credit_card_transaction

November 15, 2024

1 Credit Card Transaction: EDA

The Credit Card Transactions Dataset provides detailed records of credit card transactions, including information about transaction times, amounts, and associated personal and merchant details.

In this notebook, exploratory data analysis (EDA) is done. It covers starting from simple correlation test between numerical features to side-by-side comparison between two classes of different features. As a target feature, "is_fraud" is taken.

At the end of the notebook, summery is given based on the analysis made.

[1]:
```python
import pandas as pd
import plotly.express as px
import seaborn as sns
from matplotlib import pyplot as plt
from datetime import datetime, date
```

1.1 Import

[2]:
```python
df = pd.read_csv(
    "data/credit_card_transactions.csv",
    parse_dates= ["trans_date_trans_time", "dob"]
)

# drop columns
df.drop(columns=
        [
            "Unnamed: 0", "merchant", "cc_num",
            "first", "last", "zip","trans_num",
            "unix_time", "merch_zipcode"
        ],
        inplace= True)

df.info()
df.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1296675 entries, 0 to 1296674
```

```
Data columns (total 15 columns):
 #   Column                 Non-Null Count    Dtype
---  ------                 --------------    -----
 0   trans_date_trans_time  1296675 non-null  datetime64[ns]
 1   category               1296675 non-null  object
 2   amt                    1296675 non-null  float64
 3   gender                 1296675 non-null  object
 4   street                 1296675 non-null  object
 5   city                   1296675 non-null  object
 6   state                  1296675 non-null  object
 7   lat                    1296675 non-null  float64
 8   long                   1296675 non-null  float64
 9   city_pop               1296675 non-null  int64
 10  job                    1296675 non-null  object
 11  dob                    1296675 non-null  datetime64[ns]
 12  merch_lat              1296675 non-null  float64
 13  merch_long             1296675 non-null  float64
 14  is_fraud               1296675 non-null  int64
dtypes: datetime64[ns](2), float64(5), int64(2), object(6)
memory usage: 148.4+ MB
```

[2]:

```
  trans_date_trans_time       category     amt gender  \
0   2019-01-01 00:00:18       misc_net    4.97      F
1   2019-01-01 00:00:44    grocery_pos  107.23      F
2   2019-01-01 00:00:51  entertainment  220.11      M
3   2019-01-01 00:01:16  gas_transport   45.00      M
4   2019-01-01 00:03:06       misc_pos   41.96      M

                          street            city state      lat      long  \
0                 561 Perry Cove  Moravian Falls    NC  36.0788  -81.1781
1   43039 Riley Greens Suite 393          Orient    WA  48.8878 -118.2105
2       594 White Dale Suite 530     Malad City    ID  42.1808 -112.2620
3    9443 Cynthia Court Apt. 038         Boulder    MT  46.2306 -112.1138
4               408 Bradley Rest        Doe Hill    VA  38.4207  -79.4629

   city_pop                                job        dob  merch_lat  \
0      3495          Psychologist, counselling 1988-03-09  36.011293
1       149  Special educational needs teacher 1978-06-21  49.159047
2      4154        Nature conservation officer 1962-01-19  43.150704
3      1939                    Patent attorney 1967-01-12  47.034331
4        99     Dance movement psychotherapist 1986-03-28  38.674999

   merch_long  is_fraud
0  -82.048315         0
1 -118.186462         0
2 -112.154481         0
3 -112.561071         0
```

```
4  -78.632459         0
```

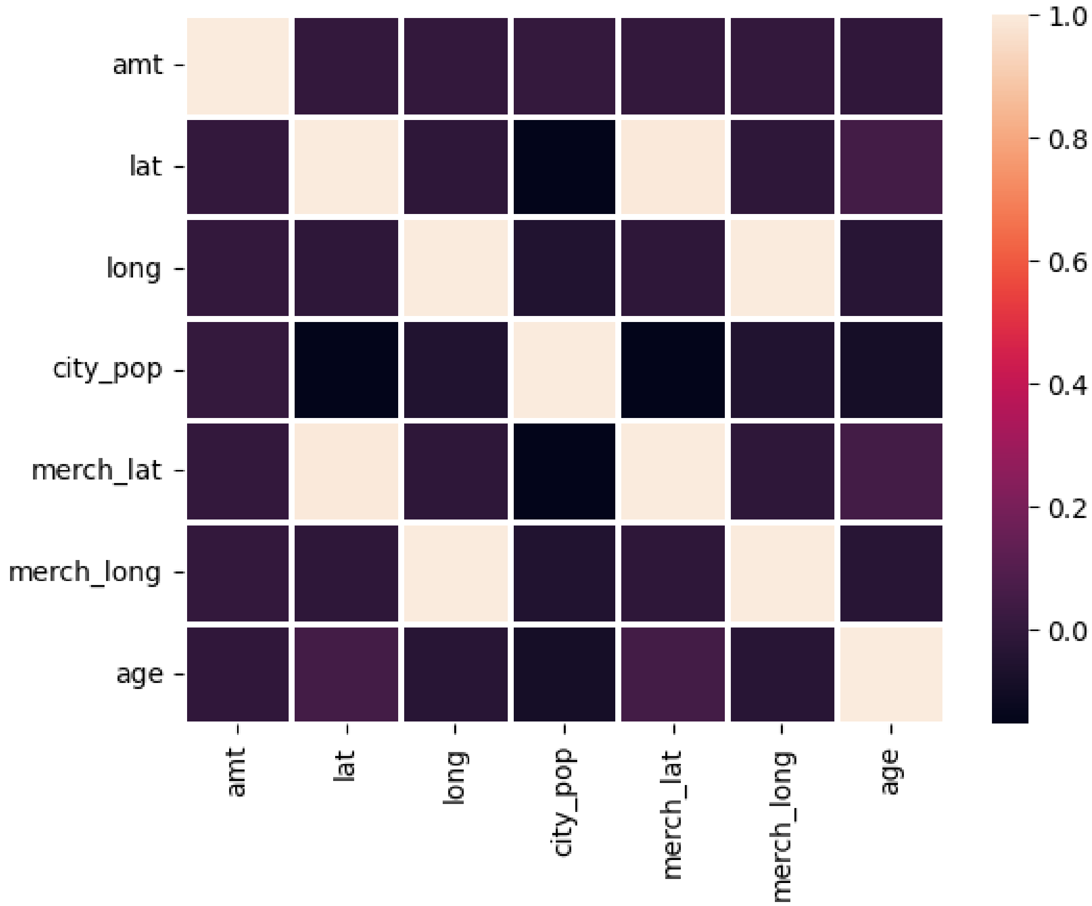
1.2 Explore

[3]:
```
# Create "age" column
df["age"]= [
    (x.year - y.year - ((x.day, x.month) < (y.day, y.month))) for x, y in␣
 ↪zip(df["trans_date_trans_time"], df["dob"])
]
```

[4]:
```
# check for multicollinearity
corr = df.select_dtypes("number").drop(columns= "is_fraud").corr()
corr
```

[4]:
```
                  amt       lat      long  city_pop  merch_lat  merch_long  \
amt          1.000000 -0.001926 -0.000187  0.005818  -0.001873   -0.000151
lat         -0.001926  1.000000 -0.015533 -0.155730   0.993592   -0.015509
long        -0.000187 -0.015533  1.000000 -0.052715  -0.015452    0.999120
city_pop     0.005818 -0.155730 -0.052715  1.000000  -0.154781   -0.052687
merch_lat   -0.001873  0.993592 -0.015452 -0.154781   1.000000   -0.015431
merch_long  -0.000151 -0.015509  0.999120 -0.052687  -0.015431    1.000000
age         -0.009757  0.048016 -0.029457 -0.091893   0.047627   -0.029382

                  age
amt         -0.009757
lat          0.048016
long        -0.029457
city_pop    -0.091893
merch_lat    0.047627
merch_long  -0.029382
age          1.000000
```

[5]:
```
sns.heatmap(corr, linewidths= 1);
```



Features with high correlation: * lat and merch_lat * long and merch_long

So, drop either of one from each pair.

