credit-card-fraud-detection

August 24, 2023

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from imblearn.under_sampling import RandomUnderSampler
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
import os
```

[3]:
```
df = pd.read_csv(r"C:\Users\Hello\Downloads\Externs\Externs\Mini␣
↪projects\fraudTrain.csv")
df1 = pd.read_csv(r"C:\Users\Hello\Downloads\Externs\Externs\Mini␣
↪projects\fraudTest.csv")
```

[4]:
```
df.head(10)
```

[4]:
```
   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
5           5   2019-01-01 00:04:08     4767265376804500
6           6   2019-01-01 00:04:42       30074693890476
7           7   2019-01-01 00:05:08     6011360759745864
8           8   2019-01-01 00:05:18     4922710831011201
9           9   2019-01-01 00:06:01     2720830304681674

                              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
5     fraud_Stroman, Hudson and Erdman  gas_transport   94.63   Jennifer
6                 fraud_Rowe-Vandervort    grocery_net   44.54     Kelsey
7                 fraud_Corwin-Collins  gas_transport   71.65     Steven
```

8	fraud_Herzog Ltd	misc_pos	4.27	Heather
9	fraud_Schoen, Kuphal and Nitzsche	grocery_pos	198.39	Melissa

	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
5	Conner	F	4655 David Island	...	40.3750	-75.2045
6	Richards	F	889 Sarah Station Suite 624	...	37.9931	-100.9893
7	Williams	M	231 Flores Pass Suite 720	...	38.8432	-78.6003
8	Chase	F	6888 Hicks Stream Suite 954	...	40.3359	-79.6607
9	Aguilar	F	21326 Taylor Squares Suite 708	...	36.5220	-87.3490

	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
5	2158	Transport planner	1961-06-19
6	2691	Arboriculturist	1993-08-16
7	6018	Designer, multimedia	1947-08-21
8	1472	Public affairs consultant	1941-03-07
9	151785	Pathologist	1974-03-28

	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
5	189a841a0a8ba03058526bcfe566aab5	1325376248	40.653382	-76.152667
6	83ec1cc84142af6e2acf10c44949e720	1325376282	37.162705	-100.153370
7	6d294ed2cc447d2c71c7171a3d54967c	1325376308	38.948089	-78.540296
8	fc28024ce480f8ef21a32d64c93a29f5	1325376318	40.351813	-79.958146
9	3b9014ea8fb80bd65de0b1463b00b00e	1325376361	37.179198	-87.485381

	is_fraud
0	0
1	0
2	0
3	0
4	0
5	0
6	0

```
7           0
8           0
9           0

[10 rows x 23 columns]
```

[5]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1296675 entries, 0 to 1296674
Data columns (total 23 columns):
Unnamed: 0               1296675 non-null int64
trans_date_trans_time    1296675 non-null object
cc_num                   1296675 non-null int64
merchant                 1296675 non-null object
category                 1296675 non-null object
amt                      1296675 non-null float64
first                    1296675 non-null object
last                     1296675 non-null object
gender                   1296675 non-null object
street                   1296675 non-null object
city                     1296675 non-null object
state                    1296675 non-null object
zip                      1296675 non-null int64
lat                      1296675 non-null float64
long                     1296675 non-null float64
city_pop                 1296675 non-null int64
job                      1296675 non-null object
dob                      1296675 non-null object
trans_num                1296675 non-null object
unix_time                1296675 non-null int64
merch_lat                1296675 non-null float64
merch_long               1296675 non-null float64
is_fraud                 1296675 non-null int64
dtypes: float64(5), int64(6), object(12)
memory usage: 227.5+ MB
```

[6]:
```python
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 555719 entries, 0 to 555718
Data columns (total 23 columns):
Unnamed: 0               555719 non-null int64
trans_date_trans_time    555719 non-null object
cc_num                   555719 non-null int64
merchant                 555719 non-null object
category                 555719 non-null object
amt                      555719 non-null float64
```

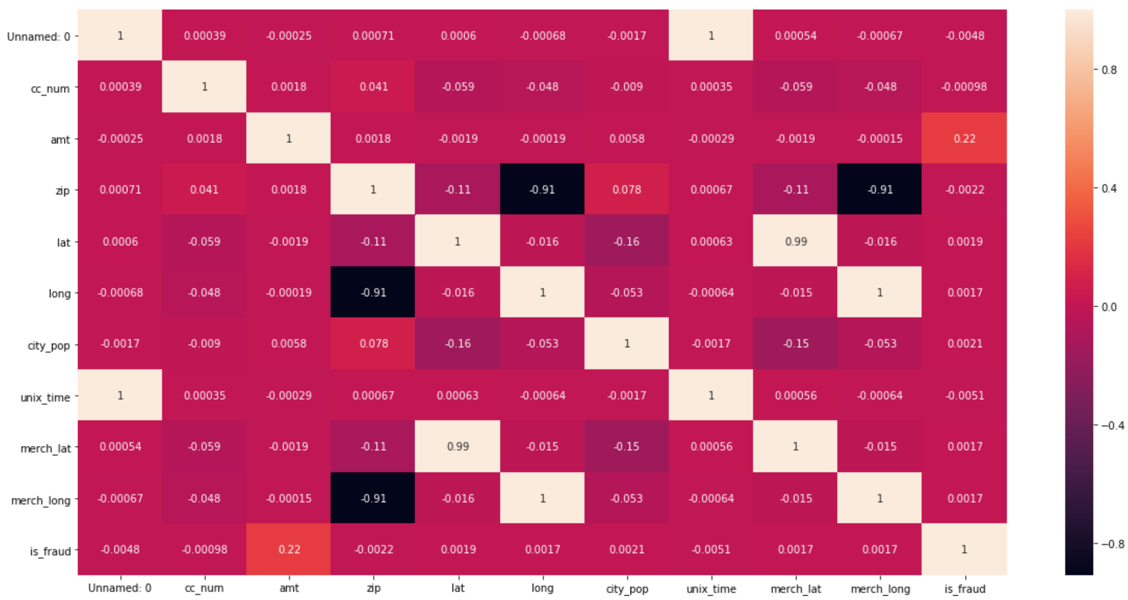
```
first                    555719 non-null object
last                     555719 non-null object
gender                   555719 non-null object
street                   555719 non-null object
city                     555719 non-null object
state                    555719 non-null object
zip                      555719 non-null int64
lat                      555719 non-null float64
long                     555719 non-null float64
city_pop                 555719 non-null int64
job                      555719 non-null object
dob                      555719 non-null object
trans_num                555719 non-null object
unix_time                555719 non-null int64
merch_lat                555719 non-null float64
merch_long               555719 non-null float64
is_fraud                 555719 non-null int64
dtypes: float64(5), int64(6), object(12)
memory usage: 97.5+ MB
```

