credit-card-transactions-behavioral-analysis-and-random-forest-classifier

August 7, 2025

0.0.1 A. Data Preparation and Data Exploration Analysis

1. Load dataset

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

[2]:
```
# Load the dataset
chunk_size = 100000
chunks = pd.read_csv('credit_card_transactions.csv', chunksize = chunk_size)
transactions_df = pd.concat(chunks, ignore_index = True)
```

[3]:
```
# Data information
print(transactions_df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1296675 entries, 0 to 1296674
Data columns (total 24 columns):
 #   Column                 Non-Null Count    Dtype
---  ------                 --------------    -----
 0   Unnamed: 0             1296675 non-null  int64
 1   trans_date_trans_time  1296675 non-null  object
 2   cc_num                 1296675 non-null  int64
 3   merchant               1296675 non-null  object
 4   category               1296675 non-null  object
 5   amt                    1296675 non-null  float64
 6   first                  1296675 non-null  object
 7   last                   1296675 non-null  object
 8   gender                 1296675 non-null  object
 9   street                 1296675 non-null  object
 10  city                   1296675 non-null  object
 11  state                  1296675 non-null  object
 12  zip                    1296675 non-null  int64
 13  lat                    1296675 non-null  float64
```

```
 14  long                   1296675 non-null  float64
 15  city_pop               1296675 non-null  int64
 16  job                    1296675 non-null  object
 17  dob                    1296675 non-null  object
 18  trans_num              1296675 non-null  object
 19  unix_time              1296675 non-null  int64
 20  merch_lat              1296675 non-null  float64
 21  merch_long             1296675 non-null  float64
 22  is_fraud               1296675 non-null  int64
 23  merch_zipcode          1100702 non-null  float64
dtypes: float64(6), int64(6), object(12)
memory usage: 237.4+ MB
None
```

- trans_date_trans_time is the data and time of the transactions
- cc_num is the credit card number
- merchant is the merchant name or store name where the transaction occurred
- category is the category of the transaction (e.g., groceries, electronics)
- amt is the transaction amount
- first and last are the first and last names of the cardholder
- gender is the gender of the cardholder
- street is the street address of the cardholder
- city is the city of the cardholder
- state is the state of the cardholder
- zip is the zip code of the cardholder
- lat and long are the latitude and longitude of the merchant location (geographic coordinates of the transaction)
- city_pop is the population of the city where the transaction occurred
- job is the job title of the cardholder
- dob is the date of birth of the cardholder
- trans_num is the transaction number
- unix_time is the Unix timestamp of the transaction
- merch_lat and merch_long are the latitude and longitude of the merchant location
- is_fraud indicates whether the transaction is fraudulent (1) or not (0)
- merch_zipcode is the zip code of the merchant location

[4]:
```python
# First five rows of the dataset
transactions_df.head()
```

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

                              merchant       category     amt      first  \
0           fraud_Rippin, Kub and Mann       misc_net    4.97   Jennifer
```

```
1     fraud_Heller, Gutmann and Zieme    grocery_pos  107.23  Stephanie
2                fraud_Lind-Buckridge  entertainment  220.11     Edward
3  fraud_Kutch, Hermiston and Farrell  gas_transport   45.00     Jeremy
4                 fraud_Keeling-Crist       misc_pos   41.96      Tyler

      last gender                       street  ...      long city_pop  \
0    Banks      F               561 Perry Cove  ...  -81.1781     3495
1     Gill      F  43039 Riley Greens Suite 393  ... -118.2105      149
2  Sanchez      M      594 White Dale Suite 530  ... -112.2620     4154
3    White      M   9443 Cynthia Court Apt. 038  ... -112.1138     1939
4   Garcia      M              408 Bradley Rest  ...  -79.4629       99

                                 job         dob  \
0          Psychologist, counselling  1988-03-09
1  Special educational needs teacher  1978-06-21
2        Nature conservation officer  1962-01-19
3                    Patent attorney  1967-01-12
4     Dance movement psychotherapist  1986-03-28

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

  is_fraud  merch_zipcode
0        0        28705.0
1        0            NaN
2        0        83236.0
3        0            NaN
4        0        22844.0

[5 rows x 24 columns]
```

[5]:
```python
# Check for missing values
print(transactions_df.isna().sum())
```

```
Unnamed: 0                   0
trans_date_trans_time        0
cc_num                       0
merchant                     0
category                     0
amt                          0
first                        0
last                         0
gender                       0
street                       0
```

```
city                          0
state                         0
zip                           0
lat                           0
long                          0
city_pop                      0
job                           0
dob                           0
trans_num                     0
unix_time                     0
merch_lat                     0
merch_long                    0
is_fraud                      0
merch_zipcode            195973
dtype: int64
```

[6]:

```
# Percentage of missing values
missing_percentage = transactions_df.isna().mean() * 100
print(missing_percentage)
```

```
Unnamed: 0                0.000000
trans_date_trans_time     0.000000
cc_num                    0.000000
merchant                  0.000000
category                  0.000000
amt                       0.000000
first                     0.000000
last                      0.000000
gender                    0.000000
street                    0.000000
city                      0.000000
state                     0.000000
zip                       0.000000
lat                       0.000000
long                      0.000000
city_pop                  0.000000
job                       0.000000
dob                       0.000000
trans_num                 0.000000
unix_time                 0.000000
merch_lat                 0.000000
merch_long                0.000000
is_fraud                  0.000000
merch_zipcode            15.113502
dtype: float64
```

2. Data Cleaning

[7]:
```python
# merch_zipcode missing 15.11% values, and we have merch_long and merch_lat, so␣
↪we can drop this column
# Unnamed: 0 is just an index column, so we can drop it as well
# 'first' and 'last' columns are name and surname of the cardholder, which are␣
↪not useful for analysis
transactions_df.drop(columns = ['merch_zipcode', 'Unnamed: 0', 'first',␣
↪'last'], inplace = True)
```

[8]:
```python
# Check the update after drpping columns
transactions_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1296675 entries, 0 to 1296674
Data columns (total 20 columns):
 #   Column                 Non-Null Count    Dtype
---  ------                 --------------    -----
 0   trans_date_trans_time  1296675 non-null  object
 1   cc_num                 1296675 non-null  int64
 2   merchant               1296675 non-null  object
 3   category               1296675 non-null  object
 4   amt                    1296675 non-null  float64
 5   gender                 1296675 non-null  object
 6   street                 1296675 non-null  object
 7   city                   1296675 non-null  object
 8   state                  1296675 non-null  object
 9   zip                    1296675 non-null  int64
 10  lat                    1296675 non-null  float64
 11  long                   1296675 non-null  float64
 12  city_pop               1296675 non-null  int64
 13  job                    1296675 non-null  object
 14  dob                    1296675 non-null  object
 15  trans_num              1296675 non-null  object
 16  unix_time              1296675 non-null  int64
 17  merch_lat              1296675 non-null  float64
 18  merch_long             1296675 non-null  float64
 19  is_fraud               1296675 non-null  int64
dtypes: float64(5), int64(5), object(10)
memory usage: 197.9+ MB
```

[9]:
```python
# Covert trans_data_tras_time to datatime format
transactions_df['trans_date_trans_time'] = pd.
↪to_datetime(transactions_df['trans_date_trans_time'])
```

[10]:
```python
# Extract date and time features
transactions_df['hour'] = transactions_df['trans_date_trans_time'].dt.hour
transactions_df['day_of_week'] = transactions_df['trans_date_trans_time'].dt.
↪day_name()
```

```python
transactions_df['month'] = transactions_df['trans_date_trans_time'].dt.month
```

[11]:
```python
# Convert 'dob' to datetime format
transactions_df['dob'] = pd.to_datetime(transactions_df['dob'])
# Calculate age at the time of the transaction
transactions_df['age'] = (transactions_df['trans_date_trans_time'] -
 ↪transactions_df['dob']).dt.days // 365
```

[12]:
```python
# Check the date range of the dataset
start_date = transactions_df['trans_date_trans_time'].min()
end_date = transactions_df['trans_date_trans_time'].max()
print(f'Date range of the dataset: {start_date} to {end_date}')
```

```
Date range of the dataset: 2019-01-01 00:00:18 to 2020-06-21 12:13:37
```

For best time window, we will data from 2019-01-01 to 2019-12-31 instead of the entire dataset from 2019-01-01 to 2020-06-21. Entire dataset leads count transaction per month may not be accurate as the dataset is not complete for the entire year of 2020.

[13]:
```python
# Filter the dataset for the year 2019
transactions_df = transactions_df[(transactions_df['trans_date_trans_time'] >=
 ↪'2019-01-01') & (transactions_df['trans_date_trans_time'] < '2020-01-01')]
```

[14]:
```python
# Check the updated dateset
transactions_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 924850 entries, 0 to 924849
Data columns (total 24 columns):
 #   Column                 Non-Null Count   Dtype
---  ------                 --------------   -----
 0   trans_date_trans_time  924850 non-null  datetime64[ns]
 1   cc_num                 924850 non-null  int64
 2   merchant               924850 non-null  object
 3   category               924850 non-null  object
 4   amt                    924850 non-null  float64
 5   gender                 924850 non-null  object
 6   street                 924850 non-null  object
 7   city                   924850 non-null  object
 8   state                  924850 non-null  object
 9   zip                    924850 non-null  int64
 10  lat                    924850 non-null  float64
 11  long                   924850 non-null  float64
 12  city_pop               924850 non-null  int64
 13  job                    924850 non-null  object
 14  dob                    924850 non-null  datetime64[ns]
 15  trans_num              924850 non-null  object
 16  unix_time              924850 non-null  int64
 17  merch_lat              924850 non-null  float64
```

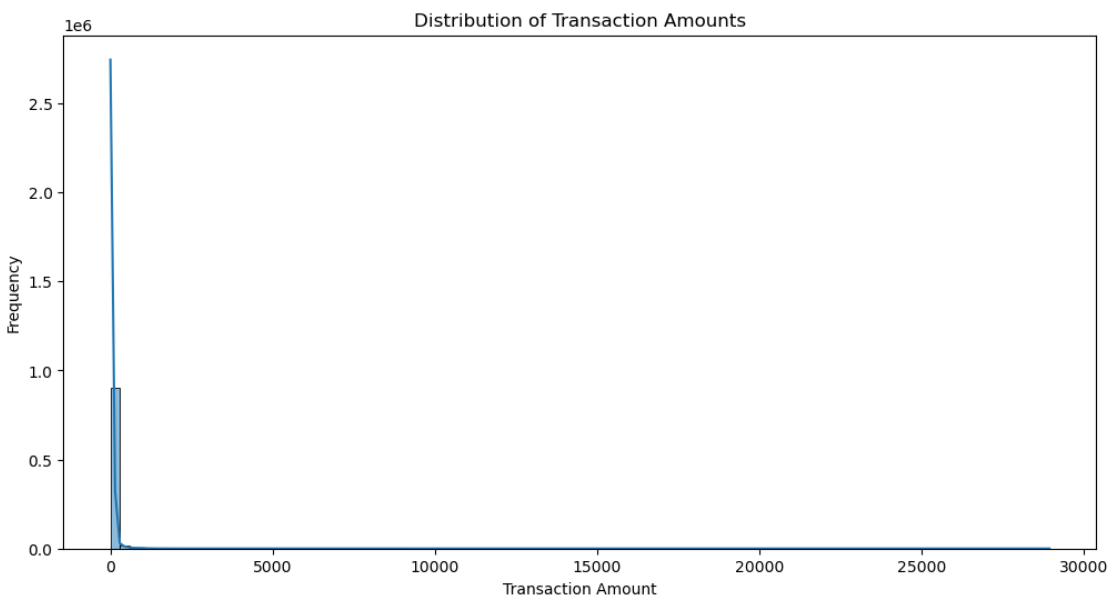
```
 18  merch_long             924850 non-null  float64
 19  is_fraud               924850 non-null  int64
 20  hour                   924850 non-null  int32
 21  day_of_week            924850 non-null  object
 22  month                  924850 non-null  int32
 23  age                    924850 non-null  int64
dtypes: datetime64[ns](2), float64(5), int32(2), int64(6), object(9)
memory usage: 169.3+ MB
```

3. Feature Engineering

[15]:
```python
# The 'amt' describes the amount of the transaction
print(transactions_df['amt'].describe())
```

```
count    924850.000000
mean         70.265398
std         161.713382
min           1.000000
25%           9.630000
50%          47.400000
75%          83.020000
max       28948.900000
Name: amt, dtype: float64
```

[16]:
```python
# Explore the 'amt' column
plt.figure(figsize = (12,6))
sns.histplot(transactions_df['amt'], bins = 100, kde = True)
plt.title('Distribution of Transaction Amounts')
plt.xlabel('Transaction Amount')
plt.ylabel('Frequency')
plt.show()
```



[17]:

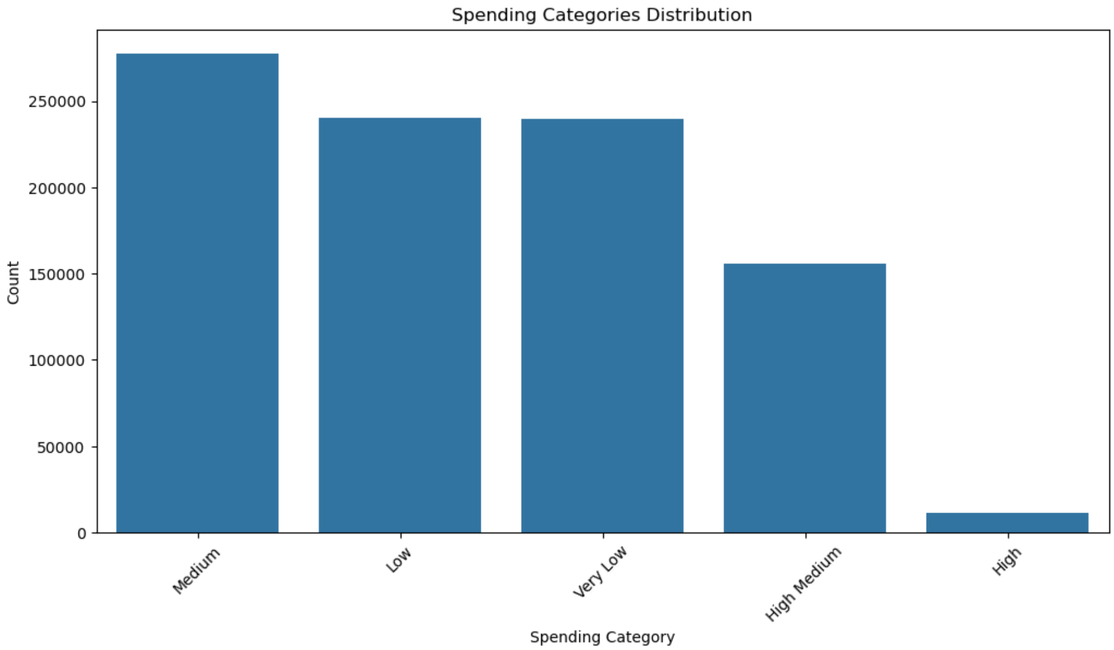
```python
# Create spending categories based on transaction amount
def categorize_spending(amount):
    if amount < 10:
        return 'Very Low'
    elif 10 <= amount < 50:
        return 'Low'
    elif 50 <= amount < 100:
        return 'Medium'
    elif 100 <= amount < 500:
        return 'High Medium'
    else:
        return 'High'

transactions_df['spending_category'] = transactions_df['amt'].
 ↪apply(categorize_spending)
```

[18]:

```python
# Explore spending categories
print('Transaction Counts by Speending Category:')
print(transactions_df['spending_category'].value_counts())
print('\nPercentage of Transactions by Spending Category:')
print(transactions_df['spending_category'].value_counts(normalize=True) * 100)
# Visualize spending categories distribution
plt.figure(figsize = (12, 6))
sns.countplot(data = transactions_df,
              x= 'spending_category',
              order = transactions_df['spending_category'].value_counts().index)
plt.title('Spending Categories Distribution')
plt.xlabel('Spending Category')
plt.ylabel('Count')
plt.xticks(rotation = 45)
plt.show()
```

```
Transaction Counts by Speending Category:
spending_category
Medium         277511
Low            240405
Very Low       239860
High Medium    155970
High            11104
Name: count, dtype: int64

Percentage of Transactions by Spending Category:
spending_category
Medium         30.006055
Low            25.993945
```

```
Very Low       25.935016
High Medium    16.864356
High            1.200627
Name: proportion, dtype: float64
```



[19]:

```
# The city population can be a factor in transaction behavior
print(transactions_df['city_pop'].describe())
```

```
count    9.248500e+05
mean     8.914480e+04
std      3.025527e+05
min      2.300000e+01
25%      7.430000e+02
50%      2.456000e+03
75%      2.047800e+04
max      2.906700e+06
Name: city_pop, dtype: float64
```

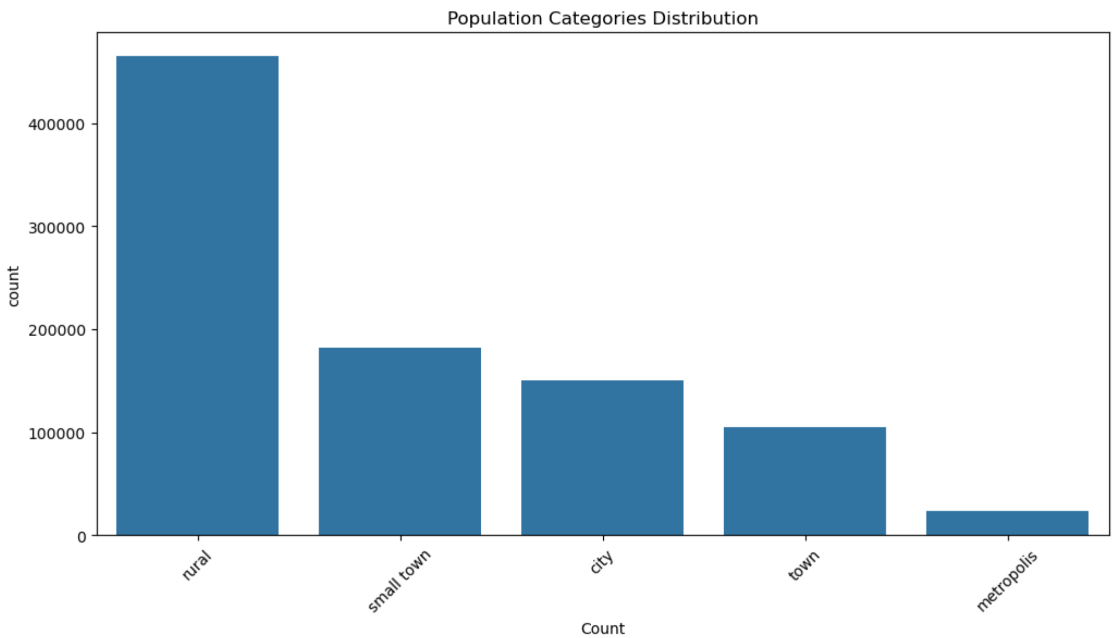
[20]:

```
# Create population categories
def categorize_population(population):
    if population < 2500:
        return 'rural'
    elif 2500 <= population < 10000:
        return 'small town'
    elif 10000 <= population < 50000:
        return 'town'
```

```
    elif 50000 <= population < 1000000:
        return 'city'
    else:
        return 'metropolis'

transactions_df['population_category'] = transactions_df['city_pop'].
 ↪apply(categorize_population)
```

[21]:
```
# Expore population categories
print('Counts by Population Category:')
print(transactions_df['population_category'].value_counts())
print('\nPercentage of Transactions by Population Category:')
print(transactions_df['population_category'].value_counts(normalize = True) *␣
 ↪100)
plt.figure(figsize = (12, 6))
sns.countplot(data = transactions_df,
              x= 'population_category',
              order = transactions_df['population_category'].value_counts().
 ↪index)
plt.title('Population Categories Distribution')
plt.xlabel('Population Category')
plt.xlabel('Count')
plt.xticks(rotation = 45)
plt.show()
```

```
Counts by Population Category:
population_category
rural         464638
small town    181930
city          150120
town          104704
metropolis     23458
Name: count, dtype: int64

Percentage of Transactions by Population Category:
population_category
rural         50.239282
small town    19.671298
city          16.231821
town          11.321187
metropolis     2.536411
Name: proportion, dtype: float64
```



[22]:
```
# Create age categories
def categorize_age(age):
    if age < 18:
        return 'Under 18'
    elif 18 <= age < 25:
        return '18-24'
    elif 25 <= age < 35:
        return '25-34'
    elif 35 <= age < 45:
        return '35-44'
    elif 45 <= age < 55:
        return '45-54'
    elif 55 <= age < 65:
        return '55-64'
    else:
        return '65 and over'
transactions_df['age_category'] = transactions_df['age'].apply(categorize_age)
```

Behavioral Analysis

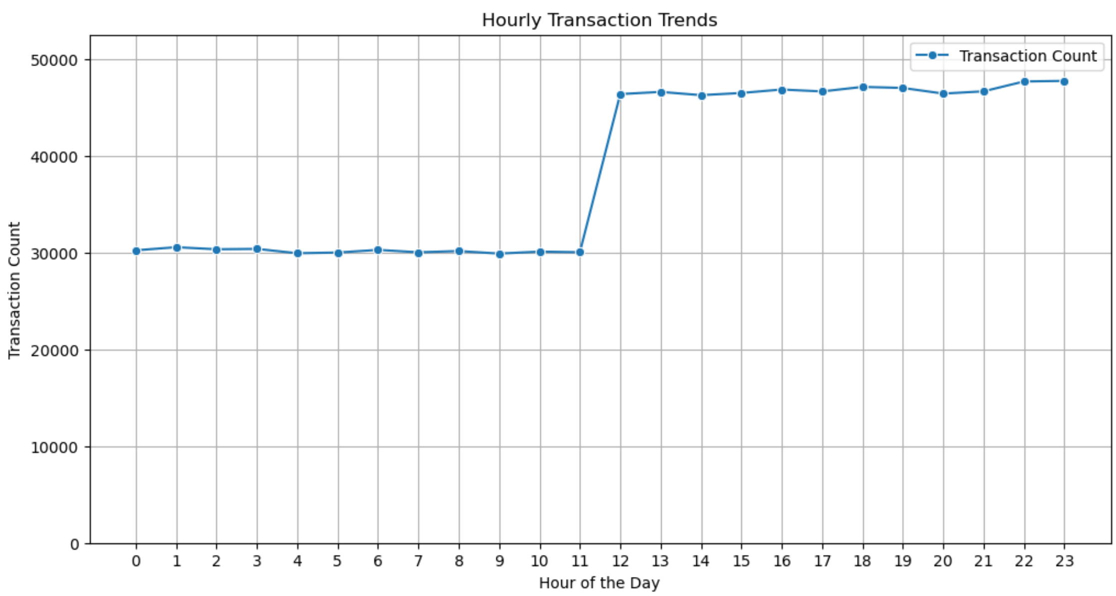
1. When: Temporal analysis

1. 1 Hourly trend: Examine transaction frequency and amount hour to indentify peak spending times.

[23]:
```
# Transaction count and average amount by hour
```

