```
! pip install -U imbalanced-learn
## Install imblearn package as well will be needing that in code
```

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import KBinsDiscretizer as KD
from sklearn.preprocessing import LabelEncoder
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
from collections import Counter
## we need to first download the imblearn package
from imblearn.over_sampling import BorderlineSMOTE, SMOTE, SVMSMOTE, SMOTENC
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/externals/six.py:31: FutureWarning: The module is deprecated in version 0.21 and will be removed in versi
  "(https://pypi.org/project/six/).", FutureWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/utils/deprecation.py:144: FutureWarning: The sklearn.neighbors.base module is  deprecated in version 0.22
  warnings.warn(message, FutureWarning)
```

Question 1: Load

- Programmatically download and load into your favorite analytical tool the transactions data. This data, which is in line-delimited JSON format, can be found here.
- Please describe the structure of the data. Number of records and fields in each record?
- Please provide some additional basic summary statistics for each field. Be sure to include a count of null, minimum, maximum, and unique values where appropriate.

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

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

Programmatically download and load into your favorite analytical tool the transactions data. This data, which is in line-delimited JSON format, can be found here.

```
df = pd.read_json('/content/drive/MyDrive/transactions.txt', lines = True)
```

Please describe the structure of the data. Number of records and fields in each record?

There are 786363 records in total with 29 columns.

Various Columns in the dataset are -- Columns List = ['accountNumber', 'customerId', 'creditLimit', 'availableMoney', 'transactionDateTime', 'transactionAmount', 'merchantName', 'acqCountry', 'merchantCountryCode', 'posEntryMode', 'posConditionCode', 'merchantCategoryCode', 'currentExpDate', 'accountOpenDate', 'dateOfLastAddressChange', 'cardCVV', 'enteredCVV', 'cardLast4Digits', 'transactionType', 'echoBuffer', 'currentBalance', 'merchantCity', 'merchantState', 'merchantZip', 'cardPresent', 'posOnPremises', 'recurringAuthInd', 'expirationDateKeyInMatch', 'isFraud']

```
df.shape, df.columns
```

```
((786363, 29),
 Index(['accountNumber', 'customerId', 'creditLimit', 'availableMoney',
        'transactionDateTime', 'transactionAmount', 'merchantName',
        'acqCountry', 'merchantCountryCode', 'posEntryMode', 'posConditionCode',
        'merchantCategoryCode', 'currentExpDate', 'accountOpenDate',
        'dateOfLastAddressChange', 'cardCVV', 'enteredCVV', 'cardLast4Digits',
        'transactionType', 'echoBuffer', 'currentBalance', 'merchantCity',
        'merchantState', 'merchantZip', 'cardPresent', 'posOnPremises',
        'recurringAuthInd', 'expirationDateKeyInMatch', 'isFraud'],
       dtype='object'))
```

Please provide some additional basic summary statistics for each field. Be sure to include a count of null, minimum, maximum, and unique values where appropriate.

We can observe that in this particular dataset the missing values are represented as empty strings therefore, I planned to impute the entries which has missing values Below, I have in detail described the count of Null, NA, and empty strings in the dataset. Also, I have provided the basic statistics of all the columns which are numeric type.

Analysis- There are 6 columns [echoBuffer, merchantCity, merchantState, merchantZip, posOnPremises, recurringAuthInd] where all records are empty strings, hence are of no use to us, so I will be dropping those columns from the dataset.

```
print("Number of null values in the dataframe \n",df.isnull().sum())
print("Number of NA entries in dataframe: \n", df.isna().sum())
print("Number of empty strings in the dataframe \n",df.eq('').sum())
```

```
Number of null values in the dataframe
 accountNumber              0
customerId                 0
creditLimit                0
availableMoney             0
transactionDateTime        0
transactionAmount          0
merchantName               0
acqCountry                 0
merchantCountryCode        0
posEntryMode               0
posConditionCode           0
merchantCategoryCode       0
currentExpDate             0
accountOpenDate            0
dateOfLastAddressChange    0
cardCVV                    0
enteredCVV                 0
cardLast4Digits            0
transactionType            0
echoBuffer                 0
currentBalance             0
merchantCity               0
merchantState              0
merchantZip                0
cardPresent                0
posOnPremises              0
recurringAuthInd           0
expirationDateKeyInMatch   0
isFraud                    0
dtype: int64
Number of NA entries in dataframe:
 accountNumber              0
customerId                 0
creditLimit                0
availableMoney             0
transactionDateTime        0
transactionAmount          0
merchantName               0
acqCountry                 0
merchantCountryCode        0
posEntryMode               0
posConditionCode           0
merchantCategoryCode       0
currentExpDate             0
accountOpenDate            0
dateOfLastAddressChange    0
cardCVV                    0
enteredCVV                 0
cardLast4Digits            0
transactionType            0
echoBuffer                 0
currentBalance             0
merchantCity               0
merchantState              0
merchantZip                0
cardPresent                0
posOnPremises              0
recurringAuthInd           0
```

```
# Basic Statistics for the Transaction dataset
df.describe()
```

	accountNumber	customerId	creditLimit	availableMoney	transactionAmount	cardCVV	enteredCVV	cardLast4Digits	currentBalance
count	7.863630e+05	7.863630e+05	786363.000000	786363.000000	786363.000000	786363.000000	786363.000000	786363.000000	786363.000000
mean	5.372326e+08	5.372326e+08	10759.464459	6250.725369	136.985791	544.467338	544.183857	4757.417799	4508.739089
std	2.554211e+08	2.554211e+08	11636.174890	8880.783989	147.725569	261.524220	261.551254	2996.583810	6457.442068
min	1.000881e+08	1.000881e+08	250.000000	-1005.630000	0.000000	100.000000	0.000000	0.000000	0.000000
25%	3.301333e+08	3.301333e+08	5000.000000	1077.420000	33.650000	310.000000	310.000000	2178.000000	689.910000
50%	5.074561e+08	5.074561e+08	7500.000000	3184.860000	87.900000	535.000000	535.000000	4733.000000	2451.760000
75%	7.676200e+08	7.676200e+08	15000.000000	7500.000000	191.480000	785.000000	785.000000	7338.000000	5291.095000
max	9.993896e+08	9.993896e+08	50000.000000	50000.000000	2011.540000	998.000000	998.000000	9998.000000	47498.810000

Dropping columns where all the records are empty string.

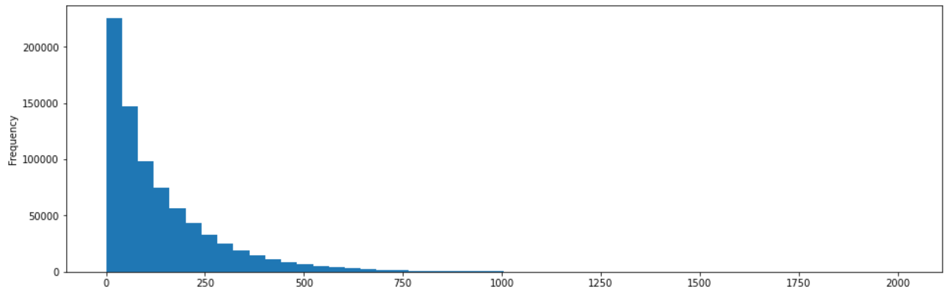
```
df_copy = df.drop(['echoBuffer', 'merchantCity', 'merchantState', 'merchantZip', 'posOnPremises', 'recurringAuthInd'], axis=1)
```

Question 2: Plot

- Plot a histogram of the processed amounts of each transaction, the transactionAmount column.
- Report any structure you find and any hypotheses you have about that structure.

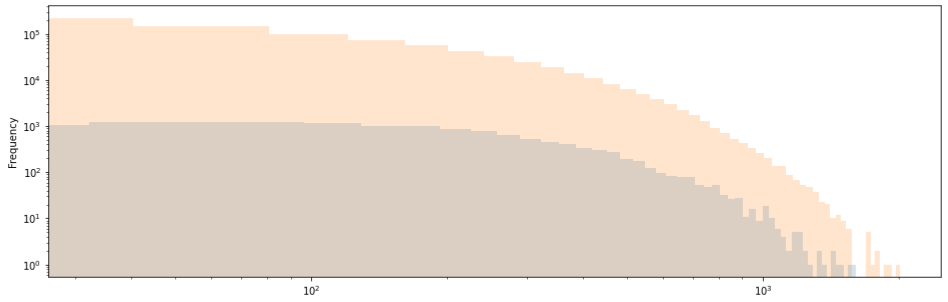
```
df_copy['transactionAmount'].plot(kind = 'hist', figsize = (16,5), bins= 50 )
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f0fcd8d2080>
```



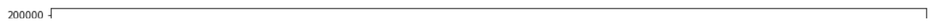
```
df_f = df_copy[df_copy.isFraud == True]
df_nf = df_copy[df_copy.isFraud == False]
df_f['transactionAmount'].plot(kind = 'hist', figsize = (16,5), bins= 50, alpha = 0.2, logy = True, logx = True)
df_nf['transactionAmount'].plot(kind = 'hist', figsize = (16,5), bins= 50, alpha = 0.2, logy = True, logx= True)
### Rightly skewed plot for the transactionAmount
print(df_copy.transactionAmount.describe())
```

```
count    786363.000000
mean        136.985791
std         147.725569
min           0.000000
25%          33.650000
50%          87.900000
75%         191.480000
max        2011.540000
Name: transactionAmount, dtype: float64
```



```
bin = KD(n_bins=4, encode='ordinal', strategy='quantile')
transBinned = np.array(df_copy['transactionAmount']).reshape(-1,1)
bin.fit(transBinned)
df_copy['transBinned'] = bin.transform(transBinned)
df_f = df_copy[df_copy.isFraud == True]
df_nf = df_copy[df_copy.isFraud == False]
print("Cases where there is Fraud  ----\n",
      df_copy[df_copy.isFraud == True].groupby('transBinned').agg({'isFraud':'count'}))
print("Cases where there is NO Fraud  ----\n",
      df_copy[df_copy.isFraud == False].groupby('transBinned').agg({'isFraud':'count'}))
df_f['transBinned'].plot(kind = 'hist', figsize = (16,5), bins= 50, alpha = 0.9)
df_nf['transBinned'].plot(kind = 'hist', figsize = (16,5), bins= 50, alpha = 0.2)
```

```
Cases where there is Fraud  ----
              isFraud
transBinned
0.0             1106
1.0             2058
2.0             3455
3.0             5798
Cases where there is NO Fraud  ----
              isFraud
transBinned
0.0           195412
1.0           194579
2.0           193154
3.0           190801
<matplotlib.axes._subplots.AxesSubplot at 0x7f0fcd465c50>
```



Report any structure you find and any hypotheses you have about that structure.

-- We observe that the Transaction Amount is rightly skewed as majority of the transactions are between the mean and the first two standard deviatiosn. We will now observe how does the TransactionAmount affects the Fraud vs NonFraud classification.

First Plot -- We observe that the plot for the TransactionAmount columns is rightly skewed. As I observed that the transaction is exponential in nature, I plotted another variation to observe the plot in the linear scale along with Fraud and Non Fraud Classes.

Second Plot -- We observe the Transaction Amount in a linear scale and observed that both Fraud and Non-Fraud cases are of same nature for the complete set of Transactions. So, I binned the Transaction Amount in 4 bins as per the quantile range and then observe the Fraud and Non-Fraud Classes.

Third Plot -- I have used KBinsDiscretizer for binning TransactionAmount and observe the class variables. We observed that the Non-Fraud Cases for all 4 bins are significantly similar, but the Fraud Cases are maximum for the 4th bin and minimum for the 1st bin. So, moving forward we will be using the binned value Transaction Amount instead of the real Transaction Amounts as the binned groupings are more descriptive about the nature of variation of Fraud and Non-Fraud cases with respect to the Transaction Amount

Question 3: Data Wrangling - Duplicate Transactions

You will notice a number of what look like duplicated transactions in the data set. One type of duplicated transaction is a reversed transaction, where a purchase is followed by a reversal. Another example is a multi-swipe, where a vendor accidentally charges a customer's card multiple times within a short time span.

- Can you programmatically identify reversed and multi-swipe transactions?

> For identifying the reversed Transaction, I obsereved that we can filter out the reverse transaction by using TransactionType = 'Reversal'. Also such Transactions also have a 'Purchase' TransactionType as well. And hence I have considered them as duplicate in nature and dropped them.

> For multiswiped transactions, as per my understanding they are usually caused due to the transaction failures, so I have sorted the dataframe on the basis of TransactionDateTime, and then applied grouping on CustomerId, TransactionAmount,and filtered all those transaction which have similar CustomerId, TransactionAmount and have occured within 120seconds after the previous transaction. As the data is sorted by time, I have calculated the time difference and filtered all those Transactions which have occurred within 120 seconds. Since we set True values to the multiSwiped Transactions, so we can filter the dataframe accordingly.

- What total number of transactions and total dollar amount do you estimate for the reversed transactions? For the multi-swipe transactions? (please consider the first transaction to be "normal" and exclude it from the number of transaction and dollar amount counts)

> total number of transactions that are reversed are - 20303 records

> total dollar amount do you estimate for the reversed transactions : 2821792.5

> total number of transactions that are multiSwiped are - 5188 records

> total dollar amount do you estimate for the multi swiped transactions - 749167.39.

- Did you find anything interesting about either kind of transaction?

> Both of these kinds of transactions represents noise and duplicacy in our dataset and we will be removing them moving forward, I also observed the distribution of Fraud vs Non-Fraud in both the cases but both of them are significant with numnber of fraud and non-fraud cases

[ ] ↳ *5 cells hidden*

Question 4: Model

Fraud is a problem for any bank. Fraud can take many forms, whether it is someone stealing a single credit card, to large batches of stolen credit card numbers being used on the web, or even a mass compromise of credit card numbers stolen from a merchant via tools like credit card skimming devices.

- Each of the transactions in the dataset has a field called isFraud. Please build a predictive model to determine whether a given transaction will be fraudulent or not. Use as much of the data as you like (or all of it).
- Provide an estimate of performance using an appropriate sample, and show your work.
- Please explain your methodology (modeling algorithm/method used and why, what features/data you found useful, what questions you have, and what you would do next with more time

```
df_copy.isFraud.sum()/df_copy.shape[0]*100
```

```
    1.5776635229052982
```

We can observe that it's a classical Imbalance Problem as the dataset contains only 1.57% records, which has isFraud = True, i.e in the given dataset the dominant class is isFraud = False.

We will be using various techniques wherein we will be handling the Class Imbalance problem and try to achieve the desired results.

Feature Engineering

We will analyze various features in the dataset and transfrom that accordingly based on the observations

Extracting Features from the data --- transactionDateTime We tried to observe the effect of transactionDateTime on isFraud.

We observed that we considered 'hour' of transaction. We have plotted both the cases Fraud and Non-Fraud cases.

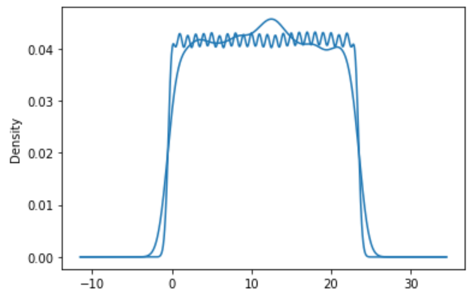
Observation 1 - We observe that for Non-Fraud the curve is sinosoidal in nature. That is the non fraud cases are consistent with respect to the transaction hour.

Observation 2 - When we observed for cases with Fraud, we see a trend that there are significant more number of Fraud cases from time range of 8-12.

Assumption - We plan to use the binned value of transactionDateTime i.e [0-23] and move forward with transactionHour Feature instead of transactionDateTime feature.

```
df_copy['transactionDateTime'] = pd.to_datetime(df_copy.transactionDateTime)
df_copy['transactionHour'] = df_copy.transactionDateTime.dt.hour
df_transHour_f = df_copy[df_copy.isFraud == True]
df_transHour_nf = df_copy[df_copy.isFraud == False]
df_transHour_nf['transactionHour'].plot(kind='density', subplots = (1,2))
df_transHour_f['transactionHour'].plot(kind = 'density', subplots = (2,2))
```

```
    array([<matplotlib.axes._subplots.AxesSubplot object at 0x7f0fcd4efeb8>],
          dtype=object)
```



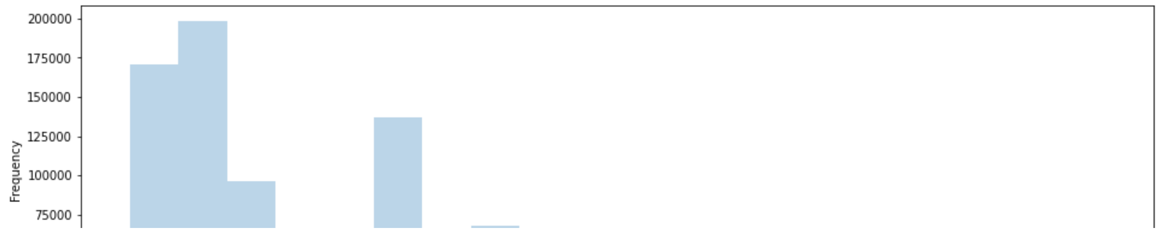
```
## Binning for TransactionDateTime feature
bin = KD(n_bins=5, encode='ordinal', strategy='uniform')
transHour = np.array(df_copy['transactionHour']).reshape(-1,1)
bin.fit(transHour)
df_copy['hourBinned'] = bin.transform(transHour)
```

Feature 2 -- Credit Limit

With Taking CreditLimit into consideration we don't see a significant difference between the Fraud and Non-fraud cases distribution. Both the plots have significant similar spikes. So, I have used credit limit the way it is.

```
df_nf['creditLimit'].plot(kind= 'hist', bins = 20, figsize = (16,5), alpha = 0.3)
df_f['creditLimit'].plot(kind= 'hist', bins = 20, figsize = (16,5))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f0fcd6795c0>
```



Feature - Merchant Name and MerchantCategoryCode

There are 1042 different merchantName and 13 merchant category codes. But we see the top 10 merchants have significantly high number of Fraud cases. Therefore, I have planned to group the merchantName and merchant category code other than the top 10 as 'others' and used them.

```
## For merchant Name I plan to  keep the top 10 merchants
temp = df_copy[df_copy.isFraud == True].groupby(by = ['merchantName']).agg({'isFraud':'count'}).sort_values(by = 'isFraud',ascending=False)
print("Merchant Names sorted by isFraud Cases number\n",temp)

d = {}  ## Mapping Dictionary for keep top 10 and rest all map to 'others' as merchantName
for i in temp.index.to_list()[:10]:
  d[i] = i
df_copy['merchantMapped'] = df_copy['merchantName'].apply(lambda x: d.get(x,'others'))
```

```
Merchant Names sorted by isFraud Cases number
                        isFraud
merchantName
Lyft                       731
ebay.com                   621
Fresh Flowers              538
Uber                       501
walmart.com                427
...                        ...
Quizno's #326636             1
Quizno's #311602             1
Quizno's #235427             1
Quizno's #230127             1
Krispy Kreme #122012         1

[1042 rows x 1 columns]
```

```
temp = df_copy[df_copy.isFraud == True].groupby(by = ['merchantCategoryCode']).agg({'isFraud':'count'}).sort_values(by = 'isFraud',ascending=False)
print("Merchant Category Codes sorted by isFraud Cases number\n",temp)
d = {}
for i in temp.index.to_list()[:10]:
  d[i] = i
df_copy['merchantCategoryMapped'] = df_copy['merchantCategoryCode'].apply(lambda x: d.get(x,'others'))
```

```
Merchant Category Codes sorted by isFraud Cases number
                        isFraud
merchantCategoryCode
online_retail             4779
online_gifts              1554
rideshare                 1232
fastfood                  1037
food                       984
entertainment              920
airline                    509
auto                       266
hotels                     244
subscriptions              209
furniture                  100
health                      88
personal care               82
```

Feature PurchaseType -

As we have removed the purchaseType = Reversal, we are left with PURCHASE and ADDRESS_VERIFICATION, as two feature type. However, I observed that there were several empty strings in the purchase_type, so instead of dropping those records and loosing information, I decided to impute empty string with 'others'.

```
temp = df_copy[df_copy.isFraud == True].groupby(by = 'transactionType').agg({'isFraud':'count'}).sort_values(by = 'isFraud',ascending=False)
print(df_copy[df_copy.isFraud == False].groupby(by = 'transactionType').agg({'isFraud':'count'}).sort_values(by = 'isFraud',ascending=False))

#Impute the null values with type = "others"
d = {}
for i in temp.index.to_list()[:10]:
  if i is "":
    d[i] = 'others'
  else:
    d[i] = i
df_copy['transactionType'] = df_copy['transactionType'].apply(lambda x: d.get(x,'others'))
```

```
                      isFraud
transactionType
PURCHASE               728293
ADDRESS_VERIFICATION    19899
                          676
```

Feature accountOpenDate and currentExpDate - With an assumption that old cards are more prone to Fraud due to less secure features, I have computed the length of the account instead of using this two features, with an understanding that more the lenght of accound will be, there is a significant chance of a fraudulent case

```
df_copy['accountOpenDate']=pd.to_datetime(df_copy['accountOpenDate'])
df_copy['accountOpenDate'] = df_copy.accountOpenDate.dt.year
df_copy['currentExpDate'] = pd.to_datetime(df_copy['currentExpDate'])
df_copy['currentExpDate'] = df_copy.currentExpDate.dt.year
df_copy['accountLenght'] = (df_copy.currentExpDate - df_copy.accountOpenDate)
```

Feature cardCVV and enteredCVV - I have combined both these features, if there is match I have assigned a True value, otherwise False, assuming that a mismatch in enteredCVV and cardCVV would be more prone to a fraudulent case

```
df_copy['CVVMatched'] = np.where(df_copy.loc[:,'cardCVV'] == df_copy.loc[:,'enteredCVV'], 1, 0)
```

Handling Missing Values - acqCountry, posEntryCode, posConditionCode, merchantCountryCode There are several entries as empty string in all these cases, so I have replaced empty string with "Others" in case of acqCountry, merchantCountryCode and in posEntryCode, posConditionCode with a random number

```
temp = df_copy[df_copy.isFraud == True].groupby(by = 'acqCountry').agg({'isFraud':'count'}).sort_values(by = 'isFraud',ascending=False)
d = {}
for i in temp.index.to_list():
  if i is "":
    d[i] = 'others'
  else:
    d[i] = i
df_copy['acqCountry'] = df_copy['acqCountry'].apply(lambda x: d.get(x,'others'))

temp = df_copy[df_copy.isFraud == True].groupby(by = 'posEntryMode').agg({'isFraud':'count'}).sort_values(by = 'isFraud',ascending=False)
d = {}
for i in temp.index.to_list():
  if i is "":
    d[i] = '99'
  else:
    d[i] = i
df_copy['posEntryMode'] = df_copy['posEntryMode'].apply(lambda x: d.get(x,'others'))

temp = df_copy[df_copy.isFraud == True].groupby(by = 'posConditionCode').agg({'isFraud':'count'}).sort_values(by = 'isFraud',ascending=False)
d = {}
for i in temp.index.to_list():
  if i is "":
    d[i] = '100'
  else:
    d[i] = i
df_copy['posConditionCode'] = df_copy['posConditionCode'].apply(lambda x: d.get(x,'others'))

temp = df_copy[df_copy.isFraud == True].groupby(by = 'merchantCountryCode').agg({'isFraud':'count'}).sort_values(by = 'isFraud',ascending=False)
d = {}
for i in temp.index.to_list():
  if i is "":
    d[i] = 'others'
  else:
    d[i] = i
df_copy['merchantCountryCode'] = df_copy['merchantCountryCode'].apply(lambda x: d.get(x,'others'))
```

```
df_copy.head()
```

	accountNumber	customerId	creditLimit	availableMoney	transactionDateTime	transactionAmount	merchantName	acqCountry	merchantCountryCode
640789	419104777	419104777	50000	50000.0	2016-01-01 00:01:02	44.09	Washington Post	US	US
28946	674577133	674577133	5000	5000.0	2016-01-01 00:01:44	329.57	staples.com	US	US
222211	958438658	958438658	20000	20000.0	2016-01-01 00:01:47	164.57	cheapfast.com	US	US
470320	851126461	851126461	10000	10000.0	2016-01-01 00:02:04	122.83	discount.com	US	US
704106	148963316	148963316	2500	2500.0	2016-01-01 00:02:19	0.00	Fast Repair	US	US

Dropping Redundant Columns--

We have performed feature engineering for various columns and thus we will be dropping all the columns which are redundant. Also, I plan to drop columns customerID, accountNumber, cardLast4Digits, dateOfLastAddressChange as I believe the features are unique and are significant to differentiate a card but not a particular transaction as fraudulent or non-fraudulent

```
df_copy = df_copy.drop(['accountNumber','customerId','cardLast4Digits','dateOfLastAddressChange', 'cardCVV', 'enteredCVV','transactionDateTime','transactionA
```

After the Feature Engineering we have following features. Below is the detailed list of all the new feature and there datatypes.

```
df_copy.dtypes , df_copy.columns, df_copy.shape
```

```
(creditLimit                   int64
 availableMoney              float64
 acqCountry                   object
 merchantCountryCode          object
 posEntryMode                 object
 posConditionCode             object
 transactionType              object
 currentBalance              float64
 cardPresent                    bool
 expirationDateKeyInMatch       bool
 isFraud                        bool
 transBinned                 float64
 mutliSwipedTransaction         bool
 transactionHour               int64
 hourBinned                  float64
 merchantMapped               object
 merchantCategoryMapped       object
 accountLenght                 int64
 CVVMatched                    int64
 dtype: object,
 Index(['creditLimit', 'availableMoney', 'acqCountry', 'merchantCountryCode',
        'posEntryMode', 'posConditionCode', 'transactionType', 'currentBalance',
        'cardPresent', 'expirationDateKeyInMatch', 'isFraud', 'transBinned',
        'mutliSwipedTransaction', 'transactionHour', 'hourBinned',
        'merchantMapped', 'merchantCategoryMapped', 'accountLenght',
        'CVVMatched'],
       dtype='object'),
 (760872, 19))
```

```
df_copy.head()
```

	creditLimit	availableMoney	acqCountry	merchantCountryCode	posEntryMode	posConditionCode	transactionType	currentBalance	cardPrese
640789	50000	50000.0	US	US	09	01	PURCHASE	0.0	Fal
28946	5000	5000.0	US	US	09	08	PURCHASE	0.0	Fal
222211	20000	20000.0	US	US	05	01	PURCHASE	0.0	Fal
470320	10000	10000.0	US	US	02	08	PURCHASE	0.0	Fal
704106	2500	2500.0	US	US	05	01	ADDRESS_VERIFICATION	0.0	Fal

Label Encoding Features of Type 'object'

I used label encoding for converting the features of 'object' type to int64 type to make the features compatible to be given as an input in the model.

```
labelencoder = LabelEncoder()
df_encode = pd.DataFrame({ 'acqCountry': df_copy.acqCountry,
                          'merchantCountryCode': df_copy.merchantCountryCode,
                          'posEntryMode':df_copy.posEntryMode,
                          'posConditionCode':df_copy.posConditionCode,
                          'transactionType':df_copy.transactionType,
                          'cardPresent':df_copy.cardPresent,
                          'expirationDateKeyInMatch':df_copy.expirationDateKeyInMatch,
                          'merchantMapped':df_copy.merchantMapped,
                          'merchantCategoryMapped':df_copy.merchantCategoryMapped,
                          'isFraud':df_copy.isFraud

})
df_encode = df_encode.apply(LabelEncoder().fit_transform)
```

```
temp = pd.DataFrame({ 'availableMoney': df_copy.availableMoney,
                          'creditLimit':df_copy.creditLimit,
                          'currentBalance': df_copy.currentBalance,
                          'transactionHour':df_copy.transactionHour,
                          'transBinned':df_copy.transBinned,
                          'accountLenght':df_copy.accountLenght,
                           'CVVMatched':df_copy.CVVMatched

})
df_encode = df_encode.join(temp)
```

```
df_encode.head()
```

	acqCountry	merchantCountryCode	posEntryMode	posConditionCode	transactionType	cardPresent	expirationDateKeyInMatch	merchantMapped	merchar
640789	3	3	2	0	1	0	0	7	
28946	3	3	2	1	1	0	0	9	
222211	3	3	1	0	1	0	0	4	
470320	3	3	0	1	1	0	0	7	
704106	3	3	1	0	0	0	0	7	

Splitting the dataset

We have splitted the dataset into train data and test data.

The test size, I have used it 30%.

Also, I have used the stratification strategy so that percent of isFraud class remains consistent in both the train as well as the test dataset.

```
y = df_encode.loc[:,'isFraud']
df_encode_copy = df_encode.drop(['isFraud'], axis = 1)
X = df_encode_copy
X_train, X_val, y_train, y_val = train_test_split(X, y, stratify= y, test_size=0.30, random_state=42)
print(X_train.shape,y_train.shape)
print(X_val.shape, y_val.shape)
X_train = X_train.reset_index(drop =True)
y_train = y_train.reset_index(drop = True)
X_val = X_val.reset_index(drop = True)
y_val = y_val.reset_index(drop = True)
X_train
```

```
(532610, 16) (532610,)
(228262, 16) (228262,)
```

	acqCountry	merchantCountryCode	posEntryMode	posConditionCode	transactionType	cardPresent	expirationDateKeyInMatch	merchantMapped	merchar
0	3	3	1	3	1	1	0	7	
1	3	3	1	0	1	1	0	7	
2	3	3	2	0	0	0	0	7	
3	3	3	2	0	1	1	0	7	
4	3	3	2	1	1	0	0	7	
...	...	...	...	...	...	...	...	...	
532605	3	3	1	0	1	0	0	4	
532606	3	3	2	1	1	1	0	7	
532607	3	3	2	0	1	0	0	7	
532608	3	3	2	0	1	1	0	7	
532609	3	3	1	0	1	0	0	7	

532610 rows × 16 columns

Baseline Classification Model

I have used typically two standard classification model.

1. Logistic Regression
2. Random Forest

Our goal is to predict the isFraud class, and we will observe the classification reports to evaluate our results.

```
def random_forest(train_x, train_y,test_x, test_y):
  clf = RandomForestClassifier(n_estimators = 10, max_depth = 10, random_state=0)
  clf.fit(train_x,train_y)
  print(classification_report(test_y, clf.predict(test_x)))
  print(confusion_matrix(test_y, clf.predict(test_x)))
```

```
print(random_forest(X, y, X_val, y_val))
```

```
              precision    recall  f1-score   support

           0       0.98      1.00      0.99    224661
           1       1.00      0.00      0.01      3601

    accuracy                           0.98    228262
   macro avg       0.99      0.50      0.50    228262
weighted avg       0.98      0.98      0.98    228262

[[224661      0]
 [  3588     13]]
None
```

```
# fit a logistic regression model to the data
def logistic_regression(train_x, train_y,test_x, test_y):
  model = LogisticRegression(max_iter = 120, random_state= 42, class_weight='auto')
  model.fit(train_x, train_y)
  print(model)
  # make predictions
  expected = test_y
  predicted = model.predict(test_x)
  # summarize the fit of the model
  print(classification_report(expected, predicted))
  print(confusion_matrix(expected, predicted))
```

```
print(logistic_regression(X, y, X_val, y_val))
```

```
LogisticRegression(C=1.0, class_weight='auto', dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=120,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=42, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/_classification.py:1272: UndefinedMetricWarning: Precision and F-score are ill-defined and being
  _warn_prf(average, modifier, msg_start, len(result))
              precision    recall  f1-score   support

           0       0.98      1.00      0.99    224661
           1       0.00      0.00      0.00      3601

    accuracy                           0.98    228262
   macro avg       0.49      0.50      0.50    228262
weighted avg       0.97      0.98      0.98    228262

[[224661      0]
 [  3601      0]]
None
```

From the above two models we observe the following,

1. Accuracy - For both the models, we have 0.98 as accuracy, but since we know that our class variable is highly imbalanced we can't use accuracy as the evaluation metrics.
2. Observing the confusion matrix, we see that in Random Forest, we get True Negatives, that is a fraud transaction is missclassified as non-fraud and the number is 3588 and in LR we get 0. In Fraud Detection, our goal is to either correctly maximize the prediction of Fraud Cases or either we try to reduce the True Negatives.

Observation

We will be using Random Forest as the BASELINE Model, and try to reduce the True Negatives that is try to increase the Recall in our case. In Case of Fraud Detection, Recall will be priortized over Precision as if we missclassify, a fraud transaction as non-fraud it can cause heavy loss to a consumer. Therefore,our goal is to maximize recall or either rigtly classify the fraud transaction

**For Solving the Imbalance Problem in the dataset*

We try to use oversample our non-dominant class using SMOTE [Synthetic Minority Oversampling Technique] strategy. SMOTE works by utilizing a k-nearest neighbor algorithm to create synthetic data. SMOTE first start by choosing random data from the minority class, then k-nearest neighbors from the data are set. Synthetic data would then made between the random data and the randomly selected k-nearest neighbor.

WE will be using the SMOTE strategy and perform oversampling in our dataset, so that both the number of fraud and non-fraud cases are same, and then try to run the Random Forest and observe the classification reports.

```
# Borderline SMOTE for Oversampling the X,y
def border_smote(X_train,y_train,X_val,y_val):
  bsmote = BorderlineSMOTE(random_state = 101, kind = 'borderline-1')
  X_oversample, y_oversample = bsmote.fit_resample(X_train, y_train)
  return X_oversample, y_oversample
```

```
X_oversample, y_oversample = border_smote(X_train,y_train,X_val,y_val)
print(random_forest(X_oversample, y_oversample, X_val, y_val))
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/utils/deprecation.py:87: FutureWarning: Function safe_indexing is deprecated; safe_indexing is deprecatec
  warnings.warn(msg, category=FutureWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/utils/deprecation.py:87: FutureWarning: Function safe_indexing is deprecated; safe_indexing is deprecatec
  warnings.warn(msg, category=FutureWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/utils/deprecation.py:87: FutureWarning: Function safe_indexing is deprecated; safe_indexing is deprecatec
  warnings.warn(msg, category=FutureWarning)
              precision    recall  f1-score   support

           0       0.99      0.96      0.97    224661
           1       0.07      0.18      0.10      3601

    accuracy                           0.95    228262
   macro avg       0.53      0.57      0.54    228262
weighted avg       0.97      0.95      0.96    228262

[[216126   8535]
 [  2942    659]]
None
```

Results after Oversamling from BorderlineSMOTE, we significantly reduced the the number of True Negatives as they were 3588 earlier, with BaseLine Random Forest which changed to 2942 with SMote-RandomForest. Also, we see a significant increase in correctly classified Fraudulent cases which changed from 13 to 659.

We can say that, this oversampling technique did show some significant result as we see that recall 0.0 increased to 0.18, which is a significant result given the imbalance in the dataset.

- **Conclusion**

> The dataset is a typical classification problem with class Imbalance. The baseline model Random Forest gave poor results, as there are very less records for IsFraud class. But, after applying the oversampling with SMOTE, we observe a significant increase in the correct prediction of Fraud as well as the increase in Recall.

> We are here analyzing the Recall metrics as in Fraud Detection, we can't ignore the case when a Fraud transaction is missclassified as non-fraud, as that can incur huge amount of loss and customer dissatisfaction as well.

> Therefore, we plan to keep the True Negatives low and thus work on the recall metrics, and thus recall and F1 score is used as our evaluation metrics.

> I was significantly able to improve upon the Baseline Model as recall and F1 score for BaselineModel was 0.0 and with SMOTE-RandomForest we were able to achieve, significantly 0.18 as recall and 0.10 and F1 score. There was a significant improvent in the Confusion metrics as well, as compared to the baseline as in Baseline were able to predict only 13 Fraud cases correctly, whereas in SMOTE-RandomForest we were able to correctly classify 659 Fraud Cases correctly.

- **Future Work**

> We know that our dataset contains a lot of columns of type 'object', we can perform statistical tests like chi-square analysis for those columns. WE can then formulate various bins and use those columns more significantly.

> In transactional dataset, we can observe the information values and weight of evidences for various columns with respect to the class variable and perform appropriate feature engineering, I think that would be very helpful for better results.

> Modeling -- We could also use One-class SVM basically treating the problem as an anomaly-detection problem i.e an unsupervised problem and train our model only with only the non-fraud class. We can then perform classification over the test data. We will observe that all the fraud transactions will be then considered as an outlier and model will have the better ability to correctly classify them.

> Weighted SVM model by assigning more weight to the less-dominant class, can also help for better classification results.