[6]:
```python
# Drop columns: multicolinarity
df.drop(columns= ["merch_lat", "merch_long",],
        inplace= True)
df.head()
```

[6]:
```
  trans_date_trans_time       category     amt gender  \
0   2019-01-01 00:00:18       misc_net    4.97      F
1   2019-01-01 00:00:44    grocery_pos  107.23      F
2   2019-01-01 00:00:51  entertainment  220.11      M
3   2019-01-01 00:01:16  gas_transport   45.00      M
4   2019-01-01 00:03:06       misc_pos   41.96      M

                        street            city state      lat      long  \
0               561 Perry Cove  Moravian Falls    NC  36.0788  -81.1781
1  43039 Riley Greens Suite 393          Orient    WA  48.8878 -118.2105
```

```
2      594 White Dale Suite 530      Malad City    ID  42.1808 -112.2620
3   9443 Cynthia Court Apt. 038         Boulder    MT  46.2306 -112.1138
4              408 Bradley Rest        Doe Hill    VA  38.4207  -79.4629

   city_pop                                job        dob  is_fraud  age
0      3495          Psychologist, counselling 1988-03-09         0   30
1       149  Special educational needs teacher 1978-06-21         0   40
2      4154        Nature conservation officer 1962-01-19         0   56
3      1939                    Patent attorney 1967-01-12         0   51
4        99     Dance movement psychotherapist 1986-03-28         0   32
```

[7]:
```
# create dataframe containing only fraudulent transactions
df_fraud = df[df["is_fraud"] == 1]
df_fraud.head()
```

[7]:
```
      trans_date_trans_time       category     amt gender  \
2449   2019-01-02 01:06:37    grocery_pos  281.06      M
2472   2019-01-02 01:47:29  gas_transport   11.52      F
2523   2019-01-02 03:05:23    grocery_pos  276.31      F
2546   2019-01-02 03:38:03  gas_transport    7.03      M
2553   2019-01-02 03:55:47    grocery_pos  275.73      F

                        street          city state      lat     long  \
2449  542 Steve Curve Suite 011  Collettsville    NC  35.9946 -81.7266
2472  27954 Hall Mill Suite 575    San Antonio    TX  29.4400 -98.4590
2523  27954 Hall Mill Suite 575    San Antonio    TX  29.4400 -98.4590
2546  542 Steve Curve Suite 011  Collettsville    NC  35.9946 -81.7266
2553  27954 Hall Mill Suite 575    San Antonio    TX  29.4400 -98.4590

      city_pop                       job        dob  is_fraud  age
2449       885            Soil scientist 1988-09-15         1   30
2472   1595797  Horticultural consultant 1960-10-28         1   58
2523   1595797  Horticultural consultant 1960-10-28         1   58
2546       885            Soil scientist 1988-09-15         1   30
2553   1595797  Horticultural consultant 1960-10-28         1   58
```

[8]:
```
# check for cardinality
df.select_dtypes("object").nunique()
```

[8]:
```
category     14
gender        2
street      983
city        894
state        51
job         494
dtype: int64
```

```
[9]: df_fraud.select_dtypes("object").nunique()
```

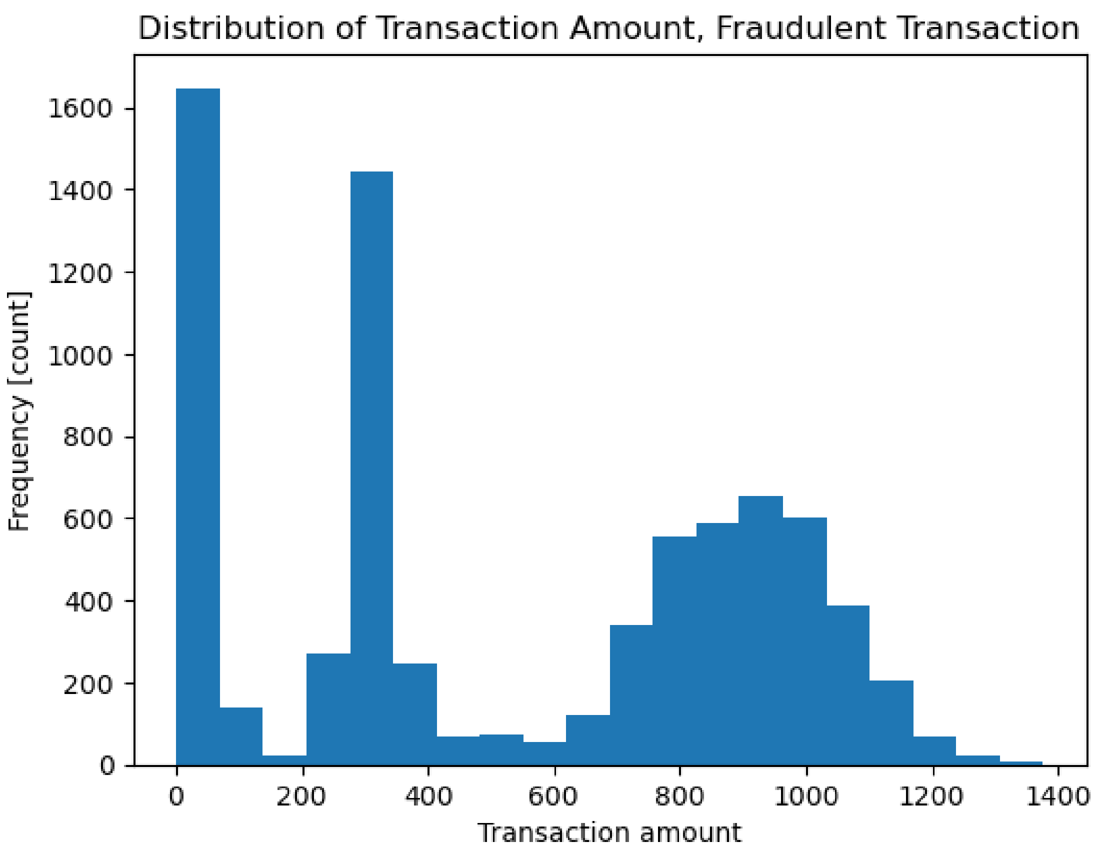
```
[9]: category     14
     gender        2
     street      762
     city        702
     state        51
     job         443
     dtype: int64
```

Due to large numbers of values in street, city and job features, drop these columns to develop model, but here we keep these features for EDA.

