Dataset https://www.kaggle.com/datasets/kartik2112/fraud-detection

Task1:- **1)Problem Statement**

The Credit card transaction fraud detection problem includes modeling past credit card transactions with the knowledge of ones that turned out to be a fraud. This model is then used to identify whether a new transaction is fraudulent or not .

2) **Problem Objective**

The aim of this project is to predict whether a credit card transaction is fraudulent or not , which is based on the transaction amount , location and other transaction related all the data.

3) **About the dataset**

- Trans_date_trans_time - Transaction time stamp
- cc_num - Credit card number
- merchant - merchant name
- category - transaction category
- amt - transaction amount
- first - first name of card holder
- Last - last name of card holder
- gender - sex of card holder
- street - transaction address
- city - transaction city
- state - transaction state
- zip - transaction zipcode
- lat - transaction latitude
- long - transaction longitude
- city _pop - population of the city
- job - job of the card holder
- dob - date of birth of card holder
- trans_num - transaction number of transaction
- unix _time - time in unix format
- merch_lat - longitude of merchant
- is_fraud - nature of transaction

Note :- is_fraud is target variable

TASK(1):- **Import Libraries** :

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
```

Data Exploration Steps for all the variables. Write down your findings after every variable exploration

Import the dataset

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

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

```
Df = pd.read_csv("/content/drive/MyDrive/fraudTest.csv")
```

Task 2:- **Data Exploration & Validation**

```
# To observe first  rows.
Df.head()
```

	Unnamed: 0	trans_date_trans_time	cc_num	merchant	category	amt	first	last
0	0	21-06-2020 12:14	2.291160e+15	fraud_Kirlin and Sons	personal_care	2.86	Jeff	Elliott
1	1	21-06-2020 12:14	3.573030e+15	fraud_Sporer-Keebler	personal_care	29.84	Joanne	Williams
2	2	21-06-2020 12:14	3.598220e+15	fraud_Swaniawski, Nitzsche and Welch	health_fitness	41.28	Ashley	Lopez
3	3	21-06-2020 12:15	3.591920e+15	fraud_Haley Group	misc_pos	60.05	Brian	Williams
4	4	21-06-2020 12:15	3.526830e+15	fraud_Johnston-Casper	travel	3.19	Nathan	Massey

5 rows × 23 columns

```
# This is formatted as code
```

There are total 23 columns in the dataset that means we have 23 features in the dataset.

Note :- "is_fraud" is the target variable.

1) Basic Details of the data

```
# To check number of unique values in each feature in the dataset.
Df.nunique()
```

```
Unnamed: 0               555719
trans_date_trans_time    226976
cc_num                      904
merchant                    693
category                     14
amt                       37256
```

```
first                        341
last                         471
gender                         2
street                       924
city                         849
state                         50
zip                          912
lat                          910
long                         910
city_pop                     835
job                          478
dob                          910
trans_num                 555719
unix_time                 544760
merch_lat                 546490
merch_long                551770
is_fraud                       2
dtype: int64
```

```
# To get more information about datatypes in the dataset
Df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 555719 entries, 0 to 555718
Data columns (total 23 columns):
 #   Column                 Non-Null Count   Dtype  
---  ------                 --------------   -----  
 0   Unnamed: 0             555719 non-null  int64  
 1   trans_date_trans_time  555719 non-null  object 
 2   cc_num                 555719 non-null  float64
 3   merchant               555719 non-null  object 
 4   category               555719 non-null  object 
 5   amt                    555719 non-null  float64
 6   first                  555719 non-null  object 
 7   last                   555719 non-null  object 
 8   gender                 555719 non-null  object 
 9   street                 555719 non-null  object 
 10  city                   555719 non-null  object 
 11  state                  555719 non-null  object 
 12  zip                    555719 non-null  int64  
 13  lat                    555719 non-null  float64
 14  long                   555719 non-null  float64
 15  city_pop               555719 non-null  int64  
 16  job                    555719 non-null  object 
 17  dob                    555719 non-null  object 
 18  trans_num              555719 non-null  object 
 19  unix_time              555719 non-null  int64  
 20  merch_lat              555719 non-null  float64
 21  merch_long             555719 non-null  float64
 22  is_fraud               555719 non-null  int64  
dtypes: float64(6), int64(5), object(12)
memory usage: 97.5+ MB
```

```
# General information about the dataset.
Df.describe()
```

	Unnamed: 0	cc_num	amt	zip	lat	long	city_
count	555719.000000	5.557190e+05	555719.000000	555719.000000	555719.000000	555719.000000	5.557190e
mean	277859.000000	4.178387e+17	69.392810	48842.628015	38.543253	-90.231325	8.822189e
std	160422.401459	1.309837e+18	156.745941	26855.283328	5.061336	13.721780	3.003909e
min	0.000000	6.041621e+10	1.000000	1257.000000	20.027100	-165.672300	2.300000e
25%	138929.500000	1.800430e+14	9.630000	26292.000000	34.668900	-96.798000	7.410000e
50%	277859.000000	3.521420e+15	47.290000	48174.000000	39.371600	-87.476900	2.408000e
75%	416788.500000	4.635330e+15	83.010000	72011.000000	41.894800	-80.175200	1.968500e
max	555718.000000	4.992350e+18	22768.110000	99921.000000	65.689900	-67.950300	2.906700e

```
#Are there any suspicious variables.(Duplicates)
Df.columns.values
```

```
array(['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)
```

To get number of rows and columns in the dataset

```
# To get number of rows and columns that is dimensions.
Df.shape
```

```
(555719, 23)
```

```
# To check null values in the dataset.
Df.isnull()
```

	Unnamed: 0	trans_date_trans_time	cc_num	merchant	category	amt	first	last	gender	street
0	False	False	False	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False	False
...	...	...	...	...	...	...	...	...	...	...
555714	False	False	False	False	False	False	False	False	False	False
555715	False	False	False	False	False	False	False	False	False	False
555716	False	False	False	False	False	False	False	False	False	False
555717	False	False	False	False	False	False	False	False	False	False
555718	False	False	False	False	False	False	False	False	False	False

555719 rows × 23 columns

```
# To check total null values in each feature.
Df.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
```

Observations:-

1)There are 23 variables(features) and 555719 observations

2)In the dataset there are no null values

3) Most of the variables are of object types in dataset , some are float type and some are of int type

```
# Display the variable formats
Df.dtypes
```

```
Unnamed: 0                int64
trans_date_trans_time    object
cc_num                  float64
merchant                 object
category                 object
amt                     float64
first                    object
last                     object
gender                   object
street                   object
city                     object
state                    object
zip                       int64
lat                     float64
long                    float64
city_pop                  int64
job                      object
dob                      object
trans_num                object
unix_time                 int64
merch_lat               float64
merch_long              float64
is_fraud                  int64
dtype: object
```

```
from datetime import datetime

# Apply function utcfromtimestamp and drop column unix_time
Df['time'] = Df['unix_time'].apply(datetime.utcfromtimestamp)
Df.drop('unix_time', axis=1)

# Add cloumn hour of day
Df['hour_of_day'] = Df.time.dt.hour
```

Time was in the unix format , so converted in the standard time and then from the time hour column in extracted.

```
# Make two columns "time" & "hour_of_day" in place of "unix_time"
Df[['time','hour_of_day']]
```

	time	hour_of_day
0	2013-06-21 12:14:25	12
1	2013-06-21 12:14:33	12
2	2013-06-21 12:14:53	12
3	2013-06-21 12:15:15	12
4	2013-06-21 12:15:17	12
...	...	...
555714	2013-12-31 23:59:07	23
555715	2013-12-31 23:59:09	23
555716	2013-12-31 23:59:15	23
555717	2013-12-31 23:59:24	23
555718	2013-12-31 23:59:34	23

555719 rows × 2 columns

Converted unix_time feature in two diffrent features named as "time" & "hour_of_day". After the conversion there no need to keep unix_time feature , better option is to drop that.

```
Df.head()
```

	Unnamed: 0	trans_date_trans_time	cc_num	merchant	category	amt	first	last
0	0	21-06-2020 12:14	2.291160e+15	fraud_Kirlin and Sons	personal_care	2.86	Jeff	Elliott
1	1	21-06-2020 12:14	3.573030e+15	fraud_Sporer-Keebler	personal_care	29.84	Joanne	Williams
2	2	21-06-2020 12:14	3.598220e+15	fraud_Swaniawski, Nitzsche and Welch	health_fitness	41.28	Ashley	Lopez
3	3	21-06-2020 12:15	3.591920e+15	fraud_Haley Group	misc_pos	60.05	Brian	Williams
				fraud_Johnston-				

```
Df.columns.values
```

```
array(['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',
       'time', 'hour_of_day'], dtype=object)
```

These are the all columns names in the dataset.

```
#What are the categorical and discrete variables? What are the continues variables.
Df.dtypes
Df.head()
```

	Unnamed: 0	trans_date_trans_time	cc_num	merchant	category	amt	first	last
0	0	21-06-2020 12:14	2.291160e+15	fraud_Kirlin and Sons	personal_care	2.86	Jeff	Elliott
1	1	21-06-2020 12:14	3.573030e+15	fraud_Sporer-Keebler	personal_care	29.84	Joanne	Williams
2	2	21-06-2020 12:14	3.598220e+15	fraud_Swaniawski, Nitzsche and Welch	health_fitness	41.28	Ashley	Lopez
3	3	21-06-2020 12:15	3.591920e+15	fraud_Haley Group	misc_pos	60.05	Brian	Williams
4	4	21-06-2020 12:15	3.526830e+15	fraud_Johnston-Casper	travel	3.19	Nathan	Massey

5 rows × 25 columns

```
# Drop the column 'Unnamed: 0' as it is not involving role in model building.
Df.drop('Unnamed: 0',axis = 1,inplace=True)
```

Converted 'trans_date_trans_time' column as individual columns called as 'trans_date' & 'trans_time'. after conversion drop trans_date_trans_time column.

```
Df.head()
```

	trans_date_trans_time	cc_num	merchant	category	amt	first	last	gender	
0	21-06-2020 12:14	2.291160e+15	fraud_Kirlin and Sons	personal_care	2.86	Jeff	Elliott	M	I
1	21-06-2020 12:14	3.573030e+15	fraud_Sporer-Keebler	personal_care	29.84	Joanne	Williams	F	
2	21-06-2020 12:14	3.598220e+15	fraud_Swaniawski, Nitzsche and Welch	health_fitness	41.28	Ashley	Lopez	F	Va
3	21-06-2020 12:15	3.591920e+15	fraud_Haley Group	misc_pos	60.05	Brian	Williams	M	I
4	21-06-2020 12:15	3.526830e+15	fraud_Johnston-	travel	3.19	Nathan	Massey	M	

```
Df['trans_year'] = np.int64([d[6:10] for d in Df['trans_date_trans_time']])
Df['trans_month'] = np.int64([d[3:5] for d in Df['trans_date_trans_time']])
Df['trans_Date'] = np.int64([d[0:2] for d in Df['trans_date_trans_time']])
```

```
Df['trans_time'] = pd.to_datetime(Df['trans_date_trans_time']).dt.time
```

```
# As we split the the column "trans_date_trans_time" in four diffrent columns as "trans_date" ,"trans_month","trans_year" & "trans_time" s
Df.drop(['trans_date_trans_time'],axis = 1,inplace=True)
```

```
# we cannot work on trans_num as there is no unique pattern, so good option will be an drop it
Df = Df.drop("trans_num",axis=1)
```

```
Df.head()
```

	cc_num	merchant	category	amt	first	last	gender	street	city	state
0	2.291160e+15	fraud_Kirlin and Sons	personal_care	2.86	Jeff	Elliott	M	351 Darlene Green	Columbia	SC
1	3.573030e+15	fraud_Sporer-Keebler	personal_care	29.84	Joanne	Williams	F	3638 Marsh Union	Altonah	UT
2	3.598220e+15	fraud_Swaniawski, Nitzsche and Welch	health_fitness	41.28	Ashley	Lopez	F	9333 Valentine Point	Bellmore	NY
3	3.591920e+15	fraud_Haley Group	misc_pos	60.05	Brian	Williams	M	32941 Krystal Mill Apt. 552	Titusville	FL
4	3.526830e+15	fraud_Johnston-Casper	travel	3.19	Nathan	Massey	M	5783 Evan Roads Apt. 465	Falmouth	MI

5 rows × 26 columns

```
#Find the frequencies of all class variables in the data.
Df.columns.values
```

```
array(['cc_num', 'merchant', 'category', 'amt', 'first', 'last', 'gender',
       'street', 'city', 'state', 'zip', 'lat', 'long', 'city_pop', 'job',
       'dob', 'unix_time', 'merch_lat', 'merch_long', 'is_fraud', 'time',
       'hour_of_day', 'trans_year', 'trans_month', 'trans_Date',
       'trans_time'], dtype=object)
```

2) Categorical Variable Exploration

Visualization For Categorical Feature Use

1. Frequency Table
2. Count Plot

1) Frequency Table: frequency table counts cross-tabulation frequencies especially for categorical, discrete variables. It will help us understanding the variable by looking at the values it is taking and data count at each value.

2) Count Plot: Used to Show the counts of observations in each categorical bin using bars.

1) merchant

```
Df['merchant'].value_counts()
```

```
fraud_Kilback LLC                       1859
fraud_Cormier LLC                       1597
fraud_Schumm PLC                        1561
fraud_Kuhn LLC                          1521
fraud_Dickinson Ltd                     1519
                                        ...
fraud_Treutel-King                       323
fraud_Satterfield-Lowe                   319
fraud_Kessler Group                      318
fraud_Jerde-Hermann                      312
fraud_Ritchie, Bradtke and Stiedemann    304
Name: merchant, Length: 693, dtype: int64
```

2) category

```
# To count number of transactions in each category.
print(Df['category'].value_counts())
plt.figure(figsize=(4,3),dpi=200)
sns.countplot(y = "category" , data = Df)
```

```
gas_transport     56370
grocery_pos       52553
home              52345
shopping_pos      49791
kids_pets         48692
```

We can see that Most of the transactions are done in gas_transport

```
personal_care     39327
```

3) first

[ ] ↳ *1 cell hidden*

4) last

[ ] ↳ *3 cells hidden*

5) state

```
print(Df['state'].value_counts())
plt.figure(figsize=(8,6),dpi=200)
sns.countplot(y = "state" , data = Df)
```

```
TX    40393
NY    35918
PA    34326
CA    24135
OH    20147
MI    19671
IL    18960
FL    18104
AL    17532
MO    16501
MN    13719
AR    13484
NC    12868
SC    12541
KY    12506
VA    12506
WI    12370
IN    11959
IA    11819
OK    11379
GA    11277
MD    11152
```

6) city

```
Df['city'].value_counts()
```

```
Birmingham     2423
Meridian       2229
Phoenix        2222
Utica          2204
San Antonio    2182
               ...
Senatobia        10
Seattle           9
Guthrie           9
Rice              8
Wever             6
Name: city, Length: 849, dtype: int64
```

7) zip

↳ 1 cell hidden

8) dob

[ ] ↳ 2 cells hidden

8) gender

[ ] ↳ 2 cells hidden

9) job

[ ] ↳ 1 cell hidden

10) is_fraud

```
Df['is_fraud'].value_counts()
```

```
0    553574
1      2145
Name: is_fraud, dtype: int64
```

That means there are total 553574 transactions are normal and 2145 transactions are fraudelent

Initially in the dataset 'gender' is in the object form so we cannot fit a model with object variable, So need to be convert into numerical feature.

```
Df['gender']=Df['gender'].apply(lambda x: 1 if x=="M" else 0)
Df['gender'].value_counts()
```

```
0    304886
1    250833
Name: gender, dtype: int64
```

```
# TO see the Updated Dataset
Df.head()
```

	cc_num	merchant	category	amt	gender	street	city	state	zip	lat
0	2.291160e+15	fraud_Kirlin and Sons	personal_care	2.86	1	351 Darlene Green	Columbia	SC	29209	33.9659
1	3.573030e+15	fraud_Sporer-Keebler	personal_care	29.84	0	3638 Marsh Union	Altonah	UT	84002	40.3207
2	3.598220e+15	fraud_Swaniawski, Nitzsche and Welch	health_fitness	41.28	0	9333 Valentine Point	Bellmore	NY	11710	40.6729
3	3.591920e+15	fraud_Haley Group	misc_pos	60.05	1	32941 Krystal Mill Apt. 552	Titusville	FL	32780	28.5697
4	3.526830e+15	fraud_Johnston-Casper	travel	3.19	1	5783 Evan Roads Apt. 465	Falmouth	MI	49632	44.2529

5 rows × 24 columns

3) Continous Variable Explorration

To Explore Continouse Variable we can use

1. Quantile function
2. Boxplot

1) Quantile Function : takes an array and a number say q between 0 and 1.

2) Boxplot : A boxplot is a standardized way of displaying the dataset based on the five-number summary: the minimum, the maximum, the sample median, and the first and third quartiles.

```
Df.columns
```

```
Index(['cc_num', 'merchant', 'category', 'amt', 'gender', 'street', 'city',
       'state', 'zip', 'lat', 'long', 'city_pop', 'job', 'dob', 'unix_time',
       'merch_lat', 'merch_long', 'is_fraud', 'time', 'hour_of_day',
       'trans_year', 'trans_month', 'trans_Date', 'trans_time'],
      dtype='object')
```

sometimes distance from the customer's home location to the merchant's location can prove out to be main reason for fraud, so taking the **difference of longitude and lattitude of respective columns**

```
Df["lat_diff"] = abs(Df.lat - Df.merch_lat)
Df["long_diff"] = abs(Df["long"] - Df["merch_long"])
```

```
Df.head()
```

	cc_num	merchant	category	amt	gender	street	city	state	zip	lat
0	2.291160e+15	fraud_Kirlin and Sons	personal_care	2.86	1	351 Darlene Green	Columbia	SC	29209	33.9659
1	3.573030e+15	fraud_Sporer-Keebler	personal_care	29.84	0	3638 Marsh Union	Altonah	UT	84002	40.3207
2	3.598220e+15	fraud_Swaniawski, Nitzsche and Welch	health_fitness	41.28	0	9333 Valentine Point	Bellmore	NY	11710	40.6729
3	3.591920e+15	fraud_Haley Group	misc_pos	60.05	1	32941 Krystal Mill Apt.	Titusville	FL	32780	28.5697

```
# So ,now  we have the difference i.e. lat_diff & long_diff ,As we know that difference between each degree of longitude and lattitude is
# So taking displacement into account as it will be difficult to calculate distance between merchant's location
# or customer's location so applying pythogoras theorem

Df["displacement"] = np.sqrt(pow((Df["lat_diff"]*110),2) + pow((Df["long_diff"]*110),2))

# here we have applied pythogoras theorem and we have multiplied with 110 because each degree of longitude and lattitude is 69 miles(appro
```

```
Df.head()
```

	cc_num	merchant	category	amt	gender	street	city	state	zip	lat
0	2.291160e+15	fraud_Kirlin and Sons	personal_care	2.86	1	351 Darlene Green	Columbia	SC	29209	33.9659
1	3.573030e+15	fraud_Sporer-Keebler	personal_care	29.84	0	3638 Marsh Union	Altonah	UT	84002	40.3207
2	3.598220e+15	fraud_Swaniawski, Nitzsche and Welch	health_fitness	41.28	0	9333 Valentine Point	Bellmore	NY	11710	40.6729
3	3.591920e+15	fraud_Haley Group	misc_pos	60.05	1	32941 Krystal Mill Apt. 552	Titusville	FL	32780	28.5697
4	3.526830e+15	fraud_Johnston-Casper	travel	3.19	1	5783 Evan Roads Apt. 465	Falmouth	MI	49632	44.2529

5 rows × 27 columns

```
# now since we got the displacement so longitudes and lattitudes columns are of no use now, so we can remove them
Df = Df.drop(columns = ["lat","long","merch_lat","merch_long","lat_diff","long_diff"])
```

```
Df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 555719 entries, 0 to 555718
Data columns (total 21 columns):
 #   Column        Non-Null Count   Dtype
---  ------        --------------   -----
 0   cc_num        555719 non-null  float64
 1   merchant      555719 non-null  object
 2   category      555719 non-null  object
 3   amt           555719 non-null  float64
 4   gender        555719 non-null  int64
 5   street        555719 non-null  object
 6   city          555719 non-null  object
 7   state         555719 non-null  object
 8   zip           555719 non-null  int64
 9   city_pop      555719 non-null  int64
 10  job           555719 non-null  object
 11  dob           555719 non-null  object
 12  unix_time     555719 non-null  int64
 13  is_fraud      555719 non-null  int64
 14  time          555719 non-null  datetime64[ns]
 15  hour_of_day   555719 non-null  int64
```

```
 16  trans_year    555719 non-null  int64
 17  trans_month   555719 non-null  int64
 18  trans_Date    555719 non-null  int64
 19  trans_time    555719 non-null  object
 20  displacement  555719 non-null  float64
dtypes: datetime64[ns](1), float64(3), int64(9), object(8)
memory usage: 89.0+ MB
```

```
# since state contains both city and zip code and street comes under city, so we can move with state column and drop street, city and zip
# we can work with cities through their population parameter, as names of cities cannot implement whether a fraud will be done or not, whi
# population of a city can.
Df = Df.drop(columns = ["city","zip","street"])
Df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 555719 entries, 0 to 555718
Data columns (total 18 columns):
 #   Column        Non-Null Count   Dtype
---  ------        --------------   -----
 0   cc_num        555719 non-null  float64
 1   merchant      555719 non-null  object
 2   category      555719 non-null  object
 3   amt           555719 non-null  float64
 4   gender        555719 non-null  int64
 5   state         555719 non-null  object
 6   city_pop      555719 non-null  int64
 7   job           555719 non-null  object
 8   dob           555719 non-null  object
 9   unix_time     555719 non-null  int64
 10  is_fraud      555719 non-null  int64
 11  time          555719 non-null  datetime64[ns]
 12  hour_of_day   555719 non-null  int64
 13  trans_year    555719 non-null  int64
 14  trans_month   555719 non-null  int64
 15  trans_Date    555719 non-null  int64
 16  trans_time    555719 non-null  object
 17  displacement  555719 non-null  float64
dtypes: datetime64[ns](1), float64(3), int64(8), object(6)
memory usage: 76.3+ MB
```

1) **amt**

```
Df['amt'].describe()
```

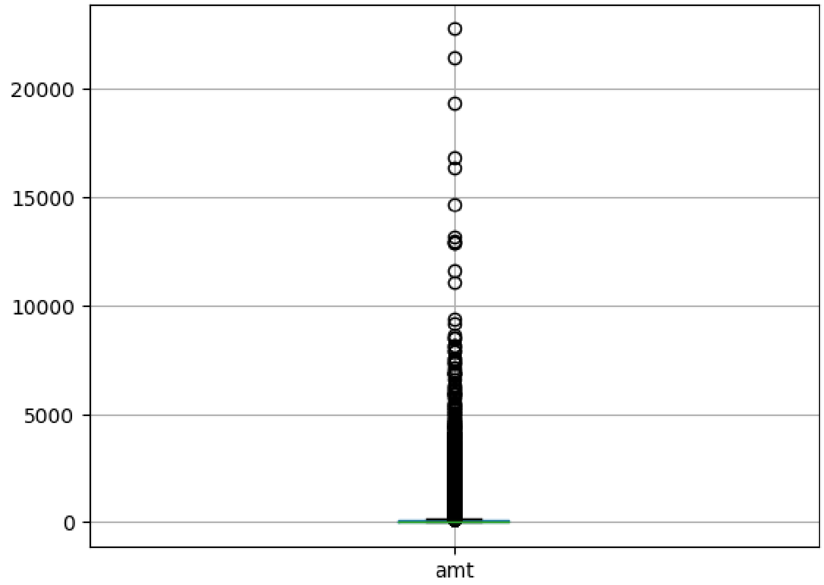
```
count    555719.000000
mean         69.392810
std         156.745941
min           1.000000
25%           9.630000
50%          47.290000
75%          83.010000
max       22768.110000
Name: amt, dtype: float64
```

```
util_percentiles=Df['amt'].quantile([0.1, 0.25, 0.5, 0.75, 0.80, 0.9,0.91,0.92,0.93,0.94,0.95,0.96,0.97,0.98,0.99,0.995,1.00])
round(util_percentiles,2)
```

```
0.100        4.08
0.250        9.63
0.500       47.29
0.750       83.01
0.800       94.40
0.900      135.55
0.910      142.38
0.920      150.93
0.930      162.74
0.940      177.45
0.950      193.05
0.960      210.08
0.970      238.74
0.980      320.49
0.990      519.85
0.995      787.16
1.000    22768.11
Name: amt, dtype: float64
```

```
Df.boxplot(column='amt')
```

```
<Axes: >
```



There are lot of outliers. need to be clean

```
Df['is_fraud'].value_counts()
```

```
0    553574
1      2145
Name: is_fraud, dtype: int64
```

0- Normal Transactions

1- Normal Transaction

```
Df['amt'].describe()
```

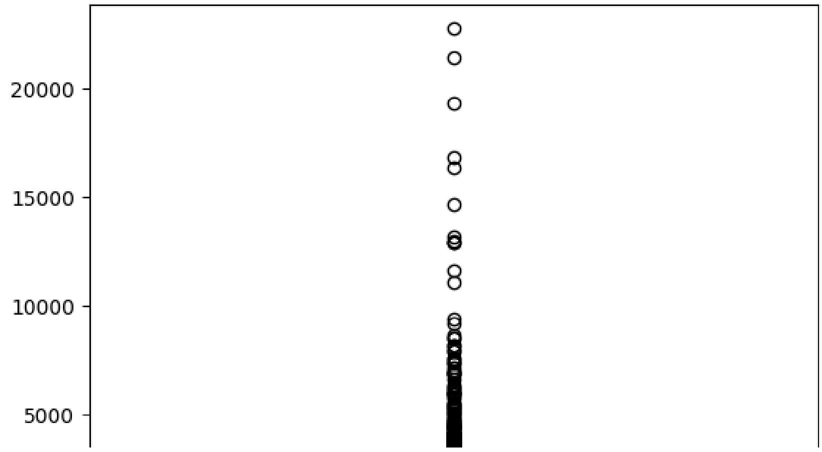
```
count    555719.000000
mean         69.392810
std         156.745941
min           1.000000
25%           9.630000
50%          47.290000
75%          83.010000
max       22768.110000
Name: amt, dtype: float64
```

```
Percentiles = Df['amt'].quantile([0.10,0.25,0.5,0.75,0.80,0.90,0.91,0.92,0.93,0.94,0.96,0.97,0.98,0.99,1.0])
Percentiles
```

```
0.10        4.0800
0.25        9.6300
0.50       47.2900
0.75       83.0100
0.80       94.4000
0.90      135.5500
0.91      142.3800
0.92      150.9300
0.93      162.7374
0.94      177.4500
0.96      210.0800
0.97      238.7400
0.98      320.4864
0.99      519.8546
1.00    22768.1100
Name: amt, dtype: float64
```

```
plt.boxplot(Df["amt"])
```

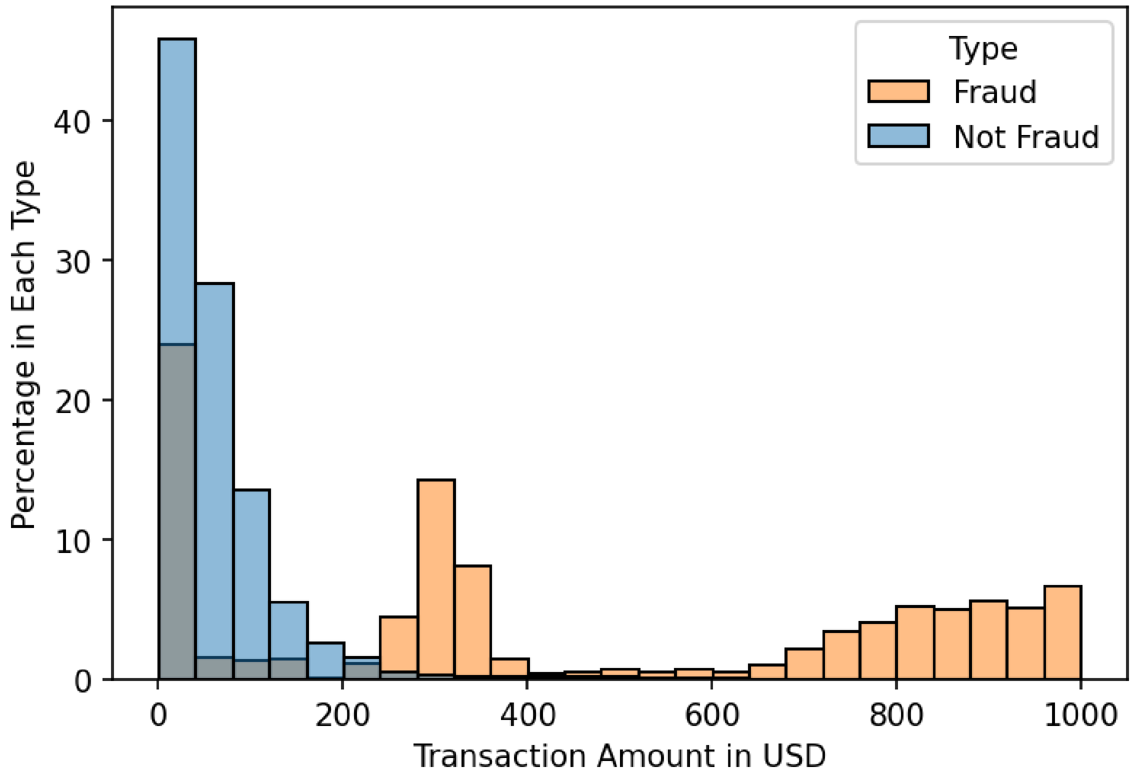
```
{'whiskers': [<matplotlib.lines.Line2D at 0x7972362b2e30>,
  <matplotlib.lines.Line2D at 0x7972362b30d0>],
 'caps': [<matplotlib.lines.Line2D at 0x7972362b3370>,
  <matplotlib.lines.Line2D at 0x7972362b3610>],
 'boxes': [<matplotlib.lines.Line2D at 0x7972362b2b90>],
 'medians': [<matplotlib.lines.Line2D at 0x7972362b38b0>],
 'fliers': [<matplotlib.lines.Line2D at 0x7972362b3b50>],
 'means': []}
```



We can see that fraud transactions are very very less as compare to the normal ones.

```
#amount vs fraud
plt.figure(figsize=(6,4),dpi=150)
ax=sns.histplot(x='amt',data=Df[Df.amt<=1000],hue='is_fraud',stat='percent',common_norm=False,bins=25)
ax.set_ylabel('Percentage in Each Type')
ax.set_xlabel('Transaction Amount in USD')
plt.legend(title='Type', labels=['Fraud', 'Not Fraud'])
```

```
<matplotlib.legend.Legend at 0x797236314c40>
```

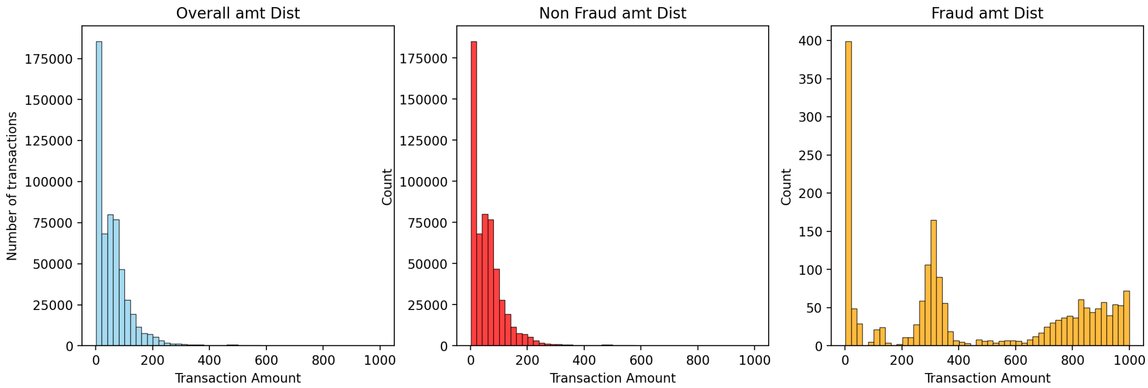


Observation :-The result is very interesting! While normal transactions tend to be around $200 or less, we can see fraudulent transactions peak around $300 and then at the $800-$1000 range.

```
fig = plt.subplots(figsize=(15,10),dpi=200)
plots = []

plots.append(sns.histplot(Df[Df.amt <= 1000].amt, bins=50, ax=plt.subplot(234),color='skyblue'))
plots.append(sns.histplot(Df[(Df.is_fraud==0) & (Df.amt<=1000)].amt, bins=50, ax=plt.subplot(235),color='red'))
plots.append(sns.histplot(Df[(Df.is_fraud==1) & (Df.amt<=1000)].amt, bins=50, ax=plt.subplot(236),color='orange'))
```

```
#setting titles
plots[0].set_title('Overall amt Dist')
plots[1].set_title('Non Fraud amt Dist')
plots[2].set_title('Fraud amt Dist')

#setting x labels
plots[0].set_xlabel('Transaction Amount')
plots[1].set_xlabel('Transaction Amount')
plots[2].set_xlabel('Transaction Amount')

#setting y label
plots[0].set_ylabel('Number of transactions')
```

```
<ipython-input-57-76452dfff7cf>:4: MatplotlibDeprecationWarning: Auto-removal of overlapping axes is de
  plots.append(sns.histplot(Df[Df.amt <= 1000].amt, bins=50, ax=plt.subplot(234),color='skyblue'))
Text(0, 0.5, 'Number of transactions')
```



Create new column as age by subtracting dob from todays date To get todays there is function called datetime.date.today()

```
import datetime as dt
Df['age']=dt.date.today().year-pd.to_datetime(Df['dob']).dt.year
```

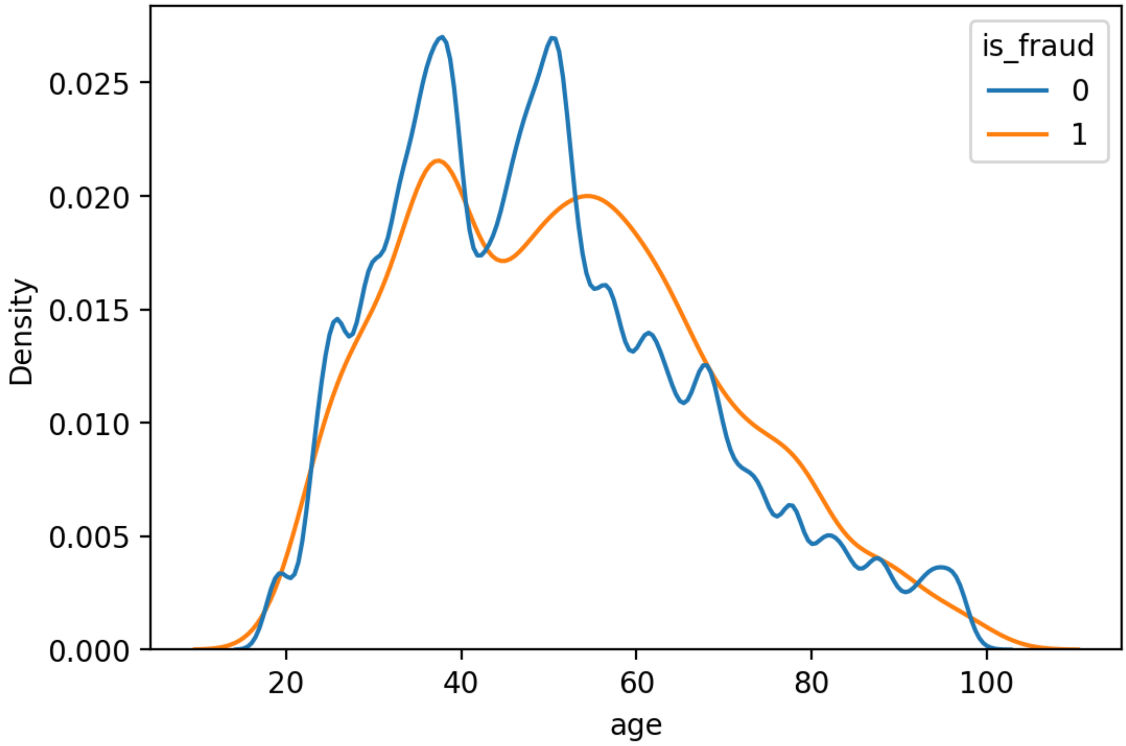
```
<ipython-input-58-1bcc528915ea>:2: UserWarning: Parsing dates in DD/MM/YYYY format when dayfirst=False (the default) was specified.
  Df['age']=dt.date.today().year-pd.to_datetime(Df['dob']).dt.year
```

```
Df.head()
```

	cc_num	merchant	category	amt	gender	state	city_pop	job	dob	unix_
0	2.291160e+15	fraud_Kirlin and Sons	personal_care	2.86	1	SC	333497	Mechanical engineer	19-03-1968	137181
1	3.573030e+15	fraud_Sporer-Keebler	personal_care	29.84	0	UT	302	Sales professional, IT	17-01-1990	137181
2	3.598220e+15	fraud_Swaniawski, Nitzsche and Welch	health_fitness	41.28	0	NY	34496	Librarian, public	21-10-1970	137181
3	3.591920e+15	fraud_Haley Group	misc_pos	60.05	1	FL	54767	Set designer	25-07-1987	137181
4	3.526830e+15	fraud_Johnston-Casper	travel	3.19	1	MI	1126	Furniture designer	06-07-1955	137181

```
plt.figure(figsize=(6,4),dpi=200)
sns.kdeplot(data=Df,x='age',hue='is_fraud',common_norm=False)
```

```
<Axes: xlabel='age', ylabel='Density'>
```

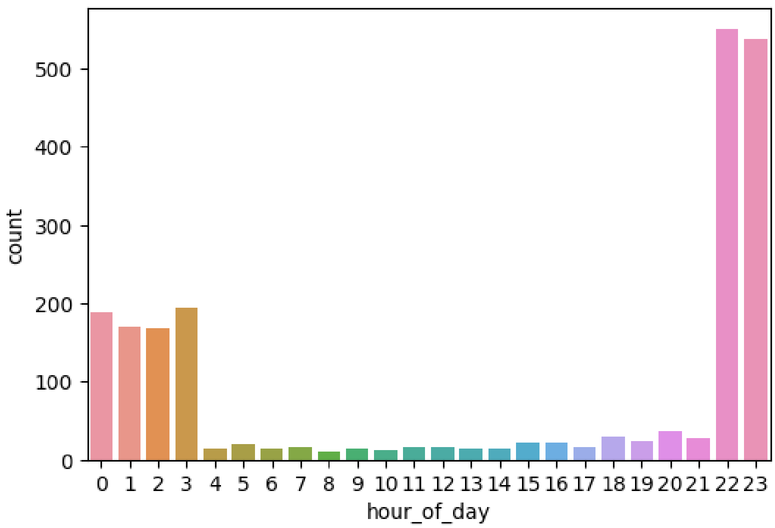


Observation :- From the graph we can see that most of the fraud transactions are done by 30-60 age group.

Observation :- There are more Fraud transactions are done by females.nearly about 1200 fraud transactions are done by females and around 1000 fraud transactions are done by males.

```
#Plotting fraud transactions with respect to the hour of day
plt.figure(figsize=(6,4),dpi=100)
sns.countplot(x="hour_of_day",data=Df[Df["is_fraud"]==1])
```

```
<Axes: xlabel='hour_of_day', ylabel='count'>
```



Observation :- From the Graph we can see that mostly fraud transactions are done in midnight around 22 hour to 24 hour of the day then in between 0 to 4 hr.In daytime fraud transactions are very less in number.

From this we can conclude that most of the fraud transactions happened during midnight.

```
#Creating a dataframe consisting of state wise fraud transactions
df1 = Df.groupby(by="state").sum()["is_fraud"].to_frame()
df1.reset_index(inplace=True)
df1 = df1.rename(columns = {"state":"State","is_fraud":"Fraudulent Transactions"})
df1.head()
```

```
<ipython-input-64-93dbd19d1292>:2: FutureWarning: The default value of numeric_only in DataFrameGroupBy
  df1 = Df.groupby(by="state").sum()["is_fraud"].to_frame()
```

	State	Fraudulent Transactions
0	AK	14
1	AL	63
2	AR	34
3	AZ	27
4	CA	76

These are the count of the fraud transactions in each states

Task 3:- Data Cleaning and Data Preparation

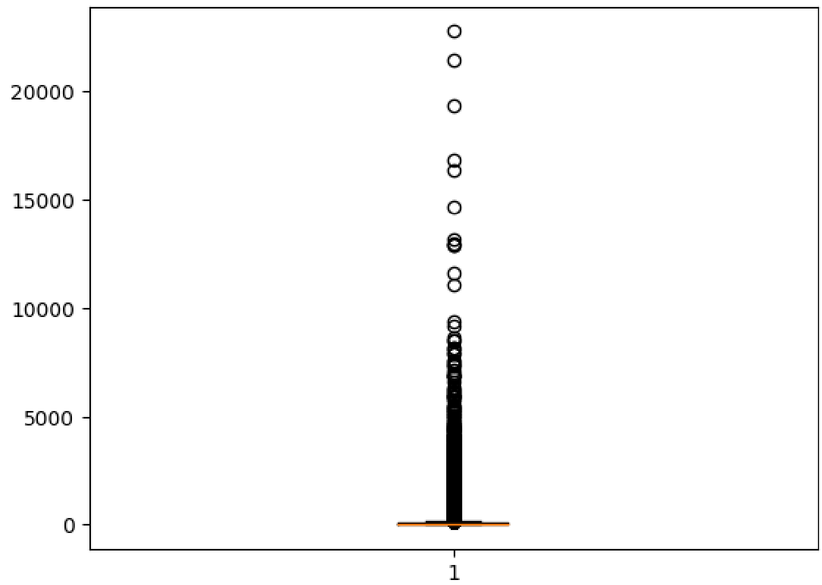
Write down Outlier treatment and missing value treatment code

```
Df['amt'].describe()
```

```
count    555719.000000
mean         69.392810
std         156.745941
min           1.000000
25%           9.630000
50%          47.290000
75%          83.010000
max       22768.110000
Name: amt, dtype: float64
```

```
plt.boxplot(Df['amt'])
```

```
{'whiskers': [<matplotlib.lines.Line2D at 0x797231649de0>,
  <matplotlib.lines.Line2D at 0x79723164a080>],
 'caps': [<matplotlib.lines.Line2D at 0x79723164a320>,
  <matplotlib.lines.Line2D at 0x79723164a5c0>],
 'boxes': [<matplotlib.lines.Line2D at 0x797231649c60>],
 'medians': [<matplotlib.lines.Line2D at 0x79723164a860>],
 'fliers': [<matplotlib.lines.Line2D at 0x79723164ab00>],
 'means': []}
```



Observation:- From the boxplot we can see that there are lot of outliers in the "amt". need to treat them

```
util_percentiles=Df['amt'].quantile([0.1, 0.25, 0.5, 0.75, 0.80, 0.9,0.91,0.92,0.93,0.94,0.95,0.96,0.97,0.98,0.99,0.995,1.00])
round(util_percentiles,2)
```

```
0.100        4.08
0.250        9.63
0.500       47.29
0.750       83.01
0.800       94.40
0.900      135.55
0.910      142.38
0.920      150.93
0.930      162.74
0.940      177.45
0.950      193.05
0.960      210.08
0.970      238.74
0.980      320.49
0.990      519.85
0.995      787.16
1.000    22768.11
Name: amt, dtype: float64
```

Observation:-From the quantile function we are able to understand that most of the data is clean around 99.5% of the data. 99.5% of the data is below 787.16$

```
(Df['amt']>1000).sum()
```

```
1583
```

```
(Df['amt']<1000).sum()
```

```
554136
```

Observation:-If we see that most of the data that is 554136 entries are below 1000$ and only 1583 is above 1000 so we can treat them as outliers. 1583 is less than 1% of the data . So , We can change them with median.

```
Df['amt'].median()
```

```
47.29
```

```
Df['amt1']=Df['amt']
Df['amt1'][Df['amt']>1000]=Df['amt'].median()
round(Df['amt1'].describe())
```

```
<ipython-input-71-89ec1a192945>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-
  Df['amt1'][Df['amt']>1000]=Df['amt'].median()
count    555719.0
mean         64.0
std          85.0
min           1.0
25%          10.0
50%          47.0
75%          82.0
max        1000.0
Name: amt1, dtype: float64
```

```
util_percentiles=Df['amt1'].quantile([0.1, 0.25, 0.5, 0.75, 0.80, 0.9,0.91,0.92,0.93,0.94,0.95,0.96,0.97,0.98,0.99,0.995,1.00])
round(util_percentiles,2)
```

```
0.100      4.08
0.250      9.63
0.500     47.29
0.750     82.46
0.800     93.67
0.900    133.89
0.910    140.25
0.920    148.24
```

```
0.930    158.96
0.940    173.24
0.950    188.66
0.960    204.81
0.970    227.71
0.980    289.91
0.990    461.31
0.995    584.89
1.000    999.69
Name: amt1, dtype: float64
```

Task 4:- Model Building

1) Linear Regreesion is not a suitable choice for the given data.

2) As we know that for a given dataset output is classification it is not continouse so we should use Logistic Regression here to get the good accuracy.

The Classification algorithm is a Supervised Learning technique that is used to identify the category of new observations on the basis of training data. In Classification, a program learns from the given dataset or observations and then classifies new observation into a number of classes or groups.

So here we will use two classification algorithm:

1. Logistic Regression
2. Decision Tree

1)Logistic Regression

```
from sklearn.linear_model import LogisticRegression
```

```
logistic= LogisticRegression()
results = logistic.fit(Df[["amt1"]+['displacement']+['hour_of_day']+['city_pop']+['gender']+['trans_month']+['trans_Date']+['trans_year']+
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/utils/validation.py:1143: DataConversionWarning: A column-vector y was passed when a
  y = column_or_1d(y, warn=True)
```

```
logistic.intercept_
```

```
array([-1.61980732e-06])
```

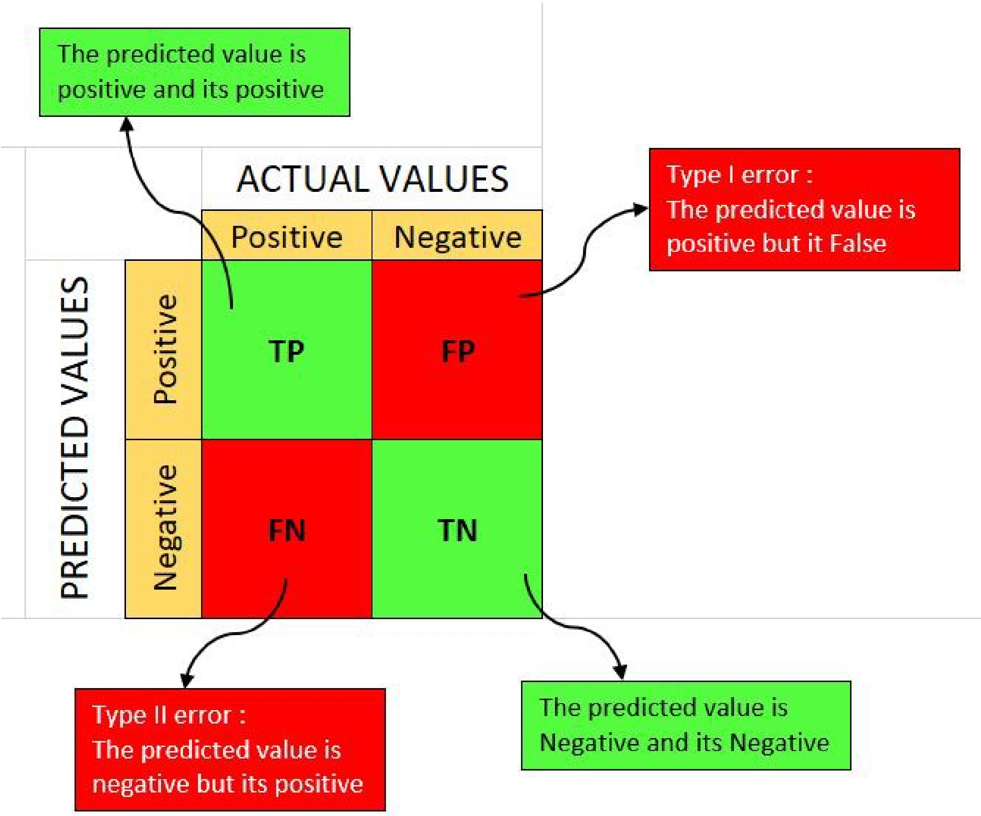
```
logistic.coef_
```

```
array([[ 7.22317091e-03, -1.28165432e-04,  7.84530331e-06,
        -4.62274403e-07, -5.93555751e-07, -2.36420070e-05,
        -5.57704480e-05, -3.27201077e-03, -3.99948579e-05]])
```

Model Validation

Confusion matrix, Sensitivity, Specificity, F1 Score, Recall, Precision etc.

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix
```



Since we need to find accuracy of the model , we will have to find confusion matrix.

True Positive (TN) = [1,1] True Negative (TN) = [0,0] False Negative (FN) = [1,0] False Positive (FP) = [0,1]

	Predicted Positive	Predicted Negative	
Actual Positive	TP *True Positive*	FN *False Negative*	Sensitivity $\frac{TP}{(TP+FN)}$
Actual Negative	FP *False Positive*	TN *True Negative*	Specificity $\frac{TN}{(TN+FP)}$
	Precision $\frac{TP}{(TP+FP)}$	Negative Predictive Value $\frac{TN}{(TN+FN)}$	Accuracy $\frac{TP+TN}{(TP+TN+FP+FN)}$

1) **Accuracy**:It is calculated by dividing the total number of correct predictions by all the predictions.

2) **Recall**: The recall is the measure to check correctly positive predicted outcomes out of the total number of positive outcomes.

3)**Precision**:Precision checks how many outcomes are actually positive outcomes out of the total positively predicted outcomes.

4)**F1 score**: is a number between 0 and 1 and is the harmonic mean of precision and recall.

5)**Sensitivity**: is calculated as the number of correct positive predictions divided by the total number of positives.

6)**Specificity**: is calculated as the number of correct negative predictions divided by the total number of negatives.

```
predict1=logistic.predict(Df[["amt1"]+['displacement']+['hour_of_day']+['city_pop']+['gender']+['trans_month']+['trans_Date']+['trans_yea
predict1
```

```
cm1 = confusion_matrix(Df[['is_fraud']],predict1)
print(cm1)
```

```
[[553391    183]
 [  1930    215]]
```

```
print("col sums", sum(cm1))
total1=sum(sum(cm1))
print("Total", total1)
```

```
col sums [555321    398]
Total 555719
```

```
accuracy1=(cm1[0,0]+cm1[1,1])/total1
accuracy1
```

```
0.9961977186311787
```

Observations:-By Looking at the accuracy of the logistic regression we can conclude that model is overfitted.

```
Df['is_fraud']
```

```
0         0
1         0
2         0
3         0
4         0
         ..
555714    0
555715    0
555716    0
555717    0
555718    0
Name: is_fraud, Length: 555719, dtype: int64
```

Individual Impact of Variable

```
import statsmodels.api as sm
m1=sm.Logit(Df['is_fraud'],Df[["amt1"]+["displacement"]+['hour_of_day']+['city_pop']+['gender']+['trans_month']+['trans_Date']+['trans_yea
m1.fit()
print(m1.fit().summary())
```

```
Optimization terminated successfully.
         Current function value: 0.018722
         Iterations 10
Optimization terminated successfully.
         Current function value: 0.018722
         Iterations 10
                           Logit Regression Results
==============================================================================
Dep. Variable:               is_fraud   No. Observations:               555719
Model:                          Logit   Df Residuals:                   555710
Method:                           MLE   Df Model:                            8
Date:                Mon, 11 Sep 2023   Pseudo R-squ.:                  0.2601
Time:                        04:39:21   Log-Likelihood:                -10404.
converged:                       True   LL-Null:                       -14061.
Covariance Type:            nonrobust   LLR p-value:                     0.000
================================================================================
                   coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
amt1             0.0072   7.21e-05     99.663      0.000       0.007       0.007
displacement     0.0004      0.001      0.512      0.609      -0.001       0.002
hour_of_day      0.0248      0.003      7.237      0.000       0.018       0.031
city_pop     -4.243e-07   1.03e-07     -4.116      0.000   -6.26e-07   -2.22e-07
gender           0.0208      0.047      0.442      0.658      -0.071       0.113
trans_month     -0.1090      0.012     -8.958      0.000      -0.133      -0.085
trans_Date      -0.0201      0.003     -7.604      0.000      -0.025      -0.015
trans_year      -0.0030    8.4e-05    -36.103      0.000      -0.003      -0.003
age              0.0094      0.001      6.961      0.000       0.007       0.012
================================================================================
```

Observations:- We can see that "displacement" & "gender" are non impactful variables , by looking at their P value . for impactful variable p value sholud be less than 0.05

Now We will build a Logistic regression model such that it includes only impactful variables.

```
m2=sm.Logit(Df['is_fraud'],Df[["amt1"]+['hour_of_day']+['city_pop']+['trans_month']+['trans_Date']+['trans_year']+['age']])
m2.fit()
print(m2.fit().summary())
```

```
Optimization terminated successfully.
         Current function value: 0.018722
         Iterations 10
Optimization terminated successfully.
         Current function value: 0.018722
         Iterations 10
                           Logit Regression Results
==============================================================================
Dep. Variable:               is_fraud   No. Observations:               555719
Model:                          Logit   Df Residuals:                   555712
Method:                           MLE   Df Model:                            6
Date:                Mon, 11 Sep 2023   Pseudo R-squ.:                  0.2601
Time:                        04:39:28   Log-Likelihood:                -10404.
converged:                       True   LL-Null:                       -14061.
Covariance Type:            nonrobust   LLR p-value:                     0.000
===============================================================================
                  coef    std err          z      P>|z|      [0.025      0.975]
-------------------------------------------------------------------------------
amt1            0.0072   7.21e-05     99.669      0.000       0.007       0.007
hour_of_day     0.0248      0.003      7.251      0.000       0.018       0.032
city_pop    -4.261e-07   1.03e-07     -4.138      0.000   -6.28e-07   -2.24e-07
trans_month    -0.1089      0.012     -8.956      0.000      -0.133      -0.085
trans_Date     -0.0201      0.003     -7.609      0.000      -0.025      -0.015
trans_year     -0.0030   7.71e-05    -39.075      0.000      -0.003      -0.003
age             0.0094      0.001      6.961      0.000       0.007       0.012
===============================================================================
```

```
# Defining user defined function for Variation Inflation Factor
def vif_cal(input_data,dependent_col):
  import statsmodels.formula.api as sm
  x_vars=input_data.drop([dependent_col], axis=1)
  xvar_names=x_vars.columns
  for i in range(0,xvar_names.shape[0]):
    y=x_vars[xvar_names[i]]
    x=x_vars[xvar_names.drop(xvar_names[i])]
    rsq=sm.ols(formula="y~x", data=x_vars).fit().rsquared
    vif=round(1/(1-rsq),2)
    print (xvar_names[i], " VIF = " , vif)
```

```
features_1= ["amt1",'hour_of_day','city_pop','trans_Date','trans_month','trans_year','age','is_fraud']
print("Features",features_1)

X_1 = Df[features_1]
print("X shape", X_1.shape)
y_1= Df['is_fraud']
print("Y shape", y_1.shape)
```

```
Features ['amt1', 'hour_of_day', 'city_pop', 'trans_Date', 'trans_month', 'trans_year', 'age', 'is_fraud']
X shape (555719, 8)
Y shape (555719,)
```

```
vif_cal(X_1,'is_fraud')
```

```
amt1  VIF =  1.01
hour_of_day  VIF =  1.04
city_pop  VIF =  1.01
trans_Date  VIF =  1.01
trans_month  VIF =  1.01
/usr/local/lib/python3.10/dist-packages/statsmodels/regression/linear_model.py:1781: RuntimeWarning: divide by zero encountered in d
  return 1 - self.ssr/self.centered_tss
trans_year  VIF =  0.0
age  VIF =  1.04
```

Observations:-Now see that all variables are impactful in the model.

```
logistic2= LogisticRegression()
results = logistic2.fit(Df[["amt1"]+['hour_of_day']+['city_pop']+['trans_month']+['trans_Date']+['trans_year']+['age']],Df[['is_fraud']])
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/utils/validation.py:1143: DataConversionWarning: A column-vector y was passed when a
  y = column_or_1d(y, warn=True)
```

```
predict1=logistic2.predict(Df[["amt1"]+['hour_of_day']+['city_pop']+['trans_month']+['trans_Date']+['trans_year']+['age']])
predict1

cm1 = confusion_matrix(Df[['is_fraud']],predict1)
print(cm1)
```

```
[[553391    183]
 [  1929    216]]
```

```
accuracy1=(cm1[0,0]+cm1[1,1])/total1
accuracy1
```

```
0.9961995181017744
```

2)Decision Tree Model

The aim is to divide the whole population or the data set into segments.
The segmentation need to be useful for business decision making. If one class is really dominating in a segments, Then it will be easy for us to classify the unknown items, Then its very easy for applying business strategy.

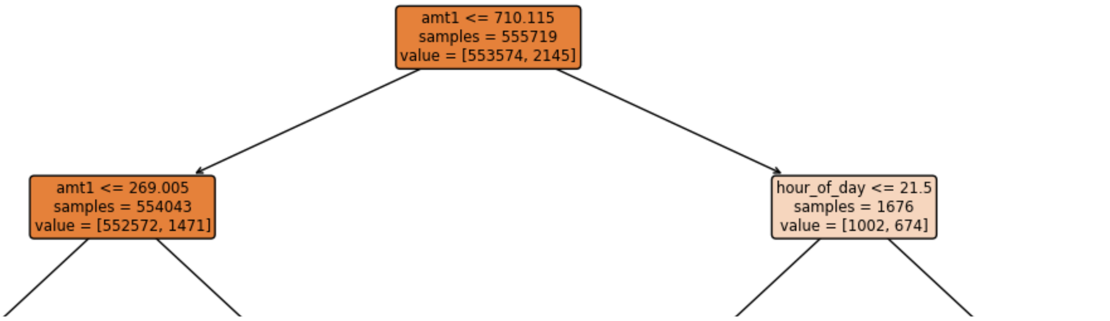
One advantage of decision tree is easy to interpret and fast. means, we can seee which variable is entering and all Accuracy is low as compare to some other models.

```
from sklearn import tree

features= ["amt1",'displacement','hour_of_day','city_pop','gender','trans_Date','trans_month','trans_year','age']
print("Features",features)

X = Df[features]
print("X shape", X.shape)
y = Df['is_fraud']
print("Y shape", y.shape)
```

```
Features ['amt1', 'displacement', 'hour_of_day', 'city_pop', 'gender', 'trans_Date', 'trans_month', 'trans_year', 'age']
X shape (555719, 9)
Y shape (555719,)
```

```
#Building Tree Model
DTree = tree.DecisionTreeClassifier(max_depth=3)
DTree.fit(X,y)

##Plotting the trees
import matplotlib.pyplot as plt
from sklearn.tree import plot_tree, export_text
plt.figure(figsize=(15,7))
plot_tree(DTree, filled=True,
                     rounded=True,
                     impurity=False,
                     feature_names = features)
print( export_text(DTree, feature_names = features))
```

```
|--- amt1 <= 710.11
|   |--- amt1 <= 269.01
|   |   |--- hour_of_day <= 21.50
|   |   |   |--- class: 0
|   |   |--- hour_of_day >  21.50
|   |   |   |--- class: 0
|   |--- amt1 >  269.01
|   |   |--- hour_of_day <= 3.50
|   |   |   |--- class: 0
|   |   |--- hour_of_day >  3.50
|   |   |   |--- class: 0
|--- amt1 >  710.11
|   |--- hour_of_day <= 21.50
|   |   |--- hour_of_day <= 3.50
|   |   |   |--- class: 0
|   |   |--- hour_of_day >  3.50
|   |   |   |--- class: 0
|   |--- hour_of_day >  21.50
|   |   |--- age <= 52.50
|   |   |   |--- class: 1
|   |   |--- age >  52.50
|   |   |   |--- class: 1
```



Model Validation


```
#Tree Validation
predict1 = DTree.predict(X)

from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y, predict1)
print (cm)

total = sum(sum(cm))
# Calculate Accouracy
accuracy = (cm[0,0]+cm[1,1])/total
print(accuracy)
```

```
[[553470    104]
 [  1699    446]]
0.9967555545158614
```

This is a overfitting problem

```
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=101)
```

```
#training Tree Model
clf = tree.DecisionTreeClassifier()
clf.fit(X_train,y_train)

predict1 = clf.predict(X_train)
predict2 = clf.predict(X_test)

#On Train Data
cm1 = confusion_matrix(y_train,predict1)
print(cm1)
total1 = sum(sum(cm1))
accuracy1 = (cm1[0,0]+cm1[1,1])/total1
print("Train Accuracy", accuracy1)
```

```
#On Test Data
cm2 = confusion_matrix(y_test,predict2)
print(cm2)
total2 = sum(sum(cm2))
accuracy2 = (cm2[0,0]+cm2[1,1])/total2
print("Test Accuracy", accuracy2)
```

```
[[442867      0]
 [     0   1708]]
Train Accuracy 1.0
[[110453    254]
 [   197    240]]
Test Accuracy 0.9959422011084719
```

We can see that model is overfitted it is due to imbalanced data.

Pruning

```
#training Tree Model
clf = tree.DecisionTreeClassifier(max_depth=5)
clf.fit(X_train,y_train)

predict1 = clf.predict(X_train)
predict2 = clf.predict(X_test)

#On Train Data
cm1 = confusion_matrix(y_train,predict1)
total1 = sum(sum(cm1))
print(cm1)
accuracy1 = (cm1[0,0]+cm1[1,1])/total1
print("Train Accuracy", accuracy1)

#On Test Data
cm2 = confusion_matrix(y_test,predict2)
print(cm2)
total2 = sum(sum(cm2))
accuracy2 = (cm2[0,0]+cm2[1,1])/total2
print("Test Accuracy", accuracy2)
```

```
[[442757    110]
 [  1168    540]]
Train Accuracy 0.9971253444300736
[[110681     26]
 [   288    149]]
Test Accuracy 0.9971748362484705
```

```
#Building Tree Model
DTree = tree.DecisionTreeClassifier(max_depth=5)
DTree.fit(X,y)

##Plotting the trees
import matplotlib.pyplot as plt
from sklearn.tree import plot_tree, export_text
plt.figure(figsize=(15,7))
plot_tree(DTree, filled=True,
                     rounded=True,
                     impurity=False,
                     feature_names = features)
print( export_text(DTree, feature_names = features))
```

```
|--- amt1 <= 710.11
|   |--- amt1 <= 269.01
|   |   |--- hour_of_day <= 21.50
|   |   |   |--- hour_of_day <= 3.50
|   |   |   |   |--- amt1 <= 23.70
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- amt1 >  23.70
|   |   |   |   |   |--- class: 0
|   |   |   |--- hour_of_day >  3.50
|   |   |   |   |--- amt1 <= 229.82
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- amt1 >  229.82
|   |   |   |   |   |--- class: 0
|   |   |--- hour_of_day >  21.50
|   |   |   |--- amt1 <= 249.23
|   |   |   |   |--- amt1 <= 16.31
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- amt1 >  16.31
|   |   |   |   |   |--- class: 0
|   |   |   |--- amt1 >  249.23
|   |   |   |   |--- amt1 <= 249.43
|   |   |   |   |   |--- class: 1
|   |   |   |   |--- amt1 >  249.43
|   |   |   |   |   |--- class: 0
|   |--- amt1 >  269.01
|   |   |--- hour_of_day <= 3.50
|   |   |   |--- amt1 <= 355.14
|   |   |   |   |--- age <= 29.50
|   |   |   |   |   |--- class: 1
|   |   |   |   |--- age >  29.50
|   |   |   |   |   |--- class: 0
|   |   |   |--- amt1 >  355.14
|   |   |   |   |--- age <= 52.50
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- age >  52.50
|   |   |   |   |   |--- class: 0
|   |   |--- hour_of_day >  3.50
|   |   |   |--- hour_of_day <= 21.50
|   |   |   |   |--- hour_of_day <= 11.50
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- hour_of_day >  11.50
|   |   |   |   |   |--- class: 0
|   |   |   |--- hour_of_day >  21.50
|   |   |   |   |--- age <= 53.50
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- age >  53.50
|   |   |   |   |   |--- class: 1
|--- amt1 >  710.11
|   |--- hour_of_day <= 21.50
|   |   |--- hour_of_day <= 3.50
|   |   |   |--- age <= 52.50
|   |   |   |   |--- city_pop <= 115302.50
|   |   |   |   |   |--- class: 1
|   |   |   |   |--- city_pop >  115302.50
|   |   |   |   |   |--- class: 0
|   |   |   |--- age >  52.50
|   |   |   |   |--- age <= 53.50
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- age >  53.50
|   |   |   |   |   |--- class: 0
|   |   |--- hour_of_day >  3.50
|   |   |   |--- amt1 <= 902.55
|   |   |   |   |--- amt1 <= 825.62
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- amt1 >  825.62
|   |   |   |   |   |--- class: 0
|   |   |   |--- amt1 >  902.55
|   |   |   |   |--- age <= 54.50
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- age >  54.50
|   |   |   |   |   |--- class: 0
|   |--- hour_of_day >  21.50
|   |   |--- age <= 52.50
|   |   |   |--- gender <= 0.50
|   |   |   |   |--- age <= 28.50
|   |   |   |   |   |--- class: 1
|   |   |   |   |--- age >  28.50
|   |   |   |   |   |--- class: 0
|   |   |   |--- gender >  0.50
|   |   |   |   |--- city_pop <= 3771.00
|   |   |   |   |   |--- class: 1
|   |   |   |   |--- city_pop >  3771.00
|   |   |   |   |   |--- class: 1
|   |   |--- age >  52.50
|   |   |   |--- amt1 <= 737.64
```

```
|   |   |   |   |--- age <= 56.00
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- age >  56.00
|   |   |   |   |   |--- class: 1
|   |   |   |--- amt1 >  737.64
|   |   |   |   |--- amt1 <= 814.36
|   |   |   |   |   |--- class: 1
|   |   |   |   |--- amt1 >  814.36
|   |   |   |   |   |--- class: 1
```

Task 5 :- Model Validation metrics calculation

1) **Sensitivity & Specificity**

Sensitivity:- The percentage of positives that are successfully classified as positive.

Sensitivity = (True Positives)/(True Positives + False Negatives)

Specificity:- Percentage of negatives that are successfully classified as negative.

Specificity=(True Negatives)/(True Negatives + False Positives)

```
import statsmodels.formula.api as sm

model = sm.logit(formula='is_fraud ~ amt1+city_pop+hour_of_day+trans_Date+trans_month+trans_year+age', data=Df)
results = model.fit()
print(results.summary())
```

```
Optimization terminated successfully.
         Current function value: 0.018722
         Iterations 11
                           Logit Regression Results
==============================================================================
Dep. Variable:               is_fraud   No. Observations:               555719
Model:                          Logit   Df Residuals:                   555711
Method:                           MLE   Df Model:                            7
Date:                Mon, 11 Sep 2023   Pseudo R-squ.:                  0.2601
Time:                        04:39:50   Log-Likelihood:                -10404.
converged:                       True   LL-Null:                       -14061.
Covariance Type:            nonrobust   LLR p-value:                     0.000
===============================================================================
                  coef    std err          z      P>|z|      [0.025      0.975]
-------------------------------------------------------------------------------
Intercept   -5.957e-06        nan        nan        nan        nan         nan
amt1            0.0072   7.21e-05     99.669      0.000      0.007       0.007
city_pop    -4.261e-07   1.03e-07     -4.138      0.000  -6.28e-07   -2.24e-07
hour_of_day     0.0248      0.003      7.251      0.000      0.018       0.032
trans_Date     -0.0201      0.003     -7.609      0.000     -0.025      -0.015
trans_month    -0.1089      0.012     -8.956      0.000     -0.133      -0.085
trans_year     -0.0030        nan        nan        nan        nan         nan
age             0.0094      0.001      6.961      0.000      0.007       0.012
===============================================================================
```

```
model = sm.logit(formula='is_fraud ~ amt1+city_pop+hour_of_day+trans_Date+trans_month+age', data=Df)
results = model.fit()
print(results.summary())
```

```
Optimization terminated successfully.
         Current function value: 0.018722
         Iterations 10
                           Logit Regression Results
==============================================================================
Dep. Variable:               is_fraud   No. Observations:               555719
Model:                          Logit   Df Residuals:                   555712
Method:                           MLE   Df Model:                            6
Date:                Mon, 11 Sep 2023   Pseudo R-squ.:                  0.2601
Time:                        04:39:56   Log-Likelihood:                -10404.
converged:                       True   LL-Null:                       -14061.
Covariance Type:            nonrobust   LLR p-value:                     0.000
===============================================================================
```

```
                  coef    std err          z      P>|z|      [0.025      0.975]
-------------------------------------------------------------------------------
Intercept      -6.0872      0.156    -39.075      0.000      -6.393      -5.782
amt1            0.0072   7.21e-05     99.669      0.000       0.007       0.007
city_pop    -4.261e-07   1.03e-07     -4.138      0.000   -6.28e-07   -2.24e-07
hour_of_day     0.0248      0.003      7.251      0.000       0.018       0.032
trans_Date     -0.0201      0.003     -7.609      0.000      -0.025      -0.015
trans_month    -0.1089      0.012     -8.956      0.000      -0.133      -0.085
age             0.0094      0.001      6.961      0.000       0.007       0.012
===============================================================================
```

Observations:-Now we can see that all the avriables in the logistic model are impactful , by checking their P value.

```
predictions = results.predict()
print(predictions[0:10])
len(predictions)
```

```
[0.00154759 0.00175997 0.00227174 0.00219654 0.00201884 0.00161935
 0.00534387 0.0018125  0.0017175  0.00315002]
555719
```

```
#Converting predicted values into classes using threshold
threshold=0.5
predicted_class1=[ 0 if x < threshold else 1 for x in predictions]
print(predicted_class1[0:10])
```

```
[0, 0, 0, 0, 0, 0, 0, 0, 0, 0]
```

Now , Find overall model accuracy , sensitivity and specificity

```
from sklearn.metrics import confusion_matrix

cm1 = confusion_matrix(Df["is_fraud"],predicted_class1)
print('Confusion Matrix : \n', cm1)

total1=sum(sum(cm1))
#from confusion matrix calculate accuracy
accuracy1=(cm1[0,0]+cm1[1,1])/total1
print ('Accuracy : ', accuracy1)

sensitivity1 = cm1[0,0]/(cm1[0,0]+cm1[0,1])
print('Sensitivity : ', sensitivity1 )

specificity1 = cm1[1,1]/(cm1[1,0]+cm1[1,1])
print('Specificity : ', specificity1)
```

```
Confusion Matrix :
 [[553404    170]
 [  1874    271]]
Accuracy :  0.9963218821022856
Sensitivity :  0.9996929046523139
Specificity :  0.12634032634032635
```

Observations:-Sensitivity is very high but as specificity is very less that means accuracy of identifying fraud transactions by the model is very less . To improve Specificity adjust the threshold value.

```
#Sensitivity vs Specificity with Different Thresholds
#Converting predicted values into classes using new threshold
threshold=0.2
predicted_class1=[ 0 if x < threshold else 1 for x in predictions]

#Confusion matrix, Accuracy, sensitivity and specificity
cm1 = confusion_matrix(Df["is_fraud"],predicted_class1)
print('Confusion Matrix : \n', cm1)

total1=sum(sum(cm1))
accuracy1=(cm1[0,0]+cm1[1,1])/total1
print ('Accuracy : ', accuracy1)

sensitivity1 = cm1[0,0]/(cm1[0,0]+cm1[0,1])
print('Sensitivity : ', sensitivity1 )
```

```
specificity1 = cm1[1,1]/(cm1[1,0]+cm1[1,1])
print('Specificity : ', specificity1)
```

```
Confusion Matrix :
 [[552714    860]
 [  1503    642]]
Accuracy :  0.9957478509822411
Sensitivity :  0.9984464588293526
Specificity :  0.2993006993006993
```

Observation:-By adjusting threshold=0.2 we are geeting specificity value is 0.3048 that means some improvement is there.

2) **Precision, Recall & F1 Score**

```
predictions = results.predict()
### Converting predicted values into classes using threshold
threshold=0.2
predicted_class1=[ 0 if x < threshold else 1 for x in predictions]

cm1 = confusion_matrix(Df["is_fraud"],predicted_class1)
print('Confusion Matrix : \n', cm1)

total1=sum(sum(cm1))
#####from confusion matrix calculate accuracy
accuracy1=(cm1[0,0]+cm1[1,1])/total1
print ('Accuracy : ', accuracy1)

Precision_Class0 = cm1[0,0]/(cm1[0,0]+cm1[1,0])
print('Precision_Class0 : ', Precision_Class0 )

Recall_Class0 = cm1[0,0]/(cm1[0,0]+cm1[0,1])
print('Recall_Class0 : ', Recall_Class0 )

F1_Class0 = 2/((1/Precision_Class0)+(1/Recall_Class0))
print('F1_Class0 : ', F1_Class0 )


Precision_Class1 = cm1[1,1]/(cm1[0,1]+cm1[1,1])
print('Precision_Class1 : ', Precision_Class1 )

Recall_Class1 = cm1[1,1]/(cm1[1,0]+cm1[1,1])
print('Recall_Class1 : ', Recall_Class1 )

F1_Class1 = 2/((1/Precision_Class1)+(1/Recall_Class1))
print('F1_Class1 : ', F1_Class1 )
```

```
Confusion Matrix :
 [[552714    860]
 [  1503    642]]
Accuracy :  0.9957478509822411
Precision_Class0 :  0.9972880658658972
Recall_Class0 :  0.9984464588293526
F1_Class0 :  0.9978669261620647
Precision_Class1 :  0.4274300932090546
Recall_Class1 :  0.2993006993006993
F1_Class1 :  0.3520701946805594
```

We can simulate all these thing by inbuilt function in sklearn.metrics that is classification_report

```
# By direct package
from sklearn.metrics import classification_report
print(classification_report(Df["is_fraud"],predicted_class1))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00    553574
           1       0.43      0.30      0.35      2145

    accuracy                           1.00    555719
   macro avg       0.71      0.65      0.67    555719
weighted avg       1.00      1.00      1.00    555719
```

Task 6:- **Handling Class Imbalance**

```
print("Actual Data :", Df.shape)

#Frequency count on target column
freq=Df['is_fraud'].value_counts()
print(freq)
print((freq/freq.sum())*100)

#Classwise data
credit_card_normal_class0 = Df[Df['is_fraud'] == 0]
credit_card_fraud_class1 = Df[Df['is_fraud'] == 1]

print("Class0 Actual :", credit_card_normal_class0.shape)
print("Class1 Actual  :", credit_card_fraud_class1.shape)
```

```
Actual Data : (555719, 20)
0    553574
1      2145
Name: is_fraud, dtype: int64
0    99.614014
1     0.385986
Name: is_fraud, dtype: float64
Class0 Actual : (553574, 20)
Class1 Actual  : (2145, 20)
```

Observations:- We can see that this data is very imbalanced , means proportion of normal transactions is very high as compare to fraud transactions.

Observations:- Only about 0.38 percent data is for fraud transactions. which is very less. Thats why need to oversampling.

Undersampling & Oversampling

Oversampling means Duplicating samples from the minority class means the class .In this class the model may not be able to learn pattern for the class with negligible entries.

Undersampling Means Deleting samples from the majority class.

Here, oversampled fraud transactions data is from 0.38% to 15% and undersampled the normal transaction data is about 85% of the total\

```
#Undersampling of class-0
# Consider 0.85 percent of class-0
credit_card_normal_class0_under = credit_card_normal_class0.sample(int(0.85*len(credit_card_normal_class0)))
print("Class0 Undersample :", credit_card_normal_class0_under.shape)

##Oversampling of Class-1
# Lets increase the size by fourty times
credit_card_fraud_class1_over = credit_card_fraud_class1.sample(40*len(credit_card_fraud_class1),replace=True)
print("Class1 Oversample :", credit_card_fraud_class1_over.shape)

#Concatenate to create the final balanced data
credit_card_balanced=pd.concat([credit_card_normal_class0_under,credit_card_fraud_class1_over])
print("Final Balannced Data :", credit_card_balanced.shape)

#Frequency count on target column in the balanced data
freq=credit_card_balanced['is_fraud'].value_counts()
print(freq)
print((freq/freq.sum())*100)
```

```
Class0 Undersample : (470537, 20)
Class1 Oversample : (85800, 20)
Final Balannced Data : (556337, 20)
0    470537
1     85800
Name: is_fraud, dtype: int64
0    84.577693
1    15.422307
Name: is_fraud, dtype: float64
```

Note:- Here ,I have oversampled fraud transactions data is about 15% and undersampled the normal transaction data is about 85% of the total

```
Df.columns
```

```
Index(['cc_num', 'merchant', 'category', 'amt', 'gender', 'state', 'city_pop',
       'job', 'dob', 'unix_time', 'is_fraud', 'time', 'hour_of_day',
       'trans_year', 'trans_month', 'trans_Date', 'trans_time', 'displacement',
       'age', 'amt1'],
      dtype='object')
```

1)Logistic Regression

```
logistic_new= LogisticRegression()
new_results = logistic_new.fit(Df[["amt1"]+['hour_of_day']+['city_pop']+['trans_month']+['trans_Date']+['age']],Df[['is_fraud']])
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/utils/validation.py:1143: DataConversionWarning: A column-vector y was passed when a
  y = column_or_1d(y, warn=True)
```

```
predict3=logistic_new.predict(credit_card_balanced[["amt1"]+['hour_of_day']+['city_pop']+['trans_month']+['trans_Date']+['age']])
predict3

cm3 = confusion_matrix(credit_card_balanced[['is_fraud']],predict3)
print(cm3)
```

```
[[470302    235]
 [ 78215   7585]]
```

```
total1=sum(sum(cm3))
#from confusion matrix calculate accuracy
accuracy3=(cm3[0,0]+cm3[1,1])/total1
print ('Accuracy : ', accuracy1)

sensitivity3 = cm3[0,0]/(cm3[0,0]+cm3[0,1])
print('Sensitivity : ', sensitivity1 )

specificity3 = cm3[1,1]/(cm3[1,0]+cm3[1,1])
print('Specificity : ', specificity1)
```

```
Accuracy :  0.9957478509822411
Sensitivity :  0.9984464588293526
Specificity :  0.2993006993006993
```

Observations:- After oversampling and undersampling, When we apply Logistic regression we get specificity increased upto certain limit

```
import statsmodels.formula.api as sm
model_new_data = sm.logit(formula='is_fraud ~ amt1+city_pop+hour_of_day+trans_Date+trans_month+age', data=credit_card_balanced)
result_new = model_new_data.fit()
print(result_new.summary())
```

```
Optimization terminated successfully.
         Current function value: 0.287935
         Iterations 7
                           Logit Regression Results
==============================================================================
Dep. Variable:               is_fraud   No. Observations:               556337
Model:                          Logit   Df Residuals:                   556330
Method:                           MLE   Df Model:                            6
Date:                Mon, 11 Sep 2023   Pseudo R-squ.:                  0.3303
Time:                        04:40:04   Log-Likelihood:            -1.6019e+05
converged:                       True   LL-Null:                   -2.3921e+05
Covariance Type:            nonrobust   LLR p-value:                     0.000
===============================================================================
                  coef    std err          z      P>|z|      [0.025      0.975]
-------------------------------------------------------------------------------
Intercept      -1.9184      0.031    -61.838      0.000      -1.979      -1.858
amt1            0.0079   3.29e-05    241.362      0.000       0.008       0.008
city_pop    -4.944e-07     2.2e-08   -22.481      0.000   -5.37e-07   -4.51e-07
hour_of_day     0.0122      0.001     19.063      0.000       0.011       0.013
trans_Date     -0.0221      0.001    -41.437      0.000      -0.023      -0.021
trans_month    -0.1191      0.002    -47.895      0.000      -0.124      -0.114
```

```
age             0.0073      0.000     27.229      0.000       0.007       0.008
==============================================================================
```

```
predictions = result_new.predict()
print(predictions[0:10])
len(predictions)
```

```
[0.04849399 0.04406997 0.11985123 0.05165274 0.13542233 0.06203062
 0.11788536 0.07297336 0.04737848 0.13113294]
556337
```

```
### Converting predicted values into classes using threshold
threshold=0.5
predicted_class1=[ 0 if x < threshold else 1 for x in predictions]
print(predicted_class1[0:10])
```

```
[0, 0, 0, 0, 0, 0, 0, 0, 0, 0]
```

```
from sklearn.metrics import confusion_matrix

cm1 = confusion_matrix(credit_card_balanced["is_fraud"],predicted_class1)
print('Confusion Matrix : \n', cm1)

total1=sum(sum(cm1))
#from confusion matrix calculate accuracy
accuracy1=(cm1[0,0]+cm1[1,1])/total1
print ('Accuracy : ', accuracy1)

sensitivity1 = cm1[0,0]/(cm1[0,0]+cm1[0,1])
print('Sensitivity : ', sensitivity1 )

specificity1 = cm1[1,1]/(cm1[1,0]+cm1[1,1])
print('Specificity : ', specificity1)
```

```
Confusion Matrix :
 [[464567   5970]
 [ 51659  34141]]
Accuracy :  0.8964135047641987
Sensitivity :  0.9873123686341351
Specificity :  0.3979137529137529
```

After Undersampling and oversampling applied logistic regression then got specificity is about 0.39 .Means Model is identifying 39% fraud transactions

Updated Sensitivity & Specificity

```
#Sensitivity vs Specificity with Different Thresholds
# Converting predicted values into classes using new threshold
threshold=0.2
predicted_class1=[ 0 if x < threshold else 1 for x in predictions]
```

```
#Confusion matrix, Accuracy, sensitivity and specificity
cm1 = confusion_matrix(credit_card_balanced["is_fraud"],predicted_class1)
print('Confusion Matrix : \n', cm1)

total1=sum(sum(cm1))
#from confusion matrix calculate accuracy
accuracy1=(cm1[0,0]+cm1[1,1])/total1
print ('Accuracy : ', accuracy1)

sensitivity1 = cm1[0,0]/(cm1[0,0]+cm1[0,1])
print('Sensitivity : ', sensitivity1 )

specificity1 = cm1[1,1]/(cm1[1,0]+cm1[1,1])
print('Specificity : ', specificity1)
```

```
Confusion Matrix :
 [[447657  22880]
 [ 32568  53232]]
Accuracy :  0.9003337904902964
Sensitivity :  0.9513747059211072
Specificity :  0.6204195804195805
```

Observations:- By adjusting threshold = 0.2 we are getting specificity is about 0.61 that is model identifying 61% fraud transactions.

Updated Precision, Recall and F1-Score

```
#####from confusion matrix calculate accuracy
accuracy1=(cm1[0,0]+cm1[1,1])/total1
print ('Accuracy : ', accuracy1)

Precision_Class0 = cm1[0,0]/(cm1[0,0]+cm1[1,0])
print('Precision_Class0 : ', Precision_Class0 )

Recall_Class0 = cm1[0,0]/(cm1[0,0]+cm1[0,1])
print('Recall_Class0 : ', Recall_Class0 )

F1_Class0 = 2/((1/Precision_Class0)+(1/Recall_Class0))
print('F1_Class0 : ', F1_Class0 )


Precision_Class1 = cm1[1,1]/(cm1[0,1]+cm1[1,1])
print('Precision_Class1 : ', Precision_Class1 )

Recall_Class1 = cm1[1,1]/(cm1[1,0]+cm1[1,1])
print('Recall_Class1 : ', Recall_Class1 )

F1_Class1 = 2/((1/Precision_Class1)+(1/Recall_Class1))
print('F1_Class1 : ', F1_Class1 )
```

```
Accuracy :  0.9003337904902964
Precision_Class0 :  0.9321817897860378
Recall_Class0 :  0.9513747059211072
F1_Class0 :  0.9416804626184051
Precision_Class1 :  0.6993903720832457
Recall_Class1 :  0.6204195804195805
F1_Class1 :  0.6575423686941054
```

```
from sklearn.metrics import classification_report
print(classification_report(credit_card_balanced["is_fraud"],predicted_class1))
```

```
              precision    recall  f1-score   support

           0       0.93      0.95      0.94    470537
           1       0.70      0.62      0.66     85800

    accuracy                           0.90    556337
   macro avg       0.82      0.79      0.80    556337
weighted avg       0.90      0.90      0.90    556337
```

Observations:- We can observe that after handeling the imbalanced data , we getting accuracy for the class 2(Fraud transactions) .i.e. specificity is 0.62 . But before it was to less.

2)Decision Tree

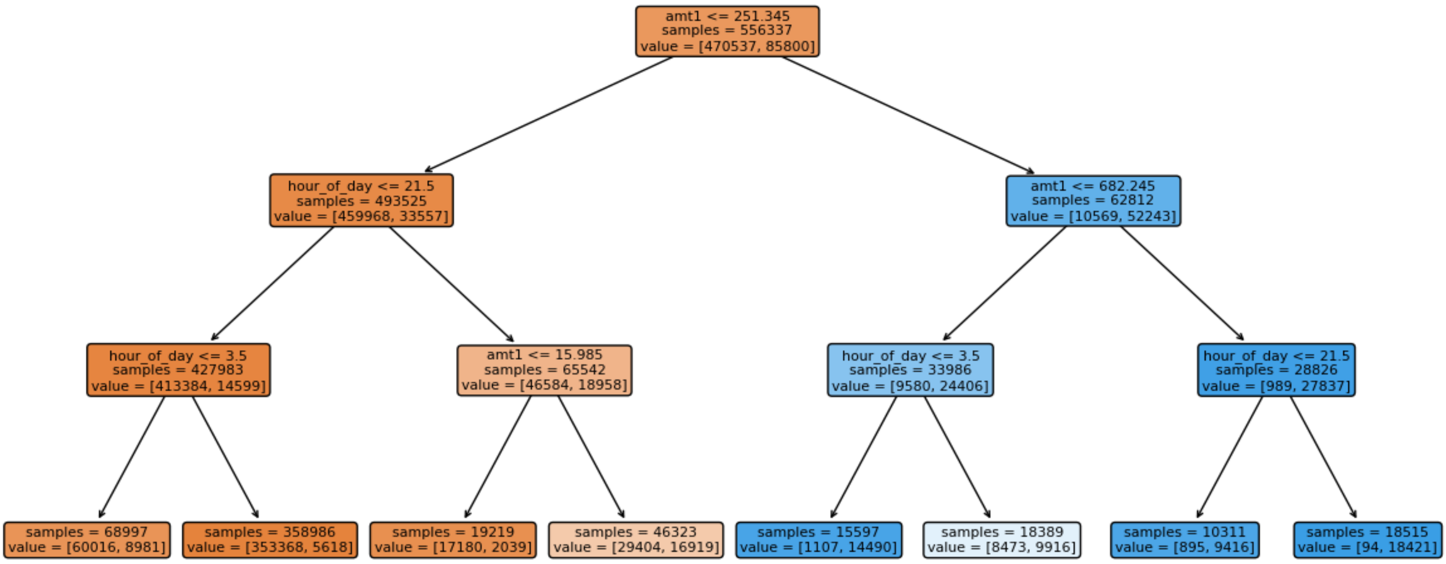
Aim of the decision tree is to divide the whole population or data set into segments.

```
from sklearn import tree

features1= ["amt1",'displacement','hour_of_day','city_pop','gender','trans_Date','trans_month','trans_year','age']
print("Features",features)

X = credit_card_balanced[features1]
print("X shape", X.shape)
y = credit_card_balanced['is_fraud']
print("Y shape", y.shape)
```

```
Features ['amt1', 'displacement', 'hour_of_day', 'city_pop', 'gender', 'trans_Date', 'trans_month', 'trans_year', 'age']
X shape (556337, 9)
Y shape (556337,)
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=101)


DTree = tree.DecisionTreeClassifier(max_depth=3)
DTree.fit(X,y)

##Plotting the trees
import matplotlib.pyplot as plt
from sklearn.tree import plot_tree, export_text
plt.figure(figsize=(15,7))
plot_tree(DTree, filled=True,
                     rounded=True,
                     impurity=False,
                     feature_names = features)
print( export_text(DTree, feature_names = features))
```

```
     |--- amt1 <= 251.35
     |   |--- hour_of_day <= 21.50
     |   |   |--- hour_of_day <= 3.50
     |   |   |   |--- class: 0
     |   |   |--- hour_of_day >  3.50
     |   |   |   |--- class: 0
     |   |--- hour_of_day >  21.50
     |   |   |--- amt1 <= 15.98
     |   |   |   |--- class: 0
     |   |   |--- amt1 >  15.98
     |   |   |   |--- class: 0
     |--- amt1 >  251.35
     |   |--- amt1 <= 682.24
     |   |   |--- hour_of_day <= 3.50
     |   |   |   |--- class: 1
     |   |   |--- hour_of_day >  3.50
     |   |   |   |--- class: 1
     |   |--- amt1 >  682.24
     |   |   |--- hour_of_day <= 21.50
     |   |   |   |--- class: 1
     |   |   |--- hour_of_day >  21.50
     |   |   |   |--- class: 1
```




```
#Tree Validation
predict2 = DTree.predict(X)

from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y, predict2)
print (cm)

total = sum(sum(cm))
# Calculate Accouracy
accuracy = (cm[0,0]+cm[1,1])/total
print(accuracy)
```

```
[[459968  10569]
 [ 33557  52243]]
0.9206847648098185
```

```
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=101)
```

```
clf = tree.DecisionTreeClassifier()
clf.fit(X_train,y_train)

predict1 = clf.predict(X_train)
predict2 = clf.predict(X_test)

#On Train Data
cm1 = confusion_matrix(y_train,predict1)
print(cm1)
total1 = sum(sum(cm1))
accuracy1 = (cm1[0,0]+cm1[1,1])/total1
print("Train Accuracy", accuracy1)

#On Test Data
cm2 = confusion_matrix(y_test,predict2)
print(cm2)
total2 = sum(sum(cm2))
accuracy2 = (cm2[0,0]+cm2[1,1])/total2
print("Test Accuracy", accuracy2)
```

```
[[376320      0]
 [     0  68749]]
Train Accuracy 1.0
[[94001   216]
 [    0 17051]]
Test Accuracy 0.9980587410576266
```

Pruning

Pruning helps us to avoid overfitting .We can avoid overfitting by changing the tuning parameters like 'max_depth' & 'max_leaf_nodes'

```
clf = tree.DecisionTreeClassifier(max_depth=5)
clf.fit(X_train,y_train)

predict1 = clf.predict(X_train)
predict2 = clf.predict(X_test)

#On Train Data
cm1 = confusion_matrix(y_train,predict1)
total1 = sum(sum(cm1))
print(cm1)
accuracy1 = (cm1[0,0]+cm1[1,1])/total1
print("Train Accuracy", accuracy1)

#On Test Data
cm2 = confusion_matrix(y_test,predict2)
print(cm2)
total2 = sum(sum(cm2))
accuracy2 = (cm2[0,0]+cm2[1,1])/total2
print("Test Accuracy", accuracy2)
```

```
[[366825   9495]
 [ 15022  53727]]
Train Accuracy 0.9449141593775348
[[91824  2393]
 [ 3685 13366]]
Test Accuracy 0.9453751303159939
```

Note :- Adjust the pruning parameters till we get the train accuracy nearly equal to the test accuracy. That will be fix the size of the decision tree.

Note:- There are two prunning parameters 1) **max_depth** & 2) **max_leaf_nodes**

Observations:- In this case if we take **max_depth = 5** that will give train and test accuracy nearly same.

```
#Building Tree Model
DTree = tree.DecisionTreeClassifier(max_depth=5)
DTree.fit(X,y)

##Plotting the trees
import matplotlib.pyplot as plt
from sklearn.tree import plot_tree, export_text
plt.figure(figsize=(15,7))
plot_tree(DTree, filled=True,
                     rounded=True,
                     impurity=False,
                     feature_names = features)
print( export_text(DTree, feature_names = features))
```

```
|--- amt1 <= 251.35
|   |--- hour_of_day <= 21.50
|   |   |--- hour_of_day <= 3.50
|   |   |   |--- amt1 <= 23.70
|   |   |   |   |--- amt1 <= 6.96
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- amt1 >  6.96
|   |   |   |   |   |--- class: 1
|   |   |   |--- amt1 >  23.70
|   |   |   |   |--- amt1 <= 47.30
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- amt1 >  47.30
|   |   |   |   |   |--- class: 0
|   |   |--- hour_of_day >  3.50
|   |   |   |--- amt1 <= 50.59
|   |   |   |   |--- amt1 <= 47.28
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- amt1 >  47.28
|   |   |   |   |   |--- class: 0
|   |   |   |--- amt1 >  50.59
|   |   |   |   |--- amt1 <= 229.82
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- amt1 >  229.82
|   |   |   |   |   |--- class: 0
|   |--- hour_of_day >  21.50
|   |   |--- amt1 <= 15.98
|   |   |   |--- amt1 <= 6.66
|   |   |   |   |--- city_pop <= 187.00
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- city_pop >  187.00
|   |   |   |   |   |--- class: 0
|   |   |   |--- amt1 >  6.66
|   |   |   |   |--- amt1 <= 10.72
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- amt1 >  10.72
|   |   |   |   |   |--- class: 0
|   |   |--- amt1 >  15.98
|   |   |   |--- amt1 <= 49.80
|   |   |   |   |--- amt1 <= 47.28
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- amt1 >  47.28
|   |   |   |   |   |--- class: 1
|   |   |   |--- amt1 >  49.80
|   |   |   |   |--- amt1 <= 209.83
```

ROC(Receiver operating characteristics)

```
|   |   |   |   |   |--- class: 1
```

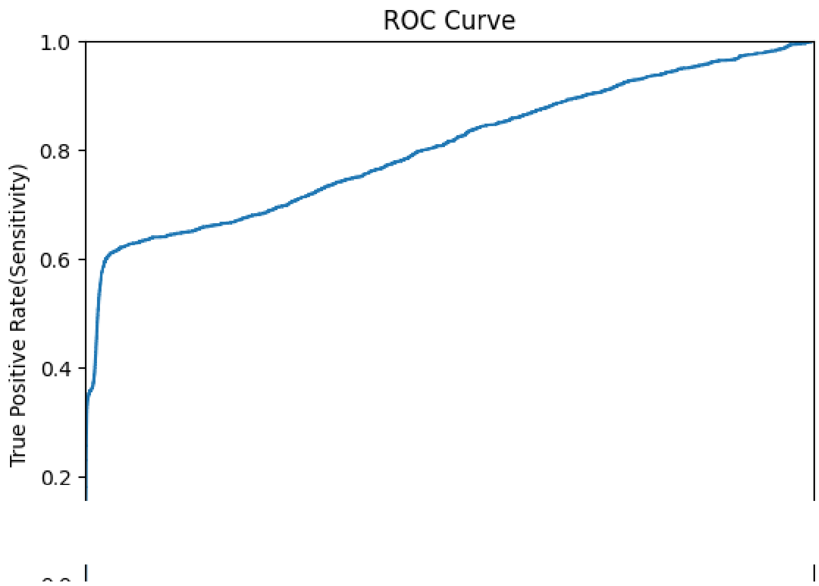
ROC - Receiver operating characteristics curve is drawn by taking false positive root on X-axis and True positive rate on Y-axis.

Roc curve gives us an idea on the performance of model under all possible values of threshold.

```
from sklearn.metrics import roc_curve, auc
import matplotlib.pyplot as plt

actual = credit_card_balanced["is_fraud"]
false_positive_rate, true_positive_rate, thresholds = roc_curve(actual, predictions)
print("false_positive_rate", false_positive_rate)
print("true_positive_rate", true_positive_rate)
print("thresholds", thresholds)
```

```
false_positive_rate [0.         0.         0.         ... 0.99613633 0.99613633 1.        ]
true_positive_rate [0.00000000e+00 5.36130536e-04 1.01398601e-03 ... 9.99592075e-01
 1.00000000e+00 1.00000000e+00]
thresholds [1.99676558 0.99676558 0.99637216 ... 0.01932923 0.01932549 0.00656006]
|   |   |   |--- hour_of_day >  21.50
```

```
import matplotlib.pyplot as plt
plt.title('ROC Curve')
plt.plot(false_positive_rate, true_positive_rate)
plt.xlim([-0,1])
plt.ylim([-0,1])
plt.ylabel('True Positive Rate(Sensitivity)')
plt.xlabel('False Positive Rate(Specificity)')
plt.show()
```



AUC

```
roc_auc = auc(false_positive_rate, true_positive_rate)
roc_auc
```

```
0.8043085965168606
```

Observations:- We are getting AUC is 0.80 , but for the good model AUC is should be near to 1.

Task 7:- Feature Engineering

Sometimes the information is hidden columns, we have to extract the hidden patterns and create new columns.

Machine learning algorithm will be able to eaisily find the patterns from these new columns and improve their accuracy

This process of creating new columns is known as feature engineering.

```
credit_card_balanced.head()
```

	cc_num	merchant	category	amt	gender	state	city_pop	job	dob	unix_time	is_fraud	tim
333654	4.210080e+18	fraud_Flatley Group	misc_pos	37.47	0	OR	1420	Systems analyst	11-11-1965	1382837161	0	2013-10-2 01:26:0
342581	6.762820e+11	fraud_McLaughlin, Armstrong and Koepp	travel	3.99	0	GA	3430	Editor, commissioning	25-03-1950	1383225832	0	2013-10-3 13:23:5
102041	3.564840e+15	fraud_Pacocha-O'Reilly	grocery_pos	110.65	1	CA	198	Armed forces training and education officer	31-03-1959	1374887493	0	2013-07-2 01:11:3
330715	4.800400e+15	fraud_Medhurst PLC	shopping_net	4.54	1	NE	1063	Research scientist (maths)	02-04-1928	1382760544	0	2013-10-2 04:09:0
53866	3.572980e+15	fraud_Hyatt, Russel and Gleichner	health_fitness	53.26	1	NE	614	Associate Professor	20-06-1967	1373408357	0	2013-07-0 22:19:1

1) One-Hot encoding

One hot encoding is a process of converting categorical data into numeric data. So that model can predict well.

```
# To get dummy variables:
one_hot_data = pd.get_dummies(credit_card_balanced['category'])
print("one_hot_data \n" , one_hot_data.sample(10))
```

```
one_hot_data
        entertainment  food_dining  gas_transport  grocery_net  grocery_pos  \
514964              0            0              0            0            0
211748              0            1              0            0            0
335911              0            0              0            0            1
272580              0            0              0            0            1
431310              0            0              0            0            0
245048              0            0              0            0            0
304747              0            0              0            0            0
24000               1            0              0            0            0
376711              0            0              0            0            0
377199              1            0              0            0            0

        health_fitness  home  kids_pets  misc_net  misc_pos  personal_care  \
514964               1     0          0         0         0              0
211748               0     0          0         0         0              0
335911               0     0          0         0         0              0
272580               0     0          0         0         0              0
431310               1     0          0         0         0              0
245048               0     0          0         0         0              0
304747               0     0          0         1         0              0
24000                0     0          0         0         0              0
376711               0     0          0         0         0              0
377199               0     0          0         0         0              0

        shopping_net  shopping_pos  travel
514964             0             0       0
211748             0             0       0
335911             0             0       0
272580             0             0       0
431310             0             0       0
245048             1             0       0
304747             0             0       0
24000              0             0       0
376711             1             0       0
377199             0             0       0
```

```
credit_card_with_dummies = pd.concat([credit_card_balanced,one_hot_data],axis=1)
credit_card_with_dummies.head()
```

	cc_num	merchant	category	amt	gender	state	city_pop	job	dob	unix_time	...	grocery_pos
333654	4.210080e+18	fraud_Flatley Group	misc_pos	37.47	0	OR	1420	Systems analyst	11-11-1965	1382837161	...	0
342581	6.762820e+11	fraud_McLaughlin, Armstrong and Koepp	travel	3.99	0	GA	3430	Editor, commissioning	25-03-1950	1383225832	...	0
102041	3.564840e+15	fraud_Pacocha-O'Reilly	grocery_pos	110.65	1	CA	198	Armed forces training and education officer	31-03-1959	1374887493	...	1
330715	4.800400e+15	fraud_Medhurst PLC	shopping_net	4.54	1	NE	1063	Research scientist (maths)	02-04-1928	1382760544	...	0
53866	3.572980e+15	fraud_Hyatt, Russel and Gleichner	health_fitness	53.26	1	NE	614	Associate Professor	20-06-1967	1373408357	...	0

5 rows × 34 columns

1) Logistic Regression

```
prev_cols = ['amt1','hour_of_day','city_pop','trans_month','trans_Date','age']
encoded_cols = list(one_hot_data.columns.values)

all_pred_cols = prev_cols + encoded_cols

X1 = credit_card_with_dummies[all_pred_cols]

y1 = credit_card_with_dummies['is_fraud']

logistic_reg_one_hot = LogisticRegression()
new_results = logistic_reg_one_hot.fit(X1,y1)
```

```
predict5=logistic_reg_one_hot.predict(X1)
predict5

cm5 = confusion_matrix(credit_card_with_dummies[['is_fraud']],predict5)
print(cm5)
```

```
[[464052   6485]
 [ 46619  39181]]
```

```
total1=sum(sum(cm5))
#from confusion matrix calculate accuracy
accuracy5=(cm5[0,0]+cm5[1,1])/total1
print ('Accuracy : ', accuracy1)

sensitivity5 = cm5[0,0]/(cm5[0,0]+cm5[0,1])
print('Sensitivity : ', sensitivity1 )

specificity5 = cm5[1,1]/(cm5[1,0]+cm5[1,1])
print('Specificity : ', specificity1)
```

```
Accuracy :  0.9449141593775348
Sensitivity :  0.9513747059211072
Specificity :  0.6204195804195805
```

```
credit_card_with_dummies.columns
```

```
Index(['cc_num', 'merchant', 'category', 'amt', 'gender', 'state', 'city_pop',
       'job', 'dob', 'unix_time', 'is_fraud', 'time', 'hour_of_day',
       'trans_year', 'trans_month', 'trans_Date', 'trans_time', 'displacement',
       'age', 'amt1', 'entertainment', 'food_dining', 'gas_transport',
       'grocery_net', 'grocery_pos', 'health_fitness', 'home', 'kids_pets',
       'misc_net', 'misc_pos', 'personal_care', 'shopping_net', 'shopping_pos',
       'travel'],
      dtype='object')
```

```
import statsmodels.formula.api as sm
model_new_data = sm.logit(formula='is_fraud ~ amt1+hour_of_day+city_pop+trans_month+trans_Date+age+entertainment+food_dining+gas_transport
result_new_OH = model_new_data.fit()
print(result_new_OH.summary())
```

```
Warning: Maximum number of iterations has been exceeded.
         Current function value: 0.262286
         Iterations: 35
/usr/local/lib/python3.10/dist-packages/statsmodels/base/model.py:607: ConvergenceWarning: Maximum Likelihood optimization failed to
  warnings.warn("Maximum Likelihood optimization failed to "
                           Logit Regression Results
==============================================================================
Dep. Variable:               is_fraud   No. Observations:               556337
Model:                          Logit   Df Residuals:                   556317
Method:                           MLE   Df Model:                           19
Date:                Mon, 11 Sep 2023   Pseudo R-squ.:                  0.3900
Time:                        04:40:42   Log-Likelihood:            -1.4592e+05
converged:                      False   LL-Null:                   -2.3921e+05
Covariance Type:            nonrobust   LLR p-value:                     0.000
==================================================================================
                     coef    std err          z      P>|z|      [0.025      0.975]
----------------------------------------------------------------------------------
Intercept         -3.0469   2.35e+05   -1.3e-05      1.000   -4.61e+05    4.61e+05
amt1               0.0085   3.89e-05    219.530      0.000       0.008       0.009
hour_of_day        0.0873      0.001     90.588      0.000       0.085       0.089
city_pop       -5.382e-07   2.28e-08    -23.630      0.000   -5.83e-07   -4.94e-07
trans_month       -0.1239      0.003    -47.791      0.000      -0.129      -0.119
trans_Date        -0.0235      0.001    -42.391      0.000      -0.025      -0.022
age                0.0074      0.000     26.441      0.000       0.007       0.008
entertainment     -1.3974   2.35e+05  -5.94e-06      1.000   -4.61e+05    4.61e+05
food_dining       -0.5676   2.35e+05  -2.41e-06      1.000   -4.61e+05    4.61e+05
gas_transport      1.1562   2.35e+05   4.92e-06      1.000   -4.61e+05    4.61e+05
grocery_net        1.0771   2.35e+05   4.58e-06      1.000   -4.61e+05    4.61e+05
grocery_pos        1.2915   2.35e+05   5.49e-06      1.000   -4.61e+05    4.61e+05
health_fitness    -0.6074   2.35e+05  -2.58e-06      1.000   -4.61e+05    4.61e+05
home              -0.9631   2.35e+05   -4.1e-06      1.000   -4.61e+05    4.61e+05
kids_pets         -0.6758   2.35e+05  -2.87e-06      1.000   -4.61e+05    4.61e+05
misc_net          -0.9779   2.35e+05  -4.16e-06      1.000   -4.61e+05    4.61e+05
misc_pos          -0.2017   2.35e+05  -8.58e-07      1.000   -4.61e+05    4.61e+05
personal_care     -0.3256   2.35e+05  -1.39e-06      1.000   -4.61e+05    4.61e+05
shopping_net       1.0852   2.35e+05   4.62e-06      1.000   -4.61e+05    4.61e+05
```

```
shopping_pos      -1.0783   2.35e+05  -4.59e-06      1.000   -4.61e+05    4.61e+05
travel            -0.8623   2.35e+05  -3.67e-06      1.000   -4.61e+05    4.61e+05
=================================================================================
```

2) Decision Tree

```
from sklearn import tree

features= ['amt1','hour_of_day','city_pop','trans_month','trans_Date','age','entertainment', 'food_dining', 'gas_transport',
       'grocery_net', 'grocery_pos', 'health_fitness', 'home', 'kids_pets',
       'misc_net', 'misc_pos', 'personal_care', 'shopping_net', 'shopping_pos',
       'travel']
print("Features",features)

X1 = credit_card_with_dummies[features]
print("X shape", X.shape)
y1 = credit_card_with_dummies['is_fraud']
print("Y shape", y.shape)
```

```
Features ['amt1', 'hour_of_day', 'city_pop', 'trans_month', 'trans_Date', 'age', 'entertainment', 'food_dining', 'gas_transport', 'g
X shape (556337, 9)
Y shape (556337,)
```

```
DTree = tree.DecisionTreeClassifier(max_depth=3)
DTree.fit(X1,y1)

##Plotting the trees
import matplotlib.pyplot as plt
from sklearn.tree import plot_tree, export_text
plt.figure(figsize=(15,7))
plot_tree(DTree, filled=True,
                     rounded=True,
                     impurity=False,
                     feature_names = features)
print( export_text(DTree, feature_names = features))
```

```
|--- amt1 <= 251.35
|   |--- hour_of_day <= 21.50
|   |   |--- hour_of_day <= 3.50
|   |   |   |--- class: 0
|   |   |--- hour_of_day >  3.50
|   |   |   |--- class: 0
|   |--- hour_of_day >  21.50
|   |   |--- shopping_net <= 0.50
|   |   |   |--- class: 0
|   |   |--- shopping_net >  0.50
```

```
#Tree Validation
predict6 = DTree.predict(X1)

from sklearn.metrics import confusion_matrix
cm7 = confusion_matrix(y1, predict6)
print (cm7)

total = sum(sum(cm7))
# Calculate Accouracy
accuracy = (cm7[0,0]+cm7[1,1])/total
print(accuracy)
```

```
[[460151  10386]
 [ 27437  58363]]
0.9320142287857899
```

```
from sklearn.model_selection import train_test_split

X_train1, X_test1, y_train1, y_test1 = train_test_split(X1, y1, test_size=0.2, random_state=101)

X_train1
```

	amt1	hour_of_day	city_pop	trans_month	trans_Date	age	entertainment	food_dining	gas_transport	grocery_net	grocery_
160634	79.67	20	419	8	16	33	0	0	0	0	
322667	34.01	8	47249	10	22	43	0	0	0	0	
62070	102.42	23	5211	7	12	36	0	1	0	0	
412237	4.28	12	757530	11	30	44	0	0	0	0	
518773	99.74	9	2456	12	23	29	0	0	0	0	
...	...	...	...	...	...	...	...	...	...	...	
70681	105.98	10	736284	7	15	71	0	0	0	0	
151587	79.47	3	2456	8	13	29	0	0	0	0	
460836	890.64	1	11256	12	11	51	0	0	0	0	
46877	75.30	5	765	7	7	51	0	0	0	0	
545658	5.23	12	899	12	29	56	0	0	0	0	

445069 rows × 20 columns

```
#training Tree Model
clf2 = tree.DecisionTreeClassifier(max_depth=8)
clf2.fit(X_train1,y_train1)

predict1 = clf2.predict(X_train1)
predict2 = clf2.predict(X_test1)

#On Train Data
cm1 = confusion_matrix(y_train1,predict1)
print(cm1)
total1 = sum(sum(cm1))
accuracy1 = (cm1[0,0]+cm1[1,1])/total1
print("Train Accuracy", accuracy1)

#On Test Data
cm2 = confusion_matrix(y_test1,predict2)
print(cm2)
total2 = sum(sum(cm2))
```

```
accuracy2 = (cm2[0,0]+cm2[1,1])/total2
print("Test Accuracy", accuracy2)
```

```
[[372647   3673]
 [  5768  62981]]
Train Accuracy 0.9787875587830202
[[93210  1007]
 [ 1469 15582]]
Test Accuracy 0.9777474206420534
```

```
# On train data
sensitivity1 = cm1[0,0]/(cm1[0,0]+cm1[0,1])
print('Sensitivity : ', sensitivity1 )

specificity1 = cm1[1,1]/(cm1[1,0]+cm1[1,1])
print('Specificity : ', specificity1)
```

```
Sensitivity :  0.9902396896258503
Specificity :  0.9161005978268775
```

```
# On test data
sensitivity2 = cm2[0,0]/(cm2[0,0]+cm2[0,1])
print('Sensitivity : ', sensitivity2 )

specificity2 = cm2[1,1]/(cm2[1,0]+cm2[1,1])
print('Specificity : ', specificity2)
```

```
Sensitivity :  0.9893119076175213
Specificity :  0.9138466952084922
```

```
DTree = tree.DecisionTreeClassifier(max_depth=8)
DTree.fit(X1,y1)

##Plotting the trees
import matplotlib.pyplot as plt
from sklearn.tree import plot_tree, export_text
plt.figure(figsize=(15,7))
plot_tree(DTree, filled=True,
                     rounded=True,
                     impurity=False,
                     feature_names = features)
print( export_text(DTree, feature_names = features))
```

```
|--- amt1 <= 251.35
|   |--- hour_of_day <= 21.50
|   |   |--- hour_of_day <= 3.50
|   |   |   |--- amt1 <= 23.70
|   |   |   |   |--- gas_transport <= 0.50
|   |   |   |   |   |--- grocery_net <= 0.50
|   |   |   |   |   |   |--- age <= 52.50
|   |   |   |   |   |   |   |--- misc_pos <= 0.50
|   |   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |   |   |--- misc_pos >  0.50
|   |   |   |   |   |   |   |   |--- class: 1
|   |   |   |   |   |   |--- age >  52.50
|   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |--- grocery_net >  0.50
|   |   |   |   |   |   |--- amt1 <= 17.11
|   |   |   |   |   |   |   |--- age <= 28.50
|   |   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |   |   |--- age >  28.50
|   |   |   |   |   |   |   |   |--- class: 1
|   |   |   |   |   |   |--- amt1 >  17.11
|   |   |   |   |   |   |   |--- city_pop <= 145.50
|   |   |   |   |   |   |   |   |--- class: 1
|   |   |   |   |   |   |   |--- city_pop >  145.50
|   |   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |--- gas_transport >  0.50
|   |   |   |   |   |--- amt1 <= 23.30
|   |   |   |   |   |   |--- amt1 <= 22.14
|   |   |   |   |   |   |   |--- trans_Date <= 30.50
|   |   |   |   |   |   |   |   |--- class: 1
|   |   |   |   |   |   |   |--- trans_Date >  30.50
|   |   |   |   |   |   |   |   |--- class: 1
|   |   |   |   |   |   |--- amt1 >  22.14
|   |   |   |   |   |   |   |--- trans_month <= 9.00
|   |   |   |   |   |   |   |   |--- class: 1
|   |   |   |   |   |   |   |--- trans_month >  9.00
|   |   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |--- amt1 >  23.30
|   |   |   |   |   |   |--- amt1 <= 23.62
|   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |   |--- amt1 >  23.62
|   |   |   |   |   |   |   |--- class: 1
|   |   |   |--- amt1 >  23.70
|   |   |   |   |--- shopping_net <= 0.50
|   |   |   |   |   |--- food_dining <= 0.50
|   |   |   |   |   |   |--- amt1 <= 244.53
|   |   |   |   |   |   |   |--- shopping_pos <= 0.50
|   |   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |   |   |--- shopping_pos >  0.50
|   |   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |   |--- amt1 >  244.53
|   |   |   |   |   |   |   |--- city_pop <= 110819.50
|   |   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |   |   |--- city_pop >  110819.50
|   |   |   |   |   |   |   |   |--- class: 1
|   |   |   |   |   |--- food_dining >  0.50
|   |   |   |   |   |   |--- age <= 52.00
|   |   |   |   |   |   |   |--- class: 1
|   |   |   |   |   |   |--- age >  52.00
|   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |--- shopping_net >  0.50
|   |   |   |   |   |--- amt1 <= 47.35
|   |   |   |   |   |   |--- age <= 53.50
|   |   |   |   |   |   |   |--- amt1 <= 46.81
|   |   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |   |   |--- amt1 >  46.81
|   |   |   |   |   |   |   |   |--- class: 1
|   |   |   |   |   |   |--- age >  53.50
|   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |--- amt1 >  47.35
|   |   |   |   |   |   |--- class: 0
|   |   |--- hour_of_day >  3.50
|   |   |   |--- shopping_net <= 0.50
|   |   |   |   |--- amt1 <= 22.66
|   |   |   |   |   |--- gas_transport <= 0.50
|   |   |   |   |   |   |--- amt1 <= 17.30
|   |   |   |   |   |   |   |--- grocery_net <= 0.50
|   |   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |   |   |--- grocery_net >  0.50
|   |   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |   |--- amt1 >  17.30
|   |   |   |   |   |   |   |--- kids_pets <= 0.50
|   |   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |   |   |--- kids_pets >  0.50
|   |   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |--- gas_transport >  0.50
```

```
|   |   |   |   |   |--- gas_transport >  0.50
|   |   |   |   |   |   |--- amt1 <= 20.58
|   |   |   |   |   |   |   |--- amt1 <= 18.98
|   |   |   |   |   |   |   |   |--- class: 1
|   |   |   |   |   |   |   |--- amt1 >  18.98
|   |   |   |   |   |   |   |   |--- class: 1
|   |   |   |   |   |   |--- amt1 >  20.58
|   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |--- amt1 >  22.66
|   |   |   |   |   |--- amt1 <= 229.82
|   |   |   |   |   |   |--- food_dining <= 0.50
|   |   |   |   |   |   |   |--- amt1 <= 216.00
|   |   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |   |   |--- amt1 >  216.00
|   |   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |   |--- food_dining >  0.50
|   |   |   |   |   |   |   |--- amt1 <= 107.31
|   |   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |   |   |--- amt1 >  107.31
|   |   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |--- amt1 >  229.82
|   |   |   |   |   |   |--- home <= 0.50
|   |   |   |   |   |   |   |--- trans_month <= 6.50
|   |   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |   |   |--- trans_month >  6.50
|   |   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |   |--- home >  0.50
|   |   |   |   |   |   |   |--- amt1 <= 236.47
|   |   |   |   |   |   |   |   |--- class: 1
|   |   |   |   |   |   |   |--- amt1 >  236.47
|   |   |   |   |   |   |   |   |--- class: 0
|   |   |   |--- shopping_net >  0.50
|   |   |   |   |--- amt1 <= 47.28
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- amt1 >  47.28
|   |   |   |   |   |--- amt1 <= 47.31
|   |   |   |   |   |   |--- age <= 52.50
|   |   |   |   |   |   |   |--- age <= 47.50
|   |   |   |   |   |   |   |   |--- class: 1
|   |   |   |   |   |   |   |--- age >  47.50
|   |   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |   |--- age >  52.50
|   |   |   |   |   |   |   |--- hour_of_day <= 11.50
|   |   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |   |   |--- hour_of_day >  11.50
|   |   |   |   |   |   |   |   |--- class: 1
|   |   |   |   |   |--- amt1 >  47.31
|   |   |   |   |   |   |--- class: 0
|   |--- hour_of_day >  21.50
|   |   |--- shopping_net <= 0.50
|   |   |   |--- amt1 <= 6.66
|   |   |   |   |--- city_pop <= 187.00
|   |   |   |   |   |--- city_pop <= 172.50
|   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |--- city_pop >  172.50
|   |   |   |   |   |   |--- age <= 50.00
|   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |   |--- age >  50.00
|   |   |   |   |   |   |   |--- amt1 <= 2.90
|   |   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |   |   |--- amt1 >  2.90
|   |   |   |   |   |   |   |   |--- class: 1
|   |   |   |   |--- city_pop >  187.00
|   |   |   |   |   |--- trans_month <= 6.50
|   |   |   |   |   |   |--- age <= 63.50
|   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |   |--- age >  63.50
|   |   |   |   |   |   |   |--- age <= 64.50
|   |   |   |   |   |   |   |   |--- class: 1
|   |   |   |   |   |   |   |--- age >  64.50
|   |   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |--- trans_month >  6.50
|   |   |   |   |   |   |--- class: 0
|   |   |   |--- amt1 >  6.66
|   |   |   |   |--- amt1 <= 24.06
|   |   |   |   |   |--- amt1 <= 16.49
|   |   |   |   |   |   |--- travel <= 0.50
|   |   |   |   |   |   |   |--- misc_pos <= 0.50
|   |   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |   |   |--- misc_pos >  0.50
|   |   |   |   |   |   |   |   |--- class: 1
|   |   |   |   |   |   |--- travel >  0.50
|   |   |   |   |   |   |   |--- amt1 <= 9.98
|   |   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |   |   |--- amt1 >  9.98
|   |   |   |   |   |   |   |   |--- class: 1
```

```
|   |   |   |   |   |   |   |   |--- class: 1
|   |   |   |   |   |--- amt1 >  16.49
|   |   |   |   |   |   |--- home <= 0.50
|   |   |   |   |   |   |   |--- entertainment <= 0.50
|   |   |   |   |   |   |   |   |--- class: 1
|   |   |   |   |   |   |   |--- entertainment >  0.50
|   |   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |   |--- home >  0.50
|   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |--- amt1 >  24.06
|   |   |   |   |   |--- shopping_pos <= 0.50
|   |   |   |   |   |   |--- amt1 <= 209.83
|   |   |   |   |   |   |   |--- food_dining <= 0.50
|   |   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |   |   |--- food_dining >  0.50
|   |   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |   |--- amt1 >  209.83
|   |   |   |   |   |   |   |--- home <= 0.50
|   |   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |   |   |--- home >  0.50
|   |   |   |   |   |   |   |   |--- class: 1
|   |   |   |   |   |--- shopping_pos >  0.50
|   |   |   |   |   |   |--- amt1 <= 47.40
|   |   |   |   |   |   |   |--- amt1 <= 47.13
|   |   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |   |   |--- amt1 >  47.13
|   |   |   |   |   |   |   |   |--- class: 1
|   |   |   |   |   |   |--- amt1 >  47.40
|   |   |   |   |   |   |   |--- class: 0
|   |   |--- shopping_net >  0.50
|   |   |   |--- amt1 <= 47.26
|   |   |   |   |--- class: 0
|   |   |   |--- amt1 >  47.26
|   |   |   |   |--- amt1 <= 47.54
|   |   |   |   |   |--- city_pop <= 1288121.50
|   |   |   |   |   |   |--- age <= 52.50
|   |   |   |   |   |   |   |--- trans_Date <= 26.50
|   |   |   |   |   |   |   |   |--- class: 1
|   |   |   |   |   |   |   |--- trans_Date >  26.50
|   |   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |   |--- age >  52.50
|   |   |   |   |   |   |   |--- class: 1
|   |   |   |   |   |--- city_pop >  1288121.50
|   |   |   |   |   |   |--- class: 0
|   |   |   |   |--- amt1 >  47.54
|   |   |   |   |   |--- class: 0
|--- amt1 >  251.35
|   |--- travel <= 0.50
|   |   |--- misc_pos <= 0.50
|   |   |   |--- amt1 <= 692.99
|   |   |   |   |--- grocery_pos <= 0.50
|   |   |   |   |   |--- hour_of_day <= 21.50
|   |   |   |   |   |   |--- entertainment <= 0.50
|   |   |   |   |   |   |   |--- home <= 0.50
|   |   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |   |   |--- home >  0.50
|   |   |   |   |   |   |   |   |--- class: 1
|   |   |   |   |   |   |--- entertainment >  0.50
|   |   |   |   |   |   |   |--- amt1 <= 427.93
|   |   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |   |   |--- amt1 >  427.93
|   |   |   |   |   |   |   |   |--- class: 1
|   |   |   |   |   |--- hour_of_day >  21.50
|   |   |   |   |   |   |--- shopping_net <= 0.50
|   |   |   |   |   |   |   |--- kids_pets <= 0.50
|   |   |   |   |   |   |   |   |--- class: 1
|   |   |   |   |   |   |   |--- kids_pets >  0.50
|   |   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |   |--- shopping_net >  0.50
|   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |--- grocery_pos >  0.50
|   |   |   |   |   |--- amt1 <= 262.27
|   |   |   |   |   |   |--- hour_of_day <= 3.50
|   |   |   |   |   |   |   |--- trans_month <= 11.50
|   |   |   |   |   |   |   |   |--- class: 1
|   |   |   |   |   |   |   |--- trans_month >  11.50
|   |   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |   |--- hour_of_day >  3.50
|   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |--- amt1 >  262.27
|   |   |   |   |   |   |--- city_pop <= 2242042.50
|   |   |   |   |   |   |   |--- amt1 <= 267.06
|   |   |   |   |   |   |   |   |--- class: 1
|   |   |   |   |   |   |   |--- amt1 >  267.06
|   |   |   |   |   |   |   |   |--- class: 1
|   |   |   |   |   |   |--- city_pop >  2242042.50
```

```
|   |   |   |   |   |   |   |--- class: 0
|   |   |   |--- amt1 >  692.99
|   |   |   |   |--- hour_of_day <= 21.50
|   |   |   |   |   |--- hour_of_day <= 3.50
|   |   |   |   |   |   |--- age <= 53.50
|   |   |   |   |   |   |   |--- city_pop <= 229.00
|   |   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |   |   |--- city_pop >  229.00
|   |   |   |   |   |   |   |   |--- class: 1
|   |   |   |   |   |   |--- age >  53.50
|   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |--- hour_of_day >  3.50
|   |   |   |   |   |   |--- amt1 <= 730.42
|   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |   |--- amt1 >  730.42
|   |   |   |   |   |   |   |--- amt1 <= 825.62
|   |   |   |   |   |   |   |   |--- class: 1
|   |   |   |   |   |   |   |--- amt1 >  825.62
|   |   |   |   |   |   |   |   |--- class: 1
|   |   |   |   |--- hour_of_day >  21.50
|   |   |   |   |   |--- city_pop <= 2242042.50
|   |   |   |   |   |   |--- age <= 52.00
|   |   |   |   |   |   |   |--- city_pop <= 88.00
|   |   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |   |   |--- city_pop >  88.00
|   |   |   |   |   |   |   |   |--- class: 1
|   |   |   |   |   |   |--- age >  52.00
|   |   |   |   |   |   |   |--- age <= 53.50
|   |   |   |   |   |   |   |   |--- class: 1
|   |   |   |   |   |   |   |--- age >  53.50
|   |   |   |   |   |   |   |   |--- class: 1
```

Task 8:- Ensemble Method

1) Random Forest

Random forest is a ensemble method, in which we develop small size of decision trees and each of trees will grow by predicting the random subset of predictors.
In random forest there is a parameter call as max_features , in which we can allow subsets of predictors means we can allow some features only for each model.For regression problem size of subset is P/3 and in classification problem is $\sqrt{P}$. several predictors are not used for a building a small tree.small tree is a weak learner.However we grow large number small decision tree and aggregate and ensembled all their predictions.we get improvement in predictions accuracy.

```
from sklearn.ensemble import RandomForestClassifier
forest=RandomForestClassifier(n_estimators=100, max_features=4, max_depth=8)

forest.fit(X_train1,y_train1)
```

```
RandomForestClassifier
RandomForestClassifier(max_depth=8, max_features=4)
```

```
predict1 = forest.predict(X_train1)
predict2 = forest.predict(X_test1)

#On Train Data
cm1 = confusion_matrix(y_train1,predict1)
print(cm1)
total1 = sum(sum(cm1))
accuracy1 = (cm1[0,0]+cm1[1,1])/total1
print("Train Accuracy", accuracy1)

#On Test Data
cm2 = confusion_matrix(y_test1,predict2)
print(cm2)
total2 = sum(sum(cm2))
accuracy2 = (cm2[0,0]+cm2[1,1])/total2
print("Test Accuracy", accuracy2)
```

```
[[375375    945]
 [ 21255  47494]]
Train Accuracy 0.9501200937382743
[[93948   269]
```

```
 [ 5322 11729]]
Test Accuracy 0.9497519502462523
```

```
#On Test Data
cm = confusion_matrix(y_test1,predict2)
print(cm)
total = sum(sum(cm))
accuracy = (cm[0,0]+cm2[1,1])/total
print("Test Accuracy", accuracy)

sensitivity_2 = cm[0,0]/(cm[0,0]+cm[0,1])
print('Sensitivity : ', sensitivity_2 )

specificity_2 = cm2[1,1]/(cm[1,0]+cm[1,1])
print('Specificity : ', specificity_2)
```

```
[[93948   269]
 [ 5322 11729]]
Test Accuracy 0.9497519502462523
Sensitivity :  0.9971448889266268
Specificity :  0.6878775438390711
```

We can see by random forest , got specificity is 0.69 that means around 69% fraud transactions are detected by the random forest model.

```
from sklearn import tree
tree = tree.DecisionTreeClassifier(max_depth=9)
tree.fit(X_train1,y_train1)
```

```
▾      DecisionTreeClassifier
DecisionTreeClassifier(max_depth=9)
```

```
#Accuracy on train data
print("Decision Tree Results \n")
print("Accuracy on train data" , tree.score(X_train1, y_train1))
print("Accuracy on test data" , tree.score(X_test1, y_test1))
```

```
Decision Tree Results

Accuracy on train data 0.9829981418611496
Accuracy on test data 0.981809684725168
```

2) Boosting.

GBM-Gradient Boosting Method is ensemble method, In which instead of building a model we build multiple models colate their results. By building multiple models we get bit of lift in accuracy.

```
import time
from sklearn.ensemble import GradientBoostingClassifier
import xgboost
from xgboost.sklearn import XGBClassifier
from sklearn.metrics import confusion_matrix , f1_score
from sklearn import preprocessing
```

```
from sklearn.ensemble import GradientBoostingClassifier
boost=GradientBoostingClassifier(n_estimators=100,learning_rate=0.1, verbose=1)
##fitting the gradient boost classifier
start_time = time.time()
boost.fit(X_train1,y_train1)
print("Time taken by GBM "+ str((time.time() - start_time))+ " Seconds")
```

```
      Iter       Train Loss   Remaining Time
         1           0.7545            1.21m
         2           0.6885            1.20m
         3           0.6360            1.21m
         4           0.5973            1.20m
         5           0.5665            1.19m
         6           0.5383            1.17m
         7           0.5155            1.19m
         8           0.4945            1.24m
         9           0.4771            1.28m
```

```
        10           0.4544            1.31m
        20           0.3295            1.09m
        30           0.2736            1.31m
        40           0.2439            1.18m
        50           0.2214           55.85s
        60           0.2016           42.55s
        70           0.1831           30.79s
        80           0.1734           20.10s
        90           0.1618            9.74s
       100           0.1528            0.00s
Time taken by GBM 96.15234518051147 Seconds
```

1) GBM Result

```
# predicting Gradient boosting model on the train Data
boost_predict_train=boost.predict(X_train1)
cm1 = confusion_matrix(y_train1,boost_predict_train)
print(cm1)

accuracy_train=f1_score(y_train, boost_predict_train, average='micro')
print("train accuracy", accuracy_train)
```

```
[[373803   2517]
 [  7282  61467]]
train accuracy 0.9779831891234843
```

```
# predicting Gradient boosting model on the test Data
boost_predict_test=boost.predict(X_test1)
cm1 = confusion_matrix(y_test1,boost_predict_test)
print(cm1)

accuracy_test=f1_score(y_test1, boost_predict_test, average='micro')
print("test accuracy", accuracy_test)
```

```
[[93533   684]
 [ 1904 15147]]
test accuracy 0.9767408419311931
```

```
cm_1 = confusion_matrix(y_test1,boost_predict_test)
print(cm_1)



sensitivity_1 = cm_1[0,0]/(cm_1[0,0]+cm_1[0,1])
print('Sensitivity : ', sensitivity_1 )

specificity_1 = cm_1[1,1]/(cm_1[1,0]+cm_1[1,1])
print('Specificity : ', specificity_1)
```

```
[[93533   684]
 [ 1904 15147]]
Sensitivity :  0.9927401636647314
Specificity :  0.8883349950149552
```

Feature Importance Plot

```
Importances = pd.Series(boost.feature_importances_,index=X_train1.columns)
Importances.nlargest(10).plot.bar(color='red')
plt.show()
```

We can see that 'amt' feature is very important in the model.

We can see that in GBM model, we get specificity is 0.8902 that is our model is detecting almost 89% fraud.

2) XGB Model

```
# Creating XGB friendly data and matrices
train_labels = y_train1.values
train_labels = preprocessing.LabelEncoder().fit_transform(train_labels)

test_labels = y_test1.values
test_labels = preprocessing.LabelEncoder().fit_transform(test_labels)

matrix_train = xgboost.DMatrix(X_train1,label=train_labels)
matrix_test = xgboost.DMatrix(X_test1,label=test_labels)


params = {
    'max_depth': 8,
    'eta':0.1, #Learning Rate
    'eval_metric':'merror', # Multiclass classification error rate.
    'num_class': 2
}

start_time = time.time()

model=xgboost.train(params=params,
                    dtrain=matrix_train,
                    num_boost_round=100,     #Number of trees
                    early_stopping_rounds=4, # Stop after 4 rounds, if test error doesn't improve.
                    evals=[(matrix_test,'test')]
                   )

print("Time taken by XGB "+ str((time.time() - start_time))+ " Seconds")
```

```
[0]	test-merror:0.02226
[1]	test-merror:0.02025
[2]	test-merror:0.02109
[3]	test-merror:0.02142
[4]	test-merror:0.02145
[5]	test-merror:0.02081
Time taken by XGB 11.956237077713013 Seconds
```

```
###prediction using XGB on the train Data
boost_predict_train=model.predict(matrix_train)
cm_4 = confusion_matrix(train_labels,boost_predict_train)
print(cm_4)

accuracy_train=f1_score(train_labels, boost_predict_train, average='micro')
print("train accuracy", accuracy_train)
```

```
[[372700   3620]
 [  5204  63545]]
train accuracy 0.9801738606822762
```

```
###prediction using XGB on the test Data
boost_predict_test=model.predict(matrix_test)
cm_5 = confusion_matrix(test_labels,boost_predict_test)
print(cm_5)
```

```
accuracy_test=f1_score(test_labels, boost_predict_test, average='micro')
print("test accuracy", accuracy_test)
```

```
[[93228   989]
 [ 1327 15724]]
test accuracy 0.9791853902289966
```

```
sensitivity_5 = cm_5[0,0]/(cm_5[0,0]+cm_5[0,1])
print('Sensitivity : ', sensitivity_5 )

specificity_5 = cm_5[1,1]/(cm_5[1,0]+cm_5[1,1])
print('Specificity : ', specificity_5)
```

```
Sensitivity :  0.9895029559421336
Specificity :  0.9221746525130491
```