[7]:
```
df.isnull().sum()
```

[7]:
```
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
```

1 Data Visualization

[8]:
```python
fig, ax = plt.subplots(figsize=(20,10))
sns.heatmap(df.corr(), annot=True)
plt.show()
```



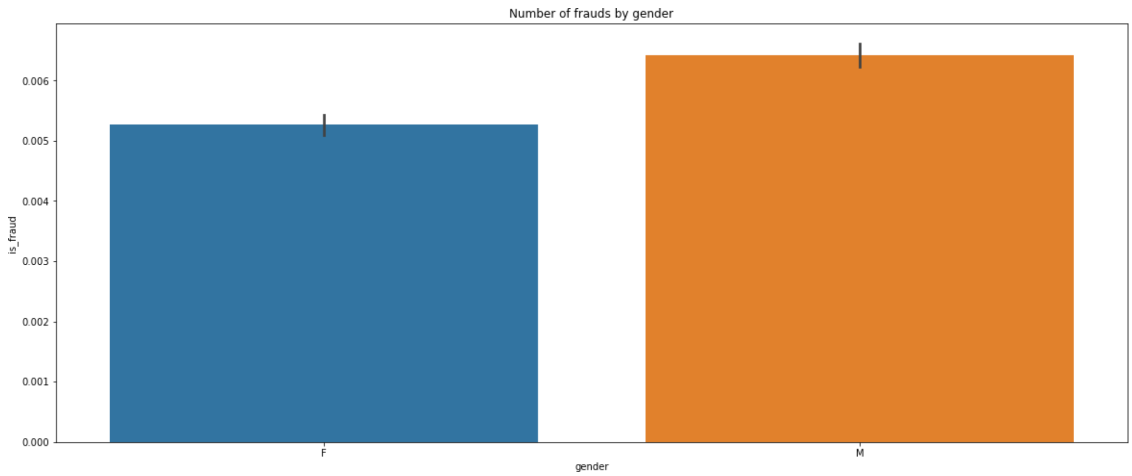
[9]:
```python
df.loc[df['is_fraud'] == 1].sort_values('amt', ascending=False).head(2)
```

[9]:
```
         Unnamed: 0 trans_date_trans_time            cc_num           merchant  \
1262544     1262544   2020-06-08 22:14:13  3562793934111141     fraud_Kuhn LLC
514148       514148   2019-08-10 22:10:23  3500969075198072  fraud_Metz-Boehm

            category      amt    first     last gender               street  \
1262544  shopping_pos  1376.04   Meagan  Edwards      F  10376 Bullock Rapid
514148   shopping_pos  1371.81  Kenneth  Sanchez      M    0110 Ashley Forest

         ...      lat      long city_pop                             job  \
1262544  ...  38.9456  -75.9777      777  Television production assistant
514148   ...  47.2271 -117.0819      895    Clothing/textile technologist

                dob                         trans_num   unix_time  merch_lat  \
1262544  1997-04-17  9a7f96694d672499c10b6085fadecd30  1370729653  38.004592
514148   1999-05-31  20cf5453224328229e06ae7b4df10302  1344636623  47.065996

         merch_long  is_fraud
1262544  -75.446751         1
514148  -116.262297         1
```

[2 rows x 23 columns]

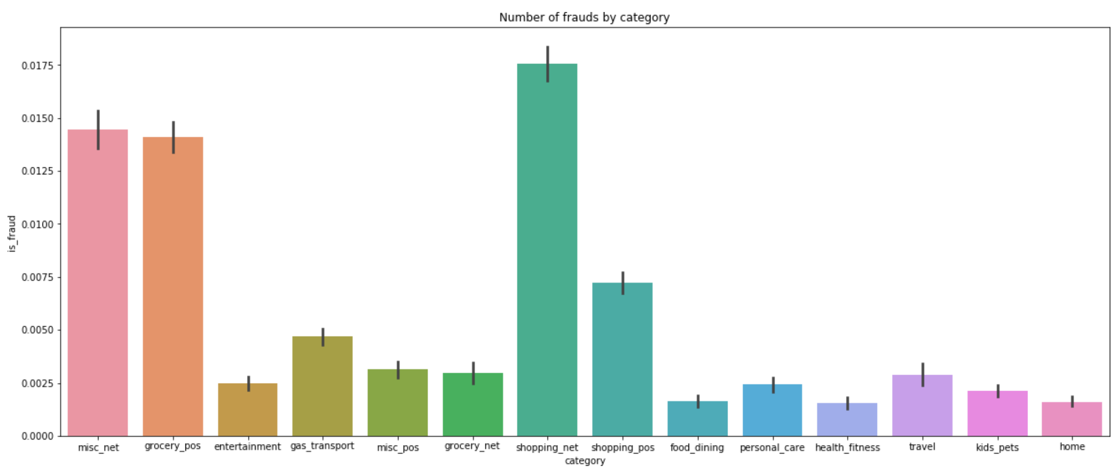
[10]:
```python
# Gender
plt.figure(figsize=(20,8))
plt.title("Number of frauds by gender")
sns.barplot(x="gender", y="is_fraud" ,data=df)
```

[10]: <matplotlib.axes._subplots.AxesSubplot at 0x2a984e3c390>



[11]:
```python
# Category
plt.figure(figsize=(20,8))
plt.title("Number of frauds by category")
sns.barplot(x="category", y="is_fraud" ,data=df)
```

[11]: <matplotlib.axes._subplots.AxesSubplot at 0x2a9885a6860>



2 Preprocessing

[12]:
```python
print("Number of is_fraud data",df['is_fraud'].value_counts())
```

```
Number of is_fraud data 0    1289169
1       7506
Name: is_fraud, dtype: int64
```

[13]:
```python
from sklearn.utils import resample
df_minority = df[df.iloc[:,22].values==0] # .iloc[:,22] = is_fraud
df_majority = df[df.iloc[:,22].values==1]

# Downsample majority class
df_minority_downsampled = resample(df_minority,
                                   n_samples=7506,     # to match minority class
                                   random_state=42)    # reproducible results

# Combine minority class with downsampled majority class
df_downsampled = pd.concat([df_minority_downsampled, df_majority])

# Display new class counts
df_downsampled.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 15012 entries, 123118 to 1295733
Data columns (total 23 columns):
Unnamed: 0               15012 non-null int64
trans_date_trans_time    15012 non-null object
cc_num                   15012 non-null int64
merchant                 15012 non-null object
category                 15012 non-null object
amt                      15012 non-null float64
first                    15012 non-null object
last                     15012 non-null object
gender                   15012 non-null object
street                   15012 non-null object
city                     15012 non-null object
state                    15012 non-null object
zip                      15012 non-null int64
lat                      15012 non-null float64
long                     15012 non-null float64
city_pop                 15012 non-null int64
job                      15012 non-null object
dob                      15012 non-null object
trans_num                15012 non-null object
unix_time                15012 non-null int64
merch_lat                15012 non-null float64
merch_long               15012 non-null float64
```

```
is_fraud                    15012 non-null int64
dtypes: float64(5), int64(6), object(12)
memory usage: 2.7+ MB
```

[14]:
```
print("Number of is_fraud data",df_downsampled["is_fraud"].value_counts())
```

```
Number of is_fraud data 1    7506
0    7506
Name: is_fraud, dtype: int64
```

2.1 Train Data

[15]:
```
# Train data
# Change date to be date type
df_downsampled["trans_date_trans_time"] = pd.
 ↪to_datetime(df_downsampled["trans_date_trans_time"])
# Create column week number
df_downsampled["week_number"] = df_downsampled["trans_date_trans_time"].dt.
 ↪dayofweek
assert df_downsampled["week_number"].max() == 6
# Create column month number
df_downsampled["month_number"] = df_downsampled["trans_date_trans_time"].dt.
 ↪month
assert df_downsampled["month_number"].max() == 12
# Create column year
df_downsampled["year"] = df_downsampled["trans_date_trans_time"].dt.year
df_downsampled.head()
```

[15]:
```
        Unnamed: 0 trans_date_trans_time            cc_num  \
123118      123118   2019-03-10 03:24:30    30011465039817
675160      675160   2019-10-14 15:40:47  2288813824604479
133167      133167   2019-03-14 15:21:51  2266735643685262
261154      261154   2019-05-10 09:04:20  4384910379661778
111322      111322   2019-03-04 12:54:01  2356276337669917

                   merchant        category    amt     first     last gender  \
123118    fraud_Huels-Nolan   gas_transport  67.66      Lisa   Garcia      F
675160   fraud_Yost-Rogahn   personal_care  47.79   Barbara   Norman      F
133167  fraud_Roob-Okuneva  health_fitness  24.17    Carlos    Chung      M
261154       fraud_Howe Ltd        misc_pos  51.69  Michelle  Russell      F
111322  fraud_Mayert Group    shopping_pos   5.89  Benjamin   Harris      M

                    street  ...                       job         dob  \
123118   213 Gill Expressway  ...  Human resources officer  1971-10-14
675160  6278 Stephanie Unions  ...                Herbalist  1981-08-29
133167       8957 Russell Key  ...                  Curator  1972-07-25
261154      55505 Christy Via  ...          Naval architect  1949-04-24
```

```
111322        0881 Lori Pines  ...         Paediatric nurse   1981-02-15

                                trans_num   unix_time  merch_lat  merch_long  \
123118  6744f95a0c456529c4a35cb30a5cb396  1331349870  42.974691  -73.944930
675160  7c53e2c5bb6aa689753574d9f8ae623f  1350229247  41.046486  -74.132901
133167  0b3a94c9a2f622d2f3c3399a6cc3910b  1331738511  34.956184  -86.986784
261154  35caf2d1468a377e45235274b005aa02  1336640660  46.851874  -97.269843
111322  4ea34c698a6a4ad782a74a051f136aca  1330865641  38.303450  -75.346029

        is_fraud  week_number  month_number  year
123118         0            6             3  2019
675160         0            0            10  2019
133167         0            3             3  2019
261154         0            4             5  2019
111322         0            0             3  2019

[5 rows x 26 columns]
```

2.2 Test Data

[16]:
```python
# Test Data
# Change date to be date type
df1["trans_date_trans_time"] = pd.to_datetime(df1["trans_date_trans_time"])
# Create column week number
df1["week_number"] = df1["trans_date_trans_time"].dt.dayofweek
assert df1["week_number"].max() == 6
# Create column month number
df1["month_number"] = df1["trans_date_trans_time"].dt.month
assert df1["month_number"].max() == 12
# Create column year
df1["year"] = df1["trans_date_trans_time"].dt.year
df1.head()
```

[16]:
```
   Unnamed: 0 trans_date_trans_time            cc_num  \
0           0   2020-06-21 12:14:25  2291163933867244
1           1   2020-06-21 12:14:33  3573030041201292
2           2   2020-06-21 12:14:53  3598215285024754
3           3   2020-06-21 12:15:15  3591919803438423
4           4   2020-06-21 12:15:17  3526826139003047

                               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  ...                     job  \
0   Elliott      M          351 Darlene Green  ...     Mechanical engineer
1  Williams      F           3638 Marsh Union  ...  Sales professional, IT
2     Lopez      F        9333 Valentine Point  ...       Librarian, public
3  Williams      M  32941 Krystal Mill Apt. 552  ...            Set designer
4    Massey      M     5783 Evan Roads Apt. 465  ...      Furniture designer

          dob                         trans_num   unix_time  merch_lat  \
0  1968-03-19  2da90c7d74bd46a0caf3777415b3ebd3  1371816865  33.986391
1  1990-01-17  324cc204407e99f51b0d6ca0055005e7  1371816873  39.450498
2  1970-10-21  c81755dbbbea9d5c77f094348a7579be  1371816893  40.495810
3  1987-07-25  2159175b9efe66dc301f149d3d5abf8c  1371816915  28.812398
4  1955-07-06  57ff021bd3f328f8738bb535c302a31b  1371816917  44.959148

   merch_long  is_fraud  week_number  month_number  year
0  -81.200714         0            6             6  2020
1 -109.960431         0            6             6  2020
2  -74.196111         0            6             6  2020
3  -80.883061         0            6             6  2020
4  -85.884734         0            6             6  2020

[5 rows x 26 columns]
```

2.3 Category (One-Hot Endcoding)

Category is Nominal Data that cannot work with model,So I will change category to numerical by One Hot Encoding

2.3.1 Train Data

[18]:
```
category_onehot = pd.get_dummies(df_downsampled.category, prefix="category")
df_downsampled = df_downsampled.join(category_onehot)
df_downsampled.head()
```

[18]:
```
     Unnamed: 0 trans_date_trans_time               cc_num  \
126         126   2019-01-01 01:33:52     3567879740649740
159         159   2019-01-01 01:56:51       30442439074871
215         215   2019-01-01 02:38:49  4710826438164847414
404         404   2019-01-01 05:19:42        4464457352619
727         727   2019-01-01 09:27:35     3554849923339851

                                  merchant       category     amt    first  \
126                   fraud_Koss and Sons  gas_transport   58.79    Tanya
159  fraud_Parisian, Schiller and Altenwerth      misc_net   14.03    Linda
215            fraud_Strosin-Cruickshank    grocery_pos  128.24     Juan
404                 fraud_Vandervort-Funk    grocery_pos  124.33  Breanna
727                   fraud_Larson-Moen  entertainment   65.74     John
```

```
         last gender                       street  ... category_grocery_pos  \
126  Williams      F                566 Megan Well  ...                    0
159   Sanchez      F    6574 William Hill Apt. 375  ...                    0
215     Henry      M    9795 Lori Island Suite 346  ...                    1
404 Rodriguez      F  118 Cabrera Springs Apt. 105  ...                    1
727    Hudson      M                886 Nicole Key  ...                    0

     category_health_fitness  category_home  category_kids_pets  \
126                        0              0                   0
159                        0              0                   0
215                        0              0                   0
404                        0              0                   0
727                        0              0                   0

     category_misc_net  category_misc_pos category_personal_care  \
126                  0                  0                      0
159                  1                  0                      0
215                  0                  0                      0
404                  0                  0                      0
727                  0                  0                      0

     category_shopping_net  category_shopping_pos  category_travel
126                      0                      0                0
159                      0                      0                0
215                      0                      0                0
404                      0                      0                0
727                      0                      0                0

[5 rows x 40 columns]
```

2.4 Test Data

[19]:
```
category_onehot_test_data = pd.get_dummies(df1.category, prefix="category")
df1 = df1.join(category_onehot_test_data)
df1.head()
```

[19]:
```
   Unnamed: 0 trans_date_trans_time            cc_num  \
0           0   2020-06-21 12:14:25  2291163933867244
1           1   2020-06-21 12:14:33  3573030041201292
2           2   2020-06-21 12:14:53  3598215285024754
3           3   2020-06-21 12:15:15  3591919803438423
4           4   2020-06-21 12:15:17  3526826139003047

                               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  ... category_grocery_pos  \
0   Elliott      M             351 Darlene Green  ...                    0
1  Williams      F              3638 Marsh Union  ...                    0
2     Lopez      F          9333 Valentine Point  ...                    0
3  Williams      M  32941 Krystal Mill Apt. 552  ...                    0
4    Massey      M      5783 Evan Roads Apt. 465  ...                    0

   category_health_fitness  category_home  category_kids_pets  \
0                        0              0                   0
1                        0              0                   0
2                        1              0                   0
3                        0              0                   0
4                        0              0                   0

   category_misc_net  category_misc_pos  category_personal_care  \
0                  0                  0                       1
1                  0                  0                       1
2                  0                  0                       0
3                  0                  1                       0
4                  0                  0                       0

   category_shopping_net  category_shopping_pos  category_travel
0                      0                      0                0
1                      0                      0                0
2                      0                      0                0
3                      0                      0                0
4                      0                      0                1

[5 rows x 40 columns]
```

2.5 Gender

Change gender from nominal to numerical

[20]:
```python
# Train data
df_downsampled["gender"] = df_downsampled["gender"].replace(["F","M"],[0,1])
# Test data
df1["gender"] = df1["gender"].replace(["F","M"],[0,1])

print("Gender of train dataset", df_downsampled["gender"].value_counts())
print("Gender of test dataset", df1["gender"].value_counts())
```

```
Gender of train dataset 0    7975
1    7091
```

```
Name: gender, dtype: int64
Gender of test dataset 0    304886
1    250833
Name: gender, dtype: int64
```

2.6 Merchant

Convert Marchant to be numerical data

[21]:
```python
# Train data
from sklearn.preprocessing import LabelEncoder
label_encoder = LabelEncoder()
x_train = df_downsampled['merchant']
df_downsampled['merchant_number'] = label_encoder.fit_transform(x_train)

# Test data
x_test = df1['merchant']
df1['merchant_number'] = label_encoder.fit_transform(x_test)

print('Merchant Number of train dataset',df_downsampled['merchant_number'])
print('Merchant Number of test dataset',df1['merchant_number'])
```

```
Merchant Number of train dataset 126        332
159        475
215        608
404        645
727        376
          ...
1295710    645
1295733    332
1295801    442
1296013    300
1296098    104
Name: merchant_number, Length: 15066, dtype: int32
Merchant Number of test dataset 0         319
1         591
2         611
3         222
4         292
         ...
555714    507
555715    264
555716    496
555717     75
555718    125
Name: merchant_number, Length: 555719, dtype: int32
```

2.7 Age

Find Age from date of birth data

[23]:
```
from datetime import date
def calculate_age(row):
    today = date.today()
    return today.year - row["dob"].year - ((today.month, today.day) <␣
 ↪(row["dob"].month, row["dob"].day))

# Train data
df_downsampled["dob"] = pd.to_datetime(df_downsampled["dob"])
df_downsampled["age"] = df_downsampled["dob"]
df_downsampled["age"] = df_downsampled.apply (lambda row: calculate_age(row),␣
 ↪axis=1)

# Test data
df1["dob"] = pd.to_datetime(df1["dob"])
df1["age"] = df1["dob"]
df1["age"] = df1.apply (lambda row: calculate_age(row), axis=1)

print("Age of train dataset", df_downsampled["age"].head(3))
print("Age of test dataset", df1["age"].head(3))
```

```
Age of train dataset 126     65
159     42
215     59
Name: age, dtype: int64
Age of test dataset 0     55
1     33
2     52
Name: age, dtype: int64
```

2.7.1 Job

Convert Marchant to be numerical data

[24]:
```
from sklearn.preprocessing import LabelEncoder
label_encoder = LabelEncoder()

# Train data
x_train = df_downsampled["job"]
df_downsampled["job_number"] = label_encoder.fit_transform(x_train)
print(df_downsampled["job_number"])

# Test data
x_test = df1["job"]
df1["job_number"] = label_encoder.fit_transform(x_test)
print(df1["job_number"])
```

```
126        354
159        478
215        205
404        459
727         58
          ...
1295710    423
1295733    222
1295801    155
1296013     70
1296098     86
Name: job_number, Length: 15066, dtype: int32
0         275
1         392
2         259
3         407
4         196
         ...
555714    460
555715    198
555716    294
555717     58
555718    276
Name: job_number, Length: 555719, dtype: int32
```

3 Select Data

For select features I would like to do 2 experiments: ExtraTreesClassifier, .abs().nlargest(), because i would like to find the best acurracy and the best prediction

[25]:
```python
# Unselect converted data
select_data = df_downsampled
select_data.columns
```

