CS 422 - Data Mining

In [1]:
```python
import os

import numpy as np
import pandas as pd

import warnings
warnings.filterwarnings("ignore")

import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

from sklearn import metrics
from sklearn import decomposition
from sklearn.decomposition import PCA
from sklearn_pandas import DataFrameMapper

from sklearn.pipeline import Pipeline
from sklearn2pmml import sklearn2pmml
from sklearn2pmml.pipeline import PMMLPipeline
from sklearn2pmml.decoration import ContinuousDomain

from sklearn.feature_selection import SelectFromModel
from feature_selector import FeatureSelector
from sklearn.svm import LinearSVC

from sklearn.linear_model import LinearRegression
from sklearn.linear_model import LogisticRegression
from sklearn.linear_model import SGDClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.cluster import KMeans
from sklearn.ensemble import RandomForestClassifier

from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report

from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline

from skl2onnx.common.data_types import FloatTensorType
from skl2onnx import convert_sklearn
import onnxruntime as rt
from onnx.tools.net_drawer import GetPydotGraph,GetOpNodeProducer
from onnxmltools.convert.common.shape_calculator import calculate_linear_classifier_output_shapes
#from skl2onnx.operator_converters.RandomForest import convert_sklearn_random_forest_classifier
```


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Abstract

Data mining is the process to discover meaningful patterns and rules by analyzing and exploring a large quantity of data. This project has the same objective. During the development of the project, I learned a couple of things like how to read, understand different python packages and libraries, what should be the approach to make the best model, and I also understand that along with the accuracy of the model, efficiency of the model is also important. So, avoiding the brunt force approach would be the better choice.

In this project, in order to make a decent model, first of all, I performed data processing then applied various algorithms for feature extraction, and also applied various classification algorithms for model selection. Lastly, I found the accuracy to validate the selected model.

As all the features are nearly correlated with each other, feature extraction/selection became a very difficult task. Here, which features we can retain and which feature we can remove were very ambiguous tasks because, with every set of features, we got somewhat similar accuracy. So, in the future, I would like to find some prominent and profound algorithms for feature extraction.

Overview

Problem Statement : The objective of this project is to build a model that generalizes well out of sample.

Relevant literature : See References

Proposed methodology : The first few steps will be preprocessing, scaling, and bifurcating data into training and testing datasets. Then I am planning to find the correlations between the features, which will help me to find out which feature to retain for making a decent predictive model. After that, I will apply the PCA for feature extraction. The last step will be identifying the correct classification method and validate that method by finding the accuracy score.

Load the data

In [2]:
```python
#pull zip data: unzip and use delimiter to present the data
df = pd.read_csv('data_public.csv.gz',compression='gzip',quotechar='"',na_values='?')
df
```

Out[2]:

	A	B	C	D	E	F	G	H	I	J	
0	231.420023	-12.210984	217.624839	-15.611916	140.047185	76.904999	131.591871	198.160805	82.873279	127.350084	224.59
1	-38.019270	-14.195695	9.583547	22.293822	-25.578283	-18.373955	-0.094457	-33.711852	-8.356041	23.792402	4.19
2	-39.197085	-20.418850	21.023083	19.790280	-25.902587	-19.189004	-2.953836	-25.299219	-6.612401	26.285392	5.91
3	221.630408	-5.785352	216.725322	-9.900781	126.795177	85.122288	108.857593	197.640135	82.560019	157.105143	212.98
4	228.558412	-12.447710	204.637218	-13.277704	138.930529	91.101870	115.598954	209.300011	89.961688	130.299732	201.79
...	...	...	...	...	...	...	...	...	...	...	
1199995	-24.786494	-10.521166	15.328284	17.262938	-27.448018	-31.558757	-2.868037	-20.349796	-8.638853	28.820524	1.94
1199996	-39.555214	-14.965132	18.463720	18.127835	-26.634431	-24.569557	0.058442	-22.117532	-8.618300	30.395884	-8.07
1199997	223.972417	-17.367537	213.833218	-11.930115	127.344101	88.436019	118.061876	199.927061	80.655941	148.959437	202.63
1199998	-58.147084	-42.018043	-42.593154	-122.341090	-10.619619	-119.306608	-57.133497	-9.801039	54.972452	-88.305990	34.89
1199999	249.063156	-6.378220	212.761858	-15.055532	124.103066	85.608298	122.830182	196.326863	85.209367	117.895202	214.75

1200000 rows × 16 columns

There are 1200000 rows and 16 columns. Among 16 columns, 15 columns (A to O) are the features.

In [3]:
```python
# describe is used to get the first hand information about the data: mean, std and max are important
df.describe()
```

Out[3]:

	A	B	C	D	E	F	G	H	
count	1.200000e+06	1.200000e+06	1.200000e+06	1.200000e+06	1.200000e+06	1.200000e+06	1.200000e+06	1.200000e+06	1.200000
mean	5.068656e+01	-1.883373e+01	7.162152e+01	-1.355120e+01	2.944177e+01	-6.185189e+00	3.174186e+01	5.112504e+01	3.300077
std	1.292492e+02	1.446355e+01	1.052808e+02	4.689774e+01	7.282278e+01	7.309100e+01	6.660329e+01	1.034053e+02	4.217119
min	-7.308940e+01	-8.322357e+01	-5.972853e+01	-1.375818e+02	-3.829826e+01	-1.485917e+02	-6.654137e+01	-4.246089e+01	-1.818542
25%	-3.793679e+01	-1.786669e+01	7.553164e+00	-1.471337e+01	-2.436286e+01	-3.072492e+01	-3.484185e+00	-2.629661e+01	-7.594991
50%	-3.197847e+01	-1.369876e+01	1.348796e+01	-8.004308e+00	-1.897058e+01	-2.475391e+01	1.491431e+00	-1.817028e+01	3.769369
75%	2.280020e+02	-1.055606e+01	2.123439e+02	1.955806e+01	1.289018e+02	7.834417e+01	1.151840e+02	1.915891e+02	7.984842
max	2.687738e+02	4.460108e+00	2.561698e+02	3.263799e+01	1.579843e+02	1.229186e+02	1.660534e+02	2.329496e+02	1.112970

Data Processing & Analysis

Check missing values

In [4]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1200000 entries, 0 to 1199999
Data columns (total 16 columns):
 #   Column  Non-Null Count    Dtype
---  ------  --------------    -----
 0   A       1200000 non-null  float64
 1   B       1200000 non-null  float64
 2   C       1200000 non-null  float64
 3   D       1200000 non-null  float64
 4   E       1200000 non-null  float64
 5   F       1200000 non-null  float64
 6   G       1200000 non-null  float64
 7   H       1200000 non-null  float64
 8   I       1200000 non-null  float64
 9   J       1200000 non-null  float64
 10  K       1200000 non-null  float64
 11  L       1200000 non-null  float64
 12  M       1200000 non-null  float64
 13  N       1200000 non-null  float64
 14  O       1200000 non-null  float64
 15  Class   1200000 non-null  int64
dtypes: float64(15), int64(1)
memory usage: 146.5 MB
```

Data has no null values and all values are quantitaive with d_type=float

Dividing data into training and testing dataset

In data mining, classification involves the problem of predicting which category or class a new observation belongs in. The derived model (classifier) is based on the analysis of a set of training data where each data is given a class label. The trained model (classifier) is then used to predict the class label for new, unseen data. How these predicted labels match with the actual label is measured by the accuracy score.

In [5]:
```python
# Divide the original data into training and testing datasets.
X = df.iloc[:, 0:15]
y = df.iloc[:, 15:16]
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.2)
```

Divide the data into two parts : training data: 80% and testing data: 20%

In [6]:
```python
# Print out the shape of our training and testing data
print(X_train.shape, y_train.shape)
print(X_test.shape, y_test.shape)
```

```
(960000, 15) (960000, 1)
(240000, 15) (240000, 1)
```

In [7]:
```python
# Training data
training_data = pd.concat([X_train, y_train], axis=1)
training_data
```

Out[7]:

	A	B	C	D	E	F	G	H	I	J	
911594	-27.160523	-13.700044	6.818825	15.790279	-26.000085	-30.629241	0.539321	-26.628793	-8.819376	18.896737	1.992
743547	-27.584746	-12.979409	18.096758	22.906784	-23.632237	-32.541539	0.903096	-30.586956	-9.105422	26.097855	-3.843
621002	-38.638346	-18.009977	4.285438	17.892621	-21.486458	-22.958471	-3.849228	-25.232118	-6.477778	22.986912	-4.040
588940	242.241894	-11.909141	213.479889	-15.557743	136.486340	86.109511	128.344139	187.885060	91.084920	118.327899	230.877
58688	228.617241	-9.228906	217.928034	-11.253405	139.765987	85.111584	115.295166	210.649678	79.831568	133.468924	194.822
...	...	...	...	...	...	...	...	...	...	...	
553648	-68.694960	-45.326247	-41.001884	-116.048611	-17.955541	-118.285370	-49.612378	-11.469429	58.007141	-87.874902	36.418
299343	-33.164322	-17.232624	10.617718	14.355796	-24.656636	-32.384607	-2.782146	-27.194002	-7.384795	29.547066	-3.034
833881	240.744714	-11.241850	229.992378	-13.597989	137.514287	82.015525	121.605338	202.702097	82.935884	137.795586	239.636
436111	-30.655485	-18.962051	9.454669	19.547695	-23.989608	-23.427035	2.578773	-27.641007	-5.211700	31.599690	0.443
65471	242.406900	-13.575521	214.442268	-13.289500	129.396076	71.025455	126.121947	207.873466	68.808784	136.494782	226.927

960000 rows × 16 columns

In [8]:
```python
# Testing data
testing_data = pd.concat([X_test, y_test], axis=1)
testing_data
```

Out[8]:

	A	B	C	D	E	F	G	H	I	J	
1136439	225.648997	-13.731120	221.289499	-12.408939	126.959048	78.584186	141.078372	186.733569	82.118753	118.499900	224.04
199318	-24.982032	-19.440267	6.460562	19.452010	-24.474221	-23.615340	6.719175	-24.143542	-7.688412	25.220467	0.55
856546	-32.767983	-17.257092	9.467110	18.230884	-23.222568	-26.755245	-3.744454	-29.080396	-8.738639	29.673518	6.08
617982	-60.008311	-44.399269	-43.702554	-112.809949	-11.869548	-112.777588	-57.298683	-13.314031	56.018298	-87.014369	44.48
593061	-56.912076	-38.705003	-41.776887	-122.629803	-21.278678	-126.547513	-54.650071	-6.763798	52.507909	-98.423481	36.23
...	...	...	...	...	...	...	...	...	...	...	
1044564	-39.399252	-13.169591	11.926470	21.332491	-30.525694	-22.900351	-1.519542	-23.922903	-3.303903	28.767759	5.36
617689	-56.797071	-46.093155	-45.942639	-119.426217	-24.682692	-123.402683	-51.540198	-9.909776	48.500402	-95.488424	36.04
1150796	214.752585	-15.346523	206.460619	-11.559674	131.807974	96.815106	119.040882	198.961709	94.224328	125.011293	209.71
440295	-63.331278	-48.263279	-33.832963	-110.334870	-14.942922	-121.056501	-50.201184	-3.265795	53.015934	-96.309222	53.37
89003	-62.041504	-47.006499	-44.672893	-120.234527	-16.394202	-120.400609	-55.036211	-11.544652	45.001467	-92.142254	48.47

240000 rows × 16 columns

Principal Component Analysis

PCA reduces the number of features in a model. This makes the model less expressive, and as such might potentially reduce overfitting. At the same time, it also makes the model more prone to underfitting. So, I am taking 95% variance as a threshold.

During the development, one of the perspectives is changed about PCA. First, the difference between feature selection and feature extraction. Apparently, feature selection keeps a subset of the original features while feature extraction creates new ones. I was under the assumption that PCA fell under feature selection since it combined features. But there is a little more to it than just combining features, PCA uses the original features to create linear combinations and showcases them as new features.

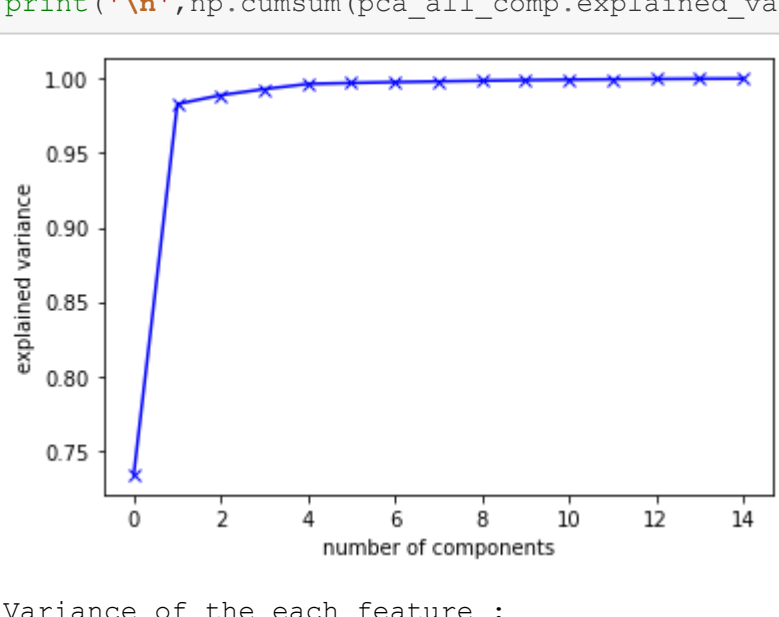
In [9]:
```python
# First scale the data
features = df.columns
scaler = StandardScaler()
df_scaled = pd.DataFrame(scaler.fit_transform(df.drop('Class',axis=1)))
df_scaled
```

Out[9]:

	0	1	2	3	4	5	6	7	8	9	10	11
0	1.398333	0.457892	1.386800	-0.043941	1.518831	1.136805	1.499176	1.421937	1.182621	1.123217	1.531100	0.048383
1	-0.686316	0.320671	-0.589262	0.764323	-0.755534	-0.166762	-0.477999	-0.820431	-0.980689	-0.222670	-0.792750	0.613532
2	-0.695429	-0.109594	-0.480605	0.710940	-0.759987	-0.177913	-0.520931	-0.739075	-0.939343	-0.190270	-0.774695	0.830704
3	1.322591	0.902156	1.378256	0.077838	1.336854	1.249231	1.157837	1.416902	1.175193	1.509929	1.408750	0.200674
4	1.376193	0.441525	1.263438	0.005832	1.503497	1.331041	1.259054	1.529661	1.350708	1.161552	1.290718	0.332113
...	...	...	...	...	...	...	...	...	...	...	...	...
1199995	-0.583934	0.574725	-0.534696	0.657050	-0.781209	-0.347150	-0.519643	-0.691211	-0.987396	-0.157322	-0.816495	0.547687
1199996	-0.698200	0.267472	-0.504915	0.675492	-0.770037	-0.251527	-0.475704	-0.708306	-0.986908	-0.136848	-0.922171	0.491340
1199997	1.340711	0.101371	1.350786	0.034566	1.344392	1.294568	1.296033	1.439018	1.130041	1.404063	1.299614	0.304915
1199998	-0.842045	-1.602949	-1.084858	-2.319727	-0.550122	-1.547680	-1.334400	-0.589197	0.521012	-1.679556	-0.469105	-1.858541
1199999	1.534838	0.861166	1.340609	-0.032077	1.299886	1.255880	1.367625	1.404202	1.238016	1.000337	1.427378	-0.106262

1200000 rows × 15 columns

In [10]:
```python
# Apply PCA on all the components
pca_all_comp = decomposition.PCA(n_components=15)
pca_all_comp.fit(df_scaled)

plt.plot(np.cumsum(pca_all_comp.explained_variance_ratio_),'bx-')
plt.xlabel('number of components')
plt.ylabel('explained variance')
plt.show()

print("Variance of the each feature :")
print('\n',pca_all_comp.explained_variance_ratio_)
print("\n Cumulative percentage variance of the each feature :")
print('\n',np.cumsum(pca_all_comp.explained_variance_ratio_*100))
```




```
Variance of the each feature :

 [7.33864677e-01 2.49030223e-01 5.94772600e-03 4.07704155e-03
 3.46584323e-03 6.57804933e-04 5.61838589e-04 4.71665772e-04
 4.61722639e-04 3.82898239e-04 3.11013079e-04 2.56592626e-04
 2.01142386e-04 1.84748847e-04 1.25062088e-04]

 Cumulative percentage variance of the each feature :

 [ 73.38646773  98.28949      98.8842626   99.29196676  99.63855108
  99.70433157  99.76051543  99.80768201  99.85385427  99.8921441
  99.92324541  99.94890467  99.96901891  99.98749379 100.        ]
```

As we can see, the first two components hold more than 95% of the variance.

Method - 2 (How many optimal numbers of components acquire 95% of the variance?)

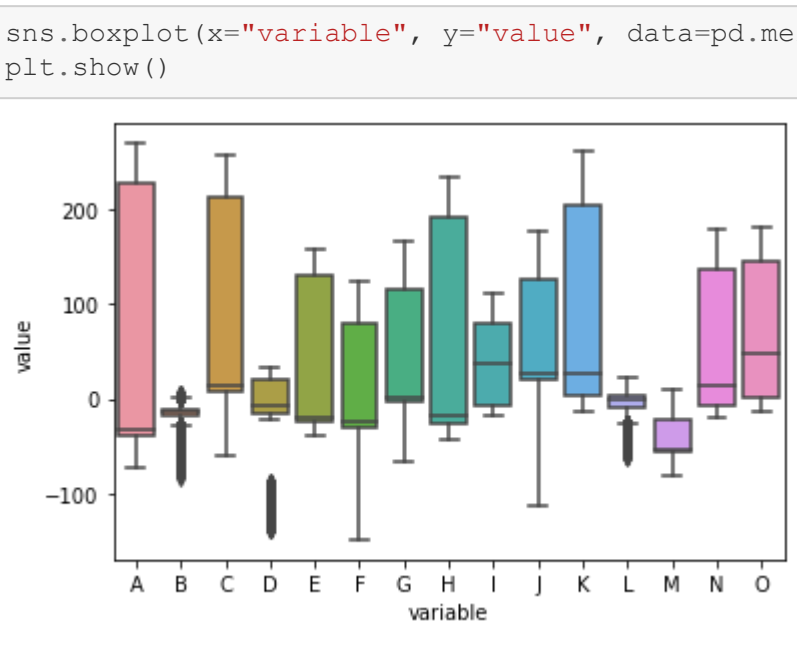
In [11]:
```python
pca = decomposition.PCA(n_components=0.95)
pca.fit(df_scaled)

print("The optimal number of components to maintain 95% variance : {}".format(pca.n_components_))
```

```
The optimal number of components to maintain 95% variance : 2
```

Visualization of the data for better understanding

Figure - 1

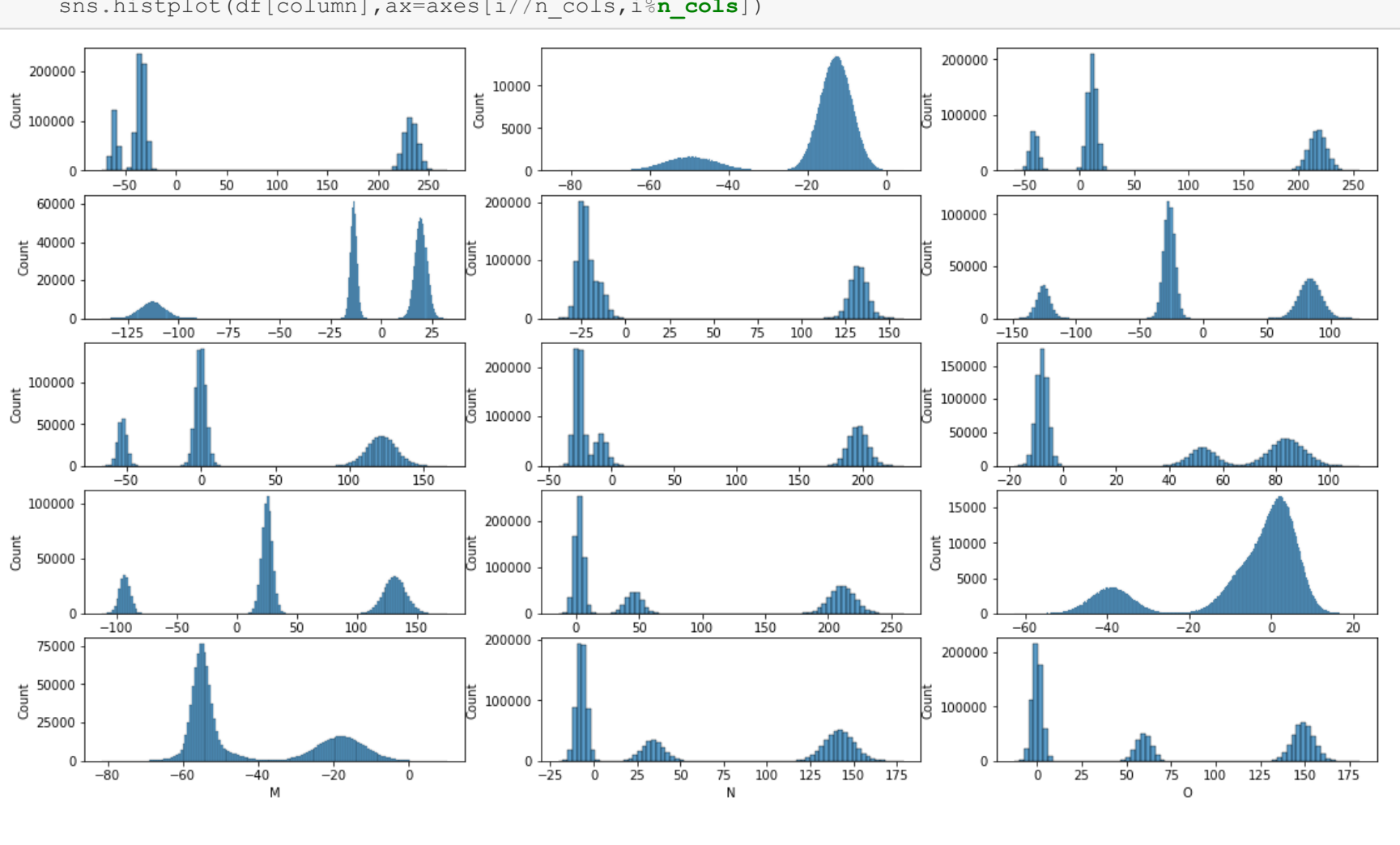
In [12]:
```python
sns.boxplot(x="variable", y="value", data=pd.melt(df.iloc[:,:15]))
plt.show()
```



Boxplot shows that variable B, D, L have potential outliers. We can see that some features have higher spread and even negative median value.

Figure - 2

In [13]:
```python
n_rows=5
n_cols=3
fig, axes = plt.subplots(nrows=n_rows, ncols=n_cols)
fig.set_size_inches(18.5, 10.5, forward=True)
for i, column in enumerate(df.columns[:15]):
    sns.histplot(df[column],ax=axes[i//n_cols,i%n_cols])
```



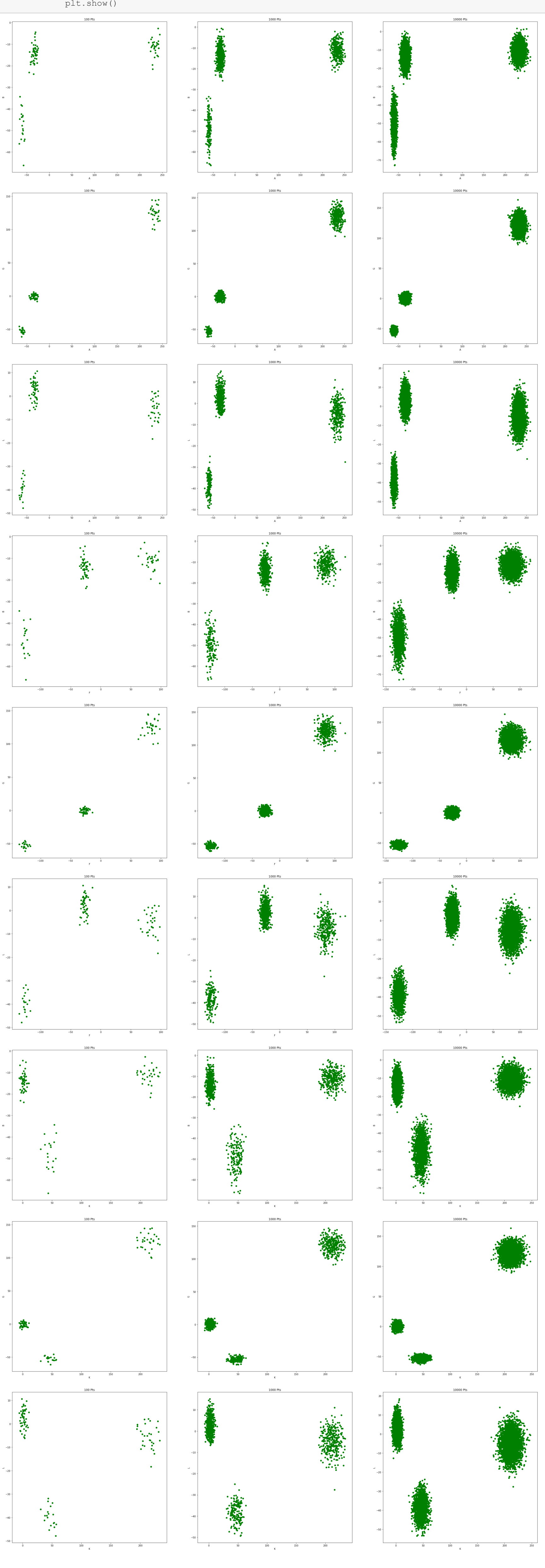
Histplots for univariate distribution and we see that the data has multiple peaks or modes. It doesn't follow normal distribution

Figure - 3

I decided to plot the features against each other in form of cluster to see if anything interesting showed up. Since there is too much data, I thought it be best to plot in sizes of 100, 1000, & 10000 to get a decent visual.

Here, I will not plot all the pair of features since it takes too much space, I'll only showcase a few of the plots by skipping a few.

In [14]:
```python
features = training_data.columns[:-1]

for i in range(0, len(features), 5):
    for j in range(1, len(features), 5):
        if i != j:
            plt.figure(figsize=(40, 40))
            plt.subplot(3,3,1)
            plt.plot(training_data[features[i]].head(100), training_data[features[j]].head(100), "go")
            plt.xlabel(features[i])
            plt.ylabel(features[j])
            plt.title("100 Pts")

            plt.subplot(3,3,2)
            plt.plot(training_data[features[i]].head(1000), training_data[features[j]].head(1000), "go"
)
            plt.xlabel(features[i])
            plt.ylabel(features[j])
            plt.title("1000 Pts")

            plt.subplot(3,3,3)
            plt.plot(training_data[features[i]].head(10000), training_data[features[j]].head(10000), "g
o")
            plt.xlabel(features[i])
            plt.ylabel(features[j])
            plt.title("10000 Pts")
            plt.show()
```

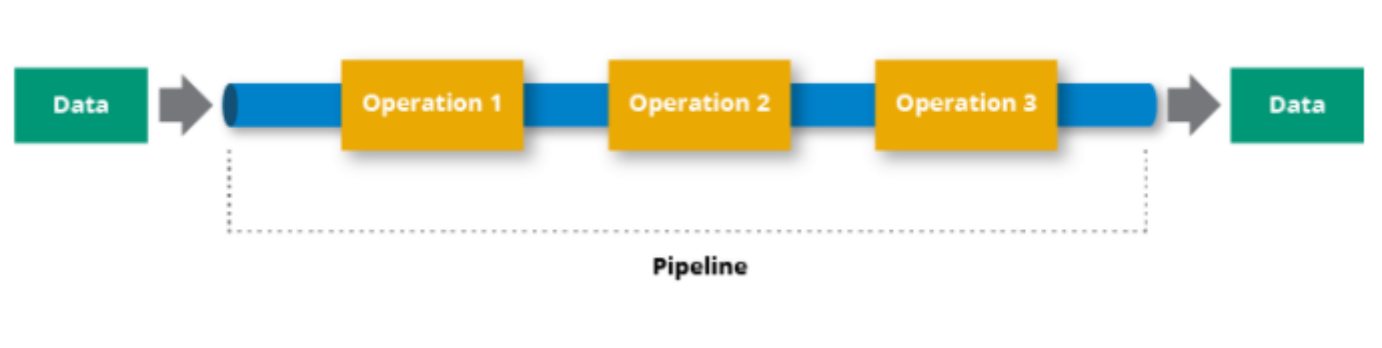


What Is a Data Pipeline?

Before getting into the feature selection/extraction and Model training & validation, It is very important to know what is data pipeline?

A data pipeline is a series of data processing steps. Data has to pass through various operations and stages before mold into the final model.

- Obtaining our data
- Scrubbing / Cleaning our data
- Exploring / Visualizing our data will allow us to find patterns and trends
- Modeling our data will give us our predictive power as a wizard
- Interpreting our data

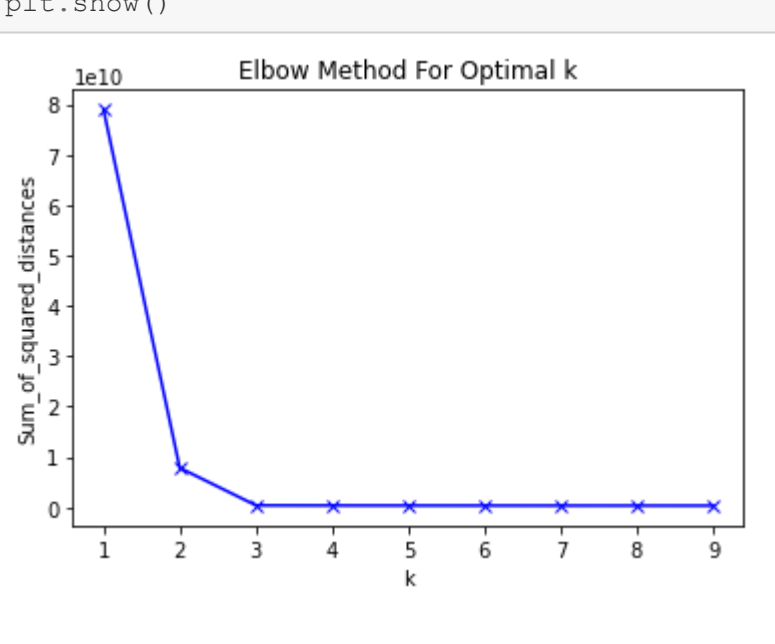


Feature Extraction, Model Training and Model Validation

Why I choose classification analysis over cluster analysis ?

In [15]:
```python
K = range(1,10)
Sum_of_squared_distances = []
for k in K:
    km = KMeans(n_clusters=k)
    km = km.fit(X_train)
    Sum_of_squared_distances.append(km.inertia_)
```

In [16]:
```python
# A plot to display what the optimal K will be
plt.plot(K, Sum_of_squared_distances, 'bx-')
plt.xlabel('k')
plt.ylabel('Sum_of_squared_distances')
plt.title('Elbow Method For Optimal k')
plt.show()
```



We can see that 3 is the optimal k. Now I can utilize this within the pipeline. The pipeline will then be used to predict on the X_test df.

In [17]:
```python
pipeline_cluster=PMMLPipeline([('mapper',DataFrameMapper([(X_train.columns.values,
                                                           [StandardScaler()])])),
                         ('pca',PCA(n_components=2)),
                         ('cluster',KMeans(n_clusters=3))])
pipeline_cluster.fit(X_train,y_train)
results=pipeline_cluster.predict(X_test)
actual=np.concatenate(y_test.values)
print('Accuracy:', metrics.accuracy_score(actual,results))
```

```
Accuracy: 0.1669
```

In [18]:
```python
print('I got just', metrics.accuracy_score(actual,results)*100, 'of the accuracy.')
```

```
I got just 16.689999999999998 of the accuracy.
```

In [19]:
```python
pipeline_c0=PMMLPipeline([('mapper',DataFrameMapper([(X_train.columns.values,
                                                      [StandardScaler()])])),
                         ('pca',PCA(n_components=2)),
                         ('classifier',DecisionTreeClassifier(max_depth=3))])
pipeline_c0.fit(X_train,y_train)
results=pipeline_c0.predict(X_test)
actual=np.concatenate(y_test.values)
print('Accuracy:', metrics.accuracy_score(actual,results))
accuracy_with_all_feature = metrics.accuracy_score(actual,results)*100
```

```
Accuracy: 0.5007208333333333
```

In [20]:
```python
print('I got', accuracy_with_all_feature, 'of the accuracy. which is better than the cluster analysis.'
)
```

```
I got 50.072083333333325 of the accuracy. which is better than the cluster analysis.
```

Feature Selection/Extraction

Though It is not a feasible approach, First of all, I am using the brute force approach where one by one I will remove each and every feature and try to identify which feature removals decreased the accuracy of the model. I believed that whatever the features we will get using this method are considered as an important feature and must be retained.

In [21]:
```python
feature_columns='ABCDEFGHIJKLMNO'
for i in range(0,len(feature_columns)):
    pipeline=PMMLPipeline([('mapper',DataFrameMapper([(X_train.columns.drop([feature_columns[i:i+1]]).v
alues,
                                                       [StandardScaler()])])),
                            ('pca',PCA(n_components=2)),
                            ('classifier',DecisionTreeClassifier(max_depth=3))])
    pipeline.fit(training_data.drop([feature_columns[i:i+1]],axis=1),training_data['Class'])
    results=pipeline.predict(X_test)
    actual=np.concatenate(y_test.values)
    print("Dropped feature:",feature_columns[i:i+1],", Accuracy:",metrics.accuracy_score(actual,results
))
```

```
Dropped feature: A , Accuracy: 0.5006958333333333
Dropped feature: B , Accuracy: 0.500725
Dropped feature: C , Accuracy: 0.5007333333333334
Dropped feature: D , Accuracy: 0.5007333333333334
Dropped feature: E , Accuracy: 0.50075
Dropped feature: F , Accuracy: 0.5007375
Dropped feature: G , Accuracy: 0.5007291666666667
Dropped feature: H , Accuracy: 0.5007375
Dropped feature: I , Accuracy: 0.5007333333333334
Dropped feature: J , Accuracy: 0.5006916666666666
Dropped feature: K , Accuracy: 0.500725
Dropped feature: L , Accuracy: 0.5006625
Dropped feature: M , Accuracy: 0.5007416666666666
Dropped feature: N , Accuracy: 0.5007541666666666
Dropped feature: O , Accuracy: 0.5007375
```

By analyzing the above result, I can not be able to conclude anything about the importance of the feature, which features we should retain, and which ones are preferable to drop. So, now we have to apply different feature selection techniques to identify the important features.

We have to use supervised technique as our data have a target variable. According to the below link, I will try different filter, wrapper, Embedded methods to identify the correlation between different features.

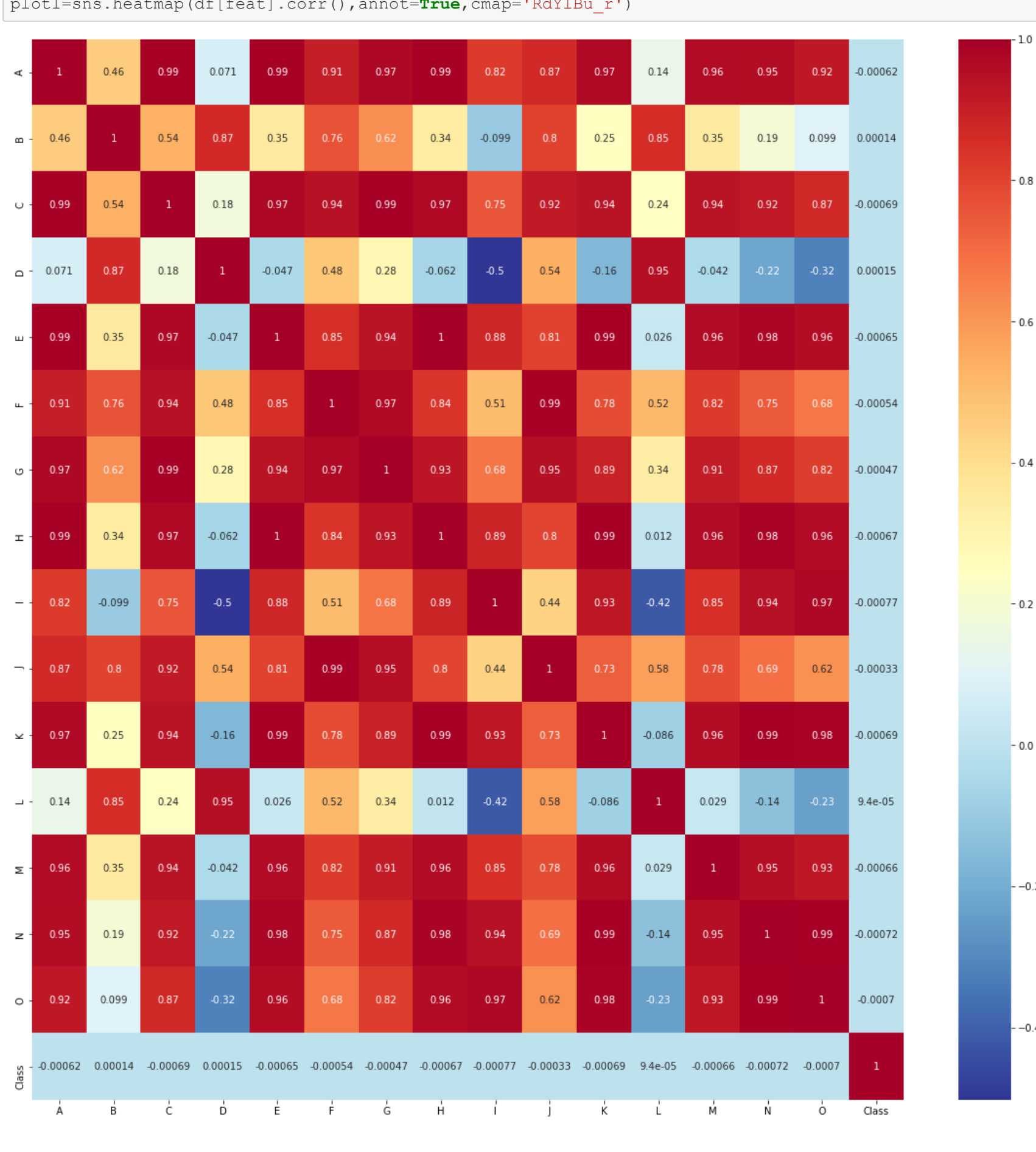
https://www.analyticsvidhya.com/blog/2020/10/feature-selection-techniques-in-machine-learning/

https://scikit-learn.org/stable/modules/feature_selection.html

Correlation Coefficient : Correlation is a measure of the linear relationship of 2 or more variables. Through correlation, we can predict one variable from the other. The logic behind using correlation for feature selection is that the good variables are highly correlated with the target. Furthermore, variables should be correlated with the target but should be uncorrelated among themselves.

Throughout the feature selection, I am using RandomForestClassifier().

In [22]:
```python
correlation1=df.corr('pearson')
feat=correlation1.index
plt.figure(figsize=(20,20))
plot1=sns.heatmap(df[feat].corr(),annot=True,cmap='RdYlBu_r')
```



Now I want to find the correlations between the pair of features. From that correlated features, I will get to know that which set of features I should retain and and which ones are preferable to drop.

In [23]:
```python
def get_redundant_pairs(df):
    '''Get diagonal and lower triangular pairs of correlation matrix'''
    pairs_to_drop = set()
    cols = df.columns
    for i in range(0, df.shape[1]):
        for j in range(0, i+1):
            pairs_to_drop.add((cols[i], cols[j]))
    return pairs_to_drop

def get_top_abs_correlations(df, n=5):
    au_corr = df.corr().abs().unstack()
    labels_to_drop = get_redundant_pairs(df)
    au_corr = au_corr.drop(labels=labels_to_drop).sort_values(ascending=False)
    return au_corr[0:n]

print("Top Absolute Correlations")
print(get_top_abs_correlations(training_data, 30))
```

```
Top Absolute Correlations
E  H    0.997115
K  N    0.992158
A  C    0.992003
H  K    0.990871
A  E    0.990704
F  J    0.989863
E  K    0.989220
N  O    0.988922
A  H    0.988808
C  G    0.988346
K  O    0.982992
H  N    0.982406
E  N    0.979926
A  G    0.972212
C  E    0.971813
I  O    0.970961
F  G    0.969058
A  K    0.968828
C  H    0.968355
E  M    0.964798
H  M    0.964671
   O    0.962886
A  M    0.958953
E  O    0.958899
K  M    0.956621
A  N    0.953094
D  L    0.949514
G  J    0.949436
M  N    0.947426
C  F    0.943501
dtype: float64
```

After observing the pair of features and correlation heatmap, I decided to follow the approach where if one feature is correlated with other features by 95% or above then we retain only one feature among them, and the rest of the features will be dropped.

With above mentioned approach I divided the features into 3 groups

- A,C,E,F,G,H,I,J,K,M,N,O
- D,L
- B

I am selecting E from first group and D from second group.

I decided to keep (B,D,E) features (from each group I am taking one feature) and finding the accuracy of the model.

In [24]:
```python
to_keep = ['B','D','E']

pipeline_keep=PMMLPipeline([('mapper',DataFrameMapper([(X_train[to_keep].columns.values,
                                                        [StandardScaler()])])),
                            ('pca',PCA(n_components=2)),
                            ('classifier',RandomForestClassifier(max_depth=3))])
pipeline_keep.fit(X_train,y_train)
results=pipeline_keep.predict(X_test)
actual=np.concatenate(y_test.values)
print('Accuracy:', metrics.accuracy_score(actual,results))
```

```
Accuracy: 0.5007416666666666
```

I decided to drop B because B have a outliers (**Figure - 1**)

In [25]:
```python
to_keep = ['D','E']

pipeline_keep=PMMLPipeline([('mapper',DataFrameMapper([(X_train[to_keep].columns.values,
                                                        [StandardScaler()])])),
                            ('pca',PCA(n_components=2)),
                            ('classifier',RandomForestClassifier(max_depth=3))])
pipeline_keep.fit(X_train,y_train)
results=pipeline_keep.predict(X_test)
actual=np.concatenate(y_test.values)
print('Accuracy:', metrics.accuracy_score(actual,results))
```

```
Accuracy: 0.5007458333333333
```

Still we are getting the accuracy around 50%. So, manual feature selection approach is not working.

Now I am going to apply some feature selection techniques which are explaind in the below link and try to improve my accuracy.
https://scikit-learn.org/stable/modules/feature_selection.html

L1-based feature selection

In [26]:
```python
from sklearn.svm import LinearSVC
pipeline_L1=PMMLPipeline([('mapper',DataFrameMapper([(X_train.columns.values,
                                                      [StandardScaler()])])),
                          ('pca',PCA(n_components=15)),
                          ('feature_selection', SelectFromModel(LinearSVC(C=0.01,penalty="l1",dual=False
))),
                          ('classifier',RandomForestClassifier(max_depth=3))])
pipeline_L1.fit(X_train,y_train)
results=pipeline_L1.predict(X_test)
actual=np.concatenate(y_test.values)
print('Accuracy:', metrics.accuracy_score(actual,results))
```

```
Accuracy: 0.5007416666666666
```

Univariate feature selection - SelectKBest

In [27]:
```python
from sklearn.feature_selection import SelectKBest

pipeline_KBest=PMMLPipeline([('mapper',DataFrameMapper([(X_train.columns.values,
                                                         [StandardScaler()])])),
                             ('pca',PCA(n_components=15)),
                             ('feature_selection', SelectKBest(k=3)),
                             ('classifier',RandomForestClassifier(max_depth=3))])
pipeline_KBest.fit(X_train,y_train)
results=pipeline_KBest.predict(X_test)
actual=np.concatenate(y_test.values)
print('Accuracy:', metrics.accuracy_score(actual,results))
```

```
Accuracy: 0.5007416666666666
```

Suitable classifier

In [28]:
```python
classifier = [LogisticRegression(),
              DecisionTreeClassifier(max_depth = 3),
              RandomForestClassifier(max_depth = 3),
              KNeighborsClassifier(),
              GaussianNB(),
              SGDClassifier(alpha=0.001, max_iter=100)]

for cls in classifier:
    print(cls)
    pipeline = PMMLPipeline([
        ('mapper',
         DataFrameMapper([
             (X_train.columns.values,StandardScaler())])),
        ('pca',
         PCA(n_components=15)),
        ('selector',
         SelectKBest(k=3)),
        ('classifier',cls)
    ])

    pipeline.fit(X_train,y_train)
    results=pipeline.predict(X_test)
    actual=np.concatenate(y_test.values)
    print('Accuracy:', metrics.accuracy_score(actual,results))
    print('\n')
```

```
LogisticRegression()
Accuracy: 0.5007416666666666


DecisionTreeClassifier(max_depth=3)
Accuracy: 0.5007458333333333


RandomForestClassifier(max_depth=3)
Accuracy: 0.5007416666666666


KNeighborsClassifier()
Accuracy: 0.41399583333333334


GaussianNB()
Accuracy: 0.5007416666666666


SGDClassifier(alpha=0.001, max_iter=100)
Accuracy: 0.5007416666666666
```

All the classifier gives me almost same accuracy except KNearest Neighbour (Which is lowest). So, I am using **DecisionTreeClassifier** with max_deapth = 3 in my final pipeline.

Making model on undersampling of the data

Now I am using totally different approach. I am splitting the data into 3 different dataframe.

- First dataframe contains the rows having 1 and 2 class labels that is called df12.
- Second dataframe contains the rows having 1 and 3 class labels that is called df13.
- Third dataframe contains the rows having 2 and 3 class labels that is called df23.

Then I am making three separate models and find the accuracy for each one. Which will give me insight that which label has more weightage on the data.

In [29]:
```python
df1 = df[df['Class'] == 1]
df2 = df[df['Class'] == 2]
df3 = df[df['Class'] == 3]
df12=pd.concat([df1,df2])
df13=pd.concat([df1,df3])
df23=pd.concat([df2,df3])
```

- Now I am implementing some functions to split the data, scale the data.
- Implement the function which gives me the optimal component of the dataframe using PCA.
- Implement the function to find accuracy using pipeline

In [30]:
```python
def SplitTheData(df):
    X = df.iloc[:, 0:15]
    y = df.iloc[:, 15:16]
    X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.2)
    return X_train,X_test,y_train,y_test

def ScaleTheData(df):
    features = df.columns
    scaler = StandardScaler()
    df_scaled = pd.DataFrame(scaler.fit_transform(df.drop('Class',axis=1)))
    return df_scaled

def PCA_RequitedComponents(df_scaled):
    pca = decomposition.PCA(n_components=0.95)
    pca.fit(df_scaled)
    return pca.n_components_

def FindAccuracy(X_train,y_train,X_test,y_test):
    pipeline=PMMLPipeline([('mapper',DataFrameMapper([(X_train.columns.values,
                                                       [StandardScaler()])])),
                           ('pca',PCA(n_components=2)),
                           ('classifier',DecisionTreeClassifier(max_depth=3))])
    pipeline.fit(X_train,y_train)
    results=pipeline.predict(X_test)
    actual=np.concatenate(y_test.values)
    print('\n Confusion Matrix')
    print(metrics.confusion_matrix(actual,results))
    print('\n classification Report')
    print(metrics.classification_report(actual,results))
    return metrics.accuracy_score(actual,results)
```

In [31]:
```python
X12_train,X12_test,y12_train,y12_test = SplitTheData(df12)
X13_train,X13_test,y13_train,y13_test = SplitTheData(df13)
X23_train,X23_test,y23_train,y23_test = SplitTheData(df23)

print("The optimal number of components to maintain 95% variance for df12: {}".format(PCA_RequitedCompo
nents(ScaleTheData(df12))))
print("The optimal number of components to maintain 95% variance for df13: {}".format(PCA_RequitedCompo
nents(ScaleTheData(df13))))
print("The optimal number of components to maintain 95% variance for df23: {}".format(PCA_RequitedCompo
nents(ScaleTheData(df23))))

print("\n Accuracy of the model with for df12 dataframe where we consider the rows having 1 and 2 class
 labels :",FindAccuracy(X12_train,y12_train,X12_test,y12_test))
print("\n Accuracy of the model with for df13 dataframe where we consider the rows having 1 and 3 class
 labels :",FindAccuracy(X13_train,y13_train,X13_test,y13_test))
print("\n Accuracy of the model with for df23 dataframe where we consider the rows having 2 and 3 class
 labels :",FindAccuracy(X23_train,y23_train,X23_test,y23_test))
```

```
The optimal number of components to maintain 95% variance for df12: 2
The optimal number of components to maintain 95% variance for df13: 2
The optimal number of components to maintain 95% variance for df23: 2

 Confusion Matrix
[[     0  39995]
 [     4 119845]]

 classification Report
              precision    recall  f1-score   support

           1       0.00      0.00      0.00     39995
           2       0.75      1.00      0.86    119849

    accuracy                           0.75    159844
   macro avg       0.37      0.50      0.43    159844
weighted avg       0.56      0.75      0.64    159844


 Accuracy of the model with for df12 dataframe where we consider the rows having 1 and 2 class labels
: 0.7497622682115063

 Confusion Matrix
[[    2 39845]
 [    4 80304]]

 classification Report
              precision    recall  f1-score   support

           1       0.33      0.00      0.00     39847
           3       0.67      1.00      0.80     80308

    accuracy                           0.67    120155
   macro avg       0.50      0.50      0.40    120155
weighted avg       0.56      0.67      0.54    120155


 Accuracy of the model with for df13 dataframe where we consider the rows having 1 and 3 class labels
: 0.6683533768881861

 Confusion Matrix
[[119764      1]
 [ 80236      1]]

 classification Report
              precision    recall  f1-score   support

           2       0.60      1.00      0.75    119765
           3       0.50      0.00      0.00     80237

    accuracy                           0.60    200002
   macro avg       0.55      0.50      0.37    200002
weighted avg       0.56      0.60      0.45    200002


 Accuracy of the model with for df23 dataframe where we consider the rows having 2 and 3 class labels
: 0.598819011809882
```

I got the higher accuracy for the model which we have made from the df12 dataframe.

In [32]:
```python
print(df1.shape)
print(df2.shape)
print(df3.shape)
print(df12.shape)
print(df13.shape)
print(df23.shape)
```

```
(199992, 16)
(599228, 16)
(400780, 16)
(799220, 16)
(600772, 16)
(1000008, 16)
```

As we can see the highest number of the rows have class label 2.

So, Undersampling of the data is required.

In [33]:
```python
# Undersampling of the data by random selection.
class1=df1
class3=df3.sample(n=199992) # select 199992 rows randomly
class2=df2.sample(n=199992) # select 199992 rows randomly
df_with_sampling=pd.concat([class1,class2,class3])
df_with_sampling
```

Out[33]:

	A	B	C	D	E	F	G	H	I	J	
11	-23.413125	-11.119531	16.910592	18.915184	-25.170026	-28.504337	-2.371616	-26.557941	-4.756554	20.160979	3.4
12	-29.249384	-13.486606	9.719229	18.708490	-21.304944	-34.440508	-1.884057	-26.843994	-9.007811	22.341808	0.4
15	-39.238696	-18.604404	15.525642	17.059754	-23.125142	-34.300873	6.034945	-25.488902	-1.199718	28.432906	0.9
24	214.501120	-12.386835	220.170860	-11.482754	136.266760	84.174828	113.271746	202.299392	79.514846	142.781926	208.6
28	244.410014	-11.742173	224.945971	-11.031026	131.058794	83.866057	131.314049	192.609849	88.551907	139.349595	198.4
...	...	...	...	...	...	...	...	...	...	...	
414898	220.252792	-12.445251	228.549879	-15.188049	136.968363	88.931645	127.123562	217.430116	82.055721	146.100794	194.0
769780	-34.976800	-11.454732	15.273580	20.770186	-29.434831	-30.651293	-2.727978	-22.530576	-13.057073	28.944970	-1.0
1046848	221.387757	-15.864191	198.715416	-10.662085	137.443924	83.521395	127.981545	213.514370	86.458663	123.687976	213.9
1150784	-56.821837	-47.691036	-53.794490	-122.438180	-13.757492	-131.461159	-54.954805	-13.652408	51.232848	-95.968326	37.0
383866	-32.976900	-14.504423	2.872470	18.671767	-23.295589	-30.323475	-4.277570	-25.204396	-8.444951	22.500665	4.5

599976 rows × 16 columns

- For sampling of the data for all the labels, we should use

from imblearn.under_sampling import NearMiss

smk=NearMiss() X_res,y_res = smk.fit_resample(df.drop('Class',axis=1),df['Class'])

- I have never implemented above method but according to the below link this is the correct way to do undersampling specially when your data is imbalanced Classification data.

https://machinelearningmastery.com/undersampling-algorithms-for-imbalanced-classification/

In [34]:
```python
print("The optimal number of components to maintain 95% variance in newly created sampled data frame:
{}".format(PCA_RequitedComponents(ScaleTheData(df_with_sampling))))
```

```
The optimal number of components to maintain 95% variance in newly created sampled data frame: 2
```

In [35]:
```python
XN_train,XN_test,yN_train,yN_test = SplitTheData(df_with_sampling)
print("Accuracy of the model which we have made from the dataframe with sampling data :",FindAccuracy(X
N_train,yN_train,XN_test,yN_test))
```

```
 Confusion Matrix
[[  361  3236 36383]
 [  307  3358 36448]
 [  309  3317 36277]]

 classification Report
              precision    recall  f1-score   support

           1       0.37      0.01      0.02     39980
           2       0.34      0.08      0.13     40113
           3       0.33      0.91      0.49     39903

    accuracy                           0.33    119996
   macro avg       0.35      0.33      0.21    119996
weighted avg       0.35      0.33      0.21    119996

Accuracy of the model which we have made from the dataframe with sampling data : 0.33331111037034566
```

- **We are not getting higher accuracy because we are doing undersampling of the data using the random selection.**
- **According to my point of view and understanding, if we are doing undersampling of the data using NearMiss() and use those train and test data to make a model then we will get more decent model and will get higher accuracy.**

Final Model: ONNX Implementation

In [36]:
```python
transformer = Pipeline(steps=[
    ('scaler',
     StandardScaler())
])

preprocessor = ColumnTransformer(transformers=[
    ('feature',
     transformer,
     df.columns[0:15])
])

classifier = DecisionTreeClassifier(max_depth = 3)
```

In [37]:
```python
pipeline = Pipeline([
    ('precprocessor',
     preprocessor),
    ('pca',
     PCA(n_components=3)),
    ('selector',
     SelectKBest(k=2)),
    ('classifier',
     classifier)
])

pipeline.fit(X_train, y_train);
```

In [38]:
```python
print(metrics.accuracy_score(y_test.values.ravel(),pipeline.predict(X_test)))
```

```
0.5007208333333333
```

Covert pipeline to ONNX file.

In [39]:
```python
input_types = dict([(x, FloatTensorType([None, 1])) for x in X_train.columns.values])

try:
    model_onnx = convert_sklearn(pipeline,
                                 'pipeline_onnx',
                                initial_types=list(input_types.items()))
except Exception as e:
    print(e)

with open("./pipeline/pipeline.onnx", "wb") as f:
    f.write(model_onnx.SerializeToString())
```

In [40]:
```python
inputs_onnx = {k: np.array(v).astype(np.float32)[:, np.newaxis] for k, v in X_test.to_dict(orient='lis
t').items()}

session_onnx = rt.InferenceSession("./pipeline/pipeline.onnx")
predict_onnx = session_onnx.run(None, inputs_onnx)
print("predict", predict_onnx[0])
```

```
predict [2 2 2 ... 2 2 2]
```

In [41]:
```python
np.unique(np.array(predict_onnx[0]), return_counts=True)
```

Out[41]:
```
(array([1, 2, 3], dtype=int64), array([     3, 239988,      9], dtype=int64))
```

In [42]:
```python
np.unique(predict_onnx[0] == testing_data.iloc[:,15], return_counts=True)
```

Out[42]:
```
(array([False,  True]), array([119827, 120173], dtype=int64))
```

Conclusion

- Data after cleaning and EDA : Data is multimodal with few outliers and doesn't follow normal distribution
- Optimal Dimensionality is 2
- Scaling and transformation improve accuracy
- This is a mutliclass classification problem and models which are better in multiclassification improve accuracy.
- Results of feature selection at a certain extent are inconclusive.
- Use of Pipeline can save time and streamine process.
- High correlation found between the features.
- We can achieve the higher accuracy with sampling of the data.
- Segregating data on basis of class and using binary classfiers improve accuracy and provide better estimate

Reference :

https://www.pluralsight.com/guides/evaluating-a-data-mining-model

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https://scikit-learn.org/stable/modules/feature_selection.html

https://stackoverflow.com/questions/17778394/list-highestcorrelation-pairs-from-a-large-correlation-matrix-in-pandas

Notebook: Individual Project - Pipeline - ONNX - Example.ipynb

Notebook: Individual Project - Pipeline - PMML - Example.ipynb

Example: Example Project - Spring 2019 - Victoria Belotti.pdf

In [ ]: