main

May 18, 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:-

category

amt

is_fraud

acct_num

trans_num

cc_num

merchant_name

merch_lat

merch_long

unixtime

customer.csv has the following data:-

first

last

gender

ssn

street

city

state

zip

lat

long

city_pop

job

dob

acct_num

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 pandas as pd
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.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.model_selection import GridSearchCV
import matplotlib.pyplot as plt
import seaborn as sns
```

1.2.2 If you have 'customers.csv', 'transactions.csv' and 'merged_data.csv', just load them and skip to step 3

1.2.3 Step 2: Data Preprocessing

1. Load the transactional data from the CSV files.

[ ]:

```python
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

[ ]:

```python
# 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.

[ ]:

```python
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)
```

1.2.4 Step 3: Feature Engineering

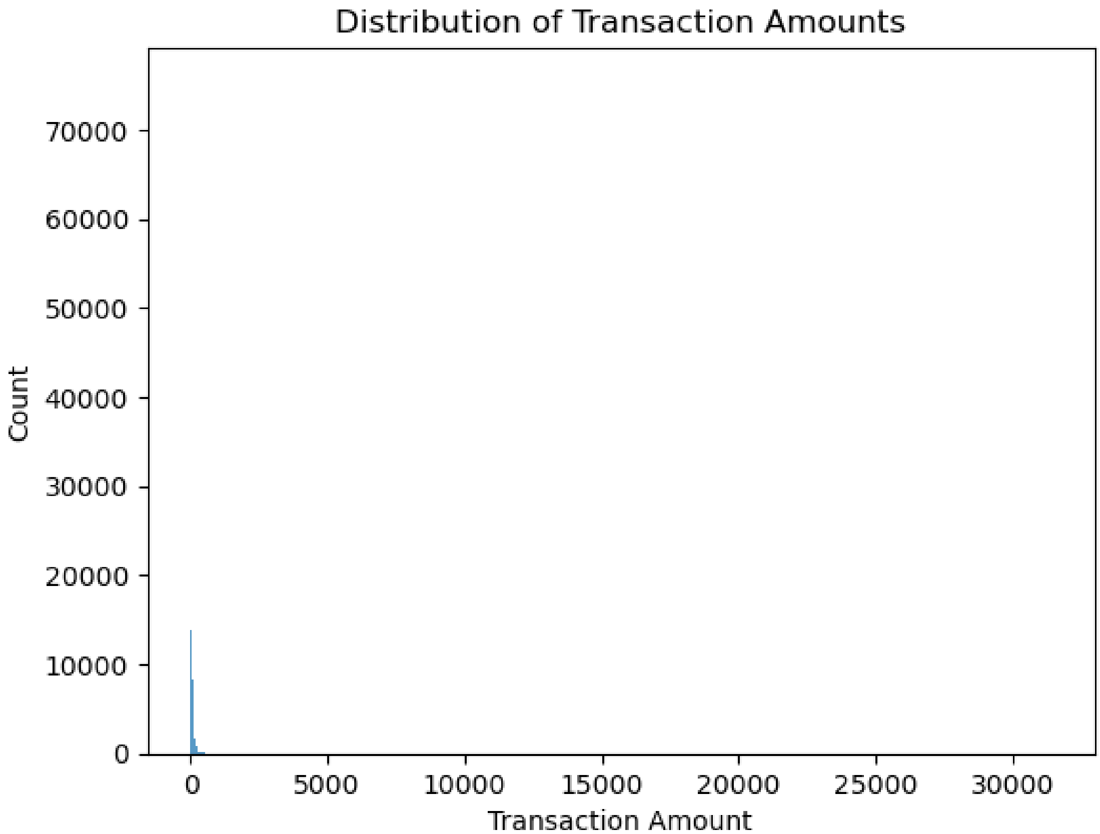
1. Dropping unwanted columns

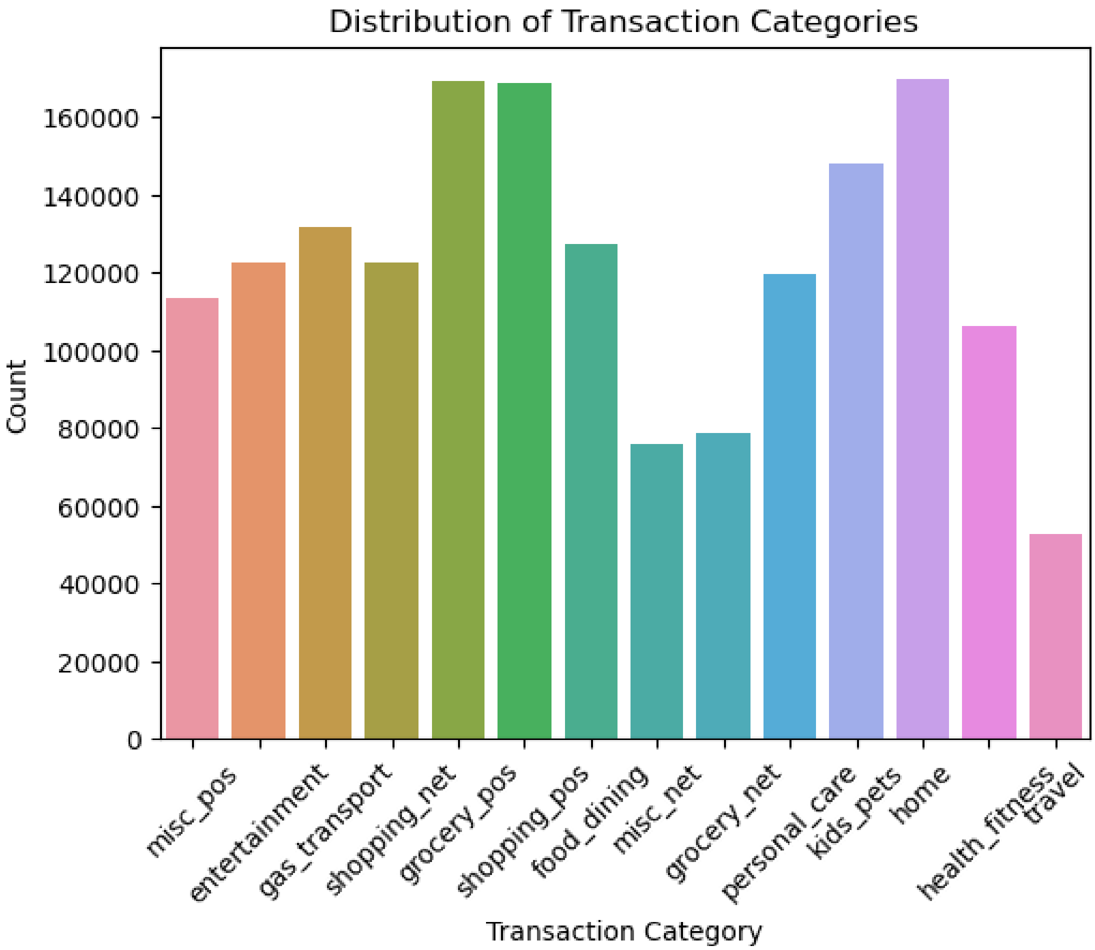
```
[ ]: # Drop unnecessary columns
#merged_data.drop(['trans_num', 'cc_num_x', 'cc_num_y', 'merchant'], axis=1,␣
 ↪inplace=True)
# Handle missing values
merged_data = pd.read_csv('merged_data.csv')
merged_data.fillna(0, inplace=True)
```

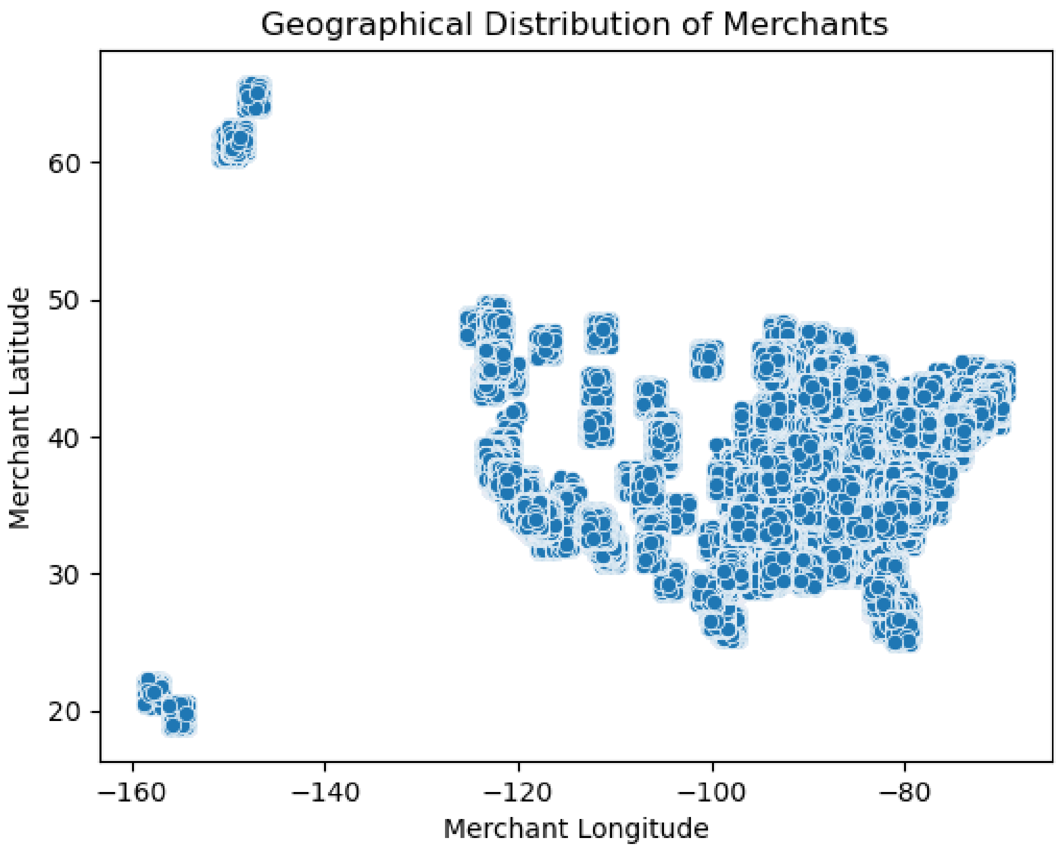
```
[ ]: merged_data
```

2. Ploting graphs

```
[ ]: # 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()
```

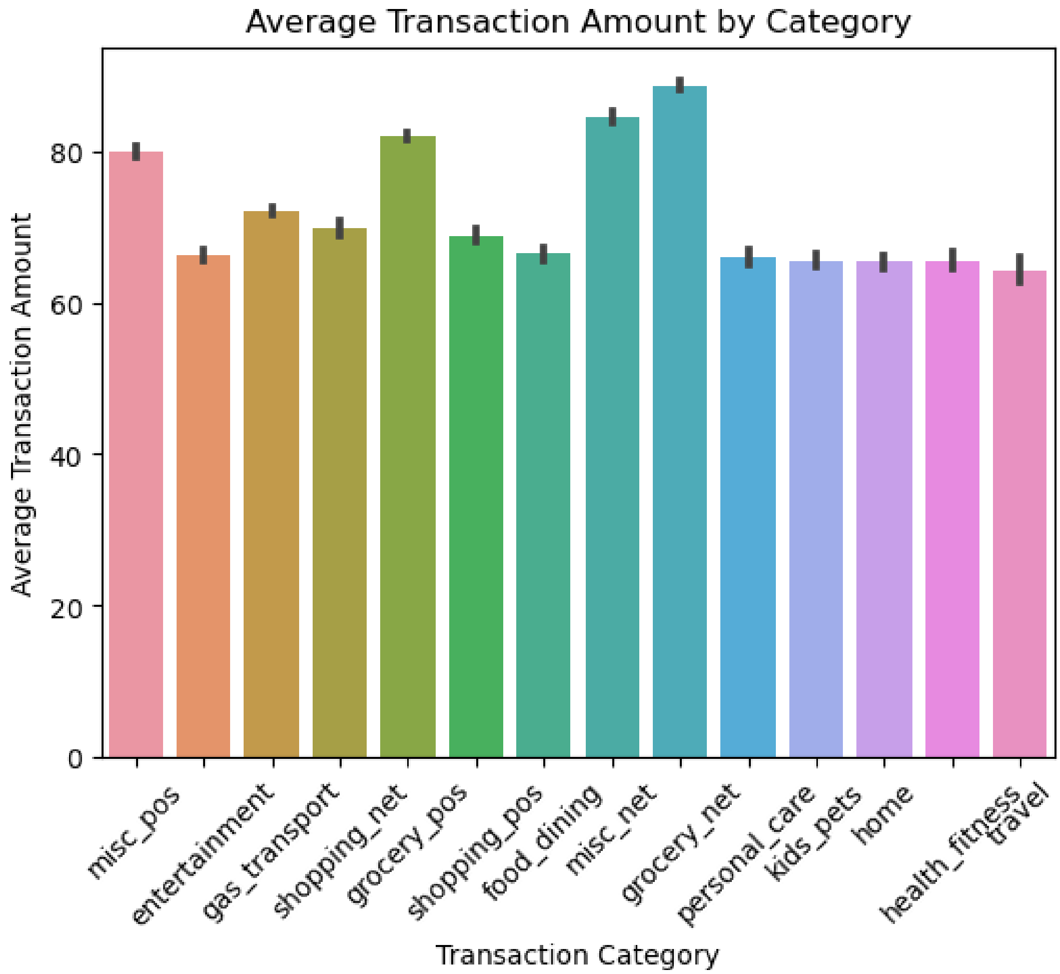

Distribution of Transaction Amounts
Count
70000
60000
50000
40000
30000
20000
10000
0
0
5000
10000
15000
20000
25000
30000
Transaction Amount

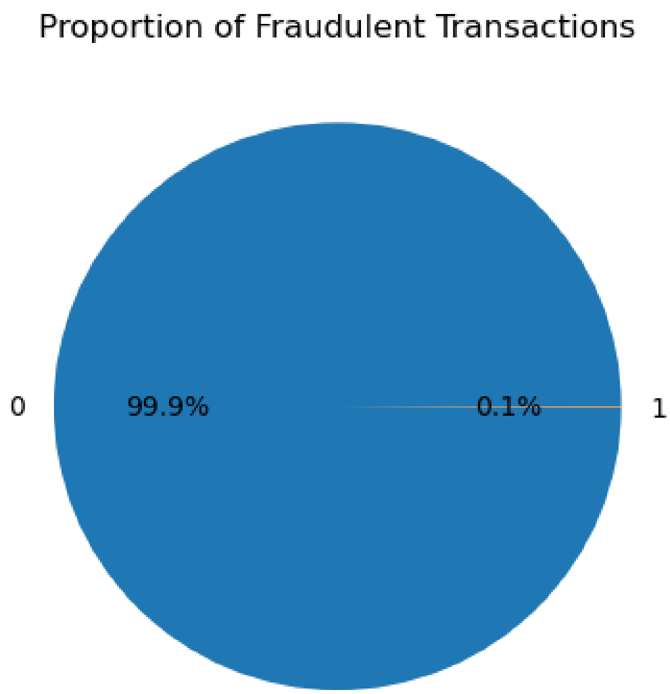

Distribution of Transaction Categories
Count
160000
140000
120000
100000
80000
60000
40000
20000
0
misc_pos
entertainment
gas_transport
shopping_net
grocery_pos
shopping_pos
food_dining
misc_net
grocery_net
personal_care
kids_pets
home
health_fitness
travel
Transaction Category

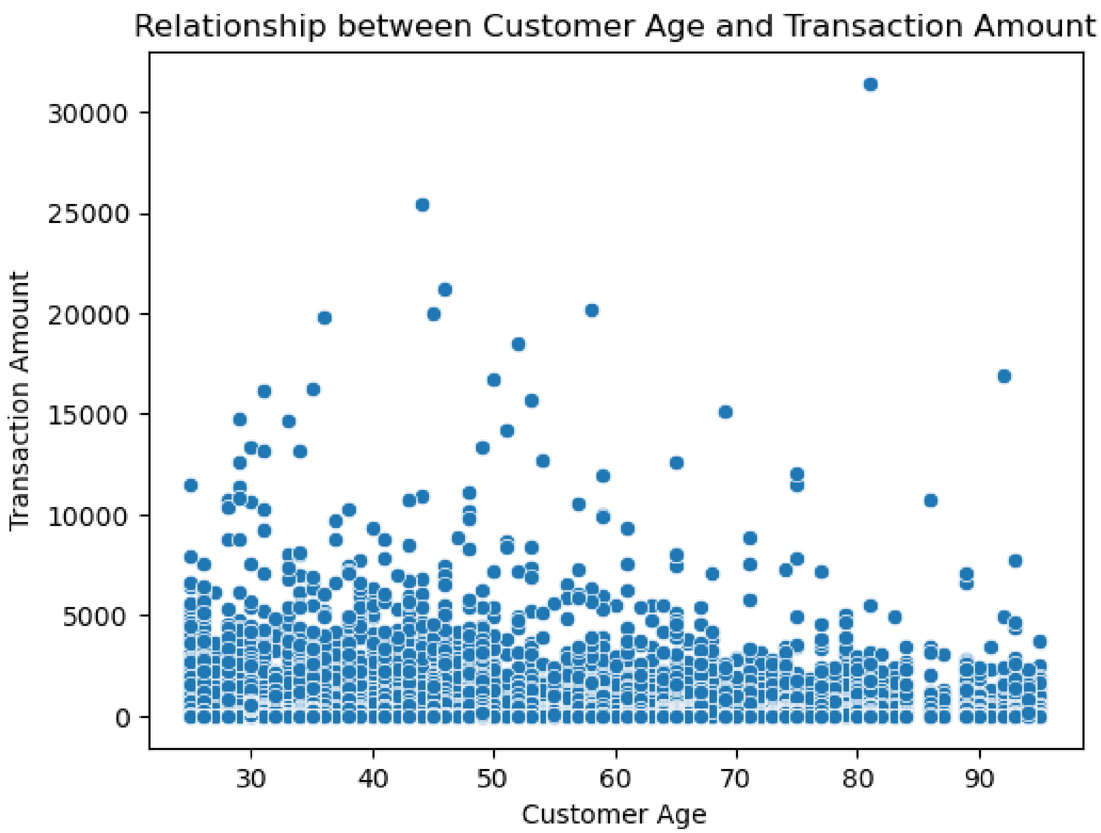


[ ]:
```
# Plot a bar chart of transaction categories with average transaction amount
sns.barplot(data=merged_data, x='category', y='amt')
plt.xlabel('Transaction Category')
plt.ylabel('Average Transaction Amount')
plt.title('Average Transaction Amount by Category')
plt.xticks(rotation=45)
plt.show()

# 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]')
```

```python
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

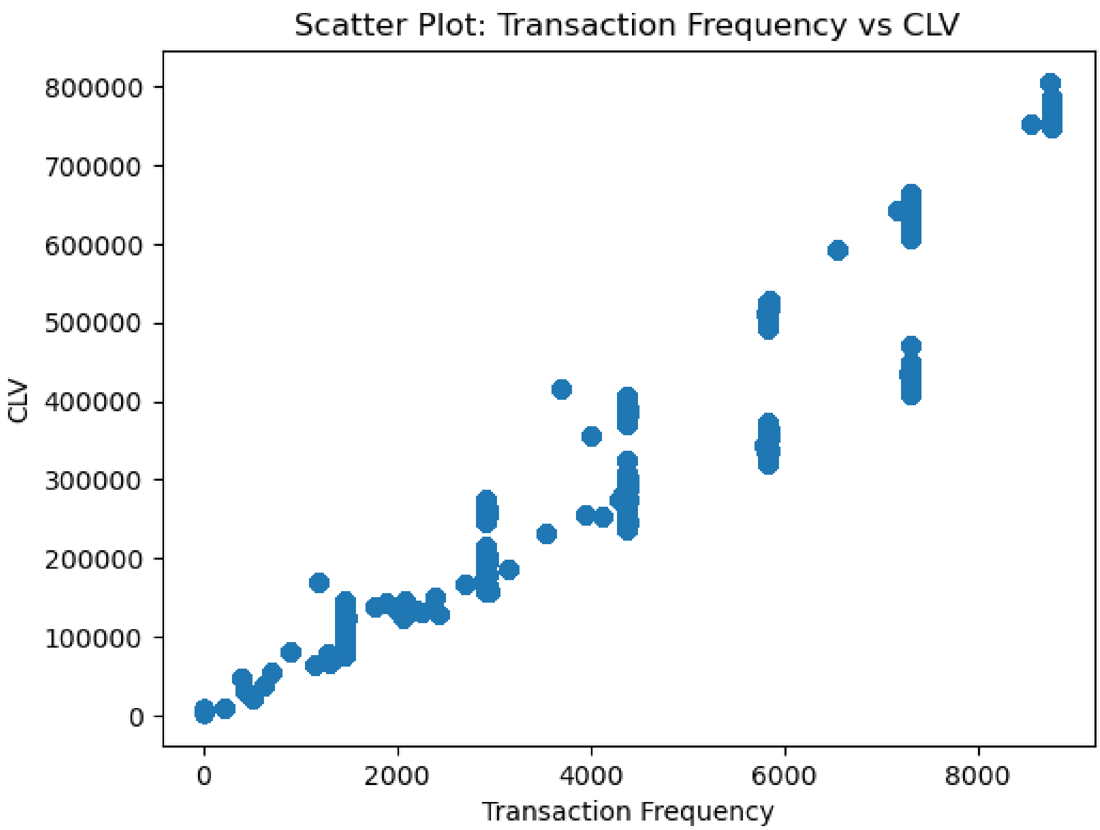
```
[ ]: # Calculate CLV
     merged_data['CLV'] = merged_data['average_transaction_amount'] *␣
      ↪merged_data['transaction_frequency']
     merged_data['CLV']
```

```
[ ]: 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
```

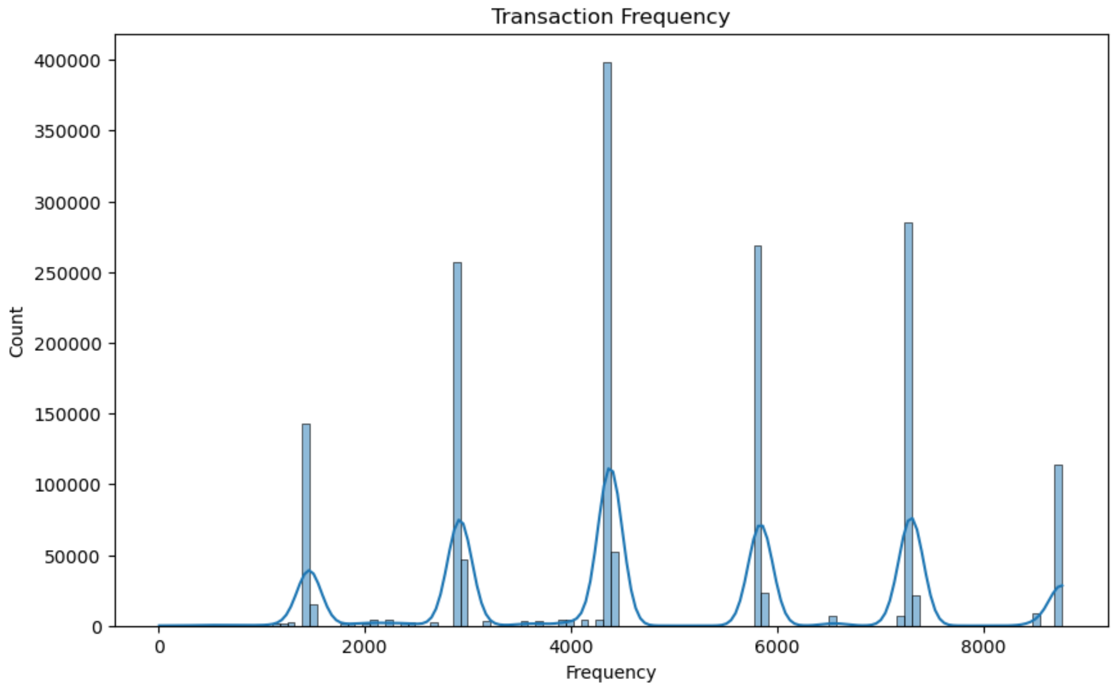
6. Ploting graphs based on new features

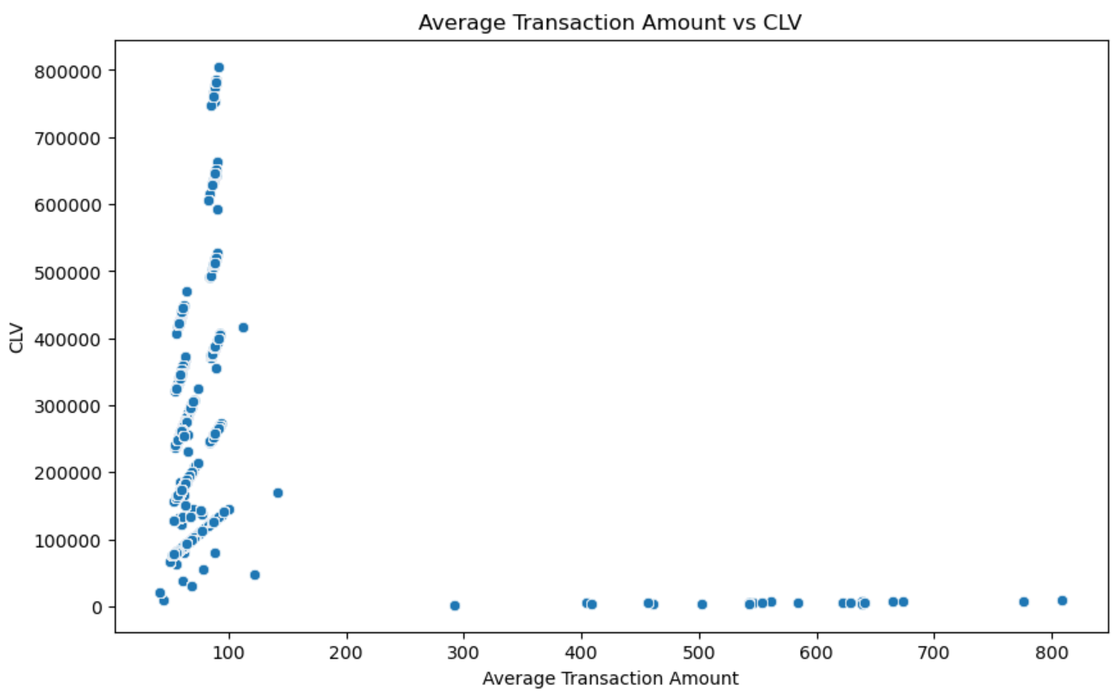
```
[ ]: import matplotlib.pyplot as plt

     # Plot scatter plot
     plt.scatter(merged_data['transaction_frequency'], merged_data['CLV'])
     plt.xlabel('Transaction Frequency')
```

```python
plt.ylabel('CLV')
plt.title('Scatter Plot: Transaction Frequency vs CLV')
plt.show()
```



[ ]:
```python
# 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.

1.2.5 Step 4: Model Training

[ ]:
```
merged_data
```

1. Creating a Linear Regression Model using new features

[ ]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
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 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])
```

```
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]
```

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

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

# 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
grid_search = GridSearchCV(reg_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, end="\n\n")

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

```
Best Hyperparameters: {'fit_intercept': True}
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]
```

3. Creating another model using Random Forest

```
[ ]: 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
```

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)
```

```
---------------------------------------------------------------------------
KeyboardInterrupt                         Traceback (most recent call last)
Cell In[16], line 16
     14 # Perform grid search with cross-validation
     15 grid_search = GridSearchCV(rf_model, param_grid, cv=5)
---> 16 grid_search.fit(X_train, y_train)
     18 # Get the best hyperparameters and model
     19 best_params = grid_search.best_params_

File ~/miniconda3/lib/python3.10/site-packages/sklearn/model_selection/_search.
 ↪py:874, in BaseSearchCV.fit(self, X, y, groups, **fit_params)
    868     results = self._format_results(
    869         all_candidate_params, n_splits, all_out, all_more_results
    870     )
    872     return results
--> 874 self._run_search(evaluate_candidates)
    876 # multimetric is determined here because in the case of a callable
    877 # self.scoring the return type is only known after calling
    878 first_test_score = all_out[0]["test_scores"]

File ~/miniconda3/lib/python3.10/site-packages/sklearn/model_selection/_search.
 ↪py:1388, in GridSearchCV._run_search(self, evaluate_candidates)
   1386 def _run_search(self, evaluate_candidates):
   1387     """Search all candidates in param_grid"""
-> 1388     evaluate_candidates(ParameterGrid(self.param_grid))
```

```
File ~/miniconda3/lib/python3.10/site-packages/sklearn/model_selection/_search.
↪py:821, in BaseSearchCV.fit.<locals>.evaluate_candidates(candidate_params, cv␣
↪more_results)
    813 if self.verbose > 0:
    814     print(
    815         "Fitting {0} folds for each of {1} candidates,"
    816         " totalling {2} fits".format(
    817             n_splits, n_candidates, n_candidates * n_splits
    818         )
    819     )
--> 821 out = parallel(
    822     delayed(_fit_and_score)(
    823         clone(base_estimator),
    824         X,
    825         y,
    826         train=train,
    827         test=test,
    828         parameters=parameters,
    829         split_progress=(split_idx, n_splits),
    830         candidate_progress=(cand_idx, n_candidates),
    831         **fit_and_score_kwargs,
    832     )
    833     for (cand_idx, parameters), (split_idx, (train, test)) in product(
    834         enumerate(candidate_params), enumerate(cv.split(X, y, groups))
    835     )
    836 )
    838 if len(out) < 1:
    839     raise ValueError(
    840         "No fits were performed. "
    841         "Was the CV iterator empty? "
    842         "Were there no candidates?"
    843     )

File ~/miniconda3/lib/python3.10/site-packages/sklearn/utils/parallel.py:63, in␣
↪Parallel.__call__(self, iterable)
     58 config = get_config()
     59 iterable_with_config = (
     60     (_with_config(delayed_func, config), args, kwargs)
     61     for delayed_func, args, kwargs in iterable
     62 )
---> 63 return super().__call__(iterable_with_config)

File ~/miniconda3/lib/python3.10/site-packages/joblib/parallel.py:1051, in␣
↪Parallel.__call__(self, iterable)
   1048 if self.dispatch_one_batch(iterator):
   1049     self._iterating = self._original_iterator is not None
-> 1051 while self.dispatch_one_batch(iterator):
   1052     pass
```

```
   1054 if pre_dispatch == "all" or n_jobs == 1:
   1055     # The iterable was consumed all at once by the above for loop.
   1056     # No need to wait for async callbacks to trigger to
   1057     # consumption.

File ~/miniconda3/lib/python3.10/site-packages/joblib/parallel.py:864, in Parallel.dispatch_one_batch(self, iterator)
    862     return False
    863 else:
--> 864     self._dispatch(tasks)
    865     return True

File ~/miniconda3/lib/python3.10/site-packages/joblib/parallel.py:782, in Parallel._dispatch(self, batch)
    780 with self._lock:
    781     job_idx = len(self._jobs)
--> 782     job = self._backend.apply_async(batch, callback=cb)
    783     # A job can complete so quickly than its callback is
    784     # called before we get here, causing self._jobs to
    785     # grow. To ensure correct results ordering, .insert is
    786     # used (rather than .append) in the following line
    787     self._jobs.insert(job_idx, job)

File ~/miniconda3/lib/python3.10/site-packages/joblib/_parallel_backends.py:208, in SequentialBackend.apply_async(self, func, callback)
    206 def apply_async(self, func, callback=None):
    207     """Schedule a func to be run"""
--> 208     result = ImmediateResult(func)
    209     if callback:
    210         callback(result)

File ~/miniconda3/lib/python3.10/site-packages/joblib/_parallel_backends.py:572, in ImmediateResult.__init__(self, batch)
    569 def __init__(self, batch):
    570     # Don't delay the application, to avoid keeping the input
    571     # arguments in memory
--> 572     self.results = batch()

File ~/miniconda3/lib/python3.10/site-packages/joblib/parallel.py:263, in BatchedCalls.__call__(self)
    259 def __call__(self):
    260     # Set the default nested backend to self._backend but do not set th
    261     # change the default number of processes to -1
    262     with parallel_backend(self._backend, n_jobs=self._n_jobs):
--> 263         return [func(*args, **kwargs)
    264                 for func, args, kwargs in self.items]
```

```
File ~/miniconda3/lib/python3.10/site-packages/joblib/parallel.py:263, in
↪<listcomp>(.0)
    259 def __call__(self):
    260     # Set the default nested backend to self._backend but do not set th
    261     # change the default number of processes to -1
    262     with parallel_backend(self._backend, n_jobs=self._n_jobs):
--> 263         return [func(*args, **kwargs)
    264                 for func, args, kwargs in self.items]

File ~/miniconda3/lib/python3.10/site-packages/sklearn/utils/parallel.py:123, i
↪_FuncWrapper.__call__(self, *args, **kwargs)
    121     config = {}
    122 with config_context(**config):
--> 123     return self.function(*args, **kwargs)

File ~/miniconda3/lib/python3.10/site-packages/sklearn/model_selection/
↪_validation.py:686, in _fit_and_score(estimator, X, y, scorer, train, test,
↪verbose, parameters, fit_params, return_train_score, return_parameters,
↪return_n_test_samples, return_times, return_estimator, split_progress,
↪candidate_progress, error_score)
    684         estimator.fit(X_train, **fit_params)
    685     else:
--> 686         estimator.fit(X_train, y_train, **fit_params)
    688 except Exception:
    689     # Note fit time as time until error
    690     fit_time = time.time() - start_time

File ~/miniconda3/lib/python3.10/site-packages/sklearn/ensemble/_forest.py:473,
↪in BaseForest.fit(self, X, y, sample_weight)
    462 trees = [
    463     self._make_estimator(append=False, random_state=random_state)
    464     for i in range(n_more_estimators)
    465 ]
    467 # Parallel loop: we prefer the threading backend as the Cython code
    468 # for fitting the trees is internally releasing the Python GIL
    469 # making threading more efficient than multiprocessing in
    470 # that case. However, for joblib 0.12+ we respect any
    471 # parallel_backend contexts set at a higher level,
    472 # since correctness does not rely on using threads.
--> 473 trees = Parallel(
    474     n_jobs=self.n_jobs,
    475     verbose=self.verbose,
    476     prefer="threads",
    477 )(
    478     delayed(_parallel_build_trees)(
    479         t,
    480         self.bootstrap,
    481         X,
```

```
    482         y,
    483         sample_weight,
    484         i,
    485         len(trees),
    486         verbose=self.verbose,
    487         class_weight=self.class_weight,
    488         n_samples_bootstrap=n_samples_bootstrap,
    489     )
    490     for i, t in enumerate(trees)
    491 )
    493 # Collect newly grown trees
    494 self.estimators_.extend(trees)

File ~/miniconda3/lib/python3.10/site-packages/sklearn/utils/parallel.py:63, in Parallel.__call__(self, iterable)
     58 config = get_config()
     59 iterable_with_config = (
     60     (_with_config(delayed_func, config), args, kwargs)
     61     for delayed_func, args, kwargs in iterable
     62 )
---> 63 return super().__call__(iterable_with_config)

File ~/miniconda3/lib/python3.10/site-packages/joblib/parallel.py:1051, in Parallel.__call__(self, iterable)
   1048 if self.dispatch_one_batch(iterator):
   1049     self._iterating = self._original_iterator is not None
-> 1051 while self.dispatch_one_batch(iterator):
   1052     pass
   1054 if pre_dispatch == "all" or n_jobs == 1:
   1055     # The iterable was consumed all at once by the above for loop.
   1056     # No need to wait for async callbacks to trigger to
   1057     # consumption.

File ~/miniconda3/lib/python3.10/site-packages/joblib/parallel.py:864, in Parallel.dispatch_one_batch(self, iterator)
    862     return False
    863 else:
--> 864     self._dispatch(tasks)
    865     return True

File ~/miniconda3/lib/python3.10/site-packages/joblib/parallel.py:782, in Parallel._dispatch(self, batch)
    780 with self._lock:
    781     job_idx = len(self._jobs)
--> 782     job = self._backend.apply_async(batch, callback=cb)
    783     # A job can complete so quickly than its callback is
    784     # called before we get here, causing self._jobs to
    785     # grow. To ensure correct results ordering, .insert is
```

```
    786     # used (rather than .append) in the following line
    787     self._jobs.insert(job_idx, job)

File ~/miniconda3/lib/python3.10/site-packages/joblib/_parallel_backends.py:208 ␣
 ↪in SequentialBackend.apply_async(self, func, callback)
    206 def apply_async(self, func, callback=None):
    207     """Schedule a func to be run"""
--> 208     result = ImmediateResult(func)
    209     if callback:
    210         callback(result)

File ~/miniconda3/lib/python3.10/site-packages/joblib/_parallel_backends.py:572 ␣
 ↪in ImmediateResult.__init__(self, batch)
    569 def __init__(self, batch):
    570     # Don't delay the application, to avoid keeping the input
    571     # arguments in memory
--> 572     self.results = batch()

File ~/miniconda3/lib/python3.10/site-packages/joblib/parallel.py:263, in␣
 ↪BatchedCalls.__call__(self)
    259 def __call__(self):
    260     # Set the default nested backend to self._backend but do not set th
    261     # change the default number of processes to -1
    262     with parallel_backend(self._backend, n_jobs=self._n_jobs):
--> 263         return [func(*args, **kwargs)
    264                 for func, args, kwargs in self.items]

File ~/miniconda3/lib/python3.10/site-packages/joblib/parallel.py:263, in␣
 ↪<listcomp>(.0)
    259 def __call__(self):
    260     # Set the default nested backend to self._backend but do not set th
    261     # change the default number of processes to -1
    262     with parallel_backend(self._backend, n_jobs=self._n_jobs):
--> 263         return [func(*args, **kwargs)
    264                 for func, args, kwargs in self.items]

File ~/miniconda3/lib/python3.10/site-packages/sklearn/utils/parallel.py:123, i␣
 ↪_FuncWrapper.__call__(self, *args, **kwargs)
    121     config = {}
    122 with config_context(**config):
--> 123     return self.function(*args, **kwargs)

File ~/miniconda3/lib/python3.10/site-packages/sklearn/ensemble/_forest.py:171,␣
 ↪in _parallel_build_trees(tree, bootstrap, X, y, sample_weight, tree_idx,␣
 ↪n_trees, verbose, class_weight, n_samples_bootstrap)
    168 else:
    169     curr_sample_weight = sample_weight.copy()
--> 171 indices = _generate_sample_indices(
```

```
    172     tree.random_state, n_samples, n_samples_bootstrap
    173 )
    174 sample_counts = np.bincount(indices, minlength=n_samples)
    175 curr_sample_weight *= sample_counts

File ~/miniconda3/lib/python3.10/site-packages/sklearn/ensemble/_forest.py:128,
 ↪in _generate_sample_indices(random_state, n_samples, n_samples_bootstrap)
    124 """
    125 Private function used to _parallel_build_trees function."""
    127 random_instance = check_random_state(random_state)
--> 128 sample_indices = random_instance.randint(0, n_samples,
 ↪n_samples_bootstrap)
    130 return sample_indices

KeyboardInterrupt:
```

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

[ ]:
```python
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)
```

1.2.6 Step 5: Model Deployment

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

[ ]:
```python
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')

# 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')
```

[ ]:
```
['linear_regression_model.pkl']
```

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