1.2.1 Transaction Amount

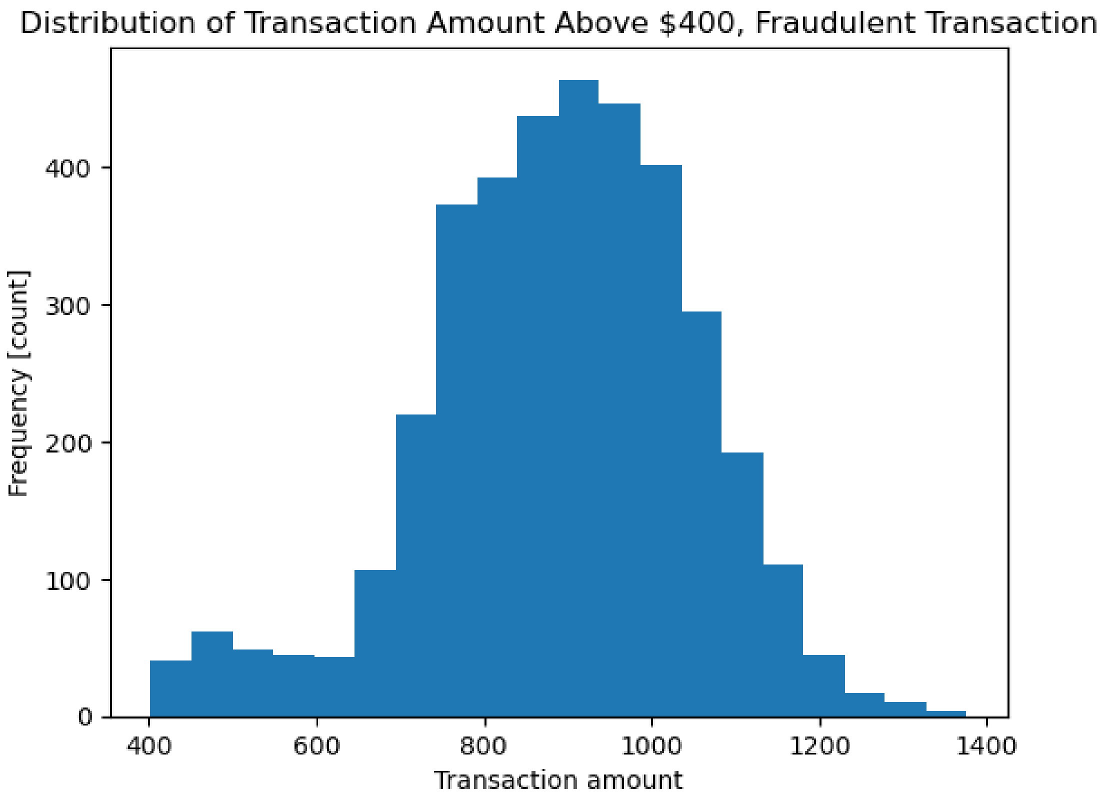
Here, transactions considered as fraud are taken. What amount of transaction were fraud?

```
[10]: plt.hist(df_fraud["amt"], bins= 20)
      plt.xlabel("Transaction amount")
      plt.ylabel("Frequency [count]")
      plt.title("Distribution of Transaction Amount, Fraudulent Transaction");
```



Let's consider the fraud amount to be greater than $400.

[11]:
```
plt.hist(df_fraud[df_fraud["amt"] > 400]["amt"], bins= 20)
plt.xlabel("Transaction amount")
plt.ylabel("Frequency [count]")
plt.title("Distribution of Transaction Amount Above $400, Fraudulent␣
↪Transaction");
```



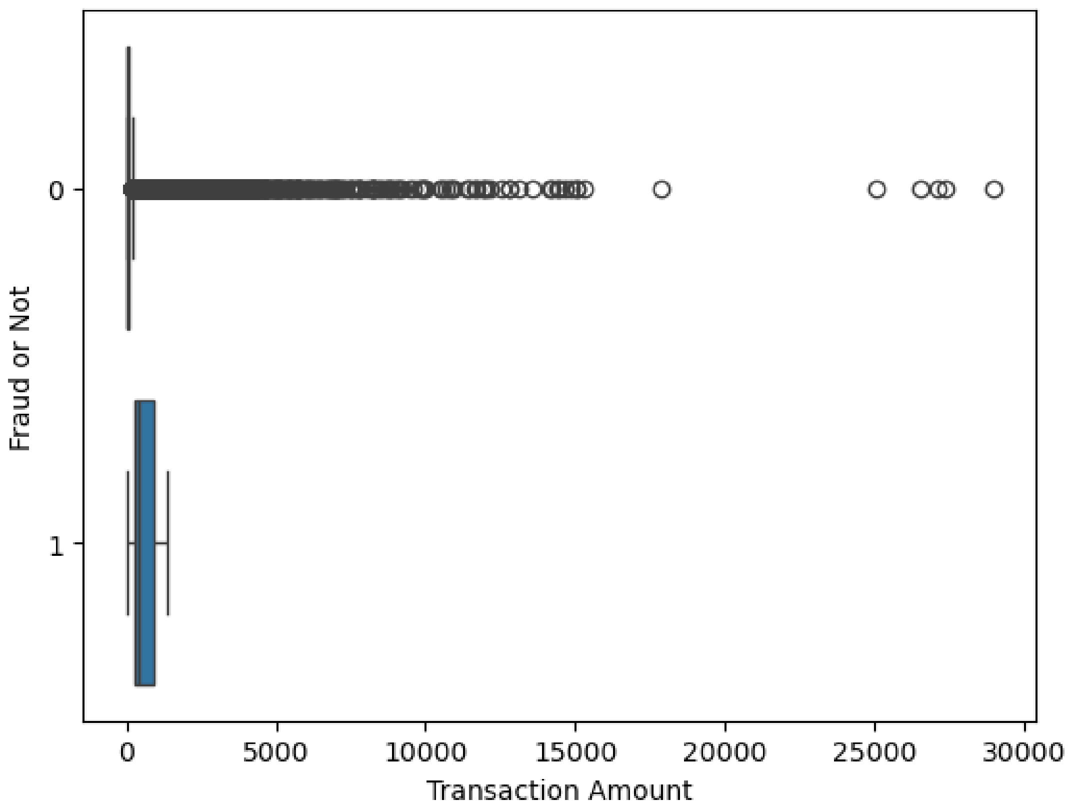
[12]:
```
df_fraud[df_fraud["amt"] > 400]["amt"].describe()
```

[12]:
```
count    3749.000000
mean      891.388087
std       159.352752
min       402.390000
25%       791.910000
50%       901.200000
75%      1001.090000
max      1376.040000
Name: amt, dtype: float64
```

1.2.2 Transaction Amount vs fraudulent transaction

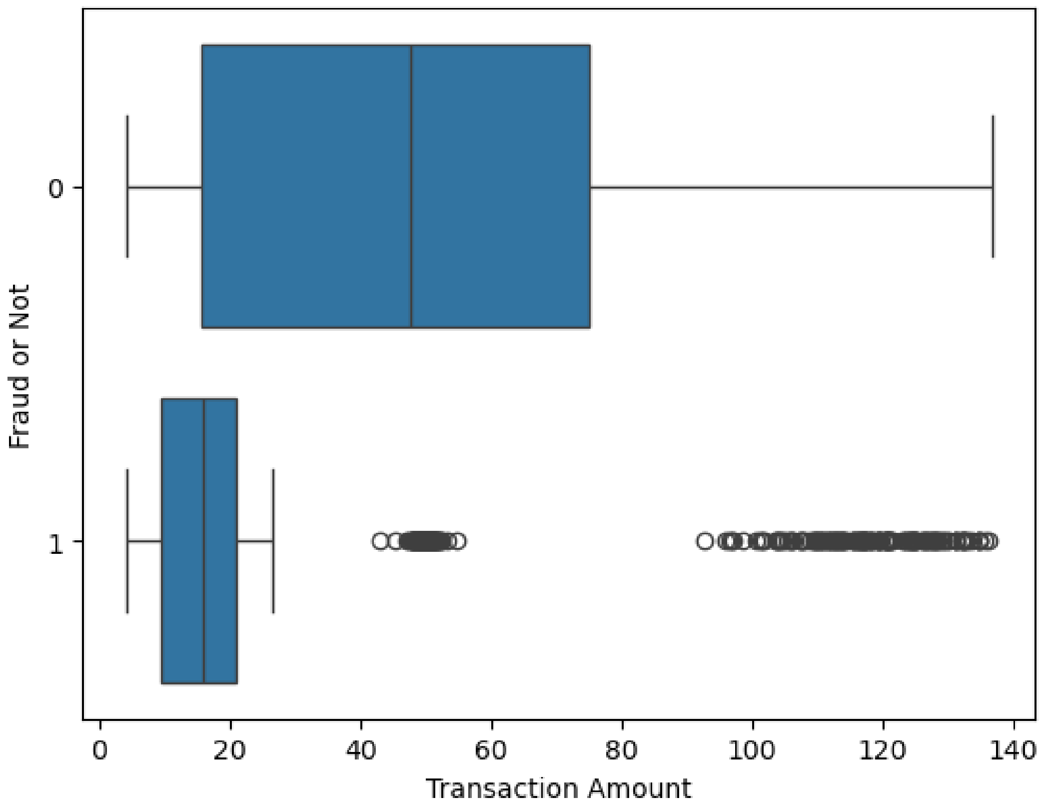
Boxplots are used to see the ranges of transaction amounts based on the fraud and non-fraudulent transactions.

[13]:
```
sns.boxplot(x= df["amt"], y= df["is_fraud"], orient= "h")
plt.xlabel("Transaction Amount")
plt.ylabel("Fraud or Not");
```



[14]:
```
q1, q9 = df["amt"].quantile([0.1, 0.9])
mask = df["amt"].between(q1, q9)
df_cleaned = df[mask]
```

[15]:
```
sns.boxplot(
    x= df_cleaned["amt"],
    y= df_cleaned["is_fraud"],
    orient= "h"
)
plt.xlabel("Transaction Amount")
plt.ylabel("Fraud or Not");
```



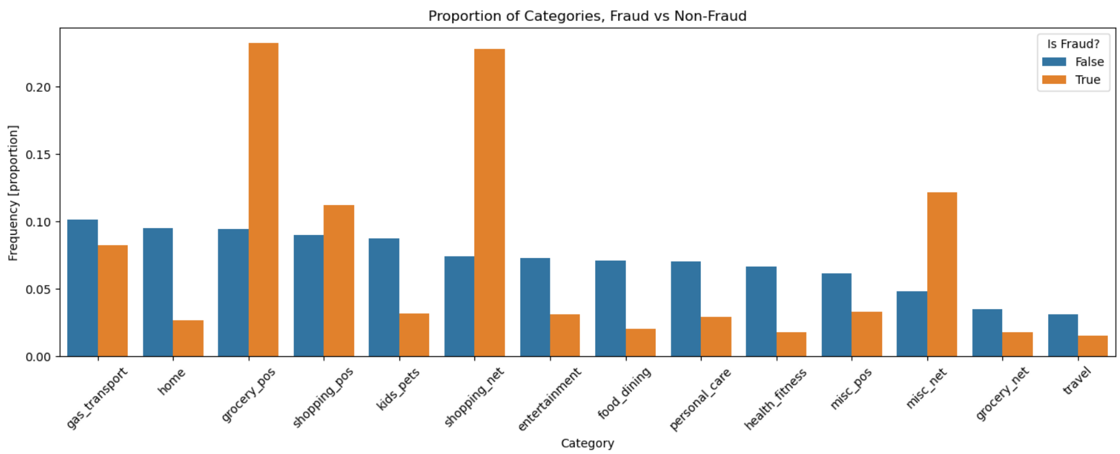
It is left skewed, as mean < median.

1.2.3 Category vs fraudulent transaction

A dataframe grouped by fraud and non-fraudulent transaction is formed to see the type of categories to be dominating.

[16]:
```
fig, ax = plt.subplots(figsize= (16, 5))
cat_counts = (
    df["category"]
    .groupby(df["is_fraud"])
    .value_counts(normalize= True)
    .to_frame()
    .reset_index()
)

sns.barplot(
    data= cat_counts,
    x= "category",
    y= "proportion",
    hue= "is_fraud",
    ax= ax,
```

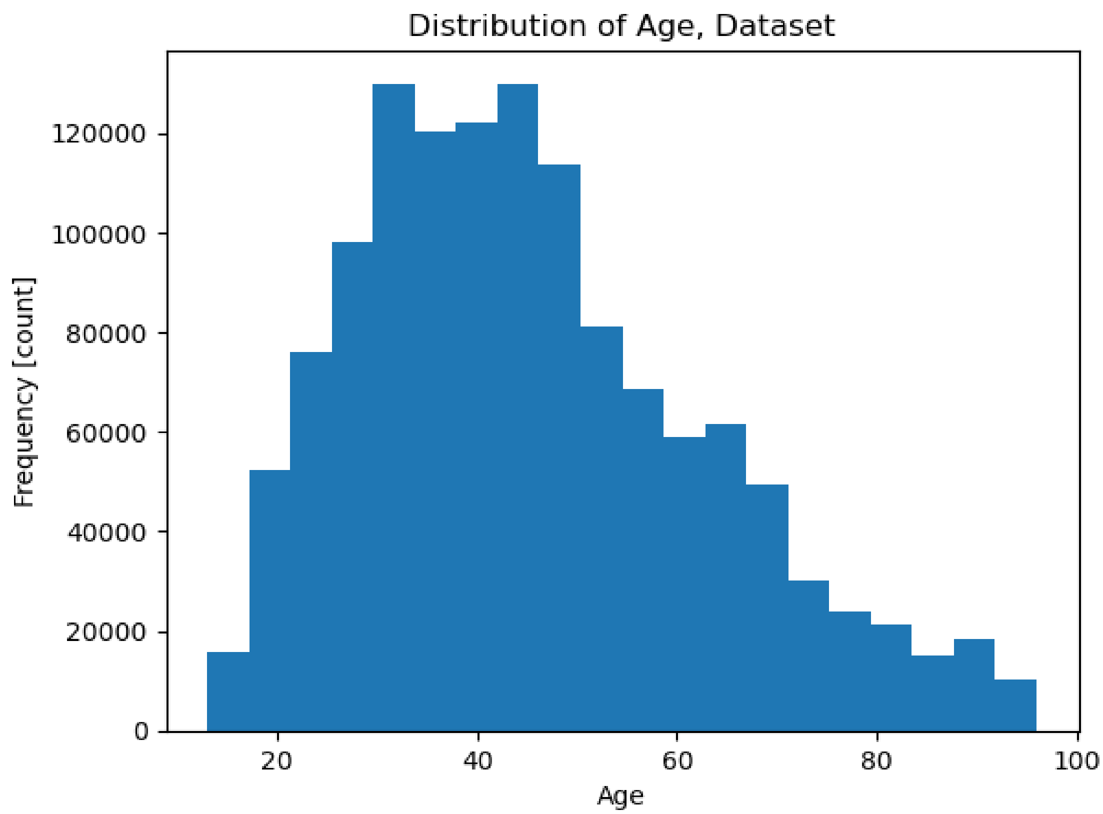
```
)
plt.xticks(rotation= 45)
plt.xlabel("Category")
plt.ylabel("Frequency [proportion]")
plt.title("Proportion of Categories, Fraud vs Non-Fraud")

handles, labels = ax.get_legend_handles_labels()
plt.legend(title= "Is Fraud?", handles= handles, labels= ["False", "True"]);
```



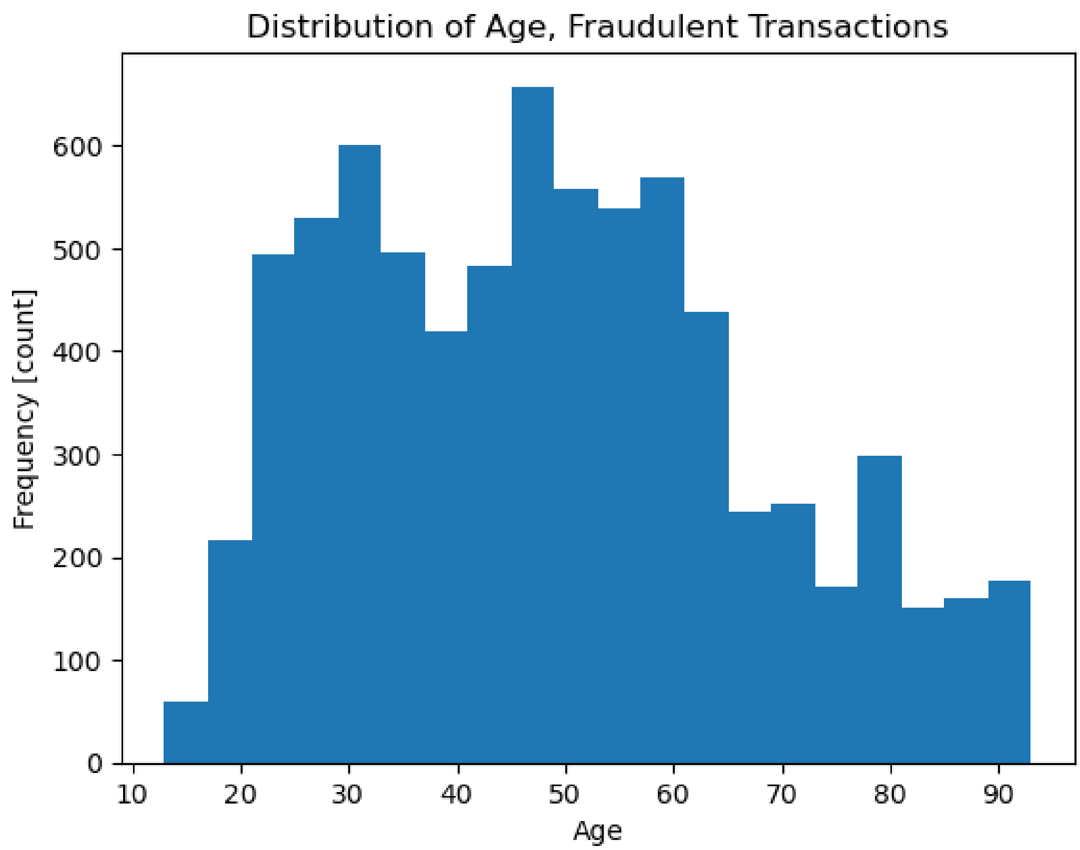
1.2.4 Age

Histograms are developed to see the distribution of age across the dataset and the fraud class.

[17]:
```
plt.hist(df["age"], bins= 20)
plt.xlabel("Age")
plt.ylabel("Frequency [count]")
plt.title("Distribution of Age, Dataset");
```

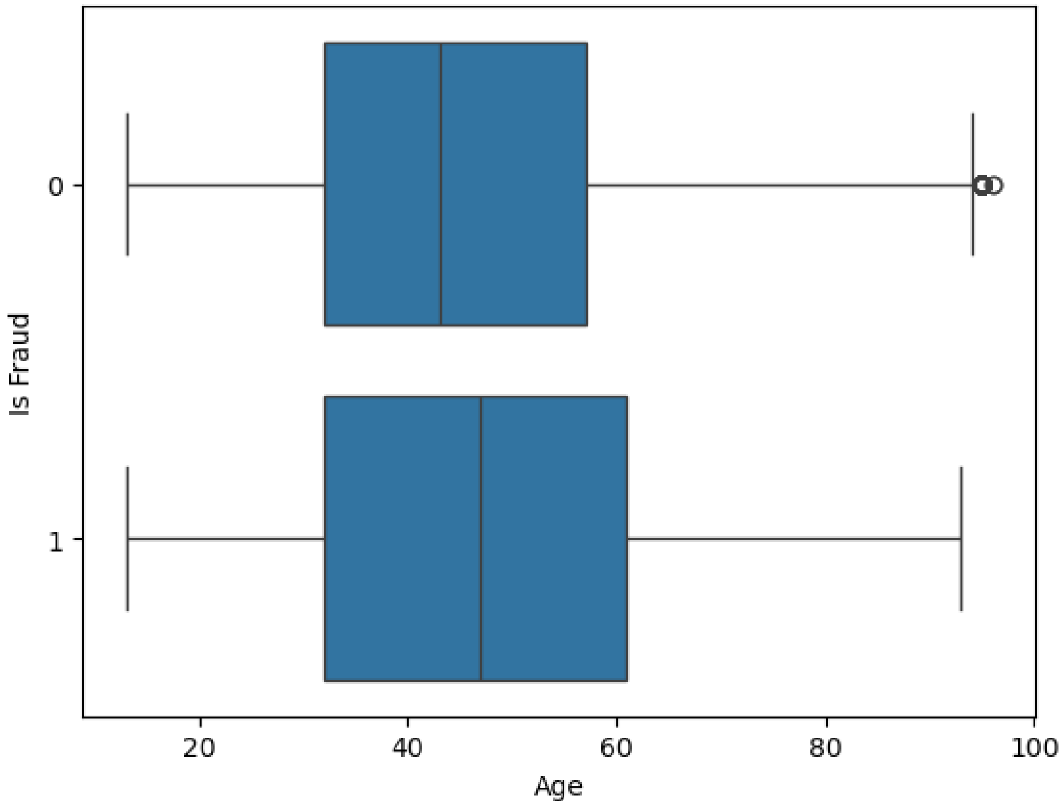


[18]:
```
plt.hist(df_fraud["age"], bins= 20)
plt.xlabel("Age")
plt.ylabel("Frequency [count]")
plt.title("Distribution of Age, Fraudulent Transactions");
```



[19]:
```
sns.boxplot(
    x= df["age"],
    y= df["is_fraud"],
    orient= "h"
)
plt.xlabel("Age")
plt.ylabel("Is Fraud")
```

[19]: Text(0, 0.5, 'Is Fraud')



1.2.5 Gender

Comparison between the two genders is made based on fraud and non-fraudulent transactions.

[20]:
```
df["gender"].value_counts()
```

[20]:
```
gender
F    709863
M    586812
Name: count, dtype: int64
```

[21]:
```
df["gender"].value_counts(normalize= True)
```

[21]:
```
gender
F    0.547449
M    0.452551
Name: proportion, dtype: float64
```

[22]:
```
gend_by_amt = df.groupby(["is_fraud", "gender"]).agg({"amt": "sum"})

gend_by_amt["perc"] = (
```

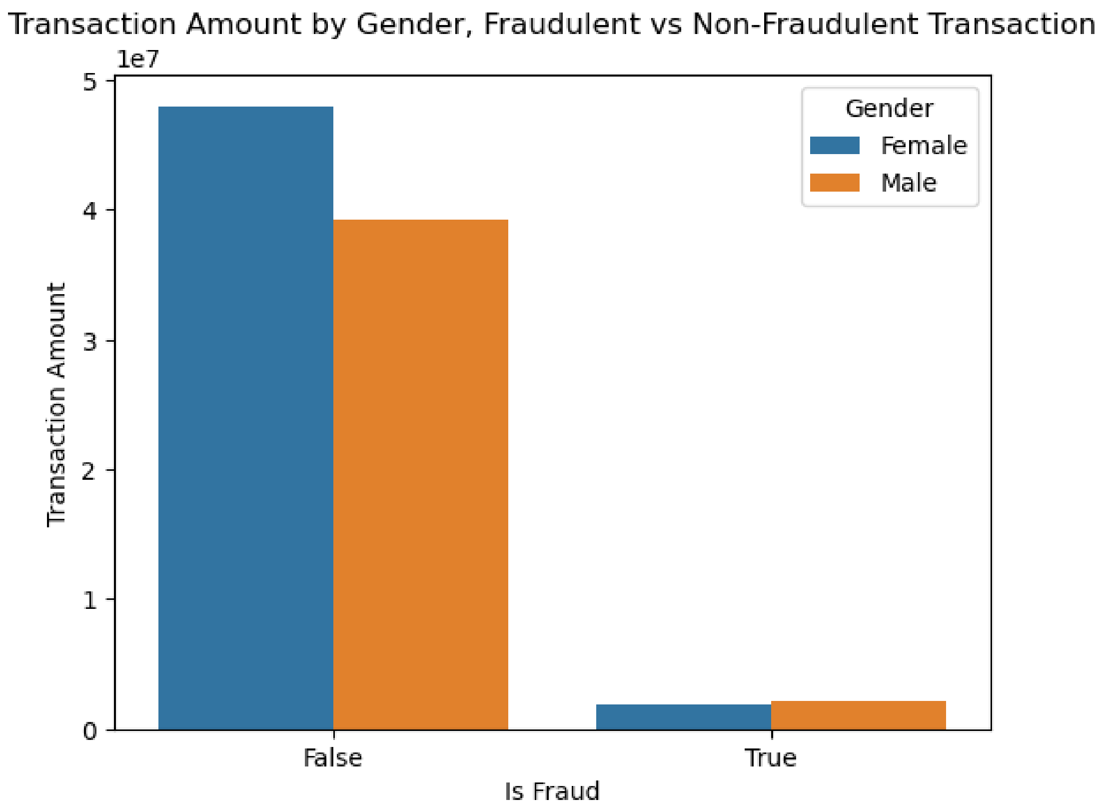
```python
    gend_by_amt.groupby(level=0)
    .apply(lambda x: x*100 / x.sum())
    .round(3)
    .droplevel(level=0)
)

gend_by_amt = gend_by_amt.reset_index()

gend_by_amt
```

[22]:

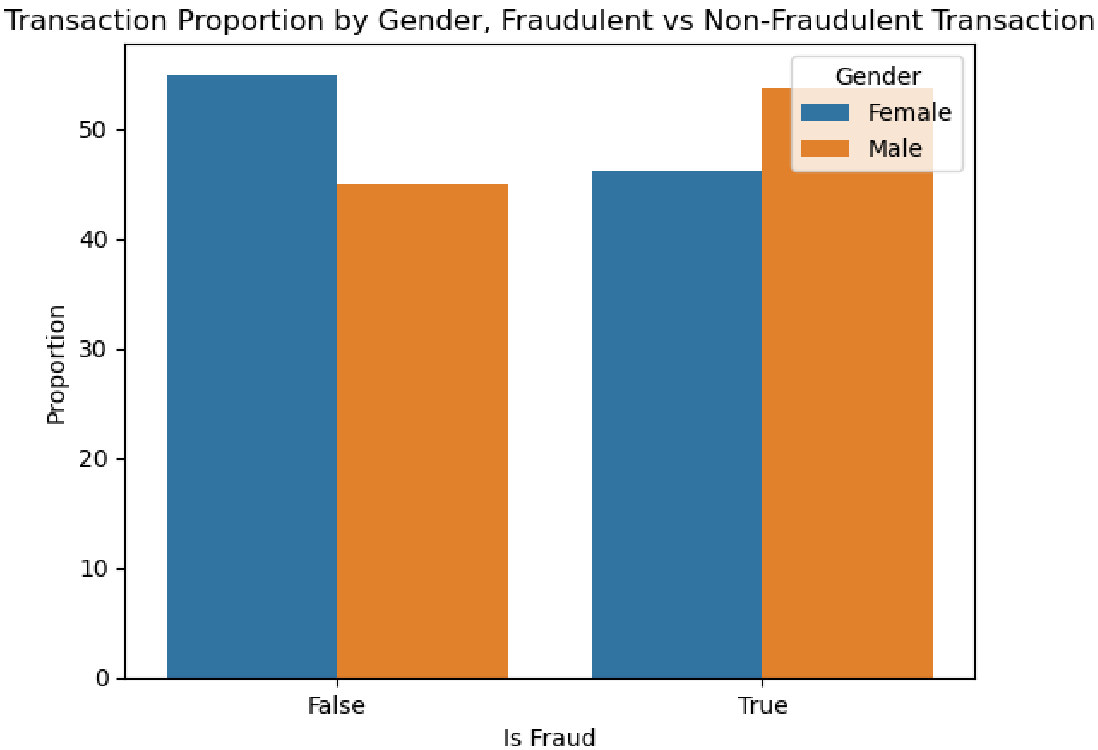
```
   is_fraud gender          amt   perc
0         0      F  47987325.49  55.01
1         0      M  39247014.80  44.99
2         1      F   1845287.34  46.27
3         1      M   2142801.27  53.73
```

[23]:

```python
fig, ax = plt.subplots()
sns.barplot(
    data= gend_by_amt,
    x= "is_fraud",
    y= "amt",
    hue= "gender",
    ax= ax
)
plt.xticks(ticks= ["0", "1"], labels= ["False", "True"])
plt.xlabel("Is Fraud")
plt.ylabel("Transaction Amount")
handles, labels= ax.get_legend_handles_labels()
plt.legend(title= "Gender", handles= handles, labels= ["Female", "Male"])
plt.title("Transaction Amount by Gender, Fraudulent vs Non-Fraudulent␣
  ↪Transaction");
```



[24]:
```
fig, ax = plt.subplots()
sns.barplot(
    data= gend_by_amt,
    x= "is_fraud",
    y= "perc",
    hue= "gender",
    ax= ax
)
plt.xticks(ticks= ["0", "1"], labels= ["False", "True"])
plt.xlabel("Is Fraud")
plt.ylabel("Proportion")
plt.title("Transaction Proportion by Gender, Fraudulent vs Non-Fraudulent␣
  ↪Transaction")
handles, labels= ax.get_legend_handles_labels()
plt.legend(title= "Gender", handles= handles, labels= ["Female", "Male"]);
```

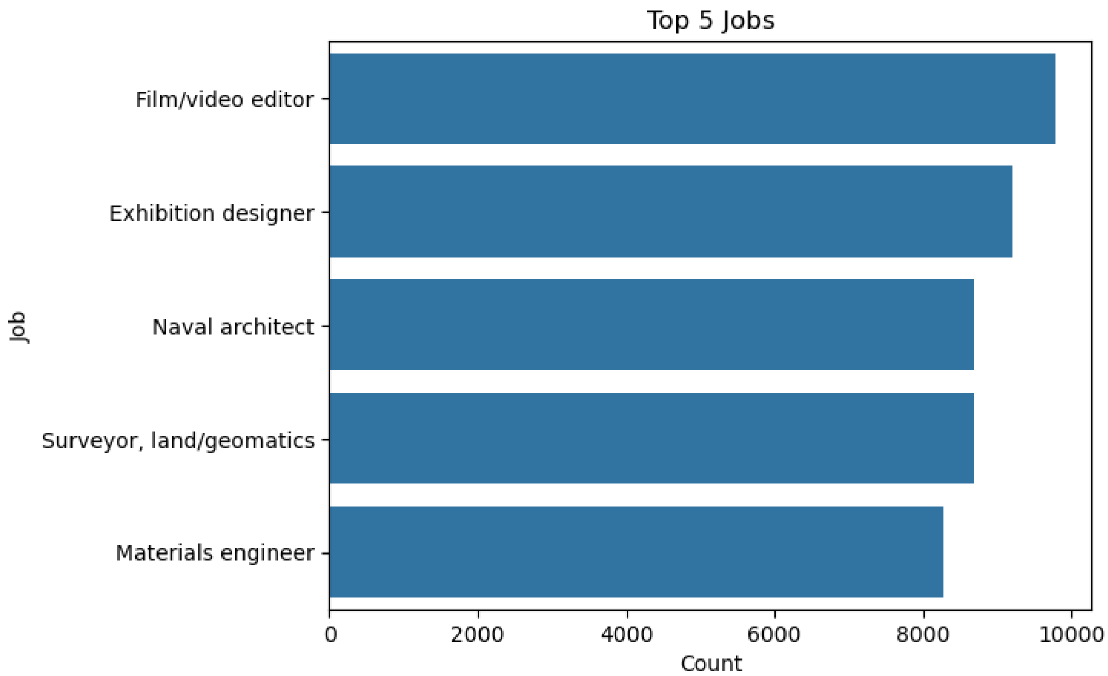


Fraudulent transactions were made more by male customers than by female customers.

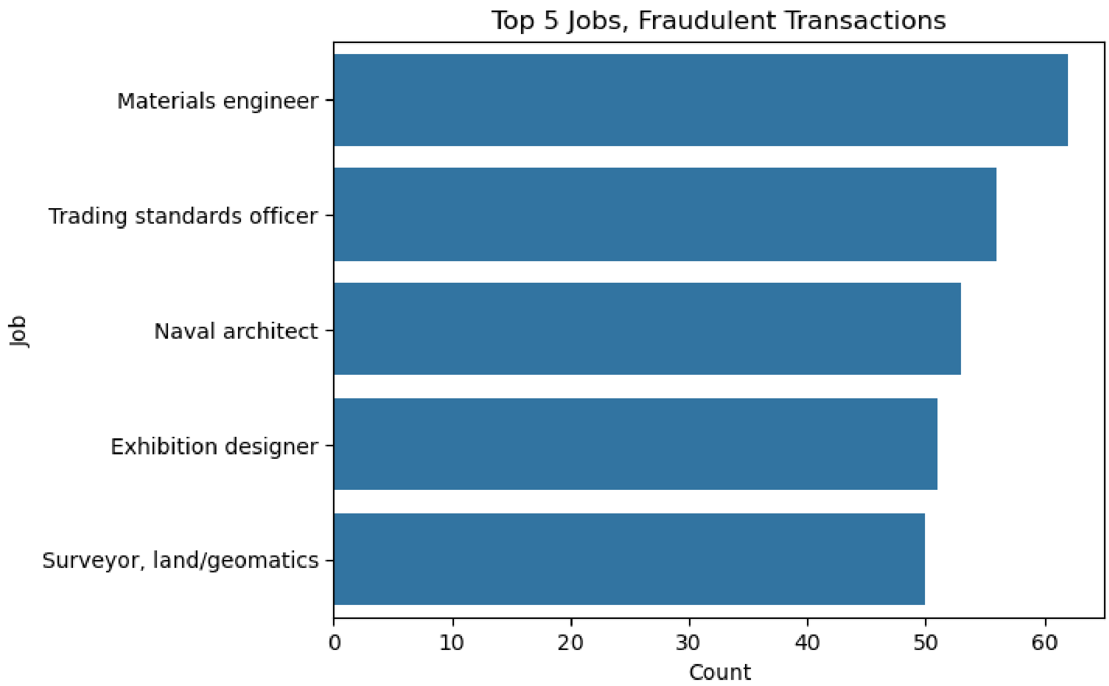
1.2.6 Job

The top 5 jobs from the overall dataset and the fraudulent transactions are taken to see the types of jobs for both groups.

[25]:
```
top_5_jobs = df["job"].value_counts().head()
sns.barplot(top_5_jobs, orient= "h")
plt.xlabel("Count")
plt.ylabel("Job")
plt.title("Top 5 Jobs");
```

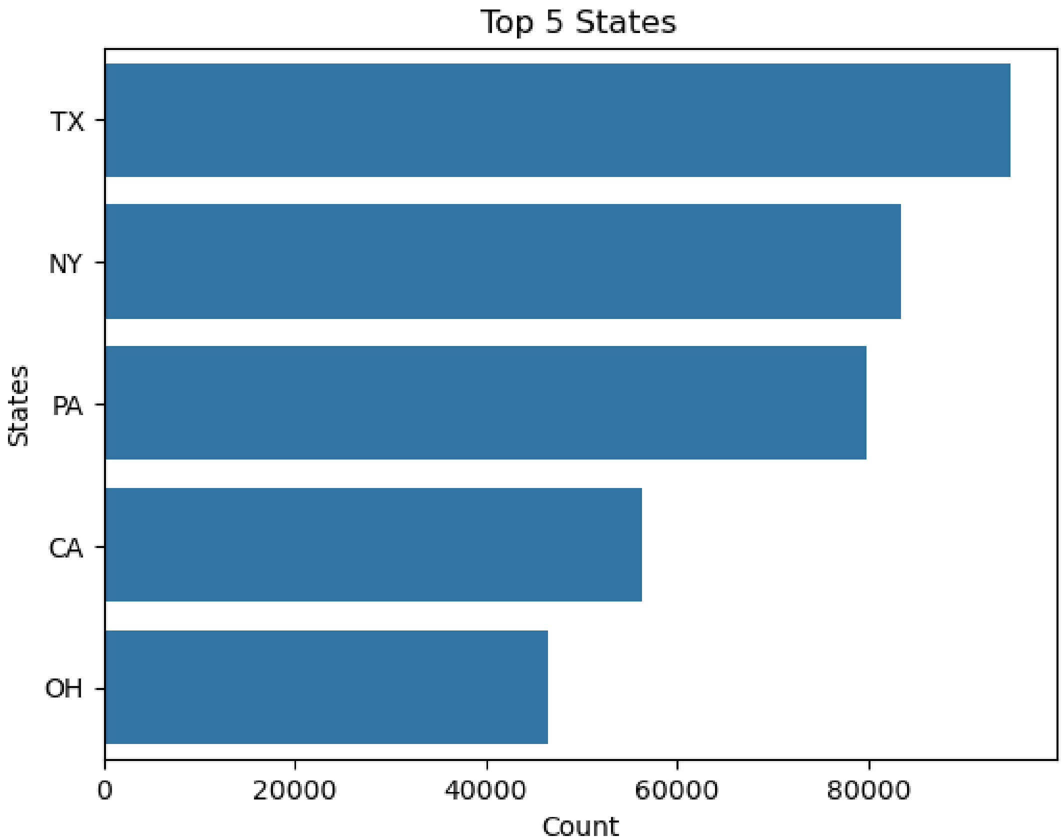


[26]:
```
top_5_jobs_fraud = df_fraud["job"].value_counts().head()
sns.barplot(top_5_jobs_fraud, orient= "h")
plt.xlabel("Count")
plt.ylabel("Job")
plt.title("Top 5 Jobs, Fraudulent Transactions");
```

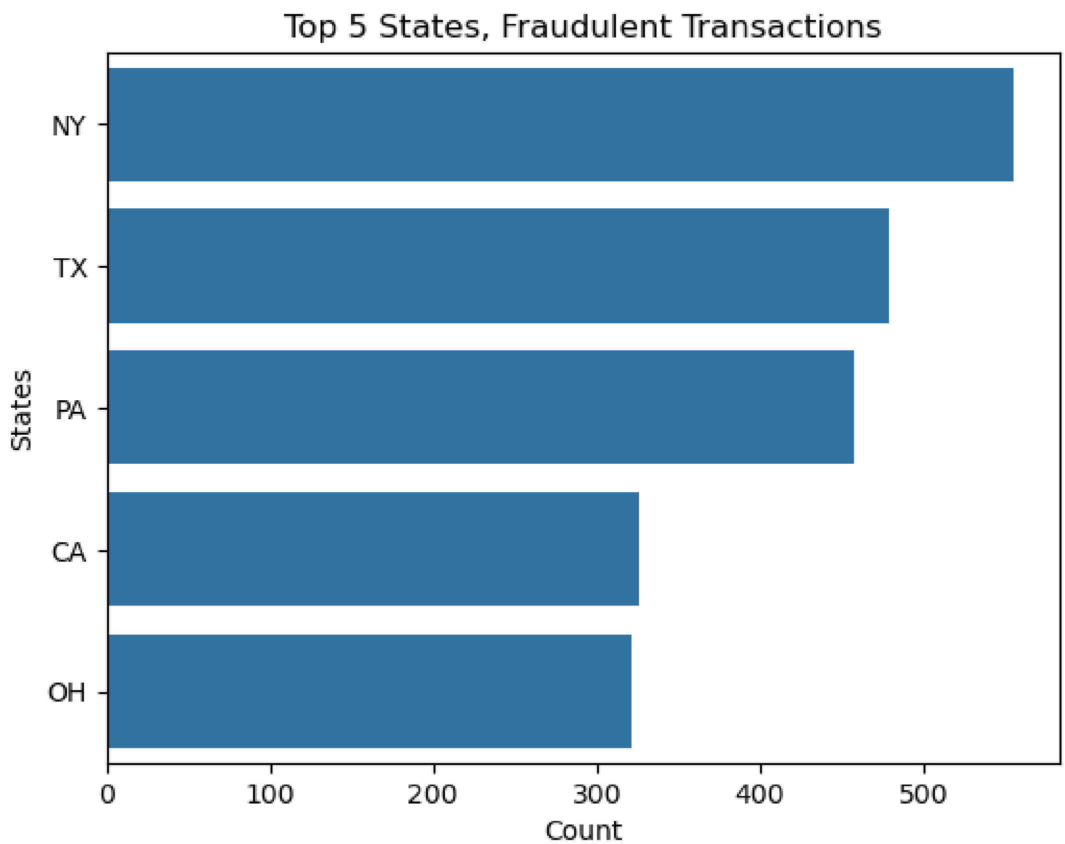


1.2.7 State

[27]:
```
top_5_states = df["state"].value_counts().head()
sns.barplot(top_5_states, orient= "h")
plt.xlabel("Count")
plt.ylabel("States")
plt.title("Top 5 States");
```

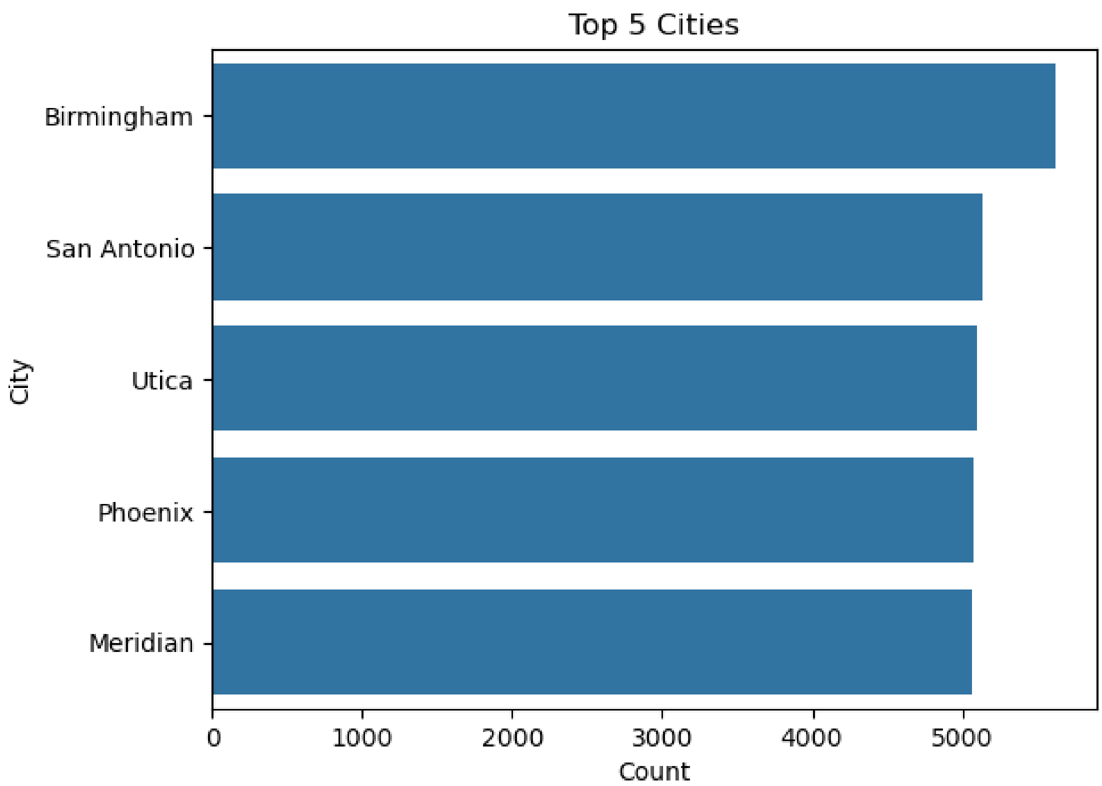


[28]:
```
top_5_states_fraud = df_fraud["state"].value_counts().head()
sns.barplot(top_5_states_fraud, orient= "h")
plt.xlabel("Count")
plt.ylabel("States")
plt.title("Top 5 States, Fraudulent Transactions");
```



City

[29]:
```
cities = df["city"].value_counts().head()
sns.barplot(cities, orient= "h")
plt.xlabel("Count")
plt.ylabel("City")
plt.title("Top 5 Cities");
```



[30]:

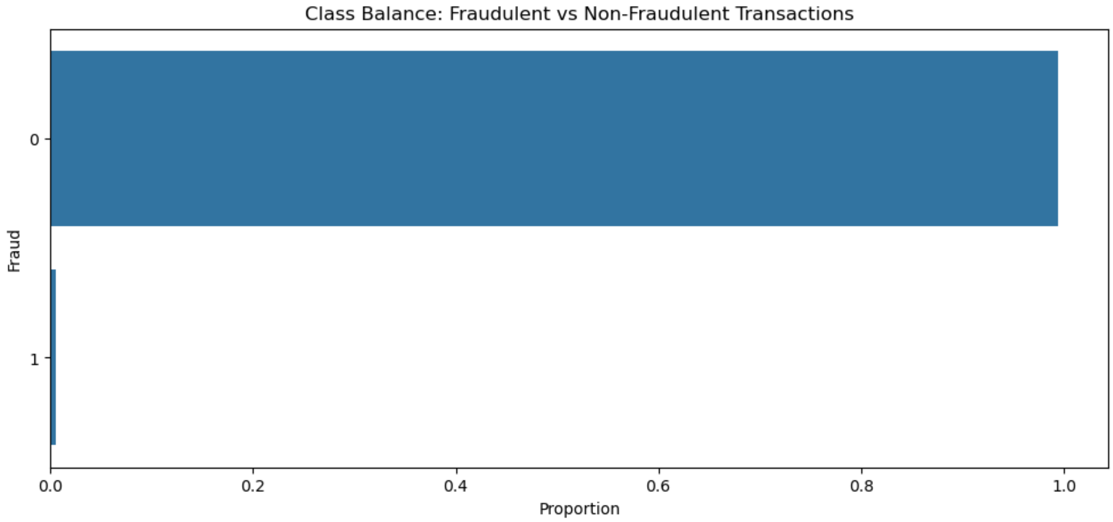
```
cities_fraud = df_fraud["city"].value_counts().head()
sns.barplot(cities_fraud, orient= "h")
plt.xlabel("Count")
plt.ylabel("City")
plt.title("Top 5 Cities, Fraudulent Transactions");
```

1.2.8 Class Balance

[31]:
```python
df["is_fraud"].value_counts(normalize= True)
```

[31]:
```
is_fraud
0    0.994211
1    0.005789
Name: proportion, dtype: float64
```

[32]:
```python
fraud_class = df["is_fraud"].value_counts(normalize= True).round(4)

fig, ax= plt.subplots(figsize= (12, 5))
sns.barplot(fraud_class, orient= "h", ax= ax)
plt.xlabel("Proportion")
plt.ylabel("Fraud")
plt.title("Class Balance: Fraudulent vs Non-Fraudulent Transactions");
```



1.3 Summary

To conclude the EDA, let's see the following points:

- the data set has 24 features with more than 1.29 million observations,
- there is multicollinarity between features,
- there are features with high cardinality,
- the amount for fraudulent transactions mostly range from \$0 to \$100, from \$300 to \$400 and from \$800 to \$1000 ,
- for non-fraudulent transactions, there is no dominating category that stands out,
- for the fraudulent transactions, grocery_pos and shopping_net categories take more than 46% of the fraudulent transactions,
- customers with ages from 30 to 50 made the most non-fraudulent transactions,
- fraudulent transactions were mostly made by customers with ages from 45 to 60,
- 55% of non-fraudulent transactions were made by females, while 45% are by males,
- 54% of fraudulent transactions were made by males, while 46% are by females,
- top 5 jobs, states, and cities were identified for both the dataset and the fraudulent transaction group,
- 99.4% of the transactions are of non-fraudulent transaction and only 0.6% are fraudulent transactions.

1.4 What is next?

- clean the dataset from outliers, multicollinear features, high and low cardinality features,
- as the data has very small number of fraudulent transactions, hence use either under sampling or over sampling to ensure class balance,
- propose predictive model that can be used for fraud detection