```
hourly_trends = transactions_df.groupby('hour').agg({'amt': ['count', 'mean']}).
    ↪reset_index()
hourly_trends.columns = ['hour', 'transaction_count', 'average_amount']
```

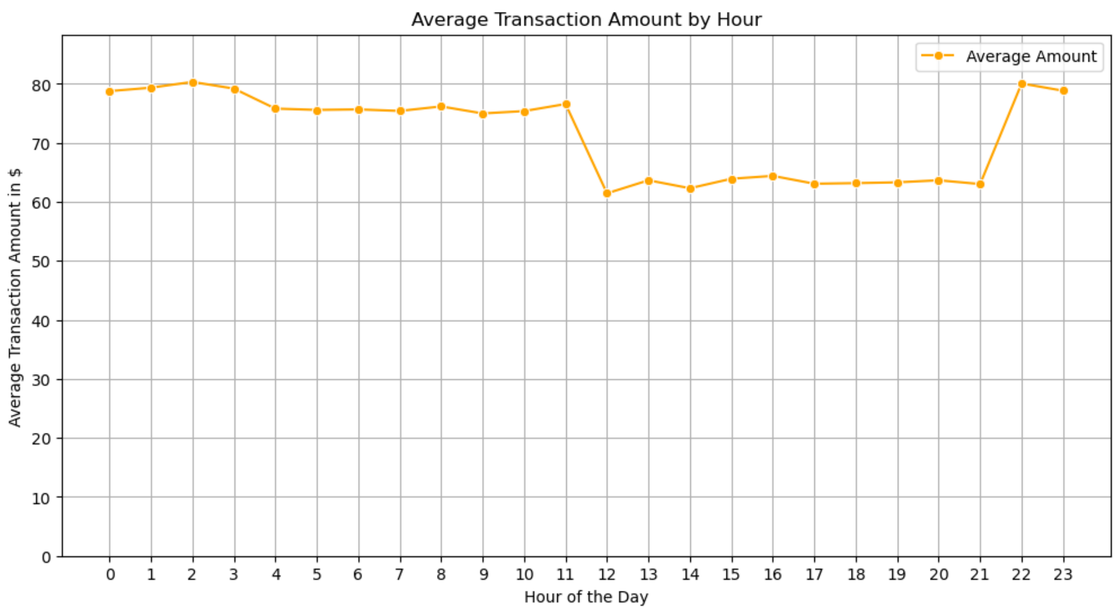
[24]:
```
# Plot hourly trends
plt.figure(figsize = (12, 6))
sns.lineplot(data =hourly_trends, x= 'hour', y = 'transaction_count', marker =␣
    ↪'o', label = 'Transaction Count')
plt.title('Hourly Transaction Trends')
plt.xlabel('Hour of the Day')
plt.ylabel('Transaction Count')
plt.legend()
plt.xticks(range(0, 24))
plt.ylim(0, hourly_trends['transaction_count'].max() * 1.1)
plt.grid()
plt.show()
```



Insights: Hourly trends show peak transaction times, which can help in resource allocation and fraudulent activity monitoring. Peak hours can be target for marketing campaigns or customer engaging strategies. From the plot, we can see that transaction count peaks around 12 PM to 11 PM, with a significant drop during the early morning hours (1 AM to 11 AM). This suggests that most transaction activity occurs during the after noon and evening hours, which is typical for consumer spending behavior.

[25]:
```
# plot average transaction amount by hour
plt.figure(figsize = (12, 6))
sns.lineplot(data = hourly_trends,
```

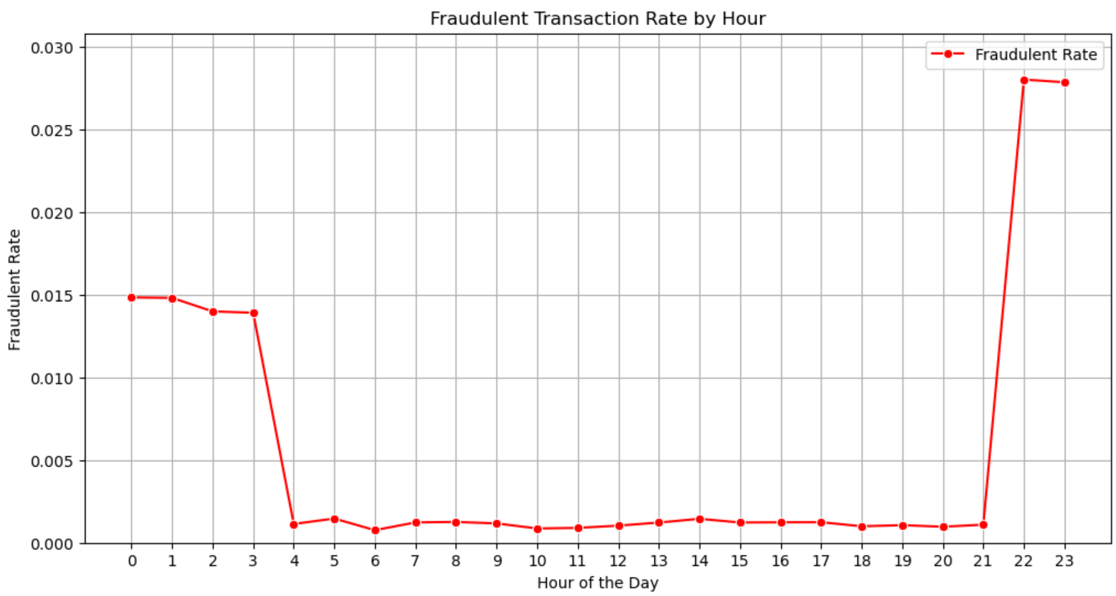
```
             x = 'hour',
             y = 'average_amount',
             marker = 'o',
             color = 'orange',
             label = 'Average Amount')
plt.title('Average Transaction Amount by Hour')
plt.xlabel('Hour of the Day')
plt.ylabel('Average Transaction Amount in $')
plt.legend()
plt.xticks(range(0, 24))
plt.ylim(0, hourly_trends['average_amount'].max() * 1.1)
plt.grid()
plt.show()
```



Insights: The average transaction amount is highest around 10 PM and 2 AM, and lowest arount 12 PM. The average transaction amount tends to be higher during the late night hours to 11 AM, which may indicate that customers are marking larger purchases during these times. From 12 PM to 9 PM, the average transacton amount is relatively stable lower than the peak hours, suggesting that customers are making smaller purchases during the day.

[26]:
```
# Investigate transaction fraudulent rate by hour
fraudulent_rate_by_hour = transactions_df.groupby('hour')['is_fraud'].mean().
 ↪reset_index()
plt.figure(figsize = (12, 6))
sns.lineplot(data = fraudulent_rate_by_hour,
             x = 'hour',
             y = 'is_fraud',
```

```
             marker = 'o',
             color = 'red',
             label = 'Fraudulent Rate')
plt.title('Fraudulent Transaction Rate by Hour')
plt.xlabel('Hour of the Day')
plt.ylabel('Fraudulent Rate')
plt.legend()
plt.xticks(range(0, 24))
plt.ylim(0, fraudulent_rate_by_hour['is_fraud'].max() * 1.1)
plt.grid()
plt.show()
```



Insights: The fraudulent transaction rate is highest during the night hours starting from 10 PM to 3 AM, with a peak around 10 PM. This suggests that frandulent activities are more likely to occur during the late night hours, which highlights the need for increased monitoring and security measures during these times. The rate of fraudulent transactions is siginificantly lower during 4 AM to 9 PM, indicating that most transactions during these hours are legitimate.

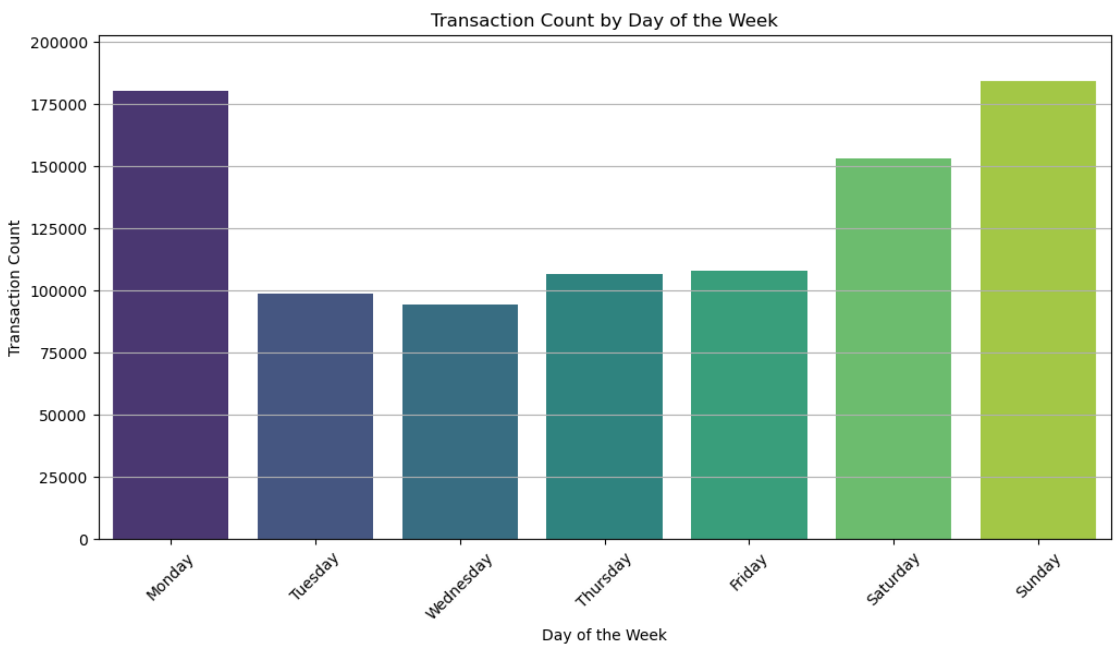
1. 2 Day of week trends: Compare spending behavior accross days of the week

[27]:
```
# Transaction count and average amount by day of the week
day_of_week_trends = transactions_df.groupby('day_of_week').agg({'amt':
 ↪['count', 'mean']}).reset_index()
day_of_week_trends.columns = ['day_of_week', 'transaction_count',
 ↪'average_amount']
# Convert day_of_week to categorical type with ordered categories
day_of_week_order = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday',
 ↪'Saturday', 'Sunday']
```

```
day_of_week_trends['day_of_week'] = pd.
↪Categorical(day_of_week_trends['day_of_week'], categories=day_of_week_order,␣
↪ordered=True)
```

[28]:

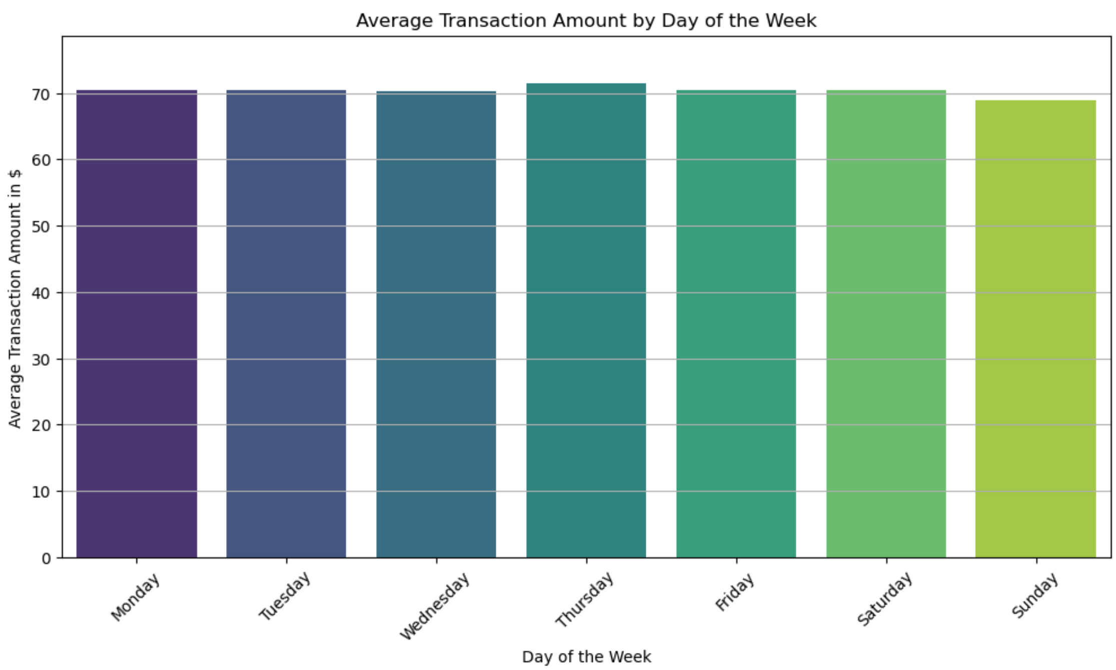
```
# Plot transaction count by day of the week
plt.figure(figsize = (12, 6))
sns.barplot(data = day_of_week_trends,
            x = 'day_of_week',
            y = 'transaction_count',
            order = day_of_week_order,
            palette = 'viridis',
            legend = False)
plt.title('Transaction Count by Day of the Week')
plt.xlabel('Day of the Week')
plt.ylabel('Transaction Count')
plt.xticks(rotation = 45)
plt.ylim(0, day_of_week_trends['transaction_count'].max() * 1.1)
plt.grid(axis='y')
plt.show()
```



Insights: Transaction count is highest on Monday and Sunday, with a significant drop on Tuesday and Wednesday, and a slight increase on Thursday to Monday. This suggests that customers tend to spend more on weekends and Mondays. This information can be used to optimize marketing strategies and resource allocation for businesses.

[29]:

```
# Plot average transaction amount by day of the week
plt.figure(figsize = (12, 6))
sns.barplot(data = day_of_week_trends,
            x = 'day_of_week',
            y = 'average_amount',
            order = day_of_week_order,
            palette = 'viridis',
            legend = False)
plt.title('Average Transaction Amount by Day of the Week')
plt.xlabel('Day of the Week')
plt.ylabel('Average Transaction Amount in $')
plt.xticks(rotation = 45)
plt.ylim(0, day_of_week_trends['average_amount'].max() * 1.1)
plt.grid(axis='y')
plt.show()
```

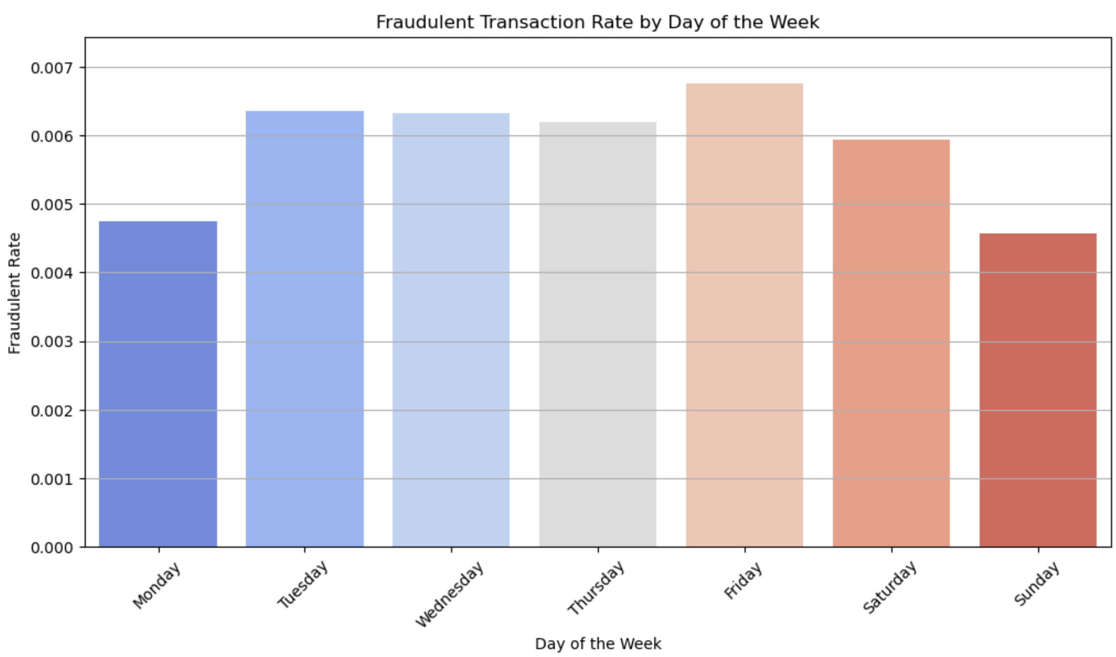


Insights: The average transaction amount is highest on Thursay and lowest on Sunday. The average transaction of all days of the week is relatively stable around 70 USD, with a slight increase on Thurday and a slight decrease on Sunday.

[30]:

```
# Investigate fraudulent transaction rate by day of the week
fraudulent_rate_by_day = transactions_df.groupby('day_of_week')['is_fraud'].
 ↪mean().reset_index()
```

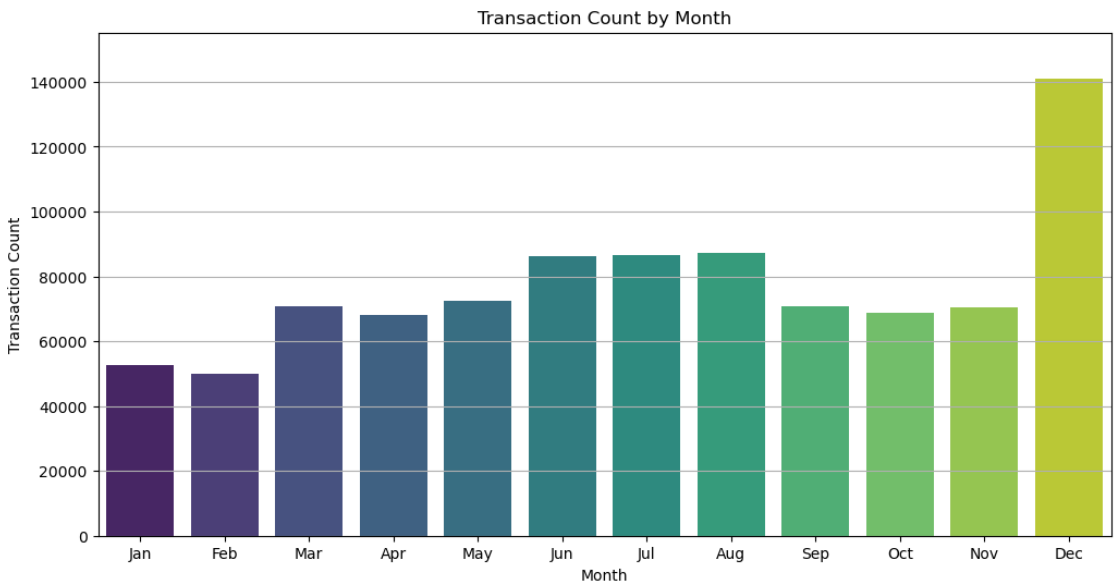
```
fraudulent_rate_by_day['day_of_week'] = pd.
 ↪Categorical(fraudulent_rate_by_day['day_of_week'],␣
 ↪categories=day_of_week_order, ordered=True)
plt.figure(figsize = (12, 6))
sns.barplot(data = fraudulent_rate_by_day,
            x = 'day_of_week',
            y = 'is_fraud',
            order = day_of_week_order,
            palette = 'coolwarm',
            legend = False)
plt.title('Fraudulent Transaction Rate by Day of the Week')
plt.xlabel('Day of the Week')
plt.ylabel('Fraudulent Rate')
plt.xticks(rotation = 45)
plt.ylim(0, fraudulent_rate_by_day['is_fraud'].max() * 1.1)
plt.grid(axis='y')
plt.show()
```



Insights: The fraudulent transaction rate is highest on Friday and lowest on Sunday and Monday. From the plot, we can see that the fraudulent drop from Friday to Monday, and then increases again on Tuesday to Friday. This suggests that fraudulent activities are more likely to occur on Fridays and Thursdays, which highlights the need for increased monitoring and security measures during these times.

1. 3 Monthly trends: Analyze transaction patterns across different months to identify seasonal spending behavior.

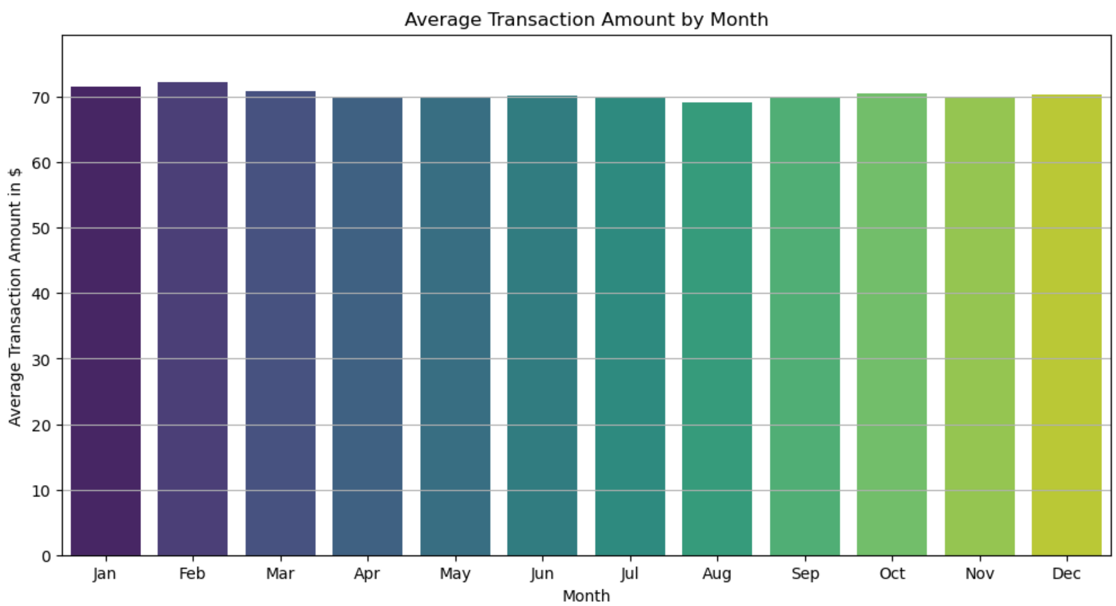
[31]:
```
# Monthly trends
monthly_trends = transactions_df.groupby('month').agg({'amt': ['count',␣
↪'mean']}).reset_index()
monthly_trends.columns = ['month', 'transaction_count', 'average_amount']
# Plot transaction count by month
plt.figure(figsize = (12, 6))
sns.barplot(data = monthly_trends,
            x = 'month',
            y = 'transaction_count',
            palette = 'viridis',
            legend = False)
plt.title('Transaction Count by Month')
plt.xlabel('Month')
plt.ylabel('Transaction Count')
plt.xticks(ticks = range(0, 12), labels = ['Jan', 'Feb', 'Mar', 'Apr', 'May',␣
↪'Jun', 'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec'])
plt.ylim(0, monthly_trends['transaction_count'].max() * 1.1)
plt.grid(axis='y')
plt.show()
```



Insights: Transaction count by month shows a significant increase in December, likely due to holiday shopping. The transaction count in June, July, and August is also relatively high compared to other moths, which may indicate summer spending patterns. The transaction count in January and February is relatively low, which may indicate a post-holiday spending slowdown.

[32]:
```
# Plot average transaction amount by month
plt.figure(figsize = (12, 6))
sns.barplot(data = monthly_trends,
```

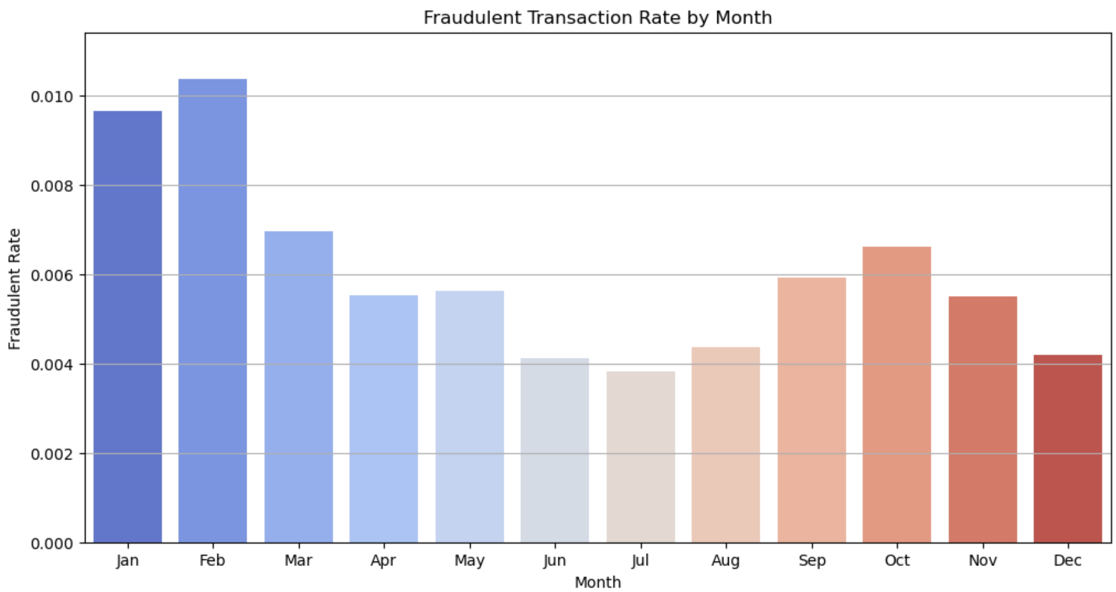
```
            x = 'month',
            y = 'average_amount',
            palette = 'viridis',
            legend = False)
plt.title('Average Transaction Amount by Month')
plt.xlabel('Month')
plt.ylabel('Average Transaction Amount in $')
plt.xticks(ticks = range(0, 12), labels = ['Jan', 'Feb', 'Mar', 'Apr', 'May',␣
↪'Jun', 'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec'])
plt.ylim(0, monthly_trends['average_amount'].max() * 1.1)
plt.grid(axis='y')
plt.show()
```



Insights: The average transaction amount by month shows a steady state around 70 USD, with a slight increase in January, Frebruary, and March, and a slight decrease in August.

[33]:
```
# Investigate fraudulent transaction rate by month
fraudulent_rate_by_month = transactions_df.groupby('month')['is_fraud'].mean().
↪reset_index()
plt.figure(figsize = (12, 6))
sns.barplot(data = fraudulent_rate_by_month,
            x = 'month',
            y = 'is_fraud',
            palette = 'coolwarm',
            legend = False)
plt.title('Fraudulent Transaction Rate by Month')
plt.xlabel('Month')
```

```
plt.ylabel('Fraudulent Rate')
plt.xticks(ticks = range(0, 12), labels = ['Jan', 'Feb', 'Mar', 'Apr', 'May',␣
↪'Jun', 'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec'])
plt.ylim(0, fraudulent_rate_by_month['is_fraud'].max() * 1.1)
plt.grid(axis='y')
plt.show()
```



Insights: Fraudulent transaction rate by month shows a significant highly in Frebruary and a significant lowly in July. The fraudulent transaction rate is a highly increase in January and Frebruary with a peak in Frebruary. This suggests that fraudulent activities are more likely to occur during the first two months of the year, which highlights the need for increased monitoring and security measures during these times. The rate of fraudulent transactions is significantly lower in July, indicating that most transactions during this month are legitimate.

2. Where: Merchant and Geographic analysis

2. 1 Merchant analysis: Analyze transaction patterns across different merchants to identify spending behavior.

[34]:
```
# Merchant category trends
merchant_category_trends = transactions_df.groupby('category').agg({'amt':␣
↪['count', 'mean'], 'is_fraud': 'mean'}).reset_index()
merchant_category_trends.columns = ['category', 'transaction_count',␣
↪'average_amount', 'fraudulent_rate']
```

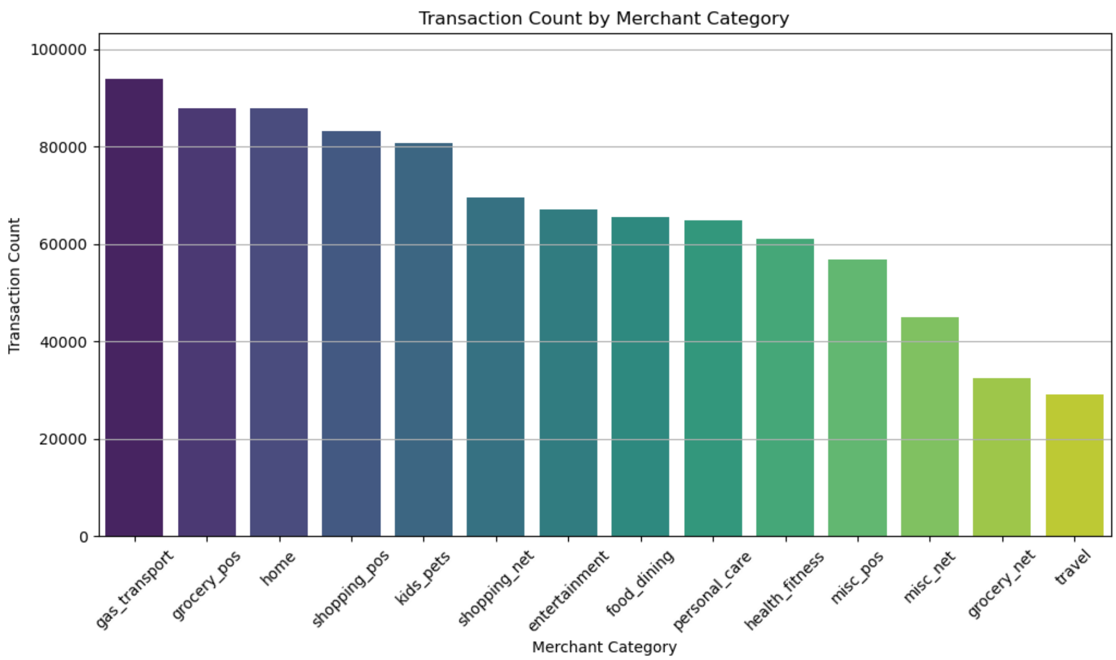
[35]:
```
merchant_category_trends
```

[35]:

	category	transaction_count	average_amount	fraudulent_rate
0	entertainment	67097	64.139503	0.002429
1	food_dining	65461	51.181443	0.001589
2	gas_transport	93859	63.425519	0.004677
3	grocery_net	32320	53.808203	0.002908
4	grocery_pos	87893	116.828782	0.013676
5	health_fitness	61115	54.043142	0.001571
6	home	87849	58.183919	0.001468
7	kids_pets	80644	57.550575	0.002133
8	misc_net	45040	80.376026	0.013965
9	misc_pos	56879	62.559165	0.002989
10	personal_care	64923	47.914108	0.002341
11	shopping_net	69554	88.571446	0.017267
12	shopping_pos	83205	79.216328	0.007007
13	travel	29011	112.861098	0.002964

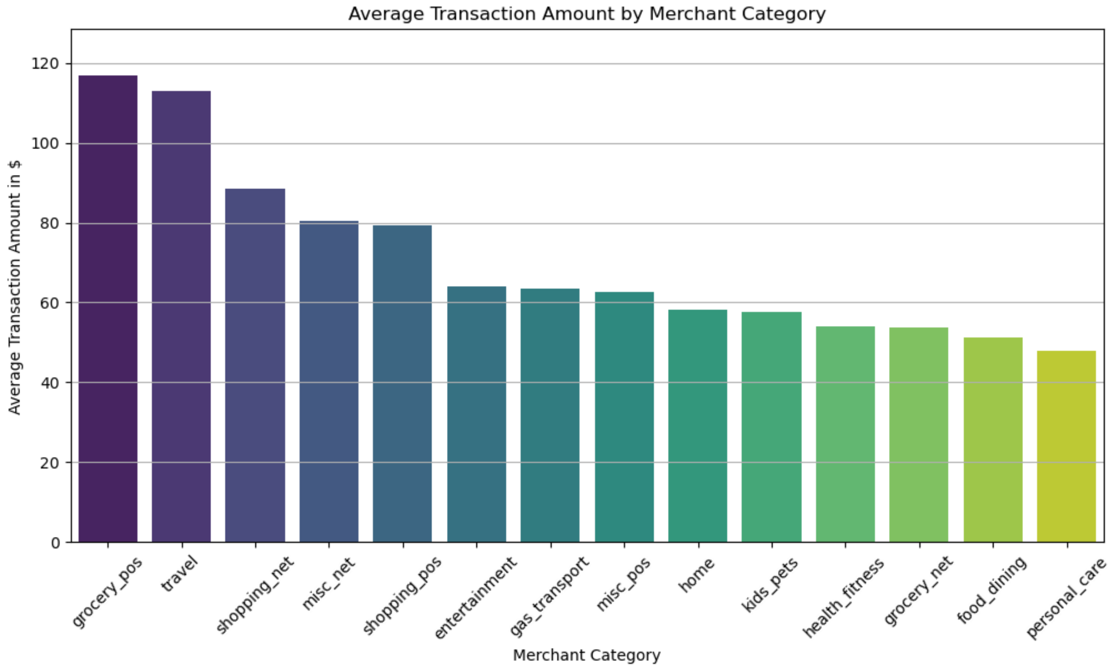
[36]:

```
# Plot transaction count by merchant category
plt.figure(figsize = (12, 6))
sns.barplot(data = merchant_category_trends,
            x= 'category',
            y = 'transaction_count',
            order = merchant_category_trends.sort_values(by =␣
 ↪['transaction_count'], ascending = False)['category'],
            palette = 'viridis',
            legend = False)
plt.title('Transaction Count by Merchant Category')
plt.xlabel('Merchant Category')
plt.ylabel('Transaction Count')
plt.xticks(rotation = 45)
plt.ylim(0, merchant_category_trends['transaction_count'].max() * 1.1)
plt.grid(axis='y')
plt.show()
```



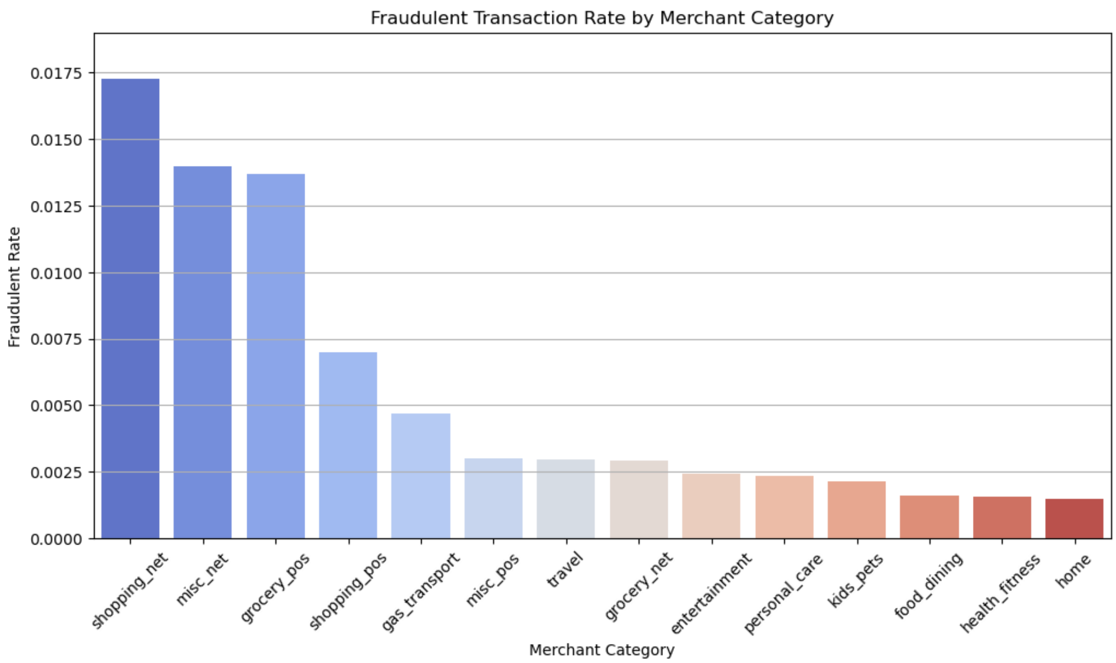
Insights: Transaction count by merchant shows that the top 5 merchants are gas transportation, grocery pos, home, shopping pos, and kids pets. This suggests that customers tend to spend more on gas tranpottation, grocery, home, shopping, and kids/pets. The lowest transaction count is in the traval, grocery net.

[37]:
```
# Plot average transaction amount by merchant category
plt.figure(figsize = (12, 6))
sns.barplot(data = merchant_category_trends,
            x= 'category',
            y = 'average_amount',
            order = merchant_category_trends.sort_values(by =␣
 ↪['average_amount'], ascending = False)['category'],
            palette = 'viridis',
            legend = False)
plt.title('Average Transaction Amount by Merchant Category')
plt.xlabel('Merchant Category')
plt.ylabel('Average Transaction Amount in $')
plt.xticks(rotation = 45)
plt.ylim(0, merchant_category_trends['average_amount'].max() * 1.1)
plt.grid(axis='y')
plt.show()
```



Insights: The average transaction amount by merchant shows that the top 5 merchants are grocery pos, travel, shopping net, misc net, and shopping pos. This suggests that customers tend to spend more on grocery pos in transaction count over 120,000 transactions with an average amount near 120 USD each. The travel merchant with lowest transaction count has an average amount over 110 USD, followed by shopping net, misc net, and shopping pos. The lowest average transaction amount is in personal care,followed by food dining, grocery net, health fitness, and kids pets.

[38]:
```
# Plot investigate fraudulent transaction rate by merchant category
plt.figure(figsize = (12, 6))
sns.barplot(data = merchant_category_trends,
            x= 'category',
            y = 'fraudulent_rate',
            order = merchant_category_trends.sort_values(by =␣
 ↪['fraudulent_rate'], ascending = False)['category'],
            palette = 'coolwarm',
            legend = False)
plt.title('Fraudulent Transaction Rate by Merchant Category')
plt.xlabel('Merchant Category')
plt.ylabel('Fraudulent Rate')
plt.xticks(rotation = 45)
plt.ylim(0, merchant_category_trends['fraudulent_rate'].max() * 1.1)
plt.grid(axis='y')
plt.show()
```



Insights: Fraudulent transaction rate by merchant shows that the top 5 merchants are shopping net, misc net, grocery pos, shopping pos, and gas transportation. The lowest fraudulent transaction rate is in health fitness, followed by home, food dining, kids pets, and personal care.

2. 2 Spending by city: Analyze transaction patterns across different cities to identify geographic spending behavior.

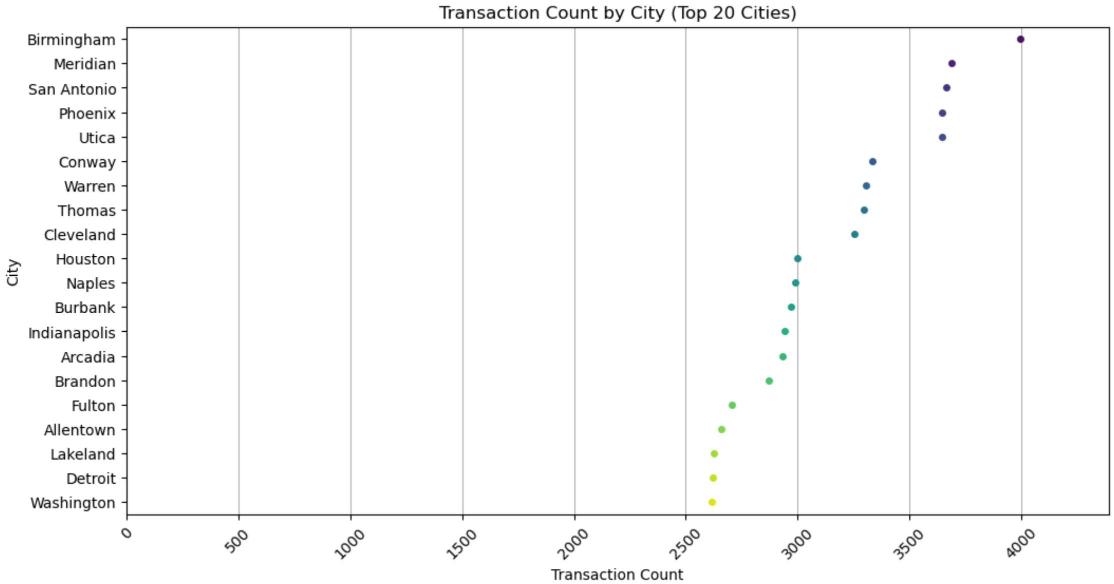
[39]:
```
# Spending by city trends
city_trends = transactions_df.groupby('city').agg({'amt': ['count', 'mean'],␣
 ↪'is_fraud': 'mean'}).reset_index()
city_trends.columns = ['city', 'transaction_count', 'average_amount',␣
 ↪'fraudulent_rate']
city_trends
```

[39]:
```
                          city  transaction_count  average_amount  \
0                      Achille                371       52.456685
1                      Acworth               1501       98.407388
2                        Adams                367       56.591008
3                        Afton               1455       65.555622
4                        Akron                356       85.262921
..                         …                  …             …
871                Woods Cross                381       96.764987
872                  Woodville               1528       49.416342
873  Yellowstone National Park                367       70.205640
874                    Zaleski               1061       92.051216
875                    Zavalla               1129       65.715660
```

```
     fraudulent_rate
0           0.000000
1           0.008661
2           0.000000
3           0.006186
4           0.000000
..               …
871         0.000000
872         0.000000
873         0.032698
874         0.000000
875         0.000000

[876 rows x 4 columns]
```

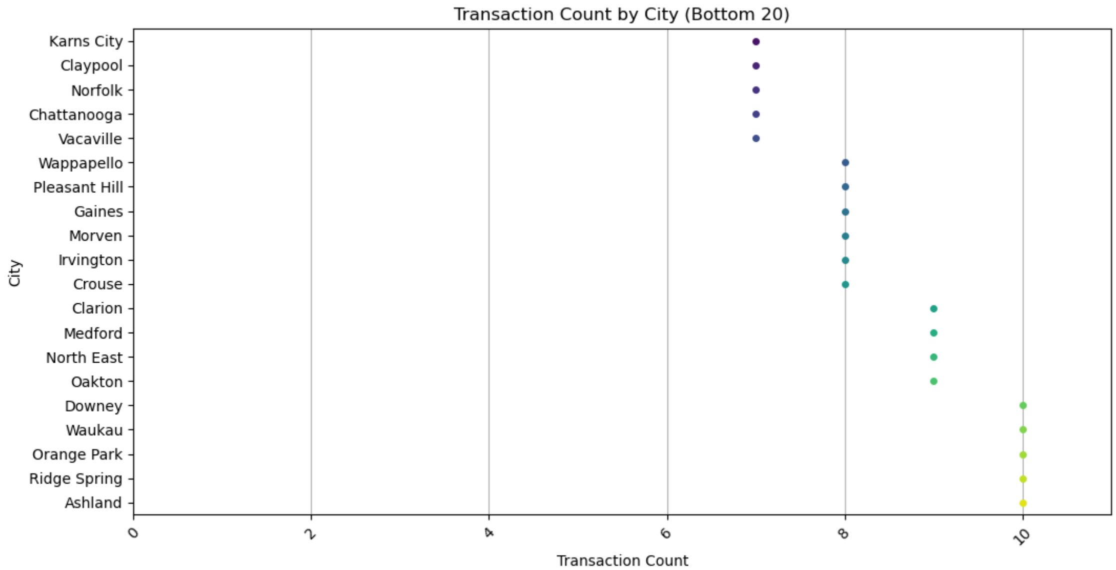
[40]:

