subramanian540_Final_Project_Milestone5

June 3, 2023

1 DSC540 - Final Project Milestone5

1.0.1 Merging the Data and Storing in a Database/Visualizing Data

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1.0.2 Project Milestone 2 - Perform data transformation and Cleaning/Formatting Flat File Source

[167]:
```python
#Load the Necessary Libraries

import requests as r
import pandas as pd
import xlrd
from bs4 import BeautifulSoup
import numpy as np
import matplotlib.pyplot as plt
```

[168]:
```python
# Load the FraudTest.csv file

fraud_data_csv = pd.read_csv('fraudTest.csv', sep=",")
fraud_data_csv.head()
```

[168]:
```
   Unnamed: 0 trans_date_trans_time        cc_num  \
0           0       6/21/2020 12:14  2.291160e+15
1           1       6/21/2020 12:14  3.573030e+15
2           2       6/21/2020 12:14  3.598220e+15
3           3       6/21/2020 12:15  3.591920e+15
4           4       6/21/2020 12:15  3.526830e+15

                              merchant        category    amt   first  \
0                 fraud_Kirlin and Sons   personal_care   2.86    Jeff
1                  fraud_Sporer-Keebler   personal_care  29.84  Joanne
2  fraud_Swaniawski, Nitzsche and Welch  health_fitness  41.28  Ashley
3                     fraud_Haley Group        misc_pos  60.05   Brian
4                 fraud_Johnston-Casper          travel   3.19  Nathan

       last gender                       street  …      lat      long  \
```

```
0   Elliott      M            351 Darlene Green  …  33.9659  -80.9355
1  Williams      F             3638 Marsh Union  …  40.3207 -110.4360
2     Lopez      F         9333 Valentine Point  …  40.6729  -73.5365
3  Williams      M  32941 Krystal Mill Apt. 552  …  28.5697  -80.8191
4    Massey      M      5783 Evan Roads Apt. 465  …  44.2529  -85.0170

   city_pop                     job         dob  \
0    333497     Mechanical engineer   3/19/1968
1       302  Sales professional, IT   1/17/1990
2     34496       Librarian, public  10/21/1970
3     54767            Set designer   7/25/1987
4      1126      Furniture designer    7/6/1955

                          trans_num   unix_time  merch_lat  merch_long  \
0  2da90c7d74bd46a0caf3777415b3ebd3  1371816865  33.986391  -81.200714
1  324cc204407e99f51b0d6ca0055005e7  1371816873  39.450498 -109.960431
2  c81755dbbbea9d5c77f094348a7579be  1371816893  40.495810  -74.196111
3  2159175b9efe66dc301f149d3d5abf8c  1371816915  28.812398  -80.883061
4  57ff021bd3f328f8738bb535c302a31b  1371816917  44.959148  -85.884734

   is_fraud
0         0
1         0
2         0
3         0
4         0

[5 rows x 23 columns]
```

[169]:
```python
# Transformation 1: Check for missing values in any of the columns that will be kept in the final data set.

for c in fraud_data_csv.columns:
    miss = fraud_data_csv[c].isnull().sum()
    if miss>0:
        print("{} has {} missing value(s).".format(c,miss))
    else:
        print("{} has no missing values.".format(c))
```

```
Unnamed: 0 has no missing values.
trans_date_trans_time has 16 missing value(s).
cc_num has no missing values.
merchant has no missing values.
category has no missing values.
amt has no missing values.
first has no missing values.
last has no missing values.
gender has no missing values.
```

```
street has no missing values.
city has no missing values.
state has no missing values.
zip has no missing values.
lat has 14 missing value(s).
long has no missing values.
city_pop has no missing values.
job has no missing values.
dob has no missing values.
trans_num has no missing values.
unix_time has no missing values.
merch_lat has 13 missing value(s).
merch_long has no missing values.
is_fraud has no missing values.
```

[170]:

```python
# Transformation 2. Delete the 'trans_num' column.

del fraud_data_csv['trans_num']
fraud_data_csv.head()
```

[170]:

```
   Unnamed: 0 trans_date_trans_time        cc_num  \
0           0       6/21/2020 12:14  2.291160e+15
1           1       6/21/2020 12:14  3.573030e+15
2           2       6/21/2020 12:14  3.598220e+15
3           3       6/21/2020 12:15  3.591920e+15
4           4       6/21/2020 12:15  3.526830e+15

                              merchant        category    amt   first  \
0                 fraud_Kirlin and Sons   personal_care   2.86    Jeff
1                  fraud_Sporer-Keebler   personal_care  29.84  Joanne
2  fraud_Swaniawski, Nitzsche and Welch  health_fitness  41.28  Ashley
3                     fraud_Haley Group        misc_pos  60.05   Brian
4                 fraud_Johnston-Casper          travel   3.19  Nathan

       last gender                       street  …    zip      lat  \
0   Elliott      M            351 Darlene Green  …  29209  33.9659
1  Williams      F             3638 Marsh Union  …  84002  40.3207
2     Lopez      F         9333 Valentine Point  …  11710  40.6729
3  Williams      M  32941 Krystal Mill Apt. 552  …  32780  28.5697
4    Massey      M     5783 Evan Roads Apt. 465  …  49632  44.2529

       long  city_pop                      job         dob   unix_time  \
0  -80.9355    333497      Mechanical engineer   3/19/1968  1371816865
1 -110.4360       302  Sales professional, IT   1/17/1990  1371816873
2  -73.5365     34496       Librarian, public  10/21/1970  1371816893
3  -80.8191     54767            Set designer   7/25/1987  1371816915
4  -85.0170      1126      Furniture designer    7/6/1955  1371816917
```

```
   merch_lat  merch_long  is_fraud
0  33.986391  -81.200714         0
1  39.450498 -109.960431         0
2  40.495810  -74.196111         0
3  28.812398  -80.883061         0
4  44.959148  -85.884734         0

[5 rows x 22 columns]
```

[171]:
```python
# Transformation 3. Delete the 'merch_lat ' column.

del fraud_data_csv['merch_lat']
fraud_data_csv.head()
```

[171]:
```
   Unnamed: 0 trans_date_trans_time        cc_num  \
0           0       6/21/2020 12:14  2.291160e+15
1           1       6/21/2020 12:14  3.573030e+15
2           2       6/21/2020 12:14  3.598220e+15
3           3       6/21/2020 12:15  3.591920e+15
4           4       6/21/2020 12:15  3.526830e+15

                              merchant        category    amt   first  \
0                 fraud_Kirlin and Sons   personal_care   2.86    Jeff
1                  fraud_Sporer-Keebler   personal_care  29.84  Joanne
2  fraud_Swaniawski, Nitzsche and Welch  health_fitness  41.28  Ashley
3                     fraud_Haley Group        misc_pos  60.05   Brian
4                 fraud_Johnston-Casper          travel   3.19  Nathan

       last gender                       street  … state    zip      lat  \
0   Elliott      M            351 Darlene Green  …    SC  29209  33.9659
1  Williams      F             3638 Marsh Union  …    UT  84002  40.3207
2     Lopez      F         9333 Valentine Point  …    NY  11710  40.6729
3  Williams      M  32941 Krystal Mill Apt. 552  …    FL  32780  28.5697
4    Massey      M     5783 Evan Roads Apt. 465  …    MI  49632  44.2529

       long  city_pop                      job         dob   unix_time  \
0  -80.9355    333497      Mechanical engineer   3/19/1968  1371816865
1 -110.4360       302  Sales professional, IT   1/17/1990  1371816873
2  -73.5365     34496        Librarian, public  10/21/1970  1371816893
3  -80.8191     54767             Set designer   7/25/1987  1371816915
4  -85.0170      1126       Furniture designer    7/6/1955  1371816917

   merch_long  is_fraud
0  -81.200714         0
1 -109.960431         0
2  -74.196111         0
```

```
3  -80.883061         0
4  -85.884734         0

[5 rows x 21 columns]
```

[172]:
```
# Transformation 4. Delete the 'merch_long' column.

del fraud_data_csv['merch_long']
fraud_data_csv.head()
```

[172]:
```
   Unnamed: 0 trans_date_trans_time        cc_num  \
0           0       6/21/2020 12:14  2.291160e+15
1           1       6/21/2020 12:14  3.573030e+15
2           2       6/21/2020 12:14  3.598220e+15
3           3       6/21/2020 12:15  3.591920e+15
4           4       6/21/2020 12:15  3.526830e+15

                              merchant       category    amt   first  \
0                 fraud_Kirlin and Sons  personal_care   2.86    Jeff
1                  fraud_Sporer-Keebler  personal_care  29.84  Joanne
2  fraud_Swaniawski, Nitzsche and Welch  health_fitness  41.28  Ashley
3                     fraud_Haley Group        misc_pos  60.05   Brian
4                 fraud_Johnston-Casper          travel   3.19  Nathan

       last gender                       street        city state    zip  \
0   Elliott      M            351 Darlene Green    Columbia    SC  29209
1  Williams      F             3638 Marsh Union     Altonah    UT  84002
2     Lopez      F         9333 Valentine Point    Bellmore    NY  11710
3  Williams      M  32941 Krystal Mill Apt. 552  Titusville    FL  32780
4    Massey      M     5783 Evan Roads Apt. 465    Falmouth    MI  49632

       lat      long  city_pop                      job         dob  \
0  33.9659  -80.9355    333497      Mechanical engineer   3/19/1968
1  40.3207 -110.4360       302  Sales professional, IT   1/17/1990
2  40.6729  -73.5365     34496        Librarian, public  10/21/1970
3  28.5697  -80.8191     54767             Set designer   7/25/1987
4  44.2529  -85.0170      1126       Furniture designer    7/6/1955

    unix_time  is_fraud
0  1371816865         0
1  1371816873         0
2  1371816893         0
3  1371816915         0
4  1371816917         0
```

[173]:
```
# Transformation 5.Convert time to a readable format
```

```
fraud_data_csv['unix_time'] = pd.to_datetime(fraud_data_csv['unix_time'],␣
↪unit='s')
fraud_data_csv.head()
```

[173]:
```
   Unnamed: 0 trans_date_trans_time        cc_num  \
0           0       6/21/2020 12:14  2.291160e+15
1           1       6/21/2020 12:14  3.573030e+15
2           2       6/21/2020 12:14  3.598220e+15
3           3       6/21/2020 12:15  3.591920e+15
4           4       6/21/2020 12:15  3.526830e+15

                              merchant        category    amt   first  \
0                fraud_Kirlin and Sons   personal_care   2.86    Jeff
1                 fraud_Sporer-Keebler   personal_care  29.84  Joanne
2  fraud_Swaniawski, Nitzsche and Welch health_fitness  41.28  Ashley
3                   fraud_Haley Group        misc_pos  60.05   Brian
4               fraud_Johnston-Casper          travel   3.19  Nathan

       last gender                       street        city state    zip  \
0   Elliott      M            351 Darlene Green    Columbia    SC  29209
1  Williams      F             3638 Marsh Union     Altonah    UT  84002
2     Lopez      F         9333 Valentine Point    Bellmore    NY  11710
3  Williams      M  32941 Krystal Mill Apt. 552  Titusville    FL  32780
4    Massey      M     5783 Evan Roads Apt. 465    Falmouth    MI  49632

       lat      long  city_pop                      job         dob  \
0  33.9659  -80.9355    333497      Mechanical engineer   3/19/1968
1  40.3207 -110.4360       302  Sales professional, IT   1/17/1990
2  40.6729  -73.5365     34496       Librarian, public  10/21/1970
3  28.5697  -80.8191     54767            Set designer   7/25/1987
4  44.2529  -85.0170      1126      Furniture designer    7/6/1955

            unix_time  is_fraud
0 2013-06-21 12:14:25         0
1 2013-06-21 12:14:33         0
2 2013-06-21 12:14:53         0
3 2013-06-21 12:15:15         0
4 2013-06-21 12:15:17         0
```

[174]:
```
# Transformation 6. Add a column heading of 'row_id' to the first column.

fraud_data_csv.rename(columns = {'Unnamed: 0' : 'row_id'}, inplace=True)
fraud_data_csv.head()
```

[174]:
```
   row_id trans_date_trans_time        cc_num  \
0       0       6/21/2020 12:14  2.291160e+15
1       1       6/21/2020 12:14  3.573030e+15
```

```
2       2       6/21/2020 12:14  3.598220e+15
3       3       6/21/2020 12:15  3.591920e+15
4       4       6/21/2020 12:15  3.526830e+15

                             merchant        category    amt   first  \
0                 fraud_Kirlin and Sons   personal_care   2.86    Jeff
1                  fraud_Sporer-Keebler   personal_care  29.84  Joanne
2  fraud_Swaniawski, Nitzsche and Welch  health_fitness  41.28  Ashley
3                     fraud_Haley Group        misc_pos  60.05   Brian
4                 fraud_Johnston-Casper          travel   3.19  Nathan

       last gender                       street        city state    zip  \
0   Elliott      M            351 Darlene Green    Columbia    SC  29209
1  Williams      F             3638 Marsh Union     Altonah    UT  84002
2     Lopez      F         9333 Valentine Point    Bellmore    NY  11710
3  Williams      M  32941 Krystal Mill Apt. 552  Titusville    FL  32780
4    Massey      M       5783 Evan Roads Apt. 465    Falmouth    MI  49632

       lat      long  city_pop                        job         dob  \
0  33.9659  -80.9355    333497        Mechanical engineer   3/19/1968
1  40.3207 -110.4360       302  Sales professional, IT   1/17/1990
2  40.6729  -73.5365     34496          Librarian, public  10/21/1970
3  28.5697  -80.8191     54767              Set designer   7/25/1987
4  44.2529  -85.0170      1126         Furniture designer    7/6/1955

            unix_time  is_fraud
0 2013-06-21 12:14:25         0
1 2013-06-21 12:14:33         0
2 2013-06-21 12:14:53         0
3 2013-06-21 12:15:15         0
4 2013-06-21 12:15:17         0
```

[175]:

```
# Transformation 7. Convert amount to a float with two decimal places

fraud_data_csv['amt'] = fraud_data_csv['amt'].round(2)
fraud_data_csv.head()
```

[175]:

```
   row_id trans_date_trans_time        cc_num  \
0       0       6/21/2020 12:14  2.291160e+15
1       1       6/21/2020 12:14  3.573030e+15
2       2       6/21/2020 12:14  3.598220e+15
3       3       6/21/2020 12:15  3.591920e+15
4       4       6/21/2020 12:15  3.526830e+15

                             merchant        category    amt   first  \
0                 fraud_Kirlin and Sons   personal_care   2.86    Jeff
1                  fraud_Sporer-Keebler   personal_care  29.84  Joanne
```

```
2  fraud_Swaniawski, Nitzsche and Welch  health_fitness  41.28  Ashley
3                      fraud_Haley Group        misc_pos  60.05   Brian
4                  fraud_Johnston-Casper          travel   3.19  Nathan

       last gender                      street        city state    zip  \
0   Elliott      M           351 Darlene Green    Columbia    SC  29209
1  Williams      F            3638 Marsh Union     Altonah    UT  84002
2     Lopez      F        9333 Valentine Point    Bellmore    NY  11710
3  Williams      M  32941 Krystal Mill Apt. 552  Titusville    FL  32780
4    Massey      M     5783 Evan Roads Apt. 465    Falmouth    MI  49632

       lat      long  city_pop                     job        dob  \
0  33.9659  -80.9355    333497     Mechanical engineer  3/19/1968
1  40.3207 -110.4360       302  Sales professional, IT  1/17/1990
2  40.6729  -73.5365     34496     Librarian, public  10/21/1970
3  28.5697  -80.8191     54767           Set designer  7/25/1987
4  44.2529  -85.0170      1126     Furniture designer   7/6/1955

            unix_time  is_fraud
0 2013-06-21 12:14:25         0
1 2013-06-21 12:14:33         0
2 2013-06-21 12:14:53         0
3 2013-06-21 12:15:15         0
4 2013-06-21 12:15:17         0
```

[176]:

```python
# Transformation 9. Identify any missing values

missing_values = fraud_data_csv.isnull().sum().sum()
print("Missing Values:\n", missing_values)
```

```
Missing Values:
 30
```

[177]:

```python
# Transformation 11. drop the duplicates
fraud_data_csv = fraud_data_csv.drop_duplicates()
fraud_data_csv.head()
```

[177]:

```
   row_id trans_date_trans_time        cc_num  \
0       0       6/21/2020 12:14  2.291160e+15
1       1       6/21/2020 12:14  3.573030e+15
2       2       6/21/2020 12:14  3.598220e+15
3       3       6/21/2020 12:15  3.591920e+15
4       4       6/21/2020 12:15  3.526830e+15

                               merchant        category    amt   first  \
0                   fraud_Kirlin and Sons   personal_care   2.86    Jeff
1                    fraud_Sporer-Keebler   personal_care  29.84  Joanne
2  fraud_Swaniawski, Nitzsche and Welch  health_fitness  41.28  Ashley
```

```
3                    fraud_Haley Group        misc_pos   60.05    Brian
4                fraud_Johnston-Casper          travel    3.19   Nathan

       last gender                         street        city state    zip  \
0   Elliott      M              351 Darlene Green    Columbia    SC  29209
1  Williams      F               3638 Marsh Union     Altonah    UT  84002
2     Lopez      F           9333 Valentine Point    Bellmore    NY  11710
3  Williams      M  32941 Krystal Mill Apt. 552  Titusville    FL  32780
4    Massey      M      5783 Evan Roads Apt. 465    Falmouth    MI  49632

       lat      long  city_pop                     job         dob  \
0  33.9659  -80.9355    333497     Mechanical engineer   3/19/1968
1  40.3207 -110.4360       302  Sales professional, IT   1/17/1990
2  40.6729  -73.5365     34496      Librarian, public  10/21/1970
3  28.5697  -80.8191     54767           Set designer   7/25/1987
4  44.2529  -85.0170      1126      Furniture designer    7/6/1955

            unix_time  is_fraud
0 2013-06-21 12:14:25         0
1 2013-06-21 12:14:33         0
2 2013-06-21 12:14:53         0
3 2013-06-21 12:15:15         0
4 2013-06-21 12:15:17         0
```

[178]:
```python
# # Transformation 12. Verify data accuracy and Check  for negative 'amount'␣
↪values

negative_amounts = fraud_data_csv[fraud_data_csv['amt'] < 0]
if not negative_amounts.empty:
    # Replace negative values with NaN
    fraud_data_csv.loc[fraud_data_csv['amt'] < 0, 'amt'] = np.nan
    print("Negative amounts found and replaced with NaN.")
else:
    print("No negative amounts found.")
```

```
No negative amounts found.
```

[179]:
```python
# After all Transformation and the final Fraud data

fraud_data_csv
```

[179]:
```
        row_id trans_date_trans_time        cc_num  \
0            0       6/21/2020 12:14  2.291160e+15
1            1       6/21/2020 12:14  3.573030e+15
2            2       6/21/2020 12:14  3.598220e+15
3            3       6/21/2020 12:15  3.591920e+15
4            4       6/21/2020 12:15  3.526830e+15
…          …                   …             …
```

```
555730  555714                   NaN  3.056060e+13
555731  555715                   NaN  3.556610e+15
555732  555716                   NaN  6.011720e+15
555733  555717                   NaN  4.079770e+12
555734  555718                   NaN  4.170690e+15

                                    merchant       category     amt    first  \
0                     fraud_Kirlin and Sons  personal_care    2.86     Jeff
1                      fraud_Sporer-Keebler  personal_care   29.84   Joanne
2       fraud_Swaniawski, Nitzsche and Welch  health_fitness   41.28   Ashley
3                         fraud_Haley Group       misc_pos   60.05    Brian
4                     fraud_Johnston-Casper         travel    3.19   Nathan
…                                        …              …       …        …
555730                fraud_Reilly and Sons  health_fitness   43.77  Michael
555731                 fraud_Hoppe-Parisian       kids_pets  111.84     Jose
555732                      fraud_Rau-Robel       kids_pets   86.88      Ann
555733                fraud_Breitenberg LLC          travel    7.99     Eric
555734                    fraud_Dare-Marvin  entertainment   38.13   Samuel

            last gender                        street         city state  \
0        Elliott      M             351 Darlene Green     Columbia    SC
1       Williams      F              3638 Marsh Union      Altonah    UT
2          Lopez      F          9333 Valentine Point     Bellmore    NY
3       Williams      M  32941 Krystal Mill Apt. 552   Titusville    FL
4         Massey      M      5783 Evan Roads Apt. 465     Falmouth    MI
…              …      …                             …            …     …
555730     Olson      M            558 Michael Estates        Luray    MO
555731   Vasquez      M            572 Davis Mountains  Lake Jackson    TX
555732    Lawson      F    144 Evans Islands Apt. 683      Burbank    WA
555733   Preston      M    7020 Doyle Stream Apt. 951         Mesa    ID
555734      Frey      M      830 Myers Plaza Apt. 384       Edmond    OK

          zip      lat      long  city_pop                      job  \
0       29209  33.9659  -80.9355    333497      Mechanical engineer
1       84002  40.3207 -110.4360       302  Sales professional, IT
2       11710  40.6729  -73.5365     34496       Librarian, public
3       32780  28.5697  -80.8191     54767            Set designer
4       49632  44.2529  -85.0170      1126      Furniture designer
…           …        …         …         …                        …
555730  63453      NaN  -91.8912       519             Town planner
555731  77566      NaN  -95.4401     28739           Futures trader
555732  99323      NaN -118.9017      3684                 Musician
555733  83643      NaN -116.4493       129             Cartographer
555734  73034      NaN  -97.4798    116001              Media buyer

              dob            unix_time  is_fraud
0       3/19/1968 2013-06-21 12:14:25         0
```

```
1        1/17/1990 2013-06-21 12:14:33        0
2       10/21/1970 2013-06-21 12:14:53        0
3        7/25/1987 2013-06-21 12:15:15        0
4         7/6/1955 2013-06-21 12:15:17        0
…             …                  …       …
555730   2/13/1966 2013-12-31 23:59:07        0
555731  12/27/1999 2013-12-31 23:59:09        0
555732  11/29/1981 2013-12-31 23:59:15        0
555733  12/15/1965 2013-12-31 23:59:24        0
555734   5/10/1993 2013-12-31 23:59:34        0

[555735 rows x 20 columns]
```

1.0.3 Project Milestone 3 - Perform data transformation and Cleaning/Formatting Website Source

[180]:
```python
#Load the required libraries

import pandas as pd
import numpy as np
import xlrd
from bs4 import BeautifulSoup
import numpy as np
import datapackage
import matplotlib.pyplot as plt
import seaborn as sns
```

[181]:
```python
# To access the Credit card web data source

data_url = 'https://datahub.io/machine-learning/creditcard/datapackage.json'

# to load Data Package into storage
package = datapackage.Package(data_url)
```

[182]:
```python
# to load only tabular data
resources = package.resources
for resource in resources:
    if resource.tabular:
        fraud_data_web = pd.read_csv(resource.descriptor['path'])
        #print (fraud_data_web)
```

[183]:
```python
# Transformation 1: Replace headers

# Step #1: Replace headers
headers = ["Time", "V1", "V2", "V3", "V4", "V5", "V6", "V7", "V8", "V9", "V10",␣
 ↪"V11", "V12", "V13", "V14", "V15", "V16", "V17", "V18", "V19", "V20", "V21",␣
 ↪"V22", "V23", "V24", "V25", "V26", "V27", "V28", "Amount", "Class"]
```

```python
fraud_data_web.columns = headers
print(fraud_data_web.columns)
```

```
Index(['Time', 'V1', 'V2', 'V3', 'V4', 'V5', 'V6', 'V7', 'V8', 'V9', 'V10',
       'V11', 'V12', 'V13', 'V14', 'V15', 'V16', 'V17', 'V18', 'V19', 'V20',
       'V21', 'V22', 'V23', 'V24', 'V25', 'V26', 'V27', 'V28', 'Amount',
       'Class'],
      dtype='object')
```

[184]:

```python
#Transformation 2: Convert time to a readable format

fraud_data_web["Time"] = pd.to_datetime(fraud_data_web["Time"], unit="s")
fraud_data_web.head()
```

[184]:

```
                 Time        V1        V2        V3        V4        V5  \
0 1970-01-01 00:00:00 -1.359807 -0.072781  2.536347  1.378155 -0.338321
1 1970-01-01 00:00:00  1.191857  0.266151  0.166480  0.448154  0.060018
2 1970-01-01 00:00:01 -1.358354 -1.340163  1.773209  0.379780 -0.503198
3 1970-01-01 00:00:01 -0.966272 -0.185226  1.792993 -0.863291 -0.010309
4 1970-01-01 00:00:02 -1.158233  0.877737  1.548718  0.403034 -0.407193

         V6        V7        V8        V9  …       V21       V22       V23  \
0  0.462388  0.239599  0.098698  0.363787  … -0.018307  0.277838 -0.110474
1 -0.082361 -0.078803  0.085102 -0.255425  … -0.225775 -0.638672  0.101288
2  1.800499  0.791461  0.247676 -1.514654  …  0.247998  0.771679  0.909412
3  1.247203  0.237609  0.377436 -1.387024  … -0.108300  0.005274 -0.190321
4  0.095921  0.592941 -0.270533  0.817739  … -0.009431  0.798278 -0.137458

        V24       V25       V26       V27       V28  Amount  Class
0  0.066928  0.128539 -0.189115  0.133558 -0.021053  149.62    '0'
1 -0.339846  0.167170  0.125895 -0.008983  0.014724    2.69    '0'
2 -0.689281 -0.327642 -0.139097 -0.055353 -0.059752  378.66    '0'
3 -1.175575  0.647376 -0.221929  0.062723  0.061458  123.50    '0'
4  0.141267 -0.206010  0.502292  0.219422  0.215153   69.99    '0'

[5 rows x 31 columns]
```

[185]:

```python
#Transformation 3: Convert amount to a float with two decimal places

fraud_data_web['Amount'] = np.round(fraud_data_web['Amount'], 2)
fraud_data_web.head()
```

[185]:

```
                 Time        V1        V2        V3        V4        V5  \
0 1970-01-01 00:00:00 -1.359807 -0.072781  2.536347  1.378155 -0.338321
1 1970-01-01 00:00:00  1.191857  0.266151  0.166480  0.448154  0.060018
2 1970-01-01 00:00:01 -1.358354 -1.340163  1.773209  0.379780 -0.503198
3 1970-01-01 00:00:01 -0.966272 -0.185226  1.792993 -0.863291 -0.010309
4 1970-01-01 00:00:02 -1.158233  0.877737  1.548718  0.403034 -0.407193
```

```
         V6        V7        V8        V9  ...       V21       V22       V23  \
0  0.462388  0.239599  0.098698  0.363787  ... -0.018307  0.277838 -0.110474
1 -0.082361 -0.078803  0.085102 -0.255425  ... -0.225775 -0.638672  0.101288
2  1.800499  0.791461  0.247676 -1.514654  ...  0.247998  0.771679  0.909412
3  1.247203  0.237609  0.377436 -1.387024  ... -0.108300  0.005274 -0.190321
4  0.095921  0.592941 -0.270533  0.817739  ... -0.009431  0.798278 -0.137458

        V24       V25       V26       V27       V28  Amount  Class
0  0.066928  0.128539 -0.189115  0.133558 -0.021053  149.62    '0'
1 -0.339846  0.167170  0.125895 -0.008983  0.014724    2.69    '0'
2 -0.689281 -0.327642 -0.139097 -0.055353 -0.059752  378.66    '0'
3 -1.175575  0.647376 -0.221929  0.062723  0.061458  123.50    '0'
4  0.141267 -0.206010  0.502292  0.219422  0.215153   69.99    '0'

[5 rows x 31 columns]
```

[186]:

```python
# Transformation 4. Identify any duplicate rows

fraud_data_web_duplicates = fraud_data_web[fraud_data_web.
 ↪duplicated(subset=fraud_data_web.columns[:-1], keep=False)]
print(fraud_data_web_duplicates)
```

```
                      Time        V1        V2        V3        V4        V5  \
32     1970-01-01 00:00:26 -0.529912  0.873892  1.347247  0.145457  0.414209
33     1970-01-01 00:00:26 -0.529912  0.873892  1.347247  0.145457  0.414209
34     1970-01-01 00:00:26 -0.535388  0.865268  1.351076  0.147575  0.433680
35     1970-01-01 00:00:26 -0.535388  0.865268  1.351076  0.147575  0.433680
112    1970-01-01 00:01:14  1.038370  0.127486  0.184456  1.109950  0.441699
...                    ...       ...       ...       ...       ...       ...
283485 1970-01-02 23:40:27 -1.457978  1.378203  0.811515 -0.603760 -0.711883
284190 1970-01-02 23:50:33 -2.667936  3.160505 -3.355984  1.007845 -0.377397
284191 1970-01-02 23:50:33 -2.667936  3.160505 -3.355984  1.007845 -0.377397
284192 1970-01-02 23:50:33 -2.691642  3.123168 -3.339407  1.017018 -0.293095
284193 1970-01-02 23:50:33 -2.691642  3.123168 -3.339407  1.017018 -0.293095

              V6        V7        V8        V9  ...       V21       V22  \
32      0.100223  0.711206  0.176066 -0.286717  ...  0.046949  0.208105
33      0.100223  0.711206  0.176066 -0.286717  ...  0.046949  0.208105
34      0.086983  0.693039  0.179742 -0.285642  ...  0.049526  0.206537
35      0.086983  0.693039  0.179742 -0.285642  ...  0.049526  0.206537
112     0.945283 -0.036715  0.350995  0.118950  ...  0.102520  0.605089
...          ...       ...       ...       ...  ...       ...       ...
283485 -0.471672 -0.282535  0.880654  0.052808  ...  0.284205  0.949659
284190 -0.109730 -0.667233  2.309700 -1.639306  ...  0.391483  0.266536
284191 -0.109730 -0.667233  2.309700 -1.639306  ...  0.391483  0.266536
284192 -0.167054 -0.745886  2.325616 -1.634651  ...  0.402639  0.259746
284193 -0.167054 -0.745886  2.325616 -1.634651  ...  0.402639  0.259746
```

```
             V23       V24       V25       V26       V27       V28  Amount  \
32     -0.185548  0.001031  0.098816 -0.552904 -0.073288  0.023307    6.14
33     -0.185548  0.001031  0.098816 -0.552904 -0.073288  0.023307    6.14
34     -0.187108  0.000753  0.098117 -0.553471 -0.078306  0.025427    1.77
35     -0.187108  0.000753  0.098117 -0.553471 -0.078306  0.025427    1.77
112     0.023092 -0.626463  0.479120 -0.166937  0.081247  0.001192    1.18
…            …         …         …         …         …         …       …
283485 -0.216949  0.083250  0.044944  0.639933  0.219432  0.116772   11.93
284190 -0.079853 -0.096395  0.086719 -0.451128 -1.183743 -0.222200   55.66
284191 -0.079853 -0.096395  0.086719 -0.451128 -1.183743 -0.222200   55.66
284192 -0.086606 -0.097597  0.083693 -0.453584 -1.205466 -0.213020   36.74
284193 -0.086606 -0.097597  0.083693 -0.453584 -1.205466 -0.213020   36.74

        Class
32        '0'
33        '0'
34        '0'
35        '0'
112       '0'
…       …
283485    '0'
284190    '0'
284191    '0'
284192    '0'
284193    '0'

[1854 rows x 31 columns]
```

[187]:
```
#Transformation 3: Convert amount to a float with two decimal places

fraud_data_web['Amount'] = np.round(fraud_data_web['Amount'], 2)
fraud_data_web.head()
```

[187]:
```
                 Time        V1        V2        V3        V4        V5  \
0 1970-01-01 00:00:00 -1.359807 -0.072781  2.536347  1.378155 -0.338321
1 1970-01-01 00:00:00  1.191857  0.266151  0.166480  0.448154  0.060018
2 1970-01-01 00:00:01 -1.358354 -1.340163  1.773209  0.379780 -0.503198
3 1970-01-01 00:00:01 -0.966272 -0.185226  1.792993 -0.863291 -0.010309
4 1970-01-01 00:00:02 -1.158233  0.877737  1.548718  0.403034 -0.407193

         V6        V7        V8        V9  …       V21       V22       V23  \
0  0.462388  0.239599  0.098698  0.363787  … -0.018307  0.277838 -0.110474
1 -0.082361 -0.078803  0.085102 -0.255425  … -0.225775 -0.638672  0.101288
2  1.800499  0.791461  0.247676 -1.514654  …  0.247998  0.771679  0.909412
3  1.247203  0.237609  0.377436 -1.387024  … -0.108300  0.005274 -0.190321
4  0.095921  0.592941 -0.270533  0.817739  … -0.009431  0.798278 -0.137458
```

```
        V24       V25       V26       V27       V28  Amount  Class
0  0.066928  0.128539 -0.189115  0.133558 -0.021053  149.62    '0'
1 -0.339846  0.167170  0.125895 -0.008983  0.014724    2.69    '0'
2 -0.689281 -0.327642 -0.139097 -0.055353 -0.059752  378.66    '0'
3 -1.175575  0.647376 -0.221929  0.062723  0.061458  123.50    '0'
4  0.141267 -0.206010  0.502292  0.219422  0.215153   69.99    '0'

[5 rows x 31 columns]
```

[188]:
```python
# Transformation 5. drops all the duplicate rows in the dataset
fraud_data_web = fraud_data_web.drop_duplicates()
fraud_data_web.head()
```

[188]:
```
                 Time        V1        V2        V3        V4        V5  \
0 1970-01-01 00:00:00 -1.359807 -0.072781  2.536347  1.378155 -0.338321
1 1970-01-01 00:00:00  1.191857  0.266151  0.166480  0.448154  0.060018
2 1970-01-01 00:00:01 -1.358354 -1.340163  1.773209  0.379780 -0.503198
3 1970-01-01 00:00:01 -0.966272 -0.185226  1.792993 -0.863291 -0.010309
4 1970-01-01 00:00:02 -1.158233  0.877737  1.548718  0.403034 -0.407193

         V6        V7        V8        V9  …       V21       V22       V23  \
0  0.462388  0.239599  0.098698  0.363787  … -0.018307  0.277838 -0.110474
1 -0.082361 -0.078803  0.085102 -0.255425  … -0.225775 -0.638672  0.101288
2  1.800499  0.791461  0.247676 -1.514654  …  0.247998  0.771679  0.909412
3  1.247203  0.237609  0.377436 -1.387024  … -0.108300  0.005274 -0.190321
4  0.095921  0.592941 -0.270533  0.817739  … -0.009431  0.798278 -0.137458

        V24       V25       V26       V27       V28  Amount  Class
0  0.066928  0.128539 -0.189115  0.133558 -0.021053  149.62    '0'
1 -0.339846  0.167170  0.125895 -0.008983  0.014724    2.69    '0'
2 -0.689281 -0.327642 -0.139097 -0.055353 -0.059752  378.66    '0'
3 -1.175575  0.647376 -0.221929  0.062723  0.061458  123.50    '0'
4  0.141267 -0.206010  0.502292  0.219422  0.215153   69.99    '0'

[5 rows x 31 columns]
```

[189]:
```python
# Transformation 6: Fix casing or inconsistent values

# Convert all values in the "Class" column to lowercase
fraud_data_web['Class'] = fraud_data_web['Class'].str.lower()

# Check the unique values in the "Class" column after fixing casing
print(fraud_data_web['Class'].unique())
fraud_data_web.head()
```

```
["'0'" "'1'"]
```

[189]:
```
                   Time        V1        V2        V3        V4        V5  \
0 1970-01-01 00:00:00 -1.359807 -0.072781  2.536347  1.378155 -0.338321
1 1970-01-01 00:00:00  1.191857  0.266151  0.166480  0.448154  0.060018
2 1970-01-01 00:00:01 -1.358354 -1.340163  1.773209  0.379780 -0.503198
3 1970-01-01 00:00:01 -0.966272 -0.185226  1.792993 -0.863291 -0.010309
4 1970-01-01 00:00:02 -1.158233  0.877737  1.548718  0.403034 -0.407193

         V6        V7        V8        V9  …       V21       V22       V23  \
0  0.462388  0.239599  0.098698  0.363787  … -0.018307  0.277838 -0.110474
1 -0.082361 -0.078803  0.085102 -0.255425  … -0.225775 -0.638672  0.101288
2  1.800499  0.791461  0.247676 -1.514654  …  0.247998  0.771679  0.909412
3  1.247203  0.237609  0.377436 -1.387024  … -0.108300  0.005274 -0.190321
4  0.095921  0.592941 -0.270533  0.817739  … -0.009431  0.798278 -0.137458

        V24       V25       V26       V27       V28  Amount  Class
0  0.066928  0.128539 -0.189115  0.133558 -0.021053  149.62    '0'
1 -0.339846  0.167170  0.125895 -0.008983  0.014724    2.69    '0'
2 -0.689281 -0.327642 -0.139097 -0.055353 -0.059752  378.66    '0'
3 -1.175575  0.647376 -0.221929  0.062723  0.061458  123.50    '0'
4  0.141267 -0.206010  0.502292  0.219422  0.215153   69.99    '0'

[5 rows x 31 columns]
```

[190]:
```python
### Project Milestone - 4 - Perform data transformation and/or cleansing steps␣
 ↪to your API data
```

[191]:
```python
## Import the required libraries

import pandas as pd
import json
import requests
import random
from concurrent import futures
```

[192]:
```python
# Importing the FraudValidation class from the fraudlabspro.fraudvalidation␣
 ↪module
#API : https://www.fraudlabspro.com/developer/api/screen-order?ref=apilist.fun

from fraudlabspro.fraudvalidation import FraudValidation
```

[193]:
```python
# Configure your API key
api_key = 'W7HNWZ1PGIEX6DPG1LIP8ATLEU2DB3BL'

# Set up the fraud validation object
fraud_validation = FraudValidation(api_key)
# Set up an empty list to store the results
results_list = []
```

```
fraud_data_api = pd.read_csv('fraud_results1.csv', sep=",")
fraud_data_api.head()
```

[193]:

```
  is_country_match is_high_risk_country distance_in_km distance_in_mile  \
0              NaN                    N              -                -
1              NaN                    N              -                -
2              NaN                    N              -                -
3              NaN                    N              -                -
4              NaN                    N              -                -

  ip_country   ip_continent       ip_region            ip_city  ip_latitude  \
0         CA  North America          Quebec           Montreal      45.5460
1         CH         Europe          Zurich             Zurich      47.3668
2         BR  South America  Santa Catarina  Balneario Camboriu    -26.9907
3         US  North America      California          Cupertino      37.3166
4         US  North America         Florida              Miami      25.7743

   ip_longitude  … card_subtype  fraudlabspro_score  \
0      -73.6252  …          NaN                 100
1        8.5498  …          NaN                 100
2      -48.6346  …          NaN                 100
3     -122.0465  …          NaN                 100
4      -80.1936  …          NaN                 100

  fraudlabspro_distribution  fraudlabspro_status  fraudlabspro_id  \
0                         0              APPROVE  20230521-SUAGLS
1                         0              APPROVE  20230521-VZALEO
2                         0              APPROVE  20230521-BSFT4Z
3                         0              APPROVE  20230521-HYWZZZ
4                         0              APPROVE  20230521-V8KLML

   fraudlabspro_version fraudlabspro_error_code    fraudlabspro_message  \
0                 1.5.1                     208  INVALID QUANTITY VALUE
1                 1.5.1                     208  INVALID QUANTITY VALUE
2                 1.5.1                     208  INVALID QUANTITY VALUE
3                 1.5.1                     208  INVALID QUANTITY VALUE
4                 1.5.1                     208  INVALID QUANTITY VALUE

  fraudlabspro_credits  device_id
0                  500        NaN
1                  500        NaN
2                  500        NaN
3                  500        NaN
4                  500        NaN

[5 rows x 56 columns]
```

[194]:
```python
#Data Transformation : 1 Replace Headers

# Replace Headers
new_headers = ['country_match', 'high_risk_country', 'distance_in_km', 'distance_in_mile',
               'ip_country', 'ip_continent', 'ip_region', 'ip_city', 'ip_latitude', 'ip_longitude',
               'ip_timezone', 'ip_elevation', 'ip_domain', 'ip_mobile_mnc', 'ip_mobile_mcc',
               'ip_mobile_brand', 'ip_netspeed', 'ip_isp_name', 'ip_usage_type', 'free_email',
               'new_domain_name', 'domain_exists', 'proxy_ip_address', 'bin_found',
               'bin_country_match', 'bin_name_match', 'bin_phone_match',
               'bin_phone_country_match', 'bin_prepaid', 'address_ship_forward',
               'bill_ship_city_match', 'bill_ship_state_match', 'bill_ship_country_match',
               'is_bill_ship_postal_match', 'is_ship_address_blacklist', 'is_phone_blacklist',
               'ip_blacklist', 'email_blacklist', 'credit_card_blacklist',
               'device_blacklist', 'user_blacklist', 'high_risk_username',
               'export_controlled_country', 'malware_exploit', 'user_order_id', 'user_order_memo',
               'card_subtype', 'fraudlabspro_score', 'fraudlabspro_distribution', 'fraudlabspro_status',
               'fraudlabspro_id', 'fraudlabspro_version', 'fraudlabspro_error_code', 'fraudlabspro_message',
               'fraudlabspro_credits', 'device_id']

fraud_data_api.columns = new_headers
fraud_data_api.head()
```

[194]:
```
  country_match high_risk_country distance_in_km distance_in_mile ip_country  \
0           NaN                 N              -                -         CA
1           NaN                 N              -                -         CH
2           NaN                 N              -                -         BR
3           NaN                 N              -                -         US
4           NaN                 N              -                -         US

    ip_continent       ip_region            ip_city  ip_latitude  \
0  North America          Quebec           Montreal      45.5460
1         Europe          Zurich             Zurich      47.3668
2  South America  Santa Catarina  Balneario Camboriu    -26.9907
3  North America      California          Cupertino      37.3166
4  North America         Florida              Miami      25.7743
```

```
   ip_longitude  … card_subtype  fraudlabspro_score  \
0      -73.6252  …          NaN                 100
1        8.5498  …          NaN                 100
2      -48.6346  …          NaN                 100
3     -122.0465  …          NaN                 100
4      -80.1936  …          NaN                 100

  fraudlabspro_distribution  fraudlabspro_status  fraudlabspro_id  \
0                         0              APPROVE  20230521-SUAGLS
1                         0              APPROVE  20230521-VZALEO
2                         0              APPROVE  20230521-BSFT4Z
3                         0              APPROVE  20230521-HYWZZZ
4                         0              APPROVE  20230521-V8KLML

   fraudlabspro_version fraudlabspro_error_code    fraudlabspro_message  \
0                 1.5.1                     208  INVALID QUANTITY VALUE
1                 1.5.1                     208  INVALID QUANTITY VALUE
2                 1.5.1                     208  INVALID QUANTITY VALUE
3                 1.5.1                     208  INVALID QUANTITY VALUE
4                 1.5.1                     208  INVALID QUANTITY VALUE

  fraudlabspro_credits  device_id
0                  500        NaN
1                  500        NaN
2                  500        NaN
3                  500        NaN
4                  500        NaN

[5 rows x 56 columns]
```

[195]:
```python
#Data Transformation : 2 # Format data into a more readable format

# Format data into a more readable format
fraud_data_api['distance_in_km'] = fraud_data_api['distance_in_km'].
 ↪replace('-', 0).astype(float)
fraud_data_api['distance_in_mile'] = fraud_data_api['distance_in_mile'].
 ↪replace('-', 0).astype(float)
fraud_data_api['ip_latitude'] = fraud_data_api['ip_latitude'].round(6)
fraud_data_api['ip_longitude'] = fraud_data_api['ip_longitude'].round(6)
fraud_data_api['fraudlabspro_score'] = fraud_data_api['fraudlabspro_score'].
 ↪astype(float)

fraud_data_api.head()
```

[195]:
```
   country_match high_risk_country  distance_in_km  distance_in_mile  \
0            NaN                 N             0.0               0.0
1            NaN                 N             0.0               0.0
```

```
2           NaN                  N           0.0                0.0
3           NaN                  N           0.0                0.0
4           NaN                  N           0.0                0.0

  ip_country   ip_continent       ip_region            ip_city  ip_latitude  \
0         CA  North America          Quebec           Montreal      45.5460
1         CH         Europe          Zurich             Zurich      47.3668
2         BR  South America  Santa Catarina  Balneario Camboriu     -26.9907
3         US  North America      California          Cupertino      37.3166
4         US  North America         Florida              Miami      25.7743

   ip_longitude  … card_subtype  fraudlabspro_score  \
0      -73.6252  …          NaN               100.0
1        8.5498  …          NaN               100.0
2      -48.6346  …          NaN               100.0
3     -122.0465  …          NaN               100.0
4      -80.1936  …          NaN               100.0

  fraudlabspro_distribution  fraudlabspro_status  fraudlabspro_id  \
0                         0              APPROVE  20230521-SUAGLS
1                         0              APPROVE  20230521-VZALEO
2                         0              APPROVE  20230521-BSFT4Z
3                         0              APPROVE  20230521-HYWZZZ
4                         0              APPROVE  20230521-V8KLML

   fraudlabspro_version fraudlabspro_error_code    fraudlabspro_message  \
0                 1.5.1                     208  INVALID QUANTITY VALUE
1                 1.5.1                     208  INVALID QUANTITY VALUE
2                 1.5.1                     208  INVALID QUANTITY VALUE
3                 1.5.1                     208  INVALID QUANTITY VALUE
4                 1.5.1                     208  INVALID QUANTITY VALUE

  fraudlabspro_credits  device_id
0                  500        NaN
1                  500        NaN
2                  500        NaN
3                  500        NaN
4                  500        NaN

[5 rows x 56 columns]
```

[196]:
```
#Data Transformation : 3 # Find duplicates
duplicates = fraud_data_api.duplicated()
fraud_data_api = fraud_data_api[~duplicates]

fraud_data_api.head()
```

```python
#Data Transformatio : 4 # Remove duplicate rows
fraud_data_api.drop_duplicates(inplace=True)
fraud_data_api.head()
```

[196]:

```
  country_match high_risk_country  distance_in_km  distance_in_mile  \
0           NaN                 N             0.0               0.0
1           NaN                 N             0.0               0.0
2           NaN                 N             0.0               0.0
3           NaN                 N             0.0               0.0
4           NaN                 N             0.0               0.0

  ip_country    ip_continent      ip_region             ip_city  ip_latitude  \
0         CA  North America          Quebec            Montreal      45.5460
1         CH         Europe          Zurich              Zurich      47.3668
2         BR  South America  Santa Catarina  Balneario Camboriu     -26.9907
3         US  North America      California           Cupertino      37.3166
4         US  North America         Florida               Miami      25.7743

   ip_longitude  … card_subtype  fraudlabspro_score  \
0      -73.6252  …          NaN               100.0
1        8.5498  …          NaN               100.0
2      -48.6346  …          NaN               100.0
3     -122.0465  …          NaN               100.0
4      -80.1936  …          NaN               100.0

  fraudlabspro_distribution  fraudlabspro_status  fraudlabspro_id  \
0                         0              APPROVE  20230521-SUAGLS
1                         0              APPROVE  20230521-VZALEO
2                         0              APPROVE  20230521-BSFT4Z
3                         0              APPROVE  20230521-HYWZZZ
4                         0              APPROVE  20230521-V8KLML

   fraudlabspro_version fraudlabspro_error_code    fraudlabspro_message  \
0                 1.5.1                     208  INVALID QUANTITY VALUE
1                 1.5.1                     208  INVALID QUANTITY VALUE
2                 1.5.1                     208  INVALID QUANTITY VALUE
3                 1.5.1                     208  INVALID QUANTITY VALUE
4                 1.5.1                     208  INVALID QUANTITY VALUE

  fraudlabspro_credits  device_id
0                  500        NaN
1                  500        NaN
2                  500        NaN
3                  500        NaN
4                  500        NaN

[5 rows x 56 columns]
```

[197]:
```python
#Data Transformation : 5 # Replace missing values in specific columns

fraud_data_api['country_match'].fillna('Unknown', inplace=True)
fraud_data_api['ip_country'].fillna('Unknown', inplace=True)
fraud_data_api.head()
```

[197]:
```
  country_match high_risk_country  distance_in_km  distance_in_mile  \
0       Unknown                 N             0.0               0.0
1       Unknown                 N             0.0               0.0
2       Unknown                 N             0.0               0.0
3       Unknown                 N             0.0               0.0
4       Unknown                 N             0.0               0.0

  ip_country   ip_continent       ip_region            ip_city  ip_latitude  \
0         CA  North America          Quebec           Montreal      45.5460
1         CH         Europe          Zurich             Zurich      47.3668
2         BR  South America  Santa Catarina  Balneario Camboriu     -26.9907
3         US  North America      California          Cupertino      37.3166
4         US  North America         Florida              Miami      25.7743

   ip_longitude  … card_subtype  fraudlabspro_score  \
0      -73.6252  …          NaN               100.0
1        8.5498  …          NaN               100.0
2      -48.6346  …          NaN               100.0
3     -122.0465  …          NaN               100.0
4      -80.1936  …          NaN               100.0

  fraudlabspro_distribution  fraudlabspro_status  fraudlabspro_id  \
0                         0              APPROVE  20230521-SUAGLS
1                         0              APPROVE  20230521-VZALEO
2                         0              APPROVE  20230521-BSFT4Z
3                         0              APPROVE  20230521-HYWZZZ
4                         0              APPROVE  20230521-V8KLML

   fraudlabspro_version fraudlabspro_error_code    fraudlabspro_message  \
0                 1.5.1                     208  INVALID QUANTITY VALUE
1                 1.5.1                     208  INVALID QUANTITY VALUE
2                 1.5.1                     208  INVALID QUANTITY VALUE
3                 1.5.1                     208  INVALID QUANTITY VALUE
4                 1.5.1                     208  INVALID QUANTITY VALUE

  fraudlabspro_credits  device_id
0                  500        NaN
1                  500        NaN
2                  500        NaN
3                  500        NaN
4                  500        NaN
```

```
[5 rows x 56 columns]
```

[198]:
```
#Data Transformation : 6 # Drop rows with missing or empty values in␣
↪ip_country, ip_region, and ip_city columns
fraud_data_api.dropna(subset=['ip_country', 'ip_region', 'ip_city'],␣
↪inplace=True)
fraud_data_api.head()

#Data Transformatio : 6 # Drop rows with '-' values in ip_country, ip_region,␣
↪and ip_city columns
fraud_data_api = fraud_data_api[(fraud_data_api['ip_country'] != '-') &␣
↪(fraud_data_api['ip_region'] != '-') & (fraud_data_api['ip_city'] != '-')]
fraud_data_api.head()
```

[198]:
```
  country_match high_risk_country  distance_in_km  distance_in_mile  \
0       Unknown                 N             0.0               0.0
1       Unknown                 N             0.0               0.0
2       Unknown                 N             0.0               0.0
3       Unknown                 N             0.0               0.0
4       Unknown                 N             0.0               0.0

  ip_country   ip_continent       ip_region            ip_city  ip_latitude  \
0         CA  North America          Quebec           Montreal      45.5460
1         CH         Europe          Zurich             Zurich      47.3668
2         BR  South America  Santa Catarina  Balneario Camboriu     -26.9907
3         US  North America      California          Cupertino      37.3166
4         US  North America         Florida              Miami      25.7743

   ip_longitude  … card_subtype  fraudlabspro_score  \
0      -73.6252  …          NaN               100.0
1        8.5498  …          NaN               100.0
2      -48.6346  …          NaN               100.0
3     -122.0465  …          NaN               100.0
4      -80.1936  …          NaN               100.0

  fraudlabspro_distribution  fraudlabspro_status  fraudlabspro_id  \
0                         0              APPROVE  20230521-SUAGLS
1                         0              APPROVE  20230521-VZALEO
2                         0              APPROVE  20230521-BSFT4Z
3                         0              APPROVE  20230521-HYWZZZ
4                         0              APPROVE  20230521-V8KLML

   fraudlabspro_version fraudlabspro_error_code    fraudlabspro_message  \
0                 1.5.1                     208  INVALID QUANTITY VALUE
1                 1.5.1                     208  INVALID QUANTITY VALUE
2                 1.5.1                     208  INVALID QUANTITY VALUE
```

```
3                1.5.1                     208  INVALID QUANTITY VALUE
4                1.5.1                     208  INVALID QUANTITY VALUE

  fraudlabspro_credits  device_id
0                  500        NaN
1                  500        NaN
2                  500        NaN
3                  500        NaN
4                  500        NaN

[5 rows x 56 columns]
```

[199]:
```python
#Data Transformatio : 7 # Fix casing or inconsistent values
fraud_data_api['ip_country'] = fraud_data_api['ip_country'].str.upper()
fraud_data_api.head()
```

[199]:
```
  country_match high_risk_country  distance_in_km  distance_in_mile  \
0       Unknown                 N             0.0               0.0
1       Unknown                 N             0.0               0.0
2       Unknown                 N             0.0               0.0
3       Unknown                 N             0.0               0.0
4       Unknown                 N             0.0               0.0

  ip_country   ip_continent       ip_region            ip_city  ip_latitude  \
0         CA  North America          Quebec           Montreal      45.5460
1         CH         Europe          Zurich             Zurich      47.3668
2         BR  South America  Santa Catarina  Balneario Camboriu     -26.9907
3         US  North America      California          Cupertino      37.3166
4         US  North America         Florida              Miami      25.7743

   ip_longitude  … card_subtype  fraudlabspro_score  \
0      -73.6252  …          NaN               100.0
1        8.5498  …          NaN               100.0
2      -48.6346  …          NaN               100.0
3     -122.0465  …          NaN               100.0
4      -80.1936  …          NaN               100.0

  fraudlabspro_distribution  fraudlabspro_status  fraudlabspro_id  \
0                         0              APPROVE  20230521-SUAGLS
1                         0              APPROVE  20230521-VZALEO
2                         0              APPROVE  20230521-BSFT4Z
3                         0              APPROVE  20230521-HYWZZZ
4                         0              APPROVE  20230521-V8KLML

   fraudlabspro_version fraudlabspro_error_code    fraudlabspro_message  \
0                 1.5.1                     208  INVALID QUANTITY VALUE
1                 1.5.1                     208  INVALID QUANTITY VALUE
```

```
2                 1.5.1                          208  INVALID QUANTITY VALUE
3                 1.5.1                          208  INVALID QUANTITY VALUE
4                 1.5.1                          208  INVALID QUANTITY VALUE

  fraudlabspro_credits  device_id
0                  500        NaN
1                  500        NaN
2                  500        NaN
3                  500        NaN
4                  500        NaN

[5 rows x 56 columns]
```

[200]:

```python
#Data Transformatio : 8 # Reset the index after dropping rows

fraud_data_api.reset_index(drop=True, inplace=True)
fraud_data_api.rename(columns={'index': 'Index_ID'}, inplace=True)
fraud_data_api.head()
```

[200]:

```
  country_match high_risk_country  distance_in_km  distance_in_mile  \
0       Unknown                 N             0.0               0.0
1       Unknown                 N             0.0               0.0
2       Unknown                 N             0.0               0.0
3       Unknown                 N             0.0               0.0
4       Unknown                 N             0.0               0.0

  ip_country   ip_continent       ip_region            ip_city  ip_latitude  \
0         CA  North America          Quebec           Montreal      45.5460
1         CH         Europe          Zurich             Zurich      47.3668
2         BR  South America  Santa Catarina  Balneario Camboriu     -26.9907
3         US  North America      California          Cupertino      37.3166
4         US  North America         Florida              Miami      25.7743

   ip_longitude  … card_subtype  fraudlabspro_score  \
0      -73.6252  …          NaN               100.0
1        8.5498  …          NaN               100.0
2      -48.6346  …          NaN               100.0
3     -122.0465  …          NaN               100.0
4      -80.1936  …          NaN               100.0

  fraudlabspro_distribution  fraudlabspro_status  fraudlabspro_id  \
0                         0              APPROVE  20230521-SUAGLS
1                         0              APPROVE  20230521-VZALEO
2                         0              APPROVE  20230521-BSFT4Z
3                         0              APPROVE  20230521-HYWZZZ
4                         0              APPROVE  20230521-V8KLML
```

```
   fraudlabspro_version fraudlabspro_error_code    fraudlabspro_message  \
0                 1.5.1                     208  INVALID QUANTITY VALUE
1                 1.5.1                     208  INVALID QUANTITY VALUE
2                 1.5.1                     208  INVALID QUANTITY VALUE
3                 1.5.1                     208  INVALID QUANTITY VALUE
4                 1.5.1                     208  INVALID QUANTITY VALUE

  fraudlabspro_credits  device_id
0                  500        NaN
1                  500        NaN
2                  500        NaN
3                  500        NaN
4                  500        NaN

[5 rows x 56 columns]
```

2 Project Milestone - 5 - Merging the Data and Storing in a Database/Visualizing Data

[201]:
```python
import sqlite3 as sql
```

[202]:
```python
conn = sql.connect("frauddata2.db")
```

[203]:
```python
c = conn.cursor()
#  function to make sure the connection is successful
c.execute("SELECT name FROM sqlite_master WHERE type='table';")
print(c.fetchall())
```

```
[]
```

[204]:
```python
#Inserting the flat file data frame into SQLite

fraud_data_csv.to_sql('fraud_data_csv', conn)
```

[204]: 555735

[205]:
```python
#Inserting the Web data frame into SQLite

fraud_data_web.to_sql('fraud_data_web', conn)
```

[205]: 283726

[206]:
```python
#Inserting the Web data frame into SQLite

fraud_data_api.to_sql('fraud_data_api', conn)
```

[206]: 43828

[207]:
```
# Read the data for the fraud data csv

sql0_fraud_data_csv = pd.read_sql("""Select * from fraud_data_csv""",conn)
sql0_fraud_data_csv.head()
```

[207]:
```
   index  row_id trans_date_trans_time        cc_num  \
0      0       0       6/21/2020 12:14  2.291160e+15
1      1       1       6/21/2020 12:14  3.573030e+15
2      2       2       6/21/2020 12:14  3.598220e+15
3      3       3       6/21/2020 12:15  3.591920e+15
4      4       4       6/21/2020 12:15  3.526830e+15

                              merchant        category    amt    first  \
0                fraud_Kirlin and Sons   personal_care   2.86     Jeff
1                 fraud_Sporer-Keebler   personal_care  29.84   Joanne
2  fraud_Swaniawski, Nitzsche and Welch  health_fitness  41.28   Ashley
3                    fraud_Haley Group        misc_pos  60.05    Brian
4                fraud_Johnston-Casper          travel   3.19   Nathan

       last gender  …        city state    zip      lat      long  city_pop  \
0   Elliott      M  …    Columbia    SC  29209  33.9659  -80.9355    333497
1  Williams      F  …     Altonah    UT  84002  40.3207 -110.4360       302
2     Lopez      F  …    Bellmore    NY  11710  40.6729  -73.5365     34496
3  Williams      M  …  Titusville    FL  32780  28.5697  -80.8191     54767
4    Massey      M  …    Falmouth    MI  49632  44.2529  -85.0170      1126

                    job         dob            unix_time is_fraud
0    Mechanical engineer   3/19/1968  2013-06-21 12:14:25        0
1  Sales professional, IT   1/17/1990  2013-06-21 12:14:33        0
2      Librarian, public  10/21/1970  2013-06-21 12:14:53        0
3           Set designer   7/25/1987  2013-06-21 12:15:15        0
4     Furniture designer    7/6/1955  2013-06-21 12:15:17        0

[5 rows x 21 columns]
```

[208]:
```
# Read the data for the fraud data web

sql1_fraud_data_web = pd.read_sql("""Select * from fraud_data_web""",conn)
sql1_fraud_data_web.head()
```

[208]:
```
   index                 Time        V1        V2        V3        V4  \
0      0  1970-01-01 00:00:00 -1.359807 -0.072781  2.536347  1.378155
1      1  1970-01-01 00:00:00  1.191857  0.266151  0.166480  0.448154
2      2  1970-01-01 00:00:01 -1.358354 -1.340163  1.773209  0.379780
3      3  1970-01-01 00:00:01 -0.966272 -0.185226  1.792993 -0.863291
4      4  1970-01-01 00:00:02 -1.158233  0.877737  1.548718  0.403034
```

```
         V5        V6        V7        V8  ...       V21       V22       V23  \
0 -0.338321  0.462388  0.239599  0.098698  ... -0.018307  0.277838 -0.110474
1  0.060018 -0.082361 -0.078803  0.085102  ... -0.225775 -0.638672  0.101288
2 -0.503198  1.800499  0.791461  0.247676  ...  0.247998  0.771679  0.909412
3 -0.010309  1.247203  0.237609  0.377436  ... -0.108300  0.005274 -0.190321
4 -0.407193  0.095921  0.592941 -0.270533  ... -0.009431  0.798278 -0.137458

        V24       V25       V26       V27       V28  Amount  Class
0  0.066928  0.128539 -0.189115  0.133558 -0.021053  149.62    '0'
1 -0.339846  0.167170  0.125895 -0.008983  0.014724    2.69    '0'
2 -0.689281 -0.327642 -0.139097 -0.055353 -0.059752  378.66    '0'
3 -1.175575  0.647376 -0.221929  0.062723  0.061458  123.50    '0'
4  0.141267 -0.206010  0.502292  0.219422  0.215153   69.99    '0'

[5 rows x 32 columns]
```

[209]:
```
# Read the data for the fraud data API

sql2_fraud_data_api = pd.read_sql("""Select * from fraud_data_api""",conn)
sql2_fraud_data_api.head()
```

[209]:
```
   index country_match high_risk_country  distance_in_km  distance_in_mile  \
0      0       Unknown                 N             0.0               0.0
1      1       Unknown                 N             0.0               0.0
2      2       Unknown                 N             0.0               0.0
3      3       Unknown                 N             0.0               0.0
4      4       Unknown                 N             0.0               0.0

  ip_country   ip_continent       ip_region            ip_city  ip_latitude  \
0         CA  North America          Quebec           Montreal      45.5460
1         CH         Europe          Zurich             Zurich      47.3668
2         BR  South America  Santa Catarina  Balneario Camboriu     -26.9907
3         US  North America      California          Cupertino      37.3166
4         US  North America         Florida              Miami      25.7743

   ... card_subtype fraudlabspro_score  fraudlabspro_distribution  \
0  ...         None              100.0                          0
1  ...         None              100.0                          0
2  ...         None              100.0                          0
3  ...         None              100.0                          0
4  ...         None              100.0                          0

  fraudlabspro_status  fraudlabspro_id fraudlabspro_version  \
0             APPROVE  20230521-SUAGLS                1.5.1
1             APPROVE  20230521-VZALEO                1.5.1
2             APPROVE  20230521-BSFT4Z                1.5.1
3             APPROVE  20230521-HYWZZZ                1.5.1
```

```
4             APPROVE  20230521-V8KLML                1.5.1

  fraudlabspro_error_code    fraudlabspro_message fraudlabspro_credits  \
0                      208  INVALID QUANTITY VALUE                  500
1                      208  INVALID QUANTITY VALUE                  500
2                      208  INVALID QUANTITY VALUE                  500
3                      208  INVALID QUANTITY VALUE                  500
4                      208  INVALID QUANTITY VALUE                  500

  device_id
0      None
1      None
2      None
3      None
4      None

[5 rows x 57 columns]
```

[210]:

```python
# Merge the data from both sources based on a common column
merged_fraud_data = pd.concat([fraud_data_csv, fraud_data_web, fraud_data_api],␣
↪axis=1)


# Create the "merged_fraud_data" table in the database
merged_fraud_data.to_sql('merged_fraud_data', conn, if_exists='replace')

# Read the merged data from the database
sql4_merged_fraud_data = pd.read_sql("SELECT * FROM merged_fraud_data", conn)
sql4_merged_fraud_data.head()
```

[210]:

```
   index  row_id trans_date_trans_time        cc_num  \
0      0       0       6/21/2020 12:14  2.291160e+15
1      1       1       6/21/2020 12:14  3.573030e+15
2      2       2       6/21/2020 12:14  3.598220e+15
3      3       3       6/21/2020 12:15  3.591920e+15
4      4       4       6/21/2020 12:15  3.526830e+15

                              merchant        category    amt    first  \
0                fraud_Kirlin and Sons   personal_care   2.86     Jeff
1                 fraud_Sporer-Keebler   personal_care  29.84   Joanne
2  fraud_Swaniawski, Nitzsche and Welch  health_fitness  41.28   Ashley
3                    fraud_Haley Group        misc_pos  60.05    Brian
4                fraud_Johnston-Casper          travel   3.19   Nathan

      last gender  … card_subtype fraudlabspro_score  \
0  Elliott      M  …         None              100.0
1 Williams      F  …         None              100.0
```

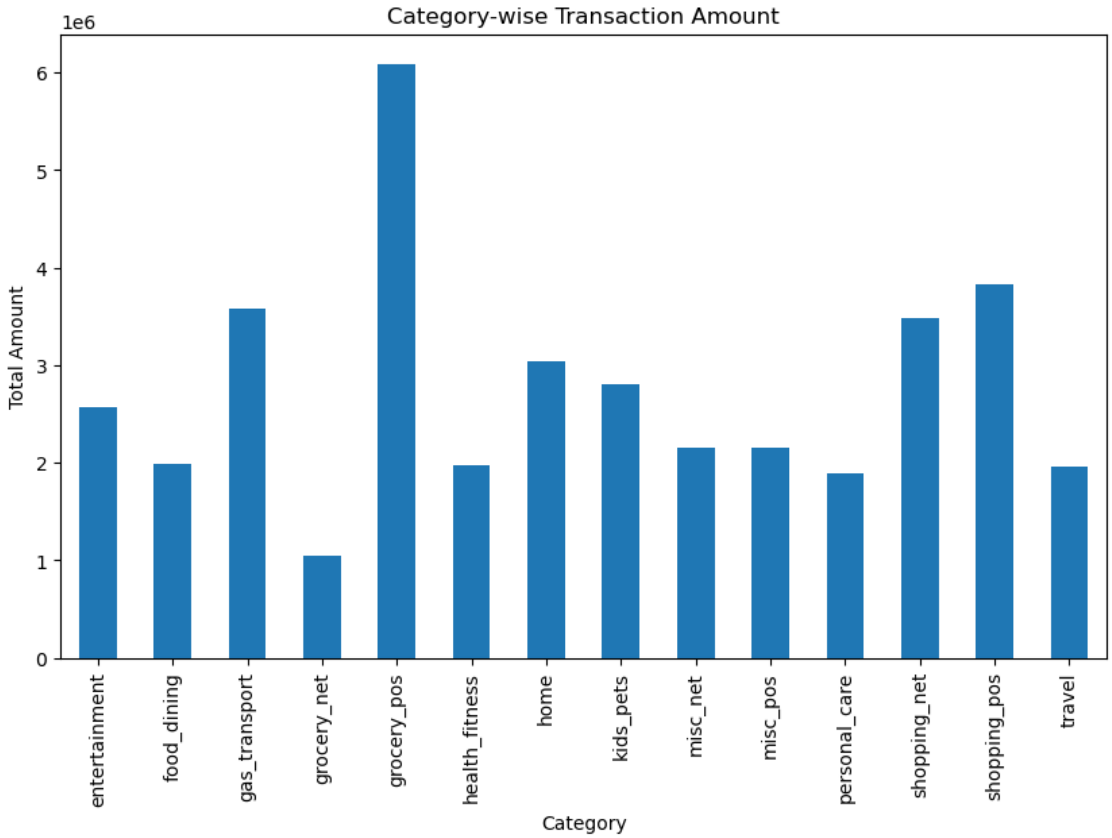
```
2     Lopez       F  …          None              100.0
3  Williams       M  …          None              100.0
4    Massey       M  …          None              100.0

  fraudlabspro_distribution  fraudlabspro_status  fraudlabspro_id  \
0                       0.0              APPROVE  20230521-SUAGLS
1                       0.0              APPROVE  20230521-VZALEO
2                       0.0              APPROVE  20230521-BSFT4Z
3                       0.0              APPROVE  20230521-HYWZZZ
4                       0.0              APPROVE  20230521-V8KLML

   fraudlabspro_version  fraudlabspro_error_code    fraudlabspro_message  \
0                 1.5.1                    208.0  INVALID QUANTITY VALUE
1                 1.5.1                    208.0  INVALID QUANTITY VALUE
2                 1.5.1                    208.0  INVALID QUANTITY VALUE
3                 1.5.1                    208.0  INVALID QUANTITY VALUE
4                 1.5.1                    208.0  INVALID QUANTITY VALUE

  fraudlabspro_credits device_id
0                500.0      None
1                500.0      None
2                500.0      None
3                500.0      None
4                500.0      None

[5 rows x 108 columns]
```

[211]:
```
# load the necessary libraries
import matplotlib.pyplot as plt
```

2.0.1 This bar plot visualizes the total transaction amount for each category. The x-axis represents the categories, while the y-axis represents the total transaction amount. Each bar corresponds to a category, and its height represents the total amount associated with that category. The accompanying labels provide the category names, and the y-axis label denotes the unit of measurement for the total amount.

[212]:
```
## Visualization 1
## Bar Plot: Category-wise Transaction Amount

# Group data by category and calculate the total transaction amount
category_amount = merged_fraud_data.groupby('category')['amt'].sum()

# Plot the bar chart
plt.figure(figsize=(10, 6))
category_amount.plot(kind='bar')
plt.xlabel('Category')
```

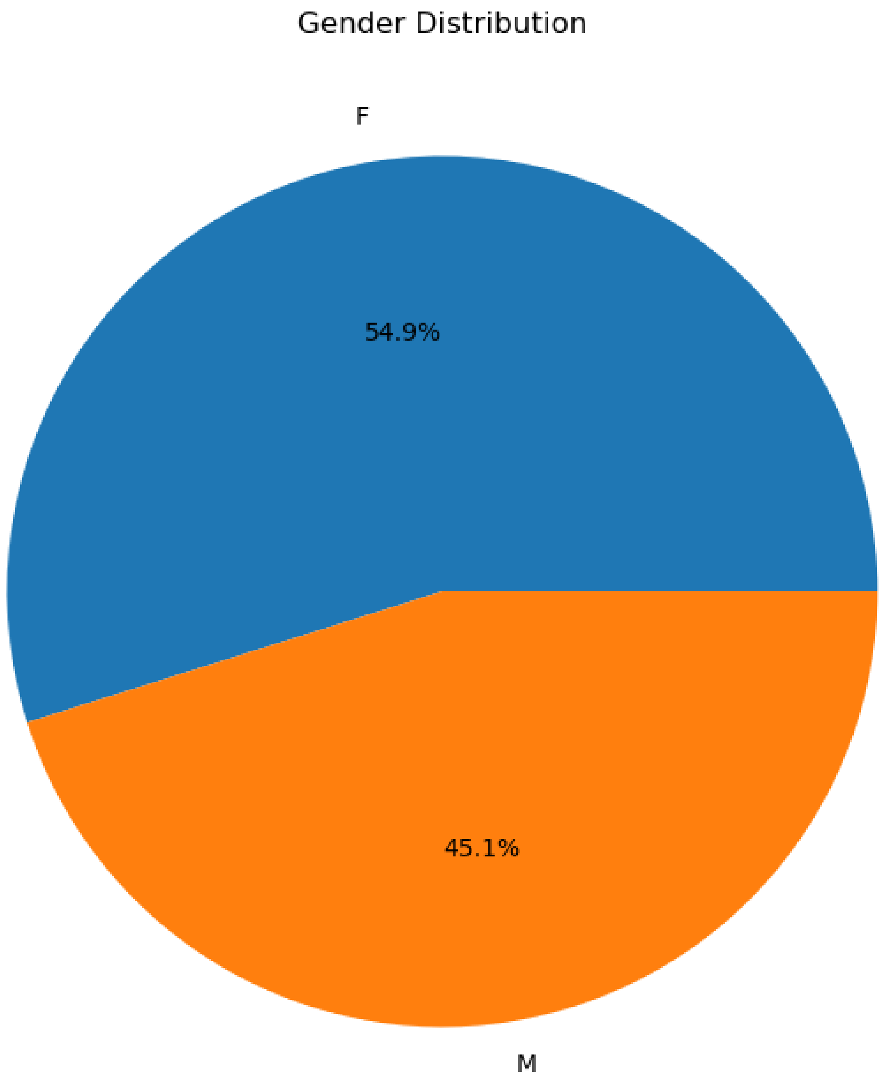
```
plt.ylabel('Total Amount')
plt.title('Category-wise Transaction Amount')
plt.show()
```



2.0.2 This pie chart visualizes the distribution of transactions by gender. Each slice of the pie represents a gender category, and its size corresponds to the proportion of transactions associated with that gender. The accompanying labels display the gender categories, and the percentages represent the relative frequency of each gender category within the dataset.

[213]:
```
## Visualization 2
## Pie Chart: Gender Distribution

# Count the number of transactions by gender
gender_counts = merged_fraud_data['gender'].value_counts()

# Plot the pie chart
plt.figure(figsize=(8, 8))
plt.pie(gender_counts, labels=gender_counts.index, autopct='%1.1f%%')
plt.title('Gender Distribution')
```

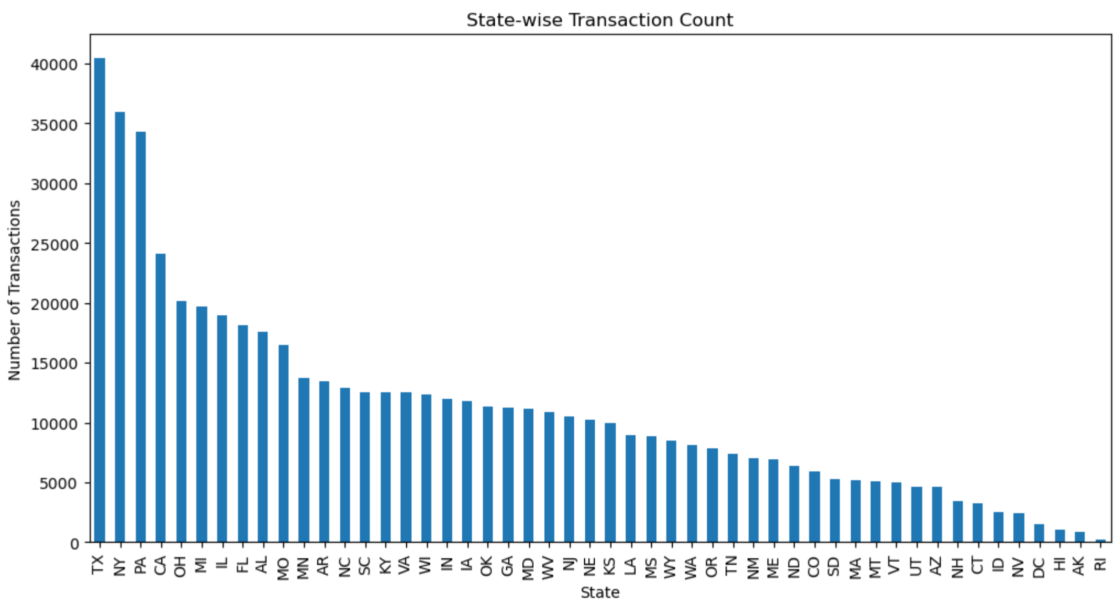
```
plt.show()
```



2.0.3 This bar plot visualizes the number of transactions for each state. The x-axis represents the states, and the y-axis represents the count of transactions. Each bar represents a state, and its height represents the number of transactions associated with that state.

[214]:
```
## Visualization 3
## Bar Plot: State-wise Transaction Count

# Count the number of transactions by state
state_counts = merged_fraud_data['state'].value_counts()
```

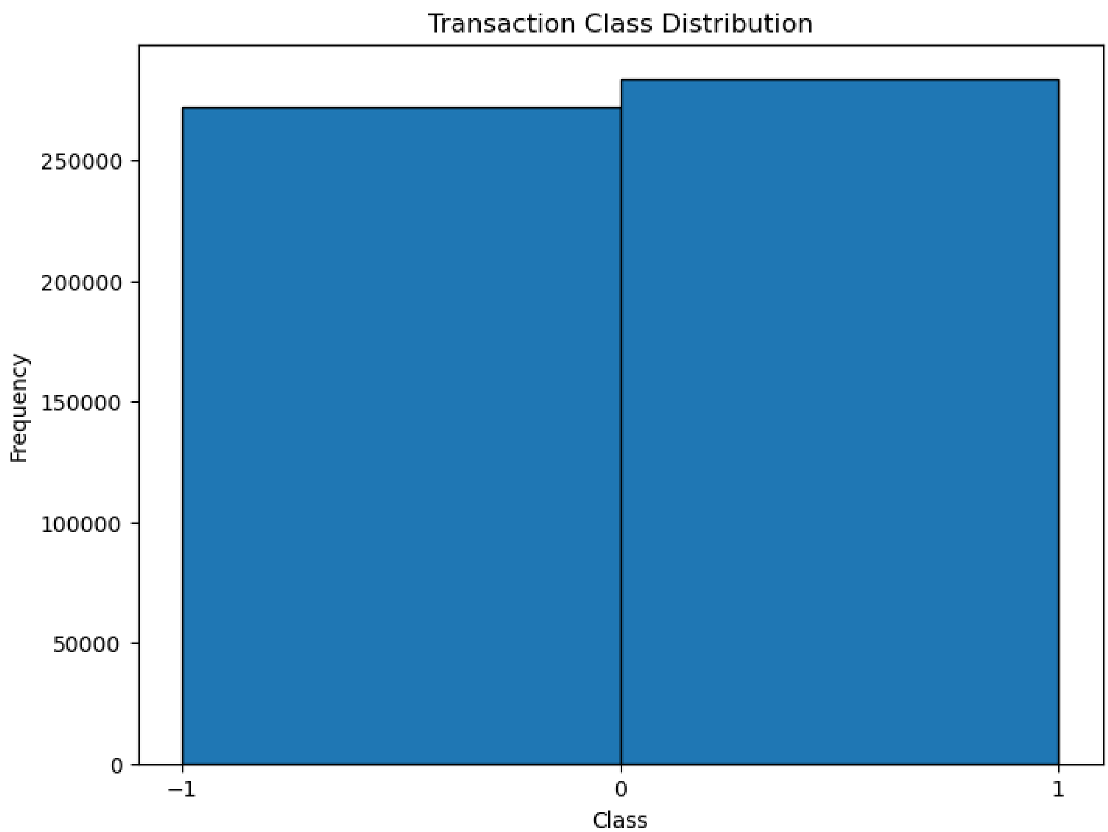
```
# Plot the bar chart
plt.figure(figsize=(12, 6))
state_counts.plot(kind='bar')
plt.xlabel('State')
plt.ylabel('Number of Transactions')
plt.title('State-wise Transaction Count')
plt.show()
```



2.0.4 This histogram visualizes the distribution of transaction classes. The x-axis represents the classes, where -1 indicates missing values, 0 represents non-fraud transactions, and 1 represents fraud transactions. The y-axis represents the frequency or count of transactions in each class.

[215]:
```
## Visualization 4
## Histogram: Transaction Class Distribution

# Remove the quotes from the 'Class' column
merged_fraud_data['Class'] = merged_fraud_data['Class'].str.replace("'", "")

# Convert the 'Class' column to float type
merged_fraud_data['Class'] = merged_fraud_data['Class'].astype(float)

# Replace missing values with a value that represents them (e.g., -1)
merged_fraud_data['Class'].fillna(-1, inplace=True)

# Convert the 'Class' column to integer type
```

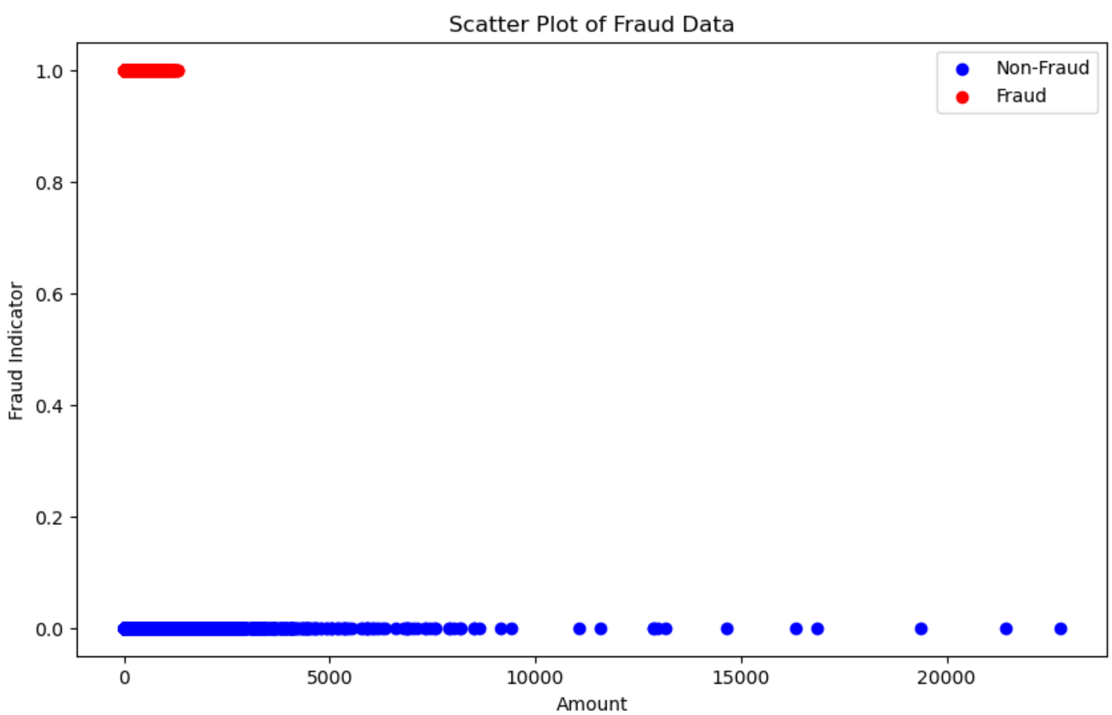
```
merged_fraud_data['Class'] = merged_fraud_data['Class'].astype(int)

# Plot the histogram of transaction class
plt.figure(figsize=(8, 6))
plt.hist(merged_fraud_data['Class'], bins=np.arange(-1, 2), edgecolor='black')
plt.xlabel('Class')
plt.ylabel('Frequency')
plt.title('Transaction Class Distribution')
plt.xticks([-1, 0, 1])
plt.show()
```



2.0.5 This scatter plot visualizes the distribution of fraud and non-fraud transactions based on their corresponding amounts. The blue points represent non-fraud transactions, while the red points represent fraud transactions.

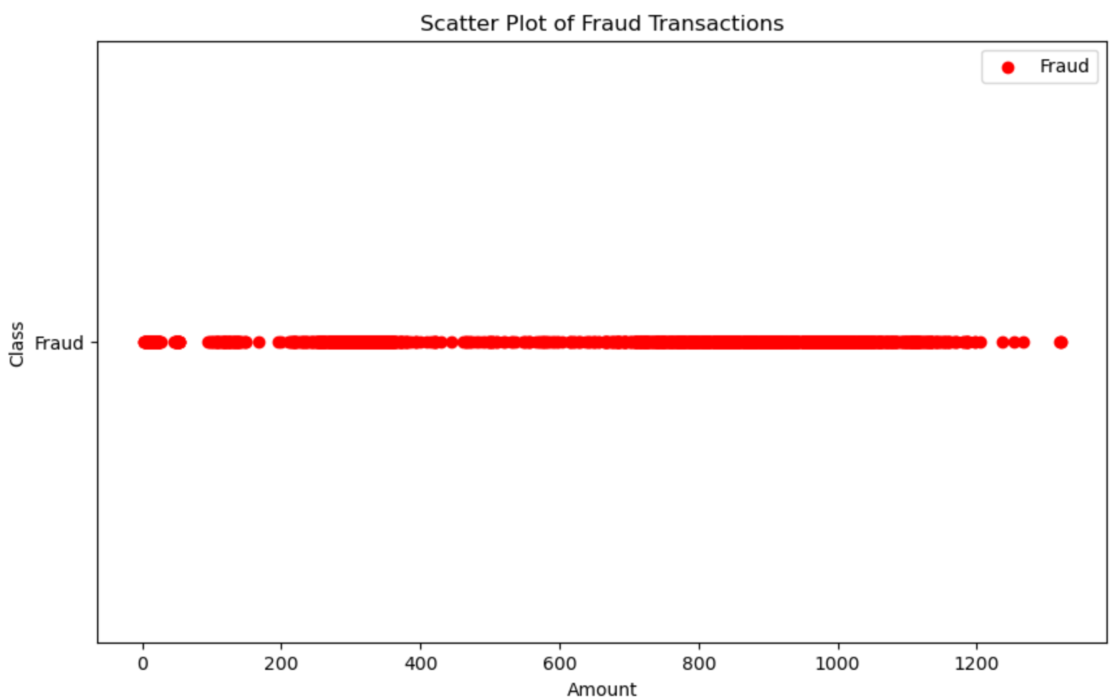
[216]:
```
## Visualization 5
## Scatter Plot: Fraud Vs Non Fraud Distribution

# Separate fraud and non-fraud transactions
fraud_transactions = merged_fraud_data[merged_fraud_data['is_fraud'] == 1]
```

```
non_fraud_transactions = merged_fraud_data[merged_fraud_data['is_fraud'] == 0]

# Create scatter plot
plt.figure(figsize=(10, 6))
plt.scatter(non_fraud_transactions['amt'], non_fraud_transactions['is_fraud'],
    color='blue', label='Non-Fraud')
plt.scatter(fraud_transactions['amt'], fraud_transactions['is_fraud'],
    color='red', label='Fraud')

# Add labels and title
plt.xlabel('Amount')
plt.ylabel('Fraud Indicator')
plt.title('Scatter Plot of Fraud Data')

# Add legend
plt.legend()

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



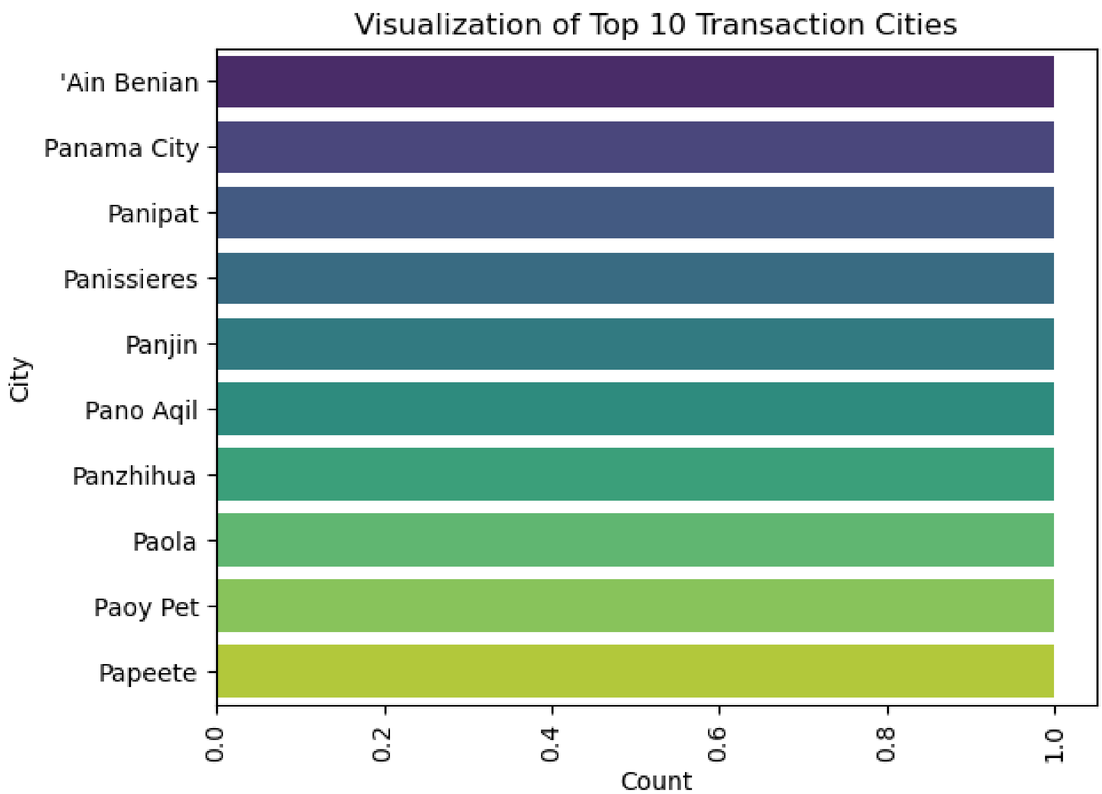
2.0.6 This Visualization refers select the amt column as the x-axis representing the transaction amount and use the 'Fraud' label as the y-axis representing the class of the transaction. We filter the data to include only fraud transactions by using the is_fraud column. The scatter plot will show the distribution of fraud transactions based on their amounts.

[217]:
```python
## Visualization 6 - Multiple Data Sources

## Read the data from the database using a UNION query
fraud_data = pd.read_sql("""
    SELECT amt, 'Fraud' AS class
    FROM fraud_data_csv
    WHERE is_fraud = 1
    UNION
    SELECT Amount, 'Fraud' AS class
    FROM fraud_data_web
    WHERE class = 1
""", conn)

# Create the scatter plot
plt.figure(figsize=(10, 6))
plt.scatter(fraud_data['amt'], fraud_data['class'], color='red', label='Fraud')
plt.xlabel('Amount')
plt.ylabel('Class')
plt.title('Scatter Plot of Fraud Transactions')
plt.legend()
plt.show()
```



2.0.7 This visualization shows the top cities with the highest transaction counts. It helps identify the cities where the most transactions occur, providing a quick overview of the geographic distribution of transactions in the dataset.

[218]:
```
## Visualization 7 - Multiple Data Sources
import seaborn as sns

# Define the number of top cities to show
N = 10  # Example: Show top 10 cities

# Retrieve the data using a UNION query
combined_data = pd.read_sql("""
    SELECT city FROM fraud_data_CSV
    UNION
    SELECT ip_city FROM fraud_data_API
""", conn)

# Get the top N cities with the highest transaction counts
top_cities = combined_data['city'].value_counts().nlargest(N)

# Plot the data for the top cities
sns.countplot(data=combined_data[combined_data['city'].isin(top_cities.index)],␣
 ↪y='city', palette='viridis')

# Add labels and title
plt.xlabel('Count')
plt.ylabel('City')
plt.title('Visualization of Top {} Transaction Cities'.format(N))

# Rotate x-axis labels for better visibility
plt.xticks(rotation=90)

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


Visualization of Top 10 Transaction Cities
'Ain Benian
Panama City
Panipat
Panissieres
Panjin
Pano Aqil
Panzhihua
Paola
Paoy Pet
Papeete
City
0.0
0.2
0.4
0.6
0.8
1.0
Count

[ ]: