credit_card_faud_detection

August 13, 2023

0.1 CODSOFT INTERNSHIP

varad patil

0.1.1 Adding the dataset from kaggle

[ ]:
```
!pip install kaggle
```

```
Requirement already satisfied: kaggle in /usr/local/lib/python3.10/dist-packages
(1.5.16)
Requirement already satisfied: six>=1.10 in /usr/local/lib/python3.10/dist-
packages (from kaggle) (1.16.0)
Requirement already satisfied: certifi in /usr/local/lib/python3.10/dist-
packages (from kaggle) (2023.7.22)
Requirement already satisfied: python-dateutil in
/usr/local/lib/python3.10/dist-packages (from kaggle) (2.8.2)
Requirement already satisfied: requests in /usr/local/lib/python3.10/dist-
packages (from kaggle) (2.31.0)
Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-packages
(from kaggle) (4.65.0)
Requirement already satisfied: python-slugify in /usr/local/lib/python3.10/dist-
packages (from kaggle) (8.0.1)
Requirement already satisfied: urllib3 in /usr/local/lib/python3.10/dist-
packages (from kaggle) (1.26.16)
Requirement already satisfied: bleach in /usr/local/lib/python3.10/dist-packages
(from kaggle) (6.0.0)
Requirement already satisfied: webencodings in /usr/local/lib/python3.10/dist-
packages (from bleach->kaggle) (0.5.1)
Requirement already satisfied: text-unidecode>=1.3 in
/usr/local/lib/python3.10/dist-packages (from python-slugify->kaggle) (1.3)
Requirement already satisfied: charset-normalizer<4,>=2 in
/usr/local/lib/python3.10/dist-packages (from requests->kaggle) (3.2.0)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-
packages (from requests->kaggle) (3.4)
```

[ ]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

0.1.2 make a temporary directory

[ ]:
```
import os
os.environ['KAGGLE_CONFIG_DIR'] = '/content/drive/MyDrive/Colab Notebooks/
↪kaggle_dataset'
```

[ ]:
```
!pwd
```

```
/content
```

[ ]:
```
%cd drive/MyDrive/Colab Notebooks/kaggle_dataset
```

```
/content/drive/MyDrive/Colab Notebooks/kaggle_dataset
```

[ ]:
```
!pwd
```

```
/content/drive/MyDrive/Colab Notebooks/kaggle_dataset
```

[ ]:
```
!kaggle datasets download -d kartik2112/fraud-detection
```

```
fraud-detection.zip: Skipping, found more recently modified local copy (use
--force to force download)
```

[ ]:
```
!unzip fraud-detection.zip
```

```
Archive:  fraud-detection.zip
replace fraudTest.csv? [y]es, [n]o, [A]ll, [N]one, [r]ename: n
replace fraudTrain.csv? [y]es, [n]o, [A]ll, [N]one, [r]ename: n
```

0.1.3 Importing Library

[ ]:
```
from logging import warning
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

[ ]:
```
train = pd.read_csv('fraudTrain.csv')
test = pd.read_csv('fraudTest.csv')
```

[ ]:
```
train.head()
```

[ ]:
```
   Unnamed: 0 trans_date_trans_time            cc_num  \
0           0   2019-01-01 00:00:18  2703186189652095
1           1   2019-01-01 00:00:44      630423337322
2           2   2019-01-01 00:00:51    38859492057661
```

```
3           3   2019-01-01 00:01:16  3534093764340240
4           4   2019-01-01 00:03:06   375534208663984

                            merchant       category     amt      first  \
0         fraud_Rippin, Kub and Mann       misc_net    4.97   Jennifer
1    fraud_Heller, Gutmann and Zieme    grocery_pos  107.23  Stephanie
2               fraud_Lind-Buckridge  entertainment  220.11     Edward
3  fraud_Kutch, Hermiston and Farrell  gas_transport   45.00     Jeremy
4                fraud_Keeling-Crist       misc_pos   41.96      Tyler

      last gender                        street  …      lat      long  \
0    Banks      F                561 Perry Cove  …  36.0788  -81.1781
1     Gill      F  43039 Riley Greens Suite 393  …  48.8878 -118.2105
2  Sanchez      M      594 White Dale Suite 530  …  42.1808 -112.2620
3    White      M   9443 Cynthia Court Apt. 038  …  46.2306 -112.1138
4   Garcia      M              408 Bradley Rest  …  38.4207  -79.4629

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

                          trans_num   unix_time  merch_lat  merch_long  \
0  0b242abb623afc578575680df30655b9  1325376018  36.011293  -82.048315
1  1f76529f8574734946361c461b024d99  1325376044  49.159047 -118.186462
2  a1a22d70485983eac12b5b88dad1cf95  1325376051  43.150704 -112.154481
3  6b849c168bdad6f867558c3793159a81  1325376076  47.034331 -112.561071
4  a41d7549acf90789359a9aa5346dcb46  1325376186  38.674999  -78.632459

   is_fraud
0         0
1         0
2         0
3         0
4         0

[5 rows x 23 columns]
```

[ ]:
```
train.columns
```

[ ]:
```
Index(['Unnamed: 0', 'trans_date_trans_time', 'cc_num', 'merchant', 'category',
       'amt', 'first', 'last', 'gender', 'street', 'city', 'state', 'zip',
       'lat', 'long', 'city_pop', 'job', 'dob', 'trans_num', 'unix_time',
       'merch_lat', 'merch_long', 'is_fraud'],
      dtype='object')
```

```
[ ]: print('train:', train.shape)
     print('test:', test.shape)
```

```
train: (1296675, 23)
test: (555719, 23)
```

0.1.4 merging both dataset

```
[ ]: data = pd.concat([train, test])
```

```
[ ]: data.head()
```

```
[ ]:   Unnamed: 0 trans_date_trans_time            cc_num  \
0           0   2019-01-01 00:00:18  2703186189652095
1           1   2019-01-01 00:00:44      630423337322
2           2   2019-01-01 00:00:51    38859492057661
3           3   2019-01-01 00:01:16  3534093764340240
4           4   2019-01-01 00:03:06   375534208663984

                            merchant       category     amt      first  \
0         fraud_Rippin, Kub and Mann       misc_net    4.97   Jennifer
1    fraud_Heller, Gutmann and Zieme    grocery_pos  107.23  Stephanie
2               fraud_Lind-Buckridge  entertainment  220.11     Edward
3  fraud_Kutch, Hermiston and Farrell  gas_transport   45.00     Jeremy
4                 fraud_Keeling-Crist       misc_pos   41.96      Tyler

      last gender                       street  …      lat      long  \
0    Banks      F               561 Perry Cove  …  36.0788  -81.1781
1     Gill      F  43039 Riley Greens Suite 393  …  48.8878 -118.2105
2  Sanchez      M      594 White Dale Suite 530  …  42.1808 -112.2620
3    White      M   9443 Cynthia Court Apt. 038  …  46.2306 -112.1138
4   Garcia      M             408 Bradley Rest  …  38.4207  -79.4629

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

                          trans_num   unix_time  merch_lat  merch_long  \
0  0b242abb623afc578575680df30655b9  1325376018  36.011293  -82.048315
1  1f76529f8574734946361c461b024d99  1325376044  49.159047 -118.186462
2  a1a22d70485983eac12b5b88dad1cf95  1325376051  43.150704 -112.154481
3  6b849c168bdad6f867558c3793159a81  1325376076  47.034331 -112.561071
4  a41d7549acf90789359a9aa5346dcb46  1325376186  38.674999  -78.632459
```

```
   is_fraud
0         0
1         0
2         0
3         0
4         0

[5 rows x 23 columns]
```

[ ]:
```python
print('data:', data.shape)
```

```
data: (1852394, 23)
```

[ ]:
```python
data.duplicated().sum()
```

[ ]:
```
0
```

[ ]:
```python
data.isnull().sum()
```

[ ]:
```
Unnamed: 0               0
trans_date_trans_time    0
cc_num                   0
merchant                 0
category                 0
amt                      0
first                    0
last                     0
gender                   0
street                   0
city                     0
state                    0
zip                      0
lat                      0
long                     0
city_pop                 0
job                      0
dob                      0
trans_num                0
unix_time                0
merch_lat                0
merch_long               0
is_fraud                 0
dtype: int64
```

[ ]:
```python
data.isnull().sum()
```

[ ]:
```
Unnamed: 0               0
trans_date_trans_time    0
cc_num                   0
merchant                 0
category                 0
amt                      0
first                    0
last                     0
gender                   0
street                   0
city                     0
state                    0
zip                      0
lat                      0
long                     0
city_pop                 0
job                      0
dob                      0
trans_num                0
unix_time                0
merch_lat                0
merch_long               0
is_fraud                 0
dtype: int64
```

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

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1852394 entries, 0 to 555718
Data columns (total 23 columns):
 #   Column                 Dtype
---  ------                 -----
 0   Unnamed: 0             int64
 1   trans_date_trans_time  object
 2   cc_num                 int64
 3   merchant               object
 4   category               object
 5   amt                    float64
 6   first                  object
 7   last                   object
 8   gender                 object
 9   street                 object
 10  city                   object
 11  state                  object
 12  zip                    int64
 13  lat                    float64
 14  long                   float64
```

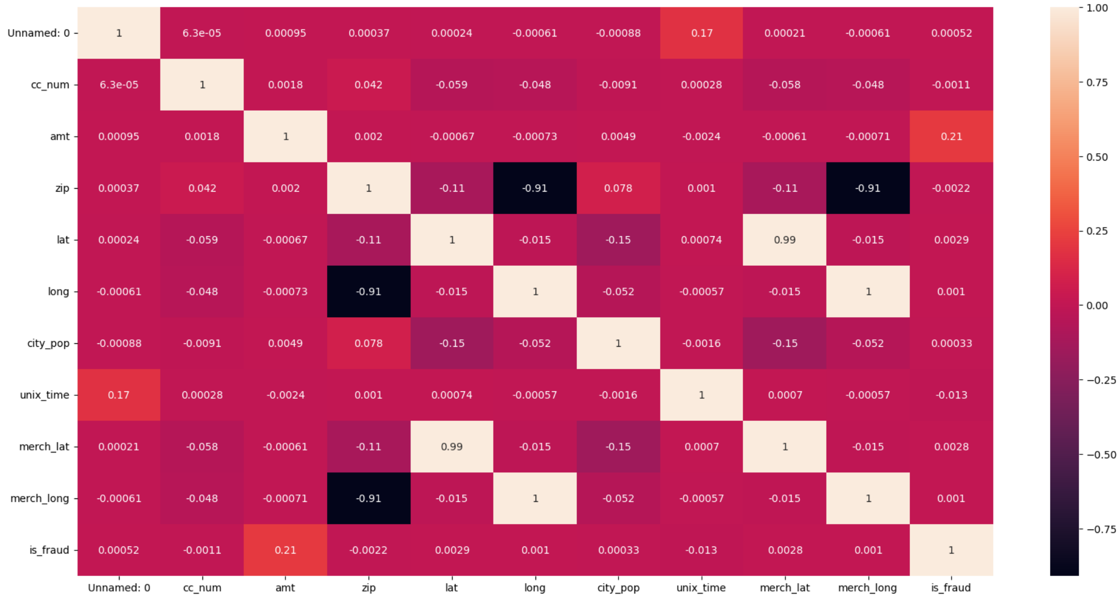
```
 15  city_pop                int64
 16  job                     object
 17  dob                     object
 18  trans_num               object
 19  unix_time               int64
 20  merch_lat               float64
 21  merch_long              float64
 22  is_fraud                int64
dtypes: float64(5), int64(6), object(12)
memory usage: 339.2+ MB
```

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

[ ]:
```
         Unnamed: 0        cc_num           amt           zip           lat  \
count  1.852394e+06  1.852394e+06  1.852394e+06  1.852394e+06  1.852394e+06
mean   5.371934e+05  4.173860e+17  7.006357e+01  4.881326e+04  3.853931e+01
std    3.669110e+05  1.309115e+18  1.592540e+02  2.688185e+04  5.071470e+00
min    0.000000e+00  6.041621e+10  1.000000e+00  1.257000e+03  2.002710e+01
25%    2.315490e+05  1.800429e+14  9.640000e+00  2.623700e+04  3.466890e+01
50%    4.630980e+05  3.521417e+15  4.745000e+01  4.817400e+04  3.935430e+01
75%    8.335758e+05  4.642255e+15  8.310000e+01  7.204200e+04  4.194040e+01
max    1.296674e+06  4.992346e+18  2.894890e+04  9.992100e+04  6.669330e+01

               long      city_pop     unix_time     merch_lat    merch_long  \
count  1.852394e+06  1.852394e+06  1.852394e+06  1.852394e+06  1.852394e+06
mean  -9.022783e+01  8.864367e+04  1.358674e+09  3.853898e+01 -9.022794e+01
std    1.374789e+01  3.014876e+05  1.819508e+07  5.105604e+00  1.375969e+01
min   -1.656723e+02  2.300000e+01  1.325376e+09  1.902742e+01 -1.666716e+02
25%   -9.679800e+01  7.410000e+02  1.343017e+09  3.474012e+01 -9.689944e+01
50%   -8.747690e+01  2.443000e+03  1.357089e+09  3.936890e+01 -8.744069e+01
75%   -8.015800e+01  2.032800e+04  1.374581e+09  4.195626e+01 -8.024511e+01
max   -6.795030e+01  2.906700e+06  1.388534e+09  6.751027e+01 -6.695090e+01

           is_fraud
count  1.852394e+06
mean   5.210015e-03
std    7.199217e-02
min    0.000000e+00
25%    0.000000e+00
50%    0.000000e+00
75%    0.000000e+00
max    1.000000e+00
```

[ ]:
```
plt.figure(figsize=(20,10))
sns.heatmap(data.corr(), annot = True)
```

[ ]: <Axes: >



[ ]:
```python
for i in data.columns:
  num = len(data[i].unique())
  print(i,':', str(num) + str(' Distinct values'))
```

```
Unnamed: 0 : 1296675 Distinct values
trans_date_trans_time : 1819551 Distinct values
cc_num : 999 Distinct values
merchant : 693 Distinct values
category : 14 Distinct values
amt : 60616 Distinct values
first : 355 Distinct values
last : 486 Distinct values
gender : 2 Distinct values
street : 999 Distinct values
city : 906 Distinct values
state : 51 Distinct values
zip : 985 Distinct values
lat : 983 Distinct values
long : 983 Distinct values
city_pop : 891 Distinct values
job : 497 Distinct values
dob : 984 Distinct values
trans_num : 1852394 Distinct values
unix_time : 1819583 Distinct values
merch_lat : 1754157 Distinct values
merch_long : 1809753 Distinct values
is_fraud : 2 Distinct values
```

[ ]:
```
data.drop(columns=['Unnamed: 0'], inplace=True)
```

0.1.5 calculating age from dob and transaction time

[ ]:
```
transaction_date = pd.to_datetime(data['trans_date_trans_time'])
birth_date = pd.to_datetime(data['dob'])
year_timedelta = np.timedelta64(1, 'Y')
data['age'] = np.int64((transaction_date - birth_date) / year_timedelta)
```

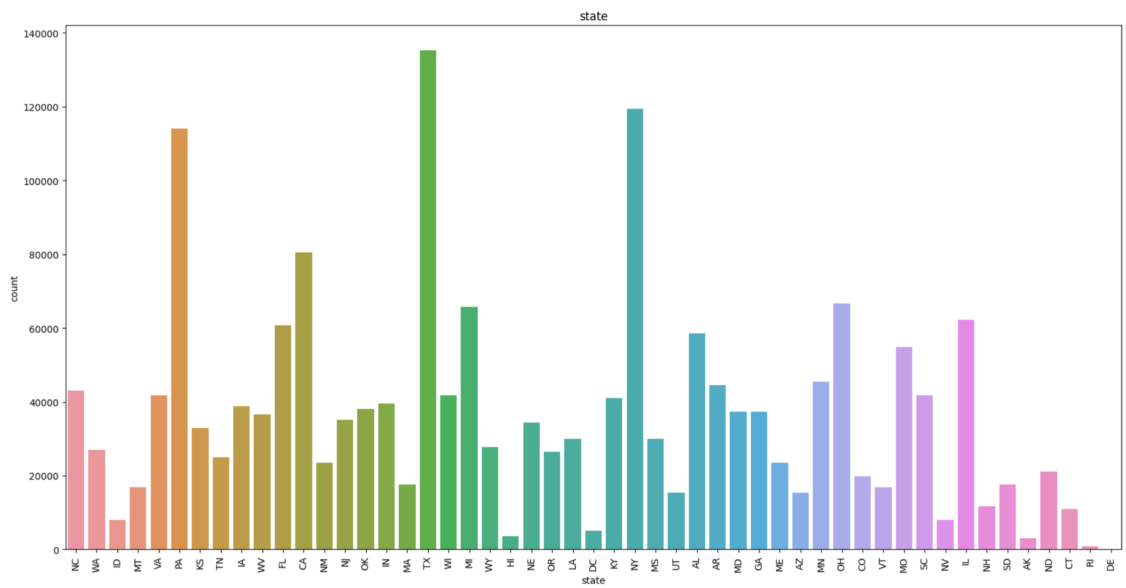
[ ]:
```
data.head()
```

[ ]:
```
  trans_date_trans_time            cc_num                            merchant  \
0   2019-01-01 00:00:18  2703186189652095          fraud_Rippin, Kub and Mann
1   2019-01-01 00:00:44      630423337322     fraud_Heller, Gutmann and Zieme
2   2019-01-01 00:00:51    38859492057661                fraud_Lind-Buckridge
3   2019-01-01 00:01:16  3534093764340240  fraud_Kutch, Hermiston and Farrell
4   2019-01-01 00:03:06   375534208663984                 fraud_Keeling-Crist

        category     amt      first     last gender  \
0       misc_net    4.97   Jennifer    Banks      F
1    grocery_pos  107.23  Stephanie     Gill      F
2  entertainment  220.11     Edward  Sanchez      M
3  gas_transport   45.00     Jeremy    White      M
4       misc_pos   41.96      Tyler   Garcia      M

                         street            city  …      long  city_pop  \
0                561 Perry Cove  Moravian Falls  …  -81.1781      3495
1  43039 Riley Greens Suite 393          Orient  … -118.2105       149
2      594 White Dale Suite 530      Malad City  … -112.2620      4154
3   9443 Cynthia Court Apt. 038         Boulder  … -112.1138      1939
4              408 Bradley Rest        Doe Hill  …  -79.4629        99

                                 job         dob  \
0          Psychologist, counselling  1988-03-09
1  Special educational needs teacher  1978-06-21
2        Nature conservation officer  1962-01-19
3                    Patent attorney  1967-01-12
4     Dance movement psychotherapist  1986-03-28

                          trans_num   unix_time  merch_lat  merch_long  \
0  0b242abb623afc578575680df30655b9  1325376018  36.011293  -82.048315
1  1f76529f8574734946361c461b024d99  1325376044  49.159047 -118.186462
2  a1a22d70485983eac12b5b88dad1cf95  1325376051  43.150704 -112.154481
3  6b849c168bdad6f867558c3793159a81  1325376076  47.034331 -112.561071
4  a41d7549acf90789359a9aa5346dcb46  1325376186  38.674999  -78.632459

   is_fraud  age
```

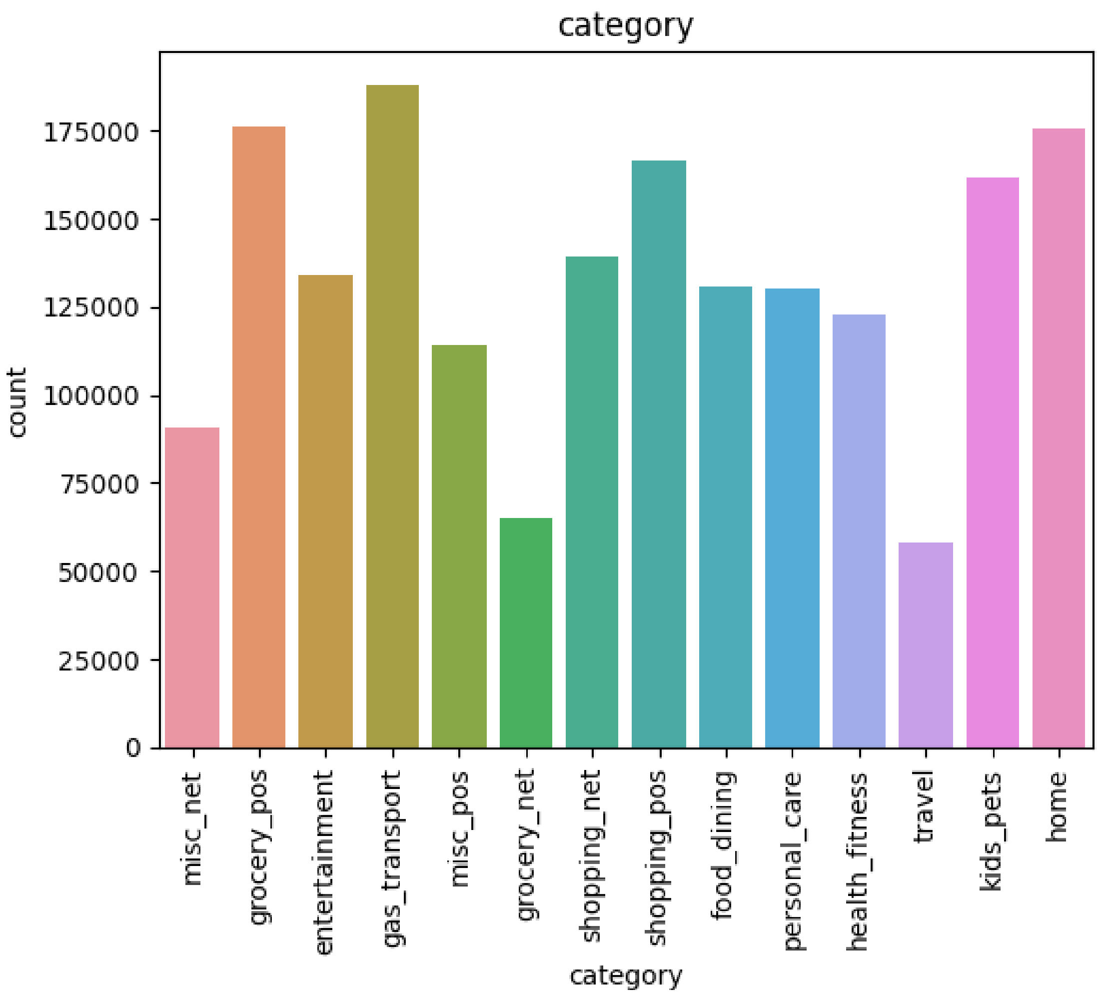
```
0          0   30
1          0   40
2          0   56
3          0   51
4          0   32

[5 rows x 23 columns]
```

0.1.6 Data Visulaization

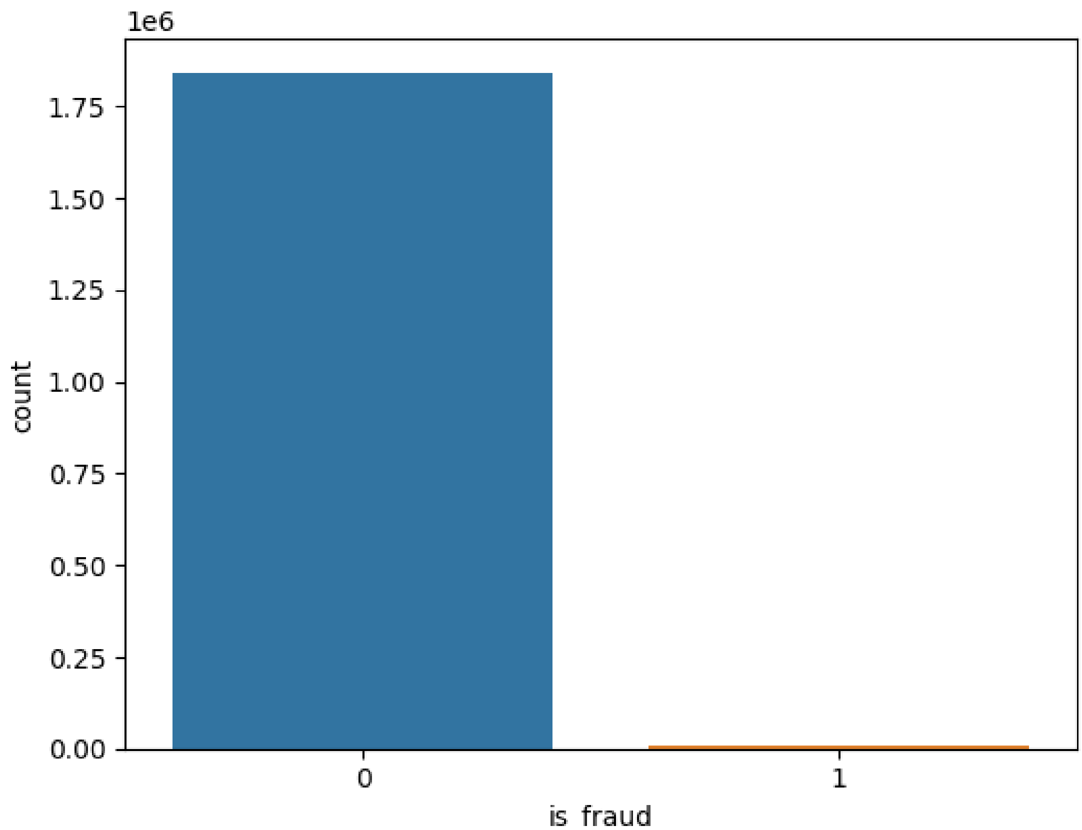
[ ]:
```python
plt.figure(figsize=(20,10))
sns.countplot(x='state', data=data)
plt.title('state')
plt.xticks(rotation=90)
plt.show()
```



[ ]:
```python
sns.countplot(x='category', data=data)
plt.title('category')
plt.xticks(rotation=90)
plt.show()
```



[ ]:
```
sns.countplot(data = data, x = data['is_fraud'])
plt.show()
```

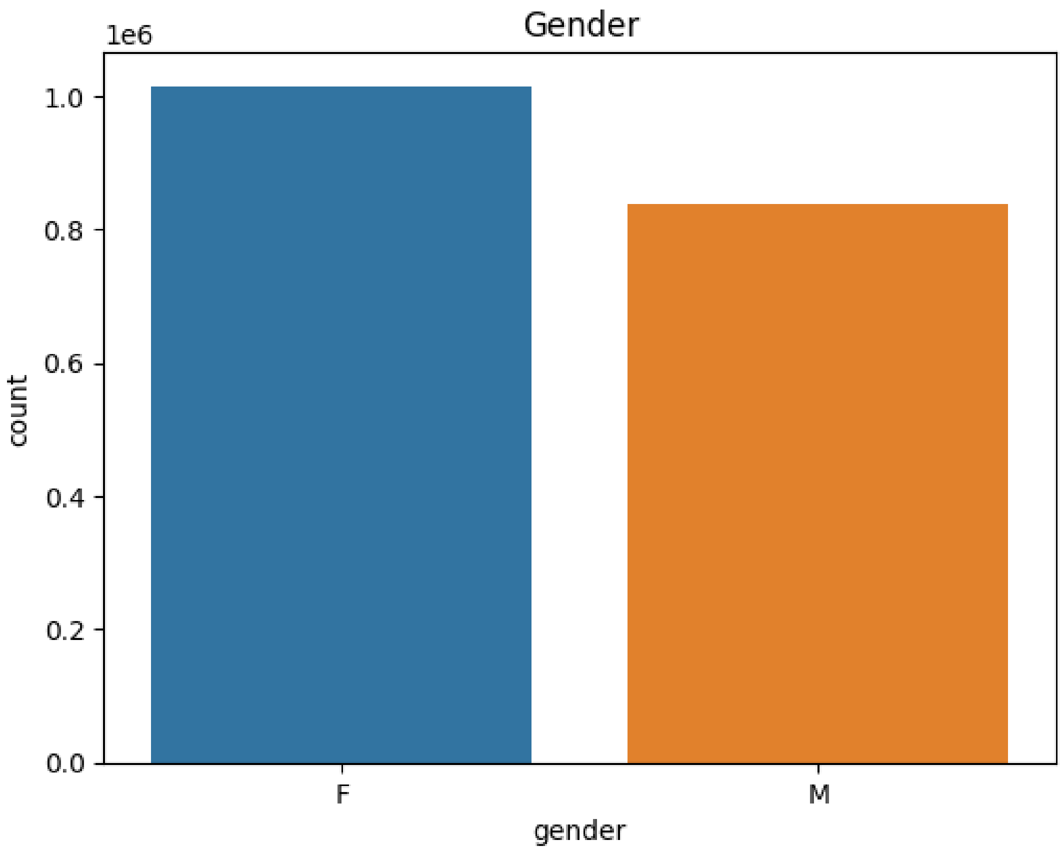



```
[ ]: print("Number of is_fraud data:\n\n",data['is_fraud'].value_counts())
```

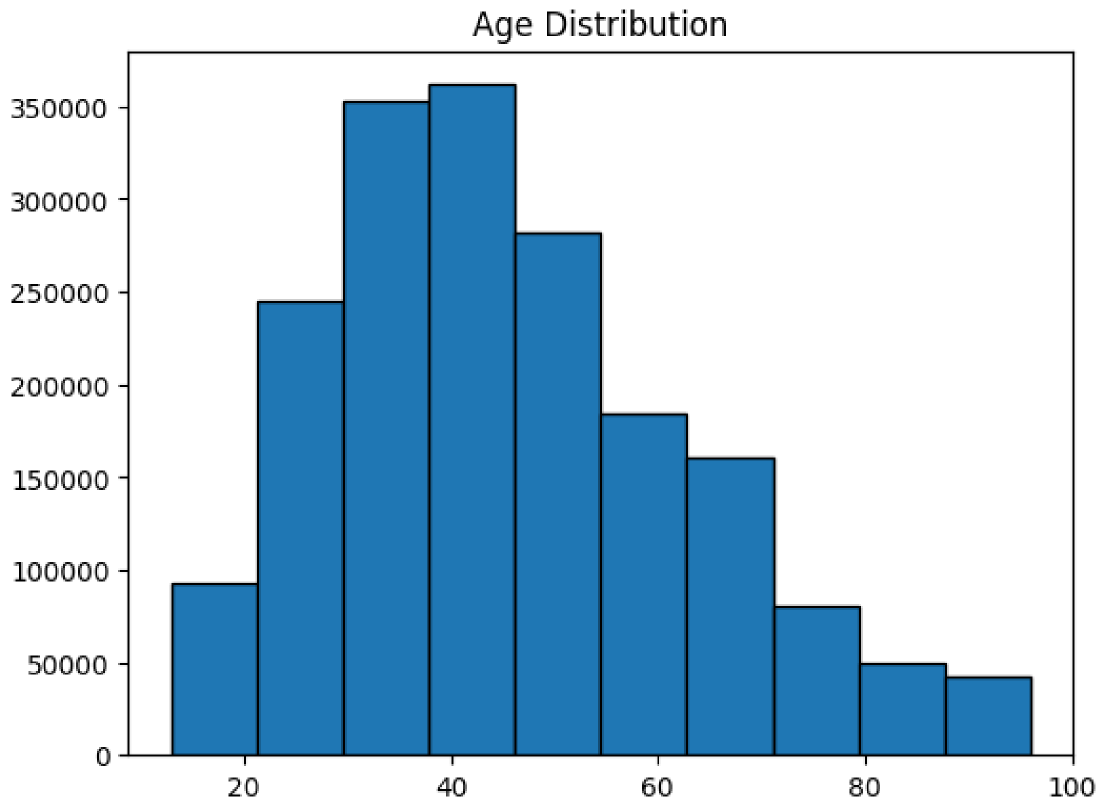
```
Number of is_fraud data:

 0    1842743
1       9651
Name: is_fraud, dtype: int64
```

from this we can see that amount fraud = 0 is more than fraud = 1. As our data is not balanced it may lead to overfitting

```
[ ]: sns.countplot(x='gender', data=data)
plt.title('Gender')
plt.show()
```

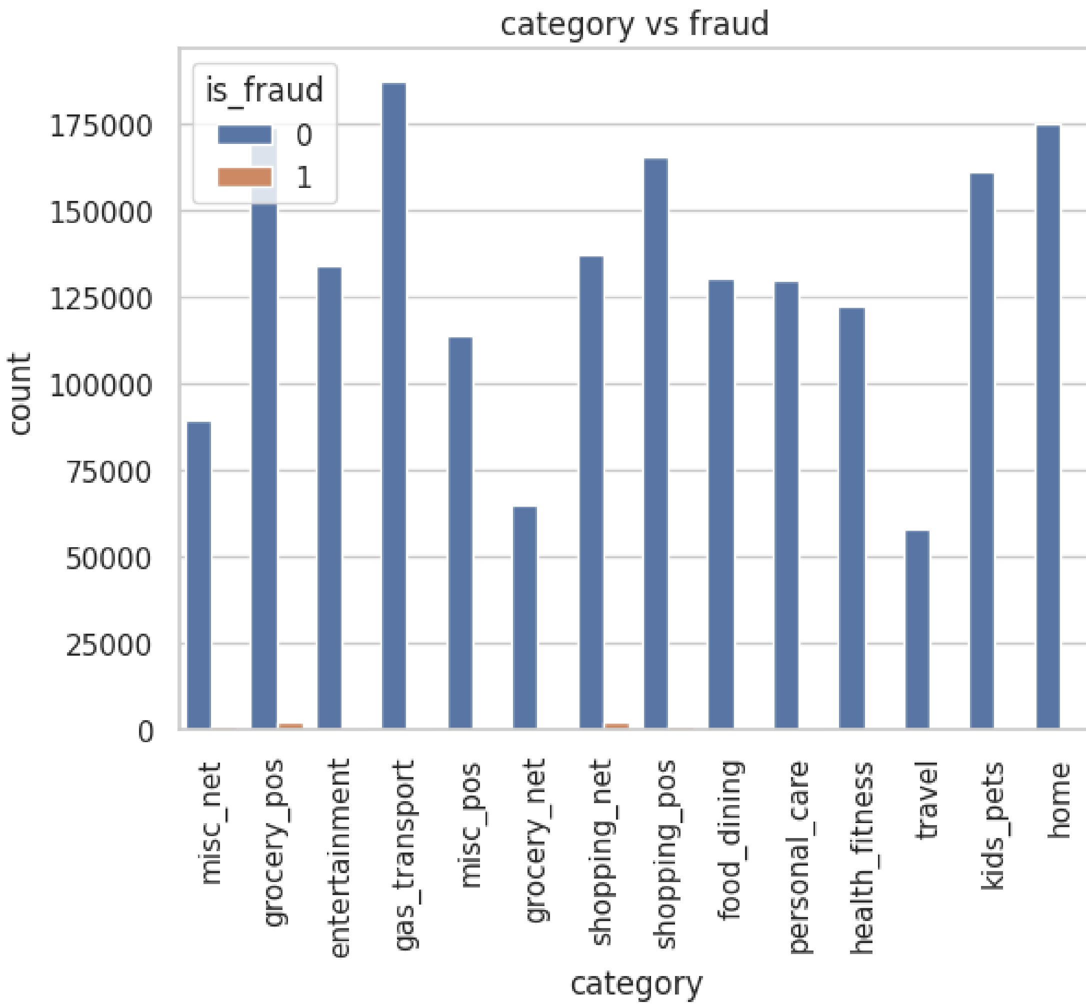


[ ]:
```
plt.hist(data['age'], edgecolor='black')
plt.title('Age Distribution')
plt.show()
```



[ ]:
```
sns.set(style="whitegrid")
sns.countplot(x='gender', hue='is_fraud', data=data)
plt.title('Gender vs fraud')
plt.show()
```


```
[ ]: sns.set(style="whitegrid")
     sns.countplot(x='category', hue='is_fraud', data=data)
     plt.title('category vs fraud')
     plt.xticks(rotation=90)
     plt.show()
```



0.1.7 Data preprocessing

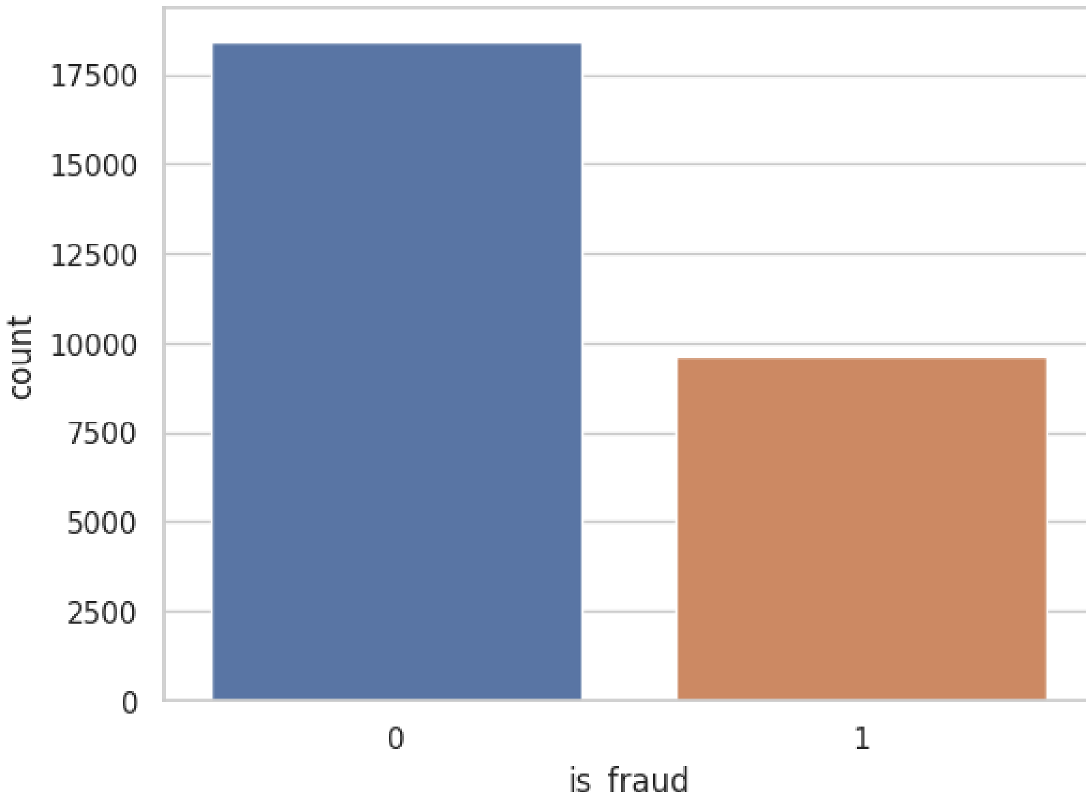
[ ]:
```
from sklearn.utils import resample, shuffle
df_minority = data[data['is_fraud'].values==1]
df_majority = data[data['is_fraud'].values==0]
#print(len(df_minority), len(df_majority))
df_majority_downsampled = resample(df_majority, n_samples=18427,␣
↪random_state=42)
new_data = pd.concat([df_minority, df_majority_downsampled])
new_data = shuffle(new_data, random_state=42 )
```

[ ]:
```
new_data.head()
```

[ ]:
```
       trans_date_trans_time               cc_num  \
691934   2019-10-21 21:46:04   4102003771126577611
```

```
995705   2020-02-11 01:24:02     4997733566924489
505622   2020-12-21 01:38:01     5540636818935089
441467   2020-12-06 23:53:03     3564182536169293
47764    2019-01-28 23:14:49      373213026644490

                                          merchant      category      amt  \
691934                           fraud_Block Group      misc_pos     4.23
995705                           fraud_Zemlak Group     misc_net   739.44
505622                               fraud_Huel Ltd     misc_net     6.74
441467                             fraud_Boyer PLC  shopping_net  1073.81
47764   fraud_Romaguera, Cruickshank and Greenholt  shopping_net  1058.01

            first        last gender                    street         city  \
691934    William  Fitzgerald      M  715 Courtney Pike Suite 932      Keller
995705  Stephanie      Taylor      F    598 Martin Pine Suite 365  Saint Paul
505622    Kenneth      Foster      M        329 Michael Extension    Lawrence
441467     Brenda     Johnson      F          56160 Nicholas Isle     Norwich
47764       Bobby       Smith      M         3495 Williams Stream   San Diego

        …      long  city_pop                          job         dob  \
691934  …  -97.2489     95035             Probation officer  1987-06-13
995705  …  -92.9487    753116             Fisheries officer  1971-08-06
505622  …  -71.1605     76383                  Geoscientist  1985-04-04
441467  …  -81.8024      1443  Research scientist (medical)  1962-03-04
47764   … -117.1593   1241364                   Comptroller  1987-11-30

                               trans_num   unix_time  merch_lat  merch_long  \
691934  1e4ee6de34a2c4b2b3c0f09f59ddb6a7  1350855964  32.144236  -96.881092
995705  1174c16a2252642d17ca7a8d6dc143ff  1360545842  44.826051  -92.038774
505622  c6646c84f4528cadacc3eaa2b42e65b6  1387589881  42.739623  -71.701152
441467  e3b6952aeef3a979761ba5d949d07757  1386373983  40.564654  -81.708551
47764   e6cbed473965d31cd4a258344dd0bd8c  1327792489  33.259031 -117.083503

        is_fraud  age
691934         0   32
995705         1   48
505622         0   35
441467         1   58
47764          1   31

[5 rows x 23 columns]
```

[ ]:
```
sns.countplot(data = data, x = new_data['is_fraud'])
plt.show()
```



[ ]:
```
print("Number of is_fraud data:\n\n",new_data['is_fraud'].value_counts())
```

```
Number of is_fraud data:

 0    18427
1     9651
Name: is_fraud, dtype: int64
```

[ ]:
```
sns.countplot(x='gender', hue='is_fraud', data=new_data)
plt.title('Gender vs fraud')
plt.show()
```

selecting the columns

```
[ ]: drops = [ 'cc_num', 'state', 'amt', 'category', 'gender',  'job', 'age',␣
     ↪'is_fraud' ]
```

```
[ ]: processed_data = new_data[drops]
```

```
[ ]: processed_data.head()
```

```
[ ]:                  cc_num state      amt      category gender  \
691934  4102003771126577611    TX     4.23      misc_pos      M
995705     4997733566924489    MN   739.44      misc_net      F
505622     5540636818935089    MA     6.74      misc_net      M
441467     3564182536169293    OH  1073.81  shopping_net      F
47764       373213026644490    CA  1058.01  shopping_net      M

                          job  age  is_fraud
691934      Probation officer   32         0
995705      Fisheries officer   48         1
505622           Geoscientist   35         0
```

```
441467  Research scientist (medical)   58          1
47764                    Comptroller   31          1
```

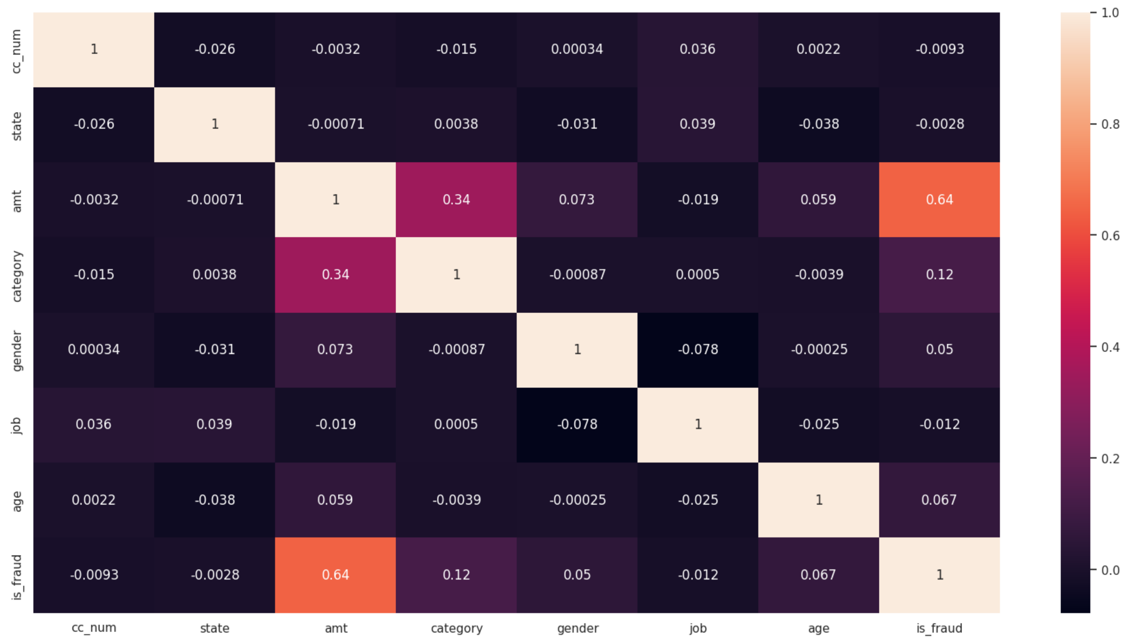
[ ]:
```python
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
processed_data['gender'] = le.fit_transform(processed_data['gender'])
processed_data['category'] = le.fit_transform(processed_data['category'])
processed_data['job'] = le.fit_transform(processed_data['job'])
processed_data['state'] = le.fit_transform(processed_data['state'])
```

[ ]:
```python
processed_data.head()
```

[ ]:
```
                     cc_num  state      amt  category  gender  job  age  \
691934  4102003771126577611     43     4.23         9       1  355   32
995705     4997733566924489     23   739.44         8       0  199   48
505622     5540636818935089     19     6.74         8       1  216   35
441467     3564182536169293     35  1073.81        11       0  396   58
47764       373213026644490      4  1058.01        11       1  102   31

        is_fraud
691934         0
995705         1
505622         0
441467         1
47764          1
```

[ ]:
```python
plt.figure(figsize=(20,10))
sns.heatmap(processed_data.corr(), annot = True)
```

[ ]:
```
<Axes: >
```



[ ]:
```
#from above matrix we can say that job, state and cc_num are not that important␣
↪for predicting fraud
x = processed_data.iloc[:,[2,4,6]].values
y = processed_data.iloc[:,-1:].values
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x,y, test_size=0.2,␣
↪random_state=42)
```

[ ]:
```
print(x_train.shape, x_test.shape)
print(y_train.shape, y_test.shape)
```

```
(22462, 3) (5616, 3)
(22462, 1) (5616, 1)
```

[ ]:
```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
x_train = sc.fit_transform(x_train)
x_test = sc.transform(x_test)
```

[ ]:
```
from sklearn.linear_model import LogisticRegression
log = LogisticRegression(random_state = 0)
log.fit(x_train, y_train)
```

[ ]:
```
LogisticRegression(random_state=0)
```

[ ]:
```
from sklearn.svm import SVC
svc = SVC(kernel = 'linear', random_state = 0)
svc.fit(x_train, y_train)
```

[ ]:
```
SVC(kernel='linear', random_state=0)
```

[ ]:
```
from sklearn.naive_bayes import GaussianNB
clf = GaussianNB()
clf.fit(x_train, y_train)
```

[ ]:
```
GaussianNB()
```

[ ]:
```
classifier = [log, svc, clf]
model = ['Logistic', 'Support Vector', 'Naive Bayes']
```

[ ]:
```
from sklearn.metrics import classification_report, confusion_matrix,␣
 ↪accuracy_score, ConfusionMatrixDisplay
for i in range(len(classifier)):
  y_pred = classifier[i].predict(x_test)
  cm = confusion_matrix(y_test, y_pred)
  accuracy = accuracy_score(y_test, y_pred)*100
  print('\nfor ' + str(model[i]) + ':\n')
  disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=['not␣
 ↪fraud', 'is_fraud'])
  plt.rcParams['axes.grid'] = False
  disp.plot()
  print('Accuracy: 'accuracy)
  print(classification_report(y_test, y_pred))
  plt.show()
```

```
for Logistic:

89.19159544159544
              precision    recall  f1-score   support

           0       0.87      0.98      0.92      3700
           1       0.95      0.72      0.82      1916

    accuracy                           0.89      5616
   macro avg       0.91      0.85      0.87      5616
weighted avg       0.90      0.89      0.89      5616
```


```
for Support Vector:

89.85042735042735
              precision    recall  f1-score   support

           0       0.88      0.97      0.93      3700
           1       0.94      0.75      0.83      1916

    accuracy                           0.90      5616
   macro avg       0.91      0.86      0.88      5616
weighted avg       0.90      0.90      0.90      5616
```


```
for Naive Bayes:

82.97720797720798
              precision    recall  f1-score   support

           0       0.80      0.99      0.88      3700
           1       0.95      0.53      0.68      1916

    accuracy                           0.83      5616
   macro avg       0.88      0.76      0.78      5616
weighted avg       0.85      0.83      0.81      5616
```

[ ]:
```
from sklearn.model_selection import cross_val_score
for i in classifier:
  accuracies  = cross_val_score(estimator=i, X = x_train, y = y_train, cv = 10)
  print('Accuracy: {:.2f} %'.format(accuracies.mean()*100))
  print("Standard Deviation: {:.2f} %".format(accuracies.std()*100))
```

```
Accuracy: 88.79 %
Standard Deviation: 0.83 %
Accuracy: 89.55 %
Standard Deviation: 0.95 %
Accuracy: 82.60 %
Standard Deviation: 1.54 %
```