```
#importing all the necessary libraries

from matplotlib import pyplot as plt
import seaborn as sns
import numpy as np
import pandas as pd
import warnings
warnings.filterwarnings(action='ignore')
```

## EDA

```
#reading train dataset
df_train = pd.read_csv('ida_2016_training_set_update.csv')

#replacing string 'na' with float np.NaN
df_train = df_train.replace('na', np.NaN)
df_train.head(10)
```

```
  class  aa_000 ab_000      ac_000 ad_000 ae_000 af_000 ag_000 ag_001
ag_002  \
0   neg   76698    NaN  2130706438    280      0      0      0      0
0
1   neg   33058    NaN           0    NaN      0      0      0      0
0
2   neg   41040    NaN         228    100      0      0      0      0
0
3   neg      12      0          70     66      0     10      0      0
0
4   neg   60874    NaN        1368    458      0      0      0      0
0
5   neg   38312    NaN  2130706432    218      0      0      0      0
0
6   neg      14      0           6    NaN      0      0      0      0
0
7   neg  102960    NaN  2130706432    116      0      0      0      0
0
8   neg   78696    NaN           0    NaN      0      0      0      0
0
9   pos  153204      0         182    NaN      0      0      0      0
0

   ...   ee_002  ee_003   ee_004   ee_005   ee_006  ee_007  ee_008
ee_009  \
0  ...  1240520  493384   721044   469792   339156  157956   73224
0
1  ...   421400  178064   293306   245416   133654   81140   97576
1500
2  ...   277378  159812   423992   409564   320746  158022   95128
514
3  ...      240      46       58       44       10       0       0
```

```
0
4  ...   622012  229790   405298   347188   286954  311560  433954
1218
5  ...   388574  288278   900430   300412     1534     338     856
0
6  ...      168      48       60       28        0       0       0
0
7  ...   715518  384948   915978  1052166  1108672  341532  129504
7832
8  ...   699290  362510  1190028  1012704   160090   63216   41202
4
9  ...   129862   26872    34044    22472    34362       0       0
0

  ef_000 eg_000
0      0      0
1      0      0
2      0      0
3      4     32
4      0      0
5      0      0
6      0      0
7      0      0
8      0      0
9      0      0

[10 rows x 171 columns]
```

The data set is enitrely numerical. The data set providers told that the columns are either numerical counters or histogram open ended bin counters. Identifying which columns are histogram bin counters.

```
import re

total_columns = np.array(df_train.columns)        #storing all the
columns of the dataframe in an array

bin_columns = []
match_list = []

pattern = re.compile(r"([a-z]{2})\_00[1-9]")      #finding histogram
columns which has 001 to 009 subscripts
for s in total_columns:
    match = pattern.findall(s)                    #findall returns
list of the matched pattern
    if match and match not in match_list:         #checking whether
the return pattern is null or not and if it is already padded to the
list or not
        match_list.append(match)                  #match_list contains
the histogram names
```

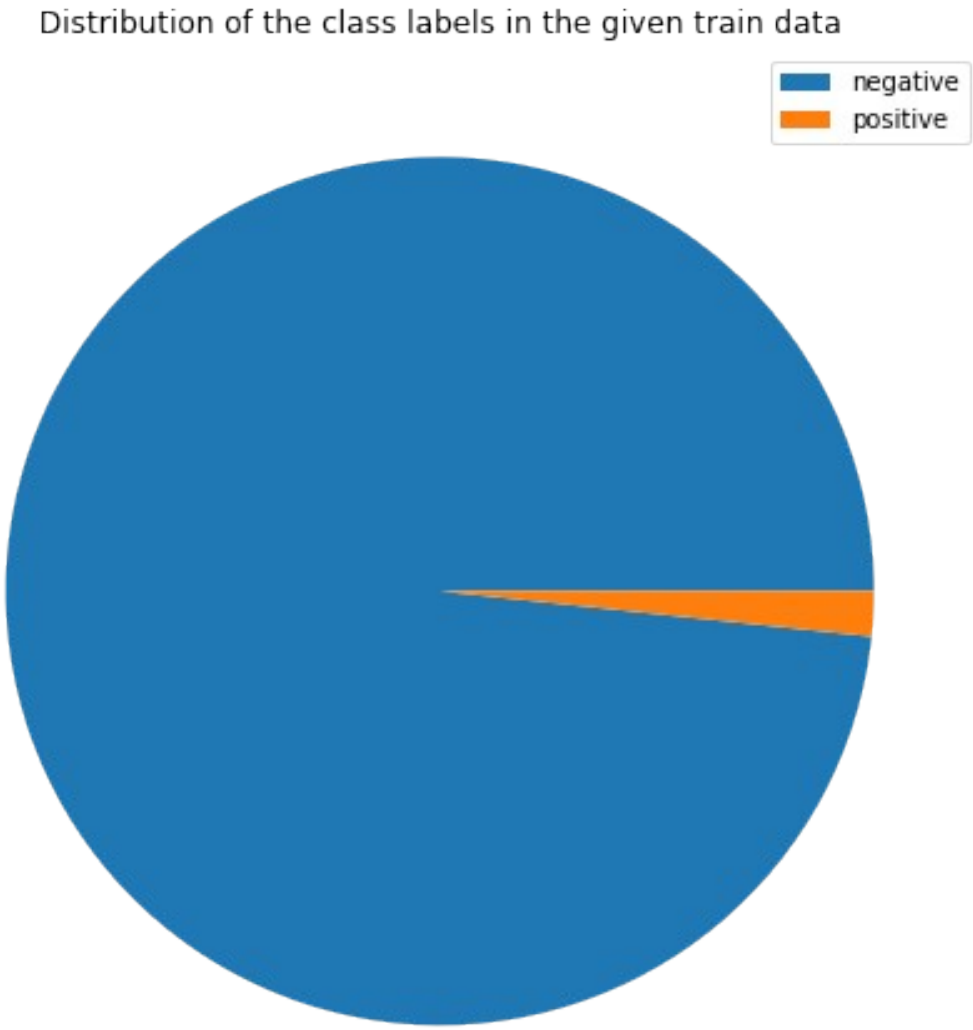
```
match_list =list(np.array(match_list).flatten())
print('the names of the histograms are {}\n'.format(match_list))

for l in match_list:
    for s in total_columns:
        x = re.compile(l+'\_[0-9]{3}').findall(s) #finding the all the
columns for each subscript in the match_list
        if x:
            bin_columns.extend(x)                #bin_columns contains
all the histogram bin counters present in the data

print('The histogram bin counter columns present in the train data set
are \n{}'.format(bin_columns))
```

```
the names of the histograms are ['ag', 'ay', 'az', 'ba', 'cn', 'cs',
'ee']

The histogram bin counter columns present in the train data set are
['ag_000', 'ag_001', 'ag_002', 'ag_003', 'ag_004', 'ag_005', 'ag_006',
'ag_007', 'ag_008', 'ag_009', 'ay_000', 'ay_001', 'ay_002', 'ay_003',
'ay_004', 'ay_005', 'ay_006', 'ay_007', 'ay_008', 'ay_009', 'az_000',
'az_001', 'az_002', 'az_003', 'az_004', 'az_005', 'az_006', 'az_007',
'az_008', 'az_009', 'ba_000', 'ba_001', 'ba_002', 'ba_003', 'ba_004',
'ba_005', 'ba_006', 'ba_007', 'ba_008', 'ba_009', 'cn_000', 'cn_001',
'cn_002', 'cn_003', 'cn_004', 'cn_005', 'cn_006', 'cn_007', 'cn_008',
'cn_009', 'cs_000', 'cs_001', 'cs_002', 'cs_003', 'cs_004', 'cs_005',
'cs_006', 'cs_007', 'cs_008', 'cs_009', 'ee_000', 'ee_001', 'ee_002',
'ee_003', 'ee_004', 'ee_005', 'ee_006', 'ee_007', 'ee_008', 'ee_009']
```

1. There are 7 different histograms.
2. Each histogram have 10 bin counters.
3. There are total 70 histogram bin features.

Distribution of classes in the train data set

```
plt.figure(figsize=(10,8))
plt.pie(df_train['class'].value_counts())
plt.title('Distribution of the class labels in the given train data')
plt.legend(['negative', 'positive'])
plt.show()
```




1. There are about 60,000 training points with 170 features in the given train data.
2. There are about 1000 positive classes indicating APS failure and 59000 negative classes indicating non APS-failure.
3. Given data set is highly imbalanced, skewed towards negative class {1}.

```
# storing target variables as labels from the train data
labels = df_train['class']

# numeric labeling of classes for negative class as '0' and for
positvie class as '1'
labels = labels.map({'neg': 0, 'pos': 1})

#dropping class labels from the train data to generate feature data
train_data = df_train.drop(['class'], axis=1)
```

```
#splitting given train data into X_train and X_cv for the validation
purpose
from sklearn.model_selection import train_test_split
X_train, X_cv, y_train, y_cv = train_test_split(train_data, labels,
stratify=labels, test_size=0.2, random_state = 8)

print('the shape of the X_train data is ',X_train.shape)
print('the sahpe of the X_cv data is ', X_cv.shape)
```

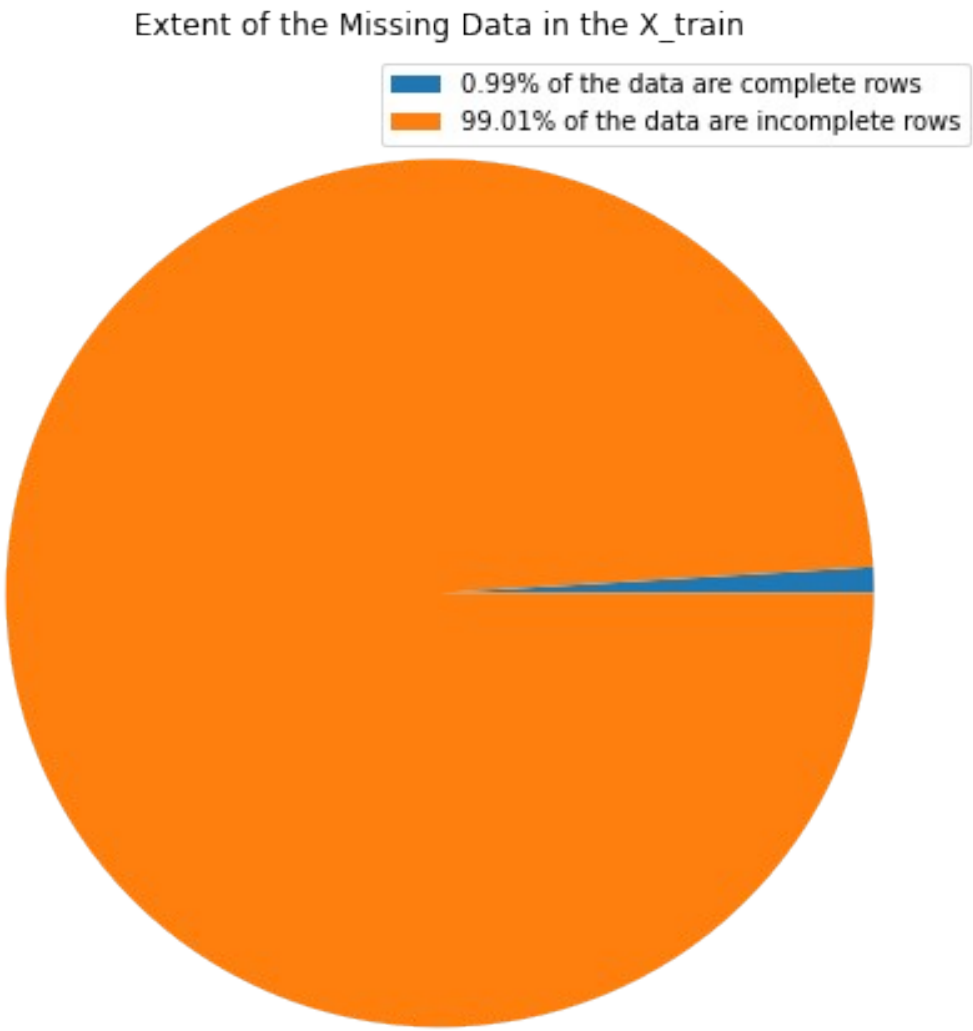
```
the shape of the X_train data is  (48000, 170)
the sahpe of the X_cv data is  (12000, 170)
```

Percentage of missing data in the train data set

```
#creating a dataframe for counting no. of rows with full values
not_missing_rows = pd.DataFrame(X_train.count(axis=1), index=
X_train.index, columns=['not_missing'])

#Finding no. of rows which contains total columns values.
not_missing_rows.loc[not_missing_rows['not_missing']==170]
```

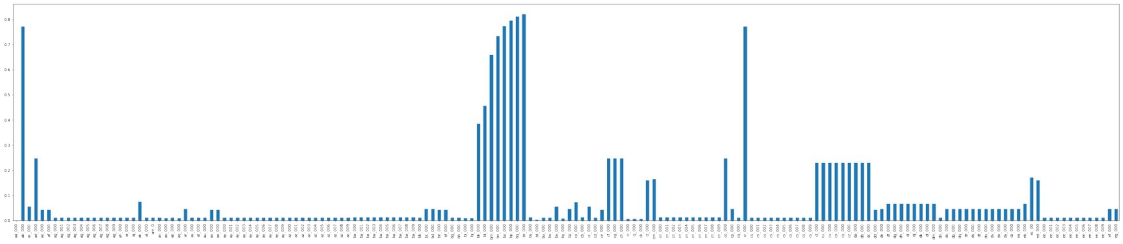
```
       not_missing
23594          170
57877          170
2721           170
9001           170
29257          170
...            ...
32283          170
38883          170
22951          170
18875          170
28253          170

[467 rows x 1 columns]
```

```
plt.figure(figsize=(10,8))
plt.pie([not_missing_rows.loc[not_missing_rows['not_missing']==170].sh
ape[0], X_train.shape[0]])
plt.title('Extent of the Missing Data in the X_train')
plt.legend(['0.99% of the data are complete rows', '99.01% of the data
are incomplete rows'])
plt.show()
```




```
#counting no. of missing values for each column in the train dataset
na_count = pd.DataFrame(X_train.isnull().sum(),
columns=['missing_count'])

#calculating missing_percentage for each column
na_count['missing_percentage'] = X_train.isnull().sum()/len(X_train)

#plotting no. of missing counts
na_count['missing_percentage'].plot.bar(figsize=(50,10))
```

```
<AxesSubplot:>
```



```
#finding the features whose missing_percentage is greater than 50%
more_than_fifty = na_count.loc[na_count['missing_percentage'] > 0.50]
more_than_fifty
```

```
        missing_count  missing_percentage
ab_000          37038            0.771625
bm_000          31659            0.659563
bn_000          35233            0.734021
bo_000          37095            0.772813
bp_000          38198            0.795792
bq_000          38971            0.811896
br_000          39405            0.820937
cr_000          37038            0.771625
```

1. There are 8 features whose missing count is greater than 50% of the data points.
2. They may not play any important factor in deciding the class of a instance, hence we discard them.

```
# Dropping the features where more than fifty percent of the column
are missing values
X_train = X_train.drop(more_than_fifty.index, axis=1)
X_cv = X_cv.drop(more_than_fifty.index, axis = 1)

print('after removing the features which contain more than 50% NaN no.
of featrues reduced to', len(X_train.columns))
```

```
after removing the features which contain more than 50% NaN no. of
featrues reduced to 162
```

Reading Test data

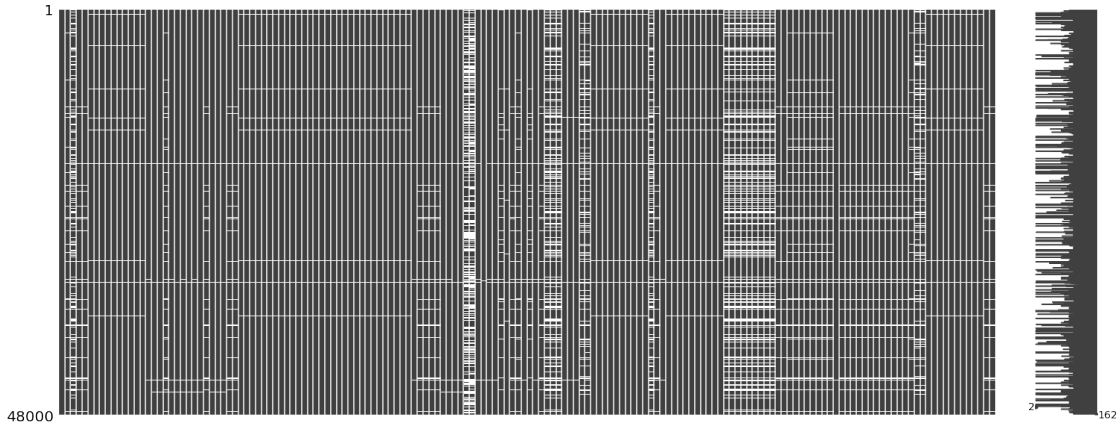
```
#reading test data set
df_test = pd.read_csv('ida_2016_test_set_update.csv')

#replacing string 'na' with float np.NaN
df_test = df_test.replace('na', np.NaN)
df_test.head()
```

```
   id class  aa_000 ab_000 ac_000 ad_000 ae_000 af_000 ag_000
ag_001  ...  \
0   1    na      60      0     20     12      0      0      0
0  ...
1   2    na      82      0     68     40      0      0      0
0  ...
2   3    na   66002      2    212    112      0      0      0
```

```
0  ...
3   4    na   59816    NaN   1010    936      0      0      0
0  ...
4   5    na    1814    NaN    156    140      0      0      0
0  ...

   ee_002  ee_003  ee_004  ee_005   ee_006  ee_007  ee_008 ee_009
ef_000  \
0    1098     138     412     654       78      88       0      0
0
1    1068     276    1620     116       86     462       0      0
0
2  495076  380368  440134  269556  1315022  153680     516      0
0
3  540820  243270  483302  485332   431376  210074  281662   3232
0
4    7646    4144   18466   49782     3176     482      76      0
0

  eg_000
0      0
1      0
2      0
3      0
4      0

[5 rows x 172 columns]
```

```
# creating test and discarding the same features from the test data
set too.
X_test = df_test.drop(['class', 'id'], axis = 1)
X_test = X_test.drop(more_than_fifty.index, axis=1)

import missingno as msno

msno.matrix(X_train)
```

```
<AxesSubplot:>
```




1. The missingness is indicated by black and observed values are indicated by white.
2. The observed values are surrounded by missing values without any pattern i.e. arbitrary.

## Imputing the dataset using Multivariate Imputer

## kNN Imputer

### https://www.youtube.com/watch?v=AHBHMQyD75U

### https://machinelearningmastery.com/knn-imputation-for-missing-values-in-machine-learning/

1. kNN Imputer uses nan_euclidean distance to findout nearest neighbors.
2. The mean of the k nearest neighbors is imputed at the missing value.
3. The distance was multiplied by the ratio of total no. of columns to the no. of non missing columns.

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.impute import KNNImputer
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import RepeatedStratifiedKFold
from sklearn.metrics import recall_score
```

evaluating the each imputed dataset for every neighbor using RandomForest Classifier against 15 cross validations generated by RepeatedStratifiedKFold

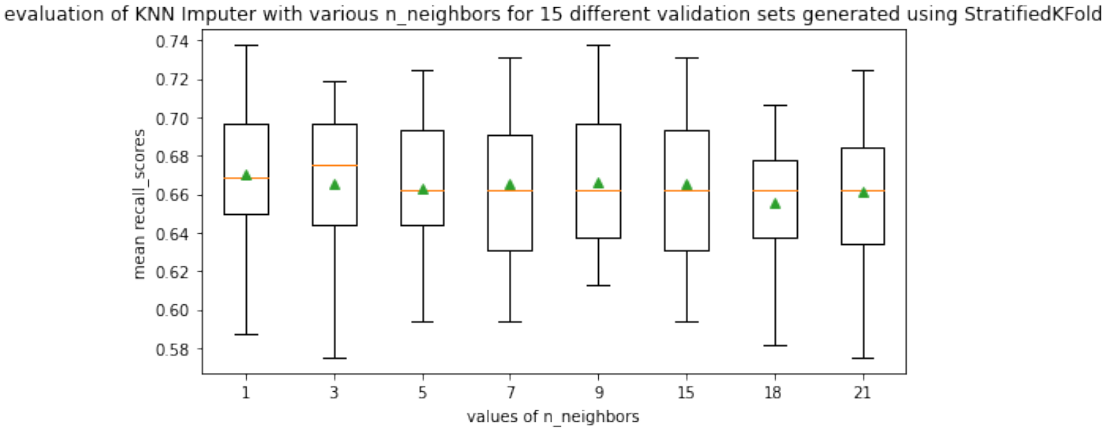
```
%%time
n_neighbors = [1,3,5,7,9,15,18,21]
results = []
for neighbor in n_neighbors:
    imp_knn = KNNImputer(n_neighbors=neighbor)
    imp_knn.fit(X_train)
    X_train_transformed = imp_knn.transform(X_train)
    model = RandomForestClassifier()
    cv = RepeatedStratifiedKFold(n_splits=5, n_repeats=3,
random_state=1)
    scores = cross_val_score(model, X_train_transformed, y_train,
```

```
scoring='recall', cv=cv, n_jobs=-1)
    results.append(scores)
    print('\n For n_neighbors =',neighbor, '\n the mean of
recall_score against 15 different validation sets  is ',
np.mean(scores),
          '\n the standard deviation of recall_score against 15
different validation sets is ', np.std(scores))
```

```
 For n_neighbors = 1
 the mean of recall_score against 15 different validation sets  is
0.67
 the standard deviation of recall_score against 15 different
validation sets is  0.03723517602124816

 For n_neighbors = 3
 the mean of recall_score against 15 different validation sets  is
0.6654166666666667
 the standard deviation of recall_score against 15 different
validation sets is  0.0356390079672385

 For n_neighbors = 5
 the mean of recall_score against 15 different validation sets  is
0.6629166666666665
 the standard deviation of recall_score against 15 different
validation sets is  0.03697315091913169

 For n_neighbors = 7
 the mean of recall_score against 15 different validation sets  is
0.6658333333333334
 the standard deviation of recall_score against 15 different
validation sets is  0.039255219044379584

 For n_neighbors = 9
 the mean of recall_score against 15 different validation sets  is
0.6662499999999999
 the standard deviation of recall_score against 15 different
validation sets is  0.03519292068963113

 For n_neighbors = 15
 the mean of recall_score against 15 different validation sets  is
0.6654166666666667
 the standard deviation of recall_score against 15 different
validation sets is  0.041824700304432

 For n_neighbors = 18
 the mean of recall_score against 15 different validation sets  is
0.6558333333333333
 the standard deviation of recall_score against 15 different
validation sets is  0.0356828234433444
```

```
 For n_neighbors = 21
 the mean of recall_score against 15 different validation sets  is
0.66125
 the standard deviation of recall_score against 15 different
validation sets is  0.04102844541697057
CPU times: user 2h 49min 7s, sys: 20min 53s, total: 3h 10min
Wall time: 3h 11min 4s
```

```
# plot model performance for comparison
plt.figure(figsize=(8,4))
plt.boxplot(results, labels=n_neighbors, showmeans=True)
plt.title('evaluation of KNN Imputer with various n_neighbors for 15
different validation sets generated using StratifiedKFold')
plt.xlabel('values of n_neighbors')
plt.ylabel('mean recall_scores')
plt.show()
```




Obesrvations:

1. The mean recall scores for all the n_neighbors are very close to eachother.
2. Since we are dealing with the missing values, the imputed values must be conservative.
3. Hence we choose n_neighbor = 15 as it has highest standard deviation of recall scores.

```
%%time
# Imputing the dataset with the conservative nearest neighbor k
knn_imp = KNNImputer(n_neighbors=15)
knn_imp.fit(X_train)
X_train_imp = knn_imp.transform(X_train)
X_cv_imp = knn_imp.transform(X_cv)
X_test_imp = knn_imp.transform(X_test)
```

```
CPU times: user 33min 50s, sys: 4min 1s, total: 37min 52s
Wall time: 34min 33s
```

```
# import pickle
# with open('train_imp.pkl', 'wb') as tr:
#     pickle.dump(X_train_imp, tr)
# with open('test_imp.pkl', 'wb') as te:
#     pickle.dump(X_test_imp, te)
# with open('cv_imp.pkl', 'wb') as cv:
#     pickle.dump(X_cv_imp, cv)

import pickle
with open('train_imp.pkl', 'rb') as tr:
    X_train_imp=pickle.load(tr)

with open('test_imp.pkl', 'rb') as te:
    X_test_imp=pickle.load(te)

with open('cv_imp.pkl', 'rb') as cv:
    X_cv_imp=pickle.load(cv)

#lookin at the imputed values
X_train_imp_df = pd.DataFrame(X_train_imp, columns=X_train.columns)
X_train_imp_df.head()
```

```
     aa_000        ac_000       ad_000     ae_000     af_000
ag_000  \
0   61990.0  7.720000e+02   578.000000   0.000000   0.000000     0.0

1   53078.0  4.261419e+08   624.666667  24.533333  28.266667     0.0

2   28914.0  2.054000e+03  1872.000000   0.000000   0.000000     0.0

3   38724.0  2.880000e+02   228.000000   0.000000   0.000000     0.0

4  181460.0  7.634000e+03  6034.000000   0.000000   0.000000     0.0


     ag_001     ag_002     ag_003     ag_004  ...     ee_002    ee_003
\
0       0.0        0.0        0.0     6560.0  ...   452862.0  238318.0

1       0.0        0.0    29368.0  2459952.0  ...   872890.0  259508.0

2       0.0        0.0        0.0    37848.0  ...   464158.0  143828.0

3       0.0        0.0        0.0    56636.0  ...   327972.0  139530.0

4  146928.0  1127254.0  4211790.0  7496468.0  ...  2533312.0  624832.0


      ee_004     ee_005     ee_006    ee_007    ee_008  ee_009
ef_000  \
```

```
0   589444.0   806720.0   502972.0  213364.0   20364.0   138.0
0.000000
1   372842.0   288924.0   214724.0  251248.0     450.0     0.0
0.133333
2   174690.0   125834.0    95102.0   56956.0   42822.0    78.0
0.000000
3   290932.0   339334.0   259082.0  148890.0  189622.0  4492.0
0.000000
4  1295930.0  1552742.0  1203654.0  461352.0   24664.0     0.0
0.000000

   eg_000
0     0.0
1     0.0
2     0.0
3     0.0
4     0.0

[5 rows x 162 columns]
```

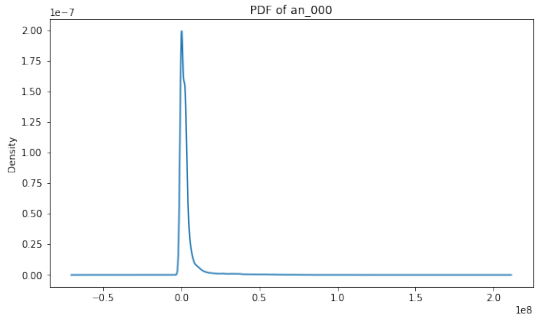
```
#https://machinelearningmastery.com/feature-selection-machine-
learning-python/
#https://machinelearningmastery.com/feature-selection-with-real-and-
categorical-data/
#https://www.youtube.com/watch?
v=2QeDRsxSF9M&list=PLDRsvGefgonmkLGDaKdh1z9zYbKCwee4u&index=2&t=1s

from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2

select_chi2 = SelectKBest(score_func=chi2, k=10)
select_chi2.fit(X_train_imp, y_train)

X_train_select = select_chi2.transform(X_train_imp)
print('After selection the shape of the train data is
',X_train_select.shape)

best_select = np.argsort(select_chi2.scores_)
features_chi2 = list(X_train.columns[best_select[-10:]])
print('Selected features are ', features_chi2)

After selection the shape of the train data is  (48000, 10)
Selected features are  ['an_000', 'cc_000', 'ci_000', 'bx_000',
'cq_000', 'bu_000', 'bv_000', 'bb_000', 'eb_000', 'dq_000']
```

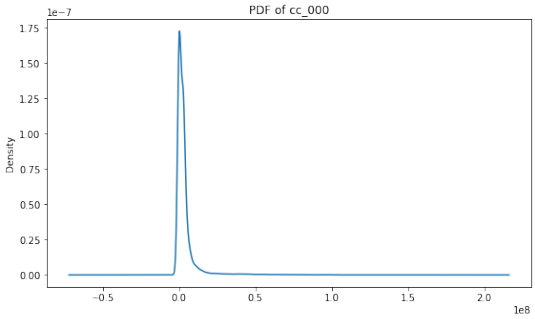
1. The scoring function chi2 in the SelectKBest wrapper calculates the observed value for each feature.
2. expected values are nothing but the given labels.
3. chi2 statistic which can be defined as sum((observed-expected)**2/expected).

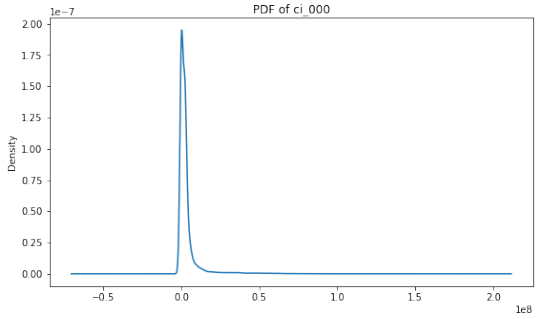
4. p values are determined by the chi2 distribution based on the degrees of freedom.

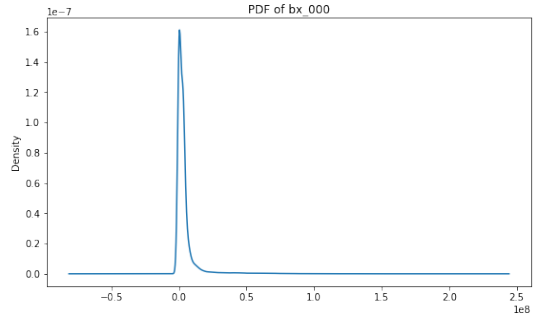
## Univariate Analysis

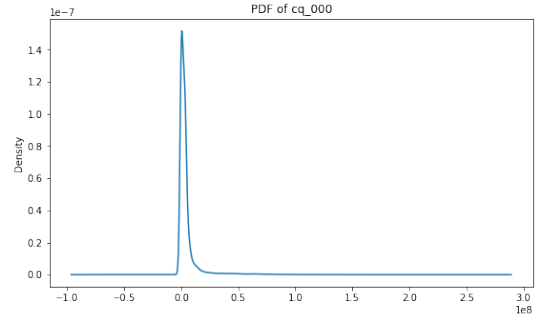
```
def pdf_plot(features):
    '''plots the Probability density function for a variable'''
    plt.figure(figsize = (20,30))
    num=1
    for feature in features:
        plt.subplot(5,2,num)
        num+=1
        X_train_imp_df[feature].plot.kde()
        plt.title('PDF of '+ str(feature))
    plt.show()

pdf_plot(features_chi2)
```

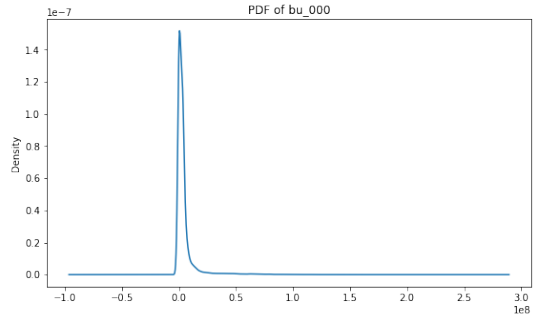


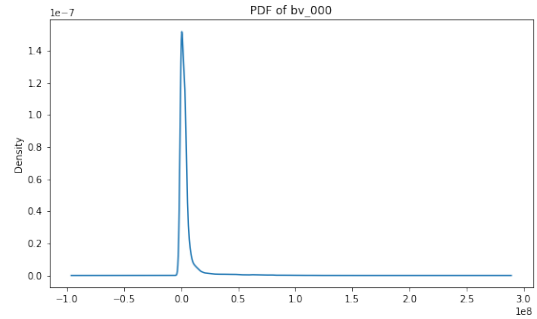



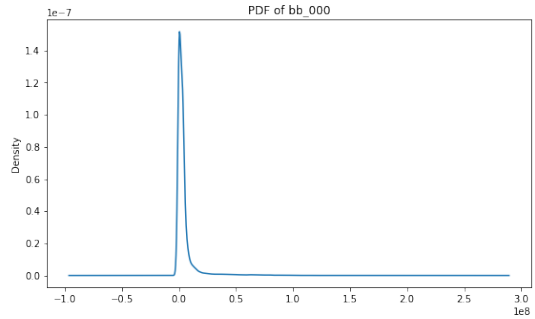



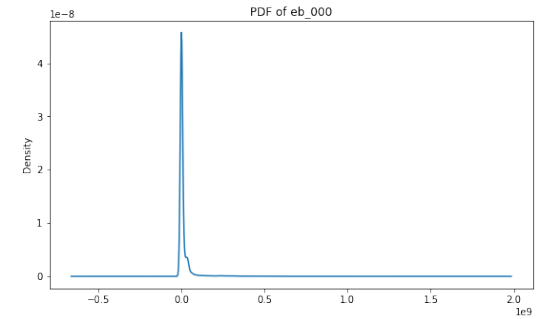



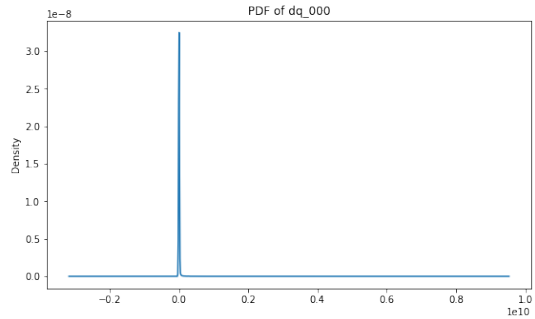



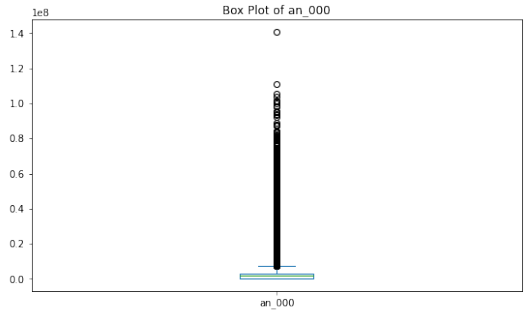



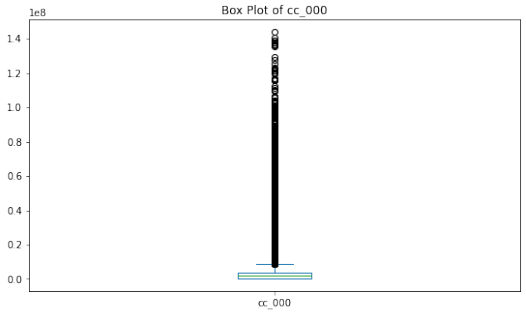



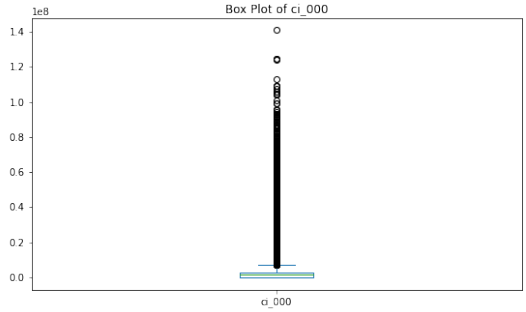

Observations:

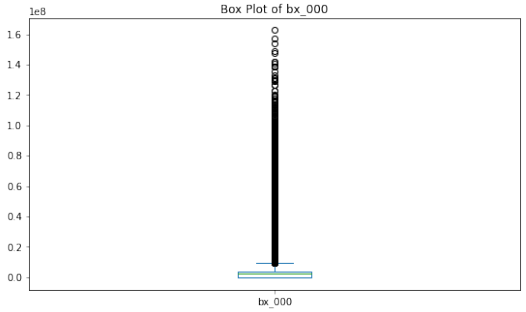
1. above subplots are the probability density function of the best 10 features selected based on chi2 test.
2. for all the features the distribution is right skewed.
3. for all the features the maximum no of values can be found around 0.
4. especially for the top 2 features i.e. 'eb_000' and 'dq_000' the standard deviation is way low relative to the rest.

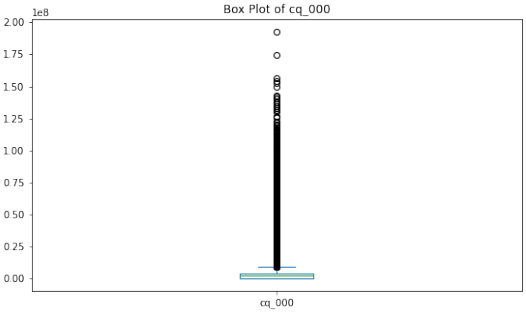
```
def box_plot(features):
    '''plots the Probability density function for a variable'''
    plt.figure(figsize = (20,30))
    num=1
    for feature in features:
        plt.subplot(5,2,num)
        num+=1
        X_train_imp_df[feature].plot.box()
        plt.title('Box Plot of '+ str(feature))
    plt.show()

box_plot(features_chi2)
```

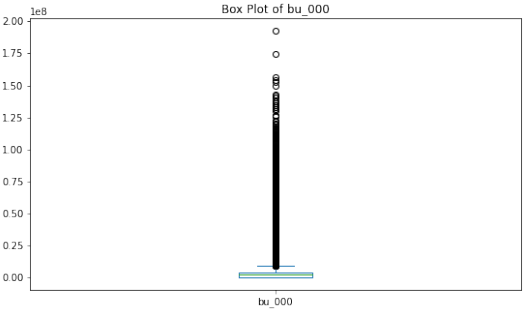


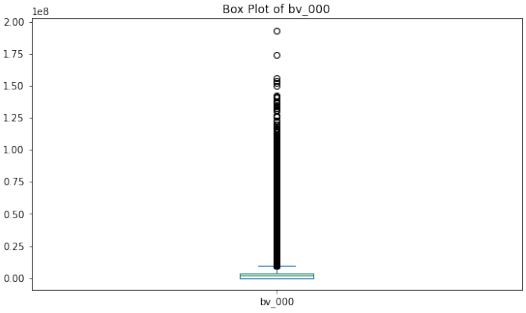



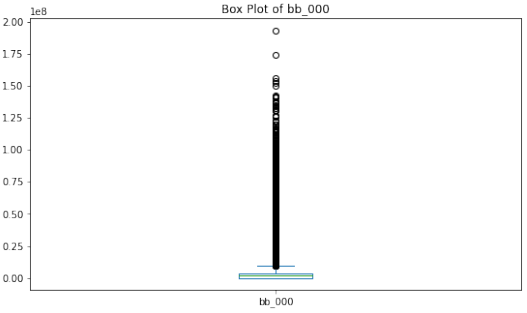



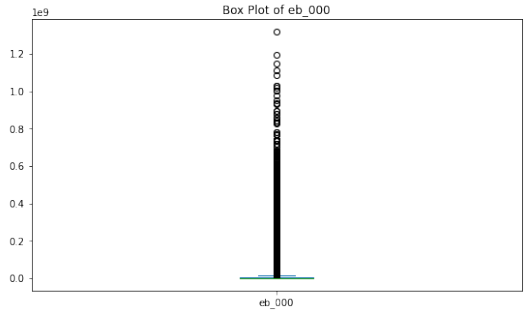



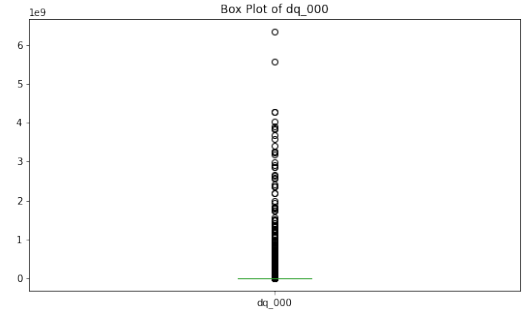



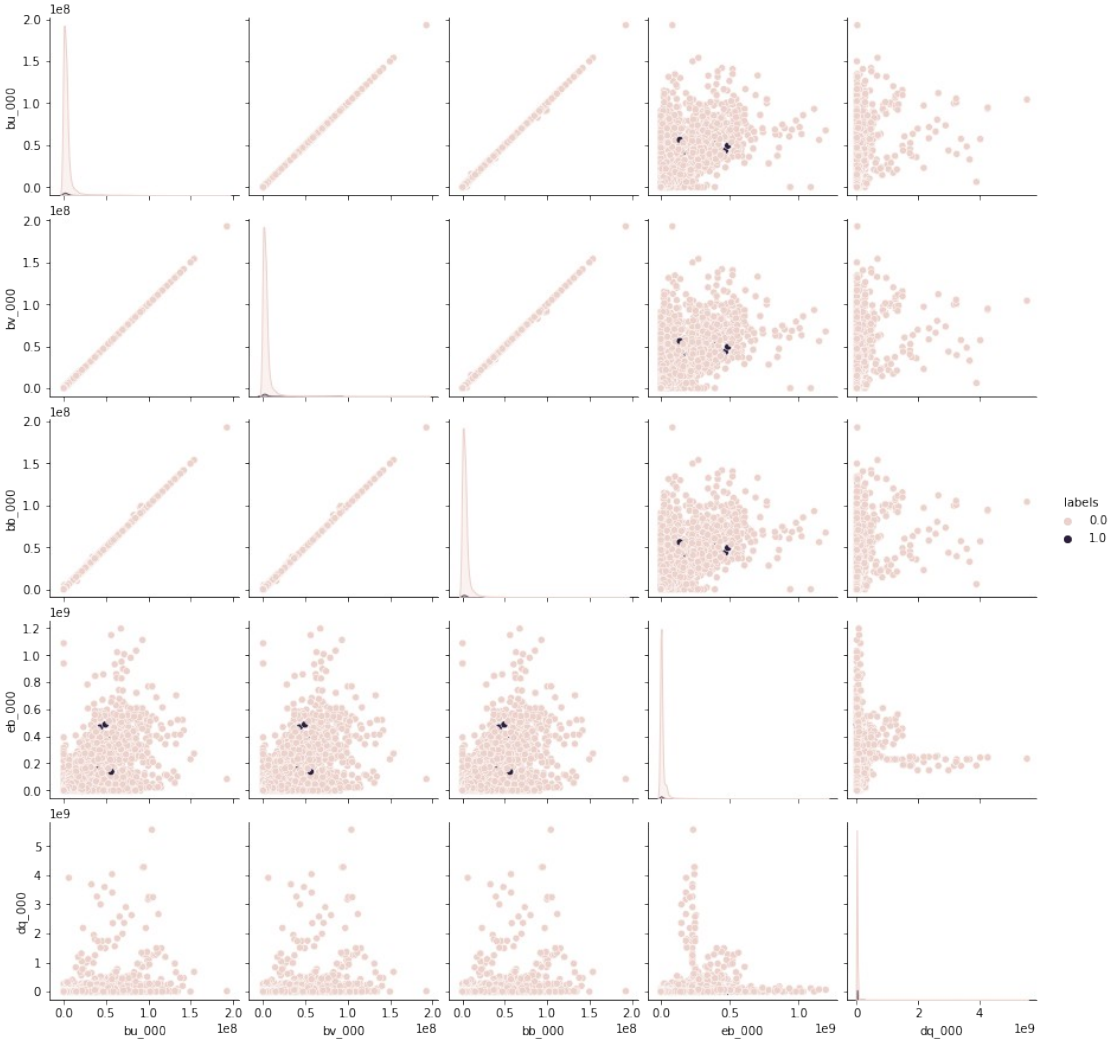

Observations:

1. For all the features the median value is around 0.
2. especially for the top 2 features 'eb_000' and 'dq_000' we cant even observe the IQR box.
3. Half of the values for all the features are appeared to be outliers.

## Multivariate analysis

```
chi2_df = X_train_imp_df[features_chi2[-5:]]
chi2_df['labels'] = y_train

sns.pairplot(chi2_df, hue='labels')
```

```
<seaborn.axisgrid.PairGrid at 0x7f85d3a065d0>
```



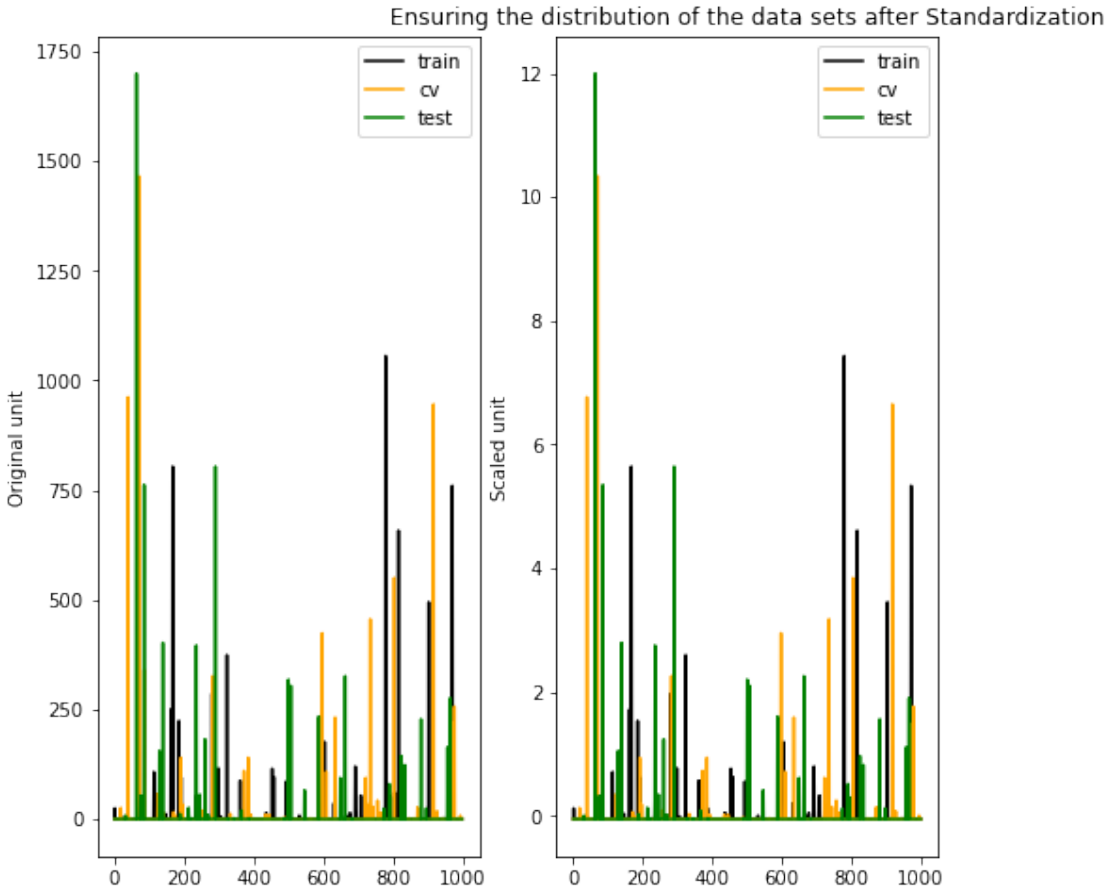

Observations:

1. The diagonal kde plots for all the top five features are all overlapping.
2. If we obesrve the plots of 'bu_000' vs 'bv_000' and 'bu_oo' vs 'bb_000' the trend is linear.

3. If we compare the plots of 'dq_000' and 'eb_000' , 'dq_000' seems to have some more useful cause most of the points are narrowly spread, where as for 'eb_000' they had spread all over and the positive points are clustered.

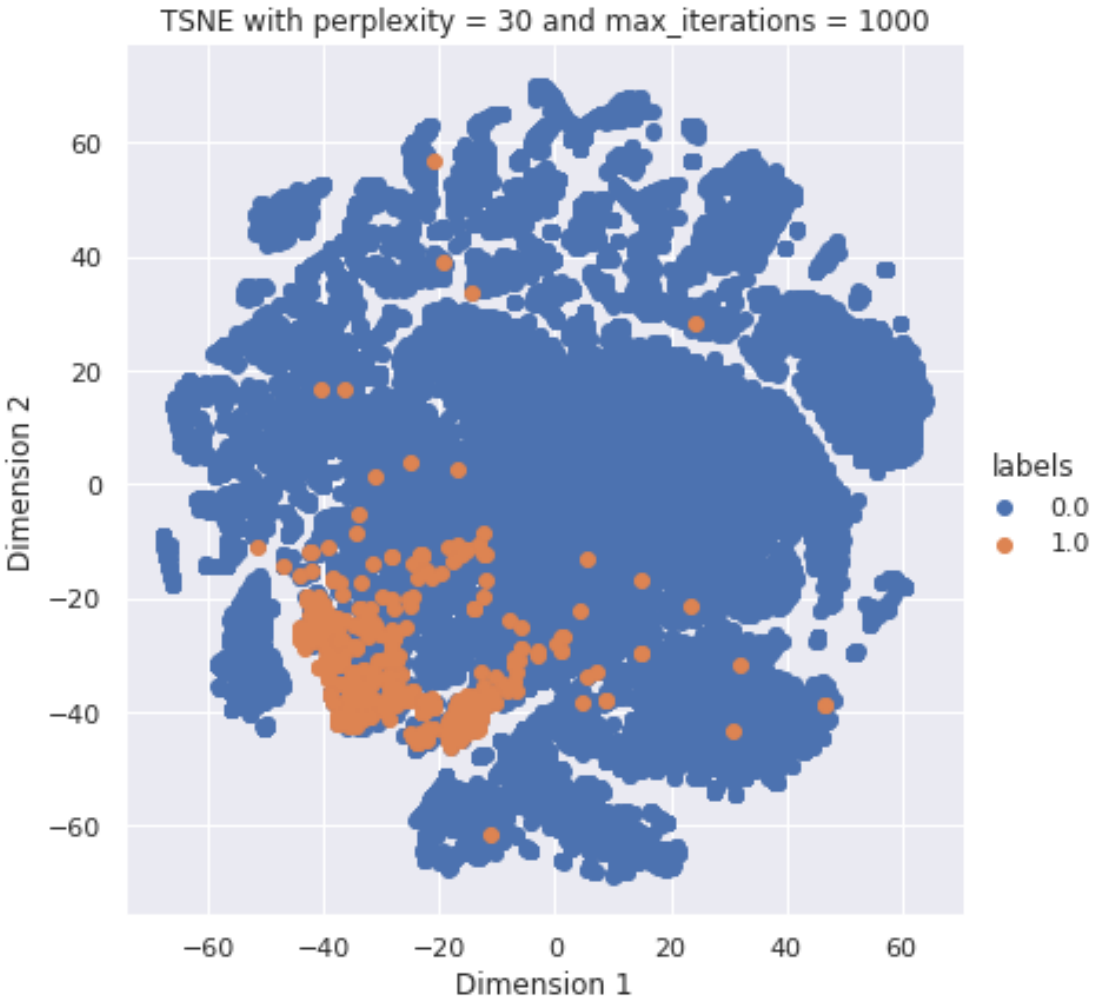
### Standardizing the data for visualization analysis

```
# standardizing data before performing dimensionality reductions
techniques
from sklearn.preprocessing import StandardScaler

std=StandardScaler()
X_train_std = std.fit_transform(X_train_imp)
X_cv_std = std.transform(X_cv_imp)
X_test_std = std.transform(X_test_imp)

#https://www.kaggle.com/an07kit/minimizing-total-cost-to-13250

X_train_scaled_head=X_train_std[0:1000,3]   #taking a sample of 1000
points with step=3 for plotting purpose
X_cv_scaled_head = X_cv_std[0:1000,3]
X_test_scaled_head=X_test_std[0:1000,3]

X_train_head=X_train_imp[0:1000,3]         #taking a sample of 1000
points with step=3 for plotting purpose
X_cv_head = X_cv_imp[0:1000,3]
X_test_head=X_test_imp[0:1000,3]

fig = plt.figure(figsize = (8, 8))
fig.add_subplot(1,2,1)
plt.plot(X_train_head,label='train', color='black')
plt.plot(X_cv_head, label='cv', color='orange')
plt.plot(X_test_head,label='test', color='green')
plt.legend(['train', 'cv', 'test'])
plt.ylabel('Original unit')
fig.add_subplot(1,2,2)
plt.plot(X_train_scaled_head,label='scaled_train', color='black')
plt.plot(X_cv_scaled_head, label='cv', color='orange')
plt.plot(X_test_scaled_head,label='scaled_test', color='green')
plt.legend(['train', 'cv', 'test'])
plt.ylabel('Scaled unit')
plt.title('Ensuring the distribution of the data sets after
Standardization')
plt.show()
```

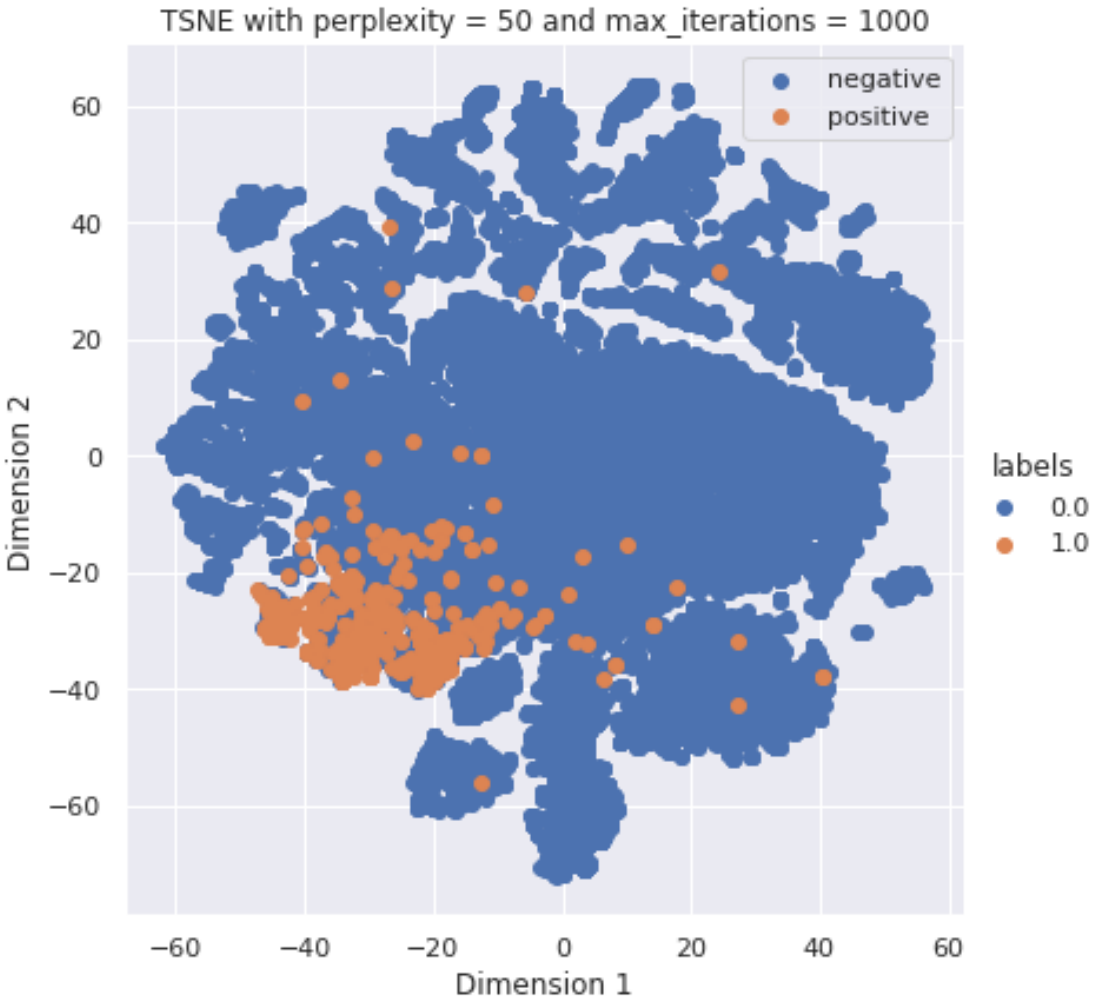



## TSNE data visualization

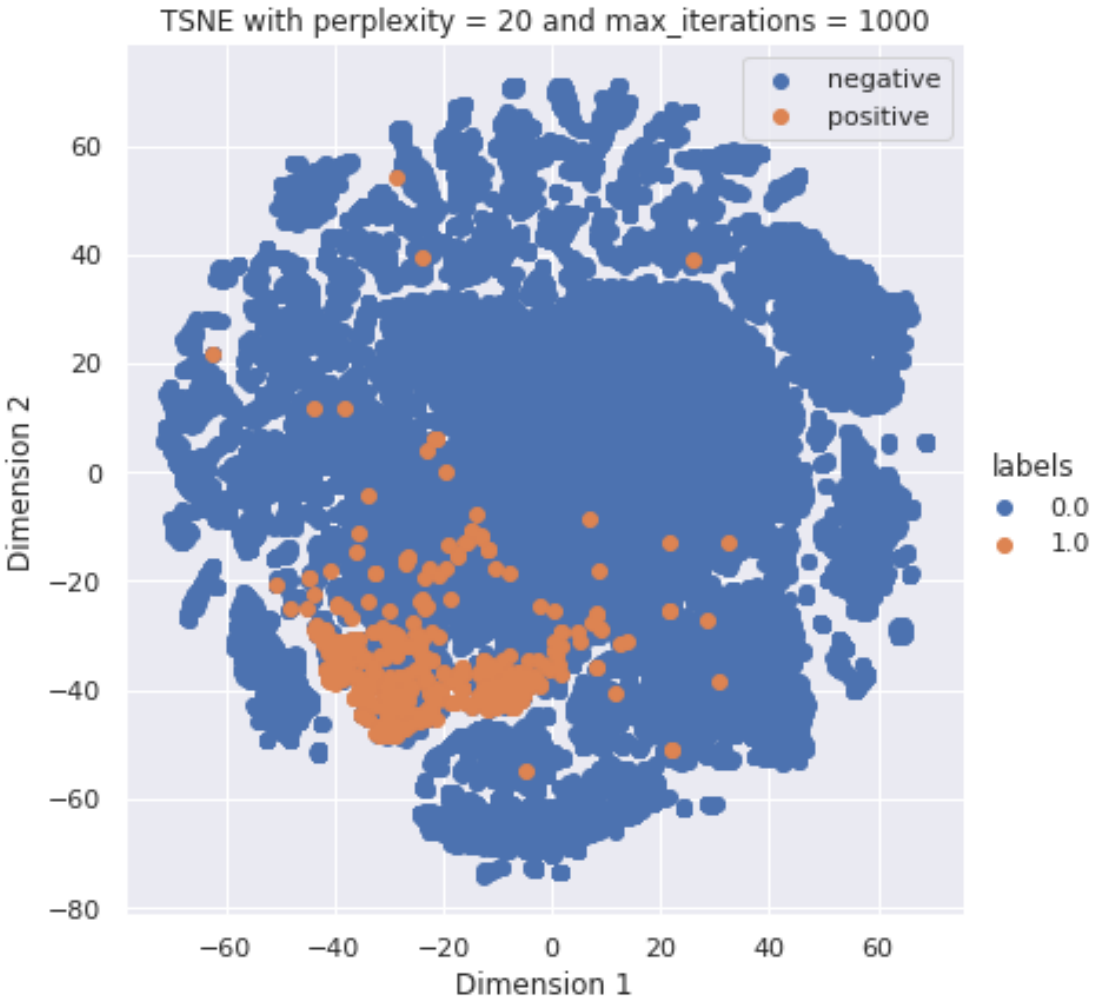
```
from sklearn.manifold import TSNE

model_tsne = TSNE(n_components=2, random_state=0)
# configuring the parameteres
# the number of components = 2
# default perplexity = 30
# default learning rate = 200
# default Maximum number of iterations for the optimization = 1000

X_train_tsne = model_tsne.fit_transform(X_train_std)
tsne_data = np.vstack((X_train_tsne.T, y_train)).T
tsne_df = pd.DataFrame(data=tsne_data, columns = ['dim_1', 'dim_2',
'labels'])

sns.set(rc={'figure.figsize':(15, 15)})
sns.FacetGrid(tsne_df, hue="labels", size=6).map(plt.scatter, 'dim_1',
'dim_2').add_legend()
plt.xlabel('Dimension 1')
plt.ylabel('Dimension 2')
plt.title('TSNE with perplexity = 30 and max_iterations = 1000')
plt.show()
```




```
model_tsne = TSNE(n_components=2, random_state=0, perplexity = 50,
n_iter=1000)

X_train_tsne = model_tsne.fit_transform(X_train_std)
tsne_data = np.vstack((X_train_tsne.T, y_train)).T
tsne_df = pd.DataFrame(data=tsne_data, columns = ['dim_1', 'dim_2',
'labels'])

sns.set(rc={'figure.figsize':(15, 15)})
sns.FacetGrid(tsne_df, hue="labels", size=6).map(plt.scatter, 'dim_1',
'dim_2').add_legend()
plt.xlabel('Dimension 1')
plt.ylabel('Dimension 2')
plt.legend(['negative', 'positive'])
plt.title('TSNE with perplexity = 50 and max_iterations = 1000')
plt.show()
```




```
model_tsne = TSNE(n_components=2, random_state=0, perplexity = 20,
n_iter=1000)

X_train_tsne = model_tsne.fit_transform(X_train_std)
tsne_data = np.vstack((X_train_tsne.T, y_train)).T
tsne_df = pd.DataFrame(data=tsne_data, columns = ['dim_1', 'dim_2',
'labels'])

sns.set(rc={'figure.figsize':(15, 15)})
sns.FacetGrid(tsne_df, hue="labels", size=6).map(plt.scatter, 'dim_1',
'dim_2').add_legend()
plt.title('TSNE with perplexity = 20 and max_iterations = 1000')
plt.xlabel('Dimension 1')
plt.ylabel('Dimension 2')
plt.legend(['negative', 'positive'])
plt.show();
```



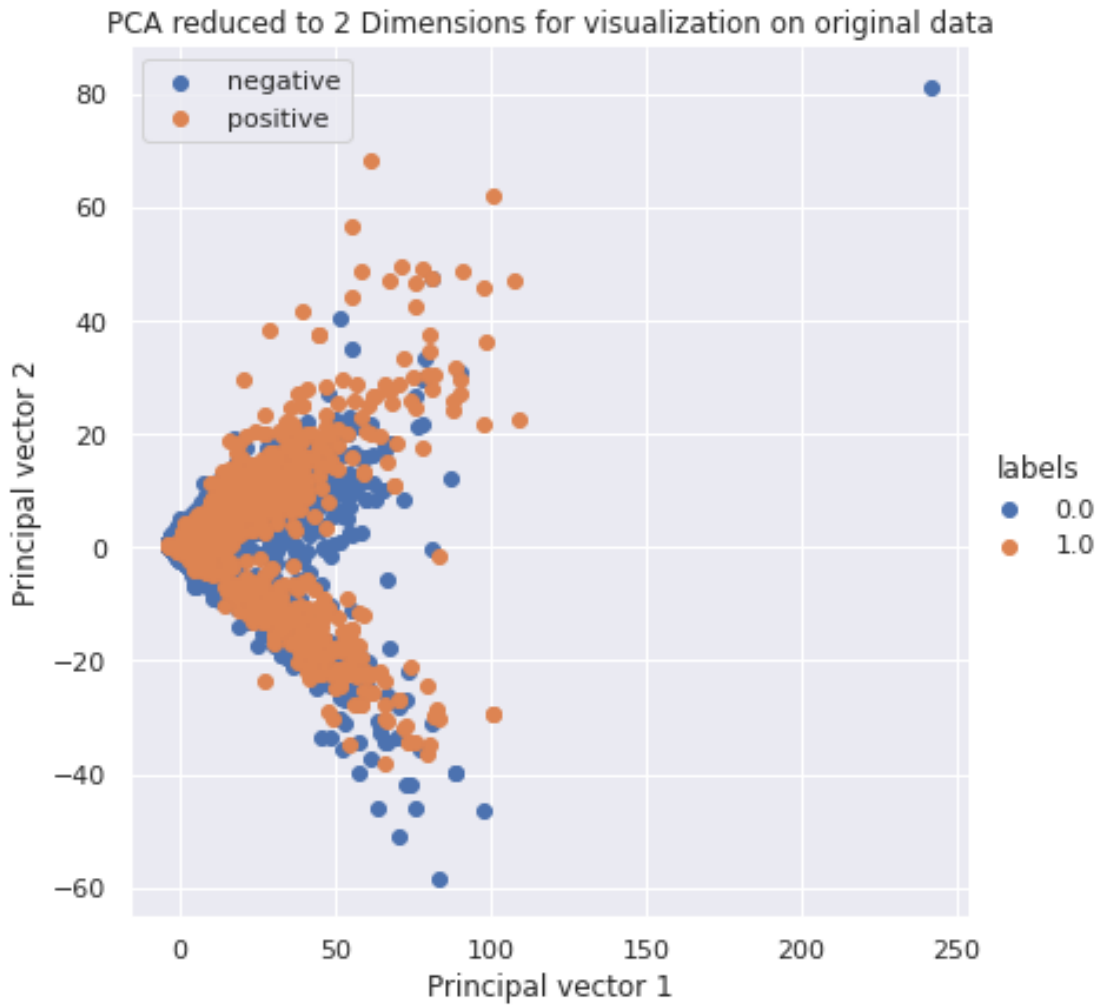

Observations:

1. The three TSNE plots seems to be stable.
2. All three contains closely clustered neighbourhoods of positive points.(Embedding the distance)
3. There are outliers surrounding the far away from the clustered neighbourhood.
4. There is a greate overlap between positive and negative instances.

## PCA for visualization

```
from sklearn.decomposition import PCA
pca = PCA(n_components=2)
X_train_pca = pca.fit_transform(X_train_std)

pca_data = np.vstack((X_train_pca.T, y_train)).T
pca_df = pd.DataFrame(data=pca_data, columns = ['principle_1',
'principle_2', 'labels'])

sns.set(rc={'figure.figsize':(15, 15)})
```

```
sns.FacetGrid(pca_df, hue="labels", size=6).map(plt.scatter,
'principle_1', 'principle_2').add_legend()
plt.title('PCA reduced to 2 Dimensions for visualization on original
data')
plt.xlabel('Principal vector 1')
plt.ylabel('Principal vector 2')
plt.legend(['negative', 'positive'])
plt.show()
```




Observations:

1. In the above plot the X and Y axis are top principle vectors of the training data where the maximum variance can be observed.
2. There is a lot of overlap between the both classes.
3. Positive class are way more spread out albeit being less no. of poisitve instances in the training data.

*Since the given data is higly imbalance i.e. for every positive instance there are 59 negative instance.*

*This will lead any model biased towards negative class.*

*To prevent this bias we oversample the training data with the help of imblearn package using SMOTE()*

*SMOTE oversamples the minority class and undersamples the majority class*

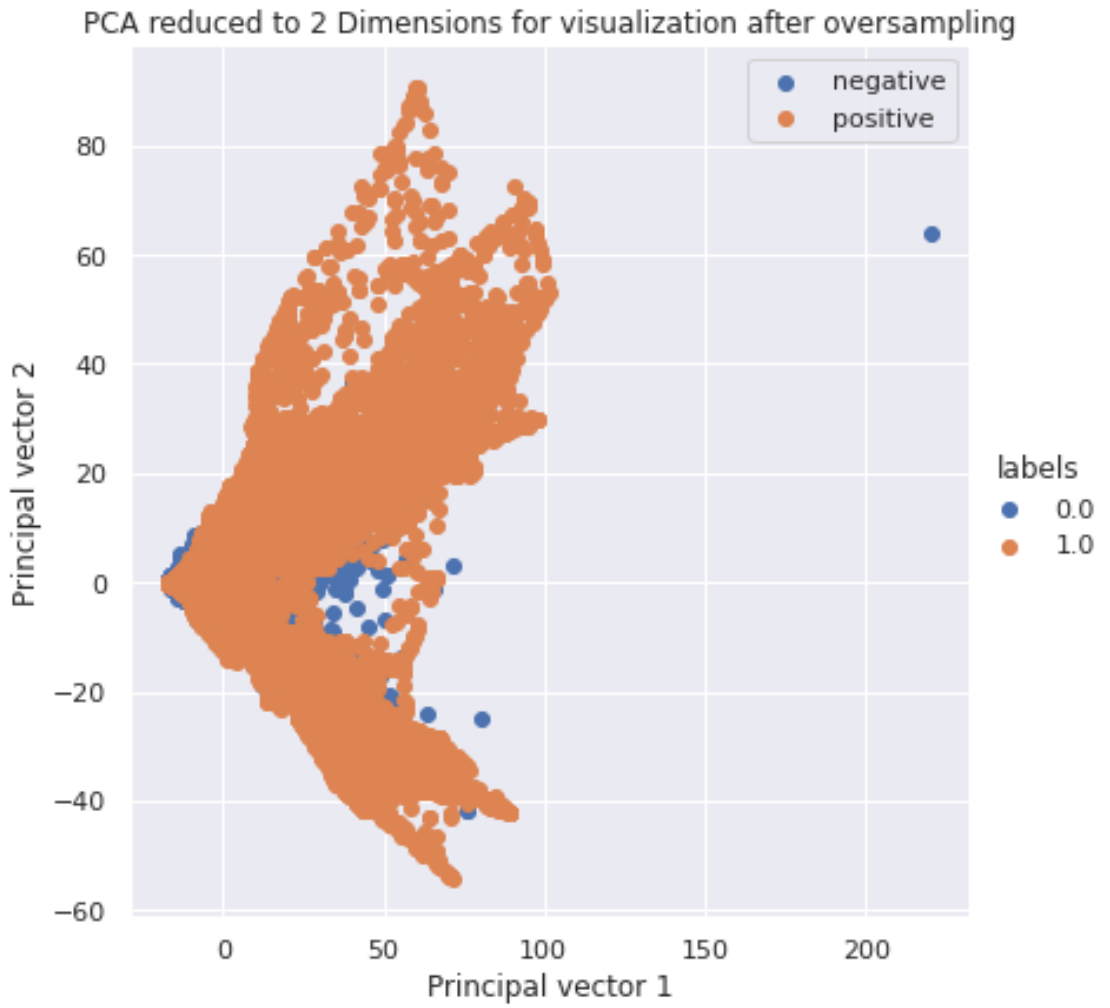
*The oversampling is based on kNN algorithm where k defines the neighborhood to generate the artificial samples*

```
from imblearn.over_sampling import SMOTE

smote = SMOTE(k_neighbors=15, random_state = 5)
X_train_smote, y_train_smote = smote.fit_resample(X_train_std,
y_train)

y_train_smote.value_counts()
```

```
0    47200
1    47200
Name: class, dtype: int64
```

After the oversampling through SMOTE() the class labels are balanced.

```
pca = PCA(n_components=2)
X_train_pca = pca.fit_transform(X_train_smote)

pca_data = np.vstack((X_train_pca.T, y_train_smote)).T
pca_df = pd.DataFrame(data=pca_data, columns = ['principle_1',
'principle_2', 'labels'])

sns.set(rc={'figure.figsize':(15, 15)})
sns.FacetGrid(pca_df, hue="labels", size=6).map(plt.scatter,
'principle_1', 'principle_2').add_legend()
plt.title('PCA reduced to 2 Dimensions for visualization after
oversampling')
plt.xlabel('Principal vector 1')
plt.ylabel('Principal vector 2')
plt.legend(['negative', 'positive'])
plt.show()
```



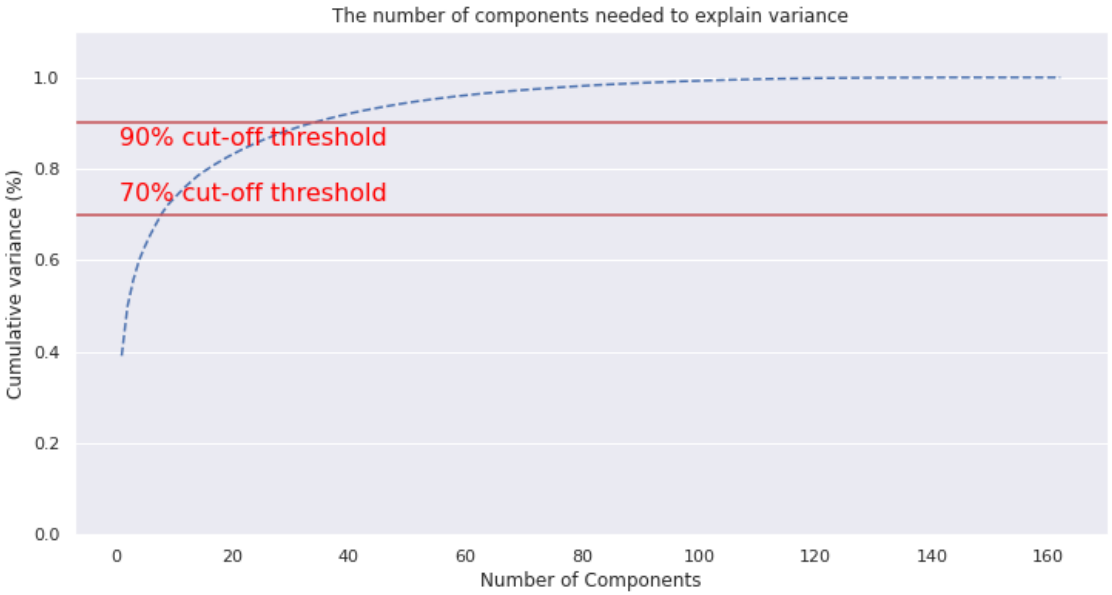

Observations:

1. The positive class points are oversampled using SMOTE which generates artificial minority class instances using kNearestNeighbor.
2. Here, the oversampling helps to detect the outliers which are surrounded by artificial instances.

## PCA for variance analysis

```
#https://www.kaggle.com/an07kit/minimizing-total-cost-to-13250

pca_variance = PCA()
pca_var_data = pca_variance.fit_transform(X_train_smote)

plt.rcParams["figure.figsize"] = (12,6)
fig, ax = plt.subplots()
xi = np.arange(1, 163, step=1)
y = np.cumsum(pca_variance.explained_variance_ratio_)
plt.ylim(0.0,1.1)
plt.plot(xi, y, linestyle='--', color='b')
```

```
plt.xlabel('Number of Components')
plt.ylabel('Cumulative variance (%)')
plt.title('The number of components needed to explain variance')
plt.axhline(y=0.70, color='r', linestyle='-')
plt.text(0.5, 0.73, '70% cut-off threshold', color = 'red',
fontsize=16)
plt.axhline(y=0.90, color='r', linestyle='-')
plt.text(0.5, 0.85, '90% cut-off threshold', color = 'red',
fontsize=16)

ax.grid(axis='x')
plt.show()
```




Observations:

1. When we plot the cumulative variance_explained by the eighen vectors, we can observe that 70% of the variance can be explained by 8 features and 90% of the variance can be explained by 34 features.
2. Reducing features in prediction decreases the bias of the model.

### Feature Engineering using PCA

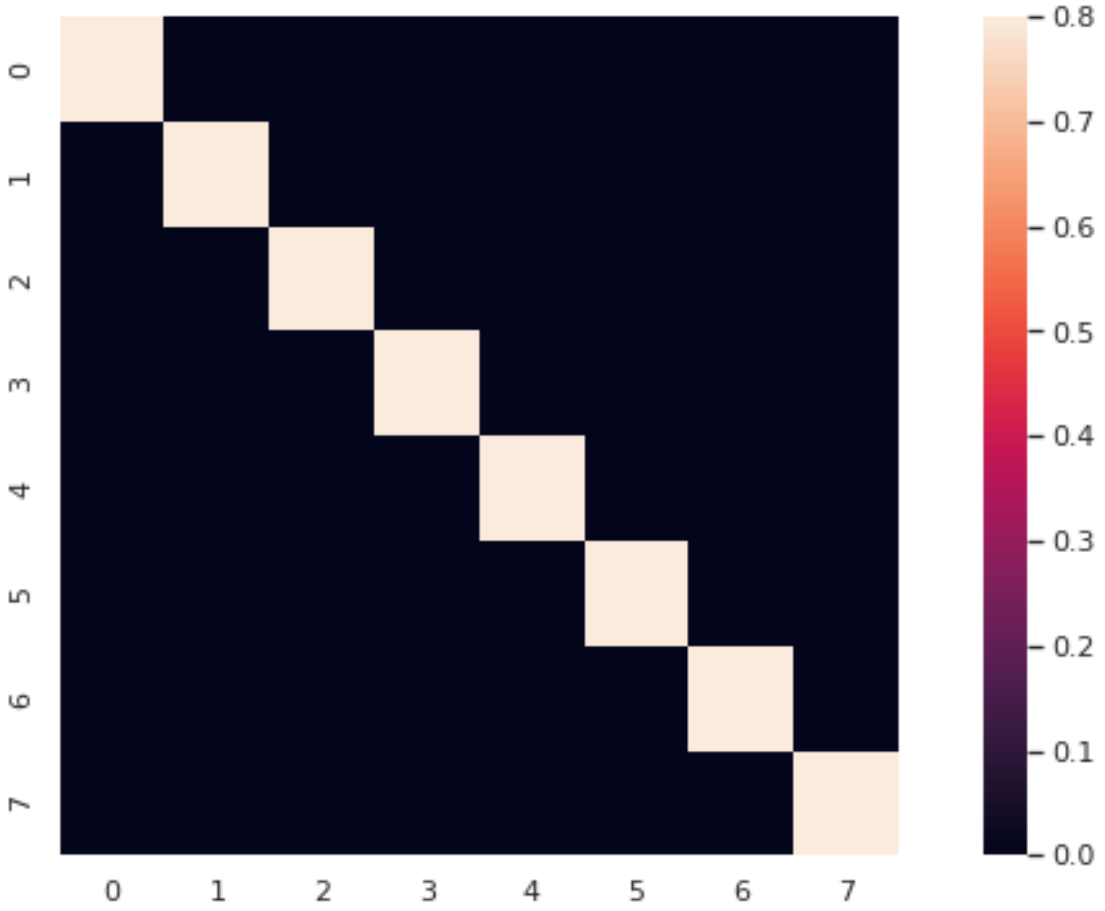
### Credits: https://www.kaggle.com/an07kit/minimizing-total-cost-to-13250

```
def pca_features(variance):
    pca = PCA(n_components=variance)
    pca.fit(X_train_smote)
    X_train_var = pca.transform(X_train_smote)
    X_cv_var = pca.transform(X_cv_std)
    X_test_var = pca.transform(X_test_std)
    print("Number of features after PCA = ", X_cv_var.shape[1])
    corrmat_pca = pd.DataFrame(X_train_var).corr()
    sns.heatmap(corrmat_pca, vmax=.8, square=True);
```

```
    plt.show()
    return X_train_var, X_cv_var, X_test_var
```

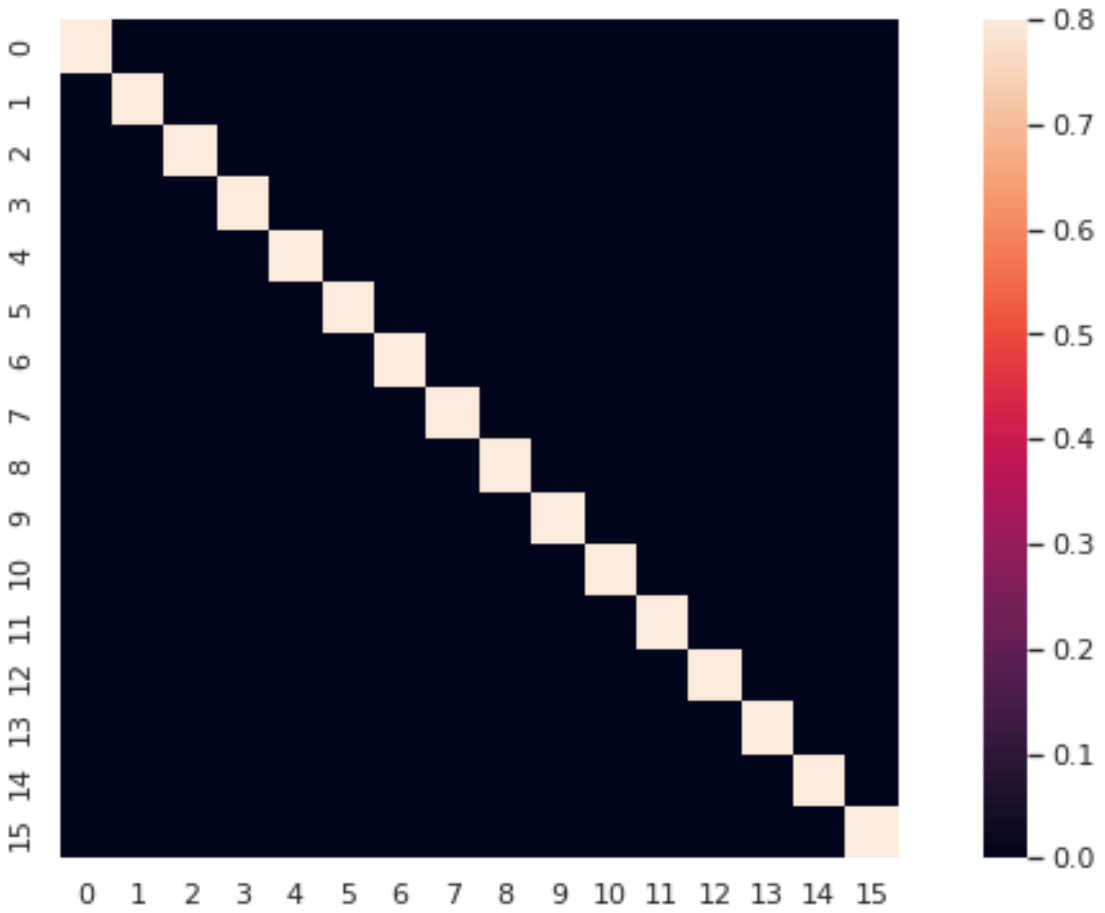
```
X_train_70, X_cv_70, X_test_70 = pca_features(0.70)
```

```
Number of features after PCA =  8
```



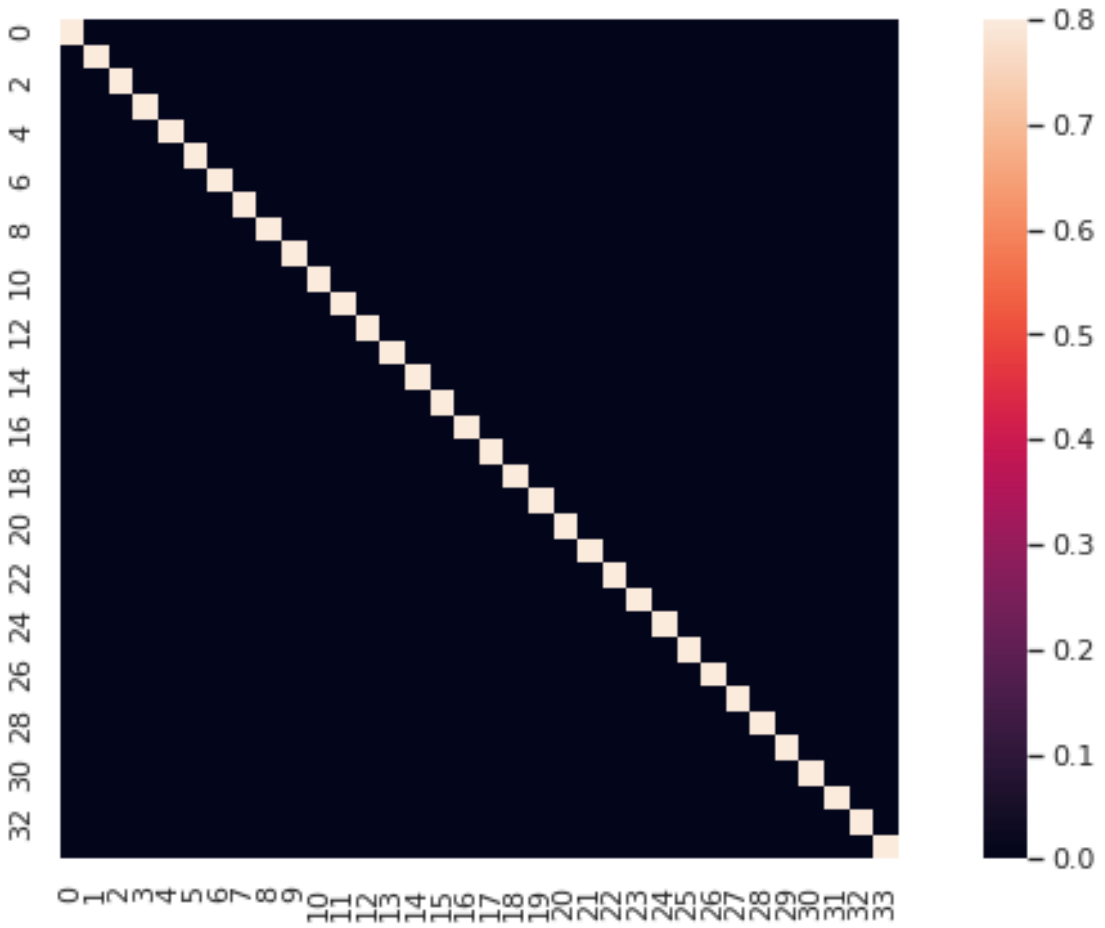

```
X_train_80, X_cv_80, X_test_80 = pca_features(0.80)
```

```
Number of features after PCA =  16
```




```
X_train_90, X_cv_90, X_test_90 = pca_features(0.90)
```

```
Number of features after PCA =  34
```




### Performance metrics

```
from sklearn.metrics import confusion_matrix

#Refered from the case study
# This function plots the confusion matrices given y_i, y_i_hat.
def plot_confusion_matrix(test_y, predict_y):
    C = confusion_matrix(test_y, predict_y)
    # C = 9,9 matrix, each cell (i,j) represents number of points of
class i are predicted class j

    A =(((C.T)/(C.sum(axis=1))).T)
    #divid each element of the confusion matrix with the sum of
elements in that column

    # C = [[1, 2],
    #     [3, 4]]
    # C.T = [[1, 3],
    #        [2, 4]]
    # C.sum(axis = 1)  axis=0 corresonds to columns and axis=1
corresponds to rows in two diamensional array
    # C.sum(axix =1) = [[3, 7]]
```

```
    # ((C.T)/(C.sum(axis=1))) = [[1/3, 3/7]
    #                           [2/3, 4/7]]

    # ((C.T)/(C.sum(axis=1))).T = [[1/3, 2/3]
    #                           [3/7, 4/7]]
    # sum of row elements = 1

    B =(C/C.sum(axis=0))
    #divid each element of the confusion matrix with the sum of
elements in that row
    # C = [[1, 2],
    #     [3, 4]]
    # C.sum(axis = 0)  axis=0 corresonds to columns and axis=1
corresponds to rows in two diamensional array
    # C.sum(axix =0) = [[4, 6]]
    # (C/C.sum(axis=0)) = [[1/4, 2/6],
    #                      [3/4, 4/6]]
    plt.figure(figsize=(20,4))

    labels = [0,1]
    # representing A in heatmap format
    cmap=sns.light_palette("blue")
    plt.subplot(1, 3, 1)
    sns.heatmap(C, annot=True, cmap=cmap, fmt=".3f",
xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.title("Confusion matrix")

    plt.subplot(1, 3, 2)
    sns.heatmap(B, annot=True, cmap=cmap, fmt=".3f",
xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.title("Precision matrix")

    plt.subplot(1, 3, 3)
    # representing B in heatmap format
    sns.heatmap(A, annot=True, cmap=cmap, fmt=".3f",
xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.title("Recall matrix")

    plt.show()
    return C

def cost(array):
    '''For the given confusion matrix which contains TN, FP, FN, TP'''
    penalty_fn = 500
```

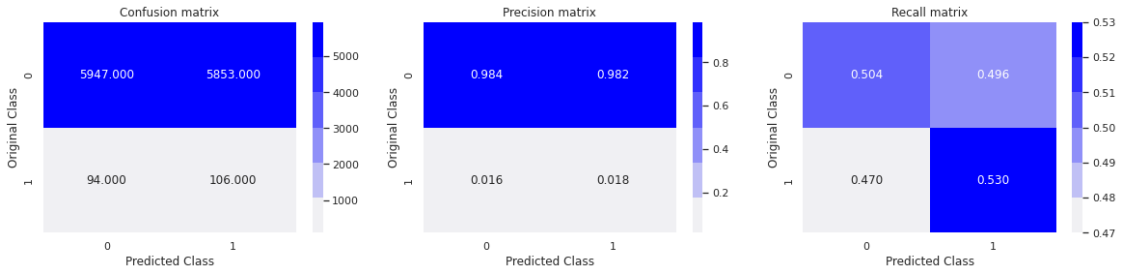
```
    penalty_fp = 10

    cost = penalty_fp*array[0][1] + penalty_fn*array[1][0]
    return cost
```

## Training of the model

```
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import RandomizedSearchCV
from sklearn.calibration import CalibratedClassifierCV
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import SGDClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import ExtraTreesClassifier
from sklearn.svm import SVC
import xgboost as xgb
```

### Random Model

```
y_cv_pred = np.zeros((len(X_cv),2))
np.random.seed(4)
for i in range(len(X_cv)):
    rand_probs = np.random.rand(1,2)
    y_cv_pred[i] = ((rand_probs/sum(sum(rand_probs)))[0])

predicted_y =np.argmax(y_cv_pred, axis=1)
random_confusion_matrix = plot_confusion_matrix(y_cv, predicted_y)
print('the cost of Random Model classifier is ',
cost(random_confusion_matrix))
```




```
the cost of Random Model classifier is  105530
```

1. Since it is a random model, we have assigned the class labels for each instance in X_cv randomly using np.random.rand
2. In the confusion matrix of random model the values are splitted almost half among True an False classes

### kNN classification model

1. We are going to test which set of features are best suitable for modelling.
2. First let us try with all the imputed features.
3. consecutively try the 70%, 80% and 90% variance explained pca feautres.

4. At the end we are going to select the feature set which results in lowest cost metric and continue with all other models.

*KNN on all the imputed featues set*

```
knn = KNeighborsClassifier()
parameters = {'n_neighbors' : [3,5,7,9,11,13,15]}
classifier = GridSearchCV(estimator=knn, param_grid=parameters,
scoring='recall', n_jobs=-1, cv=10)
classifier.fit(X_train_smote, y_train_smote)
```

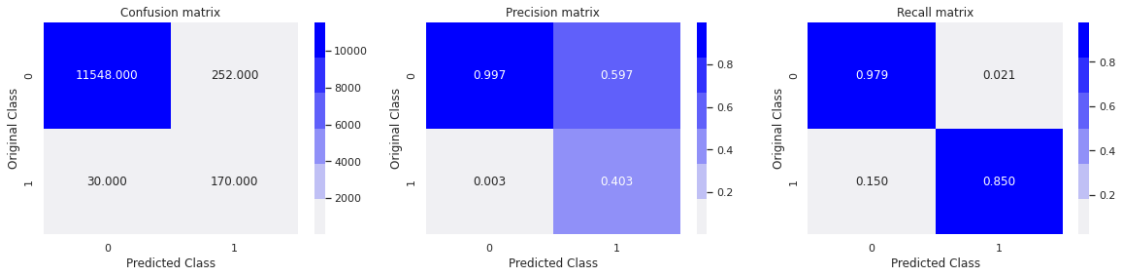
```
GridSearchCV(cv=10, estimator=KNeighborsClassifier(), n_jobs=-1,
             param_grid={'n_neighbors': [3, 5, 7, 9, 11, 13, 15]},
             scoring='recall')
```

```
classifier.best_params_
```

```
{'n_neighbors': 3}
```

```
#calibrating the model
sig_clf = CalibratedClassifierCV(classifier.best_estimator_,
method='sigmoid', n_jobs=-1)
sig_clf.fit(X_train_smote, y_train_smote)
```

```
#evaluating the model
y_cv_pred =sig_clf.predict(X_cv_std)
cn_knn_all = plot_confusion_matrix(y_cv, y_cv_pred)
print('the cost of the kNN model for all the imputed feature set',
cost(cn_knn_all))
```




```
the cost of the kNN model when tuned to best recall_score is 17520
```

*KNN on 70% variance explained pca features*

```
knn = KNeighborsClassifier()
parameters = {'n_neighbors' : [3,5,7,9,11,13,15]}
classifier = GridSearchCV(estimator=knn, param_grid=parameters,
scoring='recall', n_jobs=-1, cv=10)
classifier.fit(X_train_70, y_train_smote)
```

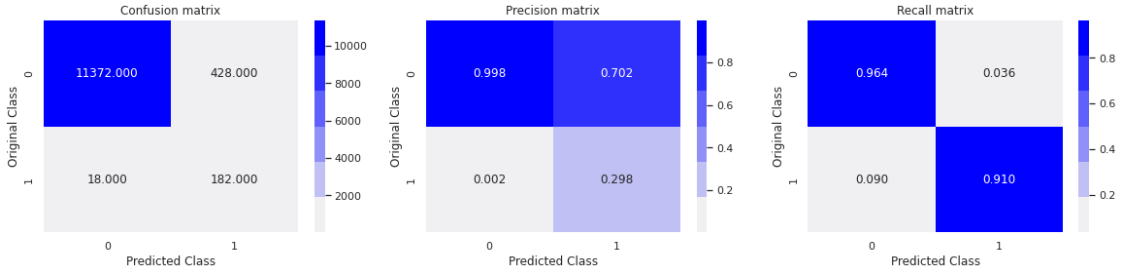
```
GridSearchCV(cv=10, estimator=KNeighborsClassifier(), n_jobs=-1,
             param_grid={'n_neighbors': [3, 5, 7, 9, 11, 13, 15]},
             scoring='recall')
```

```
classifier.best_params_
```

```
{'n_neighbors': 3}
```

```
#calibrating the model
sig_clf = CalibratedClassifierCV(classifier.best_estimator_,
method='sigmoid', n_jobs=-1)
sig_clf.fit(X_train_70, y_train_smote)
```

```
#evaluating the model
y_cv_pred =sig_clf.predict(X_cv_70)
cn_knn_70 = plot_confusion_matrix(y_cv, y_cv_pred)
print('the cost of the kNN model for 70% variance explained pca
feature set', cost(cn_knn_70))
```




```
the cost of the kNN model for 70% variance explained pca feature set
13280
```

*KNN on 80% variance explained pca features*

```
knn = KNeighborsClassifier()
parameters = {'n_neighbors' : [3,5,7,9,11,13,15]}
classifier = GridSearchCV(estimator=knn, param_grid=parameters,
scoring='recall', n_jobs=-1, cv=10)
classifier.fit(X_train_80, y_train_smote)
```

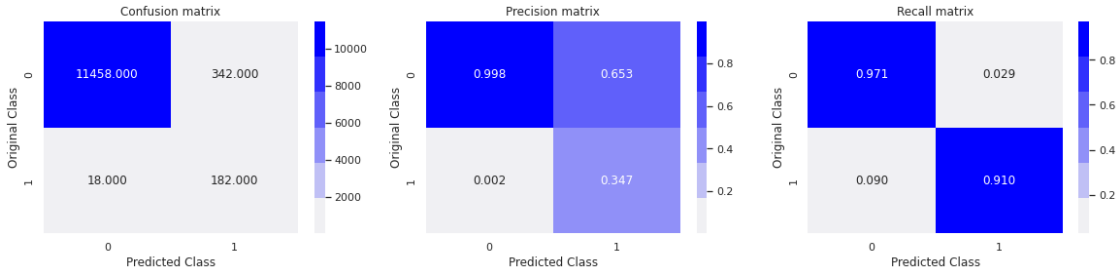
```
GridSearchCV(cv=10, estimator=KNeighborsClassifier(), n_jobs=-1,
             param_grid={'n_neighbors': [3, 5, 7, 9, 11, 13, 15]},
             scoring='recall')
```

```
classifier.best_params_
```

```
{'n_neighbors': 3}
```

```
#calibrating the model
sig_clf = CalibratedClassifierCV(classifier.best_estimator_,
method='sigmoid', n_jobs=-1)
sig_clf.fit(X_train_80, y_train_smote)
```

```
#evaluating the model
y_cv_pred =sig_clf.predict(X_cv_80)
cn_knn_80 = plot_confusion_matrix(y_cv, y_cv_pred)
print('the cost of the kNN model for 80% variance explained pca
feature set', cost(cn_knn_80))
```




the cost of the kNN model for 80% variance explained pca feature set 12420

*KNN on 90% variance explained pca features*

```
knn = KNeighborsClassifier()
parameters = {'n_neighbors' : [3,5,7,9,11,13,15]}
classifier = GridSearchCV(estimator=knn, param_grid=parameters,
scoring='recall', n_jobs=-1, cv=10)
classifier.fit(X_train_90, y_train_smote)
```

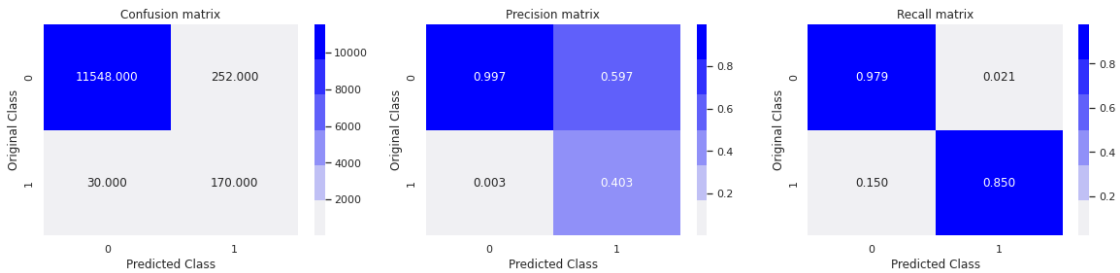
```
GridSearchCV(cv=10, estimator=KNeighborsClassifier(), n_jobs=-1,
             param_grid={'n_neighbors': [3, 5, 7, 9, 11, 13, 15]},
             scoring='recall')
```

```
classifier.best_params_
```

```
{'n_neighbors': 3}
```

```
#calibrating the model
sig_clf = CalibratedClassifierCV(classifier.best_estimator_,
method='sigmoid', n_jobs=-1)
sig_clf.fit(X_train_90, y_train_smote)
```

```
#evaluating the model
y_cv_pred =sig_clf.predict(X_cv_90)
cn_knn_90 = plot_confusion_matrix(y_cv, y_cv_pred)
print('the cost of the kNN model for 90% variance explained pca
feature set', cost(cn_knn_90))
```




the cost of the kNN model for 90% variance explained pca feature set 17520

Observations:

1. From the above four sets of features, 80% variance explained pca features has obtained lowest possible cost of 12420 with False Positives as 342 and False Negatives as 18.
2. Hence we continue our modelling with 80% variance explained pca features

### Logistic Regression Classification Model

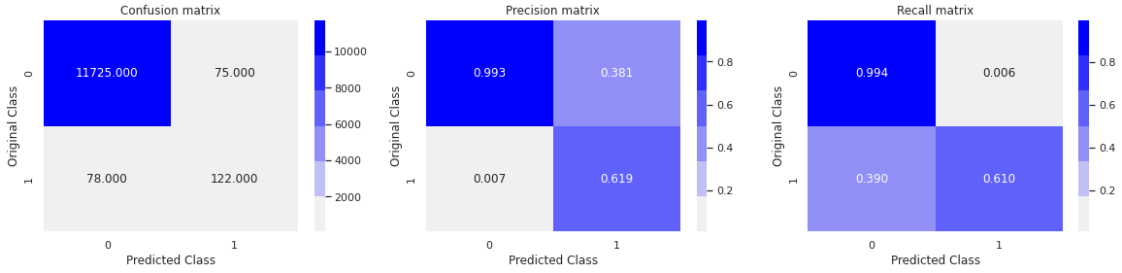
```
lr = SGDClassifier(loss='log', random_state=8)
parameters = {'alpha':[0.00001, 0.0001,0.001, 0.01, 0.1, 1, 10,  100,
1000]}
classifier = GridSearchCV(estimator=lr, param_grid=parameters, cv=10,
n_jobs=-1, scoring='recall')
classifier.fit(X_train_80, y_train_smote)
```

```
GridSearchCV(cv=10, estimator=SGDClassifier(loss='log',
random_state=8),
             n_jobs=-1,
             param_grid={'alpha': [1e-05, 0.0001, 0.001, 0.01, 0.1, 1,
10, 100,
                                   1000]},
             scoring='recall')
```

```
classifier.best_params_
```

```
{'alpha': 0.01}
```

```
# calibrating the model
sig_clf = CalibratedClassifierCV(classifier.best_estimator_,
method="sigmoid")
sig_clf.fit(X_train_80, y_train_smote)

#evaluating the model with Cross validation datas set
y_cv_pred = sig_clf.predict(X_cv_80)
cn_lr = plot_confusion_matrix(y_cv, y_cv_pred)
print('the cost of the Logistic Regression model is', cost(cn_lr))
```




```
the cost of the Linear Regression model is 39750
```

Observations:

1. Being the linear model i.e. hyper plane decision boundary we can clearly observe that they failed to account the positive instances.

2. The cost of logistic regression is 39750 with 75 False Positives and 78 False Negatives.

### SVM classifier model

```
svm = SGDClassifier(loss='hinge', random_state=2)
parameters = {'alpha':[0.00001, 0.0001,0.001, 0.01, 0.1, 1, 10,  100, 1000]}
classifier = GridSearchCV(estimator=svm, param_grid=parameters, cv=10, n_jobs=-1, scoring='recall')
classifier.fit(X_train_80, y_train_smote)
```

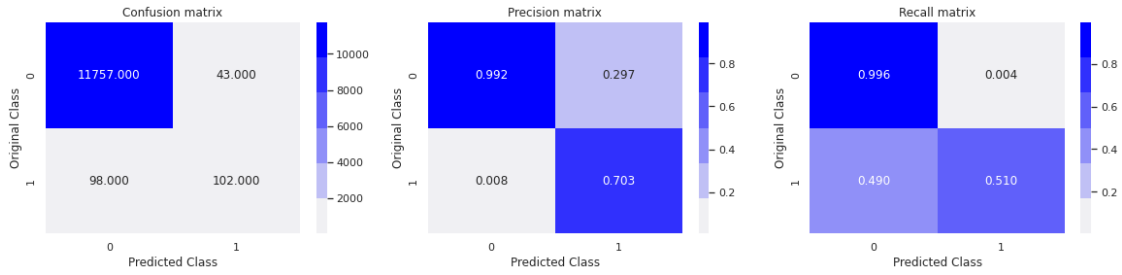
```
GridSearchCV(cv=10, estimator=SGDClassifier(random_state=2), n_jobs=-1,
             param_grid={'alpha': [1e-05, 0.0001, 0.001, 0.01, 0.1, 1, 10, 100,
                                   1000]},
             scoring='recall')
```

```
classifier.best_params_
```

```
{'alpha': 0.01}
```

```
sig_clf = CalibratedClassifierCV(classifier.best_estimator_, method="sigmoid")
sig_clf.fit(X_train_80, y_train_smote)
```

```
#evaluating the model with Cross Validation Data set
y_cv_pred = sig_clf.predict(X_cv_80)
cn_svm = plot_confusion_matrix(y_cv, y_cv_pred)
print('the cost of the SVM model is', cost(cn_svm))
```




```
the cost of the SVM model is 49430
```

Observations:

1. The same drawback of hyper plane decision boundary can be observed here too. The minimization hingeloss tries to maximize the distance the between two classes such that the probability of determining an instance increases.
2. This margin maximization between linear surfaces may have caused to increase the misclassification of Positive instances relative to linear regression.
3. The cost of the linear SVM model is 49430 which comprises of 43 False Positives and 98 False Negatives.

### RandomForrest Classifier

```
%%time
rf = RandomForestClassifier()
parameters = {'n_estimators' : [300, 350, 400, 450],
'min_samples_leaf':[2,3,5,7], 'max_depth':[4,5,6,7]}
classifier = GridSearchCV(estimator=rf, param_grid=parameters, cv=10,
n_jobs=-1, scoring='recall')
classifier.fit(X_train_80, y_train_smote)
```

```
CPU times: user 1min 43s, sys: 743 ms, total: 1min 44s
Wall time: 2h 38min 45s
```

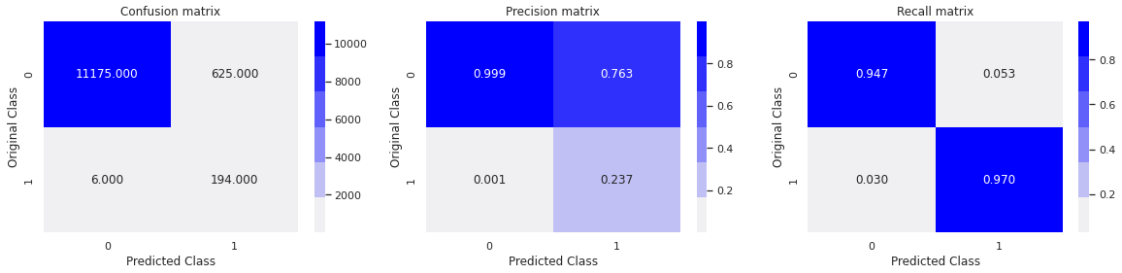
```
GridSearchCV(cv=10, estimator=RandomForestClassifier(), n_jobs=-1,
             param_grid={'max_depth': [4, 5, 6, 7],
                         'min_samples_leaf': [2, 3, 5, 7],
                         'n_estimators': [300, 350, 400, 450]},
             scoring='recall')
```

```
classifier.best_params_
```

```
{'max_depth': 7, 'min_samples_leaf': 3, 'n_estimators': 350}
```

```
# calibrating the model
sig_clf = CalibratedClassifierCV(classifier.best_estimator_,
method="sigmoid")
sig_clf.fit(X_train_80, y_train_smote)
```

```
# evaluating the model
y_cv_pred = sig_clf.predict(X_cv_80)
cn_rf = plot_confusion_matrix(y_cv, y_cv_pred)
print('the cost of the Random Forrest model is', cost(cn_rf))
```




```
the cost of the Random Forrest model is 9250
```

1. After hypertuning the Random Forrest Model using GridSearchCV with no. of base tree estimators and minimum no. of samples required to split at the node and max_depth of the tree to avoid overfitting we have got best recall score at max_depth = 7, min_samples_leaf=3, n_estimators=350.
2. After predicting the cost of the Random Forrest Classifier is 9250 with 6 False Negative and 625 False Positives.

3. The ensemble of high variance Decision Trees seems to indentify the positve class much more accurately with the use of instance sampling with replacement and majority vote.

### XGBoost Implementaion of Gradient Boosting

```
%%time
xgbc= xgb.XGBClassifier(booster='gbtree', objective='binary:logistic',
eval_metric='auc', use_label_encoder=False)
parameters = {'gamma': [0.1, 0.5, 1, 5, 10],
              'learning_rate': [0.001, 0.005, 0.01, 0.05, 0.1,],
              'max_depth': [1,2,3,4],
              'n_estimators': [350, 400, 450, 500],
              'reg_alpha': [0.01, 0.1, 1, 10,  100,  1000],
              'reg_lambda': [0.01, 0.1, 1, 10,  100,  1000]}

classifier = RandomizedSearchCV(estimator=xgbc,
param_distributions=parameters, cv=5, n_jobs=-1,
                                scoring='recall', n_iter=15)
classifier.fit(X_train_80, y_train_smote)
```

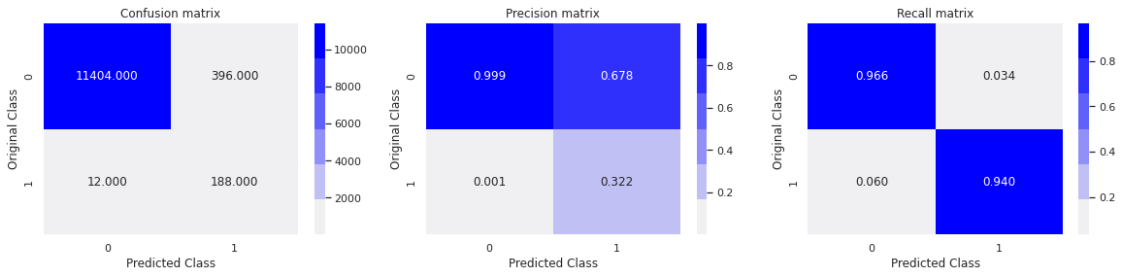
```
CPU times: user 3min 1s, sys: 469 ms, total: 3min 1s
Wall time: 1h 22min 30s
```

```
RandomizedSearchCV(cv=5,
                   estimator=XGBClassifier(base_score=None,
booster='gbtree',
                                           colsample_bylevel=None,
                                           colsample_bynode=None,
                                           colsample_bytree=None,
                                           enable_categorical=False,
                                           eval_metric='auc',
gamma=None,
                                           gpu_id=None,
importance_type=None,

interaction_constraints=None,
                                           learning_rate=None,
                                           max_delta_step=None,
max_depth=None,
                                           min_child_weight=None,
missing=na...
                                           subsample=None,
tree_method=None,
                                           use_label_encoder=False,
                                           validate_parameters=None,
                                           verbosity=None),
                   n_iter=15, n_jobs=-1,
                   param_distributions={'gamma': [0.1, 0.5, 1, 5, 10],
                                        'learning_rate': [0.001,
0.005, 0.01,
```

```
                                                    0.05, 0.1],
                                          'max_depth': [1, 2, 3, 4],
                                          'n_estimators': [350, 400,
450, 500],
                                          'reg_alpha': [0.01, 0.1, 1,
10, 100,
                                                        1000],
                                          'reg_lambda': [0.01, 0.1, 1,
10, 100,
                                                         1000]},
                    scoring='recall')

classifier.best_params_
```

```
{'reg_lambda': 10,
 'reg_alpha': 1,
 'n_estimators': 350,
 'max_depth': 4,
 'learning_rate': 0.1,
 'gamma': 5}
```

```
# calibrating the model
sig_clf = CalibratedClassifierCV(classifier.best_estimator_,
method="sigmoid")
sig_clf.fit(X_train_80, y_train_smote)

# evaluating the model
y_cv_pred = sig_clf.predict(X_cv_80)
cn_xgb = plot_confusion_matrix(y_cv, y_cv_pred)
print('the cost of the Gradient Boosting Decision Tree model is',
cost(cn_xgb))
```




```
the cost of the Gradient Boosting Decision Tree model is 9960
```

Observations:

1. Compared to RandomForest Classifier i.e. Bagging ensemble XGBoost Classifier i.e. Boosting ensemble predicts both negative instances along with positive instances more accurately.
2. The minimization of bias seems to give importance to negative class hence the False Positive of XGBoost way more lower than the False Positive of RandomForest Classifier.

3. At the end the cost of GBDT is little bit higher than the RandomForest Classifier i.e 9960 which comprises of 396 False Positives and 12 False Negatives

### Support Vector Machine with Radial Bias kernalization

```
%%time
svc  = SVC()
parameters = {'C': [8, 10, 12, 14],
              'gamma': [0.004, 0.008, 0.01, 0.03, 0.06],
              'kernel': ['rbf']}
classifier = RandomizedSearchCV(estimator=svc,
param_distributions=parameters, cv=3, n_jobs=-1, scoring='recall',
n_iter=10)
classifier.fit(X_train_80, y_train_smote)
```

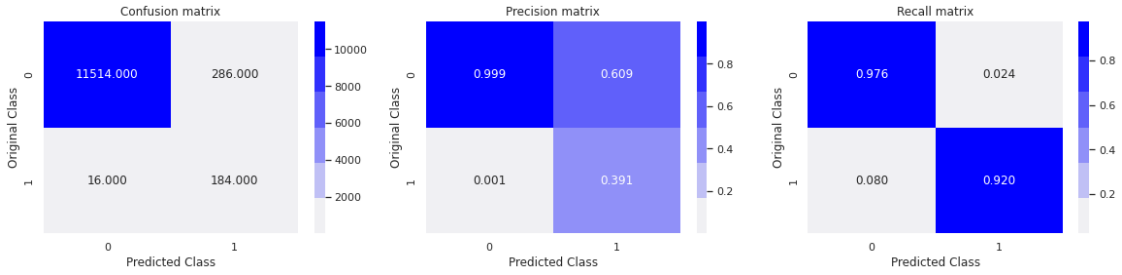
```
CPU times: user 9min 27s, sys: 585 ms, total: 9min 28s
Wall time: 31min 18s
```

```
RandomizedSearchCV(cv=3, estimator=SVC(), n_jobs=-1,
                   param_distributions={'C': [8, 10, 12, 14],
                                        'gamma': [0.004, 0.008, 0.01,
0.03,
                                                  0.06],
                                        'kernel': ['rbf']},
                   scoring='recall')
```

```
classifier.best_params_
```

```
{'kernel': 'rbf', 'gamma': 0.06, 'C': 10}
```

```
# calibrating the model
sig_clf = CalibratedClassifierCV(classifier.best_estimator_,
method="sigmoid")
sig_clf.fit(X_train_80, y_train_smote)

# evaluating the model
y_cv_pred = sig_clf.predict(X_cv_80)
cn_rbf = plot_confusion_matrix(y_cv, y_cv_pred)
print('the cost of the support vector machines of RBF kernel model
is', cost(cn_rbf))
```




```
the cost of the support vector machines of RBF kernel model is 10860
```

Observations:

1. The RBF kernel which is non linear SVM fare better compare to the linear SVM.
2. The RBF kernel has been successfull in identifying the positive class hence it results in low cost than linear SVM.
3. The costo RBF kernel SVM is 10860 which comprises of 286 False Positives and 16 False Negatives.

### Extremely Randomized Tree classifier

```
%%time
ert = ExtraTreesClassifier()
parameters = {'n_estimators' : [300, 350, 400, 450],
'min_samples_leaf':[3,5,7], 'max_depth':[3, 5, 7, 12]}
classifier = GridSearchCV(estimator=ert, param_grid=parameters, cv=10,
n_jobs=-1, scoring='recall')
classifier.fit(X_train_80, y_train_smote)
```

```
CPU times: user 14.7 s, sys: 366 ms, total: 15.1 s
Wall time: 20min 46s
```

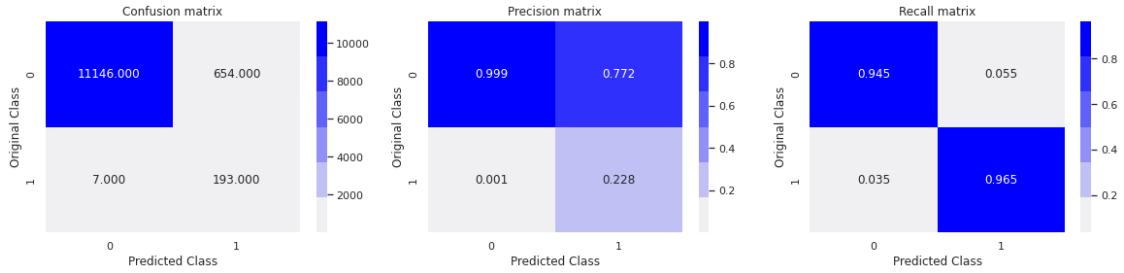
```
GridSearchCV(cv=10, estimator=ExtraTreesClassifier(), n_jobs=-1,
             param_grid={'max_depth': [3, 5, 7, 12],
                         'min_samples_leaf': [3, 5, 7],
                         'n_estimators': [300, 350, 400, 450]},
             scoring='recall')
```

```
classifier.best_params_
```

```
{'max_depth': 12, 'min_samples_leaf': 3, 'n_estimators': 300}
```

```
#calibrating the model
sig_clf = CalibratedClassifierCV(classifier.best_estimator_,
method="sigmoid")
sig_clf.fit(X_train_80, y_train_smote)
```

```
# evaluating the model
y_cv_pred = sig_clf.predict(X_cv_80)
cn_ert = plot_confusion_matrix(y_cv, y_cv_pred)
print('the cost of the Extremely Random Tree model is', cost(cn_ert))
```




```
the cost of the Extremely Random Tree model is 10040
```

Observations

1. Extremely Randomized Trees find out the best value of Tau for numerical feature by sampling randomly to findout the weighted entropy.
2. This weighted entropy is used to find out the Information Gain for every numerical feature.
3. Hence, they are faster in training relative to Random Forest Classifier.
4. The cost of Extremely Randomized Trees is 10040 which is slightly higher may be due to approximation along with 654 False Positives and 7 False Negatives.

```
import prettytable
from prettytable import PrettyTable
TB = PrettyTable()

TB.title = "The cost of the various models fitted to the oversampled
data using SMOTE and 80% variance explained pca features"
TB.field_names = ['MODEL', 'DESCRIPTION', 'False Negatives', 'False
Positives', 'COST']
TB.add_row(['RANDOM', 'ARBITRARY', 94, 5853, 105530])
TB.add_row(['SVM-LINEAR', 'LINEAR', 98, 43, 49430])
TB.add_row(['LOGISTIC REGRESSION', 'LINEAR', 78, 75, 39750])
TB.add_row(['kNN', 'NEAREST NEIGHBOR', 18, 342, 12420])
TB.add_row(['SVM-RBF', 'NON-LINEAR', 16, 286, 10860])
TB.add_row(['EXTREMELY RANDOMIZED TREE', 'ENSEMBLE', 7, 654, 10040])
TB.add_row(['XG BOOST', 'ENSEMBLE', 12, 396, 9960])
TB.add_row(['RANDOM FORREST', 'ENSEMBLE', 6, 625, 9250])

print(TB)
```

```
+-------------------------------------------------------------------------
-----------------------------------------------+
|  The cost of the various models fitted to the oversampled data using
SMOTE and 80% variance explained pca features  |
+-----------------------------------+------------------------
+----------------------+----------------------+----------+
|               MODEL               |      DESCRIPTION       |   False
Negatives    |   False Positives    |   COST   |
+-----------------------------------+------------------------
+----------------------+----------------------+----------+
|               RANDOM              |       ARBITRARY        |
94           |          5853         |  105530  |
|             SVM-LINEAR            |         LINEAR         |
98           |           43          |  49430   |
|        LOGISTIC REGRESSION        |         LINEAR         |
78           |           75          |  39750   |
|                kNN                |    NEAREST NEIGHBOR    |
18           |          342          |  12420   |
|              SVM-RBF              |       NON-LINEAR       |
16           |          286          |  10860   |
|     EXTREMELY RANDOMIZED TREE     |        ENSEMBLE        |
7            |          654          |  10040   |
|              XG BOOST             |        ENSEMBLE        |
```

```
12          |         396          |   9960   |
|           RANDOM FORREST          |        ENSEMBLE        |
6           |         625          |   9250   |
+-----------------------------------+------------------------
+----------------------+----------------------+----------+
```

Final Conclusions:

1. The Ensemble Techniques along with non-linear decision boundary models tends to fare better for identifying the positive class.
2. The main business constraint is to reduce the no. of False Negatives i.e. Predicting the actual positive as negative.
3. This can be achieved through Random Forrest Classifier.
4. There is no low latency constraint cause the inspection of trucks are generally a meticulous procedure.