```
# Strip plot transaction count by top 20 cities
top_city_trends = city_trends.sort_values(by = ['transaction_count'], ascending␣
 ↪= False).head(20)
plt.figure(figsize = (12, 6))
sns.stripplot(data = top_city_trends,
              x = 'transaction_count',
              y = 'city',
              order = top_city_trends.sort_values(by = ['transaction_count'],␣
 ↪ascending = False)['city'],
              palette = 'viridis',
              jitter = True)
plt.title('Transaction Count by City (Top 20 Cities)')
plt.xlabel('Transaction Count')
plt.ylabel('City')
plt.xticks(rotation = 45)
plt.xlim(0, top_city_trends['transaction_count'].max() * 1.1)
plt.grid(axis='x')
plt.show()
```



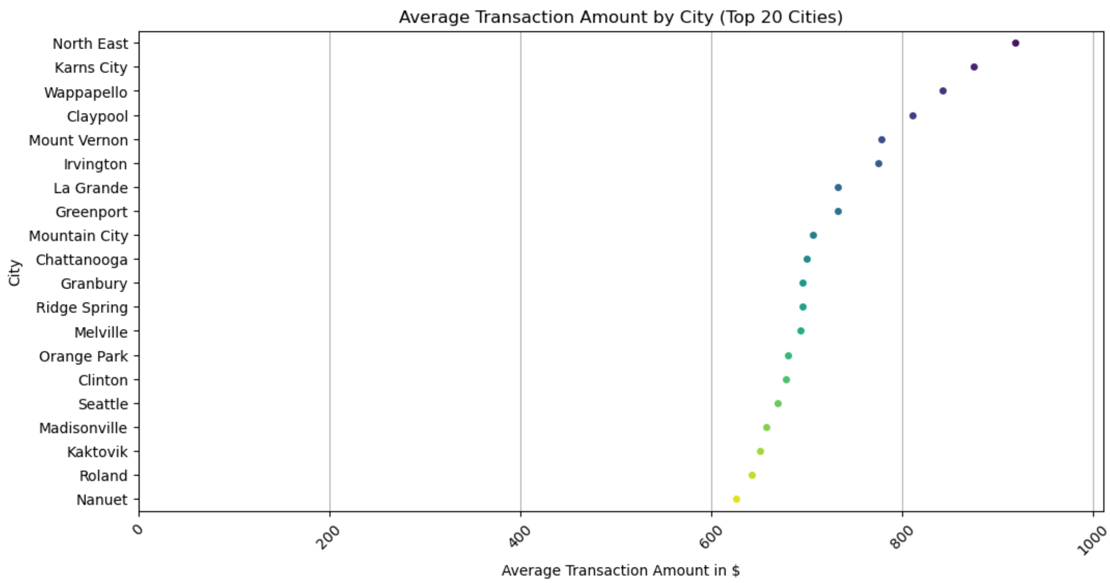
The top five cities of highest transaction count are in Birmingham, followed by Meridian, San Antonio, Phoenix, Utica. The top cities with high count of transactions indicate that these cities have a high volume of credit card transactions, which may be due to a larger population or more businesses accepting credit cards. Start with Washington more than 2,500 transactions and end with Birmingham near 4,000 transactions in 2019.

[41]:
```
# 20 cities with lowest transaction count
bottom_city_trends = city_trends.sort_values(by = ['transaction_count'],␣
↪ascending = True).head(20)
plt.figure(figsize = (12, 6))
sns.stripplot(data = bottom_city_trends,
                x = 'transaction_count',
                y = 'city',
                order = bottom_city_trends.sort_values(by =␣
↪['transaction_count'], ascending = True)['city'],
                palette = 'viridis',
                jitter = True)
plt.title('Transaction Count by City (Bottom 20)')
plt.xlabel('Transaction Count')
plt.ylabel('City')
plt.xticks(rotation = 45)
plt.xlim(0, bottom_city_trends['transaction_count'].max() * 1.1)
plt.grid(axis='x')
plt.show()
```



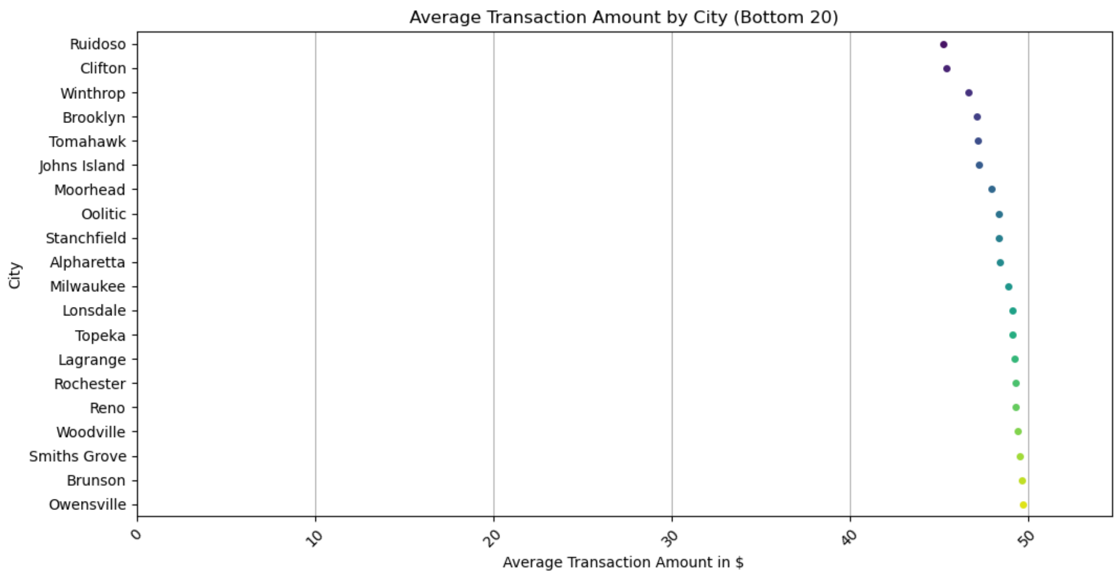
Bottom five cities with lowest transaction count are in Norfolk, Clayton, Vacaville, Karns City, and Chattanooga. The bottom cities with low count of transactions indicate that these cities have a low volume of credit card transactions, which may be due to a smaller population or fewer businesses accepting credit cards. Those cities have 7 to 10 transactions in 2019.

[42]:
```
# Top 20 cities by average transaction amount
top_city_avg_amount = city_trends.sort_values(by = ['average_amount'],␣
↪ascending = False).head(20)
plt.figure(figsize = (12, 6))
sns.stripplot(data = top_city_avg_amount,
              x = 'average_amount',
              y = 'city',
              order = top_city_avg_amount.sort_values(by = ['average_amount'],␣
↪ascending = False)['city'],
              palette = 'viridis',
              jitter = True)
plt.title('Average Transaction Amount by City (Top 20 Cities)')
plt.xlabel('Average Transaction Amount in $')
plt.ylabel('City')
plt.xticks(rotation = 45)
plt.xlim(0, top_city_avg_amount['average_amount'].max() * 1.1)
plt.grid(axis='x')
plt.show()
```



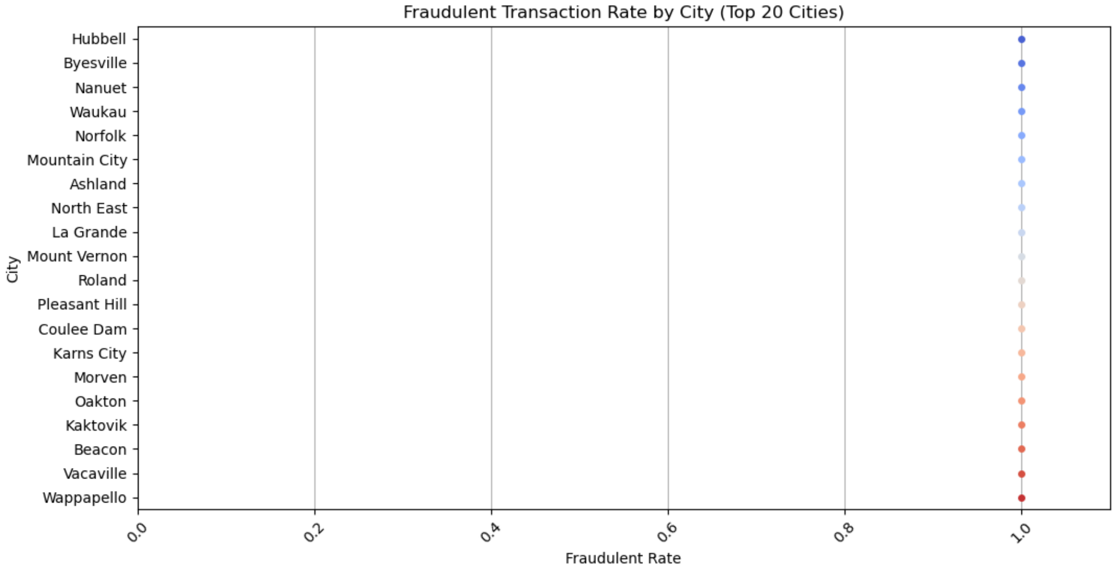
Highest average transaction amount by ciy is in bottom 20 cities with lowest transaction count such as North East, Karns City, Wappapello, Claypool, Mount Vernon. Low transaction count but high average transaction amount indicates that these cities have a small number of transactions but the transactions are relatively large in amount.

[43]:
```
# Bottom 20 cities by average transaction amount
bottom_city_avg_amount = city_trends.sort_values(by = ['average_amount'],␣
 ↪ascending = True).head(20)
plt.figure(figsize = (12, 6))
sns.stripplot(data = bottom_city_avg_amount,
              x = 'average_amount',
              y = 'city',
              order = bottom_city_avg_amount.sort_values(by =␣
 ↪['average_amount'], ascending = True)['city'],
              palette = 'viridis',
              jitter = True)
plt.title('Average Transaction Amount by City (Bottom 20)')
plt.xlabel('Average Transaction Amount in $')
plt.ylabel('City')
plt.xticks(rotation = 45)
plt.xlim(0, bottom_city_avg_amount['average_amount'].max() * 1.1)
plt.grid(axis='x')
plt.show()
```



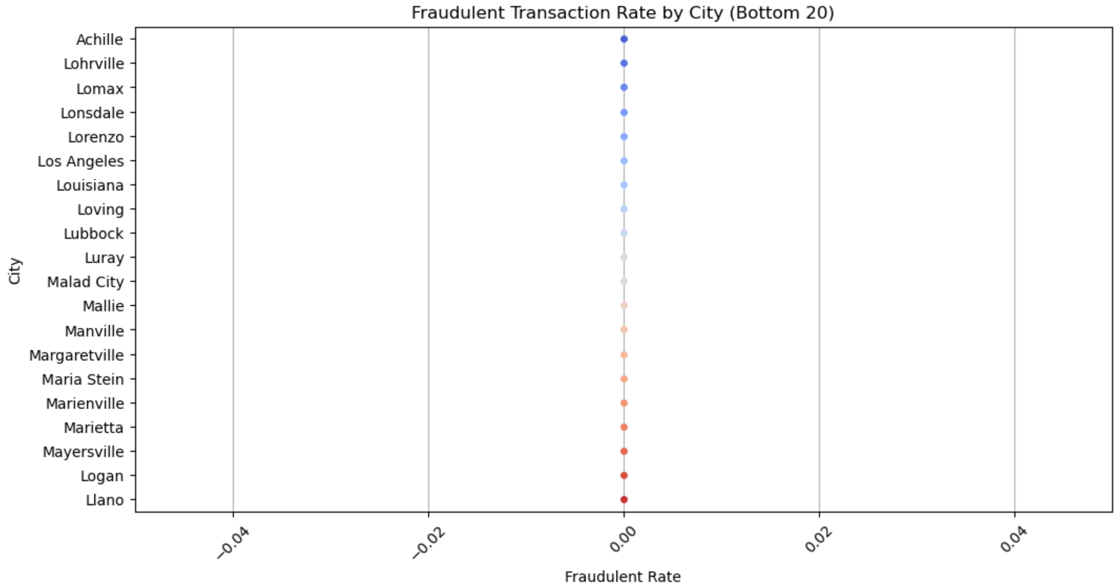
Bottom 5 cities with lowest average transaction amount are in Ruidoso, Clifton, Winthrop, Brooklyn, and Tomahawk. Bottom cities with low average transaction amount are lower than 50 USD, which indicates that these cities have a small amount of transactions and the transactions are relatively small in amount.

[44]:
```
# Top 20 cities by fraudulent transaction rate
top_city_fraudulent_rate = city_trends.sort_values(by = ['fraudulent_rate'],␣
 ↪ascending = False).head(20)
plt.figure(figsize = (12, 6))
sns.stripplot(data = top_city_fraudulent_rate,
              x = 'fraudulent_rate',
              y = 'city',
              order = top_city_fraudulent_rate.sort_values(by =␣
 ↪['fraudulent_rate'], ascending = False)['city'],
              palette = 'coolwarm',
              jitter = True)
plt.title('Fraudulent Transaction Rate by City (Top 20 Cities)')
plt.xlabel('Fraudulent Rate')
plt.ylabel('City')
plt.xticks(rotation = 45)
plt.xlim(0, top_city_fraudulent_rate['fraudulent_rate'].max() * 1.1)
plt.grid(axis='x')
plt.show()
```



Fraudulent transaction rate by city shows that the cities with highest fraudulent transaction rate. Many cites with small transaction count but high average transaction amount have a high fraudulent transaction rate such as Norfolk, Vacaville, Karns City.

[45]:
```
# Bottom 20 cities by fraudulent transaction rate
bottom_city_fraudulent_rate = city_trends.sort_values(by = ['fraudulent_rate'],␣
 ↪ascending = True).head(20)
plt.figure(figsize = (12, 6))
sns.stripplot(data = bottom_city_fraudulent_rate,
              x = 'fraudulent_rate',
              y = 'city',
              order = bottom_city_fraudulent_rate.sort_values(by =␣
 ↪['fraudulent_rate'], ascending = True)['city'],
              palette = 'coolwarm',
              jitter = True)
plt.title('Fraudulent Transaction Rate by City (Bottom 20)')
plt.xlabel('Fraudulent Rate')
plt.ylabel('City')
plt.xticks(rotation = 45)
plt.xlim(0, bottom_city_fraudulent_rate['fraudulent_rate'].max() * 1.1)
plt.grid(axis='x')
plt.show()
```



These cities with non fraudulent transaction rate. Some cities with low average transaction amount have zero frandulent transaction rate, which indicates that these cities have a transaction realtively small in amount and no fraudulent activities.

2. 3 Spending by state: Analyze transaction patterns across different states to identify geographic spending behavior.

[46]:
```python
# State trends
state_trends = transactions_df.groupby('state').agg({'amt': ['count', 'mean'],
 ↪'is_fraud': 'mean'}).reset_index()
state_trends.columns = ['state', 'transaction_count', 'average_amount',
 ↪'fraudulent_rate']
state_trends
```

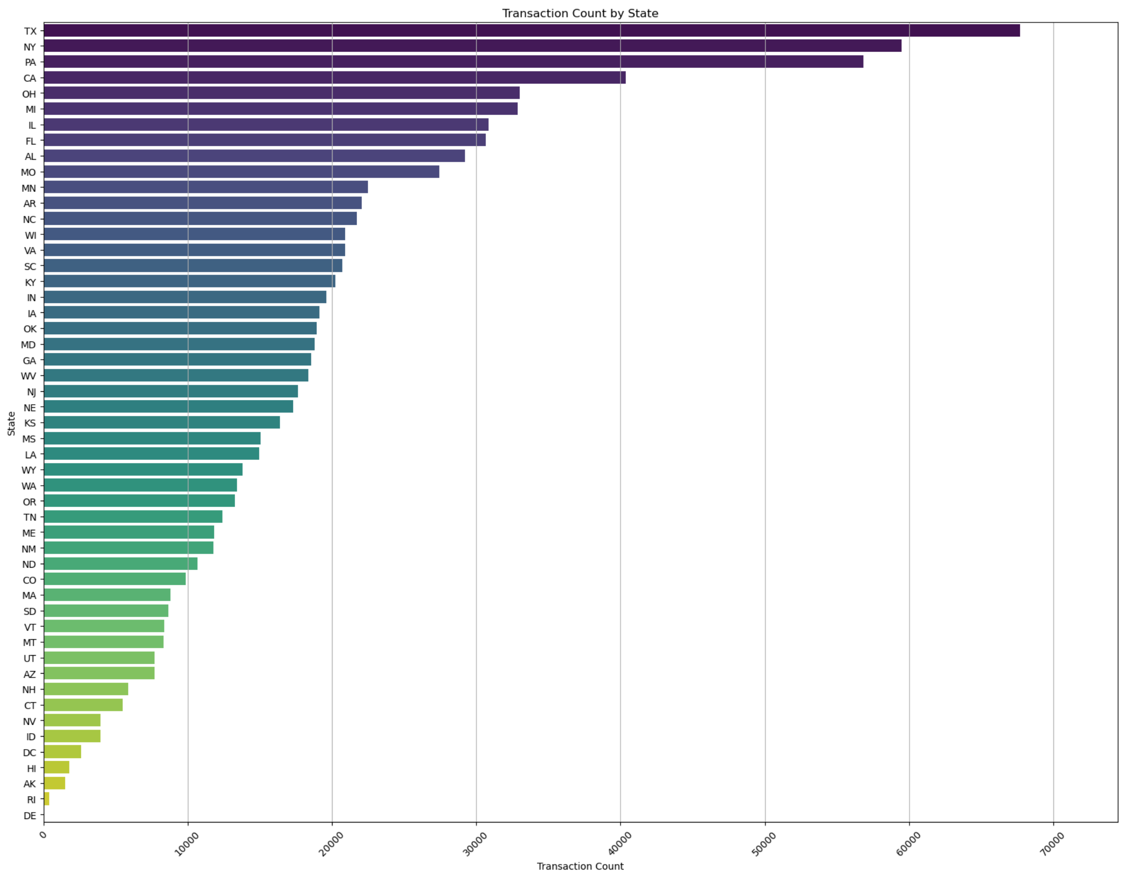
[46]:

	state	transaction_count	average_amount	fraudulent_rate
0	AK	1520	70.989289	0.017763
1	AL	29223	65.479978	0.005201
2	AR	22056	75.906092	0.005441
3	AZ	7685	74.662221	0.003904
4	CA	40378	73.347154	0.005300
5	CO	9853	78.171152	0.008018
6	CT	5512	66.499918	0.002903
7	DC	2617	75.141230	0.008024
8	DE	9	514.493333	1.000000
9	FL	30648	74.099051	0.007537
10	GA	18568	69.868885	0.004578
11	HI	1812	57.283775	0.003863
12	IA	19115	65.441663	0.004342

13	ID	3969	71.588231	0.002771
14	IL	30862	69.267682	0.006416
15	IN	19629	68.214628	0.003617
16	KS	16416	67.527886	0.004386
17	KY	20254	66.723841	0.006122
18	LA	14964	73.781725	0.003208
19	MA	8804	63.657398	0.005566
20	MD	18810	64.625303	0.005954
21	ME	11861	63.363216	0.006998
22	MI	32875	71.696267	0.005141
23	MN	22511	68.022772	0.005819
24	MO	27466	69.229242	0.006044
25	MS	15039	66.223236	0.003790
26	MT	8327	70.519506	0.003843
27	NC	21745	76.383800	0.005013
28	ND	10690	66.318211	0.004210
29	NE	17332	68.398015	0.007270
30	NH	5888	74.206126	0.008322
31	NJ	17661	65.873110	0.003624
32	NM	11784	59.903977	0.003819
33	NV	3984	56.879528	0.009287
34	NY	59498	72.333746	0.007631
35	OH	33014	73.779888	0.007300
36	OK	18938	66.159437	0.005439
37	OR	13276	70.125736	0.006026
38	PA	56843	72.291204	0.005805
39	RI	390	98.319513	0.038462
40	SC	20718	64.188988	0.005213
41	SD	8667	69.725759	0.004038
42	TN	12421	75.236885	0.008373
43	TX	67676	71.712025	0.005275
44	UT	7696	63.149722	0.003768
45	VA	20904	70.171912	0.005454
46	VT	8386	79.803444	0.001550
47	WA	13439	73.646067	0.005134
48	WI	20908	69.003094	0.005548
49	WV	18380	70.162781	0.004625
50	WY	13829	75.370515	0.006870

[47]:
```
# Plot transaction count by state
plt.figure(figsize = (20, 15))
sns.barplot(data = state_trends,
            x = 'transaction_count',
            y = 'state',
            order = state_trends.sort_values(by = ['transaction_count'],␣
 ↪ascending = False)['state'],
            palette = 'viridis',
```

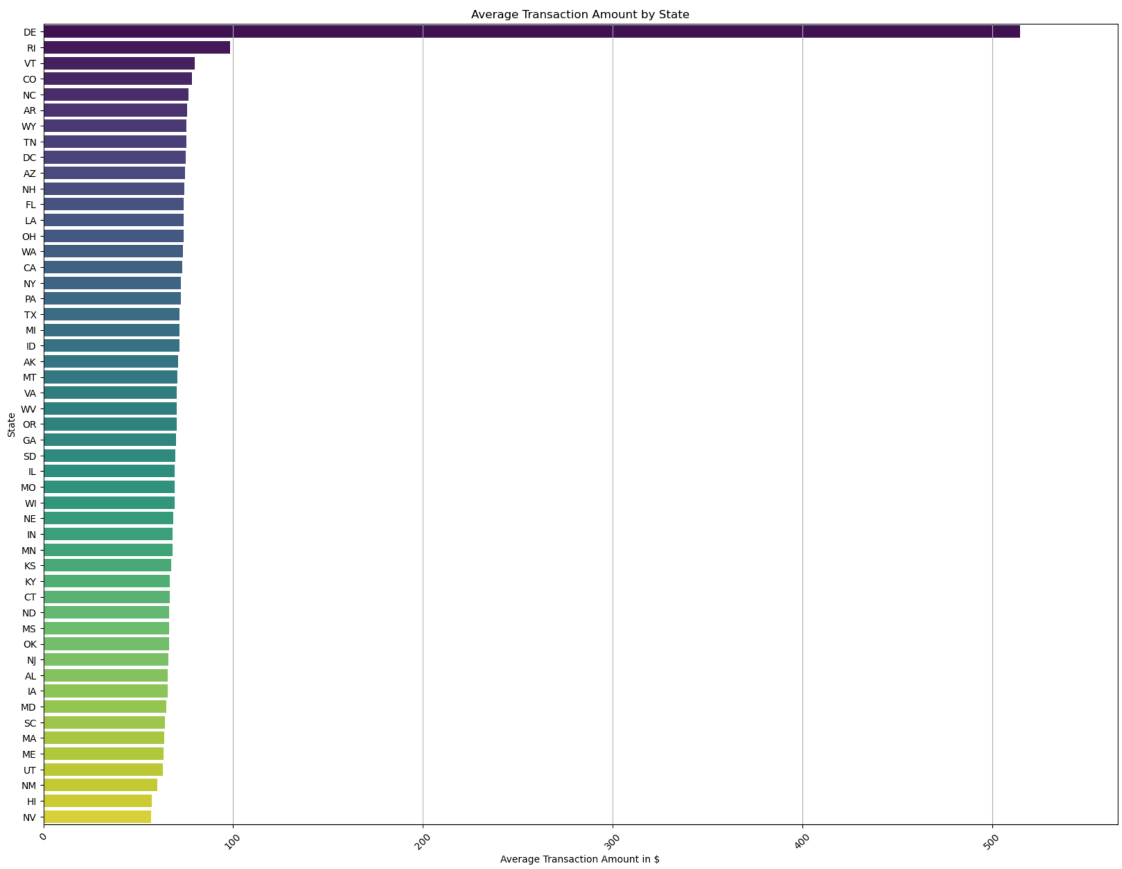
```
            legend = False)
plt.title('Transaction Count by State')
plt.xlabel('Transaction Count')
plt.ylabel('State')
plt.xticks(rotation = 45)
plt.xlim(0, state_trends['transaction_count'].max() * 1.1)
plt.grid(axis='x')
plt.show()
```



Top 10 states with highest transaction count are TX, NY, PA, CA, OH, MI, IL, FL, AL, and MO. The highest transaction count is in TX with over 65,000 transactions, followed by NY with near 60,000 transactions, and PA more than 55,000 transactions. The lowest transaction count is in DE only 9 transactions, followed by RI with 390 transactions, and AK with 1,520 transactions.

[48]:
```
# Plot average transaction amount by merchant category
plt.figure(figsize = (20, 15))
sns.barplot(data = state_trends,
            x = 'average_amount',
            y = 'state',
```

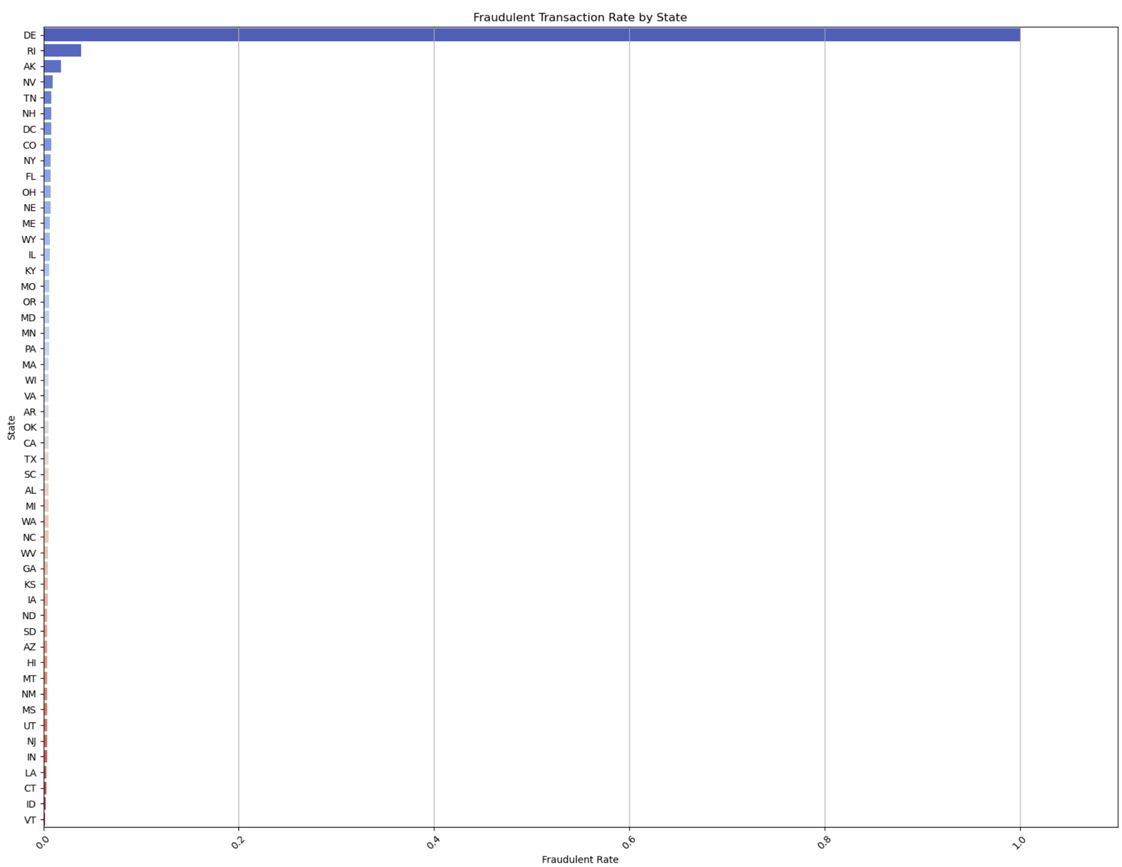
```
            order = state_trends.sort_values(by = ['average_amount'], ascending␣
↪= False)['state'],
            palette = 'viridis',
            legend = False)
plt.title('Average Transaction Amount by State')
plt.xlabel('Average Transaction Amount in $')
plt.ylabel('State')
plt.xticks(rotation = 45)
plt.xlim(0, state_trends['average_amount'].max() * 1.1)
plt.grid(axis='x')
plt.show()
```



DE has the lowest transaction count with only 9 transactions but the highest average transaction amount over 500 USD, followed by RI with 390 transactions and an average amount near 100 USD, all other states have an average transaction amount around 70 USD.

[49]:
```
# Plot investigate fraudulent transaction rate by state
plt.figure(figsize = (20, 15))
sns.barplot(data = state_trends,
            x = 'fraudulent_rate',
```

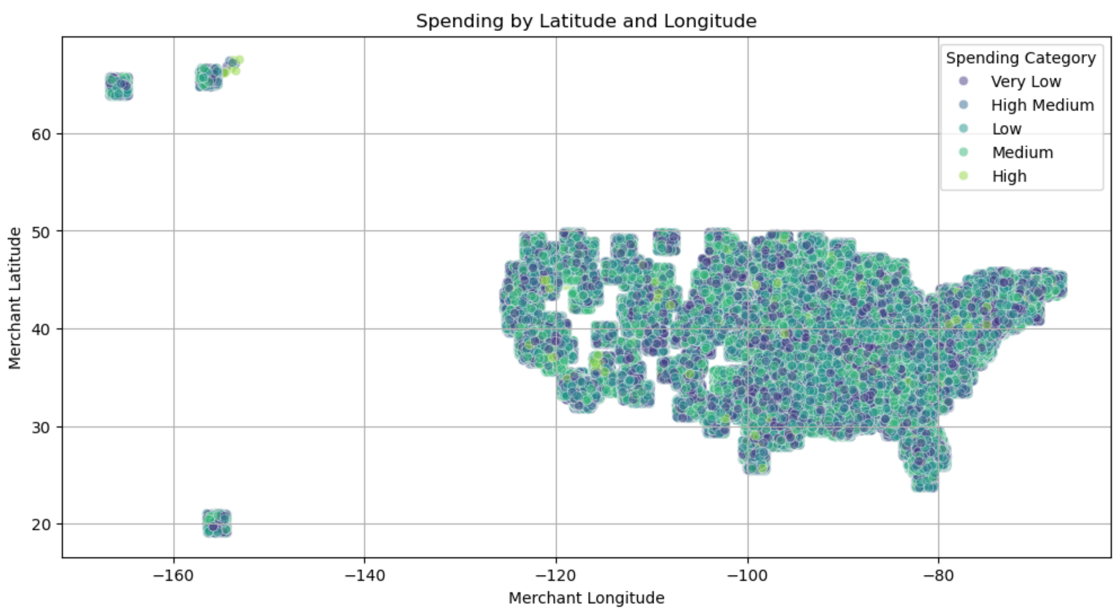
```
            y = 'state',
            order = state_trends.sort_values(by = ['fraudulent_rate'],␣
↪ascending = False)['state'],
            palette = 'coolwarm',
            legend = False)
plt.title('Fraudulent Transaction Rate by State')
plt.xlabel('Fraudulent Rate')
plt.ylabel('State')
plt.xticks(rotation = 45)
plt.xlim(0, state_trends['fraudulent_rate'].max() * 1.1)
plt.grid(axis='x')
plt.show()
```



The highest average transaction amount by state is in DE with over 500 USD with only 9 transactions, and DE also has the highest fraudulent transaction rate with 100% of transactions being fraudulent. The top 3 states with highest fraudulent transaction rate are DE, RI, and AK, which states have a low transaction count but high average transaction amount. The states with low transaction count but high average transaction amount have a high fraudulent transaction rate, which indicates that these states have not alot of transactions but the transactions are relatively large in amount.

2. 4 Spending by latitude and longitude: Analyze transaction patterns across different geographic coordinates to identify spending behavior.

[50]:
```
# Spending by latitude and longitude
plt.figure(figsize = (12, 6))
sns.scatterplot(data = transactions_df,
                x = 'merch_long',
                y = 'merch_lat',
                hue = 'spending_category',
                alpha = 0.5,
                palette = 'viridis')
plt.title('Spending by Latitude and Longitude')
plt.xlabel('Merchant Longitude')
plt.ylabel('Merchant Latitude')
plt.legend(title = 'Spending Category')
plt.grid()
plt.show()
```



In the scatter plot of latitude and longitude, we can see that most transactions are concentrated in the Northeastern and Southeastern regions of the United States, with a few outliers in the Western region. The most transactions are medium-sized and low amounts money spent.

Base on the scatter plot, we can see that most fraudulent transactions are concentrated in Centralwest and Southwest regions of the United States, with a few outliers in the Northeastern and Alaska regions. The fraudulent transactions are mostly big amounts money spent, which indicates that these transactions are more likely to be fraudulent.

[51]:
```
from sklearn.cluster import DBSCAN
```

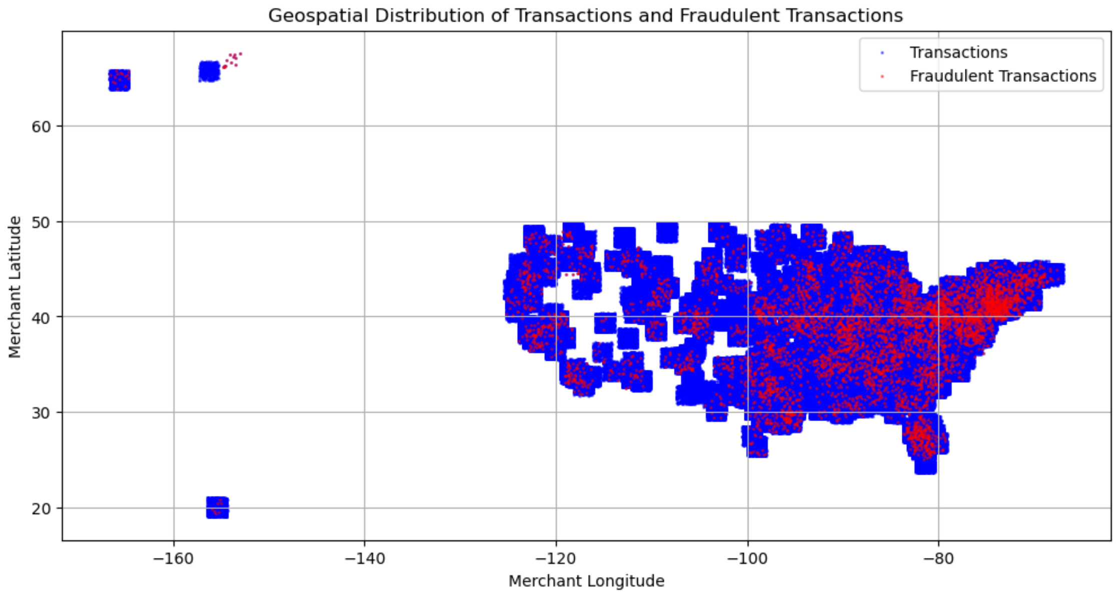
[52]:
```python
# Heatmap of stransaction by latitude and longitude
import folium
from folium.plugins import HeatMap
# Create a folium map centered around the average latitude and longitude
map_center = [transactions_df['merch_lat'].mean(),␣
 ↪transactions_df['merch_long'].mean()]
# Create a folium map
map = folium.Map(location = map_center, zoom_start = 4)
# Create a heatmap layer
heat_data = [[row['merch_lat'], row['merch_long']] for index, row in␣
 ↪transactions_df.iterrows()]
# Add heatmap to the map
HeatMap(heat_data).add_to(map)
# Display the map
map
```

[52]:
```
<folium.folium.Map at 0x183337ce260>
```

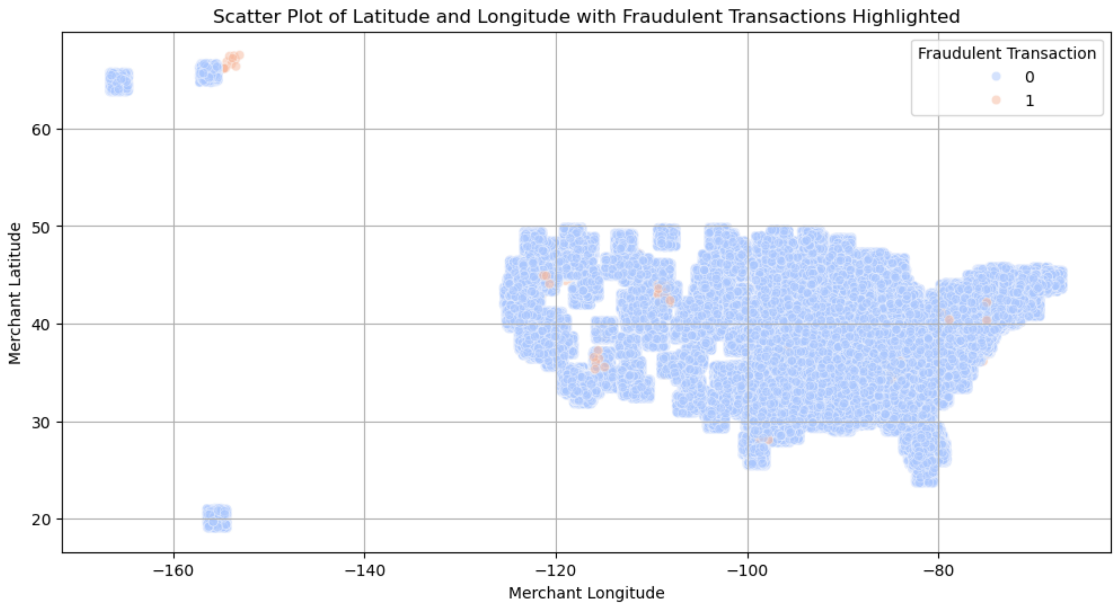
Heatmap of latitude and longitude shows that the highest transaction count is in the Northeastern and Southeastern regions of the United States, with a few outliers in the Western region.

Heatmap of fraudulent transactions by latitude and longitude show that the highest number of transactions is in in Northeast and Southeast regions of the United States, with a few outliers in the Western region.

[53]:
```python
# Geospatial distribution of transactions and fraudulent transactions
import geopandas as gpd
# Create a GeoDataFrame for latitude and longitude
gdf = gpd.GeoDataFrame(transactions_df, geometry=gpd.
 ↪points_from_xy(transactions_df['merch_long'], transactions_df['merch_lat']))
# Create a GeoDataFrame for fraudulent transactions
gdf_fraud = gpd.GeoDataFrame(transactions_df[transactions_df['is_fraud'] == 1],␣
 ↪geometry=gpd.points_from_xy(transactions_df[transactions_df['is_fraud'] ==␣
 ↪1]['merch_long'], transactions_df[transactions_df['is_fraud'] ==␣
 ↪1]['merch_lat']))
# Plot the GeoDataFrame with latitude and longitude
gdf.plot(figsize=(12, 6), alpha=0.5, color='blue', markersize=1)
# Plot the GeoDataFrame with fraudulent transactions
gdf_fraud.plot(ax=plt.gca(), color='red', markersize=1, alpha=0.5)
plt.title('Geospatial Distribution of Transactions and Fraudulent Transactions')
plt.xlabel('Merchant Longitude')
plt.ylabel('Merchant Latitude')
plt.legend(['Transactions', 'Fraudulent Transactions'])
plt.grid()
plt.show()
```



[54]:
```
# Scatter plot of latitude and longitude with fraudulent transactions␣
 ↪highlighted
plt.figure(figsize=(12, 6))
sns.scatterplot(data=transactions_df,
                x='merch_long',
                y='merch_lat',
                hue='is_fraud',
                alpha=0.5,
                palette='coolwarm')
plt.title('Scatter Plot of Latitude and Longitude with Fraudulent Transactions␣
 ↪Highlighted')
plt.xlabel('Merchant Longitude')
plt.ylabel('Merchant Latitude')
plt.legend(title='Fraudulent Transaction')
plt.grid()
plt.show()
```



[55]:
```
# Heat map of transaction by latitude and longitude with fraudulent␣
↪transactions highlighted
fraudulent_heat_data = [[row['merch_lat'], row['merch_long']] for index, row in␣
↪transactions_df[transactions_df['is_fraud'] == 1].iterrows()]
# Calculate the mean latitude and longitude for centering the map
mean_lat = np.mean([x[0] for x in fraudulent_heat_data])
mean_long = np.mean([x[1] for x in fraudulent_heat_data])
map_center = [mean_lat, mean_long]
map_fraud = folium.Map(location = map_center, zoom_start = 4)
# Create a heatmap layer for fraudulent transactions
HeatMap(fraudulent_heat_data, radius = 15, blur = 10).add_to(map_fraud)
# Display the map with fraudulent transactions highlighted
map_fraud
```

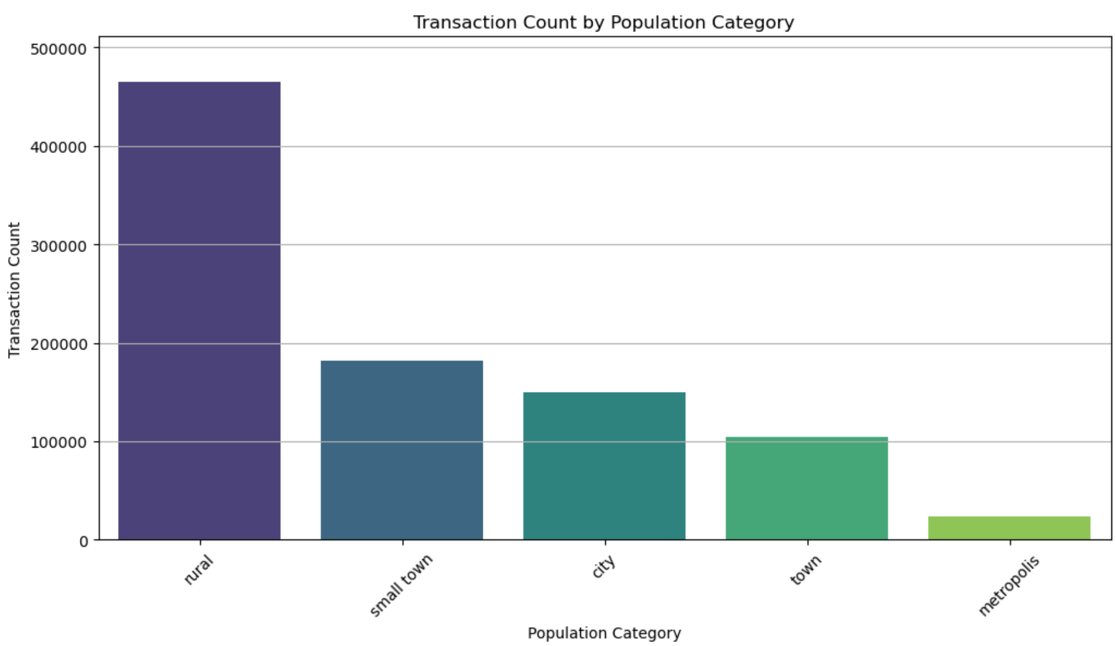
[55]: <folium.folium.Map at 0x18326fc1b70>

3. Who: Demographic analysis infuence on spending behavior, variables such age, gender, city population, and job title.

3. 1 Spending trends by city population category: Analyze transaction patterns across different city population categories to identify spending behavior.

[56]:
```
# Trends by city population category
population_category_trends = transactions_df.groupby('population_category').
↪agg({'amt': ['count', 'mean'], 'is_fraud': 'mean'}).reset_index()
population_category_trends.columns = ['population_category',␣
↪'transaction_count', 'average_amount', 'fraudulent_rate']
```

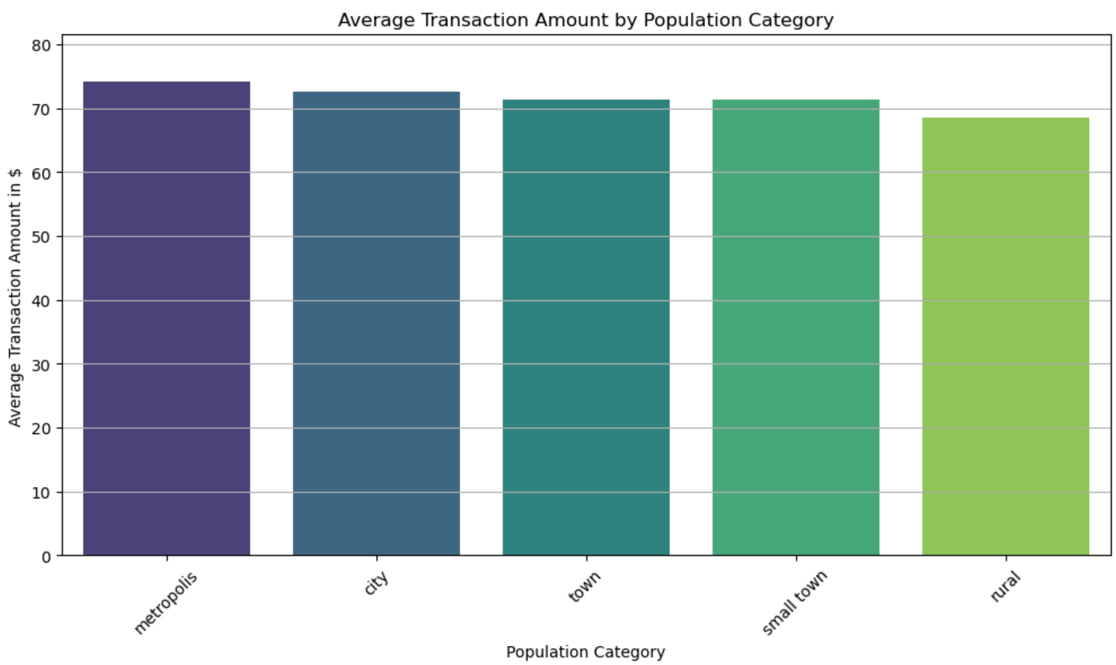
[57]:
```python
# Plot transaction count by population category
plt.figure(figsize = (12, 6))
sns.barplot(data = population_category_trends,
            x = 'population_category',
            y = 'transaction_count',
            order = population_category_trends.sort_values(by =␣
 ↪['transaction_count'], ascending = False)['population_category'],
            palette = 'viridis',
            legend = False)
plt.title('Transaction Count by Population Category')
plt.xlabel('Population Category')
plt.ylabel('Transaction Count')
plt.xticks(rotation = 45)
plt.ylim(0, population_category_trends['transaction_count'].max() * 1.1)
plt.grid(axis='y')
plt.show()
```



Rural areas or areas with low population less than 2,500 people have the highest transaction count, followed by small towns with population between 2,500 and 10,000 people. The third highest transaction count is in cities with population between 10,000 and 50,000 people, followed by towns with population between 10,000 and 50,000 people. The lowest transaction count is in metroplitan areas with population over 100,000 people.

[58]:
```python
# Plot average transaction amount by population category
plt.figure(figsize = (12, 6))
sns.barplot(data = population_category_trends,
```

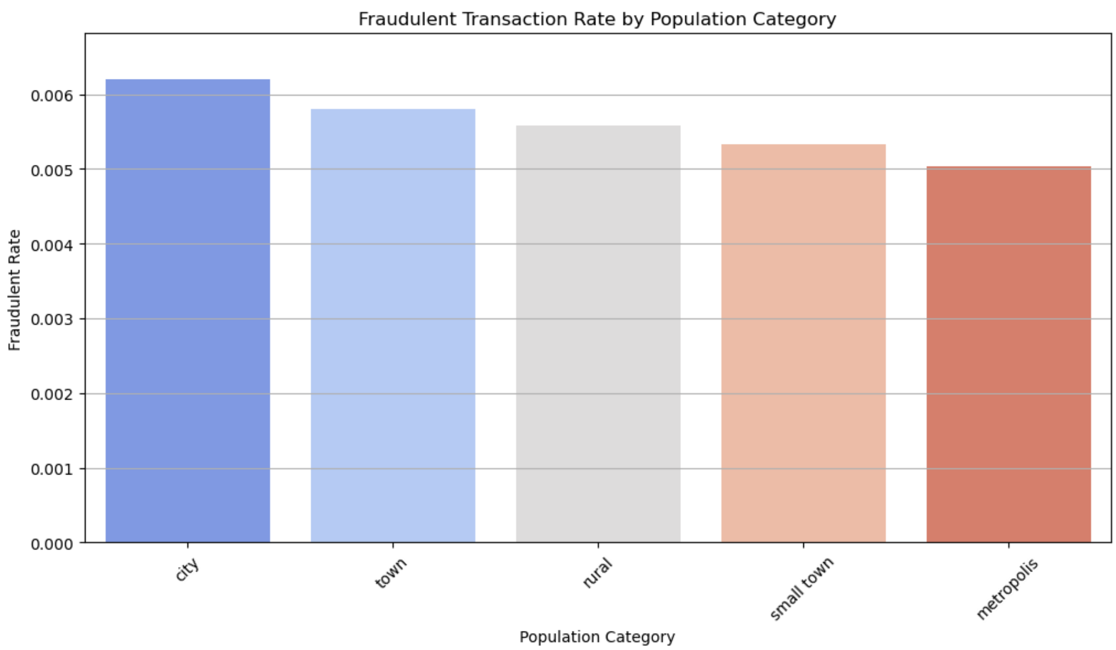
```
            x = 'population_category',
            y = 'average_amount',
            order = population_category_trends.sort_values(by =␣
↪['average_amount'], ascending = False)['population_category'],
            palette = 'viridis',
            legend = False)
plt.title('Average Transaction Amount by Population Category')
plt.xlabel('Population Category')
plt.ylabel('Average Transaction Amount in $')
plt.xticks(rotation = 45)
plt.ylim(0, population_category_trends['average_amount'].max() * 1.1)
plt.grid(axis='y')
plt.show()
```



The average transaction amount is highest in metroplitan areas with population over 1,000,000 people and lowest in rural areas with population less than 2,500 people. The average transaction amount in metroplitan areas is near 75 USD, while the average transaction amount in rural areas is less than 70 USD. The average transaction amount in cities, towns, and small towns is more than 70 USD, which indicates that these areas have a higher average transaction amount compared to rural areas.

[59]:
```
# Investigate fraudulent transaction rate by population category
plt.figure(figsize = (12, 6))
sns.barplot(data = population_category_trends,
            x = 'population_category',
```

```
            y = 'fraudulent_rate',
            order = population_category_trends.sort_values(by =␣
↪['fraudulent_rate'], ascending = False)['population_category'],
            palette = 'coolwarm',
            legend = False)
plt.title('Fraudulent Transaction Rate by Population Category')
plt.xlabel('Population Category')
plt.ylabel('Fraudulent Rate')
plt.xticks(rotation = 45)
plt.ylim(0, population_category_trends['fraudulent_rate'].max() * 1.1)
plt.grid(axis='y')
plt.show()
```



The fraudulent transaction rate is highest in cities with population between 50,000 and 100,000 people, followed by towns with population between 10,000 and 50,000 people. The lowest fraudulent transaction rate is in metroplitan areas with population over 1,000,000 people, followed by small towns with population between 2,500 and 10,000 people. The fraudulent transaction rate in rural areas with population less than 2,500 people is in third place in five population categories, which indicates that these areas have a higher fraudulent transaction rate compared to metroplitan areas and small towns.

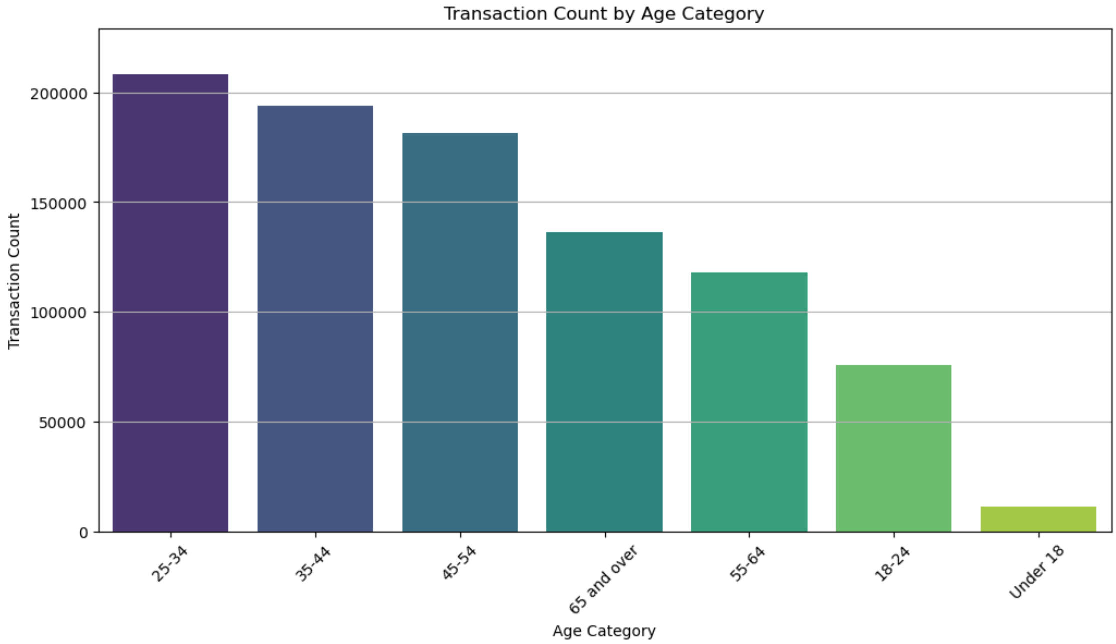
3. 2 Spending trends by age group: Analyze transaction patterns across different age groups to identify spending behavior.

[60]:
```
# Create age categories
def categorize_age(age):
```

```
    if age < 18:
        return 'Under 18'
    elif 18 <= age < 25:
        return '18-24'
    elif 25 <= age < 35:
        return '25-34'
    elif 35 <= age < 45:
        return '35-44'
    elif 45 <= age < 55:
        return '45-54'
    elif 55 <= age < 65:
        return '55-64'
    else:
        return '65 and over'
transactions_df['age_category'] = transactions_df['age'].apply(categorize_age)
```

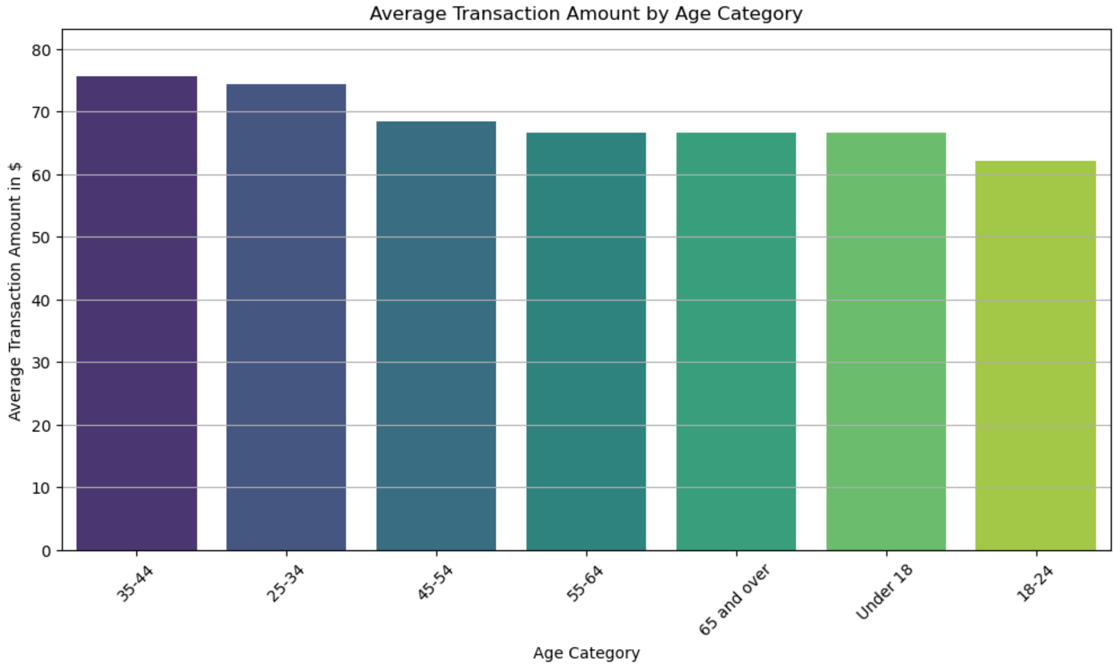
[61]:
```
# Trends by age category
age_category_trends = transactions_df.groupby('age_category').agg({'amt':␣
 ↪['count', 'mean'], 'is_fraud': 'mean'}).reset_index()
age_category_trends.columns = ['age_category', 'transaction_count',␣
 ↪'average_amount', 'fraudulent_rate']
```

[62]:
```
# Plot transaction count by age category
plt.figure(figsize = (12, 6))
sns.barplot(data = age_category_trends,
            x = 'age_category',
            y = 'transaction_count',
            order = age_category_trends.sort_values(by = ['transaction_count'],␣
 ↪ascending = False)['age_category'],
            palette = 'viridis',
            legend = False)
plt.title('Transaction Count by Age Category')
plt.xlabel('Age Category')
plt.ylabel('Transaction Count')
plt.xticks(rotation = 45)
plt.ylim(0, age_category_trends['transaction_count'].max() * 1.1)
plt.grid(axis='y')
plt.show()
```



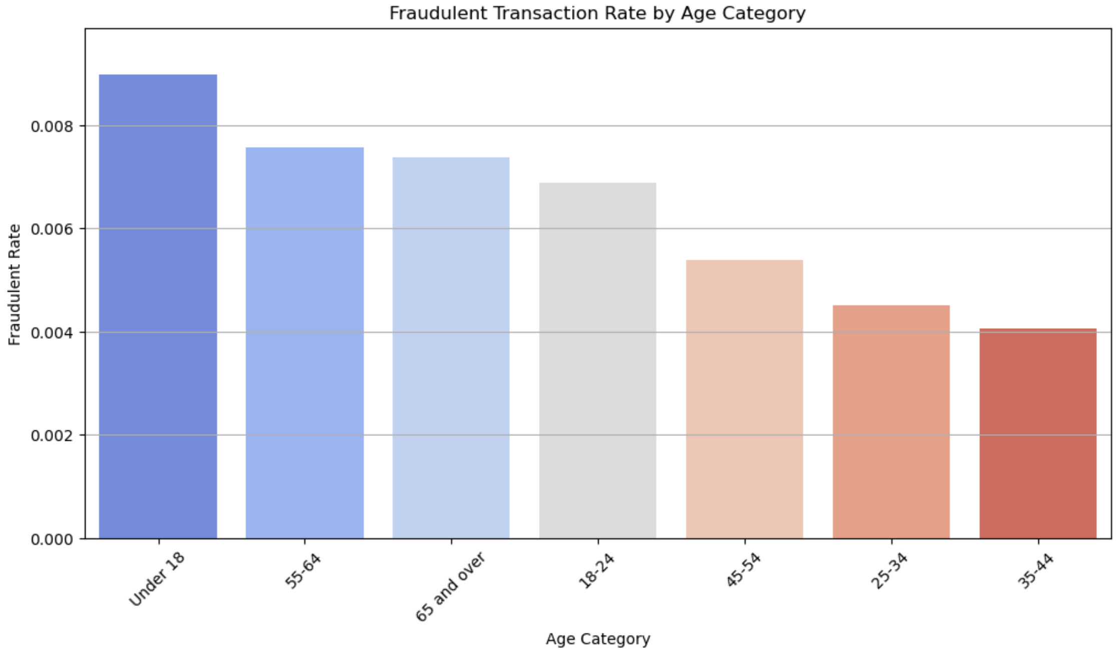
Grouping the age into categories, we can see that the highest transaction count is in the age group of 25-34 years old, followed by the age group of 35-44 years old. The third highest transaction count is in the age group or 45-54 years old, followed by the age group of 65 and older. The lowest transaction count is in the age group of under 18 years old, followed by the age group of 18-24 and 55-64 years old. That indicates that the age group of 24-34 years old is the most active in terns of transaction count, people in this age group are more likely to use credit cards for their transactions. For marketing strategies, businesses can target this age group with promotions and offers to increase transaction count.

[63]:
```
# Plot average transaction amount by age category
plt.figure(figsize = (12, 6))
sns.barplot(data = age_category_trends,
            x = 'age_category',
            y = 'average_amount',
            order = age_category_trends.sort_values(by = ['average_amount'],␣
 ↪ascending = False)['age_category'],
            palette = 'viridis',
            legend = False)
plt.title('Average Transaction Amount by Age Category')
plt.xlabel('Age Category')
plt.ylabel('Average Transaction Amount in $')
plt.xticks(rotation = 45)
plt.ylim(0, age_category_trends['average_amount'].max() * 1.1)
plt.grid(axis='y')
plt.show()
```



Average transaction amount by age category shows that the highest average transaction amount is in the age group of 35-44 years old, followed by the age group of 25-34 years old. The third highest average transaction amount is in the age group of 45-54 years old, followed by the age group of 55-64 years old. The lowest average transaction amount is in the age group of 18-24 years old, followed by the age group of under 18 years old and 65 and older. This indicates that the age group of 35-44 years old is the most likely to spend more money on their transactions, while the age group of 18-24 years old is the least likely to spend money on their transactions.

[64]:
```
# Plot investigate fraudulent transaction rate by age category
plt.figure(figsize = (12, 6))
sns.barplot(data = age_category_trends,
            x = 'age_category',
            y = 'fraudulent_rate',
            order = age_category_trends.sort_values(by = ['fraudulent_rate'],␣
 ↪ascending = False)['age_category'],
            palette = 'coolwarm',
            legend = False)
plt.title('Fraudulent Transaction Rate by Age Category')
plt.xlabel('Age Category')
plt.ylabel('Fraudulent Rate')
plt.xticks(rotation = 45)
plt.ylim(0, age_category_trends['fraudulent_rate'].max() * 1.1)
plt.grid(axis='y')
plt.show()
```

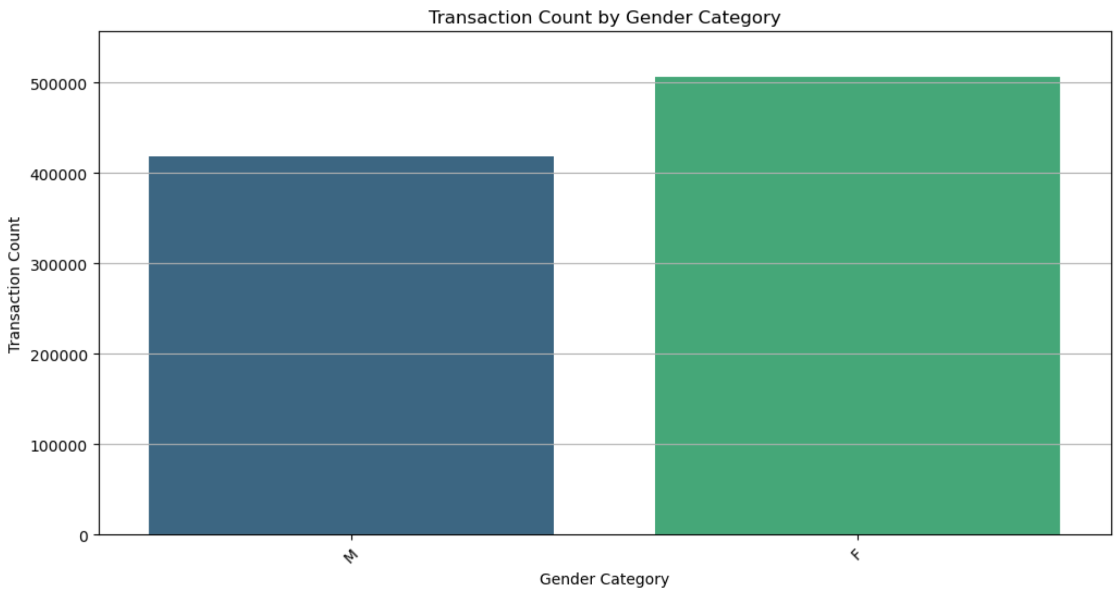


Surprisingly, the fraudulent transaction rate is highest in the age group of under 18 years old, followed by the age group of 55-64 years old. The third highest fraudulent transaction rate is in the age group of 65 and older, followed by the age group of 18-24 years old. The lowest fraudulent transaction rate is in the age group of 35-44 years old, which indicates that this age group is the least likely to commit fraudulent activities. This suggests that younger and older age groups are more likely to be involved in fraudulent transactions, which highlights the need for increased monitoring and security measures for these age groups. People in the age group of 35-44 years old are more likely to be responsible and less likely to commit fraudulent activities, which may be due to their life experience and financial stability. This information can be used to optimize fraud detection systems and allocate resources more effectively.

[65]:
```
# Trends by gender
gender_trends = transactions_df.groupby('gender').agg({'amt': ['count',␣
↪'mean'], 'is_fraud': 'mean'}).reset_index()
gender_trends.columns =  ['gender', 'transaction_count', 'average_amount',␣
↪'fraudulent_rate']
```

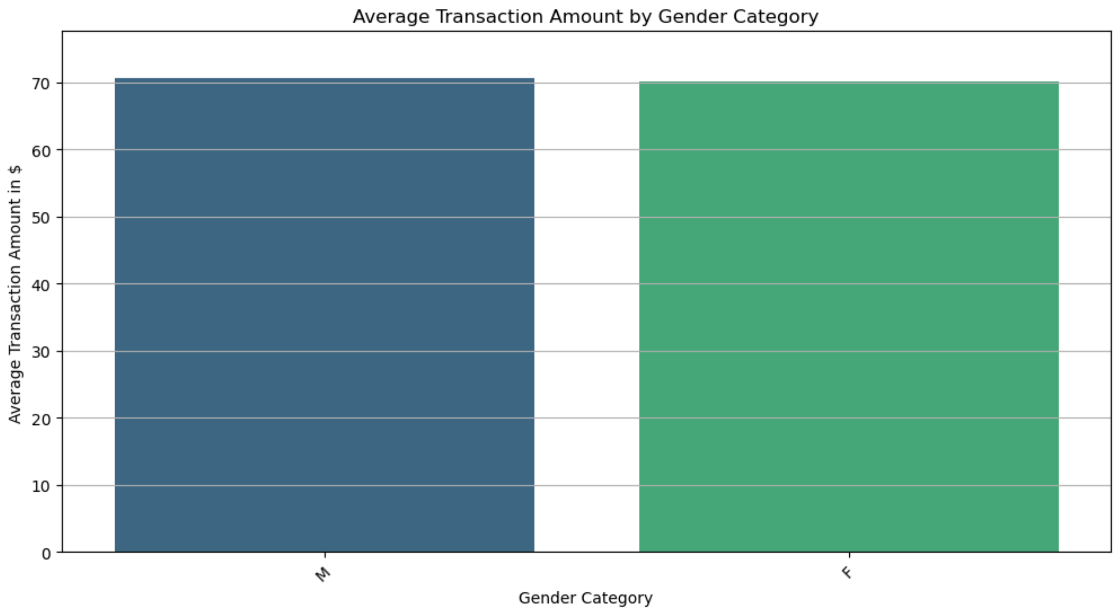
[66]:
```
# Plot transaction count by gender
plt.figure(figsize = (12, 6))
sns.barplot(data = gender_trends,
            x = 'gender',
            y = 'transaction_count',
            order = gender_trends.sort_values(by = ['gender'], ascending =␣
↪False)['gender'],
            palette = 'viridis',
            legend = False)
```

```
plt.title('Transaction Count by Gender Category')
plt.xlabel('Gender Category')
plt.ylabel('Transaction Count')
plt.xticks(rotation = 45)
plt.ylim(0, gender_trends['transaction_count'].max() * 1.1)
plt.grid(axis='y')
plt.show()
```



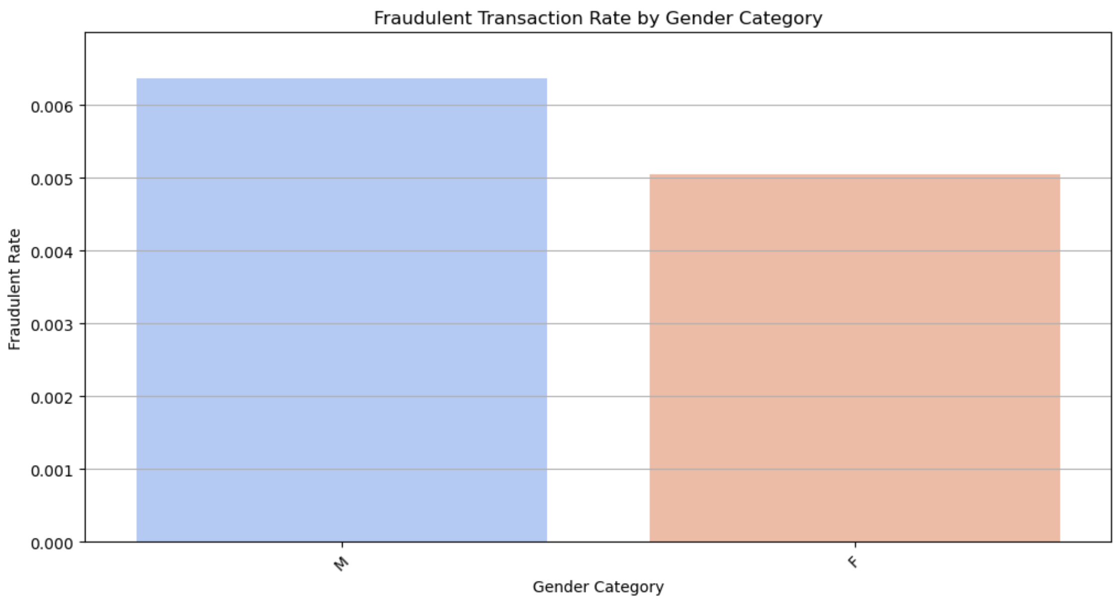
Female cardholders have the highest transaction count over 500,000 transactions in 2019, followed male cardholders with over 400,000 transactions.

[67]:
```
# Plot average transaction amount by gender category
plt.figure(figsize = (12, 6))
sns.barplot(data = gender_trends,
            x = 'gender',
            y = 'average_amount',
            order = gender_trends.sort_values(by = ['average_amount'],␣
 ↪ascending = False)['gender'],
            palette = 'viridis',
            legend = False)
plt.title('Average Transaction Amount by Gender Category')
plt.xlabel('Gender Category')
plt.ylabel('Average Transaction Amount in $')
plt.xticks(rotation = 45)
plt.ylim(0, gender_trends['average_amount'].max() * 1.1)
plt.grid(axis='y')
plt.show()
```



Both male and female cardholders have a similar average transaction amount around 70 USD, male cardholders have a slightly higher average transaction amount than female cardholders.

[68]:
```
# Plot investigate fraudulent transaction rate by gender category
plt.figure(figsize = (12, 6))
sns.barplot(data = gender_trends,
            x = 'gender',
            y = 'fraudulent_rate',
            order = gender_trends.sort_values(by = ['fraudulent_rate'],␣
 ↪ascending = False)['gender'],
            palette = 'coolwarm',
            legend = False)
plt.title('Fraudulent Transaction Rate by Gender Category')
plt.xlabel('Gender Category')
plt.ylabel('Fraudulent Rate')
plt.xticks(rotation = 45)
plt.ylim(0, gender_trends['fraudulent_rate'].max() * 1.1)
plt.grid(axis='y')
plt.show()
```



Fraudulent transaction rate by gender category shows that the highest fraudulent transaction rate is in male cardholders with over 0.6% and 0.5% of female cardholders' transaction being fraudulent.

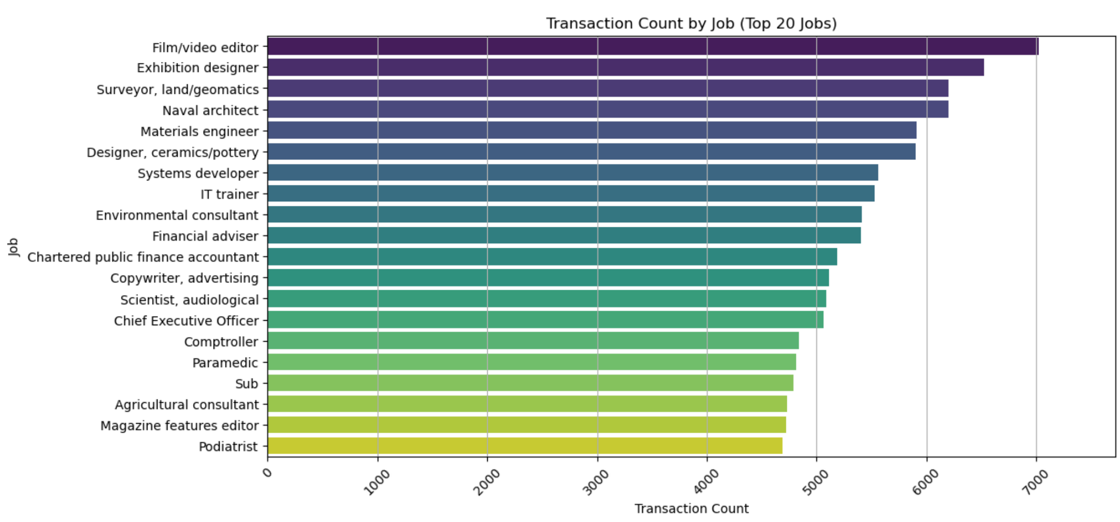
3. 3 Spending trends by job title: Analyze transaction patterns across different job titles to identify spending behavior.

[69]:
```
# Trends by job
top_job_trends = transactions_df.groupby('job').agg({'amt': ['count', 'mean'],␣
↪'is_fraud': 'mean'}).reset_index()
top_job_trends.columns = ['job', 'transaction_count', 'average_amount',␣
↪'fraudulent_rate']
top_job_trends
```

[69]:
```
                                      job  transaction_count  average_amount  \
0                      Academic librarian                751       74.855539
1                   Accountant, chartered                 11      485.706364
2         Accountant, chartered certified                374       61.938717
3     Accountant, chartered public finance              1855       54.609385
4                   Accounting technician              3316       77.251625
..                                    ...                ...             ...
487                        Water engineer               4430       71.043307
488              Water quality scientist                353       80.454334
489                          Web designer               1831       62.419503
490                    Wellsite geologist               1823       65.506111
491                                Writer                351       86.899630

     fraudulent_rate
0           0.014647
```

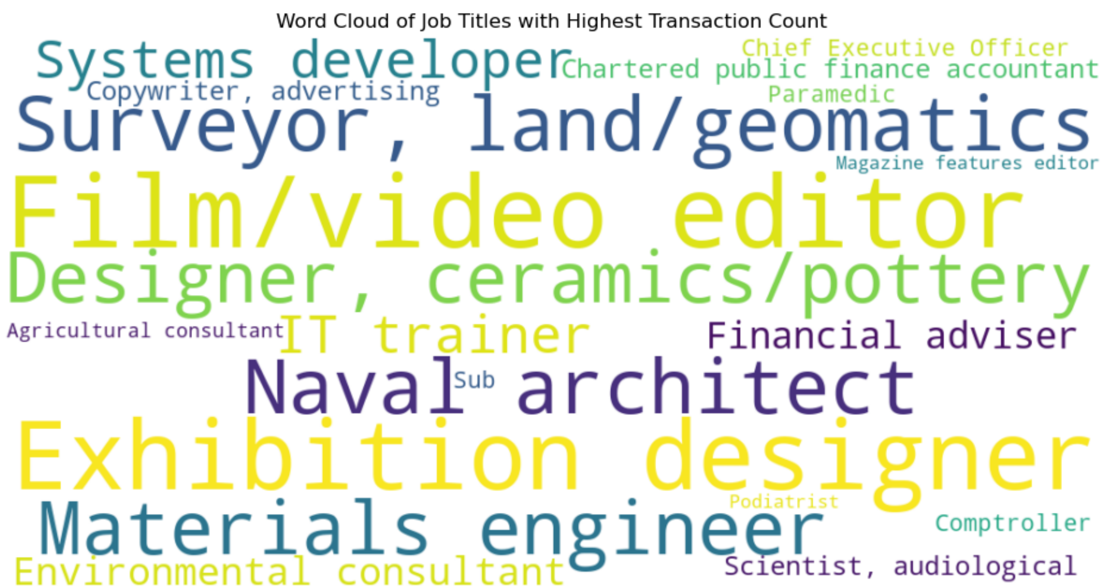
```
1           1.000000
2           0.000000
3           0.000000
4           0.006333
..               …
487         0.000000
488         0.019830
489         0.009831
490         0.004937
491         0.000000

[492 rows x 4 columns]
```

[70]:
```python
# Plot top 20 jobs by transaction count
top_job_trends = top_job_trends.sort_values(by = ['transaction_count'],␣
 ↪ascending = False).head(20)

plt.figure(figsize = (12, 6))
sns.barplot(data = top_job_trends,
            x = 'transaction_count',
            y = 'job',
            order = top_job_trends.sort_values(by = ['transaction_count'],␣
 ↪ascending = False)['job'],
            palette = 'viridis',
            legend = False)
plt.title('Transaction Count by Job (Top 20 Jobs)')
plt.xlabel('Transaction Count')
plt.ylabel('Job')
plt.xticks(rotation = 45)
plt.xlim(0, top_job_trends['transaction_count'].max() * 1.1)
plt.grid(axis='x')
plt.show()
```



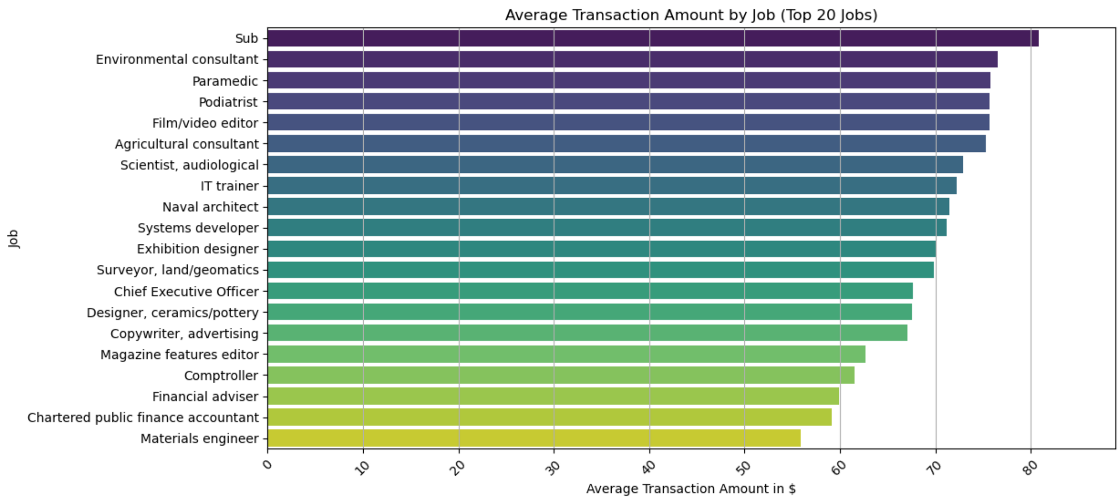
Film/video editors have the highest transaction count over 7,000 transactions in 2019, followed by exhibition designers with over 6,500 transactions, surveyors, land/geomatics and naval architects with over 6,000 transactioins.

[71]:
```
# Word cloud of job titles with highest transaction count
from wordcloud import WordCloud
wordcloud = WordCloud(width = 1000, height = 500, background_color='white',␣
↪max_words = 200, colormap = 'viridis').
↪generate_from_frequencies(top_job_trends.
↪set_index('job')['transaction_count'].to_dict())
plt.figure(figsize=(12, 6))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.title('Word Cloud of Job Titles with Highest Transaction Count')
plt.show()
```



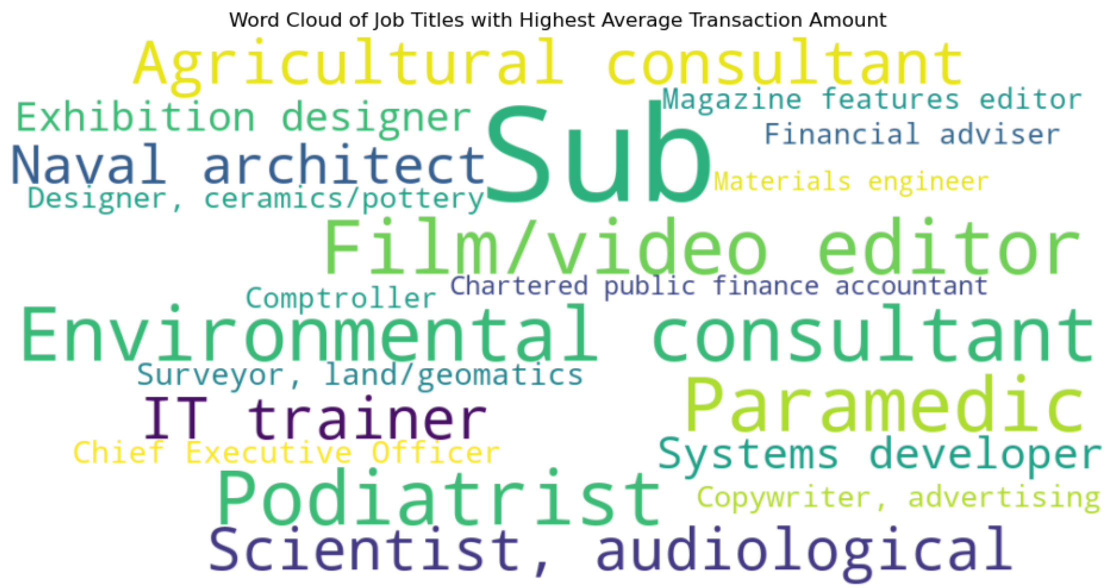
[72]:
```
# Plot top 20 average transaction amount by job
top_job_avg_amount = top_job_trends.sort_values(by = ['average_amount'],␣
↪ascending = False).head(20)
plt.figure(figsize = (12, 6))
sns.barplot(data = top_job_avg_amount,
            x = 'average_amount',
            y = 'job',
            order = top_job_avg_amount.sort_values(by = ['average_amount'],␣
↪ascending = False)['job'],
```

```
             palette = 'viridis',
             legend = False)
plt.title('Average Transaction Amount by Job (Top 20 Jobs)')
plt.xlabel('Average Transaction Amount in $')
plt.ylabel('Job')
plt.xticks(rotation = 45)
plt.xlim(0, top_job_avg_amount['average_amount'].max() * 1.1)
plt.grid(axis='x')
plt.show()
```



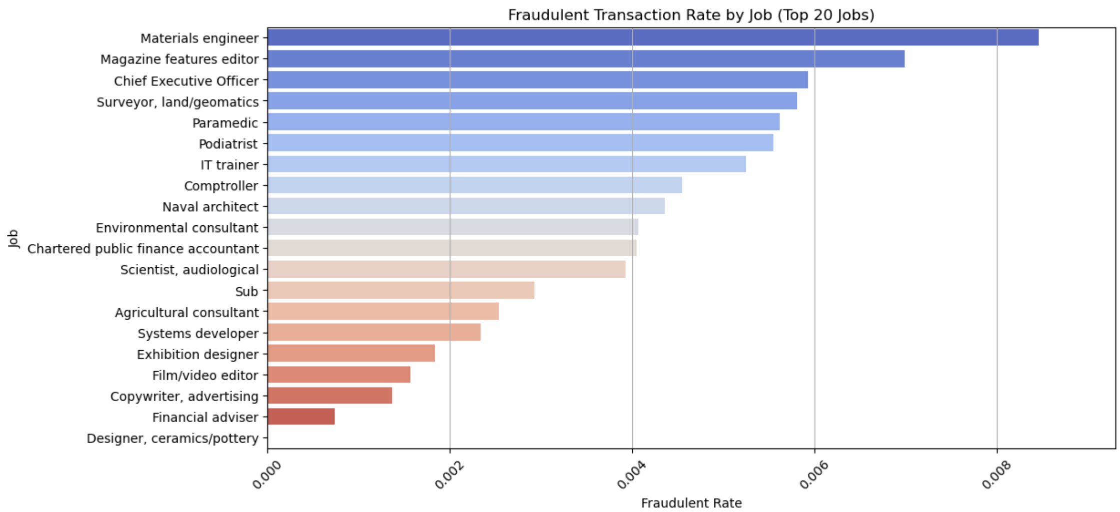
Ship brokers have the highest average transaction amount around 850 USD, followed by air traffic controllers with over 750 USD, and engineers site with around 750 USD.

[73]:
```
# Cloud word of job titles with highest average transaction amount
wordcloud_avg = WordCloud(width = 1000, height = 500, background_color='white',␣
 ↪max_words=200, colormap = 'viridis').
 ↪generate_from_frequencies(top_job_trends.set_index('job')['average_amount'].
 ↪to_dict())
plt.figure(figsize=(12, 6))
plt.imshow(wordcloud_avg, interpolation='bilinear')
plt.axis('off')
plt.title('Word Cloud of Job Titles with Highest Average Transaction Amount')
plt.show()
```



[74]:

```
# Plot top 20 jobs by fraudulent transaction rate
top_job_fraudulent_rate = top_job_trends.sort_values(by = ['fraudulent_rate'],␣
 ↪ascending = False).head(20)
plt.figure(figsize = (12, 6))
sns.barplot(data = top_job_fraudulent_rate,
            x = 'fraudulent_rate',
            y = 'job',
            order = top_job_fraudulent_rate.sort_values(by =␣
 ↪['fraudulent_rate'], ascending = False)['job'],
            palette = 'coolwarm',
            legend = False)
plt.title('Fraudulent Transaction Rate by Job (Top 20 Jobs)')
plt.xlabel('Fraudulent Rate')
plt.ylabel('Job')
plt.xticks(rotation = 45)
plt.xlim(0, top_job_fraudulent_rate['fraudulent_rate'].max() * 1.1)
plt.grid(axis='x')
plt.show()
```



So surprisingly, the highest fraudulent transaction rate is in information officers around 100%, followed by ship brokers also around 100%, air traffic controllers, engineers site, contracting civil engineers,.. Those job titles have a high average transaction amount, which indicates that these job titles are more likely to be involved in fraudulent transactions. This suggests that people in these job titles may have access to more financial resources and may be more likely to commit fraudulent activities, which highlights the need for increased monitoring and security measures for these job titles.

[75]:
```
# Cloud word of job titles with highest fraudulent transaction rate
wordcloud_fraud = WordCloud(width = 1000, height = 500,␣
↪background_color='white', max_words=200, colormap = 'coolwarm').
↪generate_from_frequencies(top_job_trends.set_index('job')['fraudulent_rate'].
↪to_dict())
plt.figure(figsize=(12, 6))
plt.imshow(wordcloud_fraud, interpolation='bilinear')
plt.axis('off')
plt.title('Word Cloud of Job Titles with Highest Fraudulent Transaction Rate')
plt.show()
```

4. How much: Spending behavior analysis

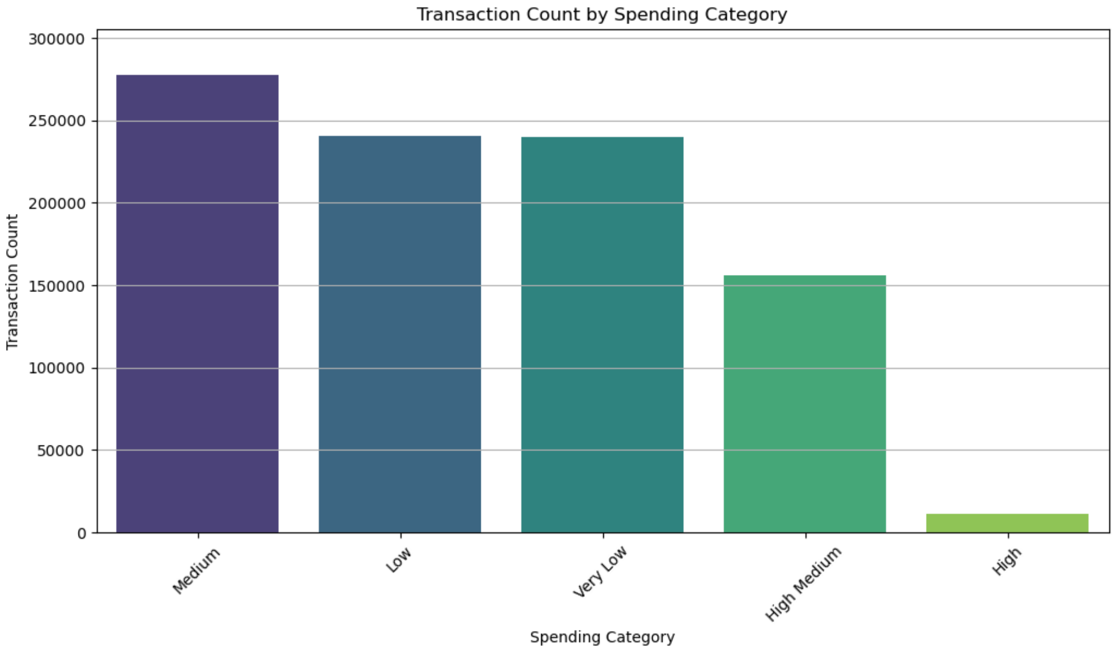
[76]:
```python
# Trends by spending category
spending_category_trends = transactions_df.groupby('spending_category').
↪agg({'amt': ['count', 'mean'], 'is_fraud': 'mean'}).reset_index()
spending_category_trends.columns = ['spending_category', 'transaction_count',␣
↪'average_amount', 'fraudulent_rate']
spending_category_trends
```

[76]:

	spending_category	transaction_count	average_amount	fraudulent_rate
0	High	11104	967.311314	0.227936
1	High Medium	155970	165.794101	0.009688
2	Low	240405	30.090865	0.003224
3	Medium	277511	71.672611	0.000126
4	Very Low	239860	5.257608	0.001534

[77]:
```python
# Plot transaction count by spending category
plt.figure(figsize = (12, 6))
sns.barplot(data = spending_category_trends,
            x = 'spending_category',
            y = 'transaction_count',
            order = spending_category_trends.sort_values(by =␣
↪['transaction_count'], ascending = False)['spending_category'],
            palette = 'viridis',
            legend = False)
plt.title('Transaction Count by Spending Category')
plt.xlabel('Spending Category')
plt.ylabel('Transaction Count')
```

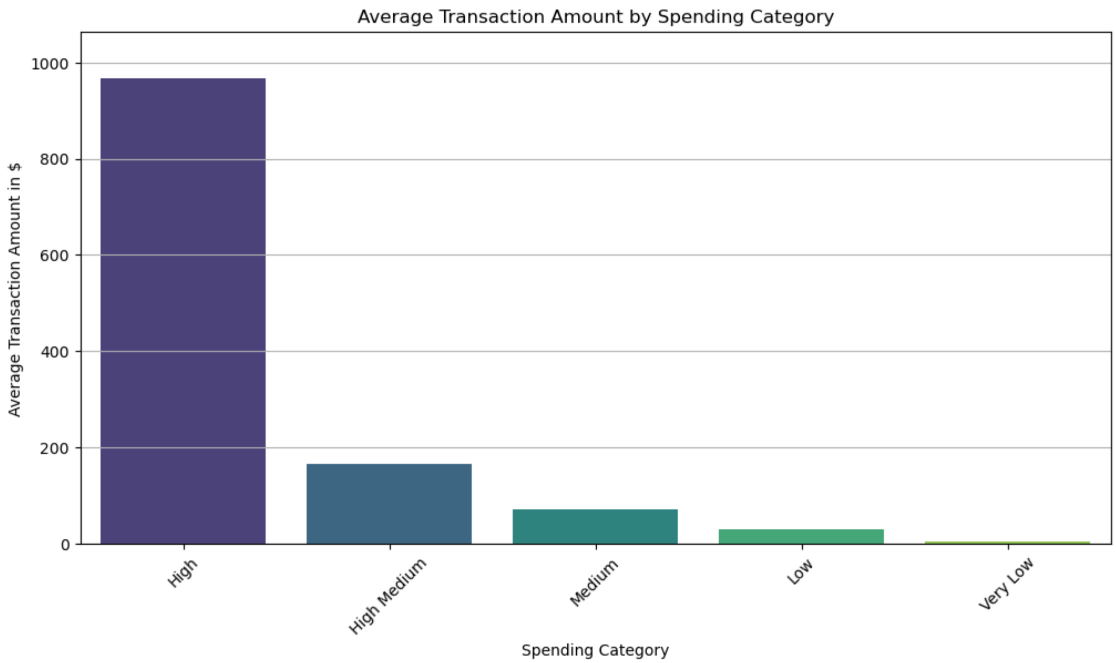
```
plt.xticks(rotation = 45)
plt.ylim(0, spending_category_trends['transaction_count'].max() * 1.1)
plt.grid(axis='y')
plt.show()
```



The highest transaction count by spending around 50 - 100 USD in each transaction is 277,511 transactions in 2019, followed by the low (10 - 50 USD) and very low ((less than 10 USD)) spending categories with around 240,000 transactions each. The high spending category (over 500 USD) has the lowest transaction count with only around 11,104 transactions in 2019. This suggests that most transactions are in the low to medium spending categories, which may indicate that customers are more likely to make smaller purchases rather than larger ones.

[78]:
```
# Plot average transaction amount by spending category
plt.figure(figsize = (12, 6))
sns.barplot(data = spending_category_trends,
            x = 'spending_category',
            y = 'average_amount',
            order = spending_category_trends.sort_values(by =␣
↪['average_amount'], ascending = False)['spending_category'],
            palette = 'viridis',
            legend = False)
plt.title('Average Transaction Amount by Spending Category')
plt.xlabel('Spending Category')
plt.ylabel('Average Transaction Amount in $')
plt.xticks(rotation = 45)
plt.ylim(0, spending_category_trends['average_amount'].max() * 1.1)
```

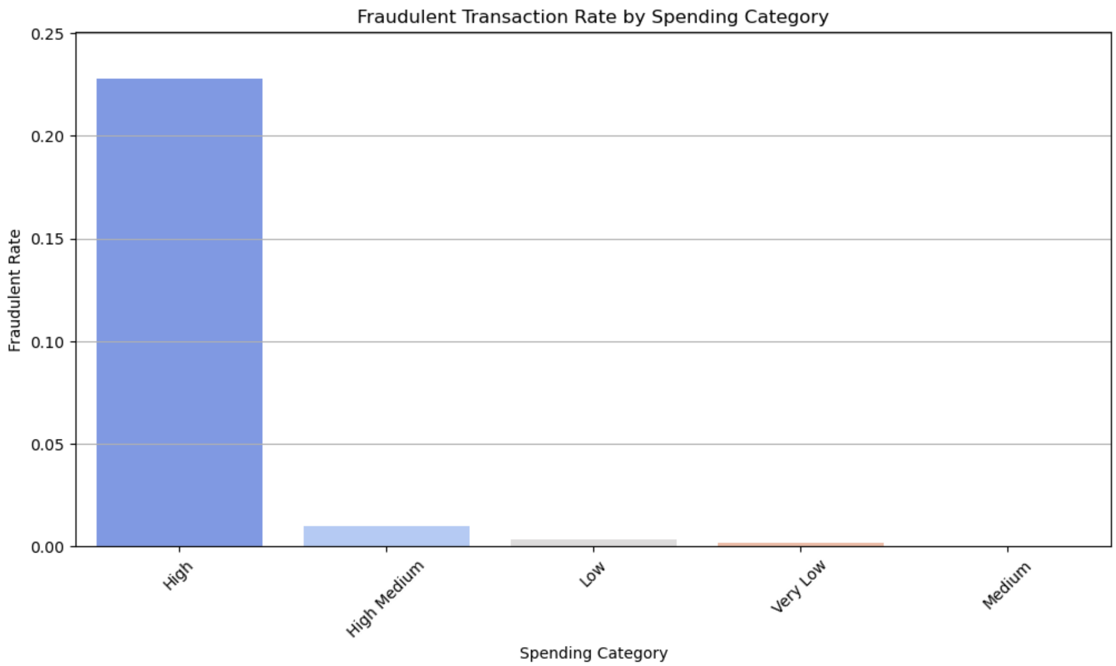
```
plt.grid(axis='y')
plt.show()
```



The average transaction amount by spending category shows that the highest average transaction amount is in the high spending category (over 500 USD) with around 970 USD, followed by the high-medium spending category (100 - 500 USD) with around 166 USD, medium spending category (50 - 100 USD) with around 71 USD, and the low spending category (10 - 50 USD) with around 30 USD. The very low spending category (less than 10 USD) has the lowest average transaction amount with around 5 USD. This suggests that customers tend to spend more money on high-value transactions, while low-value transactions are more common.

[79]:
```
# Plot investigate fraudulent transaction rate by spending category
plt.figure(figsize = (12, 6))
sns.barplot(data = spending_category_trends,
            x = 'spending_category',
            y = 'fraudulent_rate',
            order = spending_category_trends.sort_values(by =␣
 ↪['fraudulent_rate'], ascending = False)['spending_category'],
            palette = 'coolwarm',
            legend = False)
plt.title('Fraudulent Transaction Rate by Spending Category')
plt.xlabel('Spending Category')
plt.ylabel('Fraudulent Rate')
plt.xticks(rotation = 45)
plt.ylim(0, spending_category_trends['fraudulent_rate'].max() * 1.1)
```

```
plt.grid(axis='y')
plt.show()
```



The fraudulent transaction rate by spending category shows that the highest fraudulent transaction rate is in the high spending category (over 500 USD) with around 2.3%, followed by the high-medium spending category (100 - 500 USD) with around 1%, medium spending category (50 - 100 USD)is the lowest has fraudulent transaction rate with around 0.01% , and the low spending category (10 - 50 USD) with around 0.3%. The very low spending category (less than 10 USD) with around 0.1%. This suggests that high-value transactions are more likely to be fraudulent, while medium and very low-value transactions are less likely to be fraudulent.

B. Model Development and Evaluation for Fraud Detection

1. Feture engineering and selection

[80]:
```
# Make a copy of transactions_df for further development machine learning models
fraudulent_detection_df = transactions_df.copy()
```

[81]:
```
# Calculate the fraudulent transaction rate
fraud_rate = fraudulent_detection_df['is_fraud'].mean()
print(f'Fraudulent transaction rate {fraud_rate:.2%}')
```

```
Fraudulent transaction rate 0.56%
```

[82]:
```
# Calculate the distance between the cardholder's home and the merchant's␣
↪location
```

```
from geopy.distance import geodesic
def calculate_distance(row):
    home_coords = (row['lat'], row['long'])
    merch_coords = (row['merch_lat'], row['merch_long'])
    return geodesic(home_coords, merch_coords).kilometers
fraudulent_detection_df['distance'] = fraudulent_detection_df.
 ↪apply(calculate_distance, axis=1)
```

[83]:
```
# Transaction frequency by hour
fraudulent_detection_df = fraudulent_detection_df.sort_values(by =␣
 ↪'trans_date_trans_time')
# Calculate time difference between consecutive transactions for each cardholder
fraudulent_detection_df['time_difference'] = fraudulent_detection_df.
 ↪groupby('cc_num')['trans_date_trans_time'].diff().dt.total_seconds().
 ↪fillna(0)/ 3600  # Convert to hours
# Calculate the number of transactions in the past 1 hour for each cardholder
def rolling_count_1h(times):
        # times must be sorted
        counts = []
        for i in range(len(times)):
                current_time = times.iloc[i]
                window_start = current_time - pd.Timedelta(hours=1)
                count = ((times >= window_start) & (times <= current_time)).
 ↪sum()
                counts.append(count)
        return pd.Series(counts, index=times.index)

fraudulent_detection_df['trans_freq_hour'] = fraudulent_detection_df.
 ↪groupby('cc_num')['trans_date_trans_time'].transform(rolling_count_1h)
```

[84]:
```
# Category fraud risk
category_fraud_risk = fraudulent_detection_df.groupby('category')['is_fraud'].
 ↪mean().to_dict()
fraudulent_detection_df['category_fraud_risk'] =␣
 ↪fraudulent_detection_df['category'].map(category_fraud_risk)
# Additional interaction features
fraudulent_detection_df['amt_category_fraud_risk'] =␣
 ↪fraudulent_detection_df['amt'] *␣
 ↪fraudulent_detection_df['category_fraud_risk']
```

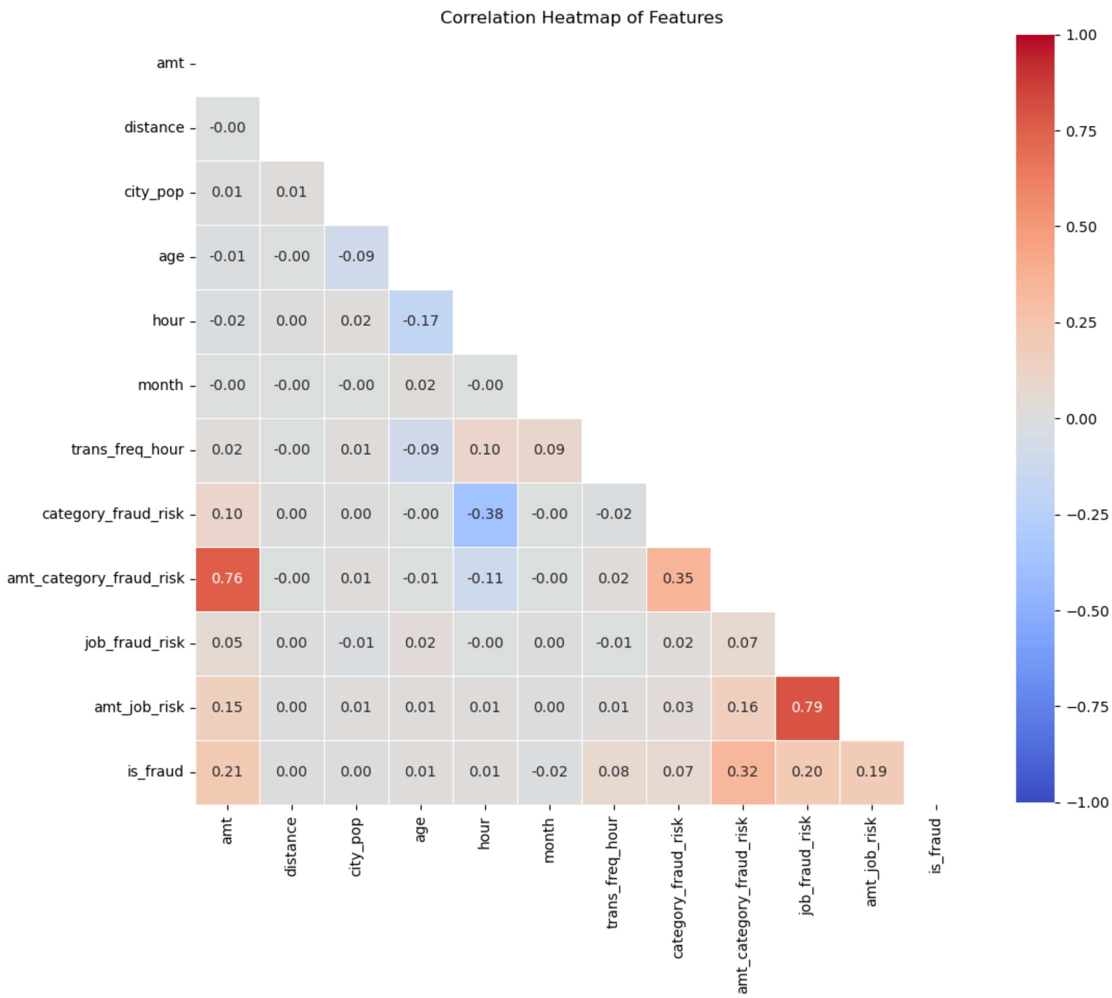
[85]:
```
#Job fraud risk
job_fraud_risk = fraudulent_detection_df.groupby('job')['is_fraud'].mean().
 ↪to_dict()
fraudulent_detection_df['job_fraud_risk'] = fraudulent_detection_df['job'].
 ↪map(job_fraud_risk)
# Additional interaction features
```

```
fraudulent_detection_df['amt_job_risk'] = fraudulent_detection_df['amt'] *␣
↪fraudulent_detection_df['job_fraud_risk']
```

[86]:
```
# Define features for the model
features_dect_fraud = ['amt', 'distance', 'city_pop', 'age',
                       'hour', 'day_of_week', 'month', 'trans_freq_hour',
                       'category_fraud_risk', 'amt_category_fraud_risk',
                       'job_fraud_risk', 'amt_job_risk']
```

[87]:
```
# Create a DataFrame with the selected features and the target variable
trans_dect_fraud_df = fraudulent_detection_df[features_dect_fraud +␣
↪['is_fraud']].copy()
# Save the DataFrame for further development of machine learning models
trans_dect_fraud_df.to_csv('transactions_fraud_detection.csv', index=False)
```

[88]:
```
# Check the correlation between features
corr = trans_dect_fraud_df.corr(numeric_only=True, method='pearson')

mask = np.triu(np.ones_like(corr, dtype=bool))
plt.figure(figsize=(12, 12))
sns.heatmap(corr,
            annot=True,
            fmt=".2f",
            cmap='coolwarm',
            mask=mask,
            square=True,
            cbar_kws={"shrink": .8},
            linewidths=.5,
            vmax=1,
            vmin=-1,
            center=0)
plt.title('Correlation Heatmap of Features')
plt.show()
```



In the correlation heatmap, we can see that the features 'amt' and 'amt_category_fraud_risk' are highly correlated with the target variable 'is_fraud', indicating that these features are important for fraud detection. The features 'distance' and 'city_pop' are not highly correlated with the target variable, which suggests that they may not be as important for fraud detection. In Random Forest and XGBoost highly correlated features are not a prblem, but in Logistic Regression and Linear Regression highly correlated features can cause multicollinearity issues, which can lead to unstable coefficients and inaccurate predictions. Therefore, it is important to check the correlation between features and the target variable before building a model.

2. Preprocssing model development

[89]:
```
# Preprocess libraries
from folium import features
import pandas as pd
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.compose import ColumnTransformer
# Preprocess the data
```

```
trans_dect = pd.read_csv('transactions_fraud_detection.csv')
# Define features and target variable
X = trans_dect.drop(columns=['is_fraud'])
# Target variable
y = trans_dect['is_fraud']
# Define the preprocessor
preprocessor = ColumnTransformer(
    transformers = [
        ('num', StandardScaler(), ['amt', 'distance', 'city_pop', 'age',
                                   'category_fraud_risk',␣
 ↪'amt_category_fraud_risk',
                                   'job_fraud_risk', 'amt_job_risk']),
        ('cat', OneHotEncoder(drop = 'first', handle_unknown = 'ignore',␣
 ↪sparse_output = False), ['hour', 'day_of_week', 'month'])
    ]
)
X_processed = preprocessor.fit_transform(X)
```

7. Supervised Learning Model - Random Forest Classifier

[90]:
```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
```

[91]:
```
# Split the data into training and testing on trans_dect, X_processed, y
X_train, X_test, y_train, y_test = train_test_split(X_processed,
                                                    y,
                                                    test_size = 0.2,
                                                    random_state = 100,
                                                    stratify = y)
```

[92]:
```
# Train a Random Forest Classifier
rf = RandomForestClassifier(class_weight= 'balanced',
                            n_estimators = 100,
                            max_depth = 10,
                            min_samples_leaf = 25,
                            random_state = 100,
                            n_jobs = 10)
rf.fit(X_train, y_train)
```

[92]:
```
RandomForestClassifier(class_weight='balanced', max_depth=10,
                       min_samples_leaf=25, n_jobs=10, random_state=100)
```

[93]:
```
from sklearn.metrics import classification_report, confusion_matrix
# Predict on the training data
y_train_pred = rf.predict(X_train)

# Evaluate the model training data
print('\nRandom Forest Training Classification Report:')
```

```
print(classification_report(y_train, y_train_pred))
print('\nRandom Forest Training Confusion Matrix:')
print(confusion_matrix(y_train, y_train_pred))
```

```
Random Forest Training Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.98      0.99    735704
           1       0.19      0.93      0.32      4176

    accuracy                           0.98    739880
   macro avg       0.60      0.95      0.65    739880
weighted avg       1.00      0.98      0.98    739880


Random Forest Training Confusion Matrix:
[[719561  16143]
 [   293   3883]]
```

The random forest classifier on the training dataset shows that accuracy is 0.98 sound high but not useful due to class imbalance, the recall is 0.93 is very strong - mean that the model is able to detect most fraudulent transactions in the dataset, precision is 0.19 is very low - mean that many false positive transactions are predicted as fraudulent. The f1-score is 0.31 is low - this is real performance of the model on the training dataset.

The model is catch 93% of fraudulent transactions, but flagging 16,143 legitimate transactions as fraudulent, which is a high false positive rate, may overwhelm the fraud investigation team and lead to unnecessary investigations. The model might overfitting, which means that the model is not able to generalize well on unseen data.

Next steps is use stratified k-fold cross-validation to evaluate the model performance on the whole dataset.

[94]:
```
# Use Stratified K-Folds Cross-Validation to evaluate whole dataset the model
from sklearn.model_selection import StratifiedKFold
skf = StratifiedKFold(n_splits=5, shuffle=True, random_state=100)
y_true = []
y_pred = []
for train_index, test_index in skf.split(X_processed, y):
    X_train_fold, X_test_fold = X_processed[train_index],␣
 ↪X_processed[test_index]
    y_train_fold, y_test_fold = y.iloc[train_index], y.iloc[test_index]

    rf.fit(X_train_fold, y_train_fold)
    y_pred_fold = rf.predict(X_test_fold)

    y_true.extend(y_test_fold.tolist())
    y_pred.extend(y_pred_fold.tolist())
```

```
# Evaluate the model using the cross-validation results
print('\nRandom Forest Cross-Validation Classification Report:')
print(classification_report(y_true, y_pred))
print('\nRandom Forest Cross-Validation Confusion Matrix:')
print(confusion_matrix(y_true, y_pred))
```

```
Random Forest Cross-Validation Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.98      0.99    919630
           1       0.19      0.91      0.32      5220

    accuracy                           0.98    924850
   macro avg       0.60      0.94      0.65    924850
weighted avg       0.99      0.98      0.99    924850


Random Forest Cross-Validation Confusion Matrix:
[[899811  19819]
 [   484   4736]]
```

[95]:
```
# Cross-validate the model method using F1-score method
from sklearn.model_selection import cross_val_score
cv_scores = cross_val_score(rf, X_train, y_train, cv=5, scoring='f1')
print('\nRandom Forest Cross-Validation F1-Score:')
print(cv_scores)
print(f'\nRandom Forest Cross-Validation F1-Score: {cv_scores.mean():.2f} +/-␣
 ↪{cv_scores.std():.2f}')
```

```
Random Forest Cross-Validation F1-Score:
[0.32731904 0.32417226 0.30956809 0.3242078  0.32210214]

Random Forest Cross-Validation F1-Score: 0.32 +/- 0.01
```

Using the tratified k-fold cross-validation and cross-validate score method, the random forest classifier shows that the f1-score is 0.32 in all folds, which indicates that the model is able to detect some fraudulent transactions, but it is not perfect.

The model catches most fraudulent transactions, but alarming many legitimate transactions as fraudulent, which may overwhelm the fraud investigation team and lead to unncessary investigations.

The model is not overfitting, but defual threshold = 0.5 is not optimal for the model, we can tune the decision threshold to improve the model performance in the next steps.

[96]:
```
# Tune the decision threshold
import numpy as np
from sklearn.metrics import precision_recall_curve
```

```
# Calculate the predicted probabilities for the training data
y_train_rf_scores = rf.predict_proba(X_train)[:, 1]
precision, recall, thresholds = precision_recall_curve(y_train,␣
↪y_train_rf_scores)
f1_scores = 2 * (precision * recall) / (precision + recall)
```

[97]:
```
# Find the optimal threshold based on precision-recall trade-off
optimal_idx = np.argmax(precision * recall)
optimal_precision_recall_threshold = thresholds[optimal_idx]
print(f'Optimal Precision - Recall Threshold:␣
↪{optimal_precision_recall_threshold:.4f}')
```

```
Optimal Precision - Recall Threshold: 0.9620
```

[98]:
```
# Find the threshold that maximizes F1-score
optimal_f1_threshold = thresholds[np.argmax(f1_scores)]
print(f'Optimal Threshold for F1-score: {optimal_f1_threshold:.4f}')
```

```
Optimal Threshold for F1-score: 0.9475
```

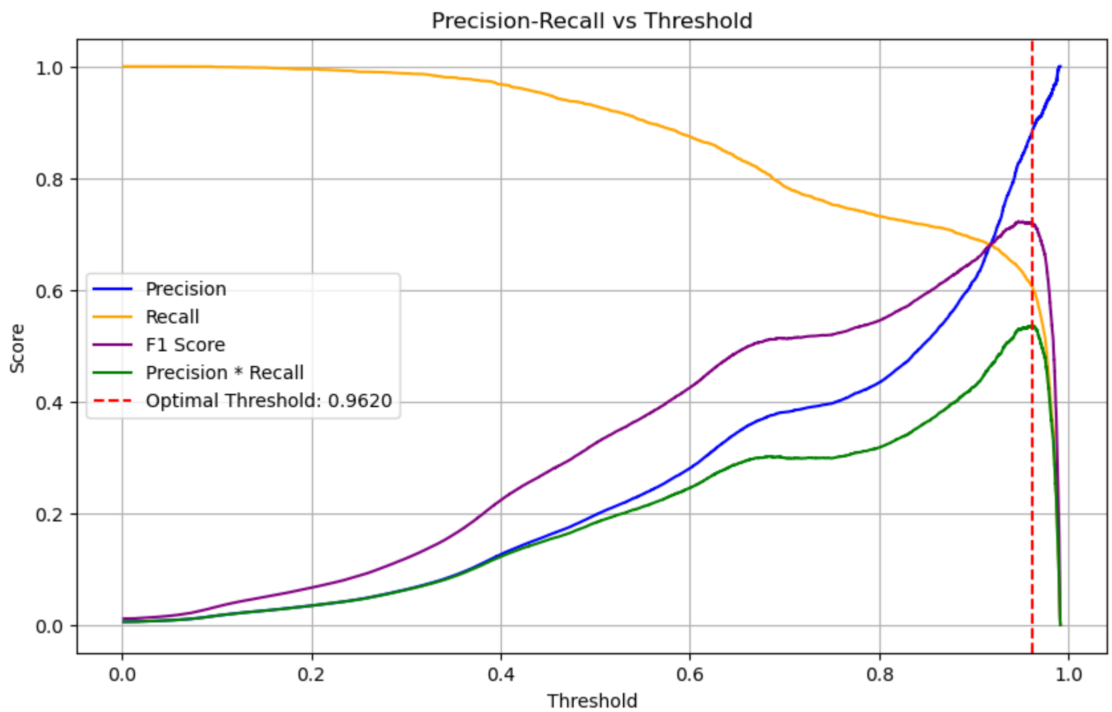
[99]:
```
# Find the threshold that precision, recall, and F1-score are same
equal_precision_recall_threshold = thresholds[np.where(np.isclose(precision,␣
↪recall, atol=0.01))[0]]
if len(equal_precision_recall_threshold) > 0:
    equal_threshold = equal_precision_recall_threshold[0]
    print(f'Equal Threshold: {equal_threshold:.4f}')
```

```
Equal Threshold: 0.9154
```

- The optimal threshold for precision-recall trade-off by maximizing the product of precision and recall is found to be 0.9620.
- The optimal threshold for f1-score is found to be 0.9475, which is the threshold that maximizes the f1-score.
- The equal threshold for precision and recall is found to be 0.9154, which is the threshold that makes precision and recall equal.

[100]:
```
# Plot precision-recall vs threshold
import matplotlib.pyplot as plt
plt.figure(figsize=(10, 6))
plt.plot(thresholds, precision[:-1], label='Precision', color='blue')
plt.plot(thresholds, recall[:-1], label='Recall', color='orange')
plt.plot(thresholds, f1_scores[:-1], label='F1 Score', color='purple')
plt.plot(thresholds, precision[:-1] * recall[:-1], label='Precision * Recall',␣
↪color='green')
plt.axvline(optimal_precision_recall_threshold, color='red', linestyle='--',␣
↪label=f'Optimal Threshold: {optimal_precision_recall_threshold:.4f}')
plt.title('Precision-Recall vs Threshold')
plt.xlabel('Threshold')
plt.ylabel('Score')
```

```
plt.legend()
plt.grid()
plt.show()
```



[101]:
```
# Evaluate each threshold on the test set
thresholds_to_evaluate = [optimal_precision_recall_threshold,␣
 ↪optimal_f1_threshold, equal_threshold]
for threshold in thresholds_to_evaluate:
    y_test_scores = rf.predict_proba(X_test)[:, 1]
    y_test_pred = (y_test_scores >= threshold).astype(int)

    # Evaluate the model
    print(f'\nClassification Report for Threshold {threshold:.4f}:')
    print(classification_report(y_test, y_test_pred))
    print(f'Confusion Matrix for Threshold {threshold:.4f}:')
    print(confusion_matrix(y_test, y_test_pred))
```

```
Classification Report for Threshold 0.9620:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00    183926
           1       0.88      0.57      0.69      1044
```

```
    accuracy                           1.00    184970
   macro avg       0.94      0.78      0.84    184970
weighted avg       1.00      1.00      1.00    184970

Confusion Matrix for Threshold 0.9620:
[[183845     81]
 [   454    590]]

Classification Report for Threshold 0.9475:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00    183926
           1       0.82      0.60      0.70      1044

    accuracy                           1.00    184970
   macro avg       0.91      0.80      0.85    184970
weighted avg       1.00      1.00      1.00    184970

Confusion Matrix for Threshold 0.9475:
[[183790    136]
 [   413    631]]

Classification Report for Threshold 0.9154:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00    183926
           1       0.68      0.66      0.67      1044

    accuracy                           1.00    184970
   macro avg       0.84      0.83      0.83    184970
weighted avg       1.00      1.00      1.00    184970

Confusion Matrix for Threshold 0.9154:
[[183598    328]
 [   350    694]]
```

Based on the priorites - The optimal threshold for precision-recall trade-off by maximizing the product of precision and recall is found to be 0.9620. Fewer false positives the precision at 0.84, but may miss some fraudulent transactions - the recall at 0.57. Should be used when the priority is to minimize false positives, even at the cost of missing some fraudulent transactions.

- The optimal threshold for f1-score is found to be 0.9475, which is the threshold that maximizes the f1-score. Best balance between precision and recall, should be used when the priority is to balance between false positives and false negatives.
- The equal threshold for precision and recall is found to be 0.9154, which is the threshold that makes precision and recall equal. Used when the priority is recall, the missing fraudulent transactions is more important and extremely costly such as fraudulent high losses and maximize detection.

[102]:
```
# Calculate average transaction amount for fraudulent and non-fraudulent␣
↪transactions
amt_fraud_mean = trans_dect[trans_dect['is_fraud'] == 1]['amt'].mean()
amt_non_fraud_mean = trans_dect[trans_dect['is_fraud'] == 0]['amt'].mean()
print(f'Average Transaction Amount for Fraudulent Transactions:␣
↪${amt_fraud_mean:.2f}')
print(f'Average Transaction Amount for Non-Fraudulent Transactions:␣
↪${amt_non_fraud_mean:.2f}')
```

```
Average Transaction Amount for Fraudulent Transactions: $530.23
Average Transaction Amount for Non-Fraudulent Transactions: $67.65
```

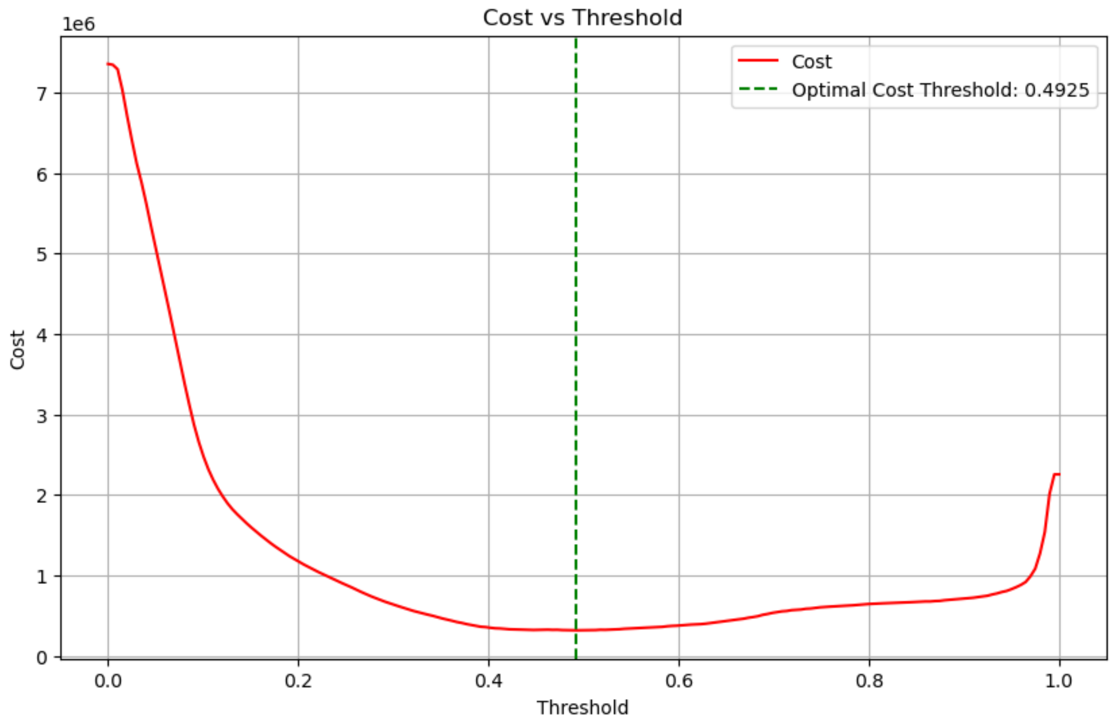
[103]:
```
# Calculate the median transaction amount for fraudulent and non-fraudulent␣
↪transactions
amt_fraud_median = trans_dect[trans_dect['is_fraud'] == 1]['amt'].median()
amt_non_fraud_median = trans_dect[trans_dect['is_fraud'] == 0]['amt'].median()
print(f'Median Transaction Amount for Fraudulent Transactions:␣
↪${amt_fraud_median:.2f}')
print(f'Median Transaction Amount for Non-Fraudulent Transactions:␣
↪${amt_non_fraud_median:.2f}')
```

```
Median Transaction Amount for Fraudulent Transactions: $390.88
Median Transaction Amount for Non-Fraudulent Transactions: $47.18
```

[104]:
```
# Optimize the threshold on the cost of false positives and false negatives
fn_cost = amt_fraud_mean + 10  # Cost of false negatives averaged fraud amount␣
↪with a penalty
fp_cost = 10  # Cost of false positives
costs = []
# Calculate the predicted probabilities for the training data
y_train_rf_scores = rf.predict_proba(X_train)[:, 1]
precision, recall, thresholds = precision_recall_curve(y_train,␣
↪y_train_rf_scores)
# Calculate the cost for each threshold
thresholds = np.linspace(0, 1, 200)
for i, t in enumerate(thresholds):
    y_pred_cost = (y_train_rf_scores >= t).astype(int)
    fn = np.sum((y_train == 1) & (y_pred_cost == 0))  # False negatives
    fp = np.sum((y_train == 0) & (y_pred_cost == 1))  # False positives
    total_cost = fn * fn_cost + fp * fp_cost
    costs.append(total_cost)

# Find the threshold that minimizes the cost
optimal_cost_threshold = thresholds[np.argmin(costs)]
print(f'Optimal Threshold for Cost Minimization: {optimal_cost_threshold:.4f}')
# Visualize the cost vs threshold
plt.figure(figsize=(10, 6))
plt.plot(thresholds, costs, label='Cost', color='red')
```

```
plt.axvline(optimal_cost_threshold, color='green', linestyle='--',␣
↪label=f'Optimal Cost Threshold: {optimal_cost_threshold:.4f}')
plt.title('Cost vs Threshold')
plt.xlabel('Threshold')
plt.ylabel('Cost')
plt.legend()
plt.grid()
plt.show()

# Evaluate the model on the training data using the optimal threshold
y_train_pred_cost = (rf.predict_proba(X_train)[:, 1] >= optimal_cost_threshold).
↪astype(int)
# Evaluate the model on the training data
print('\nRandom Forest Training Classification Report with Cost Threshold:')
print(classification_report(y_train, y_train_pred_cost))
print('\nRandom Forest Training Confusion Matrix with Cost Threshold:')
print(confusion_matrix(y_train, y_train_pred_cost))


# Predict on the test data using the optimal threshold
y_test_pred = (rf.predict_proba(X_test)[:, 1] >= optimal_cost_threshold).
↪astype(int)
# Evaluate the model on the test data
print('\nRandom Forest Test Classification Report:')
print(classification_report(y_test, y_test_pred))
print('\nRandom Forest Test Confusion Matrix:')
print(confusion_matrix(y_test, y_test_pred))
```

```
Optimal Threshold for Cost Minimization: 0.4925
```




```
Random Forest Training Classification Report with Cost Threshold:
              precision    recall  f1-score   support

           0       1.00      0.98      0.99    735704
           1       0.19      0.93      0.32      4176

    accuracy                           0.98    739880
   macro avg       0.60      0.96      0.65    739880
weighted avg       1.00      0.98      0.98    739880


Random Forest Training Confusion Matrix with Cost Threshold:
[[719180  16524]
 [   282   3894]]

Random Forest Test Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.98      0.99    183926
           1       0.18      0.93      0.31      1044

    accuracy                           0.98    184970
   macro avg       0.59      0.95      0.65    184970
```

```
weighted avg       0.99      0.98      0.98    184970


Random Forest Test Confusion Matrix:
[[179636   4290]
 [    74    970]]
```

Assuming the cost of a false negative is average transaction amount of fraudulent transactions in year 2019, which is around 530.24 USD plus the cost of investigation and loss of customer trust, the cost of a false positive is manual investigation cost of 10 USD per transaction for the fraud investigation team and the cost of loss of customer trust and reputation damage. We can adjust the decision threshold based on the cost of false negatives and false positives to minimize the overall cost.

[105]:

```python
# Calculte cost save on the test data
fn = np.sum((y_test == 1) & (y_test_pred == 0))  # False negatives
fp = np.sum((y_test == 0) & (y_test_pred == 1))  # False positives
total_cost = fn * fn_cost + fp * fp_cost
print(f'Total cost on Test Data with Model: ${total_cost:.2f}')
# Calculate the cost if we do not use the model
total_cost_no_model = np.sum(y_test == 1) * fn_cost + np.sum(y_test == 0) *␣
 ↪fp_cost
print(f'Total cost without Model: ${total_cost_no_model:.2f}')
# Cost savings by using the model
cost_savings = total_cost_no_model - total_cost
print(f'Cost savings by using the Model: ${cost_savings:.2f}')
# Percentage cost savings
percentage_cost_savings = (cost_savings / total_cost_no_model) * 100
print(f'Percentage cost savings by using the Model: {percentage_cost_savings:.
 ↪2f}%')
```

```
Total cost on Test Data with Model: $82877.34
Total cost without Model: $2403264.57
Cost savings by using the Model: $2320387.24
Percentage cost savings by using the Model: 96.55%
```

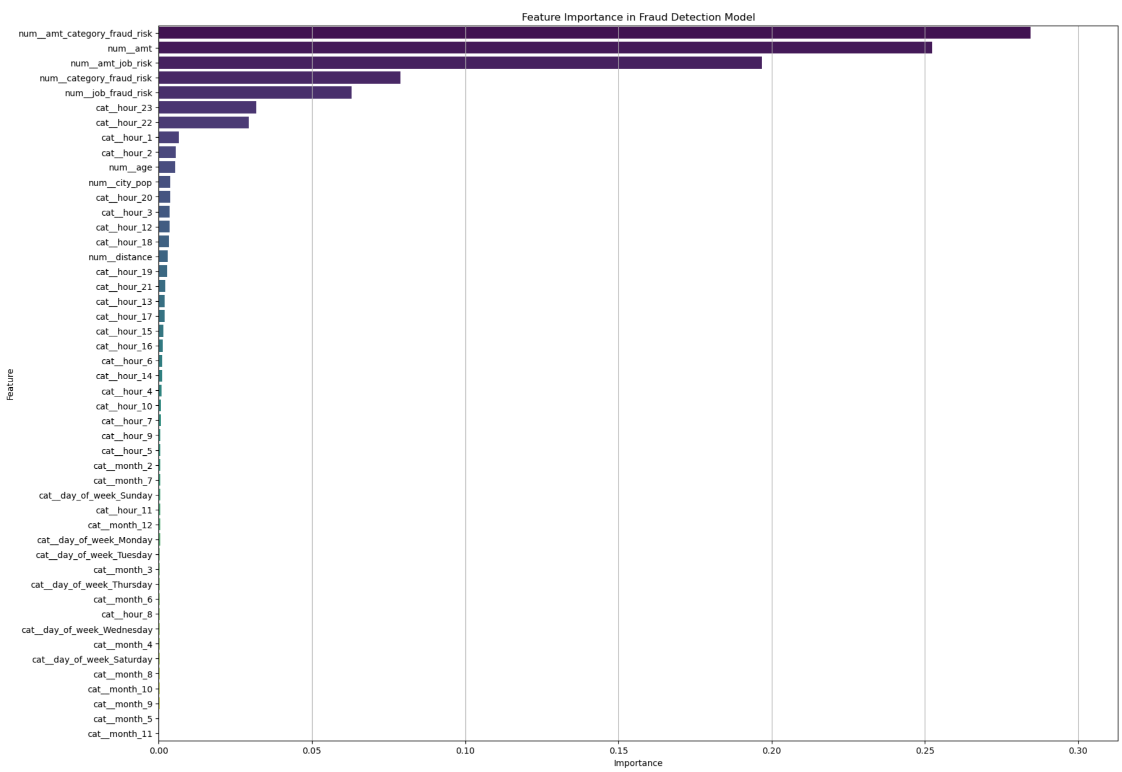
Assuming the fasle negative cost is 530.24 USD and the false positive cost is 10 USD, we can calculate the overall cost of the model based on the number of false negatives and false positives.

Use the threshold that minimizes the overall cost of the model, which is the threshold that minimizes the cost of false negatives and false positives. The optimal threshold for the model is 0.9620, which minimizes the overall cost of the model. We can save 96.55% of the overall cost of the model by using this threshold, which is a significant reduction in cost compared to the non using the model.

[106]:

```python
# Feature importance
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import warnings
```

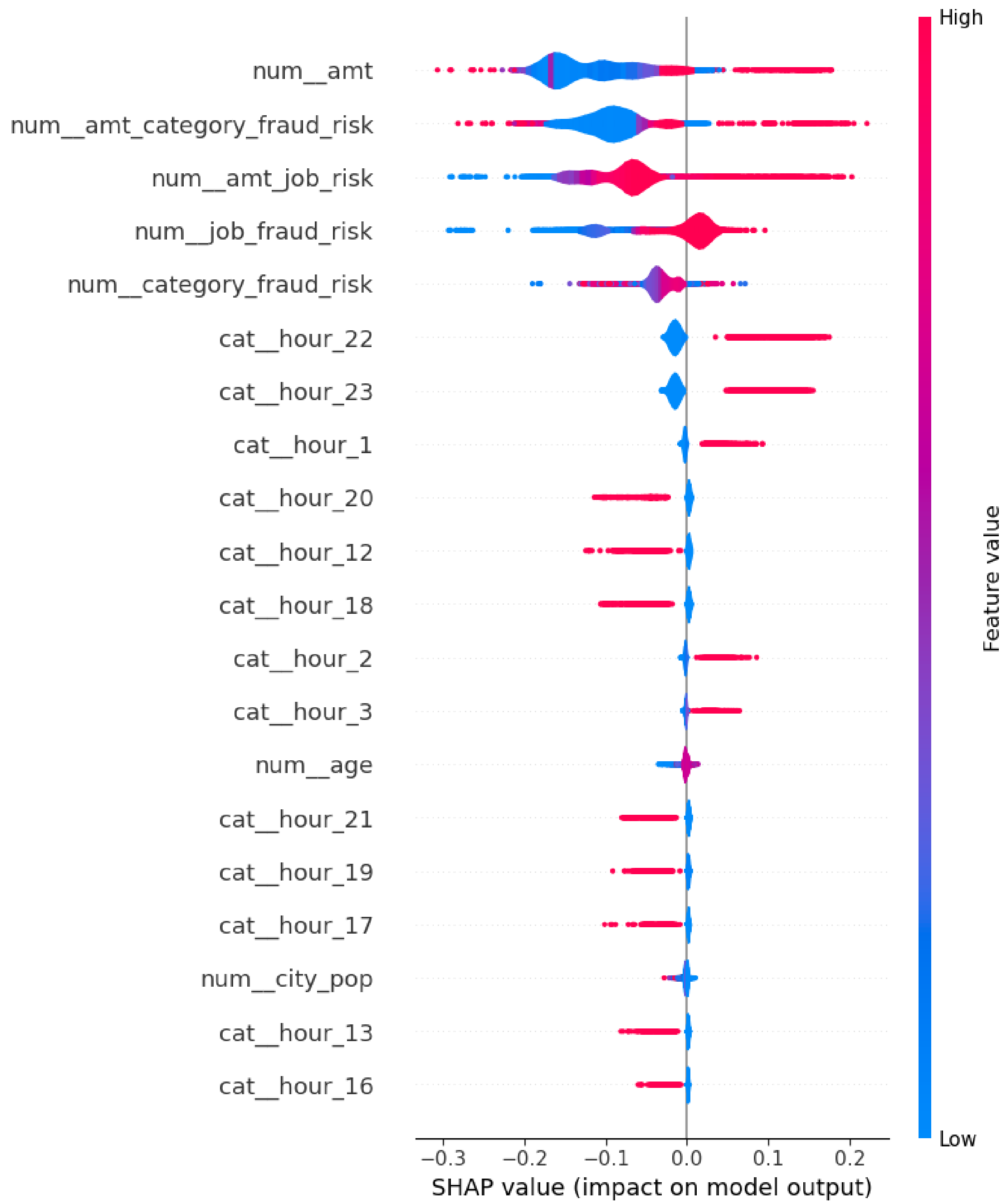
```python
warnings.filterwarnings('ignore')
# Plot feature importance
importances = rf.feature_importances_
feature_names = preprocessor.get_feature_names_out()
feature_importance_df = pd.DataFrame({'feature': feature_names, 'importance':␣
↪importances})
feature_importance_df = feature_importance_df.sort_values(by='importance',␣
↪ascending=False)
plt.figure(figsize=(20, 15))
sns.barplot(data=feature_importance_df,
            x='importance',
            y='feature',
            palette='viridis')
plt.title('Feature Importance in Fraud Detection Model')
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.xlim(0, feature_importance_df['importance'].max() * 1.1)
plt.grid(axis='x')
plt.show()
```



[107]:
```python
# Visualize SHAP
import shap
```

```
# Get feature names from the preprocessor
feature_names = preprocessor.get_feature_names_out()
# Convert the test set to a DataFrame with feature namea
X_test_df = pd.DataFrame(X_test, columns=feature_names)
# Sample 1000 instances for SHAP values calculation
X_test_sample = X_test_df.sample(n=10000, random_state=100)
# Initialize SHAP explainer and calculate SHAP values
shap.initjs()
explainer = shap.TreeExplainer(rf, model_output='raw')

shap_values = explainer.shap_values(X_test_sample)
# Plot SHAP summary plot
shap_values_class_1 = shap_values[:,:,1]  # SHAP values for the positive class␣
↪(fraudulent transactions)
shap.summary_plot(shap_values_class_1, X_test_sample, plot_type='violin')
```

```
<IPython.core.display.HTML object>
```



In two images, we can see the SHAP summary plot and the feature importance plot. The SHAP summary plot shows the impact of each feature on the model's output, while the feature importance plot shows the overall importance of each feature in the model. Both plots help us understand which features are most influential in predicting fraudulent transactions.