01-02 23:59:48   67.88   '0'  06: 050.01 - 100.00         0
252040  1970-01-02 23:59:48   10.00   '0'  04: 005.01 - 025.00         0
```

```
        year  month  day  hour weekday  dayofYear
0       1970      1    1     0     Thu          1
1       1970      1    1     0     Thu          1
2       1970      1    1     0     Thu          1
3       1970      1    1     0     Thu          1
4       1970      1    1     0     Thu          1
…        …      …   …    …     …        …
252036  1970      1    2    23     Fri          2
252037  1970      1    2    23     Fri          2
252038  1970      1    2    23     Fri          2
252039  1970      1    2    23     Fri          2
252040  1970      1    2    23     Fri          2

[252041 rows x 11 columns]
```

[7]:
```
# Create table CSV_API_FINAL_DATA from the api_ff_comb_data_final data frame
web_data_final.to_sql('WEB_FINAL_DATA', engine, index=False,␣
↪if_exists='replace')
```

[7]:
```
252041
```

[8]:
```
# Join both table using the amount interval of 10 so that we can able to add␣
↪the Fraud % from Web data to the combined data.

# Connect to the SQLite database
conn = sqlite3.connect('mydatabase.db')

# Your SQL query
query = """
SELECT T1.*
     , (CASE  WHEN T2.web_fraud_percentage IS NULL THEN 0.00 ELSE T2.
↪web_fraud_percentage END) AS web_fraud_percentage
  FROM CSV_API_FINAL_DATA T1
  LEFT OUTER JOIN
              (SELECT ROUND(Amount/10)*10 AS web_amount_interval
                         ,ROUND(((CAST(SUM(is_fraud) AS REAL) / COUNT(*))*␣
↪100),2)  AS web_fraud_percentage
                 FROM WEB_FINAL_DATA
               GROUP BY 1
        ) T2 ON ((ROUND(T1.amount/10)*10) = T2.web_amount_interval )

        """

# Fetch data from the database and store it in a DataFrame
df_project_milestone5 = pd.read_sql_query(query, conn)
```

```
# Close the database connection
conn.close()
```

[9]:
```
# Print data to check comobined data
df_project_milestone5
```

[9]:
```
        row_id trans_date_trans_time                             merch_name  \
0         2472   2019-01-02 01:47:29      fraud_Jenkins, Hauck and Friesen
1         2546   2019-01-02 03:38:03                 fraud_Erdman-Kertzmann
2         3580   2019-01-03 01:05:27               fraud_Conroy-Cruickshank
3         4693   2019-01-03 22:58:44                   fraud_Mosciski Group
4         4808   2019-01-04 00:58:03  fraud_Stokes, Christiansen and Sipes
…          …                   …                                      …
17594  1114738   2020-04-08 15:33:40                 fraud_Hermann-Gaylord
17595   136824   2019-03-16 10:32:54        fraud_Christiansen-Gusikowski
17596    37638   2019-01-22 18:04:04                        fraud_Howe Ltd
17597   453698   2019-07-20 16:17:40                   fraud_Gislason Group
17598   744851   2019-11-14 23:08:39                  fraud_Dibbert-Green

            category  amount    first     last gender  \
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1      gas_transport    7.03    Jason   Murphy      M
2      gas_transport   10.76    Misty     Hart      F
3             travel    4.50  Heather    Chase      F
4        grocery_net   14.37     Mark    Brown      M
…                …       …       …        …       …
17594       misc_pos    2.12  Sabrina  Johnson      F
17595       misc_pos   34.97    Craig     Dunn      M
17596       misc_pos    4.26   Sharon  Johnson      F
17597         travel    7.00   Daniel  Escobar      M
17598  entertainment   63.61   Joseph    Davis      M

                          street          city  … customer_age  \
0        27954 Hall Mill Suite 575   San Antonio  …         58.0
1        542 Steve Curve Suite 011  Collettsville  …         30.0
2        27954 Hall Mill Suite 575   San Antonio  …         58.0
3      6888 Hicks Stream Suite 954         Manor  …         77.0
4                  8580 Moore Cove         Wales  …         79.0
…                              …             …  …          …
17594        320 Nicholson Orchard      Thompson  …         32.0
17595        721 Jacqueline Brooks    New Boston  …         25.0
17596            7202 Jeffrey Mills        Conway  …         34.0
17597              61390 Hayes Port       Romulus  …         47.0
17598            941 Adam Stravenue      Nazareth  …         39.0

       masked_accountNumber     BIN  \
0          3401*******0220  340187
```
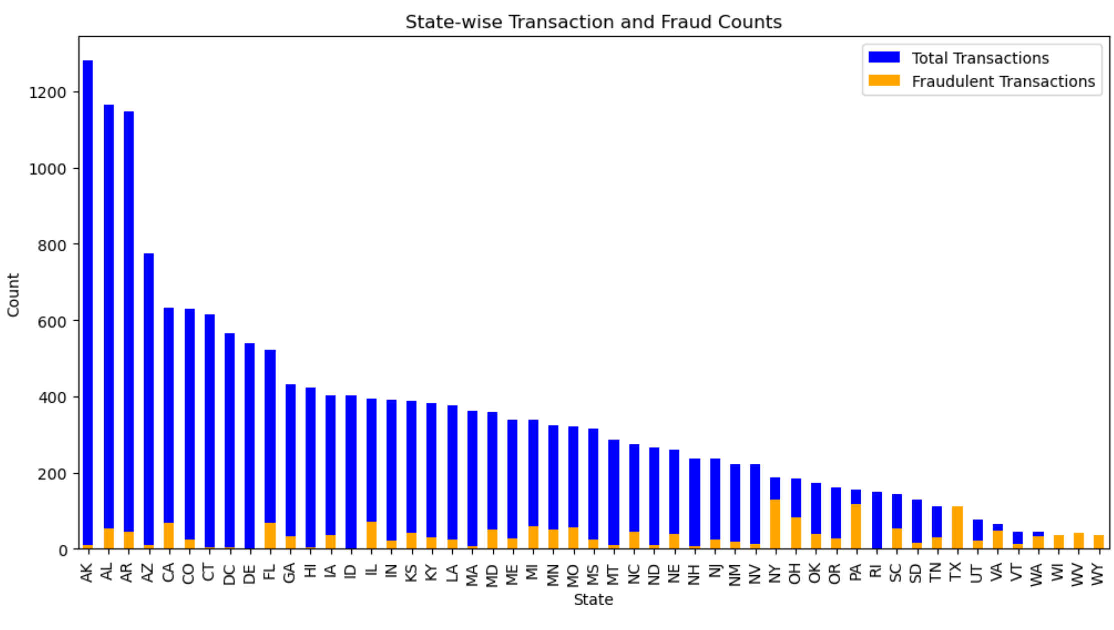

```
1           4613*****1966  461331
2          3401*******0220  340187
3         4922********1201  492271
4          3415*******6537  341546
…                      …      …
17594     4642********5942  464225
17595      1800*******0192  180011
17596     3553********4918  355362
17597      3749*******3758  374930
17598     4451********2894  445195

                                          merch_address     merch_state  \
0      {"county": "Bandera County", "state": "Texas",…           Texas
1      {"building": "BRP US Inc", "house_number": "12…  North Carolina
2      {"county": "Karnes County", "state": "Texas", …           Texas
3      {"county": "Mineral County", "state": "West Vi…   West Virginia
4      {"road": "Nome-Taylor Highway", "county": "Nom…          Alaska
…                                                   …               …
17594  {"county": "Uintah County", "state": "Utah", "…            Utah
17595  {"road": "268th Street", "county": "Jefferson …            Iowa
17596  {"county": "Jefferson County", "state": "Washi…      Washington
17597  {"road": "Carlton Rockwood Road", "town": "Ash…        Michigan
17598  {"road": "County Road 17", "county": "Deaf Smi…           Texas

      merch_postcode  merch_country_code  zip_match  state_match  \
0               None                  us          N            N
1              28777                  us          N            N
2               None                  us          N            N
3               None                  us          N            N
4               None                  us          N            N
…                  …                   …          …            …
17594           None                  us          N            N
17595           None                  us          N            N
17596           None                  us          N            N
17597          48179                  us          N            N
17598           None                  us          N            N

      web_fraud_percentage
0                     0.07
1                     0.07
2                     0.07
3                     0.31
4                     0.07
…                        …
17594                 0.31
17595                 0.06
17596                 0.31
```

```
17597                    0.07
17598                    0.05

[17599 rows x 35 columns]
```

This bar plot illustrates both the transaction counts and the fraud counts attributed to each state. Along the horizontal x-axis, the states are depicted, while the vertical y-axis denotes the count values. Each individual bar corresponds to a state and its height reflects the quantity of transactions associated with that particular state

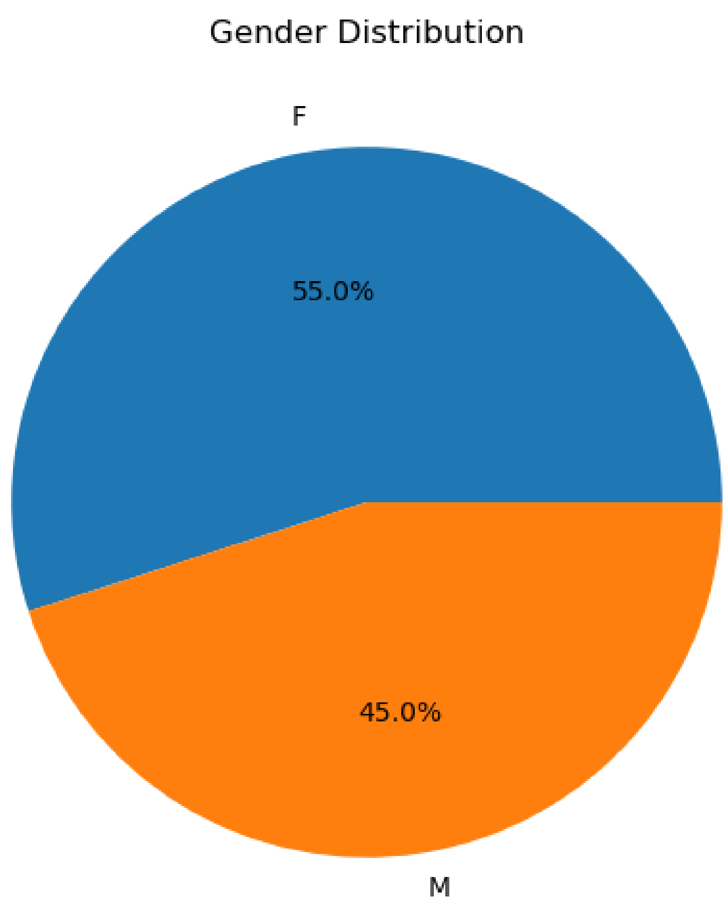
[10]:
```python
# Visualization 1 - Bar Plot: State-wise Transaction Count

# Calculate state-wise transaction and fraud counts
state_counts = df_project_milestone5['state'].value_counts()
fraud_counts = df_project_milestone5.groupby('state')['is_fraud'].sum()

# Plot the bar chart
plt.figure(figsize=(12, 6))

# Plot transaction counts as blue bars
state_counts.plot(kind='bar', color='blue', label='Total Transactions')

# Plot fraud counts as orange bars
fraud_counts.plot(kind='bar', color='orange', label='Fraudulent Transactions')

plt.xlabel('State')
plt.ylabel('Count')
plt.title('State-wise Transaction and Fraud Counts')
plt.legend()
plt.show()
```



This pie chart portrays the breakdown of transactions by gender. Each segment of the pie symbolizes a distinct gender category, with its area proportional to the percentage of transactions linked to that gender. The labels accompanying each segment indicate the gender categories, while the percentages signify the relative occurrence of each gender category within the dataset

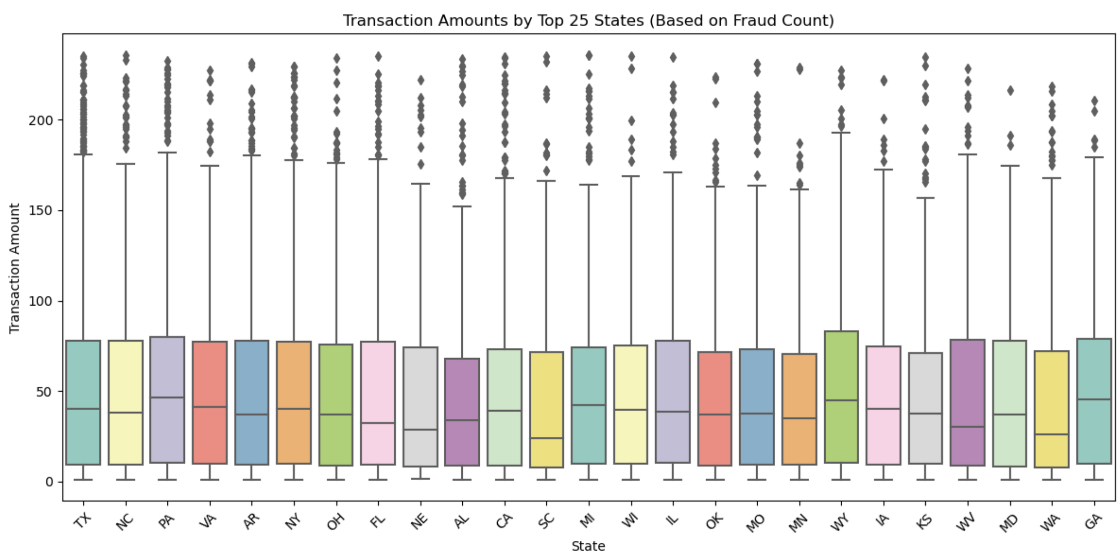
[11]:
```
# Visualization 2 - Pie Chart: Gender Distribution

# Count the number of transactions by gender
gender_counts = df_project_milestone5['gender'].value_counts()

# Plot the pie chart
plt.figure(figsize=(6, 6))
plt.pie(gender_counts, labels=gender_counts.index, autopct='%1.1f%%')
plt.title('Gender Distribution')
```

[11]:
```
Text(0.5, 1.0, 'Gender Distribution')
```



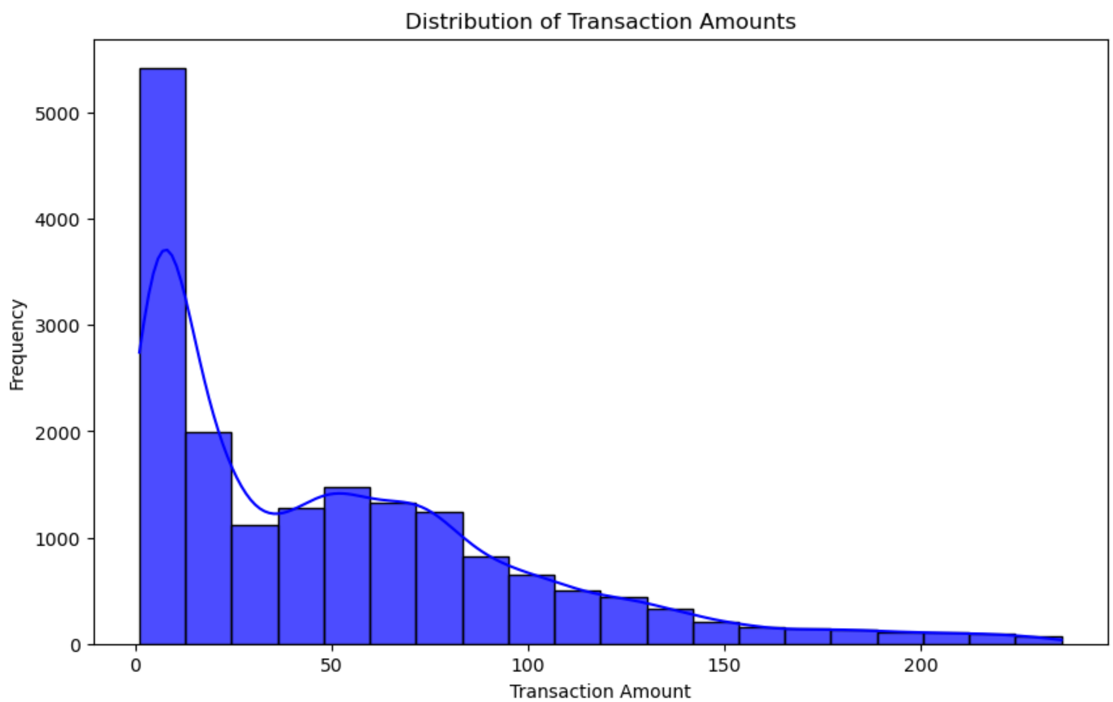
This visualization will provide insights into the distribution of transaction amounts for the top 25 states with the highest fraud counts, helping you identify any potential patterns or variations in fraudulent transactions across these states.

[12]:
```
# Visualization 3 - Box Plot of Transaction Amounts Vs Fraud Count for top 25␣
↪States

# Calculate top 25 states by fraud count
top_states_by_fraud = df_project_milestone5.groupby('state')['is_fraud'].sum().
↪nlargest(25).index

# Filter data for top 25 states by fraud count
top_states_by_fraud_data = df_project_milestone5[df_project_milestone5['state'].
↪isin(top_states_by_fraud)]

plt.figure(figsize=(12, 6))
sns.boxplot(x='state', y='amount', data=top_states_by_fraud_data,␣
↪palette='Set3')
plt.xlabel('State')
plt.ylabel('Transaction Amount')
plt.title('Transaction Amounts by Top 25 States (Based on Fraud Count)')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



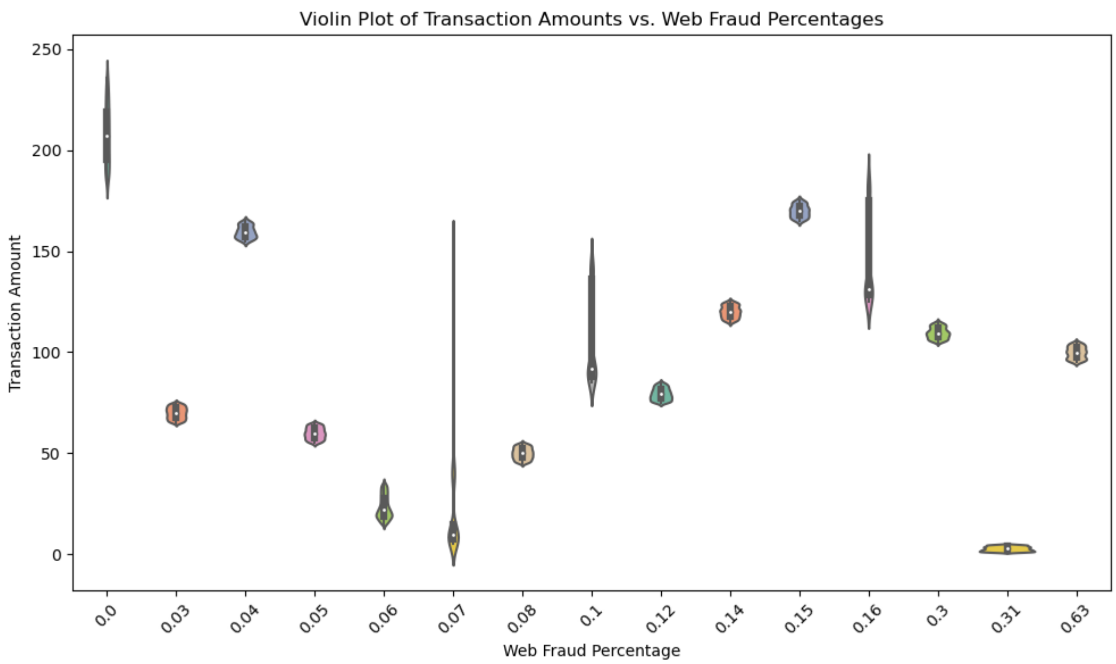
The histogram allows you to grasp the overall shape of the transaction amount distribution, including insights into the concentration of transactions around certain amounts and the spread or dispersion of transactions across the entire range of amounts. It helps you identify common transaction value ranges, potential outliers, and any patterns that may exist within the transaction data.

[13]:
```python
# Visualization 4  - Histogram of Transaction Amounts

plt.figure(figsize=(10, 6))
sns.histplot(data=df_project_milestone5, x='amount', bins=20, kde=True,␣
 ↪color='blue', alpha=0.7)
plt.title('Distribution of Transaction Amounts')
plt.xlabel('Transaction Amount')
plt.ylabel('Frequency')
plt.show()
```



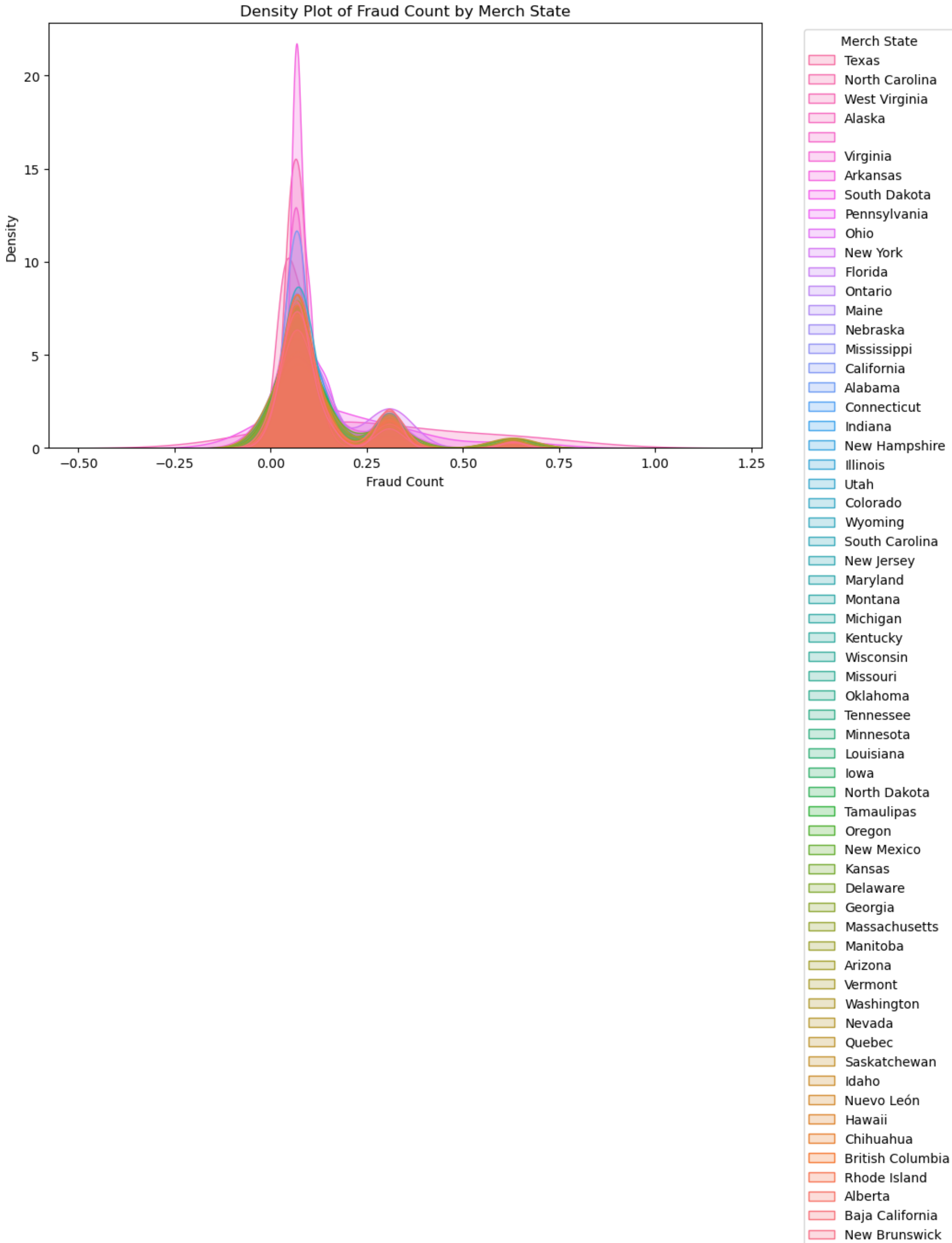
Violin plot that displays the distribution of transaction amounts for different web fraud percentage categories. Each violin plot shows the kernel density estimation of the data, allowing you to understand the density of data points at different transaction amounts for each web fraud percentage category

[14]:
```
# Visualization 5 - Violin plot - Transaction Amounts vs. Web Fraud Percentages

plt.figure(figsize=(10, 6))
sns.violinplot(x='web_fraud_percentage', y='amount',␣
 ↪data=df_project_milestone5, palette='Set2')
plt.title('Violin Plot of Transaction Amounts vs. Web Fraud Percentages')
plt.xlabel('Web Fraud Percentage')
plt.ylabel('Transaction Amount')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



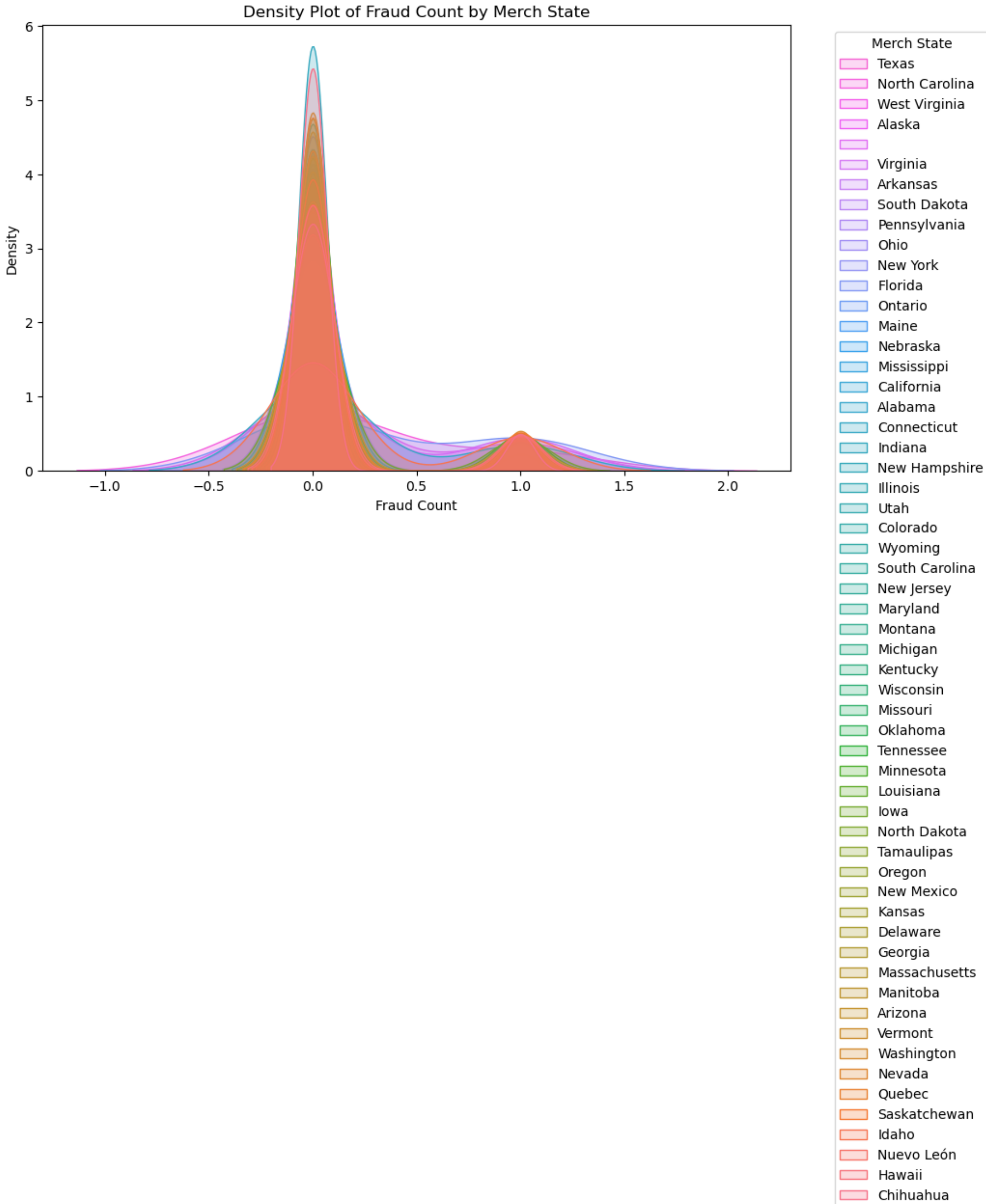
This density plot visualizes the distribution of Fraud Percentage of Web Data across different merchant states. The x-axis represents the fraud count, and the y-axis represents the density of occurrences. Each curve corresponds to a different merchant state, showing how fraud counts are distributed within that state. The legend on the side indicates the merchant states, allowing for easy comparison between their distributions

[15]:
```
# Visualization 6 - Density plot - Web Fraud Percentages by Merchant State

plt.figure(figsize=(10, 6))
plot = sns.kdeplot(data=df_project_milestone5, x='web_fraud_percentage',␣
  ↪hue='merch_state', fill=True, common_norm=False)
plt.title('Density Plot of Fraud Count by Merch State')
plt.xlabel('Fraud Count')
plt.ylabel('Density')

# Get unique merch_state values
merch_state_labels = df_project_milestone5['merch_state'].unique()

# Customize the legend labels
plt.legend(title='Merch State', labels=merch_state_labels, bbox_to_anchor=(1.
  ↪05, 1), loc='upper left')

plt.tight_layout()
plt.show()
```


Density Plot of Fraud Count by Merch State
Density
20
15
10
5
0
−0.50
−0.25
0.00
0.25
0.50
0.75
1.00
1.25
Fraud Count
Merch State
Texas
North Carolina
West Virginia
Alaska
Virginia
Arkansas
South Dakota
Pennsylvania
Ohio
New York
Florida
Ontario
Maine
Nebraska
Mississippi
California
Alabama
Connecticut
Indiana
New Hampshire
Illinois
Utah
Colorado
Wyoming
South Carolina
New Jersey
Maryland
Montana
Michigan
Kentucky
Wisconsin
Missouri
Oklahoma
Tennessee
Minnesota
Louisiana
Iowa
North Dakota
Tamaulipas
Oregon
New Mexico
Kansas
Delaware
Georgia
Massachusetts
Manitoba
Arizona
Vermont
Washington
Nevada
Quebec
Saskatchewan
Idaho
Nuevo León
Hawaii
Chihuahua
British Columbia
Rhode Island
Alberta
Baja California
New Brunswick

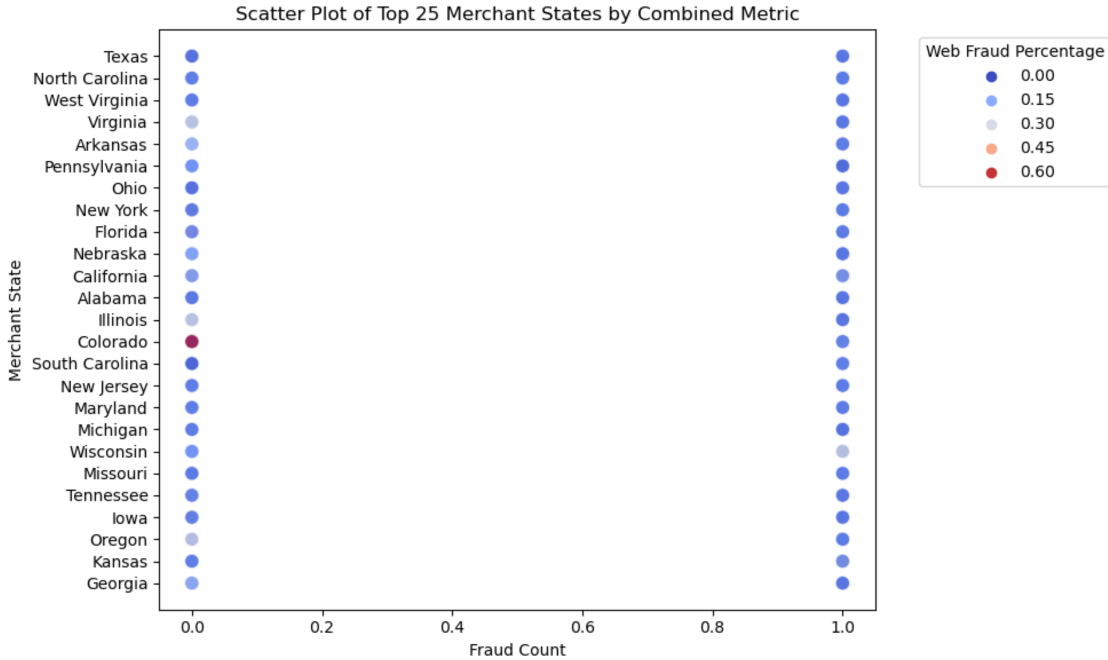
This density plot visualizes the distribution of fraud counts across different merchant states. The x-axis represents the fraud count, and the y-axis represents the density of occurrences. Each curve corresponds to a different merchant state, showing how fraud counts are distributed within that state. The legend on the side indicates the merchant states, allowing for easy comparison between their distributions

[16]:
```
# Visualization 7 - Density plot - Fraud_count by Merchant State
plt.figure(figsize=(10, 6))
plot = sns.kdeplot(data=df_project_milestone5, x='is_fraud', hue='merch_state',␣
    ↪fill=True, common_norm=False)
plt.title('Density Plot of Fraud Count by Merch State')
plt.xlabel('Fraud Count')
plt.ylabel('Density')

# Get unique merch_state values
merch_state_labels = df_project_milestone5['merch_state'].unique()

# Customize the legend labels
plt.legend(title='Merch State', labels=merch_state_labels, bbox_to_anchor=(1.
    ↪05, 1), loc='upper left')

plt.tight_layout()
plt.show()
```


Density Plot of Fraud Count by Merch State
Density
Fraud Count
0
1
2
3
4
5
6
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
Merch State
Texas
North Carolina
West Virginia
Alaska
Virginia
Arkansas
South Dakota
Pennsylvania
Ohio
New York
Florida
Ontario
Maine
Nebraska
Mississippi
California
Alabama
Connecticut
Indiana
New Hampshire
Illinois
Utah
Colorado
Wyoming
South Carolina
New Jersey
Maryland
Montana
Michigan
Kentucky
Wisconsin
Missouri
Oklahoma
Tennessee
Minnesota
Louisiana
Iowa
North Dakota
Tamaulipas
Oregon
New Mexico
Kansas
Delaware
Georgia
Massachusetts
Manitoba
Arizona
Vermont
Washington
Nevada
Quebec
Saskatchewan
Idaho
Nuevo León
Hawaii
Chihuahua

This scatter plot showcases the top 25 merchant states, ranked by a combined metric that considers both the web fraud percentage and the count of fraudulent transactions. Each point on the plot represents a merchant state, with its position along the y-axis indicating the state and its position along the x-axis representing the count of fraudulent transactions. The color of each point corresponds to the web fraud percentage associated with that state. The plot provides a visual comparison of states based on both fraudulent activity volume and the severity of web fraud. A legend on the side helps interpret the color-coded web fraud percentages

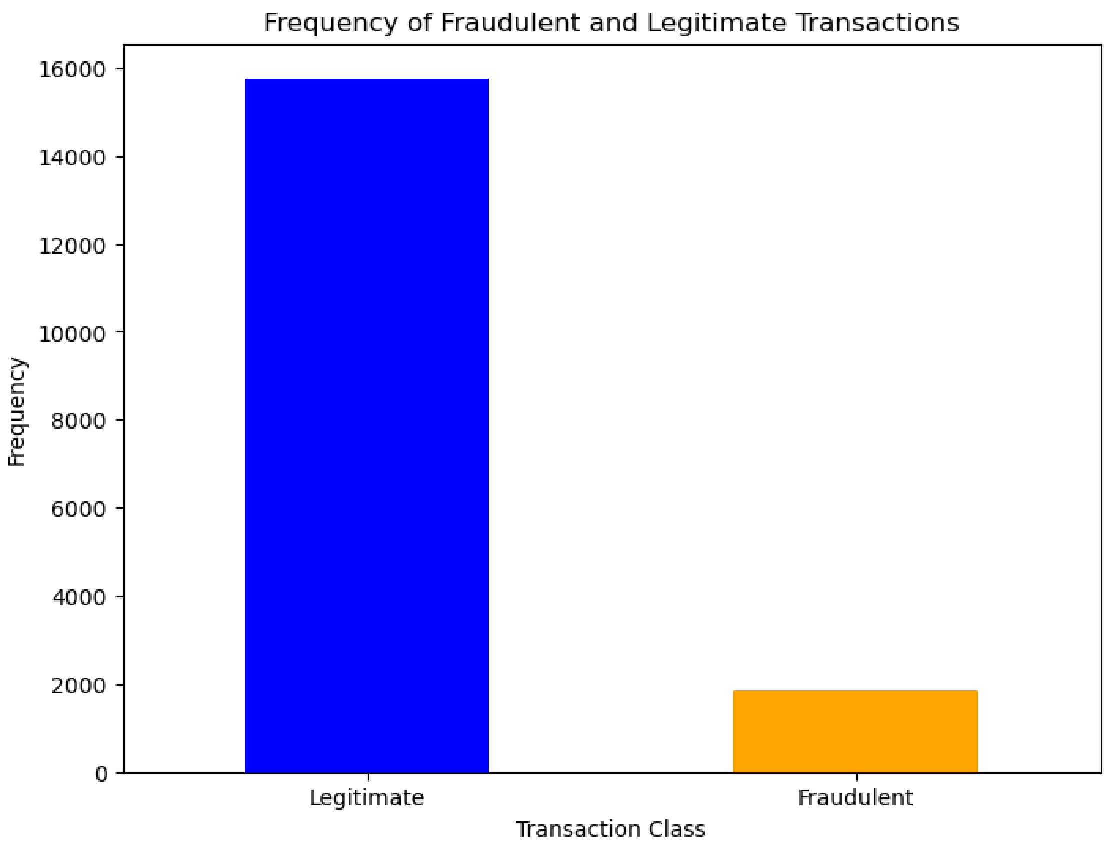
[17]:
```
# Visualization 8 - Scatter plot for the top 25 states based on both web fraud␣
↪percentage and is_fraud count

# Calculate a combined metric
df_project_milestone5['combined_metric'] =␣
↪df_project_milestone5['web_fraud_percentage'] *␣
↪df_project_milestone5['is_fraud']

# Determine the top 25 states based on the combined metric
top_25_states = df_project_milestone5.groupby('merch_state')['combined_metric'].
↪sum().nlargest(25).index

# Filter the data to include only the transactions from the top 25 states
df_top_25_states = df_project_milestone5[df_project_milestone5['merch_state'].
↪isin(top_25_states)]

# Create a scatter plot for the top 25 states using seaborn
plt.figure(figsize=(10, 6))
sns.scatterplot(data=df_top_25_states, x='is_fraud', y='merch_state',␣
↪hue='web_fraud_percentage', palette='coolwarm', alpha=0.7, s=80)
plt.title('Scatter Plot of Top 25 Merchant States by Combined Metric')
plt.xlabel('Fraud Count')
plt.ylabel('Merchant State')
plt.legend(title='Web Fraud Percentage')

# Adjust the legend position
plt.legend(title='Web Fraud Percentage', bbox_to_anchor=(1.05, 1), loc='upper␣
↪left')

plt.tight_layout()
plt.show()
```



Scatter Plot of Top 25 Merchant States by Combined Metric
Web Fraud Percentage
0.00
0.15
0.30
0.45
0.60
Merchant State
Texas
North Carolina
West Virginia
Virginia
Arkansas
Pennsylvania
Ohio
New York
Florida
Nebraska
California
Alabama
Illinois
Colorado
South Carolina
New Jersey
Maryland
Michigan
Wisconsin
Missouri
Tennessee
Iowa
Oregon
Kansas
Georgia
0.0
0.2
0.4
0.6
0.8
1.0
Fraud Count

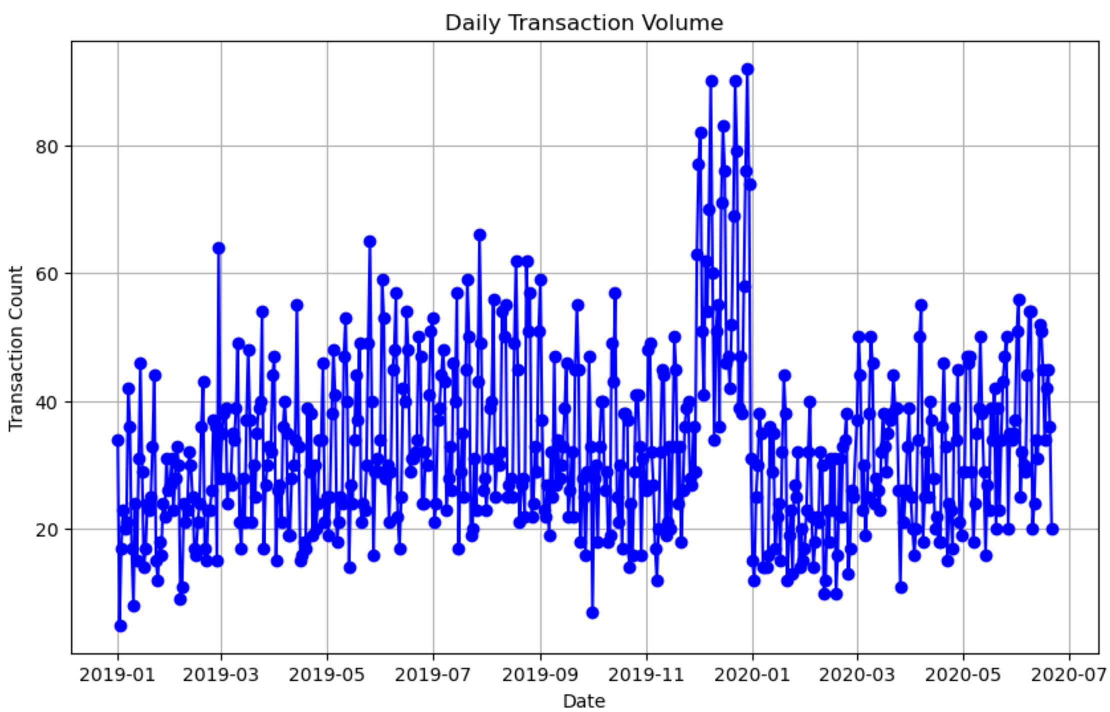
The bar plot helps visualize the class imbalance between fraudulent and legitimate transactions

[18]:
```
# Visualization 9 - Bar Plot - frequency of fraudulent and legitimate␣
↪transactions
# Count the frequency of fraudulent and legitimate transactions
fraud_counts = df_project_milestone5['is_fraud'].value_counts()

# Create a bar plot
plt.figure(figsize=(8, 6))
fraud_counts.plot(kind='bar', color=['blue', 'orange'])
plt.xlabel('Transaction Class')
plt.ylabel('Frequency')
plt.title('Frequency of Fraudulent and Legitimate Transactions')
plt.xticks([0, 1], ['Legitimate', 'Fraudulent'], rotation=0)
plt.show()
```



Line plot to visualize the daily transaction volume and identify any unusual spikes that might indicate potential fraudulent activity

[19]:
```
# Visualization 10 - Line Plot - daily transaction volume

# Convert the 'transaction_date' column to datetime
df_project_milestone5['txn_date'] = pd.
 ↪to_datetime(df_project_milestone5['txn_date'])

# Group data by date and calculate daily transaction count
daily_transaction_count = df_project_milestone5.
 ↪groupby(df_project_milestone5['txn_date'].dt.date)['row_id'].count()

# Create a line plot
plt.figure(figsize=(10, 6))
daily_transaction_count.plot(kind='line', marker='o', color='blue')
plt.xlabel('Date')
plt.ylabel('Transaction Count')
plt.title('Daily Transaction Volume')
plt.grid(True)
plt.show()
```



6 Conclusion

The credit card fraud detection project allowed me to explore the entire data science pipeline, from data cleaning and merging to visualization. I learned the significance of ethical considerations while dealing with sensitive data and presenting results. Additionally, the project gave me insights into techniques for credit card fraud detection, which can be extended further using advanced machine learning models. Overall, it was an enriching experience that deepened my understanding of data analysis and visualization in real-world applications.