main

May 25, 2023

1 Business Problem: Predicting Customer Lifetime Value (CLV)

Customer Lifetime Value (CLV) is a crucial business metric that estimates the total amount of revenue that a customer is expected to generate over their entire lifetime. The higher the CLV, the more valuable the customer is to the business. By predicting the CLV of each customer, a bank can identify its most valuable customers and focus its marketing and retention efforts on them. This can help the bank increase customer loyalty, reduce churn, and improve its overall profitability.

1.1 Data mining technique used: Regression Analysis

Regression analysis can be used to predict the CLV of each customer. By using the demographic and transactional data of customers from the given dataset, we can train a regression model to predict the total amount of revenue that each customer is expected to generate over their entire lifetime. We can use features such as age, income, transaction history, and location to train the model. Once the model is trained, we can use it to predict the CLV of new customers and identify the most valuable ones.

1.2 Data Description

' transactions.csv ' has the following data:- | cc_num | acct_num | trans_num | unix_time | category | amt | is_fraud | merchant | merch_lat | merch_long | | — | — | — | — | — | — | — | — | — | — |

category: this column conatins category of the payment like gas_transport, grocery_pos, etc

amt: This column contains amount

is_fraud: This column conatins a flag varibale for fraud transaction

acct_num: This column conatins account number of the customer

trans_num: This column conatins the unique ID for transaction

cc_num: This column conatins credit card reference number

merchant_name: This column conatins merchant name

merch_lat: This column conatins merchant latitude

merch_long: This column conatins merchent longitude

unix_time: This column conatins unix time

' customer.csv ' has the following data:- | snn | cc_num | first | last | gender | street | city | state | zip | lat | long | city_pop | job | dob | acct_num | | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — |

first: This column conatins first name of the customer

last: This column conatins last name of the customer

gender: This column conatins gender of the customer

ssn: This column conatins Social Security Number

street: This column conatins street name of the customer's address

city: This column conatins city name of the customer's address

state: TThis column conatins state name of the customer's address

zip: This column conatins zip code of the customer's address

lat: This column conatins latitude of the customer's address

long: This column conatins longitude of the customer's address

city_pop: This column conatins City Population

job: This column conatins customer's job description

dob: This column conatins customer's date of birth

acct_num: This column conatins account number of the customer

Here are the steps to build a Machine Learning Model for predicting CLV:

1.2.1 Step 1: Importing required libraries and packages

[ ]:
```
import pandas as pd
import glob
import os
import csv
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import GridSearchCV
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import learning_curve
from sklearn.preprocessing import PolynomialFeatures
```

##

If you have 'merged_data.csv', just load it and skip to step 3 or click here

1.2.2 Step 2: Data Preprocessing

1. Load the transactional data from the CSV files.

[ ]:
```
def process_transactions_files():
    for i in range(132):
        # Generate the filename
        filename = f'dataset/transactions_{i}.csv'

        # Load CSV file
        df = pd.read_csv(filename, delimiter='|')

        # Print the DataFrame
        print(f'{filename}:')
        print(df)

        # Save the DataFrame to a new CSV file
        new_filename = f'dataset/new_transactions_{i}.csv'
        df.to_csv(new_filename, index=False)

process_transactions_files()
```

2. Merge the all the transactional data into one file

[ ]:
```
# Define the directory where the files are located
directory = "dataset"

# Define the filename for the merged file
merged_filename = "transactions.csv"

# Create a CSV writer object with '|' as the delimiter for the merged file
with open(os.path.join(directory, merged_filename), 'w', newline='') as outfile:
    writer = csv.writer(outfile, delimiter='|')

    # Loop through all the files that match the pattern
    for filename in glob.glob(directory + "/transactions_[0-9]*.csv"):
        # Open the file for reading
        with open(filename, 'r') as infile:
            # Create a CSV reader object with '|' as the delimiter
            reader = csv.reader(infile, delimiter='|')

            # Loop through each row in the file and write it to the merged file
            for row in reader:
                writer.writerow(row)

trans= pd.read_csv('dataset/transactions.csv', delimiter='|')
trans.to_csv('transactions.csv', index=False)
trans
```

3. Remove any unnecessary columns and handle missing or inconsistent data.

[ ]:
```
trans.dropna()
```

4. Loading customer data from CSV file

[ ]:
```
# Load CSV file
df = pd.read_csv('dataset/customers.csv', delimiter='|')
# Print the DataFrame
print(df)
# Save the DataFrame to a new CSV file
df.to_csv('customers.csv', index=False)
```

[ ]:
```
cus= pd.read_csv('customers.csv')
cus.dropna()
cus
```

[ ]:
```
trans = pd.read_csv('transactions.csv')
cus = pd.read_csv('customers.csv')
```

```
/var/folders/df/npmhf4fs0qb8cnwm2kmptxk00000gn/T/ipykernel_18713/2234585526.py:1
: DtypeWarning: Columns (0,1,3,5,6,8,9) have mixed types. Specify dtype option
on import or set low_memory=False.
  trans = pd.read_csv('transactions.csv')
```

5. Checking for null values

[ ]:
```
null_values_trans = trans.isnull().sum()
print("transactions.csv:")
print(null_values_trans, end='\n\n')
print("customers.csv:")
null_values_cus = cus.isnull().sum()
print(null_values_cus)
```

6. Checking data types for each column

[ ]:
```
print("Data type of each column in transactions.csv:")
print(trans.dtypes, end="\n\n")
print("Data type of each column in customers.csv:")
print(cus.dtypes, end="\n\n")
```

7. Mearging both csv files into one file

[ ]:
```
merged_data = pd.merge(trans, cus, on="acct_num")
print(merged_data.columns)
merged_data.to_csv('merged_data.csv', index=False)
null_values_merged_data = merged_data.isnull().sum()
print(null_values_merged_data)
```

1.2.3 Step 3: Feature Engineering

1. Dropping unwanted columns

[ ]:
```
# Drop unnecessary columns
#merged_data.drop(['trans_num', 'cc_num_x', 'cc_num_y', 'merchant'], axis=1,␣
↪inplace=True)
# Handle missing values
merged_data = pd.read_csv('merged_data.csv')
transactions = pd.read_csv('transactions.csv')
customers = pd.read_csv('customers.csv')
merged_data.fillna(0, inplace=True)
```

```
/var/folders/df/npmhf4fs0qb8cnwm2kmptxk00000gn/T/ipykernel_10757/2695368701.py:5
: DtypeWarning: Columns (0,1,3,5,6,8,9) have mixed types. Specify dtype option
on import or set low_memory=False.
  transactions = pd.read_csv('transactions.csv')
```

[ ]:
```
transactions.shape
```

[ ]:
```
(4261035, 10)
```

[ ]:
```
customers.shape
```

[ ]:
```
(1000, 15)
```

[ ]:
```
merged_data.shape
```

[ ]:
```
(1705131, 24)
```

[ ]:
```
merged_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1705131 entries, 0 to 1705130
Data columns (total 24 columns):
 #   Column      Dtype
---  ------      -----
 0   cc_num_x    int64
 1   acct_num    int64
 2   trans_num   object
 3   unix_time   int64
 4   category    object
 5   amt         float64
 6   is_fraud    int64
 7   merchant    object
 8   merch_lat   float64
 9   merch_long  float64
 10  ssn         object
 11  cc_num_y    int64
 12  first       object
```

```
 13  last        object
 14  gender      object
 15  street      object
 16  city        object
 17  state       object
 18  zip         int64
 19  lat         float64
 20  long        float64
 21  city_pop    int64
 22  job         object
 23  dob         object
dtypes: float64(5), int64(7), object(12)
memory usage: 312.2+ MB
```

[ ]:
```
merged_data.describe()
```

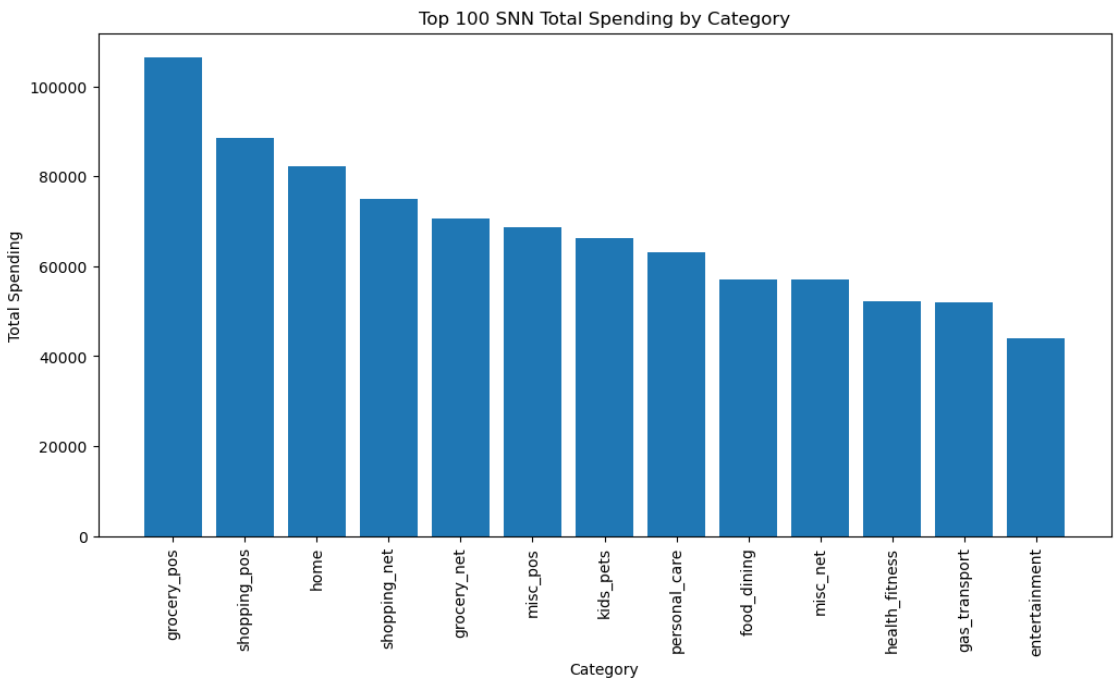
[ ]:
```
           cc_num_x      acct_num     unix_time           amt      is_fraud  \
count  1.705131e+06  1.705131e+06  1.705131e+06  1.705131e+06  1.705131e+06
mean   4.107406e+17  4.971373e+11  1.611078e+09  7.126194e+01  7.190063e-04
std    1.293583e+18  2.905397e+11  3.648932e+07  1.581055e+02  2.680466e-02
min    6.042928e+10  2.348758e+09  1.546261e+09  1.000000e+00  0.000000e+00
25%    2.131270e+14  2.593455e+11  1.577732e+09  9.580000e+00  0.000000e+00
50%    3.550106e+15  4.759571e+11  1.609511e+09  4.612000e+01  0.000000e+00
75%    4.640859e+15  7.572477e+11  1.641097e+09  8.361000e+01  0.000000e+00
max    4.983666e+18  9.993899e+11  1.672492e+09  3.141268e+04  1.000000e+00

          merch_lat    merch_long      cc_num_y           zip           lat  \
count  1.705131e+06  1.705131e+06  1.705131e+06  1.705131e+06  1.705131e+06
mean   3.737953e+01 -9.174718e+01  4.107406e+17  5.125834e+04  3.737950e+01
std    5.583652e+00  1.644449e+01  1.293583e+18  2.926924e+04  5.553923e+00
min    1.870250e+01 -1.588275e+02  6.042928e+10  1.571000e+03  1.970250e+01
25%    3.361558e+01 -9.847466e+01  2.131270e+14  2.811000e+04  3.371690e+01
50%    3.835259e+01 -8.688335e+01  3.550106e+15  4.834600e+04  3.845340e+01
75%    4.140874e+01 -7.974548e+01  4.640859e+15  7.811400e+04  4.142010e+01
max    6.577610e+01 -6.919192e+01  4.983666e+18  9.970500e+04  6.478050e+01

               long      city_pop
count  1.705131e+06  1.705131e+06
mean  -9.174640e+01  3.145833e+05
std    1.643393e+01  5.675419e+05
min   -1.578284e+02  1.710000e+03
25%   -9.867220e+01  2.198500e+04
50%   -8.692370e+01  7.443800e+04
75%   -8.000550e+01  2.701000e+05
max   -7.019160e+01  2.906700e+06
```

2. Ploting graphs

[ ]:
```
grouped_data = merged_data.groupby(['ssn', 'category'])['amt'].sum().
 ↪reset_index()
sorted_data = grouped_data.sort_values('amt', ascending=False)
# Select the top 1000 records
top_1000_data = sorted_data.head(1000)
```

Graph showing the top 100 SNN total spending by category

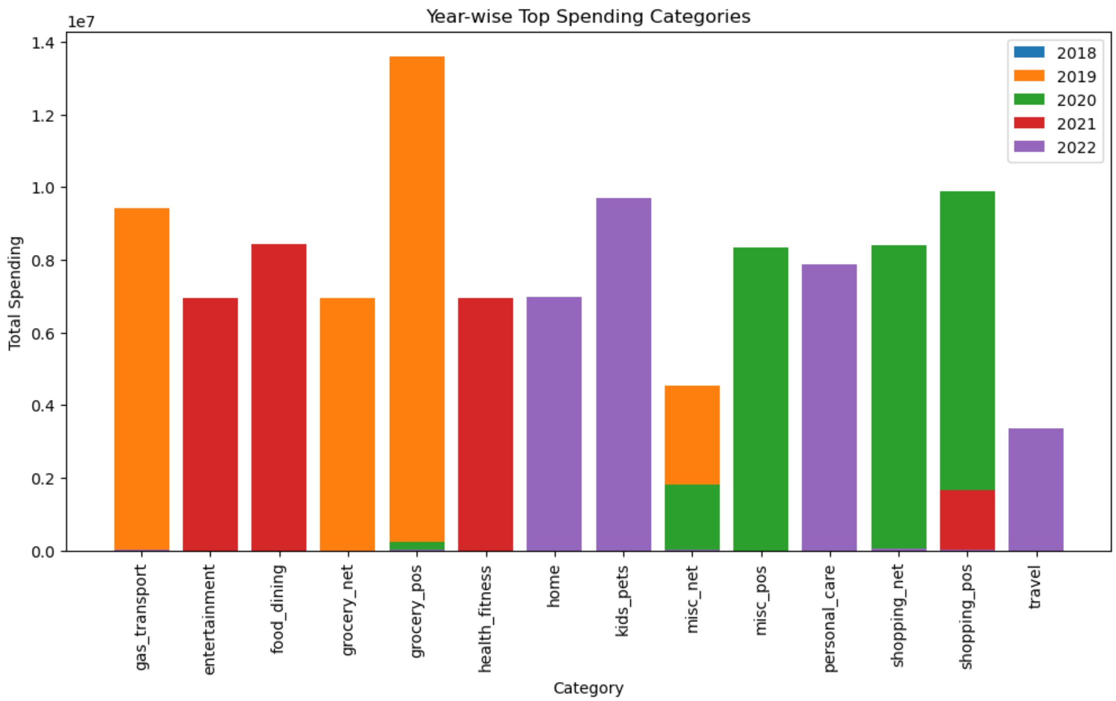
[ ]:
```
plt.figure(figsize=(12, 6))
plt.bar(top_1000_data['category'], top_1000_data['amt'])
plt.xlabel('Category')
plt.ylabel('Total Spending')
plt.title('Top 100 SNN Total Spending by Category')
plt.xticks(rotation=90)
plt.show()
```



Graph showing the year-wise top spending categories

[ ]:
```
df = merged_data
df['unix_time'] = pd.to_datetime(df['unix_time'], unit='s')
# Extract the year from the datetime
df['year'] = df['unix_time'].dt.year
# Group the data by 'year' and 'category' and calculate the sum of 'amt'
grouped_data = df.groupby(['year', 'category'])['amt'].sum().reset_index()
# Get the top spending category for each year
top_spending_categories = grouped_data.groupby('year')['amt'].idxmax()
```

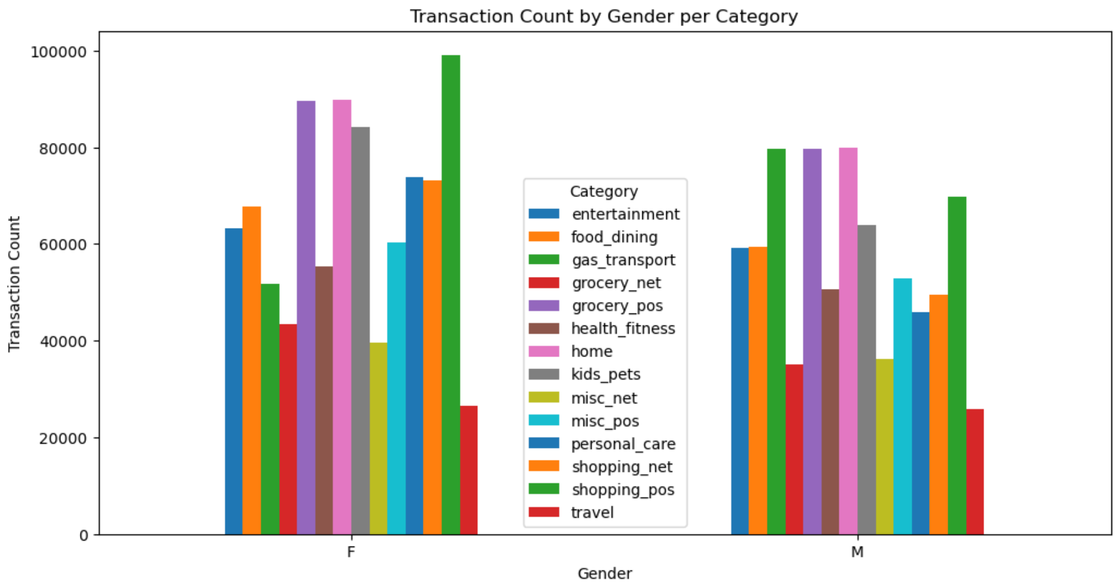
```
top_spending_data = grouped_data.loc[top_spending_categories]
# Create the bar plot
plt.figure(figsize=(12, 6))
for year in top_spending_data['year']:
    year_data = grouped_data[grouped_data['year'] == year]
    plt.bar(year_data['category'], year_data['amt'], label=str(year))
plt.xlabel('Category')
plt.ylabel('Total Spending')
plt.title('Year-wise Top Spending Categories')
plt.xticks(rotation=90)
plt.legend()
plt.show()
```



Graph showing the transaction count based on gender per category

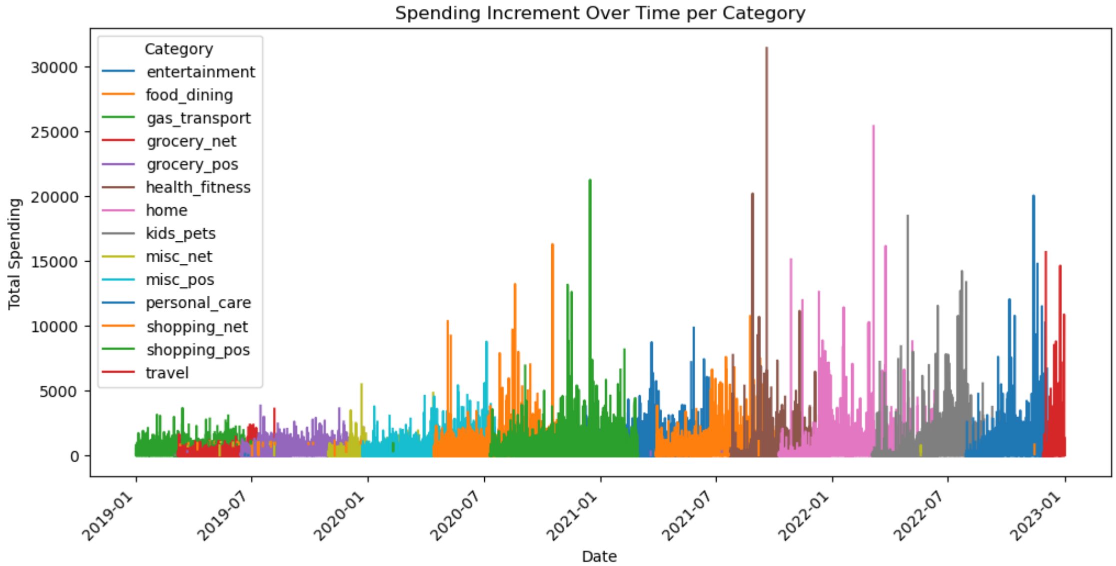
```
[ ]: grouped_data = df.groupby(['gender', 'category'])['trans_num'].count().
      ↪reset_index()
     pivot_data = grouped_data.pivot(index='gender', columns='category',␣
      ↪values='trans_num')
     pivot_data.plot(kind='bar', figsize=(12, 6))
     plt.xlabel('Gender')
     plt.ylabel('Transaction Count')
     plt.title('Transaction Count by Gender per Category')
     plt.xticks(rotation=0)
```

```
plt.legend(title='Category')
plt.show()
```



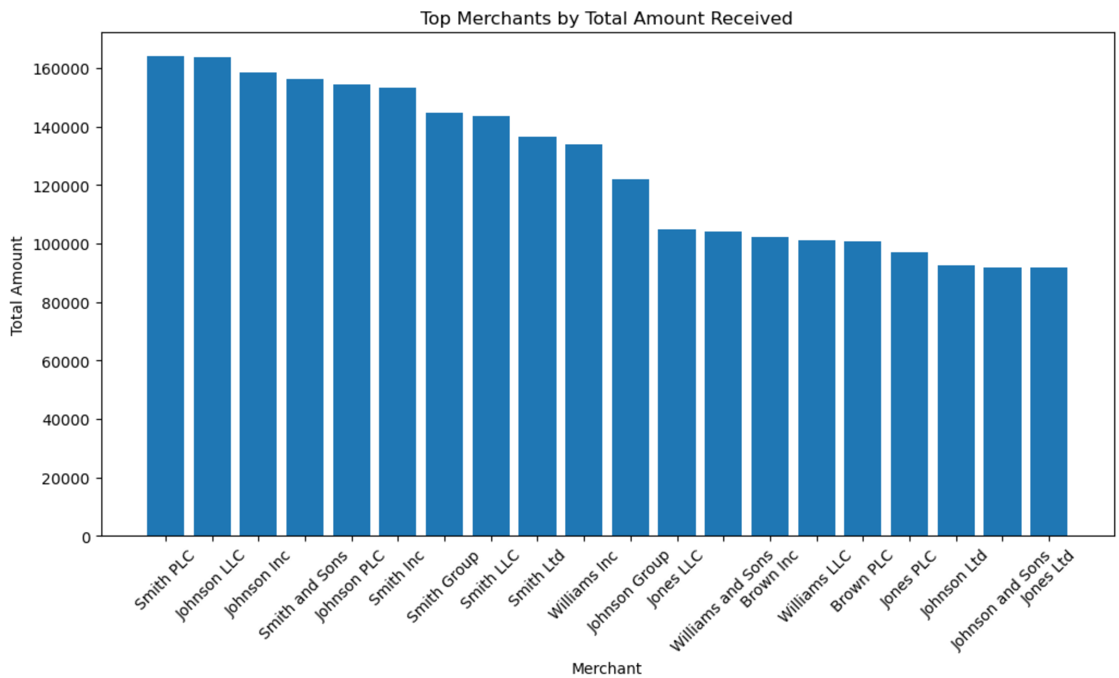
Graph showing the spending increment over time per category

[ ]:
```
df['date'] = pd.to_datetime(df['unix_time'], unit='s')
grouped_data = df.groupby(['category', 'date'])['amt'].sum().reset_index()
pivot_data = grouped_data.pivot(index='date', columns='category', values='amt')
pivot_data.plot(kind='line', figsize=(12, 6))
plt.xlabel('Date')
plt.ylabel('Total Spending')
plt.title('Spending Increment Over Time per Category')
plt.xticks(rotation=45)
plt.legend(title='Category')
plt.show()
```



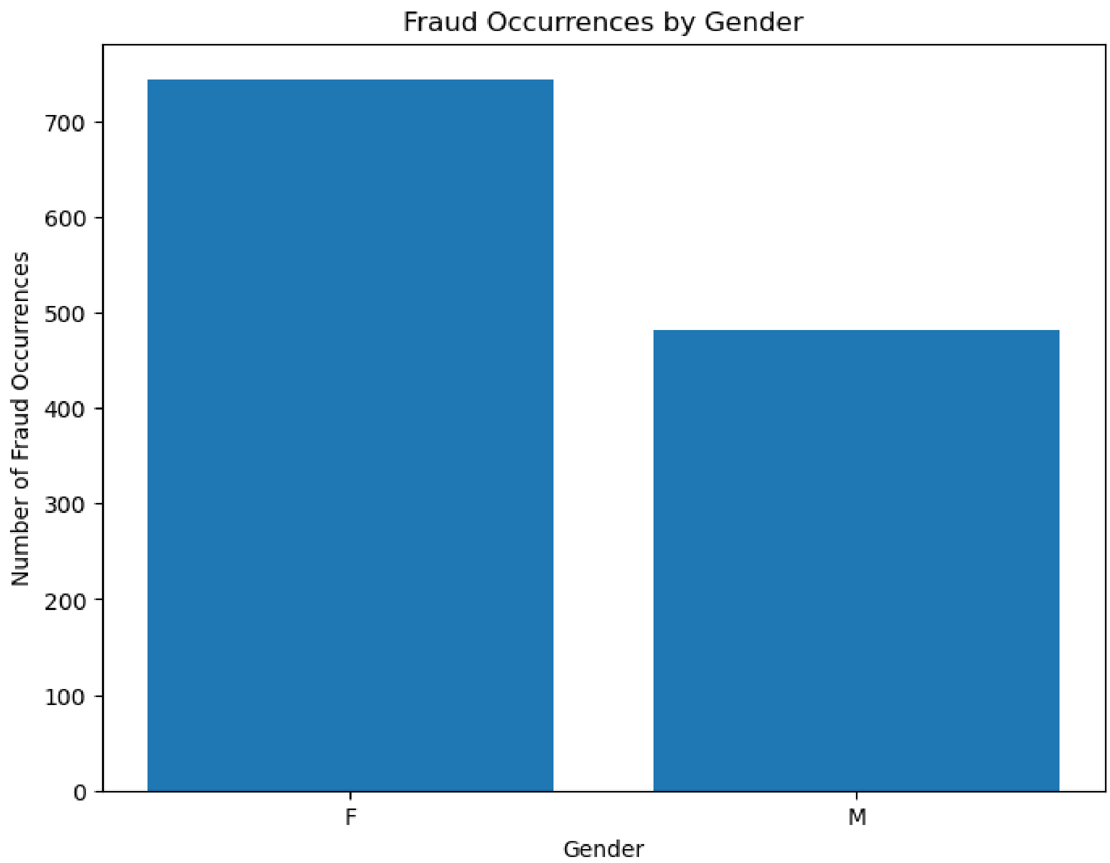
Graph showing which merchant receives a lot of money

```
[ ]: grouped_data = df.groupby('merchant')['amt'].sum().reset_index()
sorted_data = grouped_data.sort_values('amt', ascending=False)
top_merchants = sorted_data.head(20)  # Adjust the number of top merchants as␣
 ↪needed
# Create the bar plot
plt.figure(figsize=(12, 6))
plt.bar(top_merchants['merchant'], top_merchants['amt'])
plt.xlabel('Merchant')
plt.ylabel('Total Amount')
plt.title('Top Merchants by Total Amount Received')
plt.xticks(rotation=45)
plt.show()
```



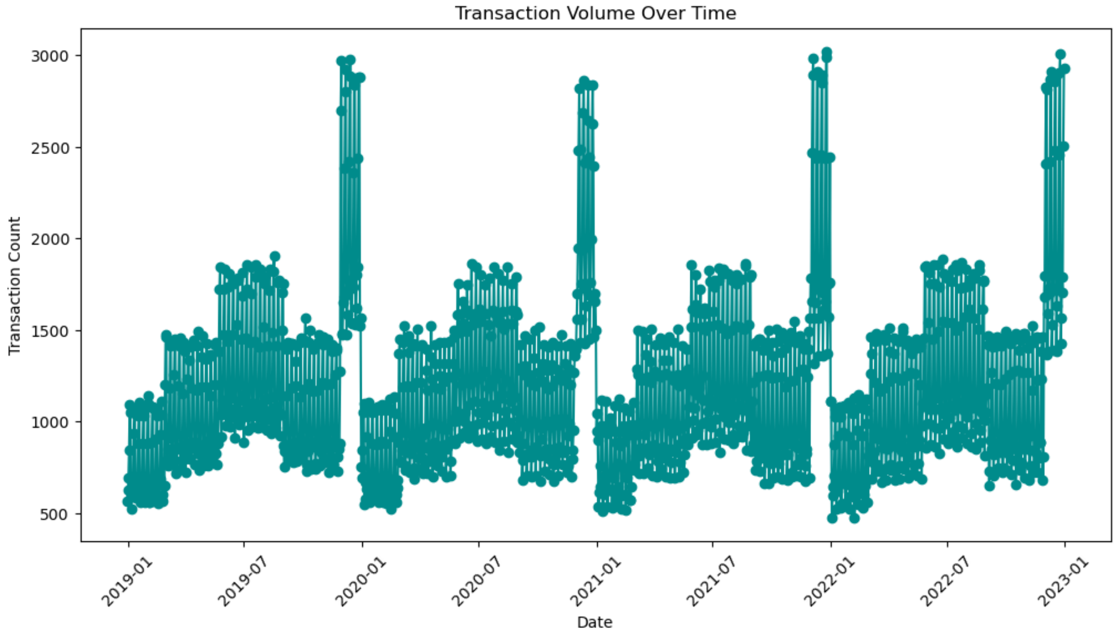
Graph showing which gender faced more fraud

[ ]:
```
grouped_data = df.groupby('gender')['is_fraud'].sum().reset_index()
plt.figure(figsize=(8, 6))
plt.bar(grouped_data['gender'], grouped_data['is_fraud'])
plt.xlabel('Gender')
plt.ylabel('Number of Fraud Occurrences')
plt.title('Fraud Occurrences by Gender')
plt.show()
```

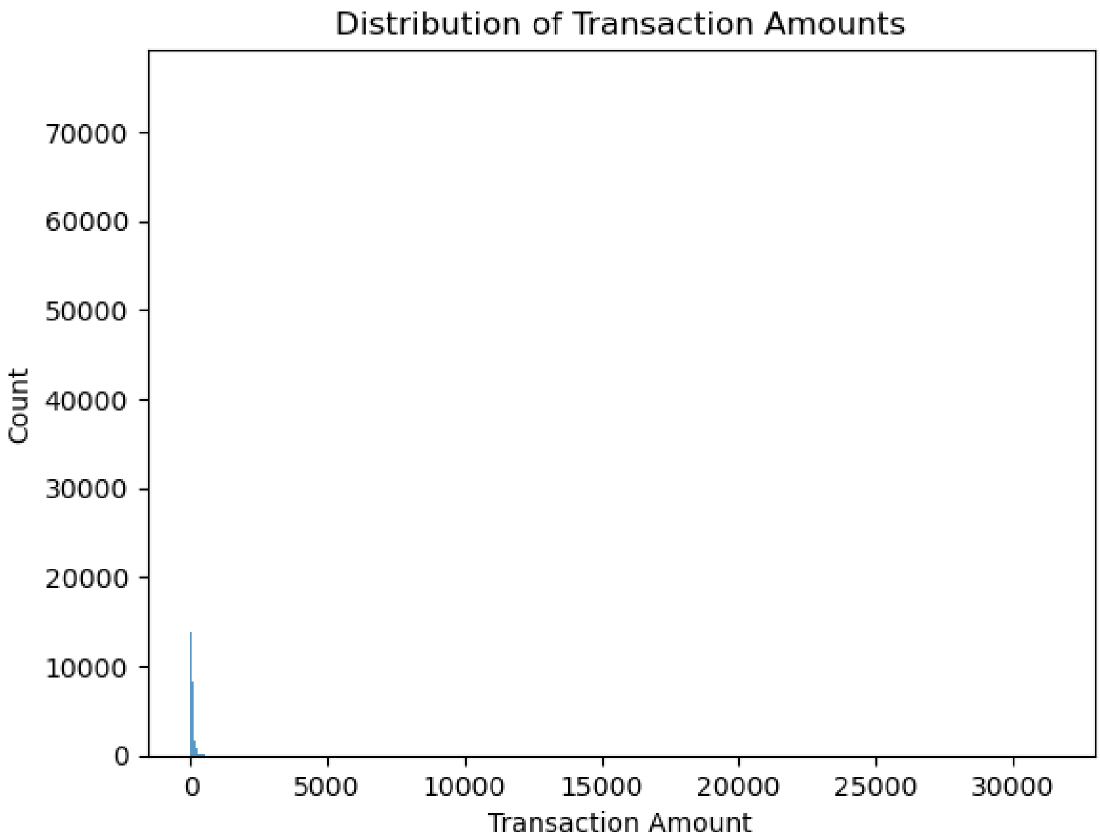


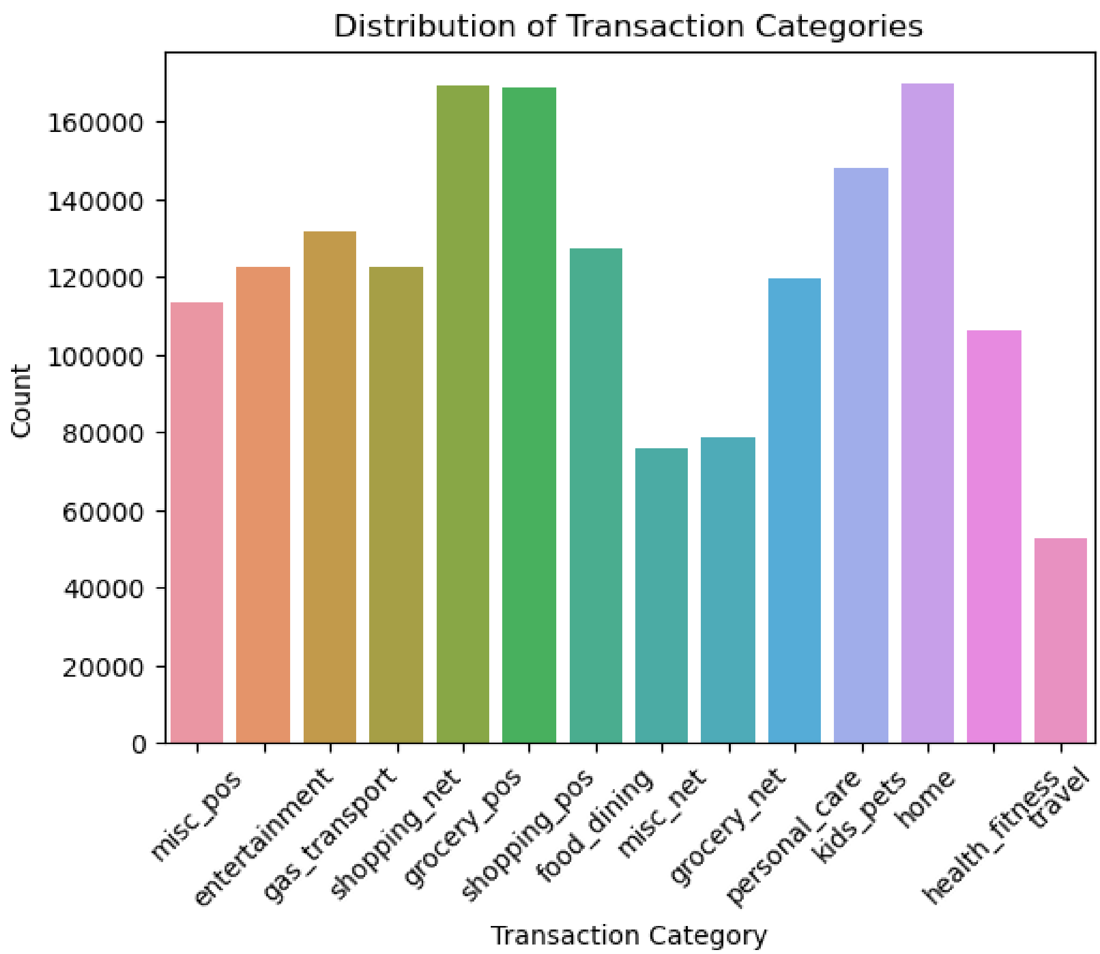
Line Plot of Transaction Volume Over Time (This graph shows the transaction volume over time)

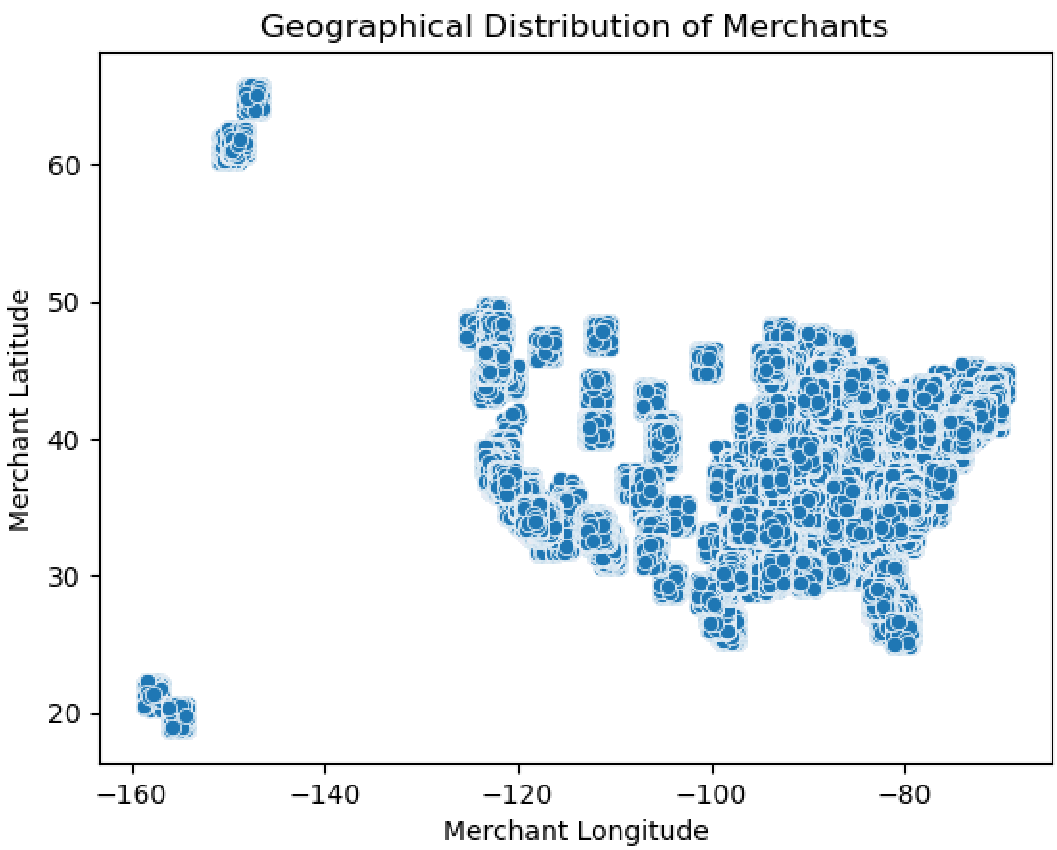
```
[ ]: df['transaction_date'] = pd.to_datetime(df['unix_time'], unit='s').dt.date
     transaction_counts = df['transaction_date'].value_counts().sort_index()

     plt.figure(figsize=(12, 6))
     transaction_counts.plot(kind='line', marker='o', color='darkcyan')
     plt.xlabel('Date')
     plt.ylabel('Transaction Count')
     plt.title('Transaction Volume Over Time')
     plt.xticks(rotation=45)
     plt.show()
```



[ ]:
```
# Plot a histogram of transaction amounts
sns.histplot(data=merged_data, x='amt')
plt.xlabel('Transaction Amount')
plt.ylabel('Count')
plt.title('Distribution of Transaction Amounts')
plt.show()

# Plot a bar chart of transaction categories
sns.countplot(data=merged_data, x='category')
plt.xlabel('Transaction Category')
plt.ylabel('Count')
plt.title('Distribution of Transaction Categories')
plt.xticks(rotation=45)
plt.show()

# Plot a scatter plot of latitude and longitude of merchants
sns.scatterplot(data=merged_data, x='merch_long', y='merch_lat')
plt.xlabel('Merchant Longitude')
plt.ylabel('Merchant Latitude')
plt.title('Geographical Distribution of Merchants')
plt.show()
```

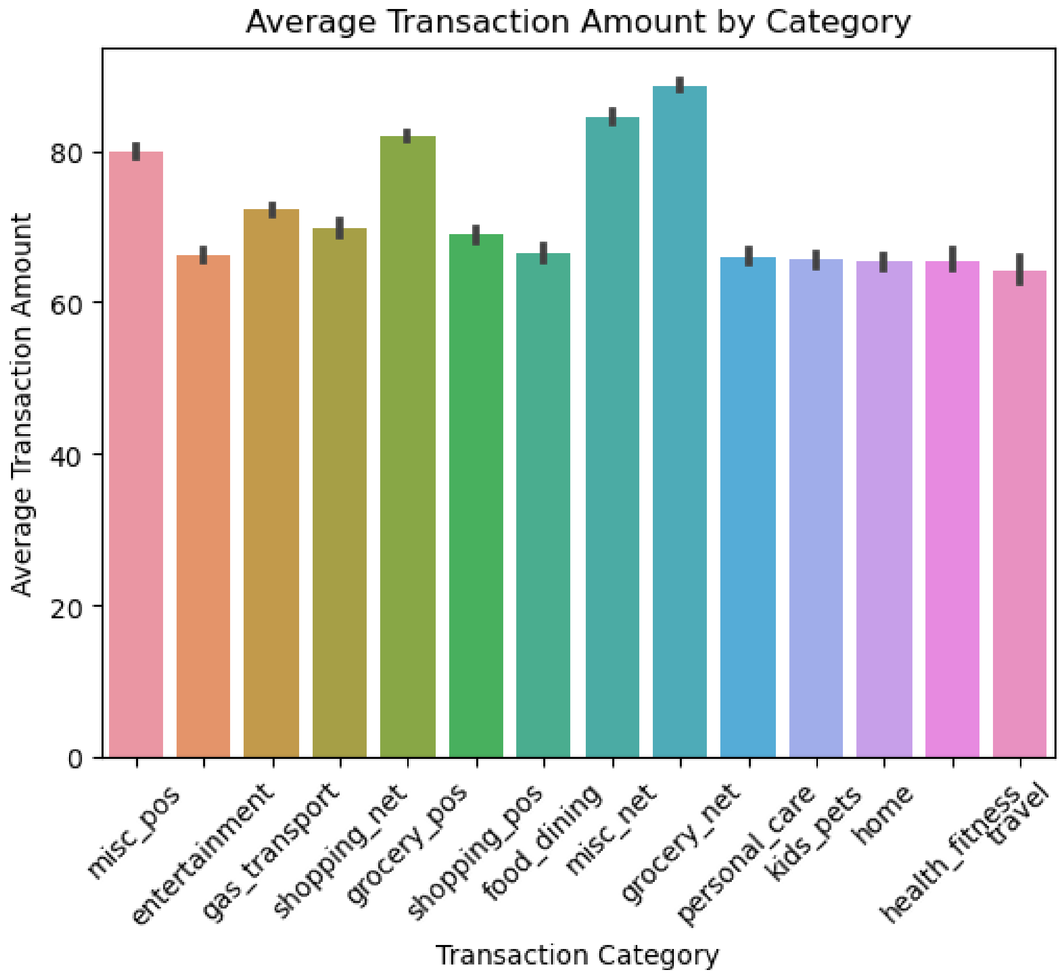

Distribution of Transaction Amounts
Count
Transaction Amount
70000
60000
50000
40000
30000
20000
10000
0
0
5000
10000
15000
20000
25000
30000

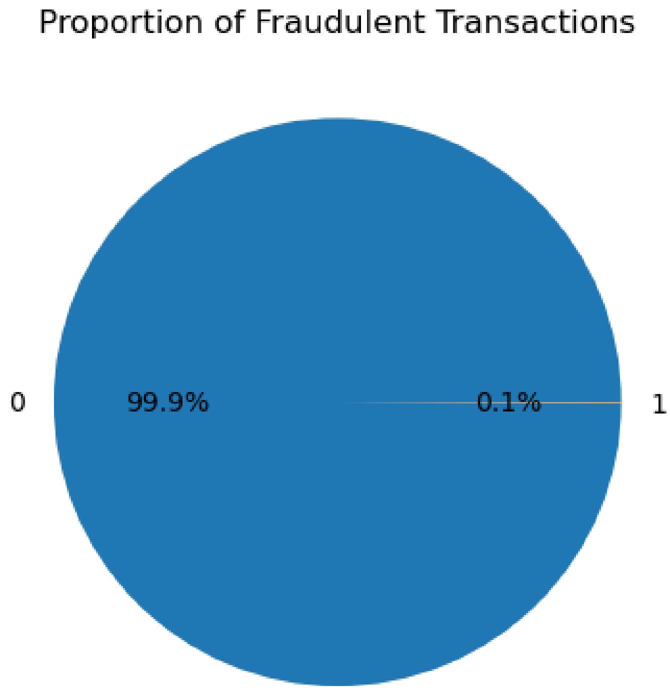

Distribution of Transaction Categories
Count
0
20000
40000
60000
80000
100000
120000
140000
160000
misc_pos
entertainment
gas_transport
shopping_net
grocery_pos
shopping_pos
food_dining
misc_net
grocery_net
personal_care
kids_pets
home
health_fitness
travel
Transaction Category

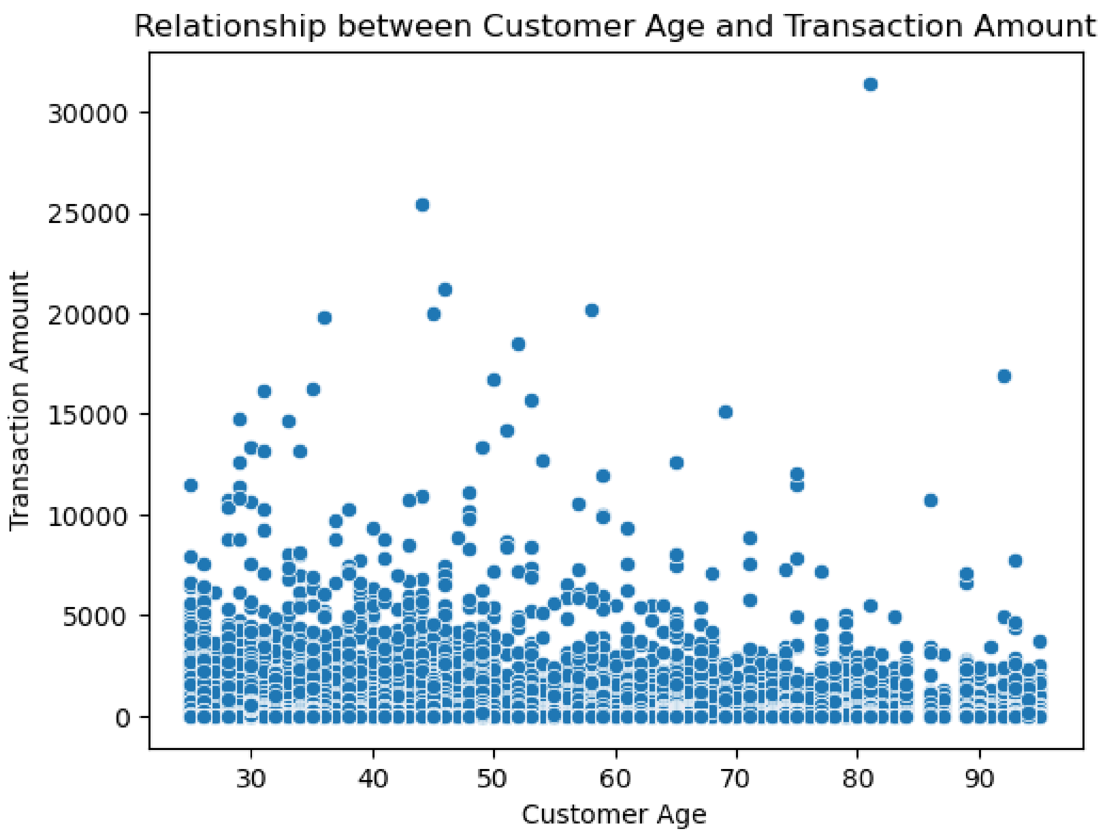


[ ]:
```
# Plot a bar chart of transaction categories with average transaction amount
sns.barplot(data=merged_data, x='category', y='amt')
plt.xlabel('Transaction Category')
plt.ylabel('Average Transaction Amount')
plt.title('Average Transaction Amount by Category')
plt.xticks(rotation=45)
plt.show()

# Plot a pie chart of transaction fraud proportions
fraud_counts = merged_data['is_fraud'].value_counts()
plt.pie(fraud_counts, labels=fraud_counts.index, autopct='%1.1f%%')
plt.title('Proportion of Fraudulent Transactions')
plt.show()

# Plot a scatter plot of customer age (derived from 'dob') and transaction␣
↪amount
merged_data['dob'] = pd.to_datetime(merged_data['dob'])
merged_data['age'] = (pd.to_datetime('today') - merged_data['dob']).
↪astype('<m8[Y]')
```

```
sns.scatterplot(data=merged_data, x='age', y='amt')
plt.xlabel('Customer Age')
plt.ylabel('Transaction Amount')
plt.title('Relationship between Customer Age and Transaction Amount')
plt.show()
```




Proportion of Fraudulent Transactions
0
99.9%
0.1%
1



3. Creating new features from the existing data that could be useful in predicting CLV

i. Frequency of Transactions: Calculate the total number of transactions made by each customer.

[ ]:
```
transaction_frequency = merged_data.groupby('acct_num')['trans_num'].count().
 ↪reset_index()
transaction_frequency.rename(columns={'trans_num': 'transaction_frequency'},␣
 ↪inplace=True)
merged_data = pd.merge(merged_data, transaction_frequency, on='acct_num',␣
 ↪how='left')
```

ii. Average Transaction Amount: Calculate the average transaction amount for each customer.

[ ]:
```
average_transaction_amount = merged_data.groupby('acct_num')['amt'].mean().
 ↪reset_index()
average_transaction_amount.rename(columns={'amt':␣
 ↪'average_transaction_amount'}, inplace=True)
merged_data = pd.merge(merged_data, average_transaction_amount, on='acct_num',␣
 ↪how='left')
```

iii. Total Transaction Amount: Calculate the total transaction amount for each customer.

[ ]:
```
total_transaction_amount = merged_data.groupby('acct_num')['amt'].sum().
 ↪reset_index()
total_transaction_amount.rename(columns={'amt': 'total_transaction_amount'},␣
 ↪inplace=True)
merged_data = pd.merge(merged_data, total_transaction_amount, on='acct_num',␣
 ↪how='left')
```

iv. Time since First Transaction: Calculate the time duration since the first transaction for each customer.

[ ]:
```
merged_data['unix_time'] = pd.to_datetime(merged_data['unix_time'], unit='s')
first_transaction_time = merged_data.groupby('acct_num')['unix_time'].min().
 ↪reset_index()
first_transaction_time['time_since_first_transaction'] = (pd.
 ↪to_datetime('today') - first_transaction_time['unix_time']).dt.days
merged_data = pd.merge(merged_data, first_transaction_time[['acct_num',␣
 ↪'time_since_first_transaction']], on='acct_num', how='left')
```

4. Creating a CLV cloumn based on 'average_transaction_amount' and 'transaction_frequency'

CLV can be calculated in various ways, depending on the specific business context and available data. Here we will be creating CLV column based on the average transaction amount and the frequency of transactions

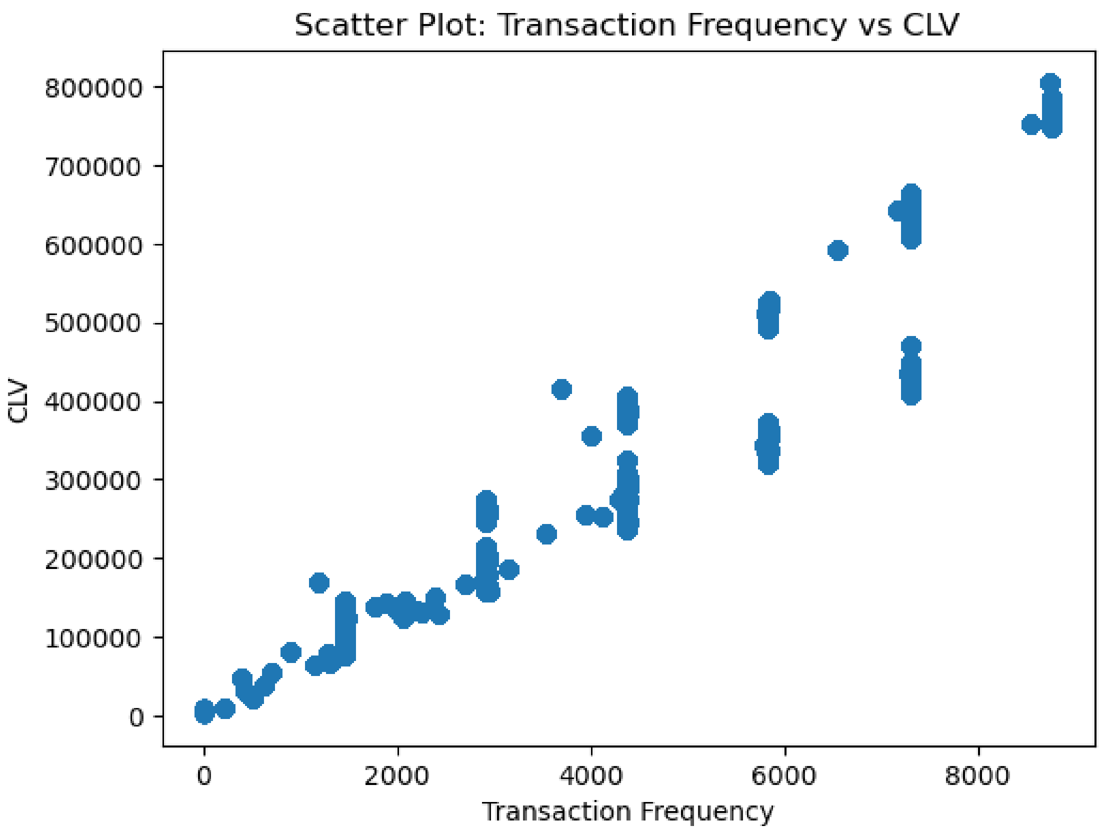
[ ]:
```
# Calculate CLV
merged_data['CLV'] = merged_data['average_transaction_amount'] *␣
 ↪merged_data['transaction_frequency']
merged_data['CLV']
```

[ ]:
```
0          123080.32
1          123080.32
2          123080.32
3          123080.32
4          123080.32
              …
1705126    169742.40
1705127    169742.40
1705128    169742.40
1705129    169742.40
1705130    169742.40
Name: CLV, Length: 1705131, dtype: float64
```

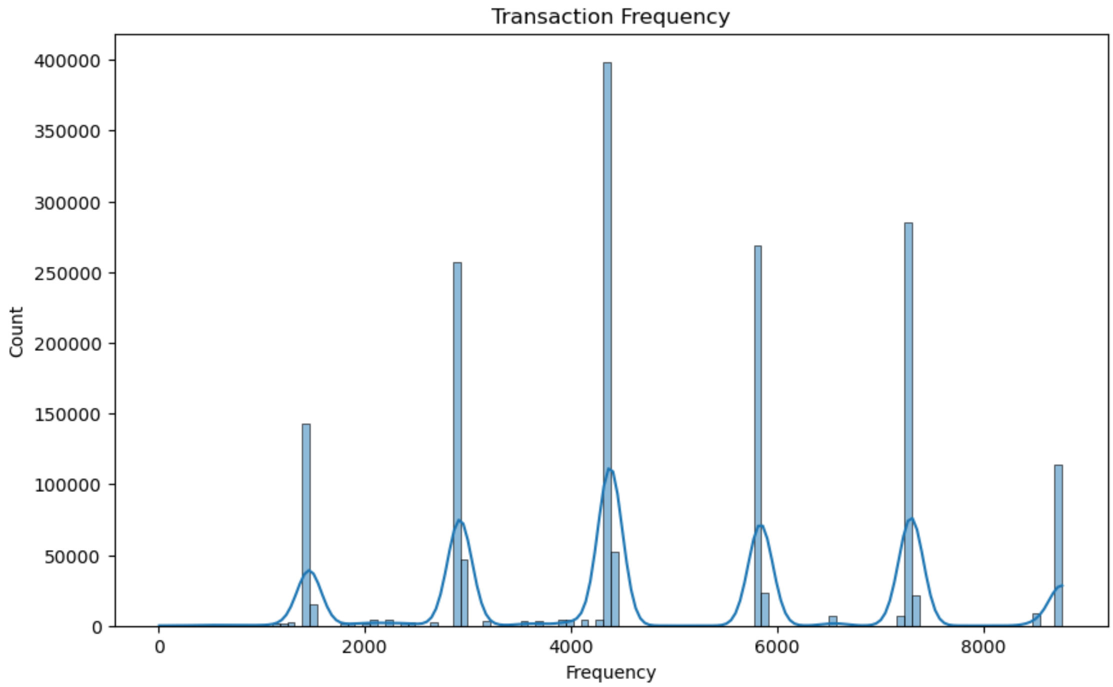
6. Ploting graphs based on new features

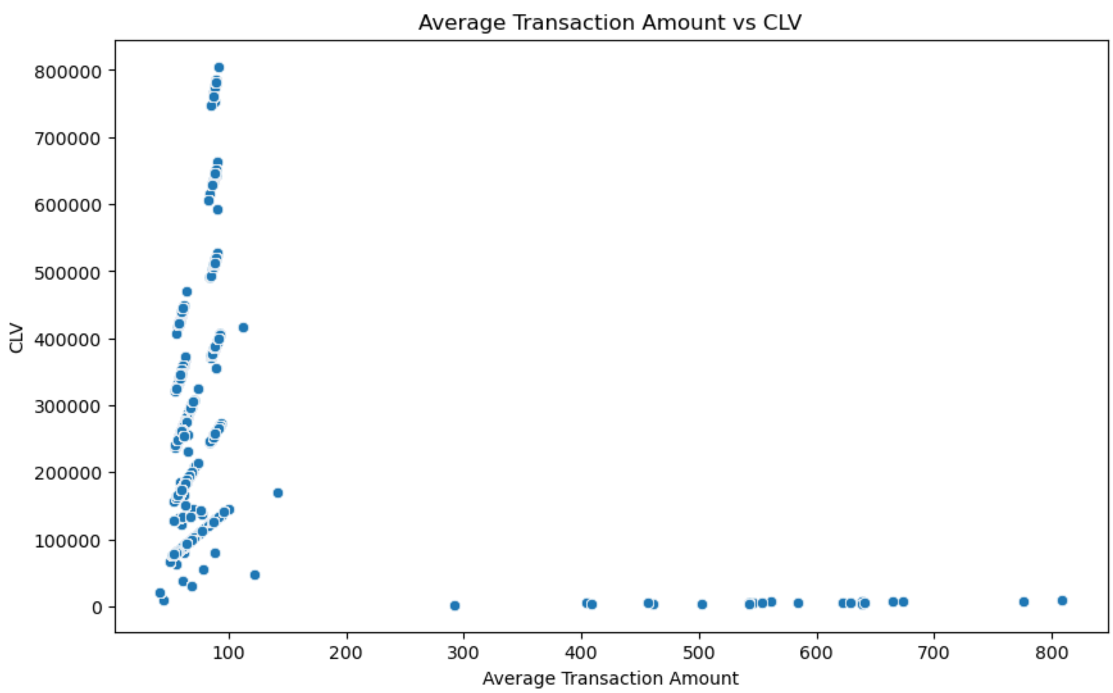
[ ]:
```
# Plot scatter plot
plt.scatter(merged_data['transaction_frequency'], merged_data['CLV'])
plt.xlabel('Transaction Frequency')
plt.ylabel('CLV')
plt.title('Scatter Plot: Transaction Frequency vs CLV')
```

```
plt.show()
```



[ ]:
```
# Plot histogram of transaction frequency
plt.figure(figsize=(10, 6))
sns.histplot(data=merged_data, x='transaction_frequency', kde=True)
plt.title('Transaction Frequency')
plt.xlabel('Frequency')
plt.ylabel('Count')
plt.show()

# Plot scatter plot of average transaction amount vs CLV
plt.figure(figsize=(10, 6))
sns.scatterplot(data=merged_data, x='average_transaction_amount', y='CLV')
plt.title('Average Transaction Amount vs CLV')
plt.xlabel('Average Transaction Amount')
plt.ylabel('CLV')
plt.show()
```





The first graph plots a histogram of the transaction frequency, showing the distribution of customer transaction frequencies. The second graph plots a scatter plot of the average transaction amount on the x-axis and the CLV on the y-axis, allowing you to visualize the relationship between these two variables.

1.2.4 Step 4: Model Training

[ ]:
```
merged_data
```

[ ]:
```
                  cc_num_x      acct_num                          trans_num  \
0         3599621836677199  767424968491  ae56f7ac5f358dc9f1687bb1c63d229c
1         3599621836677199  767424968491  7dead700180c288b8c7e269ef228f4d6
2         3599621836677199  767424968491  af5d266facca97758cd2f4f94a93708e
3         3599621836677199  767424968491  c24b06dfe405827196ae72ff9e878439
4         3599621836677199  767424968491  5807a4106d24f2346316728b991b3a74
…                        …             …                                …
1705126   6011969874869415  976596062877  55d5bce8a4fb44a738e4161e8a84354b
1705127   6011969874869415  976596062877  e0c275b51e16a50ce16c621c580d75d7
1705128   6011969874869415  976596062877  316db17a0b0888dec9e9d29c2e1aff0e
1705129   6011969874869415  976596062877  ca81fd9d698069a12aebad3474c472a1
1705130   6011969874869415  976596062877  bc79c5f69d61bae52f2296c098070c45

                  unix_time       category     amt  is_fraud  \
0       2020-02-01 18:05:36       misc_pos   28.31         0
1       2020-12-08 21:50:05  entertainment  588.07         0
2       2019-03-09 23:47:48  gas_transport    5.11         0
3       2020-07-05 16:19:06   shopping_net    1.08         0
4       2020-12-22 20:45:21  entertainment    9.66         0
…                         …              …     …       …
1705126 2022-08-26 04:27:23      kids_pets  524.40         0
1705127 2022-08-23 04:22:56      kids_pets  475.71         0
1705128 2021-09-17 10:38:34 health_fitness  478.33         0
1705129 2022-02-13 07:32:12           home  560.93         0
1705130 2022-12-24 08:03:02         travel  536.41         0

                             merchant  merch_lat  merch_long  …  \
0                         King-Nguyen  40.090754 -104.110826  …
1                           Kent-Lee  39.380580 -104.979279  …
2                     Townsend-Taylor  39.224870 -105.999769  …
3                    Wilkins-Hamilton  39.894093 -104.834570  …
4         Patterson, Fleming and Sanchez  40.640231 -105.543930  …
…                                   …         …          …  …
1705126                Yu, George and Ryan  33.205210  -92.552918  …
1705127                     Norman-Hanson  34.060344  -92.933577  …
1705128                     Trevino Group  33.631931  -93.740141  …
1705129             Brown, Watkins and Moody  32.809922  -94.270471  …
1705130                        Hanson LLC  33.197554  -93.290357  …

               dob  year                 date transaction_date   age  \
0       1936-02-26  2020  2020-02-01 18:05:36       2020-02-01  87.0
```

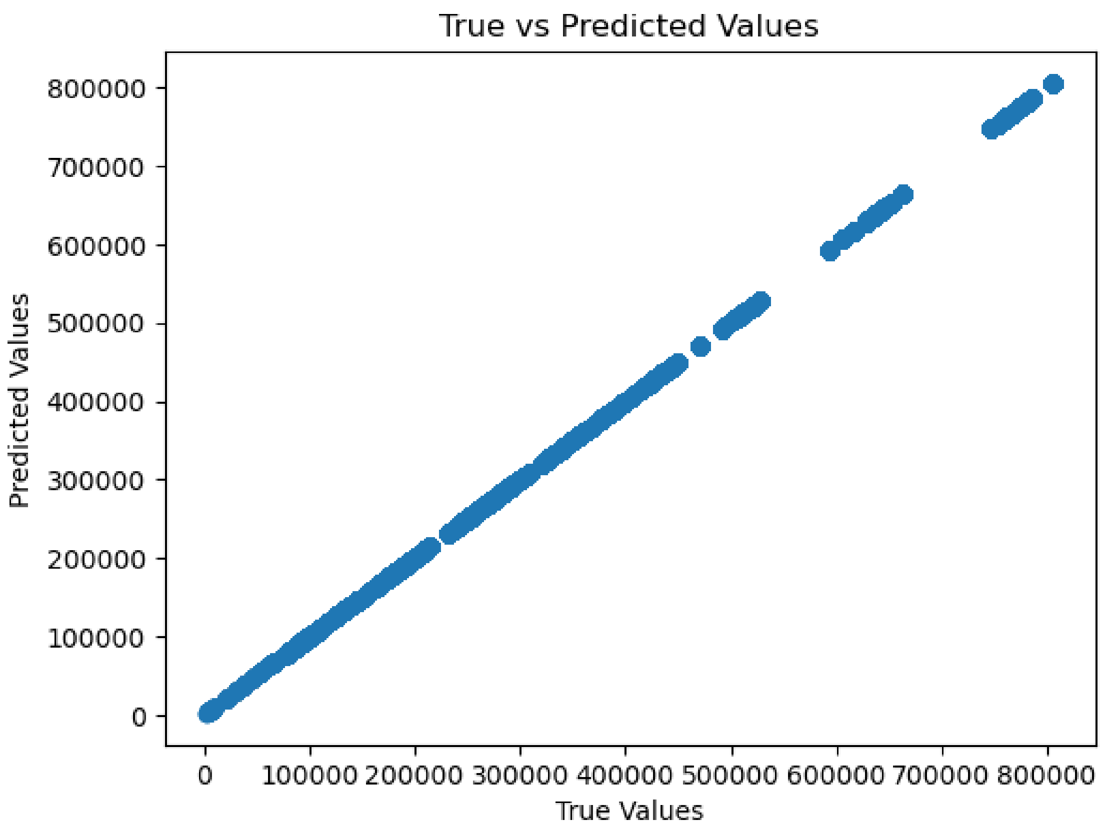
```
1        1936-02-26  2020 2020-12-08 21:50:05       2020-12-08  87.0
2        1936-02-26  2019 2019-03-09 23:47:48       2019-03-09  87.0
3        1936-02-26  2020 2020-07-05 16:19:06       2020-07-05  87.0
4        1936-02-26  2020 2020-12-22 20:45:21       2020-12-22  87.0
…             …    …                  …              …    …
1705126 1993-04-26  2022 2022-08-26 04:27:23       2022-08-26  30.0
1705127 1993-04-26  2022 2022-08-23 04:22:56       2022-08-23  30.0
1705128 1993-04-26  2021 2021-09-17 10:38:34       2021-09-17  30.0
1705129 1993-04-26  2022 2022-02-13 07:32:12       2022-02-13  30.0
1705130 1993-04-26  2022 2022-12-24 08:03:02       2022-12-24  30.0

        transaction_frequency average_transaction_amount  \
0                        2069                  59.487830
1                        2069                  59.487830
2                        2069                  59.487830
3                        2069                  59.487830
4                        2069                  59.487830
…                         …                        …
1705126                  1195                 142.043849
1705127                  1195                 142.043849
1705128                  1195                 142.043849
1705129                  1195                 142.043849
1705130                  1195                 142.043849

        total_transaction_amount  time_since_first_transaction        CLV
0                      123080.32                          1599  123080.32
1                      123080.32                          1599  123080.32
2                      123080.32                          1599  123080.32
3                      123080.32                          1599  123080.32
4                      123080.32                          1599  123080.32
…                          …                            …         …
1705126                169742.40                           922  169742.40
1705127                169742.40                           922  169742.40
1705128                169742.40                           922  169742.40
1705129                169742.40                           922  169742.40
1705130                169742.40                           922  169742.40

[1705131 rows x 33 columns]
```

1. Creating a Linear Regression Model using new features

[ ]:
```python
X = merged_data[['transaction_frequency', 'total_transaction_amount',␣
↪'average_transaction_amount']]
y = merged_data['CLV']

# Split the data into training and testing sets
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)


# Create a linear regression model
reg_model = LinearRegression()

# Train the model on the training data
reg_model.fit(X_train, y_train)

# Make predictions on the testing data
y_pred = reg_model.predict(X_test)

# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
r2_score = reg_model.score(X_test, y_test)

print("Mean Squared Error (MSE):", mse)
print("Root Mean Squared Error (RMSE):", rmse)
print("R-squared (R2) Score:", r2_score, end="\n\n\n\n")

# Print the first 10 predictions
print("Print the first 10 predictions:")
print(y_pred[:10])

# Create a scatter plot of true vs predicted values
plt.scatter(y_test, y_pred)
plt.xlabel('True Values')
plt.ylabel('Predicted Values')
plt.title('True vs Predicted Values')
plt.show()
```

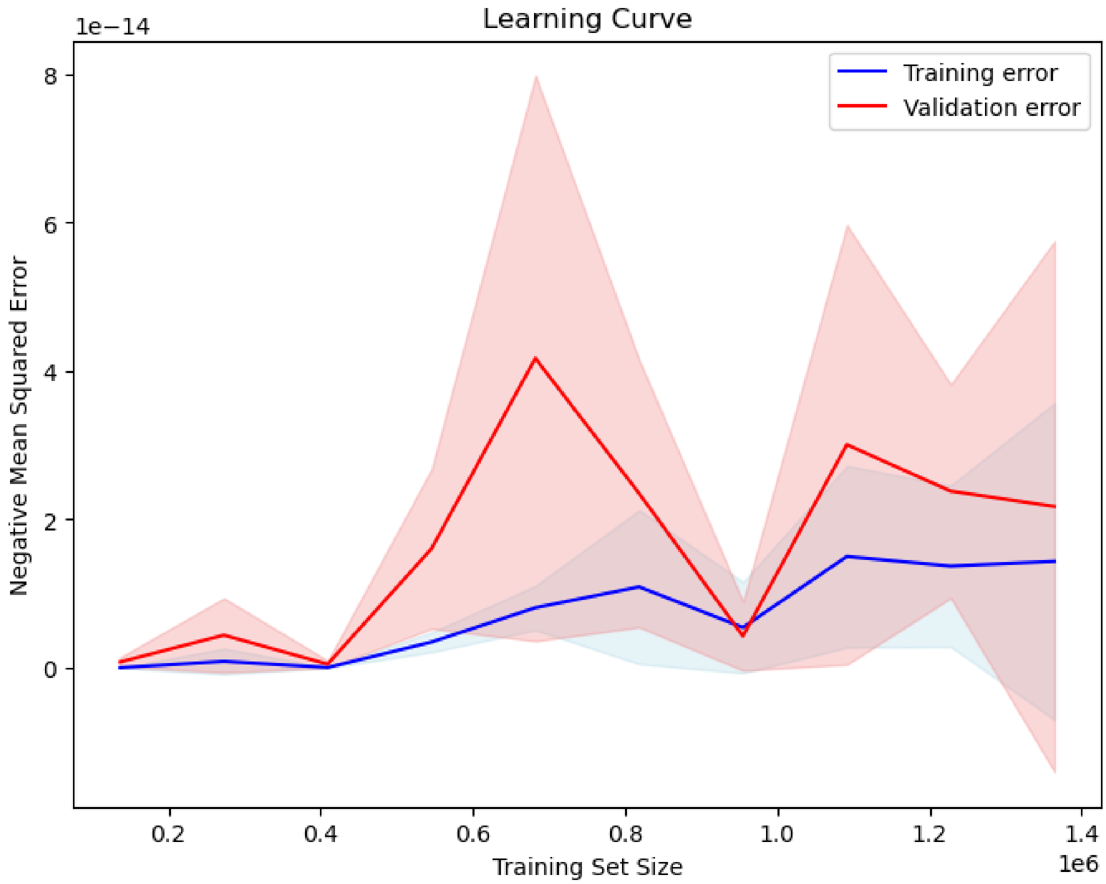
```
Mean Squared Error (MSE): 8.410641433390422e-16
Root Mean Squared Error (RMSE): 2.900110589855225e-08
R-squared (R2) Score: 1.0



Print the first 10 predictions:
[776967.92999996 264583.61000002 132891.38999997 260034.30000002
 338721.26000004 355672.88999997 390193.51999997 398775.40999997
 190180.82       773778.44999996]
```



For evaluating a linear regression model, we are focusing on metrics such as mean squared error (MSE), root mean squared error (RMSE), and R-squared (R2) score. These metrics provide insights into how well the model is able to predict continuous values. We have plotted the predicted values against the true values using a scatter plot above.

[ ]:
```
# Generate the learning curve data
train_sizes, train_scores, test_scores = learning_curve(reg_model, X, y, cv=5,␣
↪scoring='neg_mean_squared_error', train_sizes=np.linspace(0.1, 1.0, 10))

# Calculate the mean and standard deviation of training and test scores
train_mean = -np.mean(train_scores, axis=1)
train_std = np.std(train_scores, axis=1)
test_mean = -np.mean(test_scores, axis=1)
test_std = np.std(test_scores, axis=1)

# Plot the learning curve
plt.figure(figsize=(8, 6))
plt.plot(train_sizes, train_mean, label='Training error', color='blue')
plt.plot(train_sizes, test_mean, label='Validation error', color='red')

# Draw the bands
```

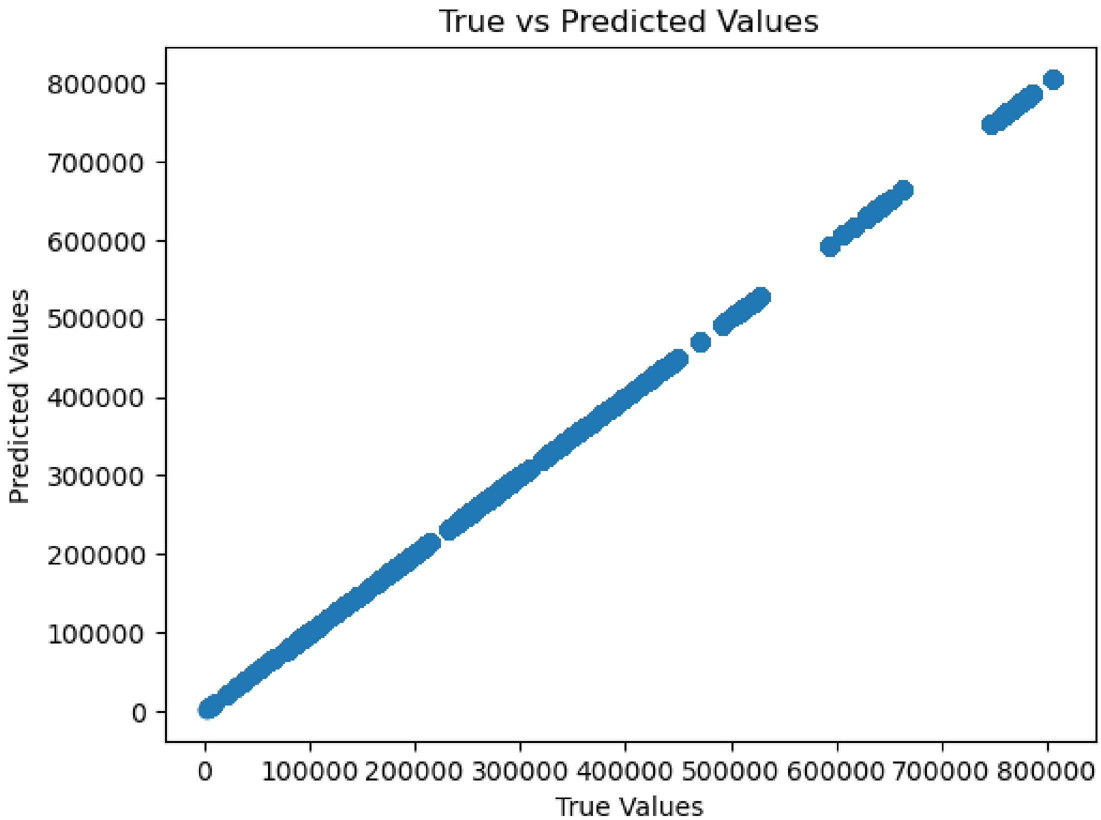
```
plt.fill_between(train_sizes, train_mean - train_std, train_mean + train_std,␣
    ↪color='lightblue', alpha=0.3)
plt.fill_between(train_sizes, test_mean - test_std, test_mean + test_std,␣
    ↪color='lightcoral', alpha=0.3)

# Add labels and title
plt.xlabel('Training Set Size')
plt.ylabel('Negative Mean Squared Error')
plt.title('Learning Curve')
plt.legend(loc='best')

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



[ ]:
```
# Create polynomial features
poly = PolynomialFeatures(degree=2)  # Adjust the degree as needed
X_poly = poly.fit_transform(X)
```

```
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_poly, y, test_size=0.2,␣
↪random_state=42)

# Create a linear regression model
reg_model = LinearRegression()

# Train the model on the training data
reg_model.fit(X_train, y_train)

# Make predictions on the testing data
y_pred = reg_model.predict(X_test)

# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
r2_score = reg_model.score(X_test, y_test)

print("Mean Squared Error (MSE):", mse)
print("Root Mean Squared Error (RMSE):", rmse)
print("R-squared (R2) Score:", r2_score)

# Create a scatter plot of true vs predicted values
plt.scatter(y_test, y_pred)
plt.xlabel('True Values')
plt.ylabel('Predicted Values')
plt.title('True vs Predicted Values')
plt.show()
```

```
Mean Squared Error (MSE): 1.22446306052368e-13
Root Mean Squared Error (RMSE): 3.499232859533186e-07
R-squared (R2) Score: 1.0
```



[ ]:
```
from sklearn.metrics import mean_squared_error, r2_score

# Calculate performance metrics for your model
y_pred = reg_model.predict(X_test)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
r2 = r2_score(y_test, y_pred)

# Calculate performance metrics for the baseline (e.g., using mean or median)
y_baseline = np.full_like(y_test, y_train.mean())  # Use mean as the baseline
baseline_mse = mean_squared_error(y_test, y_baseline)
baseline_rmse = np.sqrt(baseline_mse)
baseline_r2 = r2_score(y_test, y_baseline)

# Print the performance metrics
print("Model Performance Metrics:")
print("Mean Squared Error (MSE):", mse)
print("Root Mean Squared Error (RMSE):", rmse)
print("R-squared (R2) Score:", r2)
print()
```

```
print("Baseline Performance Metrics:")
print("Mean Squared Error (MSE):", baseline_mse)
print("Root Mean Squared Error (RMSE):", baseline_rmse)
print("R-squared (R2) Score:", baseline_r2)
```

```
Model Performance Metrics:
Mean Squared Error (MSE): 1.22446306052368e-13
Root Mean Squared Error (RMSE): 3.499232859533186e-07
R-squared (R2) Score: 1.0

Baseline Performance Metrics:
Mean Squared Error (MSE): 35180725566.10877
Root Mean Squared Error (RMSE): 187565.25682041643
R-squared (R2) Score: -7.317909870963035e-06
```

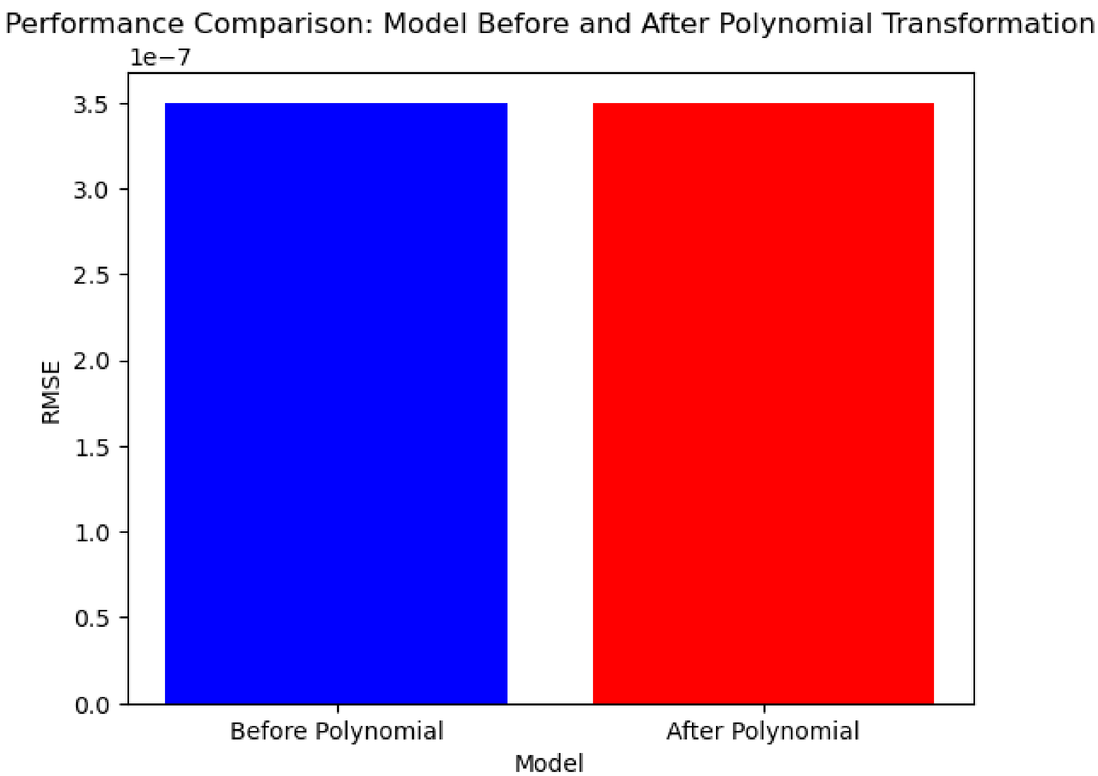
In this code, the performance metrics for the model are calculated using the predicted values y__pred and the actual values y__test. The metrics include mean squared error (MSE), root mean squared error (RMSE), and R-squared (R2) score, which measures the proportion of the variance in the target variable that is predictable by the model.

For the baseline, I have used a simple strategy such as predicting the mean or median value of the training target variable for all test instances. In the above code block, the mean value of the training target variable y__train.mean() is used as the baseline prediction y__baseline. The same performance metrics are then calculated for the baseline.

By comparing the performance metrics of the model with those of the baseline, we can assess whether the model provides better predictions than a simple baseline approach. (Lower MSE and RMSE values and higher R2 scores indicate better model performance compared to the baseline.)

[ ]:
```
# Calculate performance metrics for the model before polynomial transformation
y_pred_before = reg_model.predict(X_test)
rmse_before = np.sqrt(mean_squared_error(y_test, y_pred_before))

# Create polynomial features
poly = PolynomialFeatures(degree=2)  # Adjust the degree as needed
X_poly = poly.fit_transform(X)

# Split the data into training and testing sets
X_train_poly, X_test_poly, y_train, y_test = train_test_split(X_poly, y,␣
 ↪test_size=0.2, random_state=42)

# Create a new linear regression model
reg_model_poly = LinearRegression()

# Train the model on the polynomial features
reg_model_poly.fit(X_train_poly, y_train)

# Make predictions on the testing data with polynomial features
```

```
y_pred_poly = reg_model_poly.predict(X_test_poly)
rmse_poly = np.sqrt(mean_squared_error(y_test, y_pred_poly))

# Plot the performance comparison
labels = ['Before Polynomial', 'After Polynomial']
rmse_values = [rmse_before, rmse_poly]

plt.bar(labels, rmse_values, color=['blue', 'red'])
plt.xlabel('Model')
plt.ylabel('RMSE')
plt.title('Performance Comparison: Model Before and After Polynomial␣
 ↪Transformation')
plt.show()
```



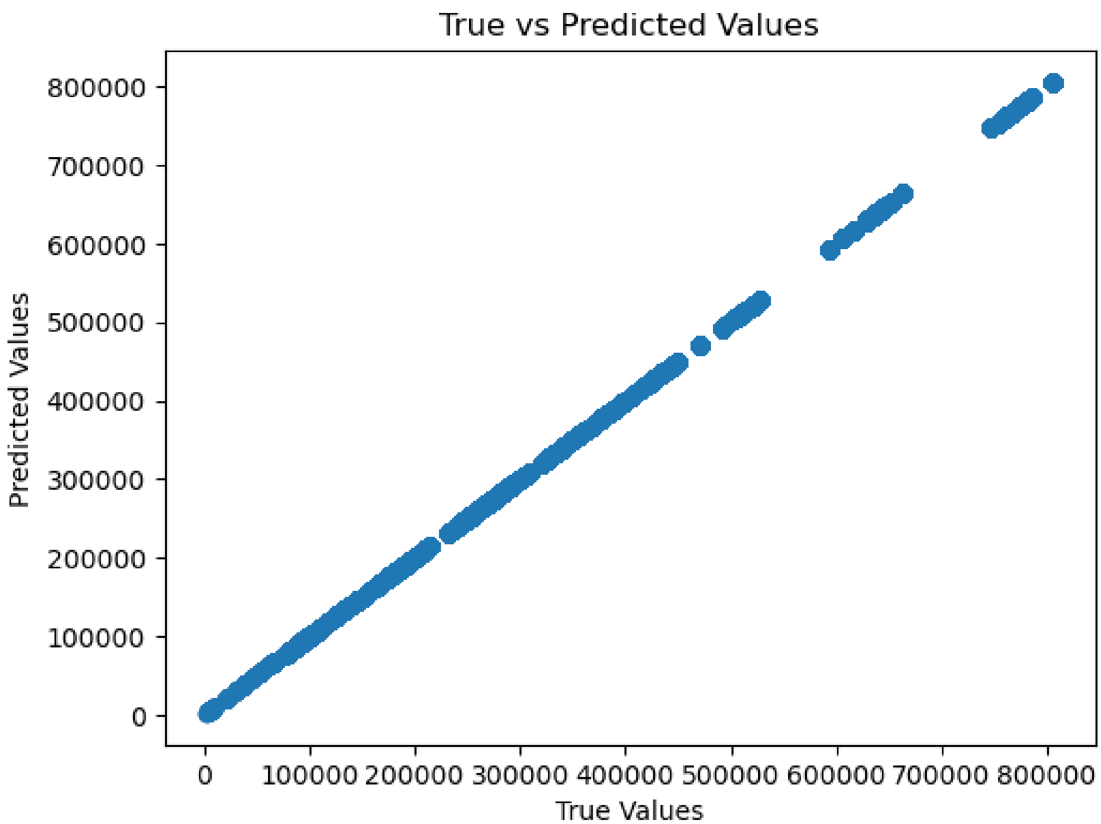
In this code, the root mean squared error (RMSE) values are calculated for the model before and after applying the polynomial features. The RMSE values are then plotted using a bar plot, where the blue bar represents the model's performance before the polynomial transformation, and the red bar represents the performance after the transformation. The x-axis shows the model labels, and the y-axis represents the RMSE values.

2. Tuning the model hyperparameters for better performance of the model

[ ]:
```python
# Define the hyperparameters to tune
param_grid = {
    'fit_intercept': [True, False]
}

# Create a linear regression model
reg_model = LinearRegression()

# Perform grid search with cross-validation
reg_model_grid_search = GridSearchCV(reg_model, param_grid, cv=5)
reg_model_grid_search.fit(X_train, y_train)

# Get the best hyperparameters and model
best_params = reg_model_grid_search.best_params_
best_model = reg_model_grid_search.best_estimator_

# Make predictions on the testing data using the best model
y_pred = best_model.predict(X_test)

# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
r2_score = best_model.score(X_test, y_test)

print("Best Hyperparameters:", best_params)
print("Mean Squared Error (MSE):", mse)
print("Root Mean Squared Error (RMSE):", rmse)
print("R-squared (R2) Score:", r2_score, end="\n\n")

# Print the first 10 predictions
print("Print the first 10 predictions:")
print(y_pred[:10])

# Create a scatter plot of true vs predicted values
plt.scatter(y_test, y_pred)
plt.xlabel('True Values')
plt.ylabel('Predicted Values')
plt.title('True vs Predicted Values')
plt.show()
```

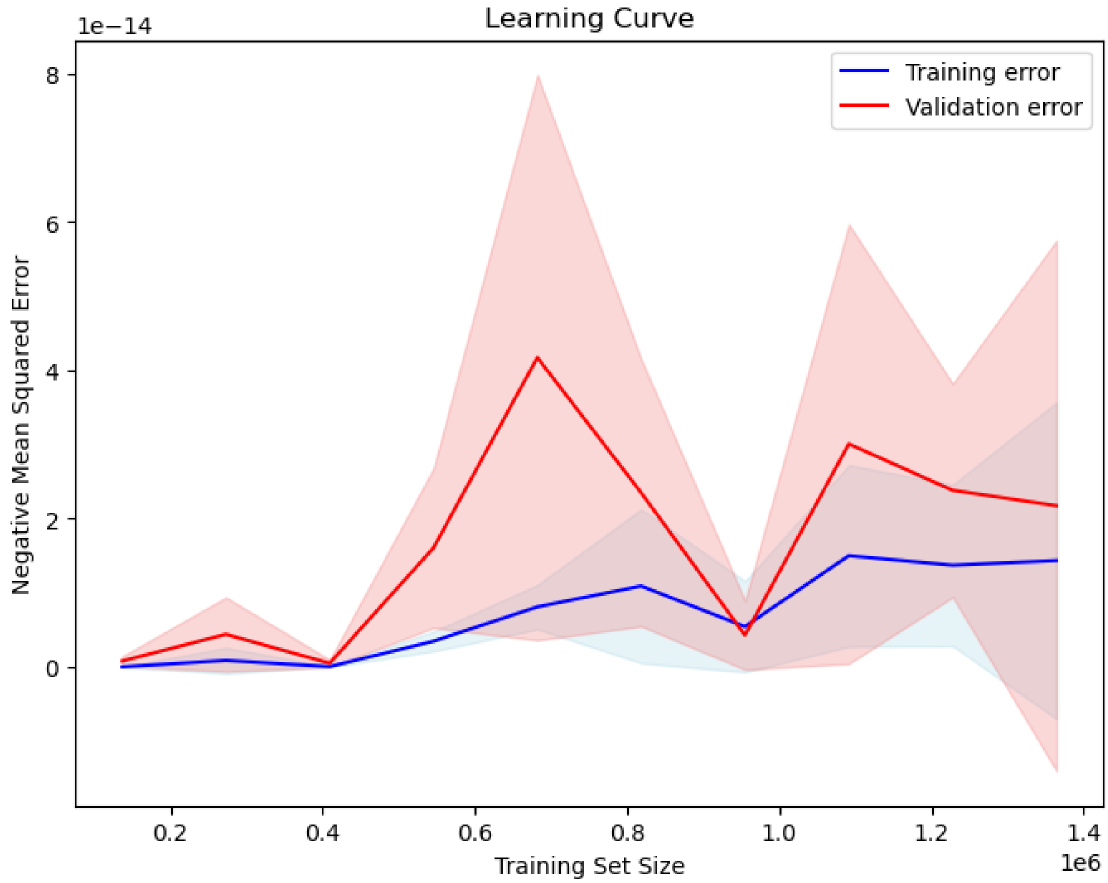
```
Best Hyperparameters: {'fit_intercept': True}
Mean Squared Error (MSE): 1.22446306052368e-13
Root Mean Squared Error (RMSE): 3.499232859533186e-07
R-squared (R2) Score: 1.0

Print the first 10 predictions:
[776967.92999964 264583.60999969 132891.38999954 260034.2999997
 338721.25999977 355672.88999956 390193.51999956 398775.40999955
```

190180.81999963 773778.44999965]



[ ]:
```python
# Generate the learning curve data
train_sizes, train_scores, test_scores = learning_curve(best_model, X, y, cv=5,␣
↪scoring='neg_mean_squared_error', train_sizes=np.linspace(0.1, 1.0, 10))

# Calculate the mean and standard deviation of training and test scores
train_mean = -np.mean(train_scores, axis=1)
train_std = np.std(train_scores, axis=1)
test_mean = -np.mean(test_scores, axis=1)
test_std = np.std(test_scores, axis=1)

# Plot the learning curve
plt.figure(figsize=(8, 6))
plt.plot(train_sizes, train_mean, label='Training error', color='blue')
plt.plot(train_sizes, test_mean, label='Validation error', color='red')

# Draw the bands
plt.fill_between(train_sizes, train_mean - train_std, train_mean + train_std,␣
↪color='lightblue', alpha=0.3)
```

```
plt.fill_between(train_sizes, test_mean - test_std, test_mean + test_std,␣
↪color='lightcoral', alpha=0.3)

# Add labels and title
plt.xlabel('Training Set Size')
plt.ylabel('Negative Mean Squared Error')
plt.title('Learning Curve')
plt.legend(loc='best')

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



[ ]:
```
from sklearn.preprocessing import PolynomialFeatures

# Create polynomial features
poly = PolynomialFeatures(degree=3)  # Adjust the degree as needed
X_train_poly = poly.fit_transform(X_train)
X_test_poly = poly.transform(X_test)
```

```python
# Create a polynomial regression model
reg_model_poly_grid_search = LinearRegression()

# Train the model on the polynomial features
reg_model_poly_grid_search.fit(X_train_poly, y_train)

# Make predictions on the testing data with polynomial features
y_pred_poly = reg_model_poly_grid_search.predict(X_test_poly)

# Evaluate the model
mse_poly = mean_squared_error(y_test, y_pred_poly)
rmse_poly = np.sqrt(mse_poly)
r2_score_poly = reg_model_poly_grid_search.score(X_test_poly, y_test)

print("Polynomial Regression Performance Metrics:")
print("Mean Squared Error (MSE):", mse_poly)
print("Root Mean Squared Error (RMSE):", rmse_poly)
print("R-squared (R2) Score:", r2_score_poly)
```

```
Polynomial Regression Performance Metrics:
Mean Squared Error (MSE): 190140917.9169767
Root Mean Squared Error (RMSE): 13789.159434750789
R-squared (R2) Score: 0.9945952703848084
```

In this code, the PolynomialFeatures class from scikit-learn is used to transform the original features into polynomial features with a higher degree. You can adjust the degree parameter to specify the desired degree of the polynomial. Then, a new linear regression model reg_model_poly is created and trained on the polynomial features X_train_poly. The model is evaluated on the testing data with polynomial features, and the performance metrics are calculated and printed.

By using polynomial features, the model becomes more flexible and can capture non-linear relationships in the data, which helps alleviate underfitting.

[ ]:
```python
from sklearn.metrics import r2_score as r2
# Create polynomial features
poly = PolynomialFeatures(degree=3)  # Adjust the degree as needed
X_poly = poly.fit_transform(X)

# Split the data into training and testing sets
X_train_poly, X_test_poly, y_train, y_test = train_test_split(X_poly, y,
 ↪test_size=0.2, random_state=42)

# Create a new linear regression model with polynomial features
reg_model_poly = LinearRegression()

# Train the model on the polynomial features
reg_model_poly.fit(X_train_poly, y_train)
```

```python
# Make predictions on the testing data with polynomial features
y_pred_poly = reg_model_poly.predict(X_test_poly)

# Evaluate the model with polynomial features
mse_poly = mean_squared_error(y_test, y_pred_poly)
rmse_poly = np.sqrt(mse_poly)
r2_score_poly = r2(y_test, y_pred_poly)

# Calculate baseline performance
y_baseline = np.full_like(y_test, y_train.mean())  # Use mean as the baseline
baseline_mse = mean_squared_error(y_test, y_baseline)
baseline_rmse = np.sqrt(baseline_mse)
baseline_r2_score = r2(y_test, y_baseline)

# Print the performance metrics
print("Polynomial Regression Performance Metrics:")
print("Mean Squared Error (MSE):", mse_poly)
print("Root Mean Squared Error (RMSE):", rmse_poly)
print("R-squared (R2) Score:", r2_score_poly)
print()
print("Baseline Performance Metrics:")
print("Mean Squared Error (MSE):", baseline_mse)
print("Root Mean Squared Error (RMSE):", baseline_rmse)
print("R-squared (R2) Score:", baseline_r2_score)
print()

# Plot the performance comparison
labels = ['Model with Polynomial Features', 'Baseline']
rmse_values = [rmse_poly, baseline_rmse]
```

```
Polynomial Regression Performance Metrics:
Mean Squared Error (MSE): 0.08810878911479278
Root Mean Squared Error (RMSE): 0.29683124686392565
R-squared (R2) Score: 0.9999999999974956

Baseline Performance Metrics:
Mean Squared Error (MSE): 35180725566.10877
Root Mean Squared Error (RMSE): 187565.25682041643
R-squared (R2) Score: -7.317909870963035e-06
```

In this code, after applying the polynomial transformation to the features using PolynomialFeatures, the polynomial regression model (reg_model_poly) is trained and evaluated on the testing data with polynomial features. The evaluation metrics, including MSE, RMSE, and R-squared score, are calculated for the polynomial model.

A baseline prediction is also generated using the mean value of the training target variable, and the baseline performance metrics are calculated. Finally, a bar plot is created to compare the RMSE values between the polynomial model and the baseline.

[ ]:
```python
#code to save all the above models
import joblib

# Save the  Linear Regression model
joblib.dump(reg_model, 'linear_regression_model.pkl')
joblib.dump(reg_model_poly_grid_search, 'reg_model_poly_grid_search.joblib')
joblib.dump(reg_model_grid_search, 'reg_model_grid_search.joblib')
```

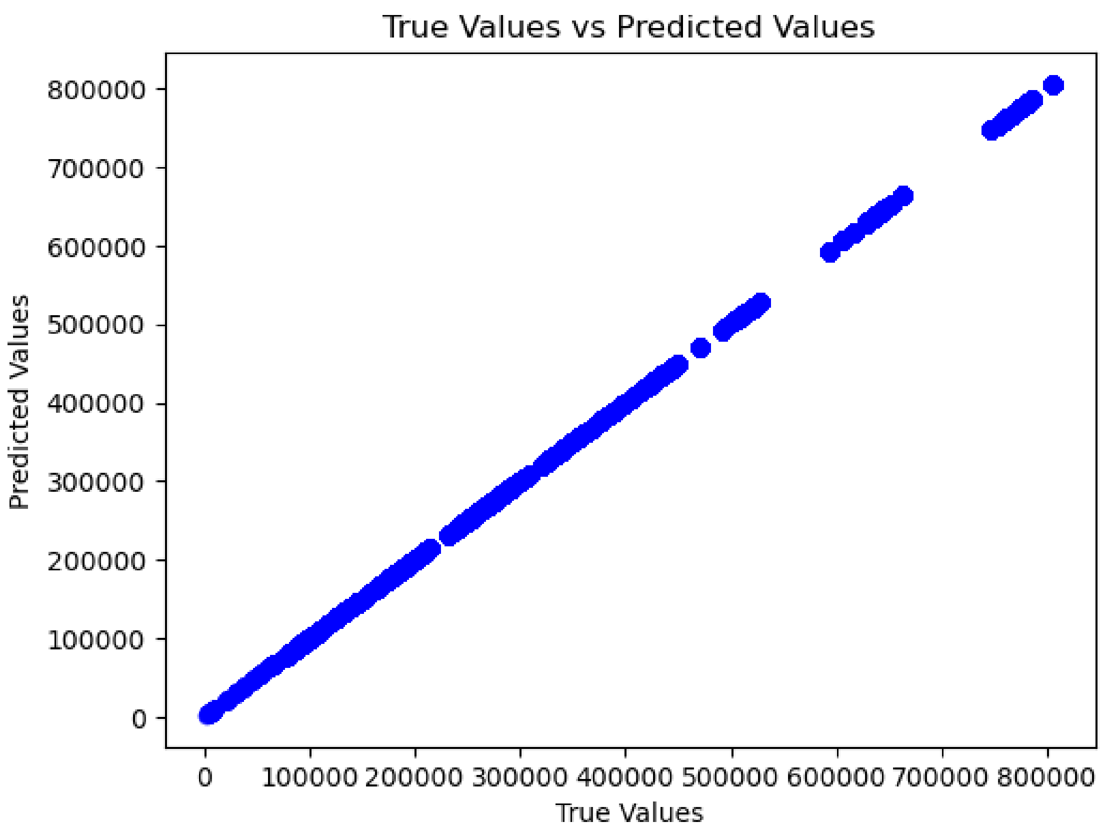
[ ]:
```
['reg_model_grid_search.joblib']
```

3. Creating another model using Random Forest

[ ]:
```python
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error

# Separate the features (X) and target variable (y)
X = merged_data[['transaction_frequency', 'total_transaction_amount',␣
↪'average_transaction_amount']]
y = merged_data['CLV']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

# Create a random forest regressor
rf_model = RandomForestRegressor(random_state=42)

# Train the model on the training data
rf_model.fit(X_train, y_train)

# Make predictions on the testing data
y_pred = rf_model.predict(X_test)

# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
r2_score = rf_model.score(X_test, y_test)

print("Mean Squared Error (MSE):", mse)
print("Root Mean Squared Error (RMSE):", rmse)
print("R-squared (R2) Score:", r2_score)
```

```
Mean Squared Error (MSE): 0.0037291912391644744
Root Mean Squared Error (RMSE): 0.06106710439479241
R-squared (R2) Score: 0.999999999999894
```

```
[ ]: import matplotlib.pyplot as plt
import matplotlib
matplotlib.rcParams['agg.path.chunksize'] = 1000  # Adjust the value as needed

# Create a scatter plot of true values versus predicted values
plt.scatter(y_test, y_pred, color='blue', alpha=0.5)
plt.xlabel('True Values')
plt.ylabel('Predicted Values')
plt.title('True Values vs Predicted Values')
plt.show()
```



The plot creates a scatter plot where the x-axis represents the true values (y_test) and the y-axis represents the predicted values (y_pred). Each data point is represented as a blue dot. This plot helps visualize the relationship between the true and predicted values.

4. Tuning the model hyperparameters for better performance of the model

```
[ ]: from sklearn.model_selection import GridSearchCV

# Define the parameter grid
param_grid = {
```

```
    'n_estimators': [100, 200, 300],   # Number of trees in the random forest
    'max_depth': [None, 5, 10],         # Maximum depth of each tree
    'min_samples_split': [2, 5, 10],    # Minimum number of samples required to␣
 ↪split a node
    'min_samples_leaf': [1, 2, 4]       # Minimum number of samples required at␣
 ↪each leaf node
}

# Create a random forest regressor
rf_model = RandomForestRegressor(random_state=42)

# Perform grid search with cross-validation
grid_search = GridSearchCV(rf_model, param_grid, cv=5)
grid_search.fit(X_train, y_train)

# Get the best hyperparameters and model
best_params = grid_search.best_params_
best_model = grid_search.best_estimator_

print("Best Hyperparameters:", best_params)
print("Best Model:", best_model)
```

```
Best Hyperparameters: {'max_depth': None, 'min_samples_leaf': 1,
'min_samples_split': 2, 'n_estimators': 100}
Best Model: RandomForestRegressor(random_state=42)
```

5. Creating another model using Gradient Boosting

[ ]:
```
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error

X = merged_data[['transaction_frequency', 'total_transaction_amount',␣
 ↪'average_transaction_amount']]
y = merged_data['CLV']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)

# Create a Gradient Boosting regressor
gb_model = GradientBoostingRegressor(random_state=42)

# Train the model on the training data
gb_model.fit(X_train, y_train)

# Make predictions on the testing data
y_pred = gb_model.predict(X_test)
```

```
# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
r2_score = gb_model.score(X_test, y_test)

print("Mean Squared Error (MSE):", mse)
print("Root Mean Squared Error (RMSE):", rmse)
print("R-squared (R2) Score:", r2_score)
```

```
Mean Squared Error (MSE): 563135.5159778388
Root Mean Squared Error (RMSE): 750.423557717799
R-squared (R2) Score: 0.9999839929498926
```

6. Tuning the model hyperparameters for better performance of the model

[ ]:
```
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.model_selection import GridSearchCV, train_test_split
from sklearn.metrics import mean_squared_error

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

# Create a Gradient Boosting regressor
gb_model = GradientBoostingRegressor(random_state=42)

# Define the hyperparameter grid
param_grid = {
    'learning_rate': [0.1, 0.01, 0.001],
    'n_estimators': [100, 200, 300],
    'max_depth': [3, 4, 5]
}

# Perform grid search with cross-validation
grid_search = GridSearchCV(gb_model, param_grid, cv=5)
grid_search.fit(X_train, y_train)

# Get the best hyperparameters and model
best_params = grid_search.best_params_
best_model = grid_search.best_estimator_

# Make predictions on the testing data using the best model
y_pred = best_model.predict(X_test)

# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
```

```
r2_score = best_model.score(X_test, y_test)

print("Best Hyperparameters:", best_params)
print("Mean Squared Error (MSE):", mse)
print("Root Mean Squared Error (RMSE):", rmse)
print("R-squared (R2) Score:", r2_score)
```

```
Best Hyperparameters: {'learning_rate': 0.1, 'max_depth': 5, 'n_estimators':
300}
Mean Squared Error (MSE): 564.3083168733981
Root Mean Squared Error (RMSE): 23.75517452837167
R-squared (R2) Score: 0.9999999839596132
```

1.2.5 Step 5: Model Deployment

Saving all the models, so that the models are ready for deployment

[ ]:
```
from sklearn.ensemble import GradientBoostingRegressor, RandomForestRegressor
from sklearn.linear_model import LinearRegression
#from sklearn.externals import joblib
import joblib
# Save the GradientBoostingRegressor model
joblib.dump(gb_model, 'gradient_boosting_model.pkl')
```

[ ]:
```
['gradient_boosting_model.pkl']
```

[ ]:
```
# Save the RandomForestRegressor model
joblib.dump(rf_model, 'random_forest_model.pkl')
```

[ ]:
```
# Save the  Linear Regression model
joblib.dump(reg_model, 'linear_regression_model.pkl')
```

[ ]:
```
import joblib
joblib.dump(grid_search, 'grid_search.joblib')
```

[ ]:
```
['grid_search.joblib']
```

1.3 Comparing all the models

1.3.1 Baseline Performance Mertics:

Mean Squared Error (MSE): 35180725566.10877 Root Mean Squared Error (RMSE): 187565.25682041643 R-squared (R2) Score: -7.317909870963035e-06 ### 1. Linear Regression Model Mean Squared Error (MSE): 8.410641433390422e-16 Root Mean Squared Error (RMSE): 2.900110589855225e-08 R-squared (R2) Score: 1.0 ### 2. Linear regression Model with polynomial features Model Performance Metrics: Mean Squared Error (MSE): 1.22446306052368e-13 Root Mean Squared Error (RMSE): 3.499232859533186e-07 R-squared (R2) Score: 1.0 ### 3. Linear Regression Model, Hyper Parameters tuned with GridSearch Best Hyperparameters: {'fit_intercept': True} Mean Squared Error (MSE): 1.22446306052368e-13 Root Mean Squared

Error (RMSE): 3.499232859533186e-07 R-squared (R2) Score: 1.0 ### 4. Linear Regression Model, Hyper Parameters tuned with GridSearch, with polynomial feature Mean Squared Error (MSE): 0.08810878911479278 Root Mean Squared Error (RMSE): 0.29683124686392565 R-squared (R2) Score: 0.9999999999974956 ### 5. Random Forest Mean Squared Error (MSE): 0.0037291912391644744 Root Mean Squared Error (RMSE): 0.06106710439479241 R-squared (R2) Score: 0.999999999999894 ### 6. Random Forest hyper parameter tuned using GridSearch Best Hyperparameters: {'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 100} Best Model: RandomForestRegressor(random_state=42) ### 7. Gradient Boosting model Mean Squared Error (MSE): 563135.5159778388 Root Mean Squared Error (RMSE): 750.423557717799 R-squared (R2) Score: 0.9999839929498926 ### 8. Gradient Boosting hyper parameters tuned using Grid Search Best Hyperparameters: {'learning_rate': 0.1, 'max_depth': 5, 'n_estimators': 300} Mean Squared Error (MSE): 564.3083168733981 Root Mean Squared Error (RMSE): 23.75517452837167 R-squared (R2) Score: 0.9999999839596132

Based on these metrics, the models that appear to have better performance are:

1. Linear Regression Model with Polynomial Features
2. Linear Regression Model with Hyperparameters Tuned using GridSearch and Polynomial Feature
3. Random Forest Model
4. Gradient Boosting Model with Hyperparameters Tuned using GridSearch
   The Linear Regression Model with Hyperparameters Tuned using GridSearch and Polynomial Feature appears to be the best performing model for CLV prediction. It has the lowest MSE and RMSE values, indicating better accuracy in predicting CLV. Additionally, it achieves a high R2 score of 0.9999999999974956, indicating a very good fit to the data.

End of CLV Part

Github Link