415-hw1

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Variable Name	Data Type	Description
accountNumber	int64	A unique identifier for the account associated with the transaction
customerId	int64	A unique identifier for the customer associated with the transaction
creditLimit	float64	The maximum amount of credit available to the customer on their account
availableMoney	float64	The amount of credit available to the customer at the time of the transaction
transactionDateTime	object	The date and time of the transaction
transactionAmount	float64	The amount of the transaction
merchantName	object	The name of the merchant where the transaction took place
acqCountry	object	The country where the acquiring bank is located
merchantCountryCode	object	The country where the merchant is located
posEntryMode	float64	The method used by the customer to enter their payment card information during the transaction
posConditionCode	float64	The condition of the point-of-sale terminal at the time of the transaction
merchantCategoryCode	object	The category of the merchant where the transaction took place

Variable Name	Data Type	Description
currentExpDate	object	The expiration date of the customer's payment card
accountOpenDate	object	The date the customer's account was opened
dateOfLastAddressChange	object	The date the customer's address was last updated
cardCVV	int64	The three-digit CVV code on the back of the customer's payment card
enteredCVV	int64	The CVV code entered by the customer during the transaction
cardLast4Digits	int64	The last four digits of the customer's payment card
transactionType	object	The type of transaction
echoBuffer	float64	An internal variable used by the financial institution
currentBalance	float64	The current balance on the customer's account
merchantCity	float64	The city where the merchant is located
merchantState	float64	The state where the merchant is located
merchantZip	float64	The ZIP code where the merchant is located
cardPresent	bool	Whether or not the customer's payment card was present at the time of the transaction
posOnPremises	float64	Whether or not the transaction took place on the merchant's premises
recurringAuthInd	float64	Whether or not the transaction was a recurring payment
expirationDateKeyInMatch	bool	Whether or not the expiration date of the payment card was entered correctly during the transaction
isFraud	bool	Whether or not the transaction was fraudulent

1.2 1 data quality checks

```
Duplicated columns: Index([], dtype='object')
Missing columns: Index(['echoBuffer', 'merchantCity', 'merchantState',
'merchantZip',
```

```
       'posOnPremises', 'recurringAuthInd'],
      dtype='object')
```

In this part, we have identified duplicated columns and columns with entirely missing data and printed the results above. And we can see that there is no duplicated columns in the dataset, and there are 6 colums with entirely missing data. For these data with entirely missing values, I haved deleted them all, since they are not of value for our future analysis with no information shown.

1.3 2 outliers in numerical variables

```
Number of outliers: 101434
Number of outliers: 786363
```

Outliers can have a significant impact on the estimation of summary statistics such as the mean and standard deviation, resulting in biased estimates. Additionally, outliers can affect regression analysis by altering the regression coefficients and leading to erroneous conclusions regarding the relationships between variables. Thus, it is necessary to detect outliers in our dataset. Right here, I have used z-score for detecting. With a absolute value of z-score 3 as a threshold, we can detect there are 101434 rows with outliers in numerical variables. Outliers can influence the estimation of summary statistics and regression coefficients, leading to biased results and incorrect conclusions. Since the primary goal of the assignment is to gain insights into the predictors of credit card fraud, which is an important problem in the financial industry, removing them can help to improve the accuracy of statistical inference. Also, compared to the length of the orignial dataset 786363, number of rows with outliers 786363 is only a small portion. And we will be identifying multiple-swipe transactions later, so this may lead to much more multiple-swipe transactions. Thus, I drop these rows with outliers here.

1.4 3 Identify columns with missing values

```
Columns with missing values: Index(['acqCountry', 'merchantCountryCode',
'posEntryMode', 'posConditionCode',
       'transactionType', 'posEntryMode_zscore', 'posConditionCode_zscore'],
      dtype='object')
```

There are 7 columns shown above with missing values. However, these columns are all for categorical variables, so we cannot replace these with the median or mean values. Thus, I will drop these rows with missing values.

1.5 4 Investigate the time variables

There are 3 time variables transactionDateTime, currentExpDate, and accountOpenDate here in the dataset. Since the type of these variables is all object, so we can convert values in these 3 columns here to the type of datetime first. However, since we need to do trasaction time comparisons and so on later, I did a further conversion from type datatime to second.

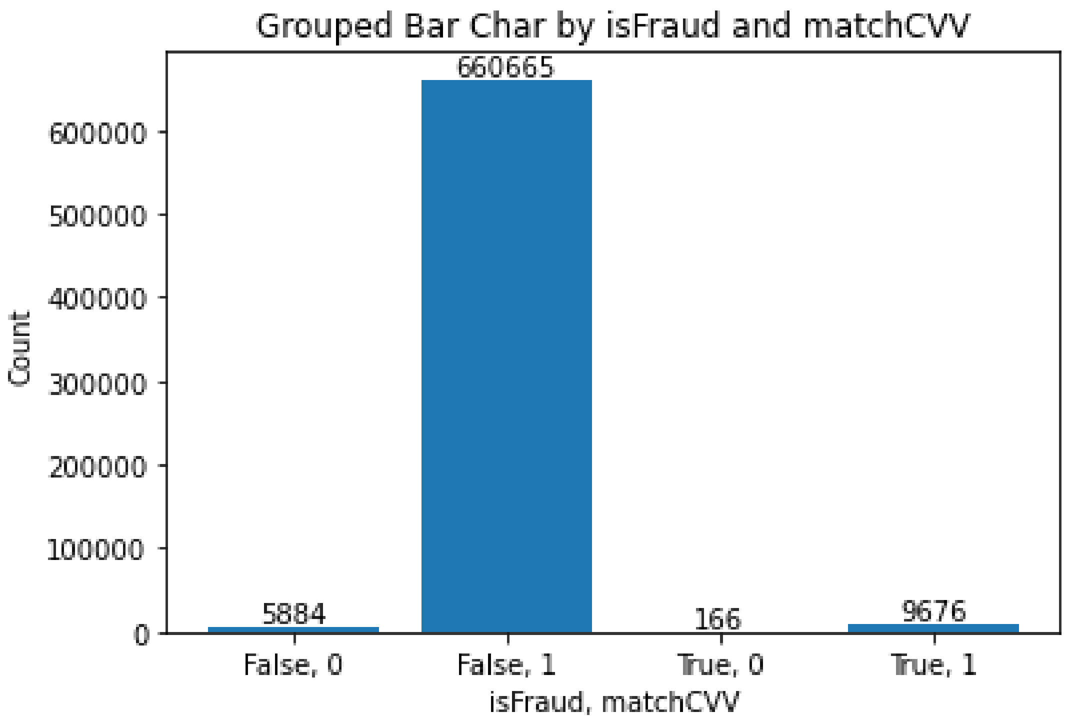
1.6 5 special treatment for some columns in the dataset

```
int64
```

The column cardCVV and enteredCVV are not of statistical value itself. However due to their unique characteristics, we can do special treatment by comparing the cardCVV and the enteredCVV to see whether the CVV are match, which means the customer entered the correct CVV. For the colums cardLast4Digits, as the name of the variable, there should be 4 digits in the variable. I have converted the intgerger in this comlumn into a string, and then I have done further cutoff or added a space to every string. Then, we get a further conversion from a string of length 4 to a integer column.

1.7 6 Analyze the relationship

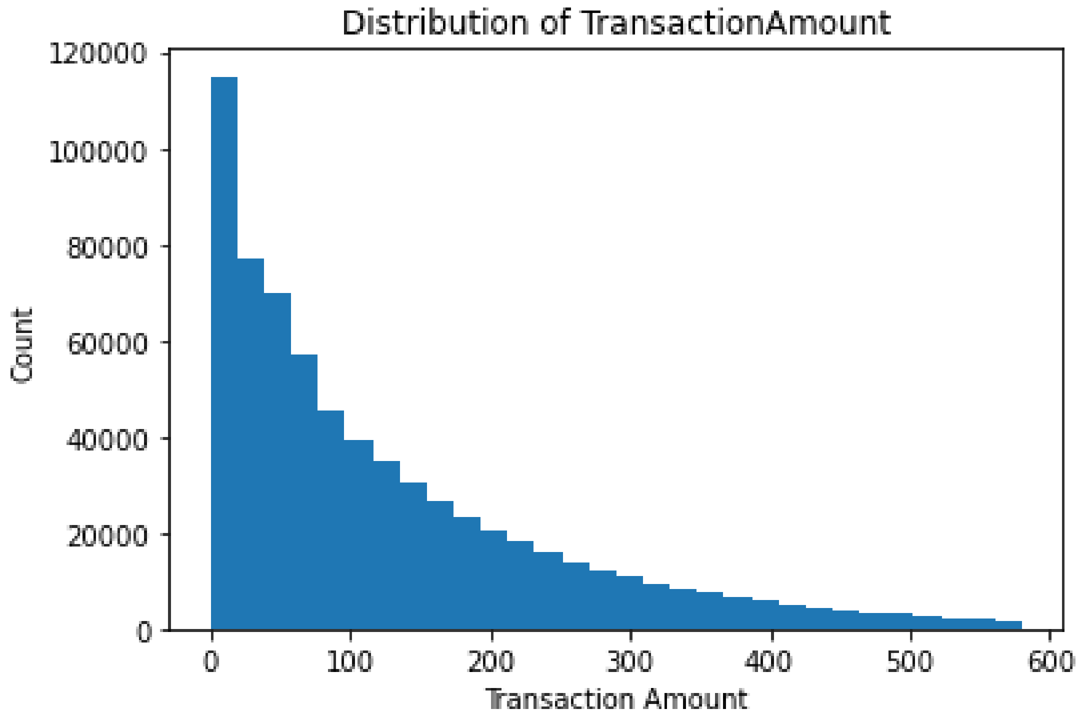
```
   isFraud  matchCVV   count
0    False         0    5884
1    False         1  660665
2     True         0     166
3     True         1    9676
```



By grouping the value of isFraud and matchCVV here, we can see there are 4 types of transactions. Most of these transactions are not fraud and with matched CVV entered to the correct CVV. And then there are some fraud transactions with matched CVV, some transaction not fraud with not matched CVV. The amount of transaction that are fraud with not matched CVV is of the least amount.

From this plot we can see that there are more not-fraud transactions than fraud transaction, and there are more matched-CVV transactions than not-matched-CVV transactions. Thus, there is not a obvious relationship between the variable isFraud and matchCVV.

1.8 7 Visualize the distribution of transactionAmount

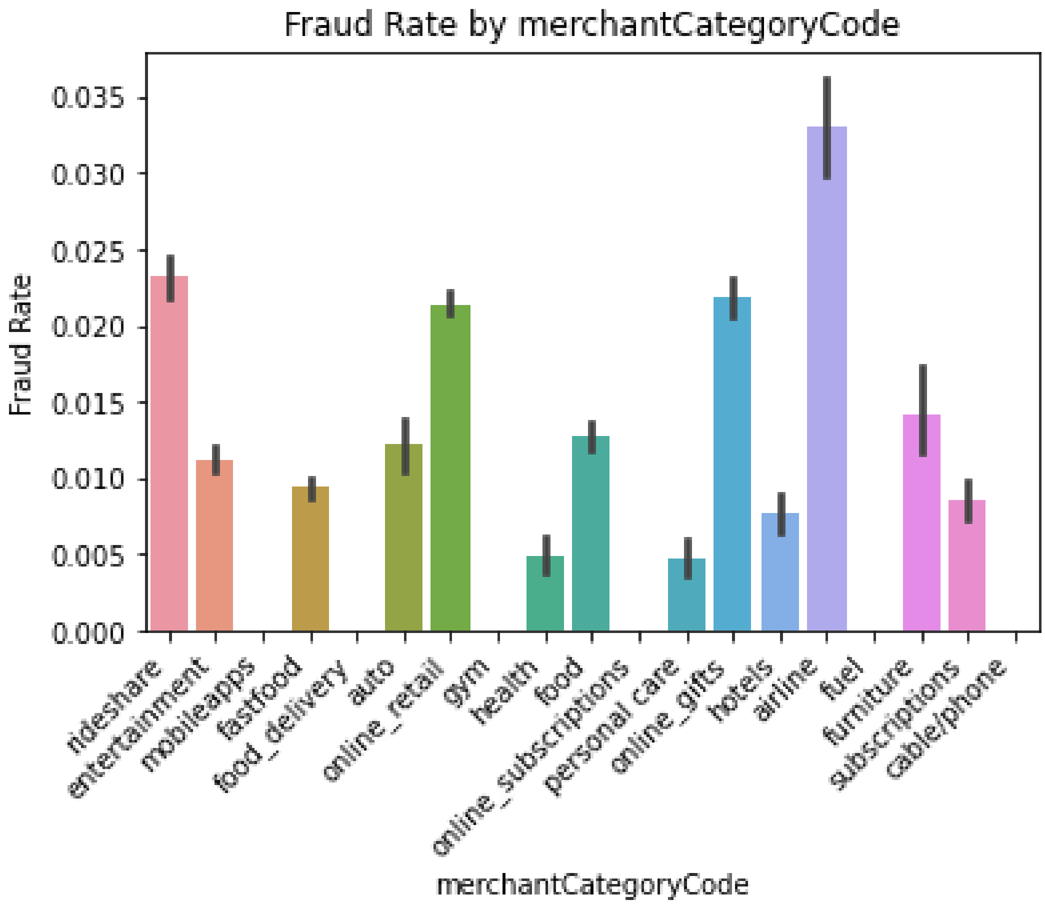


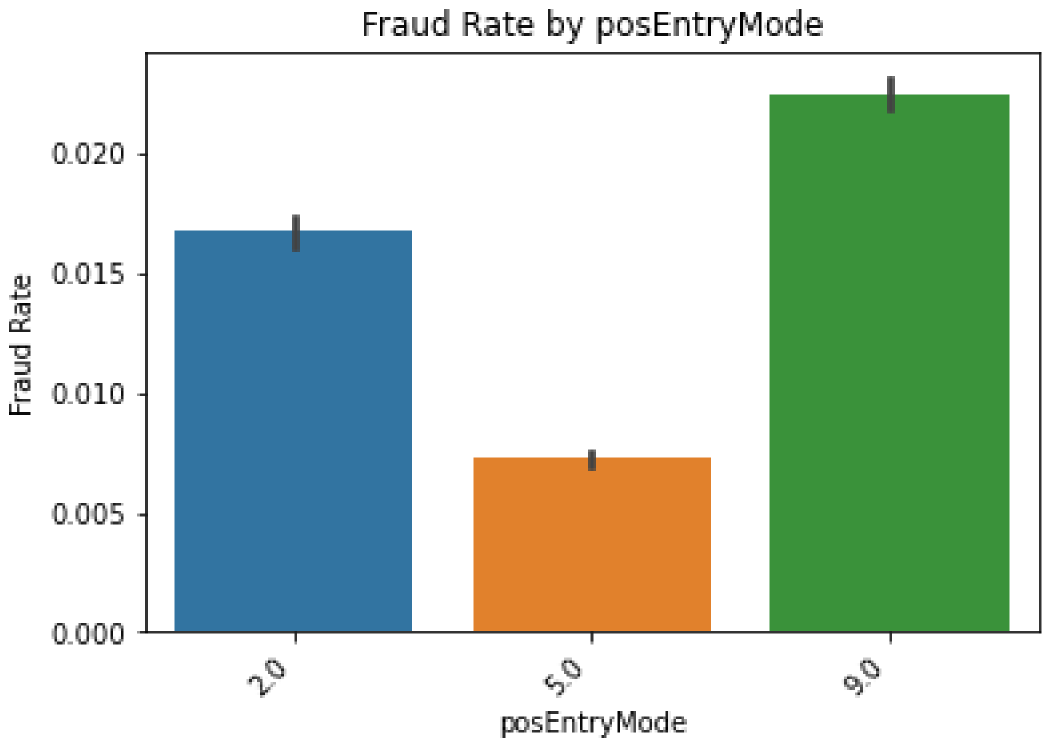
Provide a brief analysis of the observed pattern and discuss any insights or trends you can infer from the visualization.

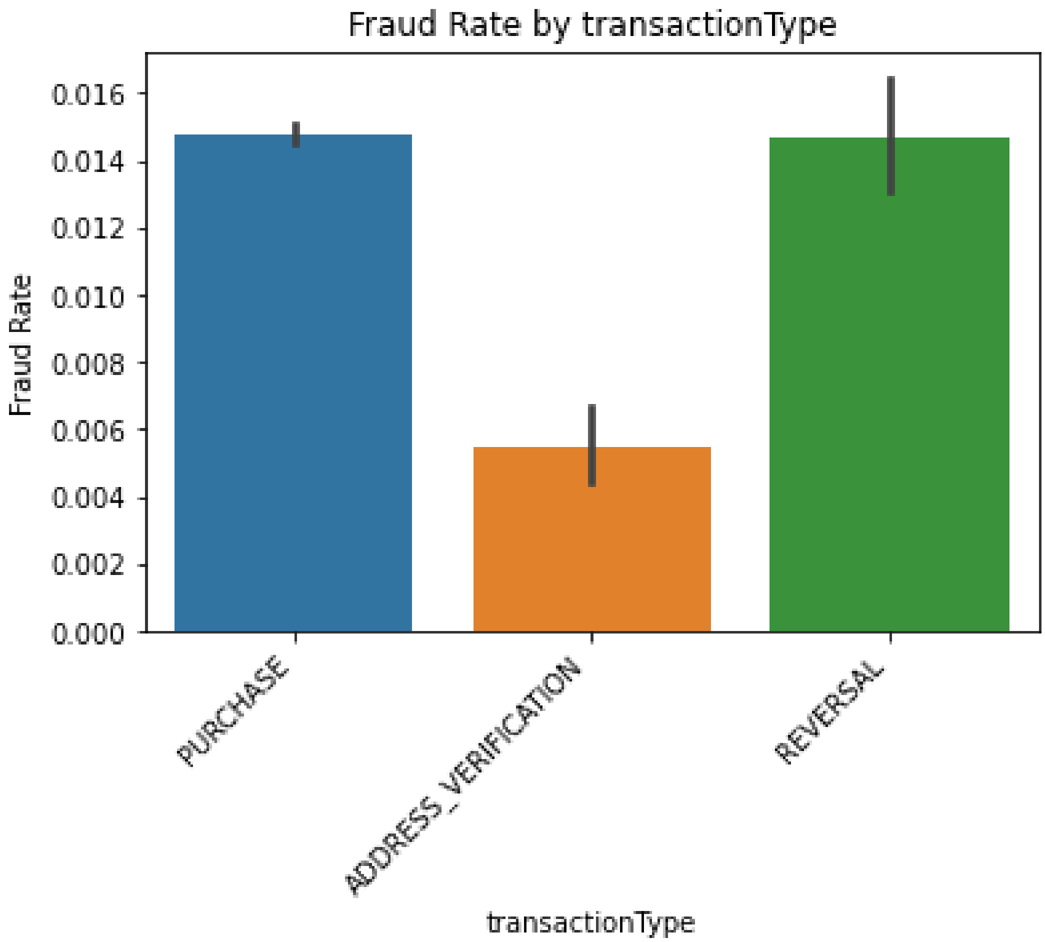
I have visualized the distribution of transactionAmount using a histogram. There is a downwrd trend in the histogram, which means there is a negative correlation between the number of transaction amount and the number of transaction, which means there are more transactions with less transaction amount, and less transactions with more transaction amount.

For this trend, a possible explaination may be that most of the credit card users are individuals or small businesses with limited capital, which is reflected in these transactions here. Also, there could be transaction amount limits omposed by financial institutions, which is further reflected in this pattern.

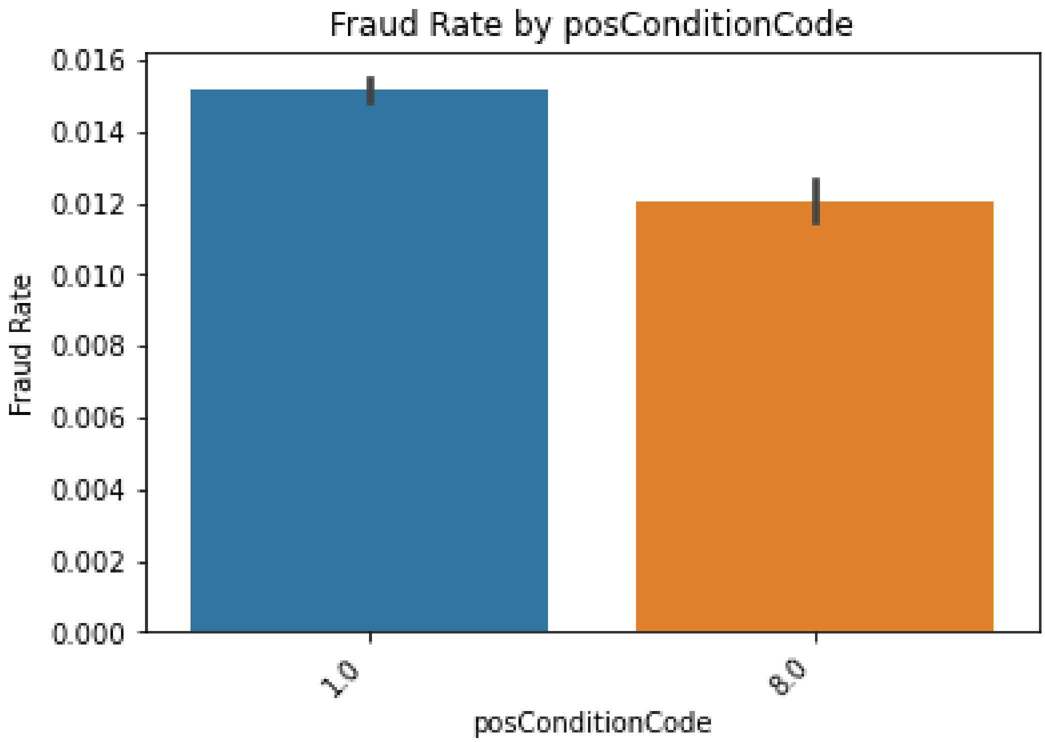
1.9 8 bar charts to display the fraud rate for each category

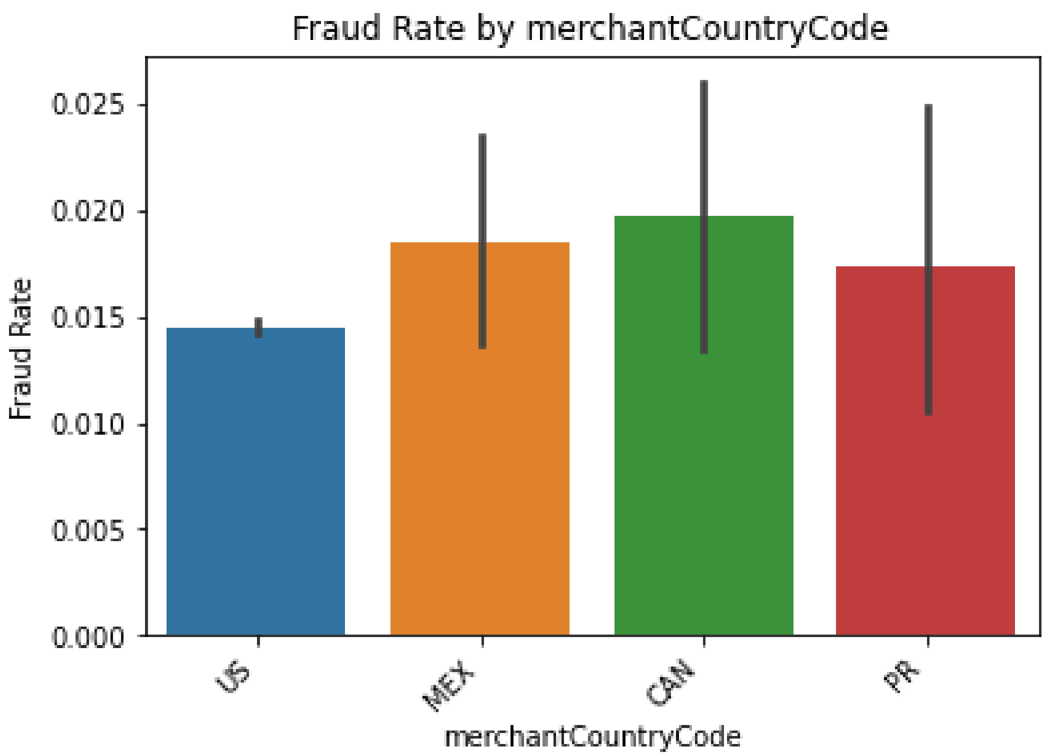



Fraud Rate by posEntryMode
Fraud Rate
0.000
0.005
0.010
0.015
0.020
2.0
5.0
9.0
posEntryMode



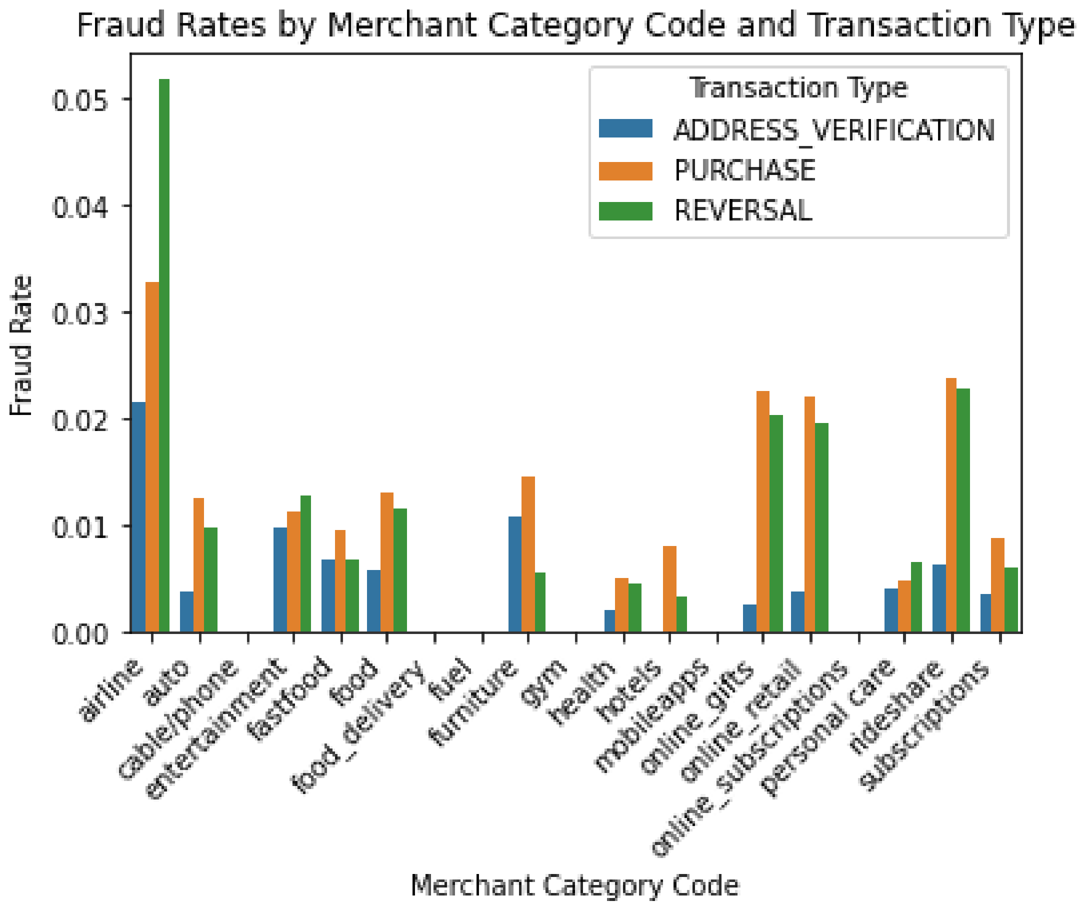
Fraud Rate by transactionType
Fraud Rate
0.016
0.014
0.012
0.010
0.008
0.006
0.004
0.002
0.000
PURCHASE
ADDRESS_VERIFICATION
REVERSAL
transactionType


Fraud Rate by posConditionCode
0.016
0.014
0.012
0.010
0.008
0.006
0.004
0.002
0.000
Fraud Rate
1.0
8.0
posConditionCode


Fraud Rate by merchantCountryCode
0.025
0.020
0.015
0.010
0.005
0.000
Fraud Rate
US
MEX
CAN
PR
merchantCountryCode

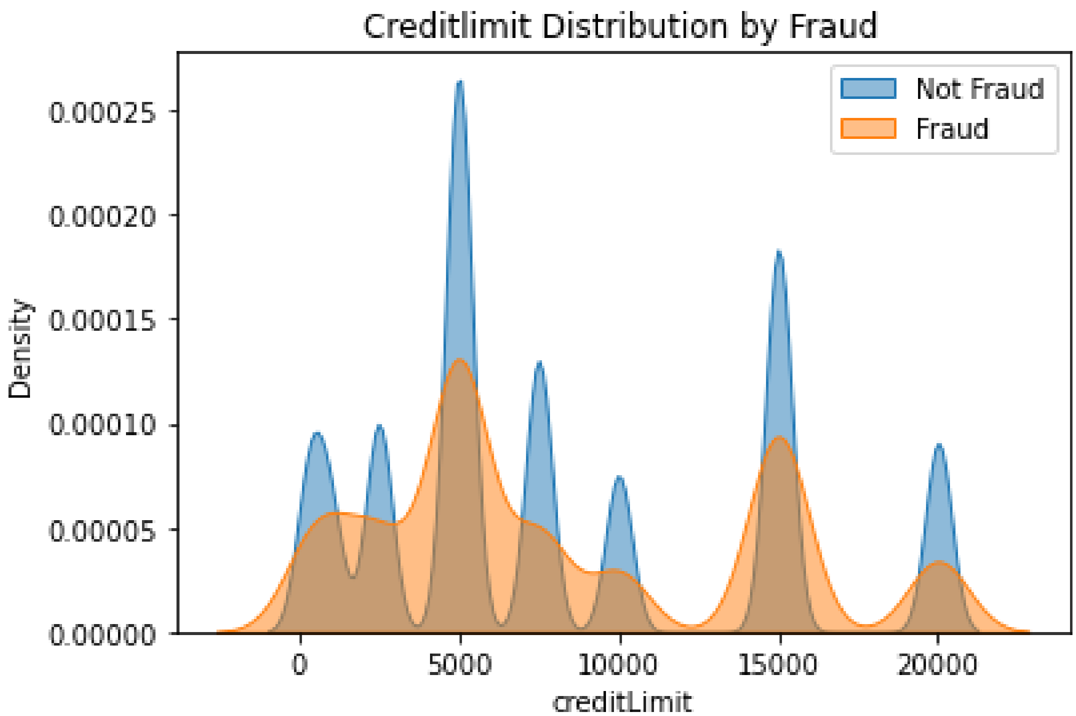
I have visualized the relationship between isFraud and categorical predictors merchantCategoryCode, posEntryMode, transactionType, posConditionCode, and merchantCountryCode, by creating bar charts here to display the fraud rate for each category of categorical variables. For there categorical variables, we can see that there are obvious fraud rate between these categories of categorical predictors merchantCategoryCode, posEntryMode, transactionType, posConditionCode, and merchantCountryCode. From the histogram of merchantCategoryCode, we can see that the fraud rate of merchant category airline, rideshare, online retails, which is of high transaction volume, lack of verification, more online transactions, and limited customer information, so there are more fraud happening in these merchant categories. From the histogram of posEntryMode, we can see that the fraud rate of the method used by the customer to enter their payment card information during the transaction represented by 9.0 PAN entry via electronic commerce, including remote chip, is greater than that of 2.0 PAN auto-entry via magnetic stripe, and 5.0 integrated circuit card read with card data reliable. Thus, we can see that more fraud will happen when the customer does not enter their payment card information online or in a less reliable way without enough verification for ohysical cards. This also corresponds to the histogram of merchantCategoryCode. From the histogram of transactionType, we can see that the fraud rate of purchase and reversal are of higher fraud rate than address verification transactions. The reason may be that purchase and reversal transactions are of higher risk and with higher profit than address verification. From the histogram of posConditionCode, we can see that the fraud rate of 1.0 the terminal is in normal working condition and functioning properly at the time of the transaction than the fraud rate 8.0 the transaction was approved online. This also corresponds to histograms above, since the 8.0 transaction is of more reliability with online approvement than a normal pos checking. From the histogram of merchantCountryCode, we can see that the fraud rates of CAN Canada, MEX Mexico, PR Puerto Rico, and US United States are listed in descending order. This may result from less effective fraud prevention measures and less developed economic conditions, which may lead to more fraud happening.

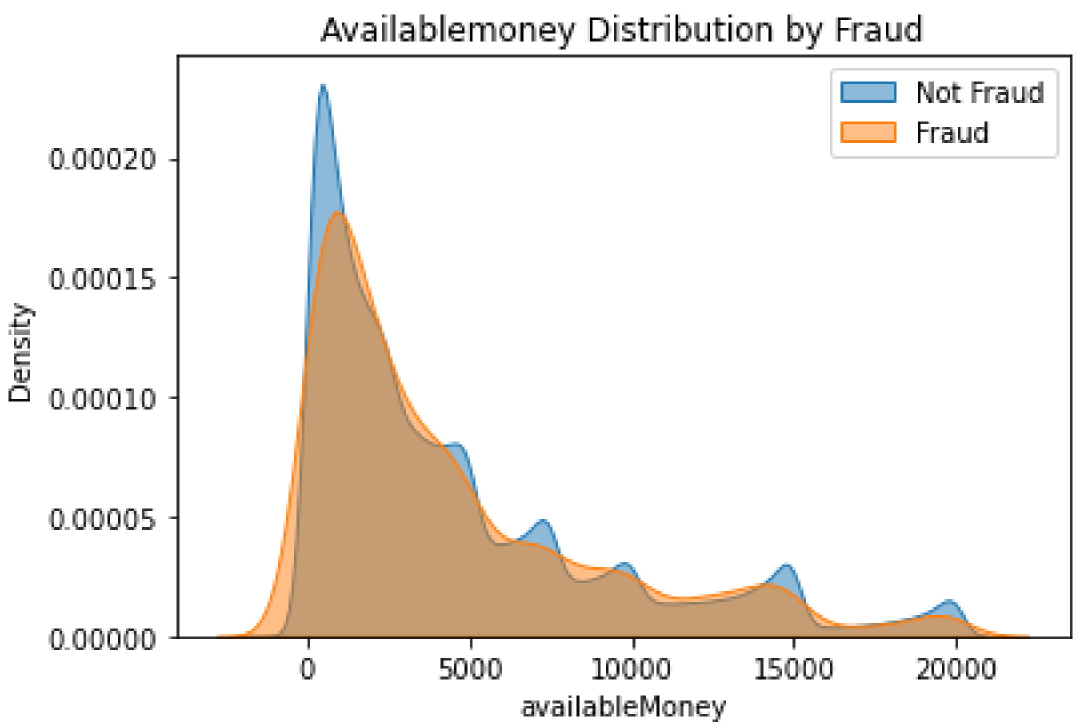
1.10 9 explore the relationship between isFraud and transactionType conditioned on merchantCategoryCode

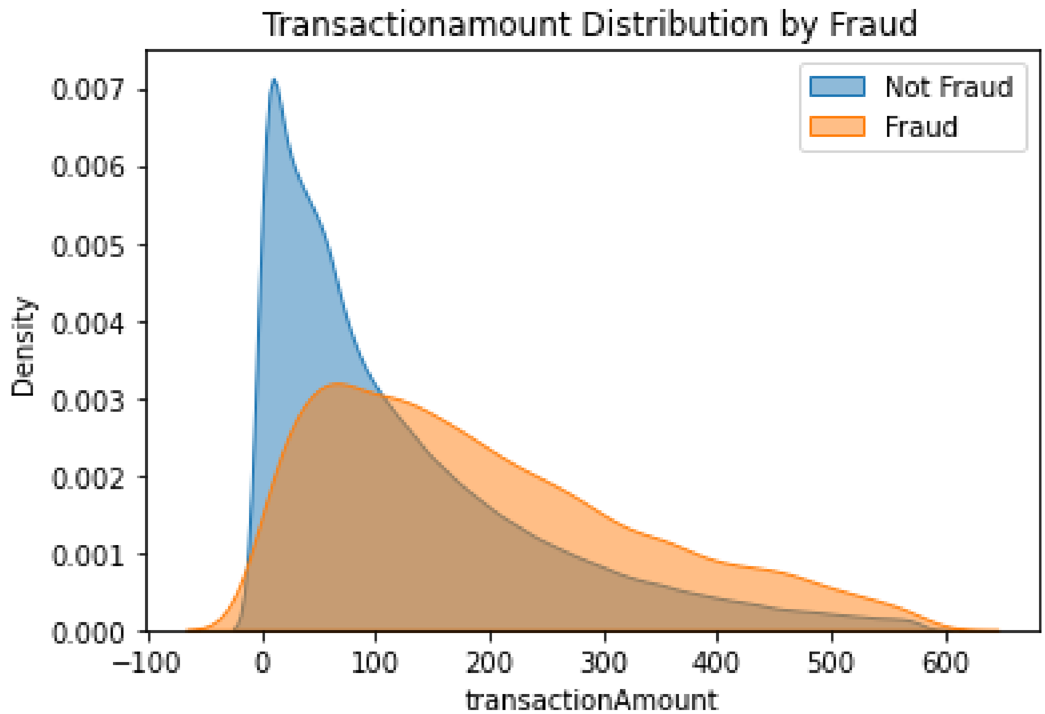


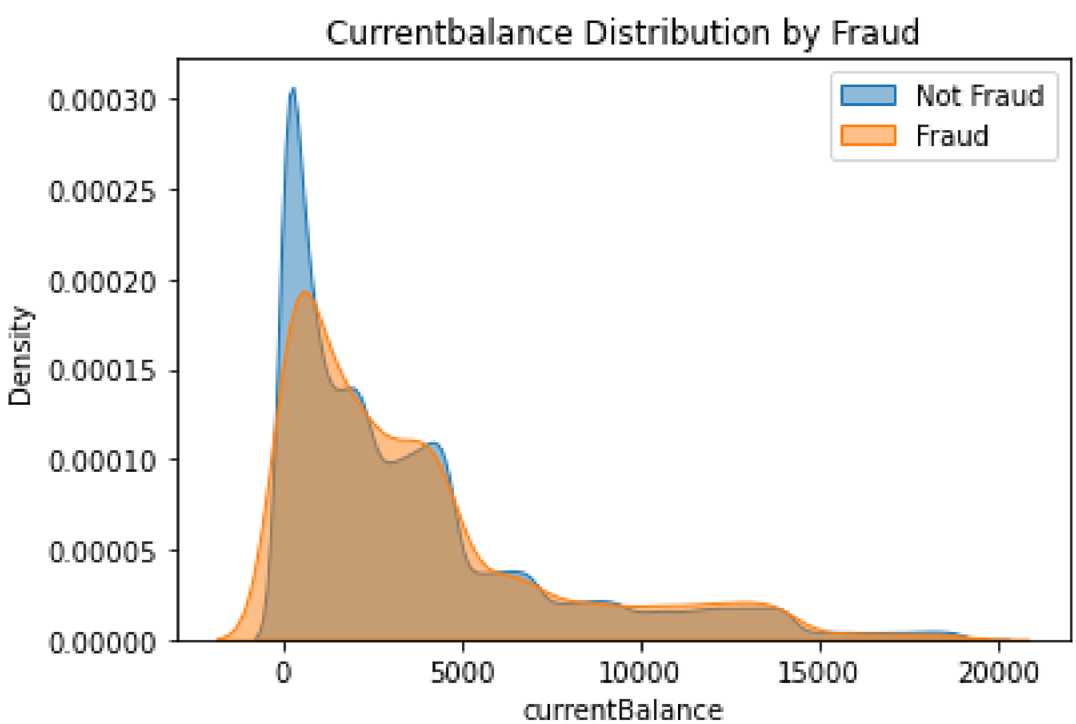
Corresponding to our results above, we can see there are higher fraud rates in airline, rideshare, and online gifts, and given every merchant category, there are higher fraud rate in purchse and reversal transactions than address verification transaction.

1.11 10 Construct conditional probability density plots for the numerical variables






Transactionamount Distribution by Fraud
Not Fraud
Fraud
Density
0.007
0.006
0.005
0.004
0.003
0.002
0.001
0.000
−100
0
100
200
300
400
500
600
transactionAmount


Currentbalance Distribution by Fraud
Not Fraud
Fraud
Density
0.00030
0.00025
0.00020
0.00015
0.00010
0.00005
0.00000
0
5000
10000
15000
20000
currentBalance

From the density plot above, we can see than there is a downward in plots of available money, transaction amount, and current balance by fraud. This means, as the available money, transaction amount, and current balance increase, the fraud rate tends to decrease. In the first density plot of creditlimit distribution, we can see that there are more fraud transaction account with rounded credit limit since there are several peaks in the plot at rounded credit limit. This may because banks tends to assigned roundedcredit values. Also, the maximum fraud rate is at 5000, which means more fraud transaction account tends to be with 5000 credit limit, since these may be more likely to be personal accounts with less information proctection procedures.

1.12 11 identify multi-swipe transactions

```
Percentage of multi-swipe transactions: 0.51%
Percentage of the total dollar amount for multi-swipe transactions: 0.44%
```

I have chosed conditions same transaction amount and transaction time of two transactions processed within 3 minutes to identify multi-swipe transactions. The estimated percentage of multi-swipe transactions is 0.51% as shows above, and the percentage of the total dollar amount for these transactions is 0.44% as shows above, excluding the first "normal" transaction from the count. Discuss any interesting findings or patterns that emerge from your analysis of multi-swipe transactions and their conditions. Since the percentage of multi-swipe transactions is a little larger than the percentage of the total dollar amount for multi-swipe transactions, so these multi-swipe transactions are of relatively less dollar amount than the average level.

1.13 12 Examine the class imbalance in the isFraud outcome variable

```
Number of fraud transactions: 9842
Number of normal transactions: 667014
Class imbalance: 0.014540759038850213
```

There are much more number of normal transactions than the number of fraud transactions, so we can see that the fraud class has only about 1.5% of the examples in the dataset, so there is an oversampling problem. When striving for higher accuracy in machine learning models, the majority class is typically favored over the minority class. This preference can have adverse effects on the performance of the minority class, leading to decreased precision, recall, and F1 scores. Moreover, in some instances, the minority class may be completely disregarded, introducing biases and inaccuracies into the predictions. However, we are really interested in the fraud class, so there is a problem of the class imbalance in the isFraud outcome variable.

1.14 13 Implement a method to mitigate class imbalance in the isFraud outcome variable

```
Number of fraud transactions after SMOTE: 666549
Number of normal transactions after SMOTE: 666549
```

I have used random oversampling to balance an imbalanced dataset here. We split the dataset into the features (nF) and the target (iF), and we create a RandomOverSampler object (ros) with a random seed of 0, and apply it to the features (nF) and the target (iF) using the fit_resample() function, which returns the resampled features (sN) and target (sI) as numpy arrays. And the number of fraud and normal transactions in the resampled dataset (sI) are shown above. Then we combine the resampled features (sN) and target (sI) into a pandas DataFrame with the same columns as the original dataset. The resulting DataFrame resampled contains the resampled data. Addressing class imbalance will improve the effectiveness and performance of a predictive model for credit card fraud detection by reducing bias, improving accuracy, reducing false negatives, increasing precision, and reducing overfitting.