task1

December 10, 2024

1 Credit Card Fraud Detection

2 Task 1: Data Understanding, Preparation and Descriptive Analytics

2.1 Required libraries

[1]:
```
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
import numpy as np
import cartopy.crs as ccrs
import cartopy.feature as cfeature
from adjustText import adjust_text
from geopy.distance import geodesic
from sklearn.preprocessing import MinMaxScaler
from imblearn.over_sampling import SMOTE
from sklearn.model_selection import train_test_split
from sklearn.cluster import DBSCAN
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import RandomizedSearchCV
from sklearn.metrics import roc_auc_score, roc_curve
from sklearn.metrics import f1_score
from xgboost import XGBClassifier
import pickle
import os
from sklearn.impute import KNNImputer
from sklearn.preprocessing import LabelEncoder
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.neural_network import MLPClassifier
from scipy.stats import chi2_contingency
from itertools import product
from sklearn.metrics import silhouette_score
```

2.2 Introduction

This report presents an exploratory analysis of the dataset provided for the Fraud Detection project. The dataset includes transaction records, customer demographics, merchant details, and city-level information. The primary objective of this analysis is to understand the data structure, identify key patterns, and prepare it for predictive modeling to classify transactions as fraudulent or legitimate.

2.3 1.1- Data Understanding

Data understanding is a critical step in any fraud detection project, as it involves exploring and analyzing the dataset to gain insights into its structure, content, and relevance for identifying fraudulent activities. This will help to ensure that the data aligns with the objectives of the fraud detection system and lays the foundation for effective model development and analysis.

This phase will involve merging multiple datasets into a cohesive structure, examining the data to understand its content and quality, and summarizing key attributes to uncover initial patterns and relationships.

2.3.1 1.1.1- Merge the Datasets

The first step involved merging the datasets to form a unified dataset for analysis.

I used the function `merge` from pandas library that implements SQL style joining operations.

In this case, `transactions` is our primary dataset, with each row representing a transaction record. I want to ensure that every transaction is retained in the final merged dataset, even if certain demographic, merchant, or city information is missing.

Using `how='left'` for each merge step ensures **all transactions are retained** in the final dataset, even if:

- **Customer data is missing**: Transactions without a matching `cc_num` in `customers` will still appear, with `NaN` for customer details
- **Merchant information is missing**: Transactions lacking a matching `merchant` in `merchants` are included, with `NaN` for merchant fields
- **City data is missing**: If a customer's `city` has no match in `cities`, the transaction is kept with `NaN` for city details

[2]:
```python
# Load Datasets
transactions = pd.read_csv('data/transactions.csv')
merchants = pd.read_csv('data/merchants.csv')
customers = pd.read_csv('data/customers.csv')
cities = pd.read_csv('data/cities.csv')

# Merge the .csv files into one
merged_data = pd.merge(transactions, customers, on='cc_num', how='left')
merged_data = pd.merge(merged_data, merchants, on='merchant', how='left')
merged_data = pd.merge(merged_data, cities, on='city', how='left')

# Print merged dataset
```

```python
print(merged_data.head())

# Save merged dataset into new file
merged_data.to_csv('data/merged_data.csv', index=False)
```

```
   index trans_date_trans_time            cc_num device_os     merchant  \
0   5381   2023-01-01 00:39:03  2801374844713453       NaN  Merchant_85
1   4008   2023-01-01 01:16:08  3460245159749480       NaN  Merchant_23
2   1221   2023-01-01 01:24:28  7308701990157768     macOS  Merchant_70
3   9609   2023-01-01 02:06:57  8454886440761098       X11  Merchant_33
4   5689   2023-01-01 02:10:54  6350332939133843       NaN  Merchant_90

      amt     trans_num  unix_time  is_fraud  first  …      job  \
0  252.75  TRANS_662964  1672533543         0   Jane  …      NaN
1  340.17  TRANS_134939  1672535768         0  Alice  …    Nurse
2   76.38  TRANS_258923  1672536268         0    Bob  …   Doctor
3  368.88  TRANS_226814  1672538817         0   Mike  …  Teacher
4  323.32  TRANS_668449  1672539054         0   Mike  …    Nurse

          dob       category  merch_lat  merch_long merchant_id      lat  \
0  2002-10-12            NaN        NaN   76.433212        85.0  41.8781
1  2001-12-23  Entertainment  27.177588  -64.857435        23.0  40.7128
2  1978-12-13    Electronics  31.730070  -67.777407        70.0  33.4484
3  1965-04-21    Electronics  -5.005953  146.873847        33.0  33.4484
4  1997-05-17      Groceries  79.065894   40.668693        90.0  40.7128

       long   city_pop  state
0  -87.6298  2716000.0     IL
1  -74.0060  8419600.0     NY
2 -112.0740  1680992.0     AZ
3 -112.0740  1680992.0     AZ
4  -74.0060  8419600.0     NY

[5 rows x 25 columns]
```

2.3.2 1.1.2- Data Examination

After merging, the dataset was examined for its structure and attribute types. Below is a brief description of the key attributes:

Attribute	Data Type	Description
index	Categorical (Nominal)	Index of the transaction record.
trans_date_trans_time	Categorical (Ordinal)	Transaction date and time.
cc_num	Categorical (Nominal)	Credit card number used for the transaction.

Attribute	**Data Type**	**Description**
`device_os`	Categorical (Nominal)	Operating system of the device used (Windows, macOS, Linux, X11, other).
`merchant`	Categorical (Nominal)	Name of the merchant involved in the transaction.
`amt`	Numerical (Ratio)	Monetary amount of the transaction.
`trans_num`	Categorical (Nominal)	Unique transaction identifier.
`unix_time`	Numerical (Interval)	Unix timestamp of the transaction (seconds since January 1, 1970).
`is_fraud`	Categorical (Nominal)	Indicates if the transaction was fraudulent (1 for fraud, 0 otherwise).
`category`	Categorical (Nominal)	Business category of the merchant (e.g., groceries, travel).
`merch_lat`	Numerical (Interval)	Latitude of the merchant's location.
`merch_long`	Numerical (Interval)	Longitude of the merchant's location.
`merchant_id`	Categorical (Nominal)	Unique identifier for the merchant.
`first`	Categorical (Nominal)	Customer's first name.
`last`	Categorical (Nominal)	Customer's last name.
`gender`	Categorical (Nominal)	Customer's gender.
`street`	Categorical (Nominal)	Customer's street address.
`city`	Categorical (Nominal)	City where the customer resides.
`zip`	Categorical (Nominal)	Zip code of the customer's address.
`job`	Categorical (Nominal)	Customer's job/profession.
`dob`	Categorical (Ordinal)	Customer's date of birth.
`lat`	Numerical (Interval)	Latitude of the city.
`long`	Numerical (Interval)	Longitude of the city.
`city_pop`	Numerical (Ratio)	Population of the city.
`state`	Categorical (Nominal)	State where the city is located.

2.3.3 1.1.3- Data Summarization

Data summarization is a foundational step that transforms raw data into actionable insights. It ensures that subsequent processes, like data visualization, feature engineering, and modeling, are based on a well-understood dataset, ultimately leading to better analytical outcomes.

[3]:
```python
# Load the merged dataset
merged_data = pd.read_csv('data/merged_data.csv')

print("General Information:")
print(merged_data.info())
```

```
General Information:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30000 entries, 0 to 29999
Data columns (total 25 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   index                  30000 non-null  int64
 1   trans_date_trans_time  29900 non-null  object
 2   cc_num                 30000 non-null  int64
 3   device_os              12036 non-null  object
 4   merchant               30000 non-null  object
 5   amt                    29900 non-null  float64
 6   trans_num              30000 non-null  object
 7   unix_time              30000 non-null  int64
 8   is_fraud               30000 non-null  int64
 9   first                  29990 non-null  object
 10  last                   29990 non-null  object
 11  gender                 29990 non-null  object
 12  street                 29990 non-null  object
 13  city                   29990 non-null  object
 14  zip                    29784 non-null  float64
 15  job                    29784 non-null  object
 16  dob                    29990 non-null  object
 17  category               29401 non-null  object
 18  merch_lat              29401 non-null  float64
 19  merch_long             29990 non-null  float64
 20  merchant_id            29990 non-null  float64
 21  lat                    10020 non-null  float64
 22  long                   10020 non-null  float64
 23  city_pop               10020 non-null  float64
 24  state                  10020 non-null  object
dtypes: float64(8), int64(4), object(13)
memory usage: 5.7+ MB
None
```

Change data types to correct ones When working with data, it is common for pandas to infer the data types of each column automatically based on the values it contains. However, some columns that are semantically categorical or identifiers might be mistakenly inferred as numeric. This misclassification can lead to incorrect data interpretation or processing. Below is the rationale for converting specific columns in the merged_data DataFrame:

[4]:
```
merged_data['index'] = merged_data['index'].astype('object')
merged_data['cc_num'] = merged_data['cc_num'].astype('object')
merged_data['is_fraud'] = merged_data['is_fraud'].astype('object')
merged_data['zip'] = merged_data['zip'].astype('object')
merged_data['merchant_id'] = merged_data['merchant_id'].astype('object')

print("General Information:")
print(merged_data.info())
```

```
General Information:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30000 entries, 0 to 29999
Data columns (total 25 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   index                  30000 non-null  object
 1   trans_date_trans_time  29900 non-null  object
 2   cc_num                 30000 non-null  object
 3   device_os              12036 non-null  object
 4   merchant               30000 non-null  object
 5   amt                    29900 non-null  float64
 6   trans_num              30000 non-null  object
 7   unix_time              30000 non-null  int64
 8   is_fraud               30000 non-null  object
 9   first                  29990 non-null  object
 10  last                   29990 non-null  object
 11  gender                 29990 non-null  object
 12  street                 29990 non-null  object
 13  city                   29990 non-null  object
 14  zip                    29784 non-null  object
 15  job                    29784 non-null  object
 16  dob                    29990 non-null  object
 17  category               29401 non-null  object
 18  merch_lat              29401 non-null  float64
 19  merch_long             29990 non-null  float64
 20  merchant_id            29990 non-null  object
 21  lat                    10020 non-null  float64
 22  long                   10020 non-null  float64
 23  city_pop               10020 non-null  float64
 24  state                  10020 non-null  object
dtypes: float64(6), int64(1), object(18)
memory usage: 5.7+ MB
```

```
None
```

[5]:
```
# Select numerical columns excluding irrelevant ones
numerical_columns = merged_data.select_dtypes(include=["number"]).
 ↪drop(['merch_lat','merch_long','lat','long'], axis=1)

# Display summary statistics for numerical columns
print("\nSummary Statistics for Numerical Variables:")
numerical_columns.describe()
```

```
Summary Statistics for Numerical Variables:
```

[5]:
```
                amt     unix_time      city_pop
count  29900.000000  3.000000e+04  1.002000e+04
mean     250.063287  1.705650e+09  3.704410e+06
std      144.106058  1.530499e+07  2.323382e+06
min        1.010000  1.672534e+09  1.680992e+06
25%      125.235000  1.696269e+09  2.328000e+06
50%      249.625000  1.706376e+09  2.716000e+06
75%      375.242500  1.718328e+09  3.979576e+06
max      499.970000  1.730124e+09  8.419600e+06
```

[6]:
```
# Select categorical columns
categorical_columns = merged_data.select_dtypes(include=["object"])

# Display summary statistics for categorical columns
print("\nSummary Statistics for Categorical Variables:")
categorical_columns.describe()
```

```
Summary Statistics for Categorical Variables:
```

[6]:
```
        index trans_date_trans_time            cc_num device_os     merchant  \
count   30000                 29900             30000     12036        30000
unique  29970                 29868              1101         5          101
top      2041   2023-10-20 21:24:16  1808228936642008   Windows  Merchant_72
freq        2                     2               237      3049          339

           trans_num  is_fraud  first      last gender  street       city  \
count          30000     30000  29990     29990  29990   29990      29990
unique         29470         2    108       108      2     102          6
top     TRANS_600014         0   Jane  Williams      F  Elm St  Test City
freq               4     29429   1489      1442  15414    1780      19970

            zip     job         dob   category  merchant_id  state
count   29784.0   29784       29990      29401      29990.0  10020
unique   1077.0       7        1062          5        100.0      5
top     39611.0  Lawyer  1965-10-17  Groceries         72.0     CA
```

```
freq       237.0    6443          237        7193          339.0    2181
```

Note:

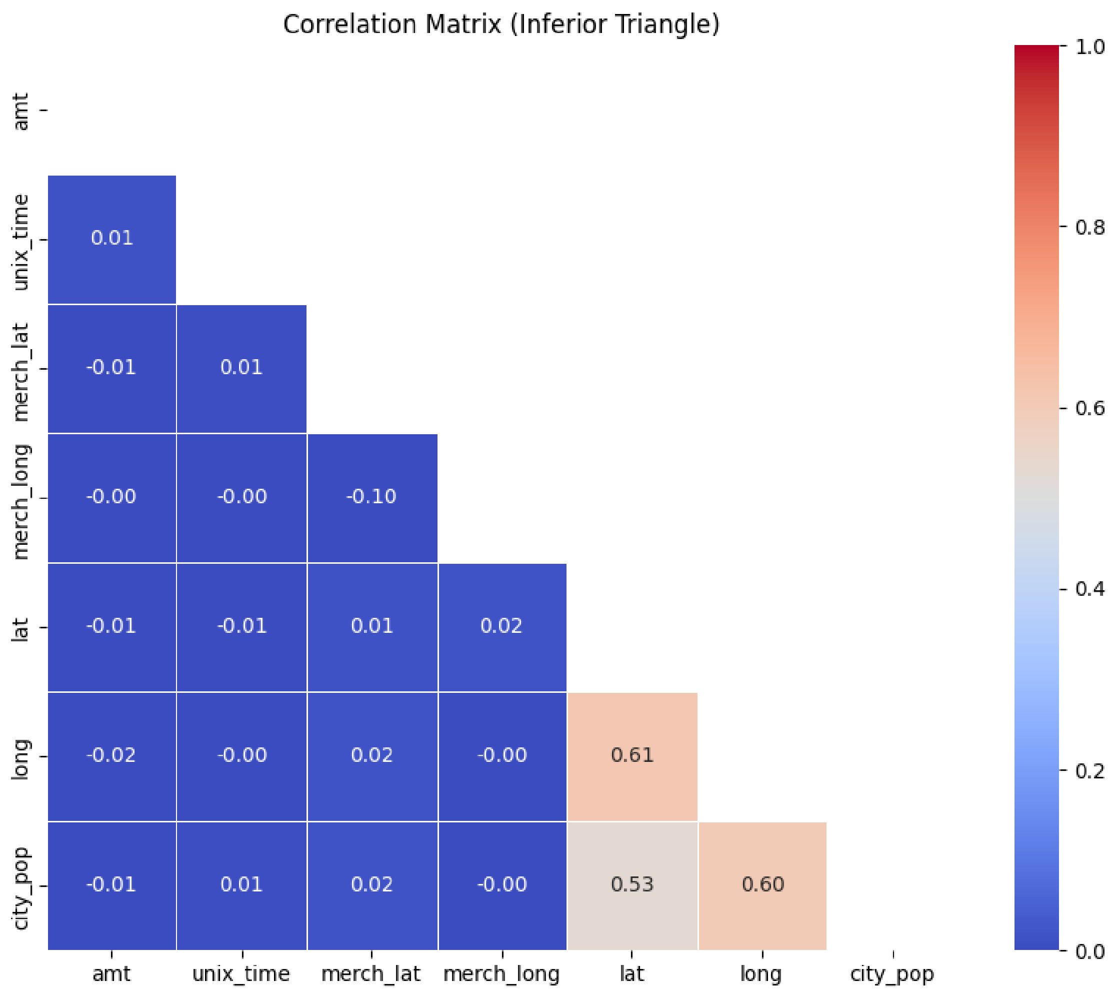
I removed some atributes from the summary table for numerical variables because these attributes are either irrelevant for descriptive analysis or do not provide meaningful insights in the context of summarization. By excluding these attributes, the summary focuses on numerical variables that have genuine analytical significance.

Analysis:

The summary statistics reveal key characteristics of the dataset. Transaction amounts range from small to mid-sized values, with a mean of 250.06, indicating a relatively consistent distribution. Fraudulent transactions are rare, accounting for only 1.9% of the data, highlighting a significant class imbalance that must be addressed during modeling. device_os has a high proportion of missing values, while "Test City" dominates the city field, likely indicating synthetic or placeholder data. The dataset includes a diverse set of merchants and categories, with "Groceries" being the most frequent category. These insights emphasize the need to handle missing values, investigate synthetic data, and carefully address class imbalance to ensure effective analysis and modeling.

Correlation Matrix

```
[7]: relevant_columns = merged_data.select_dtypes(include=['float64', 'int64']).
       ↪columns
     filtered_data = merged_data[relevant_columns]


     correlation_matrix = filtered_data.corr()
     mask = np.triu(np.ones_like(correlation_matrix, dtype=bool))

     plt.figure(figsize=(10, 8))
     sns.heatmap(correlation_matrix, mask=mask, annot=True, cmap='coolwarm', fmt=".
       ↪2f", linewidths=0.5, vmin=0, vmax=1)
     plt.title('Correlation Matrix (Inferior Triangle)')
     plt.show()
```



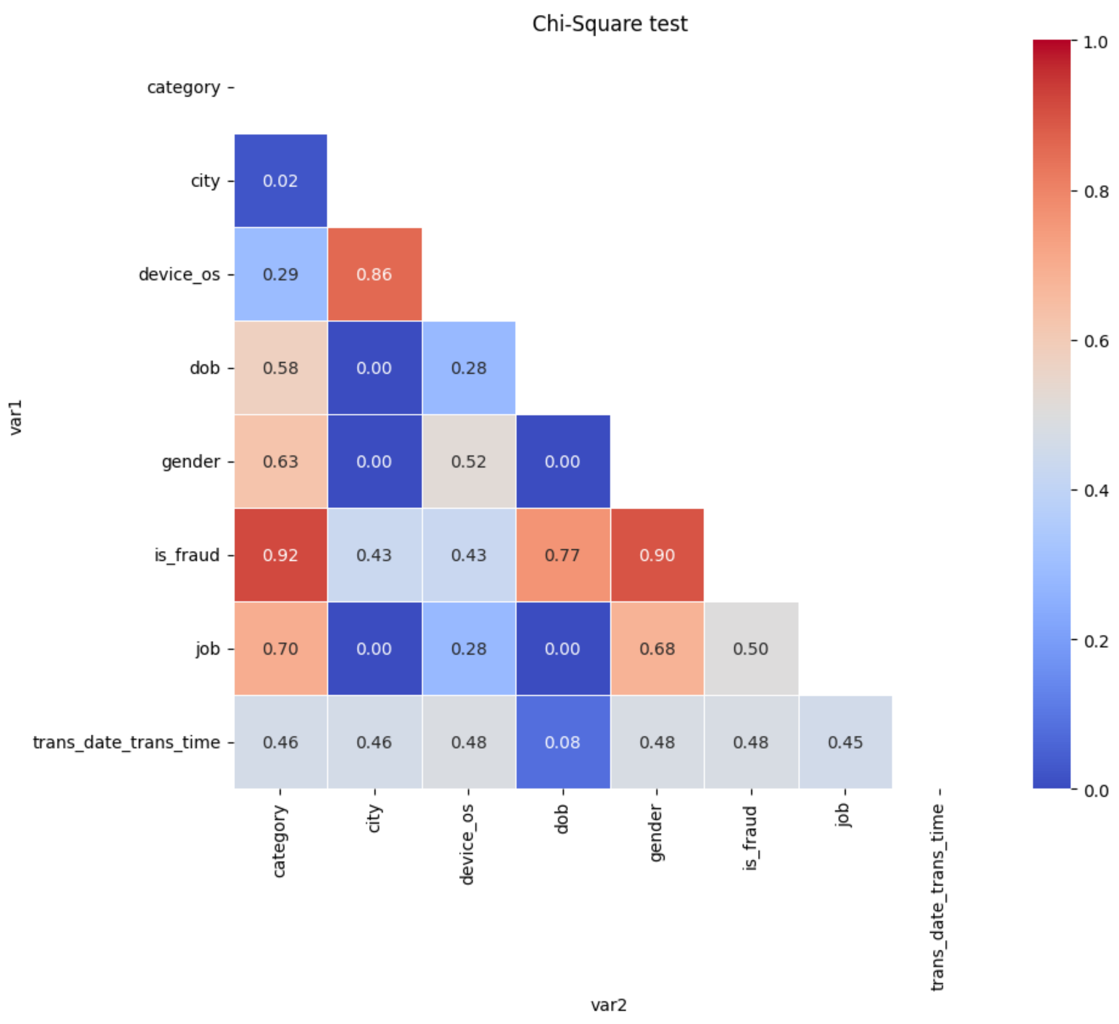
Most variables show weak or no significant correlation with each other, indicating that they are largely independent or represent distinct aspects of the data. One notable exception is the moderate positive correlation (0.61) between `lat` and `long`, suggesting a geographical alignment. Additionally, variables related to city-level information, such as `city_pop`, exhibit moderate correlations with `lat` (0.53) and `long` (0.60). This indicates that high-population cities tend to cluster in specific geographic regions, which may play a role in understanding transaction patterns.

Variables such as `amt`, `unix_time`, `merch_lat`, and `merch_long` show near-zero correlations with other features, reflecting their independence and lack of linear relationships with other variables. These variables may provide unique, standalone insights.

Interestingly, the target variable `is_fraud` does not show any strong correlation with other features. This suggests that fraud detection in this dataset might rely on more complex or non-linear patterns that are not captured by simple correlations. As a result, identifying fraud will likely require advanced feature engineering and sophisticated modeling techniques.

Chi-Square Test

```
[8]: # Chi-Square test

categorical_columns = categorical_columns.dropna()
data = categorical_columns.drop(['index', 'first', 'last', 'cc_num',␣
 ↪'trans_num', 'state', 'street', 'zip', 'merchant_id','merchant'], axis=1)


prod = product(data, repeat = 2)

result = []
for col1, col2 in prod:
    if col1 != col2:
        result.append((col1,col2,list(chi2_contingency(pd.crosstab(data[col1],␣
 ↪data[col2])))[1]))

chi_test_output = pd.DataFrame(result, columns = ['var1', 'var2', 'coeff'])
chi_matrix = chi_test_output.pivot(index='var1', columns='var2', values='coeff')
chi_matrix.fillna(1, inplace=True)


mask = np.triu(np.ones_like(chi_matrix, dtype=bool))
plt.figure(figsize=(10, 8))
sns.heatmap(chi_matrix, mask=mask, cmap='coolwarm', annot=True, fmt=".2f",␣
 ↪linewidths=0.5,vmin=0, vmax=1)
plt.title("Chi-Square test")
plt.show()
```



In the Chi-Square test heatmap, lower values indicate stronger relationships between the variables, which is desirable in this analysis as it highlights statistical dependence. The Chi-Square test operates under the null hypothesis (H) that the variables are independent, meaning there is no association between them. Lower values (often corresponding to lower p-values) provide evidence to reject the null hypothesis, suggesting that the variables are not independent and are, therefore, associated.

Using a significance threshold of 0.05, variables with values below this level indicate a statistically significant relationship. These relationships are particularly valuable in data analysis as they suggest patterns or dependencies that can inform decision-making, segmentation, or predictive modeling. For instance, variables like gender and dob or job and dob exhibit low values in the heatmap, highlighting meaningful dependencies that warrant further exploration. Conversely, higher values suggest independence and less relevance for understanding correlations.

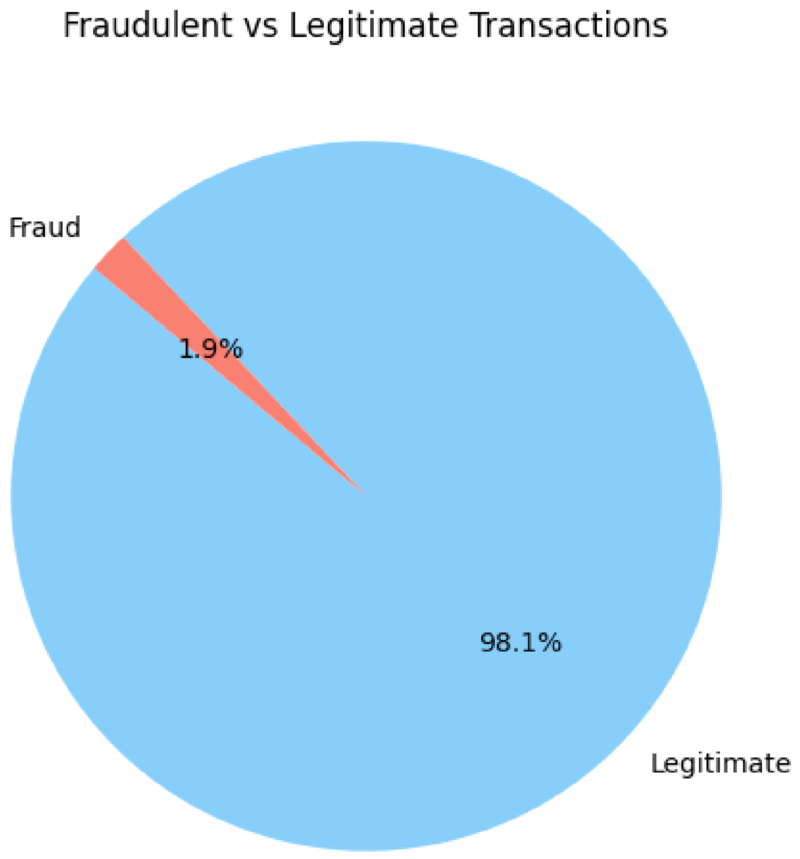
Thus, the lower the value in the heatmap, the more likely it is that the variables are correlated, providing critical insights into their potential interdependence.

2.3.4 1.1.4- Data Visualization

Data visualization is an essential step in understanding and presenting data. It simplifies complex information, uncovers hidden patterns, and supports informed decision-making. By using appropriate visualization techniques, analysts can effectively interpret relationships, trends, and anomalies, setting the stage for robust data preparation and modeling.

Fraud distribution

```
[9]: # Pie chart plot
fraud_counts = merged_data['is_fraud'].value_counts(normalize=True)
labels = ['Legitimate', 'Fraud']
plt.figure(figsize=(6, 6))
plt.pie(fraud_counts, labels=labels, autopct='%1.1f%%', startangle=140,␣
 ↪colors=['lightskyblue', 'salmon'])
plt.title('Fraudulent vs Legitimate Transactions')
plt.show()
```



What was done:

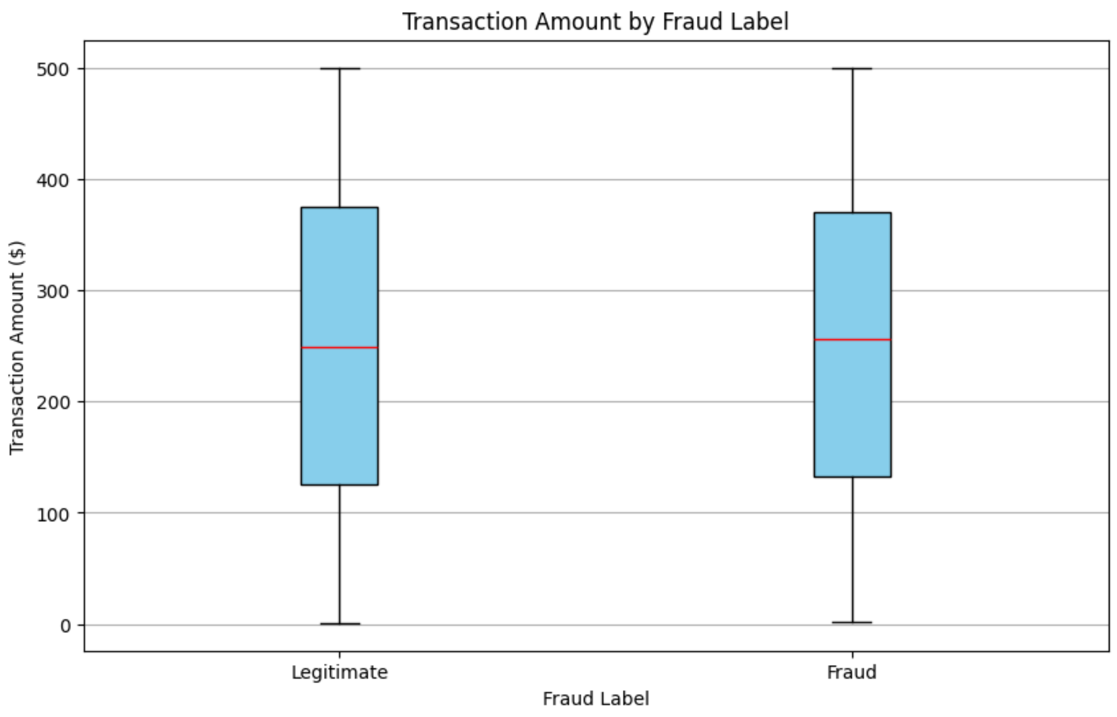
A pie chart was created to visualize the proportion of fraudulent transactions (`is_fraud` = 1) versus legitimate transactions (`is_fraud` = 0). The values were normalized to show the percentage distribution.

Analysis:

The chart reveals a significant class imbalance, with fraudulent transactions accounting for only 1.9% of all transactions. This imbalance highlights the importance of addressing this issue during model training, as it may lead to biased predictions favoring the majority class (legitimate transactions). Techniques like oversampling, undersampling, or cost-sensitive modeling will be essential.

Distribution of transaction amount

[10]:
```
# Filter data for visualization
fraud = merged_data[merged_data['is_fraud'] == 1]['amt']
legit = merged_data[merged_data['is_fraud'] == 0]['amt']

# Limit the range for better visualization
fraud = fraud[fraud <= 500]
legit = legit[legit <= 500]

# Box plot
plt.figure(figsize=(10, 6))
plt.boxplot([legit, fraud], tick_labels=['Legitimate', 'Fraud'],␣
 ↪patch_artist=True,
            boxprops=dict(facecolor='skyblue', color='black'),
            medianprops=dict(color='red'))
plt.title('Transaction Amount by Fraud Label')
plt.xlabel('Fraud Label')
plt.ylabel('Transaction Amount ($)')
plt.grid(axis='y')
plt.show()
```



What was done:

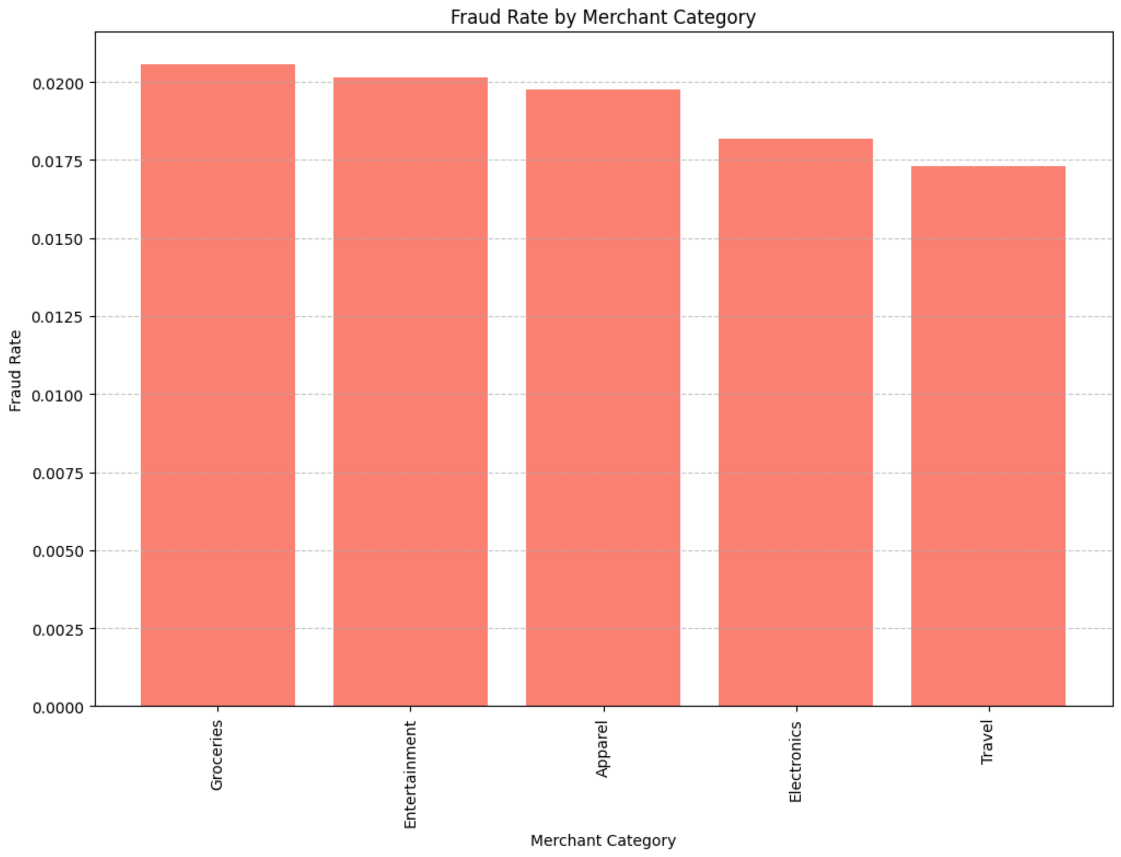
A box plot was created to compare the transaction amounts for fraudulent and legitimate transactions. To improve visibility, the range was limited to transactions under $500, because there are no transactions above that value.

Analysis:

The box plot shows that fraudulent transactions tend to have higher median amounts compared to legitimate ones. This suggests that fraudsters may target higher-value transactions. However, there is overlap between the distributions, indicating that transaction amount alone may not be a definitive predictor of fraud.

Fraud rate by merchant category

[11]:
```
fraud_rate = merged_data.groupby('category')['is_fraud'].mean().
 ↪sort_values(ascending=False)

# Bar plot
plt.figure(figsize=(12, 8))
plt.bar(fraud_rate.index, fraud_rate.values, color='salmon')
plt.xticks(rotation=90)
plt.title('Fraud Rate by Merchant Category')
plt.xlabel('Merchant Category')
plt.ylabel('Fraud Rate')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```



What was done:

A bar plot was used to display the average fraud rate for each merchant category, calculated by grouping the data by `category` and taking the mean of `is_fraud`.

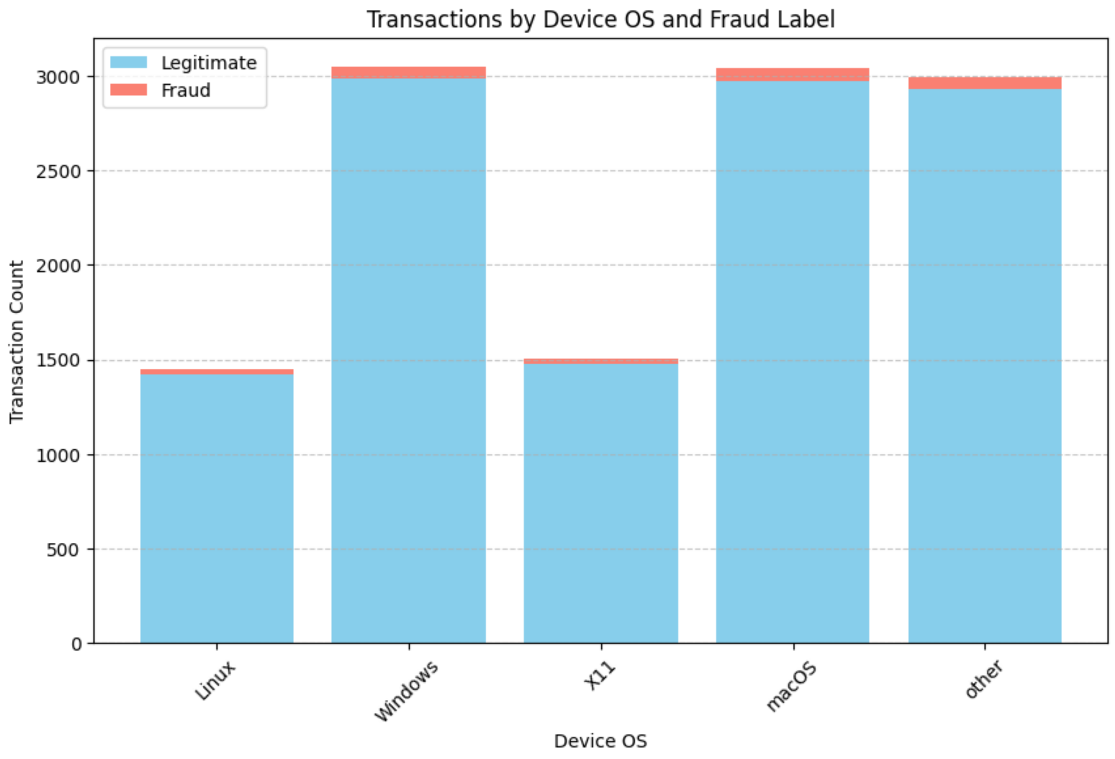
Analysis:

The chart reveals that certain merchant categories, such as “Groceries” and “Entertainment,” have slightly higher fraud rates. This insight could be useful for identifying high-risk merchant categories. However, the differences between categories are not dramatic, suggesting that other factors may play a more significant role in fraud.

OS Used in Transactions

[12]:
```
# Count of transactions by device_os and fraud label
device_os_counts = merged_data.groupby(['device_os', 'is_fraud']).size().
  ↪unstack(fill_value=0)

# Stacked bar plot
device_os = device_os_counts.index
legit_counts = device_os_counts[0]
```

```
fraud_counts = device_os_counts[1]

x = range(len(device_os))
plt.figure(figsize=(10, 6))
plt.bar(x, legit_counts, label='Legitimate', color='skyblue')
plt.bar(x, fraud_counts, label='Fraud', bottom=legit_counts, color='salmon')

plt.xticks(x, device_os, rotation=45)
plt.title('Transactions by Device OS and Fraud Label')
plt.xlabel('Device OS')
plt.ylabel('Transaction Count')
plt.legend()
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```



What was done:

A stacked bar plot was created to compare the number of transactions for each device_os, split by fraud label (is_fraud).

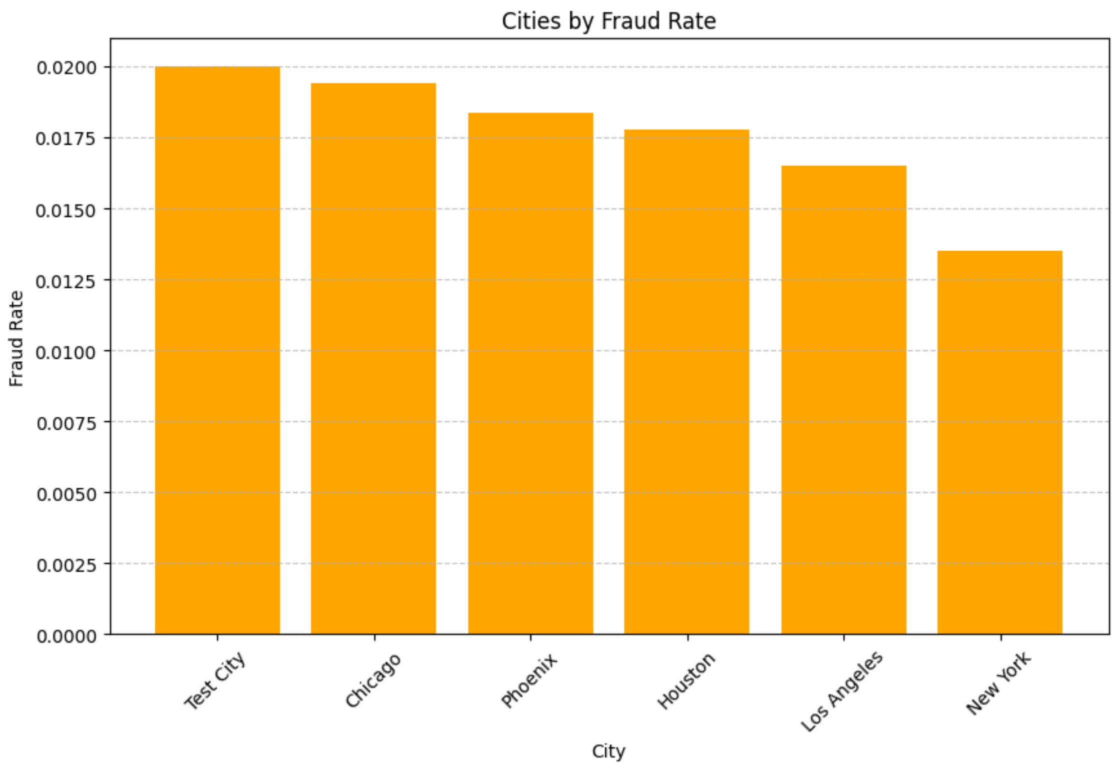
Analysis:

The chart shows that Windows and macOS have the highest number of both legitimate and fraudulent transactions, likely reflecting their popularity among users. However, the proportion of fraudulent transactions does not vary significantly across operating systems. This indicates that device

OS may not be a strong standalone feature for fraud detection.

Fraud Rate by City

```
[13]: # Calculate fraud rate per city
      city_fraud_rate = merged_data.groupby('city')['is_fraud'].mean().
       ↪sort_values(ascending=False)

      # Bar plot for fraud rate by city
      plt.figure(figsize=(10, 6))
      plt.bar(city_fraud_rate.index, city_fraud_rate.values, color='orange')
      plt.title('Cities by Fraud Rate')
      plt.xlabel('City')
      plt.ylabel('Fraud Rate')
      plt.xticks(rotation=45)
      plt.grid(axis='y', linestyle='--', alpha=0.7)
      plt.show()
```



What was done:

A bar plot was created to show the cities with the highest fraud rates. The fraud rate for each city was calculated as the mean of `is_fraud`.

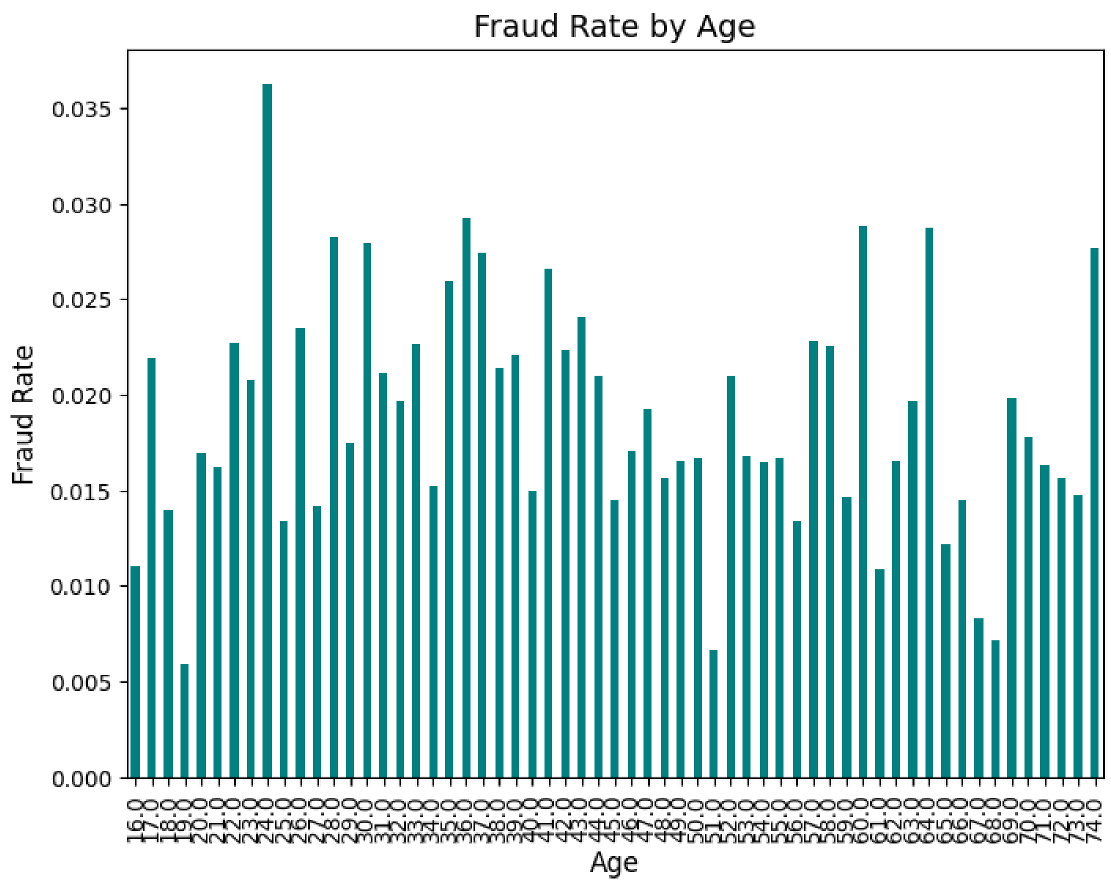
Analysis:

The chart indicates that major metropolitan areas such as Chicago, Phoenix and Houston have higher fraud rates. Upon further inspection, the inclusion of “Test City” appears to be a synthetic or placeholder entry in the dataset rather than a real location. This type of entry is likely used for testing purposes or as a default value and does not represent actual transactional data.

Its presence can distort the analysis by introducing artificial patterns or biasing the interpretation of fraud rates. For this reason, “Test City” should be excluded from the analysis to ensure that insights are based solely on genuine and reliable data. Further exploration of the relationship between fraud rates and factors such as city population, transaction volume, or merchant density can help uncover the underlying dynamics contributing to higher fraud rates in specific cities.

Fraud Rate by Customer Age

[14]:
```
# Convert `unix_time` to datetime
merged_data['transaction_date'] = pd.to_datetime(merged_data['unix_time'],␣
 ↪unit='s')

# Calculate age based on the transaction date
merged_data['age'] = merged_data['transaction_date'] - pd.
 ↪to_datetime(merged_data['dob'])
merged_data['age'] = merged_data['age'].dt.days // 365


# Calculate fraud rate by age group
fraud_rate_by_age = merged_data.groupby('age')['is_fraud'].mean()


merged_data.drop('age', axis=1, inplace=True)
merged_data.drop('transaction_date', axis=1, inplace=True)

# Bar plot
plt.figure(figsize=(8, 6))
fraud_rate_by_age.plot(kind='bar', color='teal')
plt.title('Fraud Rate by Age', fontsize=14)
plt.xlabel('Age', fontsize=12)
plt.ylabel('Fraud Rate', fontsize=12)
plt.show()
```

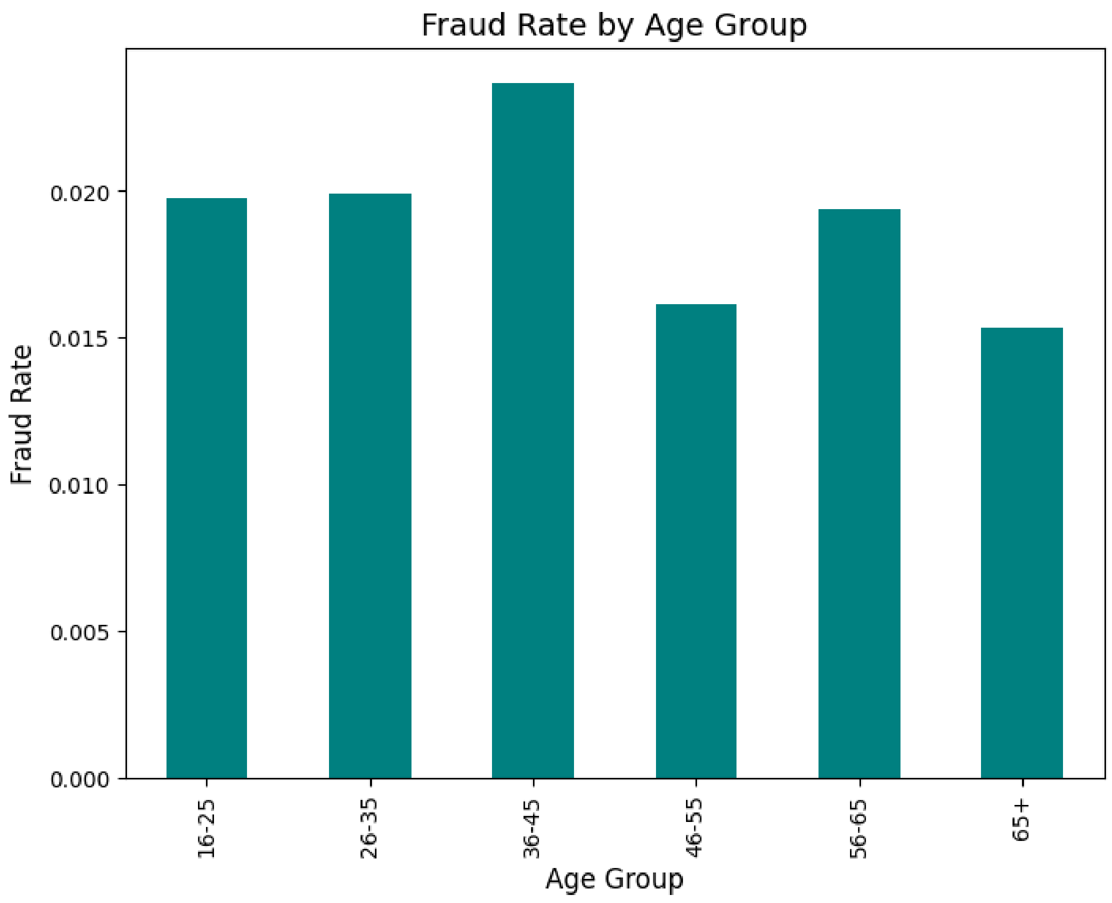


2.3.5 Fraud Rate by Customer Age Group

[15]:
```python
# Convert `unix_time` to datetime
merged_data['transaction_date'] = pd.to_datetime(merged_data['unix_time'],␣
 ↪unit='s')

# Calculate age based on the transaction date
merged_data['age'] = merged_data['transaction_date'] - pd.
 ↪to_datetime(merged_data['dob'])
merged_data['age'] = merged_data['age'].dt.days // 365

# Bin age into groups
bins = [16, 25, 35, 45, 55, 65, 100]  # Age ranges (starting at 16)
labels = ["16-25", "26-35", "36-45", "46-55", "56-65", "65+"]  # Labels for␣
 ↪each range
merged_data['age_group'] = pd.cut(merged_data['age'], bins=bins, labels=labels,␣
 ↪right=False)

merged_data['age_group'] = merged_data['age_group'].astype('category')
```

```python
# Calculate fraud rate by age group
fraud_rate_by_age = merged_data.groupby('age_group')['is_fraud'].mean()

merged_data.drop('age_group', axis=1, inplace=True)
merged_data.drop('age', axis=1, inplace=True)
merged_data.drop('transaction_date', axis=1, inplace=True)

# Bar plot
plt.figure(figsize=(8, 6))
fraud_rate_by_age.plot(kind='bar', color='teal')
plt.title('Fraud Rate by Age Group', fontsize=14)
plt.xlabel('Age Group', fontsize=12)
plt.ylabel('Fraud Rate', fontsize=12)
plt.show()
```

```
/tmp/ipykernel_12550/1159947157.py:17: FutureWarning: The default of
observed=False is deprecated and will be changed to True in a future version of
pandas. Pass observed=False to retain current behavior or observed=True to adopt
the future default and silence this warning.
  fraud_rate_by_age = merged_data.groupby('age_group')['is_fraud'].mean()
```



What was done:

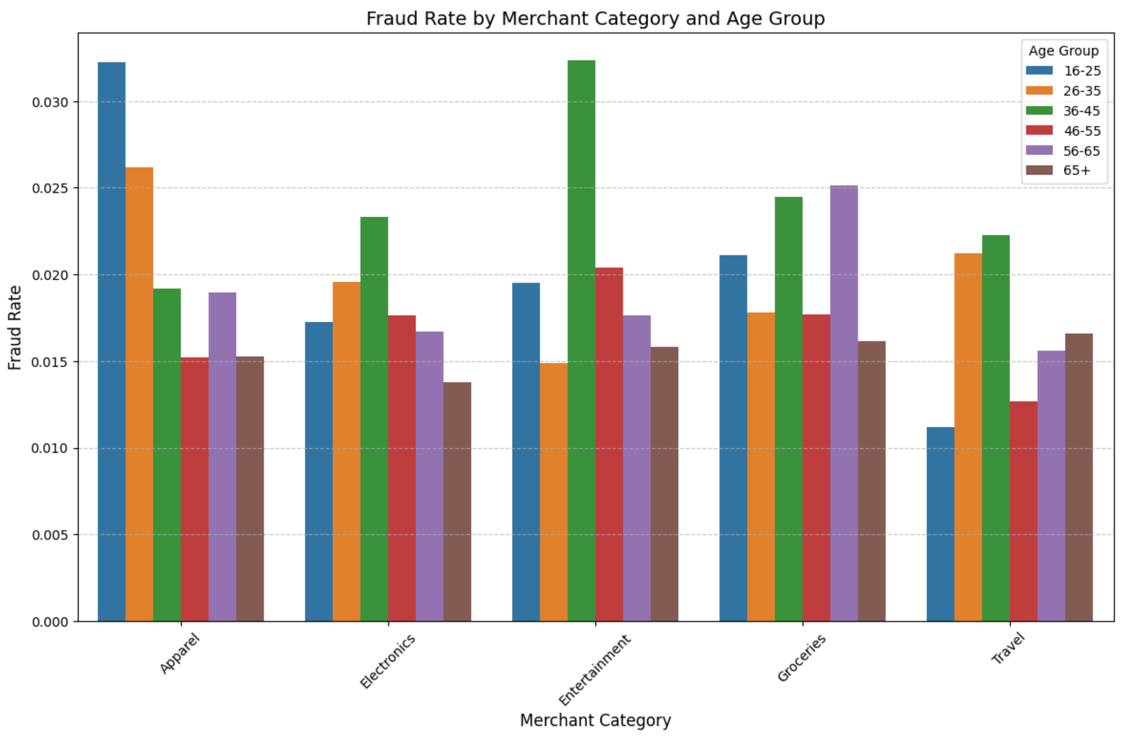
The bar chart displays the fraud rate across different age groups.

Analysis:

Fraud rates are higher among individuals aged 25-35 and 35-50, suggesting that these groups may be more frequently targeted by fraudsters or engage more in high-risk transaction behaviors. Conversely, the fraud rate is lower for individuals aged 65+, which could be due to lower transaction volumes or more cautious spending habits in this demographic. While the differences between age groups are not drastic, these insights could inform targeted fraud prevention strategies for higher-risk groups.

Fraud Rate by Merchant Category and Age Group

```
[16]: # Convert `unix_time` to datetime
merged_data['transaction_date'] = pd.to_datetime(merged_data['unix_time'],␣
 ↪unit='s')

# Calculate age based on the transaction date
merged_data['age'] = merged_data['transaction_date'] - pd.
 ↪to_datetime(merged_data['dob'])
merged_data['age'] = merged_data['age'].dt.days // 365

# Bin age into groups
bins = [16, 25, 35, 45, 55, 65, 100]  # Age ranges (starting at 16)
labels = ["16-25", "26-35", "36-45", "46-55", "56-65", "65+"]  # Labels for␣
 ↪each range
merged_data['age_group'] = pd.cut(merged_data['age'], bins=bins, labels=labels,␣
 ↪right=False)

merged_data['age_group'] = merged_data['age_group'].astype('category')


# Group data by age group and merchant category, then calculate fraud rate
fraud_rate_by_category_age = merged_data.groupby(['age_group', 'category'],␣
 ↪observed=True)['is_fraud'].mean().reset_index()

merged_data.drop('age_group', axis=1, inplace=True)
merged_data.drop('age', axis=1, inplace=True)
merged_data.drop('transaction_date', axis=1, inplace=True)

# Plot a grouped bar plot
plt.figure(figsize=(14, 8))
sns.barplot(data=fraud_rate_by_category_age, x='category', y='is_fraud',␣
 ↪hue='age_group', errorbar=None)
plt.title('Fraud Rate by Merchant Category and Age Group', fontsize=14)
plt.xlabel('Merchant Category', fontsize=12)
plt.ylabel('Fraud Rate', fontsize=12)
plt.xticks(rotation=45)
plt.legend(title='Age Group')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```



What was done:

The bar chart shows the fraud rate across merchant categories for different age groups.

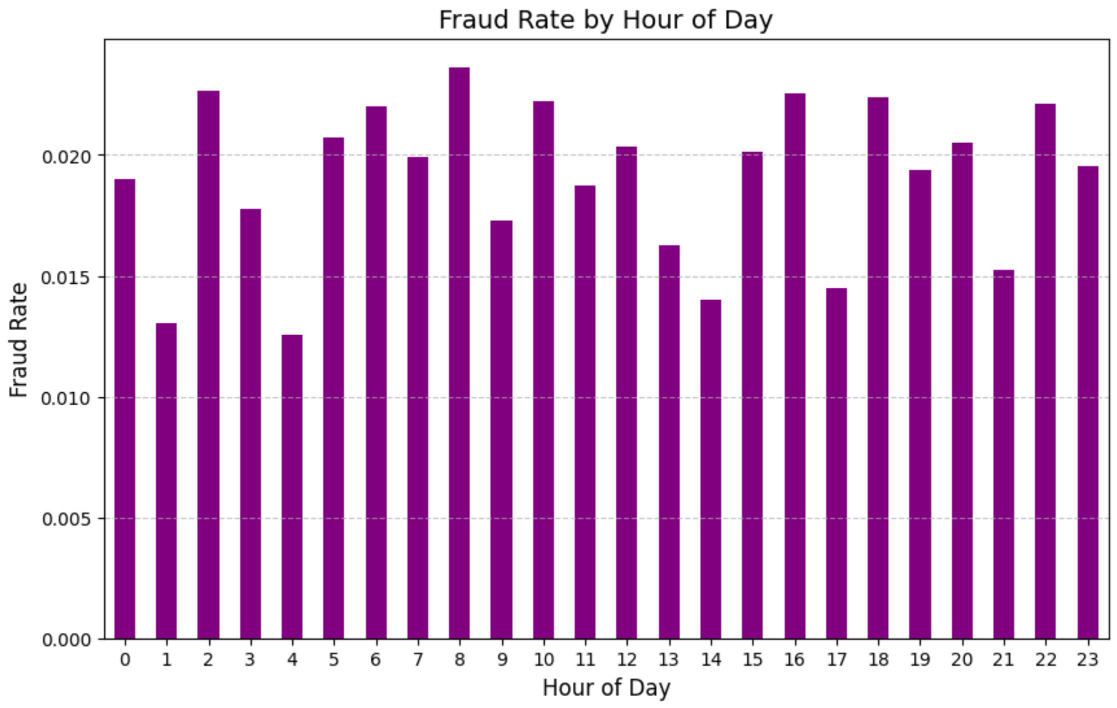
Analysis:

Younger groups (<25 and 25-35) have higher fraud rates in categories like Apparel and Travel, while middle-aged groups (35-50) show peaks in Entertainment. Older groups (65+) generally experience lower fraud rates across categories. These patterns suggest that fraudsters may target specific demographics based on category-related behaviors, such as younger individuals in Apparel and Travel or middle-aged individuals in Entertainment.

Fraud Rate by Hour of Day

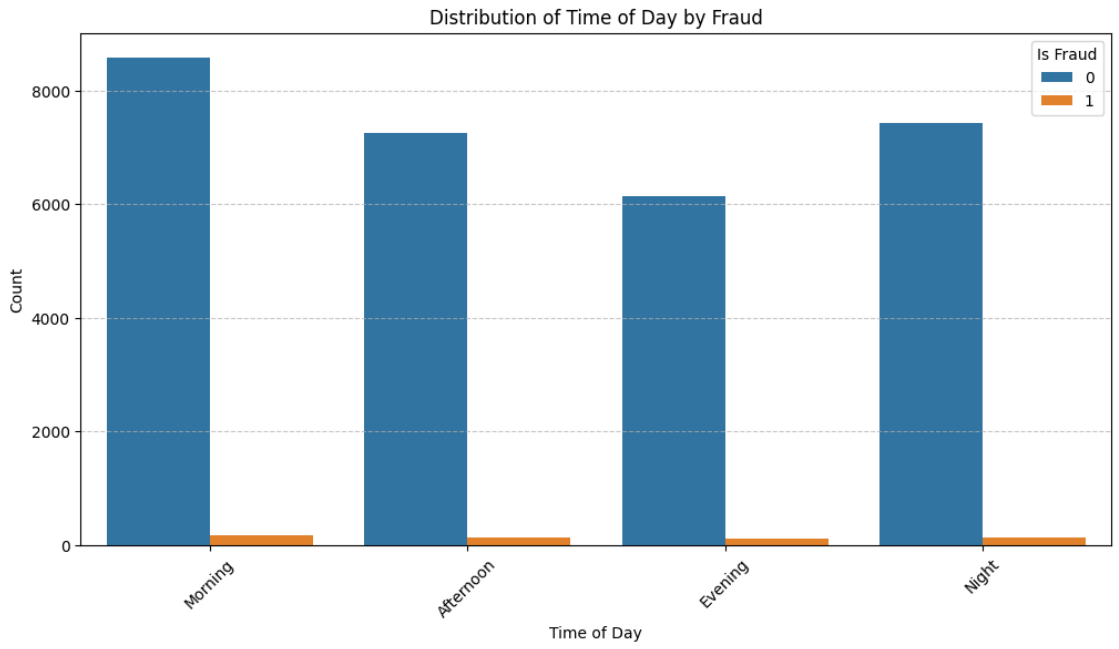
[17]:
```
# Convert Unix time to datetime and extract the hour
merged_data['hour'] = pd.to_datetime(merged_data['unix_time'], unit='s').dt.hour

# Group by hour and calculate fraud rate
fraud_rate_by_hour = merged_data.groupby('hour')['is_fraud'].mean()
```

```
merged_data.drop('hour', axis=1, inplace=True)

# Bar plot
plt.figure(figsize=(10, 6))
fraud_rate_by_hour.plot(kind='bar', color='purple')
plt.title('Fraud Rate by Hour of Day', fontsize=14)
plt.xlabel('Hour of Day', fontsize=12)
plt.ylabel('Fraud Rate', fontsize=12)
plt.xticks(rotation=0)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```



[18]:
```
def get_time_of_day(hour):
    if 5 <= hour < 12:
        return 'Morning'
    elif 12 <= hour < 18:
        return 'Afternoon'
    elif 18 <= hour < 23:
        return 'Evening'
    else:
        return 'Night'

# Convert Unix time to datetime and extract the hour
```

```
merged_data['transaction_hour'] = pd.to_datetime(merged_data['unix_time'],␣
 ↪unit='s').dt.hour

merged_data['time_of_day'] = merged_data['transaction_hour'].
 ↪apply(get_time_of_day)
# Plot da distribuição de `time_of_day` por fraude


plt.figure(figsize=(12, 6))
sns.countplot(data=merged_data, x='time_of_day', hue='is_fraud',␣
 ↪order=['Morning', 'Afternoon', 'Evening', 'Night'])
plt.title('Distribution of Time of Day by Fraud')
plt.xlabel('Time of Day')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.legend(title='Is Fraud', loc='upper right')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()


merged_data.drop('transaction_hour', axis=1, inplace=True)
merged_data.drop('time_of_day', axis=1, inplace=True)
```



Relationship Between City and Category

```
[ ]:
```

What was done:

This bar plot visualizes the fraud rate across different hours of the day. The hour was extracted from the unix_time column, and the fraud rate (is_fraud) was calculated as the mean of fraud labels for each hour. This provides insight into the temporal patterns of fraudulent activity.

Analysis:

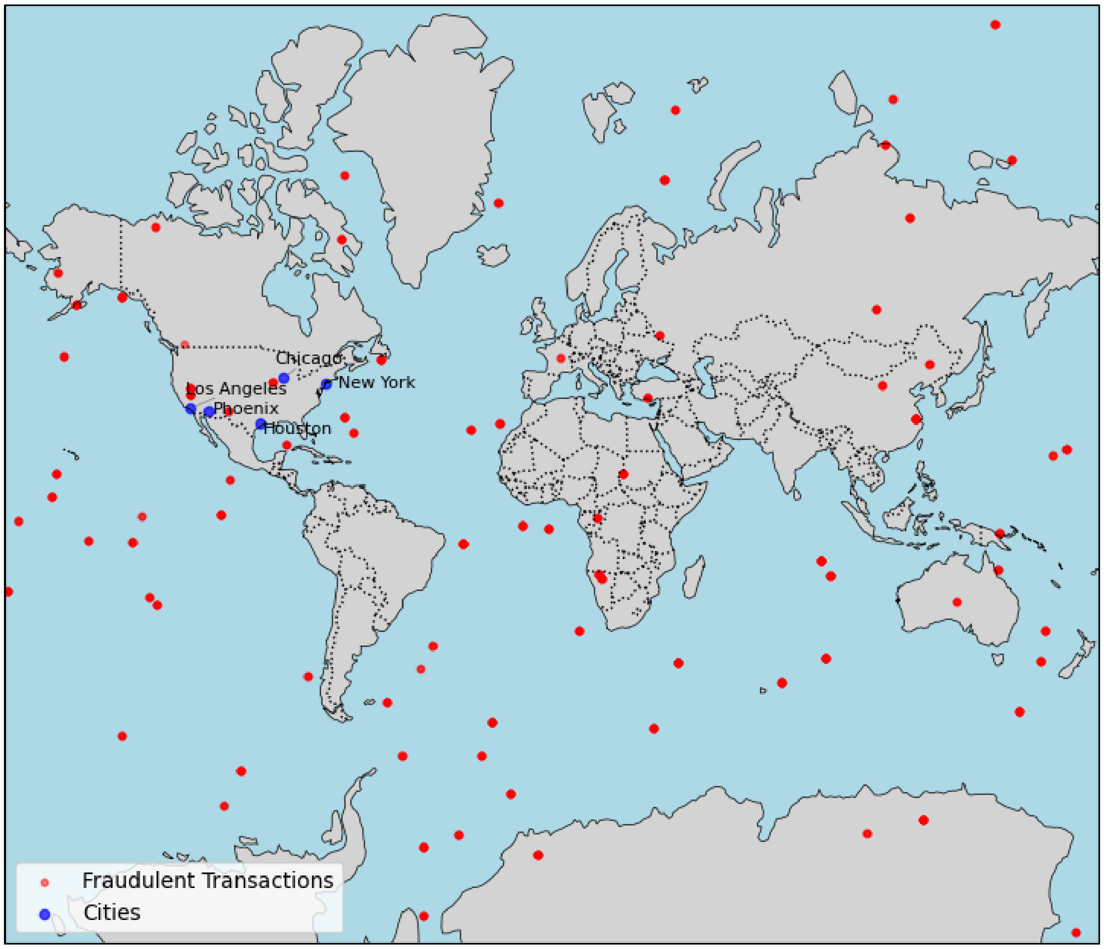
While there are peaks and dips, the fraud rate does not vary drastically across hours, suggesting that fraud occurs throughout the day with certain periods being slightly riskier.

Fraud Rate by Week

Geographic Distribution of Fraudulent Transactions and Cities

[19]:
```
# Filter fraudulent transactions
fraud_data = merged_data[merged_data['is_fraud'] == 1]

# Filter unique cities with valid coordinates
city_data_clean = merged_data[['city', 'lat', 'long']].drop_duplicates().
  ↪dropna(subset=['lat', 'long'])

# Create a figure and set up a map projection (Mercator)
fig = plt.figure(figsize=(12, 8))
ax = plt.axes(projection=ccrs.Mercator())

# Add map features
ax.add_feature(cfeature.COASTLINE, linewidth=0.5)
ax.add_feature(cfeature.BORDERS, linestyle=':')
ax.add_feature(cfeature.LAND, facecolor='lightgray')
ax.add_feature(cfeature.OCEAN, facecolor='lightblue')

# Plot fraudulent transactions as scatter points
plt.scatter(
    fraud_data['merch_long'], fraud_data['merch_lat'],
    color='red', alpha=0.5, s=10, transform=ccrs.PlateCarree(),
    label='Fraudulent Transactions'
)

# Plot city locations as blue scatter points
plt.scatter(
    city_data_clean['long'], city_data_clean['lat'],
    color='blue', alpha=0.7, s=20, transform=ccrs.PlateCarree(),
    label='Cities'
)

# Add city labels with adjustText
texts = []
for _, row in city_data_clean.iterrows():
    texts.append(plt.text(
        row['long'], row['lat'], row['city'],
        fontsize=8, transform=ccrs.PlateCarree(), color='black'
    ))
# Adjust text to avoid overlaps
adjust_text(texts, arrowprops=dict(arrowstyle="->", color='gray', lw=0.5))

# Add title and legend
plt.title('Geographic Distribution of Fraudulent Transactions and Cities',␣
 ↪fontsize=14)
plt.legend(loc='lower left', fontsize=10)

# Set extent (map boundaries) based on the data
plt.gca().set_extent([
    min(city_data_clean['long'].min(), fraud_data['merch_long'].min()) - 1,
    max(city_data_clean['long'].max(), fraud_data['merch_long'].max()) + 1,
    min(city_data_clean['lat'].min(), fraud_data['merch_lat'].min()) - 1,
    max(city_data_clean['lat'].max(), fraud_data['merch_lat'].max()) + 1
], crs=ccrs.PlateCarree())

# Show the plot
plt.show()
```

Geographic Distribution of Fraudulent Transactions and Cities



What was done:

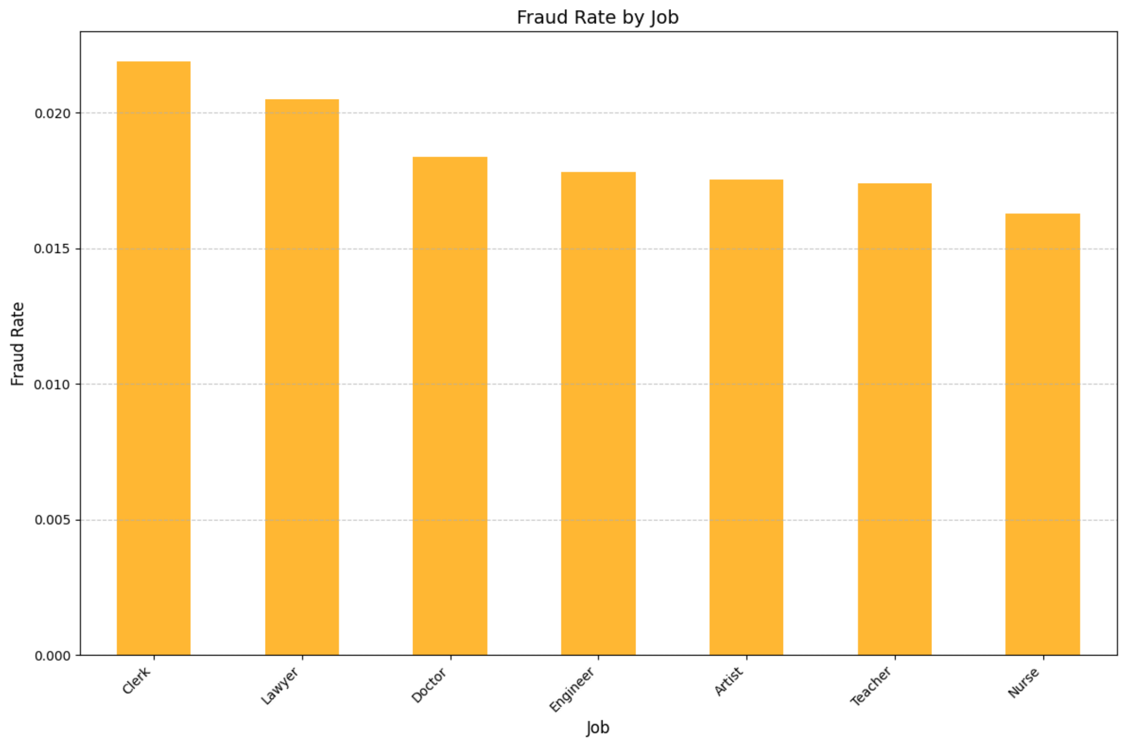
The map shows the geographic distribution of fraudulent transactions (red points) overlaid with city locations (blue points). To improve readability, city labels were dynamically adjusted using the adjustText library to avoid overlapping, with arrows indicating their original positions.

Analysis:

While some fraudulent transactions are near major urban centers like New York, Chicago, and Los Angeles, many points appear as outliers, such as those in the ocean or sparsely populated regions. This suggests that the geographic coordinates may lack strong correlation with city locations, likely due to errors or placeholders in the dataset. However, there are clusters of fraudulent transactions near certain cities that could warrant further analysis to identify potential patterns or high-risk areas.

2.3.6 Fraud Rate by Job

```
[20]: # Calculate fraud rate for each job
fraud_rate_by_job = merged_data.groupby('job')['is_fraud'].mean().
  ↪sort_values(ascending=False)

# Plot the fraud rate by job
plt.figure(figsize=(12, 8))
fraud_rate_by_job.plot(kind='bar', color='orange', alpha=0.8)
plt.title('Fraud Rate by Job', fontsize=14)
plt.xlabel('Job', fontsize=12)
plt.ylabel('Fraud Rate', fontsize=12)
plt.xticks(rotation=45, ha='right')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```



What was done:

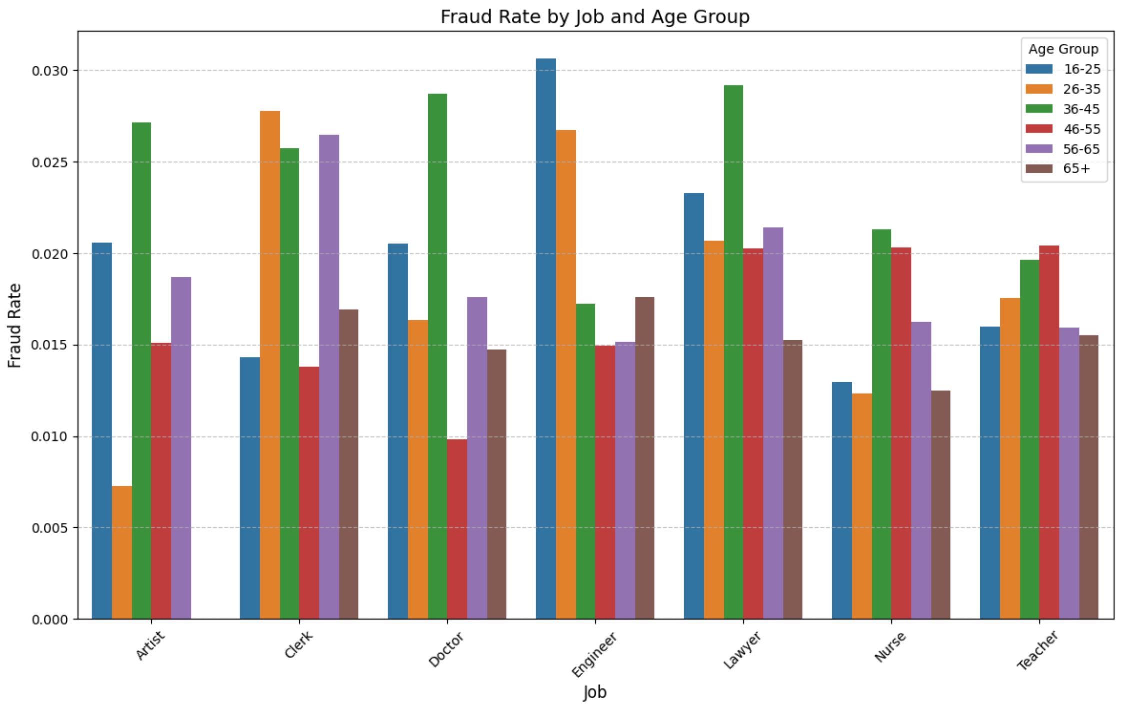
A bar chart was created to analyze the relationship between customers' jobs and the fraud rate.

Analysis:

The chart shows that certain professions, such as Clerks and Lawyers, have slightly higher fraud rates compared to other professions like Teachers and Nurses. These differences might reflect behavioral patterns, spending habits, or exposure to fraud based on the nature of the profession. The fraud rates across jobs are relatively close, indicating that job type alone may not be a strong predictor of fraud but could be considered alongside other features

2.3.7 Fraud Rate by Job and Age group

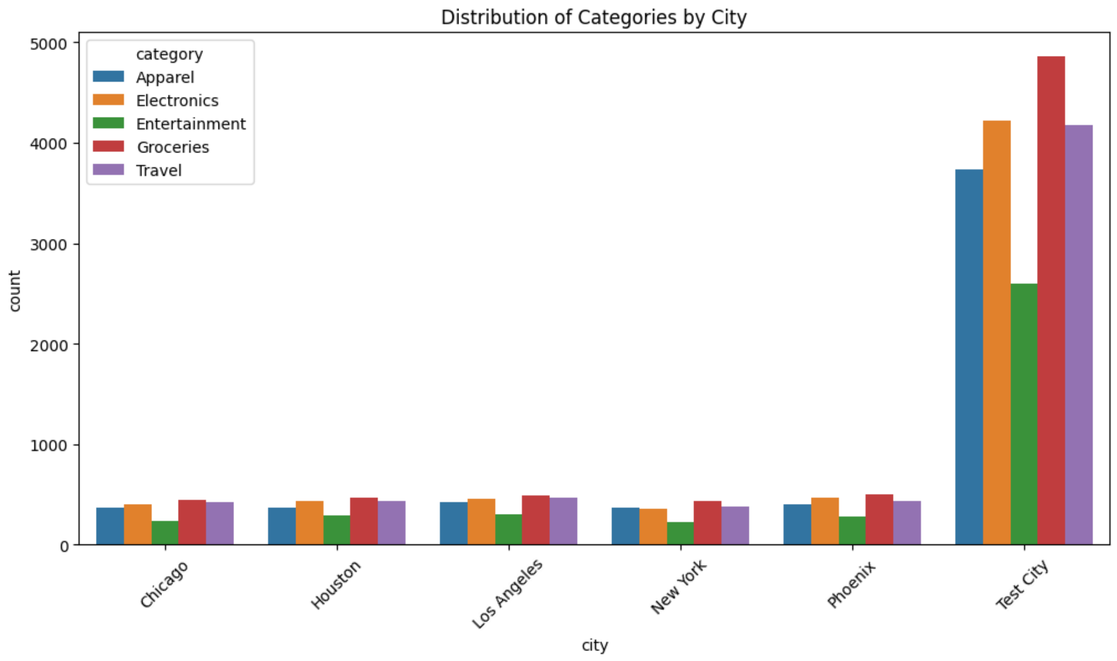
[21]:
```
# Convert `unix_time` to datetime
merged_data['transaction_date'] = pd.to_datetime(merged_data['unix_time'],␣
↪unit='s')

# Calculate age based on the transaction date
merged_data['age'] = merged_data['transaction_date'] - pd.
↪to_datetime(merged_data['dob'])
merged_data['age'] = merged_data['age'].dt.days // 365

# Bin age into groups
bins = [16, 25, 35, 45, 55, 65, 100]  # Age ranges (starting at 16)
labels = ["16-25", "26-35", "36-45", "46-55", "56-65", "65+"]  # Labels for␣
↪each range
merged_data['age_group'] = pd.cut(merged_data['age'], bins=bins, labels=labels,␣
↪right=False)

merged_data['age_group'] = merged_data['age_group'].astype('category')


# Group data by age group and job, then calculate fraud rate
fraud_rate_by_job = merged_data.groupby(['age_group', 'job'],␣
↪observed=True)['is_fraud'].mean().reset_index()

merged_data.drop('age_group', axis=1, inplace=True)
merged_data.drop('age', axis=1, inplace=True)
merged_data.drop('transaction_date', axis=1, inplace=True)

# Plot a grouped bar plot
plt.figure(figsize=(14, 8))
sns.barplot(data=fraud_rate_by_job, x='job', y='is_fraud', hue='age_group',␣
↪errorbar=None)
plt.title('Fraud Rate by Job and Age Group', fontsize=14)
plt.xlabel('Job', fontsize=12)
plt.ylabel('Fraud Rate', fontsize=12)
plt.xticks(rotation=45)
plt.legend(title='Age Group')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```



Job Distribution by Age Group

Distribution of Categories by City

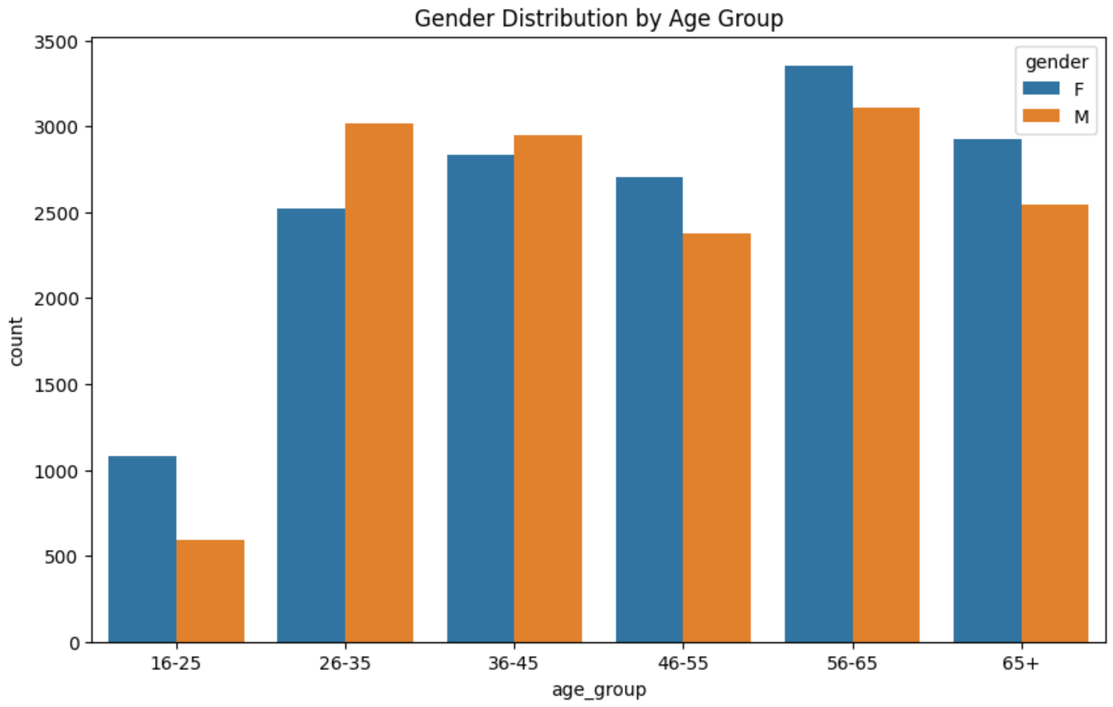
[22]:
```
category_city_count = merged_data.groupby(['city', 'category']).size().
  ↪reset_index(name='count')
plt.figure(figsize=(12, 6))
sns.barplot(data=category_city_count, x='city', y='count', hue='category')
plt.title("Distribution of Categories by City")
plt.xticks(rotation=45)
plt.show()
```



Gender Distribution by Age Group

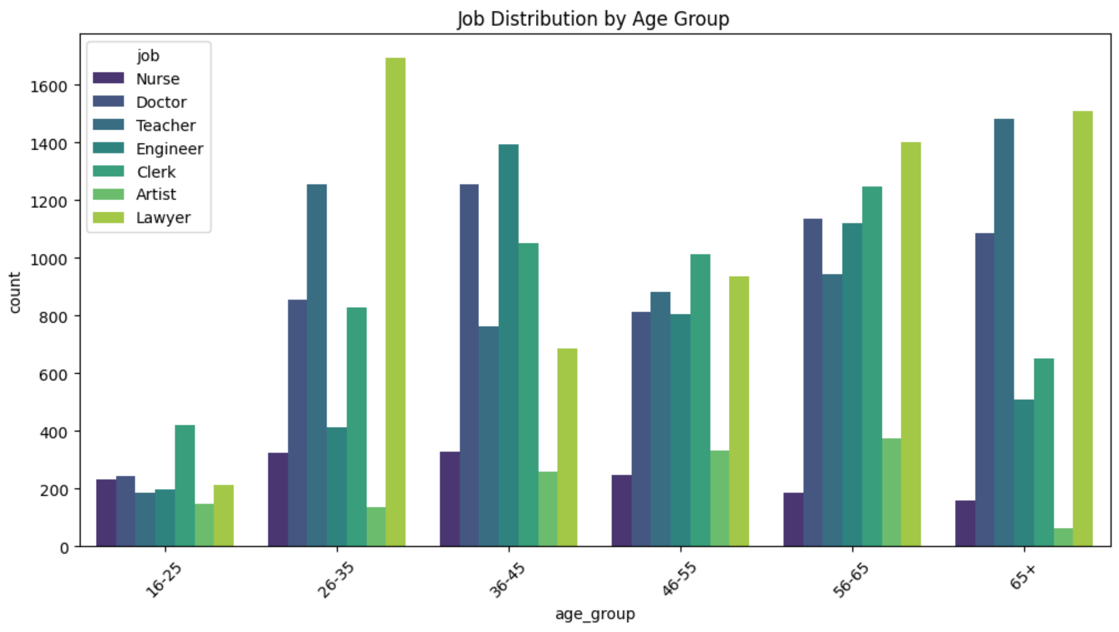
[23]:
```python
# Convert `unix_time` to datetime
merged_data['transaction_date'] = pd.to_datetime(merged_data['unix_time'],␣
 ↪unit='s')

# Calculate age based on the transaction date
merged_data['age'] = merged_data['transaction_date'] - pd.
 ↪to_datetime(merged_data['dob'])
merged_data['age'] = merged_data['age'].dt.days // 365

# Bin age into groups
bins = [16, 25, 35, 45, 55, 65, 100]  # Age ranges (starting at 16)
labels = ["16-25", "26-35", "36-45", "46-55", "56-65", "65+"]  # Labels for␣
 ↪each range
merged_data['age_group'] = pd.cut(merged_data['age'], bins=bins, labels=labels,␣
 ↪right=False)

merged_data['age_group'] = merged_data['age_group'].astype('category')

plt.figure(figsize=(10, 6))
sns.countplot(data=merged_data, x='age_group', hue='gender')
plt.title("Gender Distribution by Age Group")
plt.show()
```

```
merged_data.drop('age_group', axis=1, inplace=True)
merged_data.drop('age', axis=1, inplace=True)
merged_data.drop('transaction_date', axis=1, inplace=True)
```

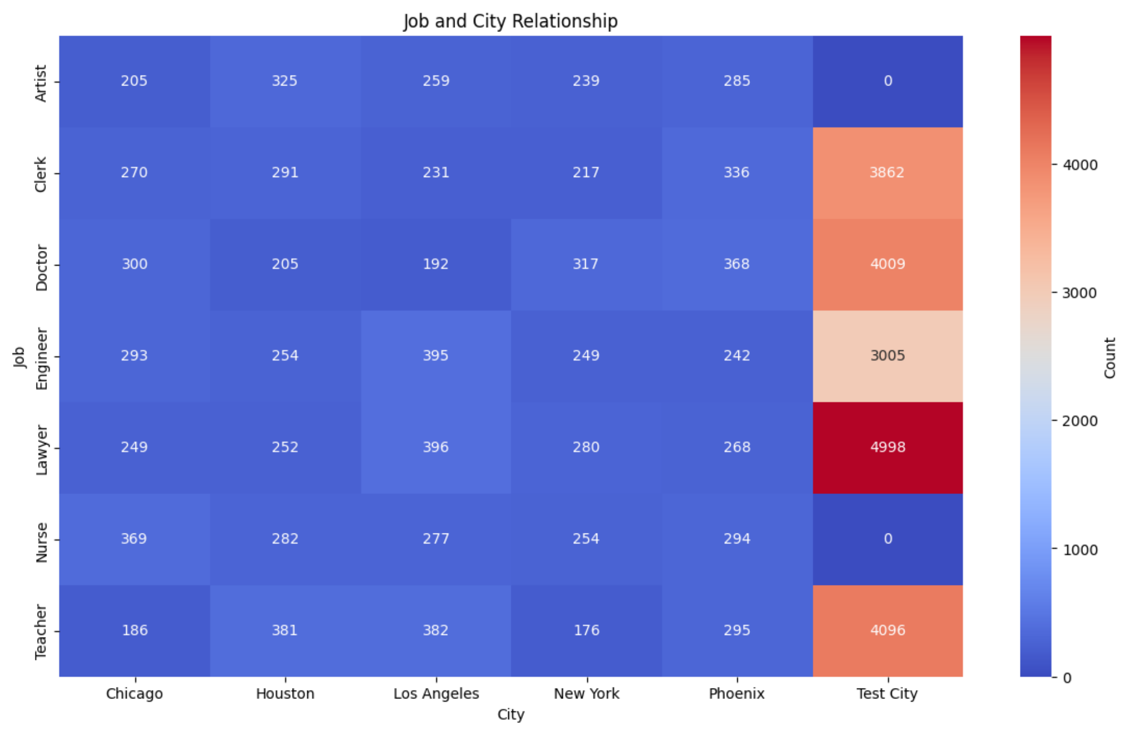


[24]:
```
# Convert `unix_time` to datetime
merged_data['transaction_date'] = pd.to_datetime(merged_data['unix_time'],␣
 ↪unit='s')

# Calculate age based on the transaction date
merged_data['age'] = merged_data['transaction_date'] - pd.
 ↪to_datetime(merged_data['dob'])
merged_data['age'] = merged_data['age'].dt.days // 365

# Bin age into groups
bins = [16, 25, 35, 45, 55, 65, 100]  # Age ranges (starting at 16)
labels = ["16-25", "26-35", "36-45", "46-55", "56-65", "65+"]  # Labels for␣
 ↪each range
merged_data['age_group'] = pd.cut(merged_data['age'], bins=bins, labels=labels,␣
 ↪right=False)

merged_data['age_group'] = merged_data['age_group'].astype('category')
```

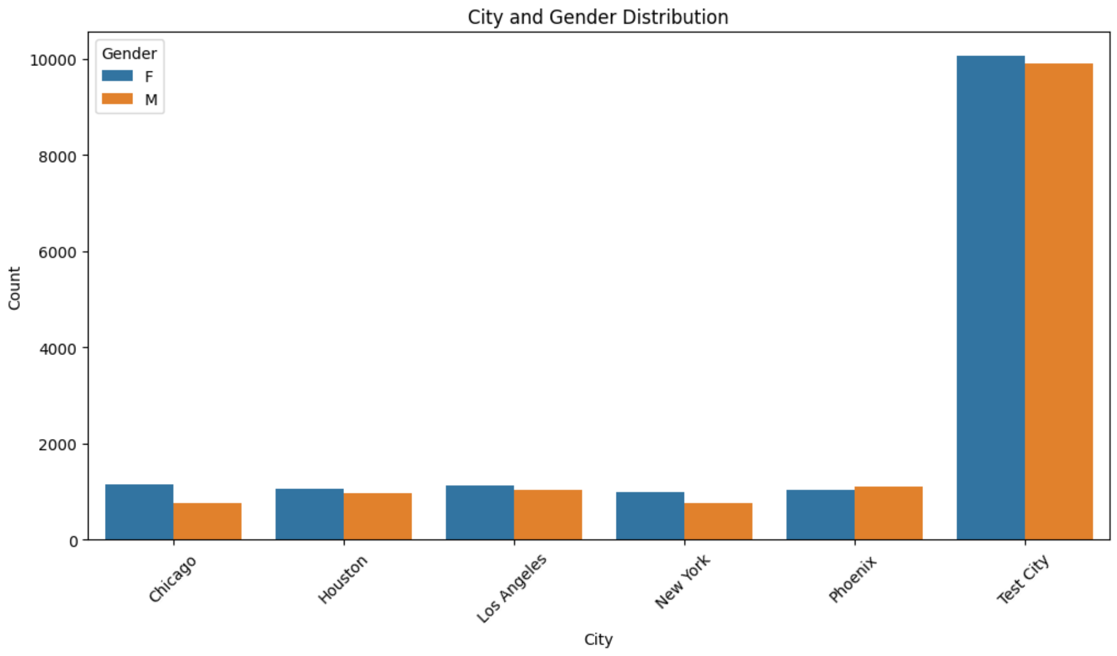
```
plt.figure(figsize=(12, 6))
sns.countplot(data=merged_data, x='age_group', hue='job', palette="viridis")
plt.title("Job Distribution by Age Group")
plt.xticks(rotation=45)
plt.show()

merged_data.drop('age_group', axis=1, inplace=True)
merged_data.drop('age', axis=1, inplace=True)
merged_data.drop('transaction_date', axis=1, inplace=True)
```



[25]:
```
job_merchant = merged_data.groupby(['job', 'city']).size().
  ↪reset_index(name='count')
pivot = job_merchant.pivot(index='job', columns='city', values='count').
  ↪fillna(0)
plt.figure(figsize=(14, 8))
sns.heatmap(pivot, annot=True, fmt=".0f", cmap="coolwarm", cbar_kws={'label':␣
  ↪'Count'})
plt.title('Job and City Relationship')
plt.xlabel('City')
plt.ylabel('Job')
plt.show()
```



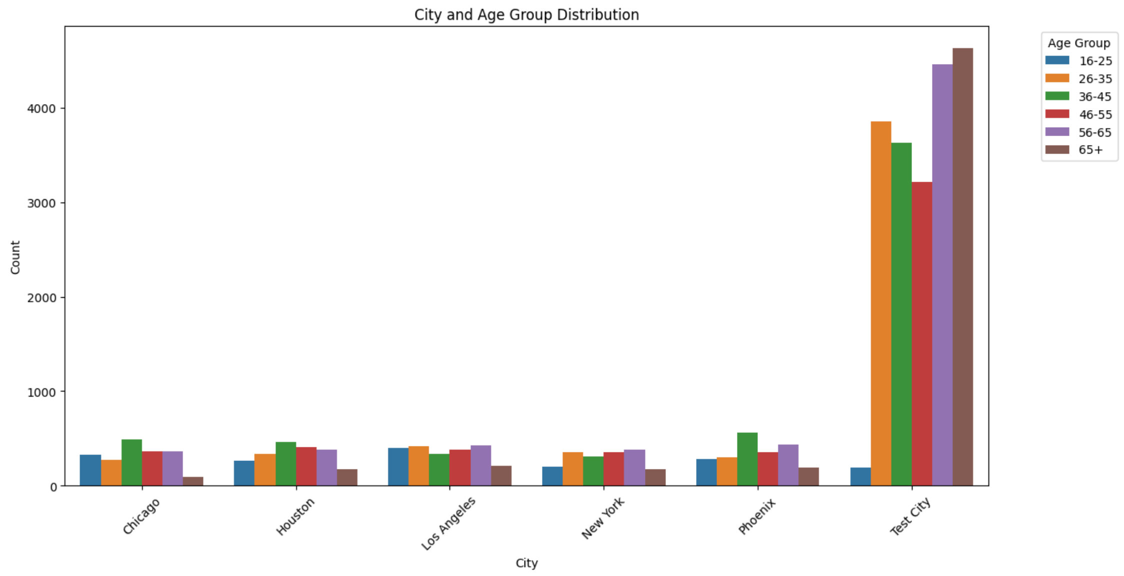
[26]:
```python
# Convert `unix_time` to datetime
merged_data['transaction_date'] = pd.to_datetime(merged_data['unix_time'],␣
  ↪unit='s')

# Calculate age based on the transaction date
merged_data['age'] = merged_data['transaction_date'] - pd.
  ↪to_datetime(merged_data['dob'])
merged_data['age'] = merged_data['age'].dt.days // 365

city_gender = merged_data.groupby(['city', 'gender']).size().
  ↪reset_index(name='count')
plt.figure(figsize=(12, 6))
sns.barplot(data=city_gender, x='city', y='count', hue='gender')
plt.title('City and Gender Distribution')
plt.xlabel('City')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.legend(title='Gender')
plt.show()
```



[27]:
```
# Bin age into groups
bins = [16, 25, 35, 45, 55, 65, 100]  # Age ranges (starting at 16)
labels = ["16-25", "26-35", "36-45", "46-55", "56-65", "65+"]  # Labels for␣
 ↪each range
merged_data['age_group'] = pd.cut(merged_data['age'], bins=bins, labels=labels,␣
 ↪right=False)

merged_data['age_group'] = merged_data['age_group'].astype('category')

city_age = merged_data.groupby(['city', 'age_group']).size().
 ↪reset_index(name='count')
plt.figure(figsize=(14, 7))
sns.barplot(data=city_age, x='city', y='count', hue='age_group', dodge=True)
plt.title('City and Age Group Distribution')
plt.xlabel('City')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.legend(title='Age Group', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.show()


merged_data.drop('age_group', axis=1, inplace=True)
merged_data.drop('age', axis=1, inplace=True)
merged_data.drop('transaction_date', axis=1, inplace=True)
```

```
/tmp/ipykernel_12550/4222894624.py:8: FutureWarning: The default of
```

```
observed=False is deprecated and will be changed to True in a future version of
pandas. Pass observed=False to retain current behavior or observed=True to adopt
the future default and silence this warning.
  city_age = merged_data.groupby(['city',
'age_group']).size().reset_index(name='count')
```



Conclusion on Data Visualization The analysis revealed several key insights about fraudulent transactions. Fraud is relatively rare in the dataset, accounting for only 1.9% of all transactions, highlighting the challenge of identifying such rare events. Geographic patterns showed clusters of fraudulent transactions near major urban centers, though significant outliers and inconsistent coordinates suggest that location data may not be highly reliable. Fraud rates varied by age group, with younger and middle-aged individuals (25-35 and 35-50) being more frequently targeted, particularly in categories like Apparel, Travel, and Entertainment. Older age groups (65+) generally experienced lower fraud rates. Certain categories, such as Travel and Entertainment, showed higher fraud activity, suggesting specific areas where fraudsters exploit vulnerabilities.

2.4 1.2- Data Preparation

Data preparation is a critical step in the machine learning pipeline, ensuring that the dataset is clean, consistent, and structured for effective modeling. This process involves handling missing values, encoding categorical variables, creating meaningful features, and addressing potential issues like class imbalance. Proper data preparation enhances the quality of the input data, reduces noise, and helps models better capture underlying patterns. In this project, the data preparation phase focuses on transforming the provided transaction data into a format suitable for building a predictive model to detect fraudulent transactions. This includes cleaning the dataset, engineering new features, scaling numerical variables, and addressing the imbalanced nature of the target variable. These steps aim to improve the accuracy and reliability of the predictive models in identifying fraud.

The data preparation process outlined below reflects the process I used for the final models, but it is important to note that this was a long and iterative journey. It required significant fine-tuning and adjustments to reach the final version. In the initial stages, I made mistakes that negatively impacted the model's performance, such as choosing inappropriate scalers, selecting variables poorly, or applying encoding techniques that did not align with the data. These errors were instrumental in the learning process, and by identifying the issues, I refined the techniques I used. In this section, I will explain the strategies I adopted to reach this version and the mistakes I made along the way.

2.4.1 1.2.1- Split Data into Train and Test Sets

[28]:
```
merged_data['is_fraud'] = merged_data['is_fraud'].astype('category') # had to␣
↪be done to run on SMOTE


X = merged_data.drop('is_fraud', axis=1)
y = merged_data['is_fraud']


X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42, stratify=y) #explicar o stratify que garante que tenha a␣
↪mesma quantidade de fraude e n fraude
```

2.4.2 1.2.2- Handle Duplicate Values

[29]:
```
# Check for duplicate transactions
print("\nDuplicate Transactions:")
print(X_train.duplicated(subset='trans_num').sum())
```

```

Duplicate Transactions:
337
```

[30]:
```
# Delete duplicate transactions
def remove_duplicates(dataframe,dataframe2):

    duplicated = dataframe[dataframe.duplicated(subset='trans_num', keep=False)]

    indices_to_keep = (
        duplicated
        .groupby('trans_num')
        .apply(lambda group: group.isnull().sum(axis=1).idxmin())  # Rows with␣
↪more NaNs
    )

    indices_to_remove = set(duplicated.index) - set(indices_to_keep)

    dataframe_cleaned = dataframe.drop(index=indices_to_remove)
    dataframe2_cleaned = dataframe2.drop(index=indices_to_remove)

    return dataframe_cleaned.reset_index(drop=True), dataframe2_cleaned.
  ↪reset_index(drop=True)

X_train, y_train = remove_duplicates(X_train,y_train)


# Check for duplicate transactions
print("\nDuplicate Transactions:")
print(X_train.duplicated(subset='trans_num').sum())
```

```
Duplicate Transactions:
0
```

```
/tmp/ipykernel_12550/3258083248.py:9: DeprecationWarning: DataFrameGroupBy.apply
operated on the grouping columns. This behavior is deprecated, and in a future
version of pandas the grouping columns will be excluded from the operation.
Either pass `include_groups=False` to exclude the groupings or explicitly select
the grouping columns after groupby to silence this warning.
  .apply(lambda group: group.isnull().sum(axis=1).idxmin())  # Rows with more
NaNs
```

2.4.3 1.2.3- Feature Engineering

[31]:
```
'''
# Convert unix_time to datetime
X_train['datetime'] = pd.to_datetime(X_train['unix_time'], unit='s')

# Extract hour, day of the week, and month
X_train['hour'] = X_train['datetime'].dt.hour
X_train['day_of_week'] = X_train['datetime'].dt.dayofweek  # 0=Monday, 6=Sunday
X_train['month'] = X_train['datetime'].dt.month

# Drop the intermediate 'datetime' column if not needed
X_train.drop('datetime', axis=1, inplace=True)


# Convert unix_time to datetime
X_test['datetime'] = pd.to_datetime(X_test['unix_time'], unit='s')

# Extract hour, day of the week, and month
X_test['hour'] = X_test['datetime'].dt.hour
X_test['day_of_week'] = X_test['datetime'].dt.dayofweek  # 0=Monday, 6=Sunday
X_test['month'] = X_test['datetime'].dt.month

# Drop the intermediate 'datetime' column if not needed
```

```
X_test.drop('datetime', axis=1, inplace=True)
'''
```

[31]:
```
"\n# Convert unix_time to datetime\nX_train['datetime'] =
pd.to_datetime(X_train['unix_time'], unit='s')\n\n# Extract hour, day of the
week, and month\nX_train['hour'] =
X_train['datetime'].dt.hour\nX_train['day_of_week'] =
X_train['datetime'].dt.dayofweek  # 0=Monday, 6=Sunday\nX_train['month'] =
X_train['datetime'].dt.month\n\n# Drop the intermediate 'datetime' column if not
needed\nX_train.drop('datetime', axis=1, inplace=True)\n\n\n# Convert unix_time
to datetime\nX_test['datetime'] = pd.to_datetime(X_test['unix_time'],
unit='s')\n\n# Extract hour, day of the week, and month\nX_test['hour'] =
X_test['datetime'].dt.hour\nX_test['day_of_week'] =
X_test['datetime'].dt.dayofweek  # 0=Monday, 6=Sunday\nX_test['month'] =
X_test['datetime'].dt.month\n\n# Drop the intermediate 'datetime' column if not
needed\nX_test.drop('datetime', axis=1, inplace=True)\n"
```

[32]:
```
#merged_data['distance'] = merged_data.apply(lambda row: geodesic((row['lat'],␣
↪row['long']), (row['merch_lat'], row['merch_long'])).km, axis=1)
```

[33]:
```
def calculate_age_and_groups(data):
   # Convert `unix_time` to datetime
    data['transaction_date'] = pd.to_datetime(data['unix_time'], unit='s')

    # Calculate age based on the transaction date
    data['age'] = data['transaction_date'] - pd.to_datetime(data['dob'])
    data['age'] = data['age'].dt.days // 365

    bins = [16, 25, 35, 45, 55, 65, 100]  # Age ranges (starting at 16)
    labels = ["16-25", "26-35", "36-45", "46-55", "56-65", "65+"]  # Labels for␣
↪each range
    data['age_group'] = pd.cut(data['age'], bins=bins, labels=labels,␣
↪right=False)

    data['age_group'] = data['age_group'].astype('object')


    return data


X_train = calculate_age_and_groups(X_train)
X_test = calculate_age_and_groups(X_test)
```

[34]:
```
def create_feature(data, new_feature, atr1, atr2):
    data[new_feature] = (
        data[atr1] + '_' + data[atr2].astype(str)
    )
```

```
create_feature(X_train,'job_age_group','job','age_group')
create_feature(X_test,'job_age_group','job','age_group')

create_feature(X_train,'category_city','category','city')
create_feature(X_test,'category_city','category','city')

X_train['transaction_hour'] = X_train['transaction_date'].dt.hour
X_test['transaction_hour'] = X_test['transaction_date'].dt.hour

X_train['hour_sin'] = np.sin(2 * np.pi * X_train['transaction_hour'] / 24)
X_train['hour_cos'] = np.cos(2 * np.pi * X_train['transaction_hour'] / 24)
X_test['hour_sin'] = np.sin(2 * np.pi * X_test['transaction_hour'] / 24)
X_test['hour_cos'] = np.cos(2 * np.pi * X_test['transaction_hour'] / 24)
```

2.4.4 1.2.4- Drop Redundant or Unnecessary Columns

Column	Reason for Removal	Expected Impact
`index`	Serves only as a transaction index, provides no informative value for prediction.	No impact on the model as it carries no predictive value.
`trans_date_trans_time`	Redundant with `unixtime`, which is more accurante because has less missing values on the original dataset .	Simplifies the dataset without losing meaningful information.
`trans_num`	Each value is unique and functions only as a transaction identifier.	No impact, as it does not contribute to fraud prediction.
`first`, `last`	Personal data irrelevant for prediction; may also violate privacy.	Improves privacy compliance and removes unnecessary variables.
`street`, `zip`	Detailed location information is not relevant; broader attributes like `city` are more useful.	Reduces unnecessary granularity.
`merchant`	Redundant with `merchant` name, which already serves as an identifier, and is already a numerical atribute	Reduces redundancy without impacting model performance.
`lat`, `long`	Latitude and longitude of cities are indirectly reflected in attributes like `city_pop` and `city`.	Simplifies the dataset, reducing dimensionality without significant information loss.
`merch_lat`, `merch_long`		
`state`		
`dob`	Created `age`	
`cc_num`		
`age`	Created `age_group`	

[35]:
```
X_train.
 ↪drop(['index','trans_num','trans_date_trans_time','zip','first','last','street','state',
                   ␣
  ↪'lat','long','merch_lat','merch_long','merchant','dob','cc_num','age','unix_time','transact
  ↪axis=1, inplace=True)

X_test.
  ↪drop(['index','trans_num','trans_date_trans_time','zip','first','last','street','state',
                   ␣
  ↪'lat','long','merch_lat','merch_long','merchant','dob','cc_num','age','unix_time','transact
  ↪axis=1, inplace=True)
```

2.4.5 1.2.5- Handle Missing Values

[36]:
```
# Check for missing values
print("\nMissing Values Train:")
print(X_train.isnull().sum())

X_train.to_csv('X_train_with_missing_values.csv', index=False)
```

```
Missing Values Train:
device_os        14107
amt                 78
gender               1
city_pop         15636
job_age_group      162
category_city      447
hour_sin             0
hour_cos             0
dtype: int64
```

[37]:
```
X_train = pd.read_csv('X_train_without_missing_values.csv')


# Check for missing values
print("\nMissing Values Train:")
print(X_train.isnull().sum())
```

```
Missing Values Train:
device_os        0
amt              0
gender           0
city_pop         0
job_age_group    0
category_city    0
hour_sin         0
hour_cos         0
dtype: int64
```

[38]:
```
print("\nMissing Values Test:")
print(X_test.isnull().sum())
```

```
Missing Values Test:
device_os         3615
amt                 21
gender               1
city_pop          4060
job_age_group       45
category_city      135
hour_sin             0
hour_cos             0
dtype: int64
```

[39]:
```
numeric_cols = X_train.select_dtypes(include=["float64", "int64"]).columns
categorical_cols = X_train.select_dtypes(include=["object"]).columns


train_means = X_train[numeric_cols].mean()


train_modes = X_train[categorical_cols].mode().iloc[0]

for col in numeric_cols:
    if col in X_test.columns:  # Garantir que a coluna exista no teste
        X_test[col] = X_test[col].fillna(train_means[col])

for col in categorical_cols:
    if col in X_test.columns:  # Garantir que a coluna exista no teste
        X_test[col] = X_test[col].fillna(train_modes[col])
"""

with open("variables/numeric_cols.pkl", "wb") as f:
    pickle.dump(numeric_cols, f)

with open("variables/categorical_cols.pkl", "wb") as f:
    pickle.dump(categorical_cols, f)

with open("variables/train_means.pkl", "wb") as f:
    pickle.dump(train_means, f)

with open("variables/train_modes.pkl", "wb") as f:
    pickle.dump(train_modes, f)
"""
print("\nMissing Values Test:")
print(X_test.isnull().sum())
```

```
Missing Values Test:
device_os        0
amt              0
gender           0
city_pop         0
job_age_group    0
category_city    0
hour_sin         0
hour_cos         0
dtype: int64
```

[40]:
```
X_train.head()
```

[40]:
```
  device_os     amt gender city_pop   job_age_group          category_city  \
0     macOS  328.06      F  2716000    Doctor_36-45      Apparel_Test City
1     other  313.53      M  2328000     Clerk_46-55  Electronics_Test City
2     other  255.81      F  2328000     Teacher_65+  Electronics_Test City
3     Linux  222.52      F  1680992    Doctor_56-65      Groceries_Phoenix
4     other  117.32      F  2328000  Engineer_56-65  Electronics_Test City

   hour_sin  hour_cos
0  0.866025 -0.500000
1  0.258819  0.965926
2  0.258819  0.965926
3 -0.707107 -0.707107
4  0.258819  0.965926
```

[41]:
```
X_test.head()
```

[41]:
```
      device_os     amt gender      city_pop job_age_group  \
24161   Windows   31.20      M  3.741345e+06  Lawyer_26-35
2107    Windows  139.18      M  3.979576e+06  Artist_46-55
27695       X11  297.05      F  3.741345e+06  Lawyer_46-55
11110   Windows  122.39      M  3.741345e+06   Clerk_46-55
28450   Windows  413.40      F  3.741345e+06 Teacher_26-35

                    category_city  hour_sin      hour_cos
24161           Apparel_Test City -0.965926 -2.588190e-01
2107      Groceries_Los Angeles  0.965926  2.588190e-01
27695            Travel_Test City -0.258819  9.659258e-01
11110            Travel_Test City -0.258819 -9.659258e-01
28450  Entertainment_Test City -1.000000 -1.836970e-16
```

2.4.6 1.2.6- Encode Categorical Variables

[42]:
```python
# One-hot encoding example

def one_hot_encoding(data):
    print("##########################")
    columns= data.select_dtypes(include=["object"]).columns.tolist()

    for column in columns:
        # Obter categorias únicas no conjunto de treino
        unique_categories = data[column].nunique()

        # Decidir sobre drop_first com base no número de categorias
        drop_first = unique_categories == 2

        print(column + ": Drop_first " + str(drop_first))

        # Aplicar get_dummies ao conjunto de treino e teste
        data = pd.get_dummies(data, columns=[column], drop_first=drop_first)

    return data

X_train = one_hot_encoding(X_train)
X_test = one_hot_encoding(X_test)

"""
X_train = X_train.rename(columns={
    'is_high_risk_age_group_0.0': 'is_high_risk_age_group_0',
    'is_high_risk_age_group_1.0': 'is_high_risk_age_group_1'
})

X_test = X_test.rename(columns={
    'is_high_risk_age_group_0.0': 'is_high_risk_age_group_0',
    'is_high_risk_age_group_1.0': 'is_high_risk_age_group_1'
})
"""
```

```
##########################

device_os: Drop_first False
gender: Drop_first True
job_age_group: Drop_first False
category_city: Drop_first False
##########################
device_os: Drop_first False
gender: Drop_first True
job_age_group: Drop_first False
category_city: Drop_first False
```

[42]:
```
"\nX_train = X_train.rename(columns={\n    'is_high_risk_age_group_0.0':
'is_high_risk_age_group_0',\n    'is_high_risk_age_group_1.0':
'is_high_risk_age_group_1'\n})\n\nX_test = X_test.rename(columns={\n
'is_high_risk_age_group_0.0': 'is_high_risk_age_group_0',\n
'is_high_risk_age_group_1.0': 'is_high_risk_age_group_1'\n})\n"
```

[43]:
```
"""
X_train.columns = X_train.columns.str.replace('[\[\]<>,]', '', regex=True)
X_test.columns = X_test.columns.str.replace('[\[\]<>,]', '', regex=True)
"""
```

```
<>:1: SyntaxWarning: invalid escape sequence '\['
<>:1: SyntaxWarning: invalid escape sequence '\['
/tmp/ipykernel_12550/2519418393.py:1: SyntaxWarning: invalid escape sequence
'\['
  """
```

[43]:
```
"\nX_train.columns = X_train.columns.str.replace('[\\[\\]<>,]', '',
regex=True)\nX_test.columns = X_test.columns.str.replace('[\\[\\]<>,]', '',
regex=True)\n"
```

[44]:
```
X_train.head()
```

[44]:
```
      amt  city_pop  hour_sin  hour_cos  device_os_Linux  device_os_Windows  \
0  328.06   2716000  0.866025 -0.500000            False              False
1  313.53   2328000  0.258819  0.965926            False              False
2  255.81   2328000  0.258819  0.965926            False              False
3  222.52   1680992 -0.707107 -0.707107             True              False
4  117.32   2328000  0.258819  0.965926            False              False

   device_os_X11  device_os_macOS  device_os_other  gender_M  …  \
0          False             True            False     False  …
1          False            False             True      True  …
2          False            False             True     False  …
3          False            False            False     False  …
4          False            False             True     False  …

   category_city_Groceries_Los Angeles  category_city_Groceries_New York  \
0                                False                             False
1                                False                             False
2                                False                             False
3                                False                             False
4                                False                             False

   category_city_Groceries_Phoenix  category_city_Groceries_Test City  \
0                            False                              False
1                            False                              False
2                            False                              False
```

```
3                             True                              False
4                            False                              False

   category_city_Travel_Chicago  category_city_Travel_Houston  \
0                         False                         False
1                         False                         False
2                         False                         False
3                         False                         False
4                         False                         False

   category_city_Travel_Los Angeles  category_city_Travel_New York  \
0                             False                          False
1                             False                          False
2                             False                          False
3                             False                          False
4                             False                          False

   category_city_Travel_Phoenix  category_city_Travel_Test City
0                         False                           False
1                         False                           False
2                         False                           False
3                         False                           False
4                         False                           False

[5 rows x 82 columns]
```

[45]:
```
X_test.head()
```

[45]:
```
          amt      city_pop  hour_sin      hour_cos  device_os_Linux  \
24161   31.20  3.741345e+06 -0.965926 -2.588190e-01            False
2107   139.18  3.979576e+06  0.965926  2.588190e-01            False
27695  297.05  3.741345e+06 -0.258819  9.659258e-01            False
11110  122.39  3.741345e+06 -0.258819 -9.659258e-01            False
28450  413.40  3.741345e+06 -1.000000 -1.836970e-16            False

       device_os_Windows  device_os_X11  device_os_macOS  device_os_other  \
24161               True          False            False            False
2107                True          False            False            False
27695              False           True            False            False
11110               True          False            False            False
28450               True          False            False            False

       gender_M  …  category_city_Groceries_Los Angeles  \
24161      True  …                                False
2107       True  …                                 True
27695     False  …                                False
11110      True  …                                False
```

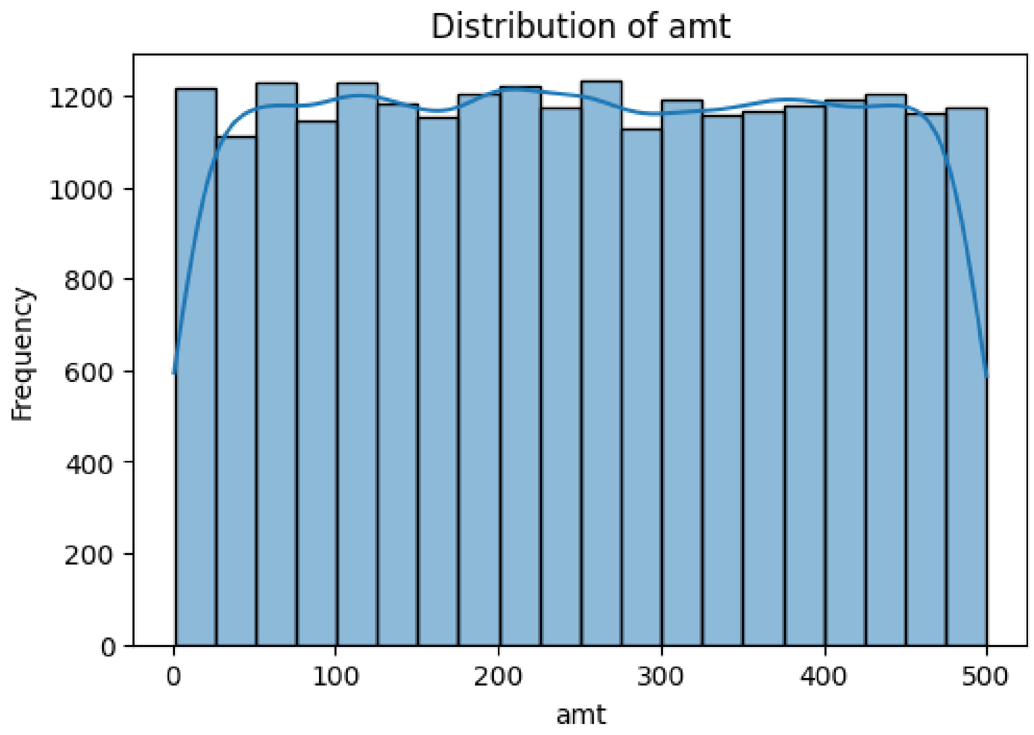
```
28450     False  …                                       False

       category_city_Groceries_New York  category_city_Groceries_Phoenix  \
24161                             False                            False
2107                              False                            False
27695                             False                            False
11110                             False                            False
28450                             False                            False

       category_city_Groceries_Test City  category_city_Travel_Chicago  \
24161                              False                         False
2107                               False                         False
27695                              False                         False
11110                              False                         False
28450                              False                         False

       category_city_Travel_Houston  category_city_Travel_Los Angeles  \
24161                         False                             False
2107                          False                             False
27695                         False                             False
11110                         False                             False
28450                         False                             False

       category_city_Travel_New York  category_city_Travel_Phoenix  \
24161                          False                         False
2107                           False                         False
27695                          False                         False
11110                          False                         False
28450                          False                         False

       category_city_Travel_Test City
24161                           False
2107                            False
27695                            True
11110                            True
28450                           False

[5 rows x 82 columns]
```

2.4.7 1.2.7- Normalize/Scale Numerical Features

Initially, I planned to use StandardScaler to standardize the data, assuming it followed a normal distribution. However, since StandardScaler performs best with normally distributed data, I decided to check the distribution of the variables using histograms.

[46]:
```
plt.figure(figsize=(6, 4))
sns.histplot(X_train['amt'], kde=True, bins=20)
```

```
plt.title(f'Distribution of {'amt'}')
plt.xlabel('amt')
plt.ylabel('Frequency')
plt.show()
```



After analyzing the plots, I realized that the data did not follow a normal distribution. Therefore, I opted for MinMaxScaler, which preserves the original shape of the data and scales the values to the range [0, 1].

[47]:
```
numerical_columns = ['amt','hour_sin', 'hour_cos','city_pop'] # Maybe add more␣
 ↪numeric collums
scaler = MinMaxScaler(feature_range=(0, 1))
X_train[numerical_columns] = scaler.fit_transform(X_train[numerical_columns])
```

[48]:
```
with open("variables/X_train.pkl", "wb") as f:
    pickle.dump(X_train, f)

with open("variables/y_train.pkl", "wb") as f:
    pickle.dump(y_train, f)

with open("variables/X_test.pkl", "wb") as f:
    pickle.dump(X_test, f)
```

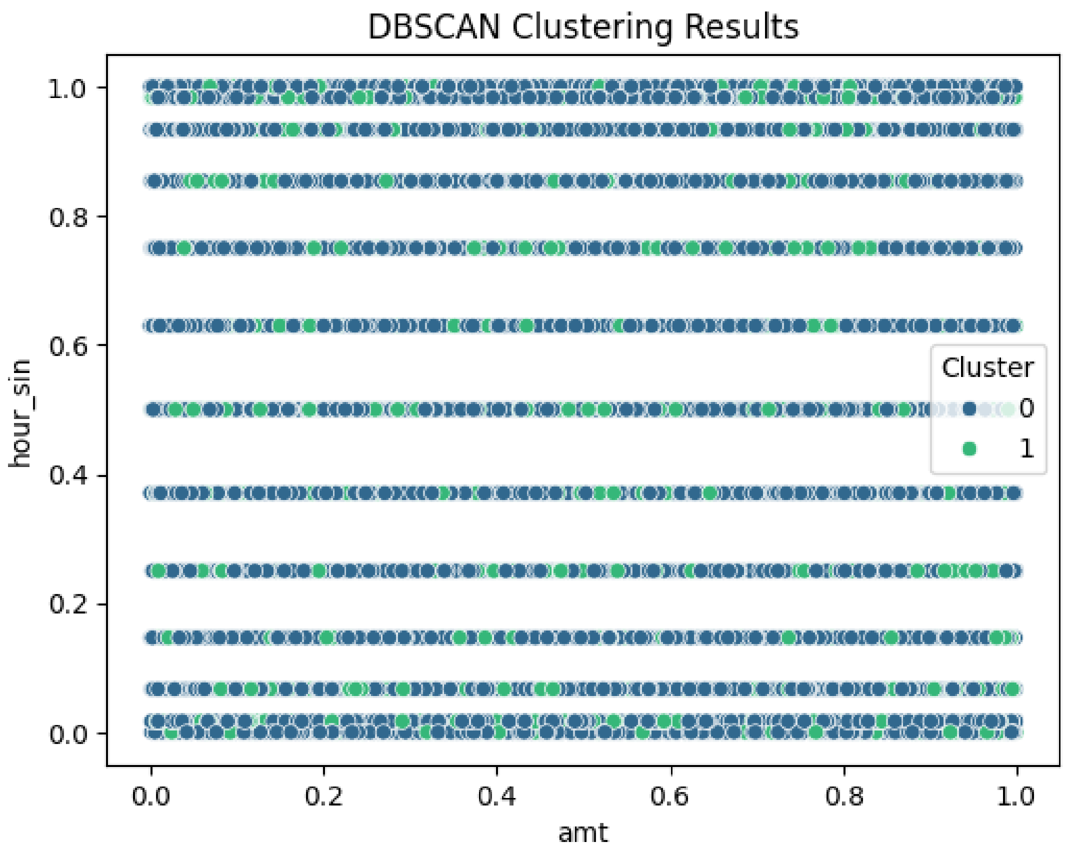
```
with open("variables/y_test.pkl", "wb") as f:
    pickle.dump(y_test, f)
```

2.5 1.3- Clustering

2.5.1 1.3.1- DBSCAN

[49]:
```
# Select numerical features for clustering
features = ['amt','hour_sin', 'hour_cos','city_pop']  # Replace with features␣
 ↪relevant to your data
data_subset = X_train[features].copy()

# Apply DBSCAN
dbscan = DBSCAN(eps=0.5, min_samples=2)  # Adjust `eps` and `min_samples` as␣
 ↪needed
clusters = dbscan.fit_predict(data_subset)

# Add cluster labels to the dataset
data_subset['cluster'] = clusters

# Check the number of clusters in DBSCAN
n_clusters_dbscan = len(set(clusters)) - (1 if -1 in clusters else 0)
print(f"DBSCAN identified {n_clusters_dbscan} clusters (excluding noise).")

# Plot the DBSCAN results
sns.scatterplot(x=data_subset[features[0]], y=data_subset[features[1]],␣
 ↪hue=data_subset['cluster'], palette='viridis')
plt.title("DBSCAN Clustering Results")
plt.xlabel(features[0])
plt.ylabel(features[1])
plt.legend(title='Cluster')
plt.show()

# 5. Evaluate Clusters
# Silhouette Score for DBSCAN (excluding noise)
dbscan_silhouette = silhouette_score(data_subset[clusters != -1],␣
 ↪clusters[clusters != -1]) if n_clusters_dbscan > 1 else "N/A"
print(f"Silhouette Score for DBSCAN (excluding noise): {dbscan_silhouette}")
```

```
DBSCAN identified 2 clusters (excluding noise).
```



```
Silhouette Score for DBSCAN (excluding noise): 0.49357258398912124
```

2.5.2 1.3.2- K-Means

[50]:
```
"""
features = ['amt','hour_sin', 'hour_cos','city_pop']  # Replace with features␣
↪relevant to your data
X_temp = X_train[features].copy()

# Test different numbers of clusters (k)
k_range = range(2, 10)
kmeans_results = {}
for k in k_range:
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(X_temp)
    labels = kmeans.labels_
    silhouette_avg = silhouette_score(X_temp, labels)
    kmeans_results[k] = silhouette_avg

# Select the best k (highest silhouette score)
```

```
best_k = max(kmeans_results, key=kmeans_results.get)
print(f"Best k for K-Means: {best_k}, Silhouette Score:␣
↪{kmeans_results[best_k]}")

kmeans = KMeans(n_clusters=best_k, random_state=42)
kmeans_labels = kmeans.fit_predict(X_temp)
X_temp['kmeans_cluster'] = kmeans_labels

# Plot the K-Means results
sns.scatterplot(x=X_temp[features[0]], y=X_temp[features[1]],␣
↪hue=kmeans_labels, palette='viridis')
plt.title("K-Means Clustering Results")
plt.xlabel(features[0])
plt.ylabel(features[1])
plt.legend(title='Cluster')
plt.show()
"""
```

[50]:
```
'\nfeatures = [\'amt\',\'hour_sin\', \'hour_cos\',\'city_pop\']  # Replace with
features relevant to your data\nX_temp = X_train[features].copy()\n\n# Test
different numbers of clusters (k)\nk_range = range(2, 10)\nkmeans_results =
{}\nfor k in k_range:\n    kmeans = KMeans(n_clusters=k, random_state=42)\n
kmeans.fit(X_temp)\n    labels = kmeans.labels_\n    silhouette_avg =
silhouette_score(X_temp, labels)\n    kmeans_results[k] = silhouette_avg\n\n#
Select the best k (highest silhouette score)\nbest_k = max(kmeans_results,
key=kmeans_results.get)\nprint(f"Best k for K-Means: {best_k}, Silhouette Score:
{kmeans_results[best_k]}")\n\nkmeans = KMeans(n_clusters=best_k,
random_state=42)\nkmeans_labels =
kmeans.fit_predict(X_temp)\nX_temp[\'kmeans_cluster\'] = kmeans_labels\n\n# Plot
the K-Means results\nsns.scatterplot(x=X_temp[features[0]],
y=X_temp[features[1]], hue=kmeans_labels,
palette=\'viridis\')\nplt.title("K-Means Clustering Results")\nplt.xlabel(featur
es[0])\nplt.ylabel(features[1])\nplt.legend(title=\'Cluster\')\nplt.show()\n'
```

2.6 1.4- Kaggle dataset preparation

[51]:
```
transactions = pd.read_csv('kaggle-data/test_transactions.csv')
merchants = pd.read_csv('kaggle-data/CreditCardTransactions/
↪CreditCardTransactions/merchants.csv')
customers = pd.read_csv('kaggle-data/CreditCardTransactions/
↪CreditCardTransactions/customers.csv')
cities = pd.read_csv('kaggle-data/CreditCardTransactions/CreditCardTransactions/
↪cities.csv')

# Merge the .csv files into one
kaggle_data = pd.merge(transactions, customers, on='cc_num', how='left')
kaggle_data = pd.merge(kaggle_data, merchants, on='merchant', how='left')
kaggle_data = pd.merge(kaggle_data, cities, on='city', how='left')

kaggle_data['index'] = kaggle_data['index'].astype('object')
kaggle_data['cc_num'] = kaggle_data['cc_num'].astype('object')
kaggle_data['zip'] = kaggle_data['zip'].astype('object')
kaggle_data['merchant_id'] = kaggle_data['merchant_id'].astype('object')


#kaggle_data = pd.read_csv('kaggle-data/test_transactions.csv')

#kaggle_data['amt'] = kaggle_data['amt'].fillna(kaggle_data['amt'].mean())
```

[52]:
```
kaggle_data = calculate_age_and_groups(kaggle_data)
```

[53]:
```
create_feature(kaggle_data,'job_age_group','job','age_group')

create_feature(kaggle_data,'category_city','category','city')


kaggle_data['transaction_hour'] =  kaggle_data['transaction_date'].dt.hour



kaggle_data['hour_sin'] = np.sin(2 * np.pi * kaggle_data['transaction_hour'] /␣
  ↪24)
kaggle_data['hour_cos'] = np.cos(2 * np.pi *  kaggle_data['transaction_hour'] /␣
  ↪24)
```

[54]:
```
index_mapping = kaggle_data['index'].values

kaggle_data.
  ↪drop(['index','trans_num','trans_date_trans_time','zip','first','last','street','state',
                  ␣
  ↪'lat','long','merch_lat','merch_long','merchant','dob','cc_num','city','age','unix_time','t
  ↪axis=1, inplace=True)
```

[55]:
```
"""
with open("variables/numeric_cols.pkl", "rb") as f:
    numeric_cols = pickle.load(f)

with open("variables/categorical_cols.pkl", "rb") as f:
    categorical_cols = pickle.load(f)

with open("variables/train_means.pkl", "rb") as f:
    train_means = pickle.load(f)

with open("variables/train_modes.pkl", "rb") as f:
    train_modes = pickle.load(f)
"""

for col in numeric_cols:
    if col in kaggle_data.columns:
        kaggle_data[col] = kaggle_data[col].fillna(train_means[col])

for col in categorical_cols:
    if col in kaggle_data.columns:
        kaggle_data[col] = kaggle_data[col].fillna(train_modes[col])
```

[56]:
```
'''
# Assuming `filtered_data` is your DataFrame with missing values
data = kaggle_data.copy()

# Convert categorical variables to numerical while preserving NaN
categorical_cols = data.select_dtypes(include=['object']).columns
label_encoders = {}

for col in categorical_cols:
    le = LabelEncoder()
    # Temporarily replace NaN with a placeholder (-1)
    data[col] = data[col].fillna('Missing')
    # Encode the categorical values
    data[col] = le.fit_transform(data[col])
    label_encoders[col] = le
    # Restore NaN in the data where 'Missing' was encoded
    if col == 'device_os':
        data[col] = data[col].replace(le.transform(['Missing'])[0], np.nan)

# Print the dataset before imputation
print("Data Before Imputation:\n", data)

# Create an object for KNNImputer and apply it to the data
imputer = KNNImputer(n_neighbors=2)
imputed_data = imputer.fit_transform(data)

# Convert the imputed data back to a DataFrame
imputed_data = pd.DataFrame(imputed_data, columns=data.columns)

# Convert the numerical columns for categorical variables back to original␣
↪labels
for col in categorical_cols:
    le = label_encoders[col]
    imputed_data[col] = imputed_data[col].round().astype(int)  # Ensure␣
↪integers before decoding
    imputed_data[col] = le.inverse_transform(imputed_data[col])
```

```
# Print the dataset after imputation
print("\n\nData After Imputation:\n", imputed_data)

# Check for remaining missing values
print("\nRemaining Missing Values:\n", imputed_data.isna().sum())
'''
```

[56]:
```
'\n# Assuming `filtered_data` is your DataFrame with missing values\ndata =
kaggle_data.copy()\n\n# Convert categorical variables to numerical while
preserving NaN\ncategorical_cols =
data.select_dtypes(include=[\'object\']).columns\nlabel_encoders = {}\n\nfor col
in categorical_cols:\n    le = LabelEncoder()\n    # Temporarily replace NaN
with a placeholder (-1)\n    data[col] = data[col].fillna(\'Missing\')\n    #
Encode the categorical values\n    data[col] = le.fit_transform(data[col])\n
label_encoders[col] = le\n    # Restore NaN in the data where \'Missing\' was
encoded\n    if col == \'device_os\':\n        data[col] =
data[col].replace(le.transform([\'Missing\'])[0], np.nan)\n\n# Print the dataset
before imputation\nprint("Data Before Imputation:\n", data)\n\n# Create an
object for KNNImputer and apply it to the data\nimputer =
KNNImputer(n_neighbors=2)\nimputed_data = imputer.fit_transform(data)\n\n#
Convert the imputed data back to a DataFrame\nimputed_data =
pd.DataFrame(imputed_data, columns=data.columns)\n\n# Convert the numerical
columns for categorical variables back to original labels\nfor col in
categorical_cols:\n    le = label_encoders[col]\n    imputed_data[col] =
imputed_data[col].round().astype(int)  # Ensure integers before decoding\n
imputed_data[col] = le.inverse_transform(imputed_data[col])\n\n# Print the
dataset after imputation\nprint("\n\nData After Imputation:\n",
imputed_data)\n\n# Check for remaining missing values\nprint("\nRemaining
Missing Values:\n", imputed_data.isna().sum())\n'
```

[57]:
```
kaggle_data = one_hot_encoding(kaggle_data)


kaggle_data.insert(4,'device_os_Linux',False)

# NOTE: I had to rename the macOs device from the "test_transactions" to macOS␣
 ↪to be the same as the trained model
```

```
##########################
device_os: Drop_first False
gender: Drop_first True
job_age_group: Drop_first False
category_city: Drop_first False
```

[58]:
```
kaggle_data.head()
```

```
[58]:          amt   city_pop  hour_sin  hour_cos  device_os_Linux  \
      0  237.193397  3979576.0       0.0       1.0            False
      1  111.790842  3979576.0       0.0       1.0            False
      2  263.236625  2716000.0       0.0       1.0            False
      3  355.424471  1680992.0       0.0       1.0            False
      4  252.471612  3979576.0       0.0       1.0            False

         device_os_Windows  device_os_X11  device_os_macOS  device_os_other  \
      0               True          False            False            False
      1               True          False            False            False
      2              False           True            False            False
      3              False          False            False             True
      4              False          False             True            False

         gender_M  …  category_city_Groceries_Los Angeles  \
      0     False  …                                False
      1     False  …                                False
      2      True  …                                False
      3     False  …                                False
      4      True  …                                False

         category_city_Groceries_New York  category_city_Groceries_Phoenix  \
      0                             False                            False
      1                             False                            False
      2                             False                            False
      3                             False                             True
      4                             False                            False

         category_city_Groceries_Test City  category_city_Travel_Chicago  \
      0                              False                         False
      1                              False                         False
      2                              False                         False
      3                              False                         False
      4                              False                         False

         category_city_Travel_Houston  category_city_Travel_Los Angeles  \
      0                         False                             False
      1                         False                              True
      2                         False                             False
      3                         False                             False
      4                         False                             False

         category_city_Travel_New York  category_city_Travel_Phoenix  \
      0                          False                         False
      1                          False                         False
      2                          False                         False
      3                          False                         False
```

```
4                          False                         False

   category_city_Travel_Test City
0                           False
1                           False
2                           False
3                           False
4                           False

[5 rows x 82 columns]
```

[59]:
```
with open("variables/kaggle_data.pkl", "wb") as f:
    pickle.dump(kaggle_data, f)

with open("variables/index_mapping.pkl", "wb") as f:
    pickle.dump(index_mapping, f)
```