[25]:
```
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', 'week_number', 'month_number',
       'year', 'category_entertainment', 'category_food_dining',
       'category_gas_transport', 'category_grocery_net',
       'category_grocery_pos', 'category_health_fitness', 'category_home',
       'category_kids_pets', 'category_misc_net', 'category_misc_pos',
       'category_personal_care', 'category_shopping_net',
       'category_shopping_pos', 'category_travel', 'merchant_number', 'age',
       'job_number'],
      dtype='object')
```

[26]:
```python
select_data = select_data[["cc_num",
        "amt", "gender", "zip",
        "lat", "long", "city_pop", "unix_time",
        "merch_lat", "merch_long", "age", "job_number",
        "week_number", "month_number", "year", "category_entertainment",
        "category_food_dining", "category_gas_transport",
        "category_grocery_net", "category_grocery_pos",
        "category_health_fitness", "category_home", "category_kids_pets",
        "category_misc_net", "category_misc_pos", "category_personal_care",
        "category_shopping_net", "category_shopping_pos", "category_travel",
        "merchant_number","is_fraud"]]
select_data.head()
```

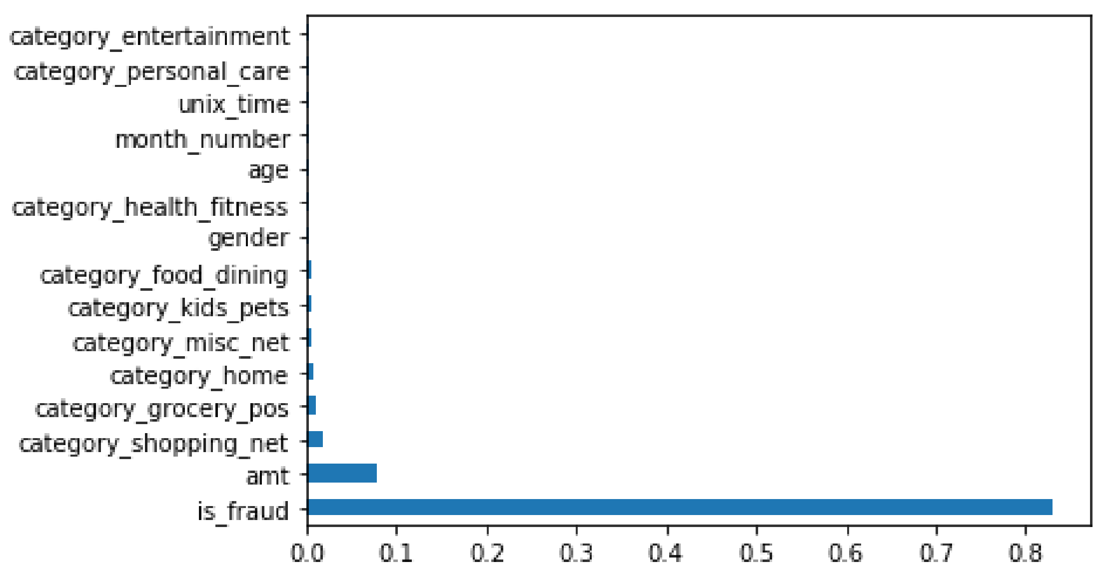
[26]:
```
                  cc_num     amt  gender    zip      lat      long  city_pop  \
126     3567879740649740   58.79       0  13615  44.0577  -76.0196      1271
159       30442439074871   14.03       0  18433  41.5744  -75.5881      6508
215  4710826438164847414  128.24       1  59542  48.8328 -108.3961       192
404        4464457352619  124.33       0  32323  29.8826  -84.5964       217
727     3554849923339851   65.74       1  74074  36.1043  -97.0609     55345

      unix_time  merch_lat  merch_long  ...  category_home  \
126  1325381632  44.015435  -76.027125  ...              0
159  1325383011  40.868184  -76.283066  ...              0
215  1325385529  49.176720 -108.757243  ...              0
404  1325395182  30.773425  -83.837856  ...              0
727  1325410055  35.359894  -97.202209  ...              0

     category_kids_pets  category_misc_net  category_misc_pos  \
126                   0                  0                  0
159                   0                  1                  0
215                   0                  0                  0
404                   0                  0                  0
727                   0                  0                  0

     category_personal_care  category_shopping_net  category_shopping_pos  \
126                       0                      0                      0
159                       0                      0                      0
215                       0                      0                      0
404                       0                      0                      0
727                       0                      0                      0

     category_travel  merchant_number  is_fraud
126                0              332         0
159                0              475         0
215                0              608         0
404                0              645         0
727                0              376         0
```

[5 rows x 31 columns]

3.1 ExtraTreesClassifier

[27]:
```python
X = select_data.iloc[:,0:31]  #independent columns
y = select_data.iloc[:,-1]    #target column i.e price range
from sklearn.ensemble import ExtraTreesClassifier
import matplotlib.pyplot as plt
model = ExtraTreesClassifier()
model.fit(X,y)
print(model.feature_importances_) #use inbuilt class feature_importances of␣
 ↪tree based classifiers
#plot graph of feature importances for better visualization
feat_importances = pd.Series(model.feature_importances_, index=X.columns)
feat_importances.nlargest(15).plot(kind='barh')
plt.show()
```

```
[1.30847723e-03 7.87207886e-02 3.34370404e-03 1.42383499e-03
 1.43687539e-03 1.36913174e-03 1.44755958e-03 2.17657707e-03
 1.42944450e-03 1.41207797e-03 3.02884839e-03 1.58295534e-03
 1.37346188e-03 2.56904042e-03 5.47966835e-04 1.73951898e-03
 3.91745194e-03 1.47505947e-03 6.93254013e-04 1.12931667e-02
 3.17239913e-03 7.67629254e-03 5.01394540e-03 5.87272181e-03
 1.02325934e-03 2.11592886e-03 1.90817434e-02 1.73688498e-03
 5.05751241e-04 1.29768180e-03 8.30214196e-01]
```



3.2 nlargest

[28]:
```
print(select_data.corr().abs().nlargest(15, 'is_fraud').index)
```

```
Index(['is_fraud', 'amt', 'category_shopping_net', 'category_grocery_pos',
       'category_home', 'category_misc_net', 'category_kids_pets',
       'category_health_fitness', 'category_food_dining',
       'category_personal_care', 'month_number', 'category_entertainment',
       'age', 'category_misc_pos', 'gender'],
      dtype='object')
```

[29]:
```
#Select Train Data
select_data_train_extra_tree =␣
↪df_downsampled[["amt","category_shopping_net","category_grocery_pos","category_home","categ
                                                              ␣
↪"category_kids_pets","category_health_fitness","gender","age","month_number",
                                                              ␣
↪"category_food_dining","unix_time","category_personal_care","category_shopping_pos","is_fra

select_data_train_abs_nlargest = df_downsampled[["amt",␣
↪"category_shopping_net", "category_grocery_pos",
                                              "category_home", "category_misc_net",␣
↪"category_kids_pets",
                                              "category_health_fitness",␣
↪"category_food_dining",
                                              "category_personal_care",␣
↪"month_number", "category_entertainment",
                                              "age", "category_misc_pos",␣
↪"gender","is_fraud"]]
```

[31]:
```
#Select Test Data
select_data_test_extra_tree =␣
↪df1[["amt","category_shopping_net","category_grocery_pos","category_home","category_misc_ne
                                                              ␣
↪"category_kids_pets","category_health_fitness","gender","age","month_number",
                                                              ␣
↪"category_food_dining","unix_time","category_personal_care","category_shopping_pos","is_fra

select_data_test_abs_nlargest = df1[["amt", "category_shopping_net",␣
↪"category_grocery_pos",
                                              "category_home", "category_misc_net",␣
↪"category_kids_pets",
                                              "category_health_fitness",␣
↪"category_food_dining",
                                              "category_personal_care",␣
↪"month_number", "category_entertainment",
```

```
                                                    'age', 'category_misc_pos',␣
↪'gender','is_fraud']]
```

[32]:
```
# Prepare X_train y_train
X_train_extra_tree =␣
↪select_data_train_extra_tree[['amt','category_shopping_net','category_grocery_pos','categor
                                                    ␣
↪'category_kids_pets','category_health_fitness','gender','age','month_number',
                                                    ␣
↪'category_food_dining','unix_time','category_personal_care','category_shopping_pos']]
y_train_extra_tree = select_data_train_extra_tree['is_fraud']

X_train_abs_nlargest = select_data_train_abs_nlargest[['amt',␣
↪'category_shopping_net', 'category_grocery_pos',
                                                    'category_home', 'category_misc_net',␣
↪'category_kids_pets',
                                                    'category_health_fitness',␣
↪'category_food_dining',
                                                    'category_personal_care',␣
↪'month_number', 'category_entertainment',
                                                    'age', 'category_misc_pos', 'gender']]
y_train_abs_nlargest = select_data_train_abs_nlargest['is_fraud']
```

[33]:
```
# Prepare X_test y_test
X_test_extra_tree =␣
↪select_data_test_extra_tree[['amt','category_shopping_net','category_grocery_pos','category
                                                    ␣
↪'category_kids_pets','category_health_fitness','gender','age','month_number',
                                                    ␣
↪'category_food_dining','unix_time','category_personal_care','category_shopping_pos']]
y_test_extra_tree = select_data_test_extra_tree['is_fraud']

X_test_abs_nlargest = select_data_test_abs_nlargest[['amt',␣
↪'category_shopping_net', 'category_grocery_pos',
                                                    'category_home', 'category_misc_net',␣
↪'category_kids_pets',
                                                    'category_health_fitness',␣
↪'category_food_dining',
                                                    'category_personal_care',␣
↪'month_number', 'category_entertainment',
                                                    'age', 'category_misc_pos', 'gender']]
y_test_abs_nlargest = select_data_test_abs_nlargest['is_fraud']
```

3.3 Scaler Data

[34]:
```
from sklearn import preprocessing
```

3.3.1 Scaler Train Data

[35]:
```
# Scale X_train
# Extra Tree
scaler = preprocessing.MinMaxScaler()
newValue = scaler.fit_transform(X_train_extra_tree)
X_train_extra_tree_scaler = pd.DataFrame(newValue, columns=X_train_extra_tree.
 ↪columns)
X_train_extra_tree_scaler
```

[35]:
```
            amt  category_shopping_net  category_grocery_pos  category_home  \
0      0.003994                    0.0                   0.0            0.0
1      0.000900                    0.0                   0.0            0.0
2      0.008795                    0.0                   1.0            0.0
3      0.008524                    0.0                   1.0            0.0
4      0.004474                    0.0                   0.0            0.0
...         ...                    ...                   ...            ...
15061  0.004588                    0.0                   1.0            0.0
15062  0.000635                    0.0                   0.0            0.0
15063  0.006693                    0.0                   1.0            0.0
15064  0.005938                    0.0                   0.0            0.0
15065  0.003708                    0.0                   0.0            0.0

       category_misc_net  category_kids_pets  category_health_fitness  gender  \
0                    0.0                 0.0                      0.0     0.0
1                    1.0                 0.0                      0.0     0.0
2                    0.0                 0.0                      0.0     1.0
3                    0.0                 0.0                      0.0     0.0
4                    0.0                 0.0                      0.0     1.0
...                  ...                 ...                      ...     ...
15061                0.0                 0.0                      0.0     1.0
15062                0.0                 0.0                      0.0     1.0
15063                0.0                 0.0                      0.0     0.0
15064                1.0                 0.0                      0.0     0.0
15065                0.0                 0.0                      0.0     1.0

          age  month_number  category_food_dining  unix_time  \
0      0.5875      0.000000                   0.0   0.000000
1      0.3000      0.000000                   0.0   0.000030
2      0.5125      0.000000                   0.0   0.000084
3      0.1875      0.000000                   0.0   0.000292
4      0.7125      0.000000                   0.0   0.000612
...       ...           ...                   ...        ...
```

```
15061  0.3625       0.454545                      0.0     0.999750
15062  0.1375       0.454545                      0.0     0.999764
15063  0.3875       0.454545                      0.0     0.999806
15064  0.3500       0.454545                      0.0     0.999947
15065  0.4500       0.454545                      1.0     1.000000

       category_personal_care  category_shopping_pos
0                         0.0                    0.0
1                         0.0                    0.0
2                         0.0                    0.0
3                         0.0                    0.0
4                         0.0                    0.0
...                       ...                    ...
15061                     0.0                    0.0
15062                     0.0                    0.0
15063                     0.0                    0.0
15064                     0.0                    0.0
15065                     0.0                    0.0

[15066 rows x 14 columns]
```

[36]:
```python
# Abs
scaler = preprocessing.MinMaxScaler()
newValue = scaler.fit_transform(X_train_abs_nlargest)
X_train_abs_nlargest_scaler = pd.DataFrame(newValue,␣
↪columns=X_train_abs_nlargest.columns)
X_train_abs_nlargest_scaler
```

[36]:
```
            amt  category_shopping_net  category_grocery_pos  category_home  \
0      0.003994                    0.0                   0.0            0.0
1      0.000900                    0.0                   0.0            0.0
2      0.008795                    0.0                   1.0            0.0
3      0.008524                    0.0                   1.0            0.0
4      0.004474                    0.0                   0.0            0.0
...         ...                    ...                   ...            ...
15061  0.004588                    0.0                   1.0            0.0
15062  0.000635                    0.0                   0.0            0.0
15063  0.006693                    0.0                   1.0            0.0
15064  0.005938                    0.0                   0.0            0.0
15065  0.003708                    0.0                   0.0            0.0

       category_misc_net  category_kids_pets  category_health_fitness  \
0                    0.0                 0.0                      0.0
1                    1.0                 0.0                      0.0
2                    0.0                 0.0                      0.0
3                    0.0                 0.0                      0.0
4                    0.0                 0.0                      0.0
```

```
...                  ...          ...            ...
15061                0.0          0.0            0.0
15062                0.0          0.0            0.0
15063                0.0          0.0            0.0
15064                1.0          0.0            0.0
15065                0.0          0.0            0.0

       category_food_dining  category_personal_care  month_number  \
0                       0.0                     0.0      0.000000
1                       0.0                     0.0      0.000000
2                       0.0                     0.0      0.000000
3                       0.0                     0.0      0.000000
4                       0.0                     0.0      0.000000
...                     ...                     ...           ...
15061                   0.0                     0.0      0.454545
15062                   0.0                     0.0      0.454545
15063                   0.0                     0.0      0.454545
15064                   0.0                     0.0      0.454545
15065                   1.0                     0.0      0.454545

       category_entertainment     age  category_misc_pos  gender
0                         0.0  0.5875                0.0     0.0
1                         0.0  0.3000                0.0     0.0
2                         0.0  0.5125                0.0     1.0
3                         0.0  0.1875                0.0     0.0
4                         1.0  0.7125                0.0     1.0
...                       ...     ...                ...     ...
15061                     0.0  0.3625                0.0     1.0
15062                     0.0  0.1375                0.0     1.0
15063                     0.0  0.3875                0.0     0.0
15064                     0.0  0.3500                0.0     0.0
15065                     0.0  0.4500                0.0     1.0

[15066 rows x 14 columns]
```

3.3.2 Scaler Test Data

[38]:
```
# Scale  X_test
#  Extra  Tree
scaler = preprocessing.MinMaxScaler()
newValue  =  scaler.fit_transform(X_test_extra_tree)
X_test_extra_tree_scaler = pd.DataFrame(newValue, columns=X_test_extra_tree.
 ↪columns)
X_test_extra_tree_scaler
```

[38]:
```
             amt  category_shopping_net  category_grocery_pos  category_home  \
0       0.000082                    0.0                   0.0            0.0
```

1	0.001267	0.0	0.0	0.0
2	0.001769	0.0	0.0	0.0
3	0.002594	0.0	0.0	0.0
4	0.000096	0.0	0.0	0.0
...	...	...	...	...
555714	0.001879	0.0	0.0	0.0
555715	0.004868	0.0	0.0	0.0
555716	0.003772	0.0	0.0	0.0
555717	0.000307	0.0	0.0	0.0
555718	0.001631	0.0	0.0	0.0

	category_misc_net	category_kids_pets	category_health_fitness \
0	0.0	0.0	0.0
1	0.0	0.0	0.0
2	0.0	0.0	1.0
3	0.0	0.0	0.0
4	0.0	0.0	0.0
...	...	...	...
555714	0.0	0.0	1.0
555715	0.0	1.0	0.0
555716	0.0	1.0	0.0
555717	0.0	0.0	0.0
555718	0.0	0.0	0.0

	gender	age	month_number	category_food_dining	unix_time \
0	1.0	0.4625	0.0	0.0	0.000000e+00
1	0.0	0.1875	0.0	0.0	4.785402e-07
2	0.0	0.4250	0.0	0.0	1.674891e-06
3	1.0	0.2250	0.0	0.0	2.990876e-06
4	1.0	0.6250	0.0	0.0	3.110511e-06
...	...	...	...	...	...
555714	1.0	0.4875	1.0	0.0	9.999984e-01
555715	1.0	0.0625	1.0	0.0	9.999985e-01
555716	0.0	0.2875	1.0	0.0	9.999989e-01
555717	1.0	0.4875	1.0	0.0	9.999994e-01
555718	1.0	0.1500	1.0	0.0	1.000000e+00

	category_personal_care	category_shopping_pos
0	1.0	0.0
1	1.0	0.0
2	0.0	0.0
3	0.0	0.0
4	0.0	0.0
...	...	...
555714	0.0	0.0
555715	0.0	0.0
555716	0.0	0.0

```
555717                    0.0                  0.0
555718                    0.0                  0.0

[555719 rows x 14 columns]
```

[39]:
```
# nlargest
scaler = preprocessing.MinMaxScaler()
newValue = scaler.fit_transform(X_test_abs_nlargest)
X_test_abs_nlargest_scaler = pd.DataFrame(newValue, columns=X_test_abs_nlargest.
 ↪columns)
X_test_abs_nlargest_scaler
```

[39]:
```
             amt  category_shopping_net  category_grocery_pos  category_home  \
0       0.000082                    0.0                   0.0            0.0
1       0.001267                    0.0                   0.0            0.0
2       0.001769                    0.0                   0.0            0.0
3       0.002594                    0.0                   0.0            0.0
4       0.000096                    0.0                   0.0            0.0
...          ...                    ...                   ...            ...
555714  0.001879                    0.0                   0.0            0.0
555715  0.004868                    0.0                   0.0            0.0
555716  0.003772                    0.0                   0.0            0.0
555717  0.000307                    0.0                   0.0            0.0
555718  0.001631                    0.0                   0.0            0.0

        category_misc_net  category_kids_pets  category_health_fitness  \
0                     0.0                 0.0                      0.0
1                     0.0                 0.0                      0.0
2                     0.0                 0.0                      1.0
3                     0.0                 0.0                      0.0
4                     0.0                 0.0                      0.0
...                   ...                 ...                      ...
555714                0.0                 0.0                      1.0
555715                0.0                 1.0                      0.0
555716                0.0                 1.0                      0.0
555717                0.0                 0.0                      0.0
555718                0.0                 0.0                      0.0

        category_food_dining  category_personal_care  month_number  \
0                        0.0                     1.0           0.0
1                        0.0                     1.0           0.0
2                        0.0                     0.0           0.0
3                        0.0                     0.0           0.0
4                        0.0                     0.0           0.0
...                      ...                     ...           ...
555714                   0.0                     0.0           1.0
555715                   0.0                     0.0           1.0
```

```
555716                  0.0                 0.0        1.0
555717                  0.0                 0.0        1.0
555718                  0.0                 0.0        1.0

        category_entertainment     age  category_misc_pos  gender
0                          0.0  0.4625                0.0     1.0
1                          0.0  0.1875                0.0     0.0
2                          0.0  0.4250                0.0     0.0
3                          0.0  0.2250                1.0     1.0
4                          0.0  0.6250                0.0     1.0
...                        ...     ...                ...     ...
555714                     0.0  0.4875                0.0     1.0
555715                     0.0  0.0625                0.0     1.0
555716                     0.0  0.2875                0.0     0.0
555717                     0.0  0.4875                0.0     1.0
555718                     1.0  0.1500                0.0     1.0

[555719 rows x 14 columns]
```

4 Model

4.1 LogisticRegression

[40]:
```python
from sklearn.linear_model import LogisticRegression
from sklearn import preprocessing
from sklearn.model_selection import cross_val_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report, confusion_matrix
```

[41]:
```python
# Extra Tree
model_ext = LogisticRegression(random_state=42)
model_ext.fit(X_train_extra_tree_scaler, y_train_extra_tree)

# nlargest
model_nr = LogisticRegression(random_state=42)
model_nr.fit(X_train_abs_nlargest_scaler, y_train_abs_nlargest)
```

[41]:
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=42, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```

[42]:
```python
# Extra Tree - Predict
y_pred_extra_tree_scaler = model_ext.predict(X_test_extra_tree_scaler)
```

```
# nlargest - Predict
y_pred_abs_nlargest_scaler = model_nr.predict(X_test_abs_nlargest_scaler)
```

[43]:
```
# Extra Tree - Confusion matrix
print("Select Data By Extra Tree")
print(pd.
 ↪DataFrame(confusion_matrix(y_test_extra_tree,y_pred_extra_tree_scaler),␣
 ↪columns=['Predicted Positive', 'Predicted Nagative'], index=['Actual␣
 ↪Positive', 'Actual Negative']))

# nlargest - Confusion matrix
print("Select Data By Abs nlargest")
print(pd.
 ↪DataFrame(confusion_matrix(y_test_abs_nlargest,y_pred_abs_nlargest_scaler),␣
 ↪columns=['Predicted Positive', 'Predicted Nagative'], index=['Actual␣
 ↪Positive', 'Actual Negative']))
```

```
Select Data By Extra Tree
                 Predicted Positive  Predicted Nagative
Actual Positive              501833               51741
Actual Negative                 657                1488
Select Data By Abs nlargest
                 Predicted Positive  Predicted Nagative
Actual Positive              499143               54431
Actual Negative                 659                1486
```

[44]:
```
# Extra Tree - Classification Report
print("Classification report (Select Data By Extra Tree)")
print(classification_report(y_test_extra_tree, y_pred_extra_tree_scaler))

# nlargest - Classification Report
print("Classification report (Select Data By Abs nlargest)")
print(classification_report(y_test_abs_nlargest, y_pred_abs_nlargest_scaler))
```

```
Classification report (Select Data By Extra Tree)
              precision    recall  f1-score   support

           0       1.00      0.91      0.95    553574
           1       0.03      0.69      0.05      2145

    accuracy                           0.91    555719
   macro avg       0.51      0.80      0.50    555719
weighted avg       0.99      0.91      0.95    555719

Classification report (Select Data By Abs nlargest)
              precision    recall  f1-score   support
```

```
           0       1.00      0.90      0.95    553574
           1       0.03      0.69      0.05      2145

    accuracy                           0.90    555719
   macro avg       0.51      0.80      0.50    555719
weighted avg       0.99      0.90      0.94    555719
```

4.2 Decision Tree

[47]:
```python
from sklearn.tree import DecisionTreeClassifier
dt_clf = DecisionTreeClassifier(criterion = 'gini', max_depth = 20,␣
 ↪random_state=42)

# Extra Tree - Fit Model
dt_clf.fit(X_train_extra_tree_scaler,  y_train_extra_tree)

# nlargest - Fit Model
dt_clf.fit(X_train_abs_nlargest_scaler, y_train_abs_nlargest)
```

[47]:
```
DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, criterion='gini',
                       max_depth=20, max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort='deprecated',
                       random_state=42, splitter='best')
```

[48]:
```python
#Extra Tree - Confusion matrix
print("Confusion Matrix(Select Data By Extra Tree)")
pred_test_extrea_tree_scaler = dt_clf.predict(X_test_extra_tree_scaler)
pd.DataFrame(confusion_matrix(y_test_extra_tree,pred_test_extrea_tree_scaler),␣
 ↪columns=['Predicted Positive', 'Predicted Nagative'], index=['Actual␣
 ↪Positive', 'Actual Negative'])
```

Confusion Matrix(Select Data By Extra Tree)

[48]:

	Predicted Positive	Predicted Nagative
Actual Positive	523678	29896
Actual Negative	1721	424

[49]:
```python
# nlargest - Confusion matrix
print("Confusion Matrix(Select Data By Abs nlargest)")
pred_test_abs_nlargest_scaler = dt_clf.predict(X_test_abs_nlargest_scaler)
pd.
 ↪DataFrame(confusion_matrix(y_test_abs_nlargest,pred_test_abs_nlargest_scaler),␣
 ↪columns=['Predicted Positive', 'Predicted Nagative'], index=['Actual␣
 ↪Positive', 'Actual Negative'])
```

Confusion Matrix(Select Data By Abs nlargest)

[49] :

	Predicted Positive	Predicted Nagative
Actual Positive	528320	25254
Actual Negative	1636	509

[50]:

```
# Extra Tree - Classification report
print("Classification report (Select Data By Extra Tree)")
print(classification_report(y_test_extra_tree, pred_test_extrea_tree_scaler))


# nlargest - Classification report
print("Classification report (Select Data By nlargest)")
print(classification_report(y_test_abs_nlargest, pred_test_abs_nlargest_scaler))
```

```
Classification report (Select Data By Extra Tree)
              precision    recall  f1-score   support

           0       1.00      0.95      0.97    553574
           1       0.01      0.20      0.03      2145

    accuracy                           0.94    555719
   macro avg       0.51      0.57      0.50    555719
weighted avg       0.99      0.94      0.97    555719

Classification report (Select Data By nlargest)
              precision    recall  f1-score   support

           0       1.00      0.95      0.98    553574
           1       0.02      0.24      0.04      2145

    accuracy                           0.95    555719
   macro avg       0.51      0.60      0.51    555719
weighted avg       0.99      0.95      0.97    555719
```

4.3 Conclusion

The best accuracy from 4 models is a Decision Tree and Selection data is nlargest has 95% and has the best True Positive but for True Negative has value less than LogisticRegression but f1-score has a little different. So, Decision Tree and Selection data is nlargest medel is the best in this project.

[ ]:

[ ]: