Note:Please note that the Data Set when it is uploaded then only it will work

```
# Code to read csv file into colaboratory:
!pip install -U -q PyDrive
from pydrive.auth import GoogleAuth
from pydrive.drive import GoogleDrive
from google.colab import auth
from oauth2client.client import GoogleCredentials

auth.authenticate_user()
gauth = GoogleAuth()
gauth.credentials = GoogleCredentials.get_application_default()
drive = GoogleDrive(gauth)

downloaded = drive.CreateFile({'id':'1dzo-nY83hcwWQSK70MpMiwnQXiNXFaiC'}) # replace the id
downloaded.GetContentFile('creditcard.csv')

import pandas as pd
data = pd.read_csv('creditcard.csv')
print(data.head(1))
```

```
   Time        V1        V2        V3  ...       V27       V28  Amount  Class
0   0.0 -1.359807 -0.072781  2.536347  ...  0.133558 -0.021053  149.62      0

[1 rows x 31 columns]
```

INTRODUCTION

```
#imports
import numpy as np
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import sys
import matplotlib.pyplot as plt
import seaborn as sns
import scipy
import sklearn
```

```
/usr/local/lib/python3.6/dist-packages/statsmodels/tools/_testing.py:19: FutureWarnir
  import pandas.util.testing as tm
```

```
#Data Importing
data = pd.read_csv('creditcard.csv')
```

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
sns.set()
%matplotlib inline

data = pd.read_csv('creditcard.csv')
print(data.shape)
data.head()
```

```
(284807, 31)
```

	Time	V1	V2	V3	V4	V5	V6	V7	
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.09
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.08
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.24
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.37
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.27

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 284807 entries, 0 to 284806
Data columns (total 31 columns):
 #   Column  Non-Null Count   Dtype  
---  ------  --------------   -----  
 0   Time    284807 non-null  float64
 1   V1      284807 non-null  float64
```

```
data.describe()
```

	Time	V1	V2	V3	V4	
count	284807.000000	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	2.848
mean	94813.859575	3.919560e-15	5.688174e-16	-8.769071e-15	2.782312e-15	-1.552
std	47488.145955	1.958696e+00	1.651309e+00	1.516255e+00	1.415869e+00	1.380
min	0.000000	-5.640751e+01	-7.271573e+01	-4.832559e+01	-5.683171e+00	-1.137
25%	54201.500000	-9.203734e-01	-5.985499e-01	-8.903648e-01	-8.486401e-01	-6.915
50%	84692.000000	1.810880e-02	6.548556e-02	1.798463e-01	-1.984653e-02	-5.433
75%	139320.500000	1.315642e+00	8.037239e-01	1.027196e+00	7.433413e-01	6.119
max	172792.000000	2.454930e+00	2.205773e+01	9.382558e+00	1.687534e+01	3.480

```
 22  V22     284807 non-null  float64
```

EXPLORING THE DATASET

```
 27  V27     284807 non-null  float64
```

```
print(data.columns)
```

```
Index(['Time', 'V1', 'V2', 'V3', 'V4', 'V5', 'V6', 'V7', 'V8', 'V9', 'V10',
       'V11', 'V12', 'V13', 'V14', 'V15', 'V16', 'V17', 'V18', 'V19', 'V20',
       'V21', 'V22', 'V23', 'V24', 'V25', 'V26', 'V27', 'V28', 'Amount',
       'Class'],
      dtype='object')
```

```
data.shape
```

```
(284807, 31)
```

```
# random_state helps assure that you always get the same output when you split the data
# this helps create reproducible results and it does not actually matter what the number i
# frac is percentage of the data that will be returned
data = data.sample(frac = 0.2, random_state = 1)
print(data.shape)
```

```
(56961, 31)
```

How many are fraud and how many are not fraud ?

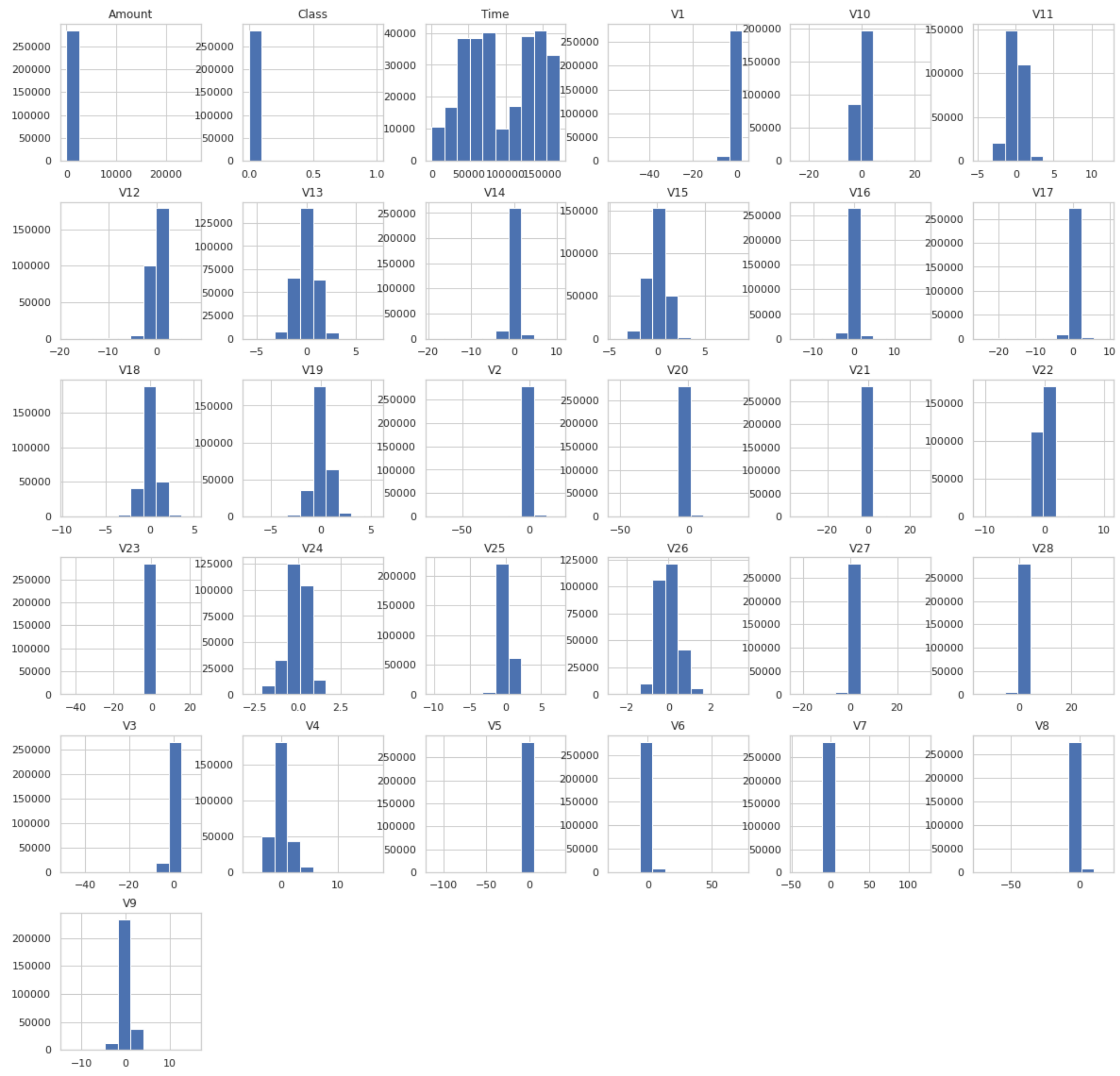
```
class_names = {0:'Not Fraud', 1:'Fraud'}
print(data.Class.value_counts().rename(index = class_names))
```

```
Not Fraud    56874
Fraud           87
Name: Class, dtype: int64
```

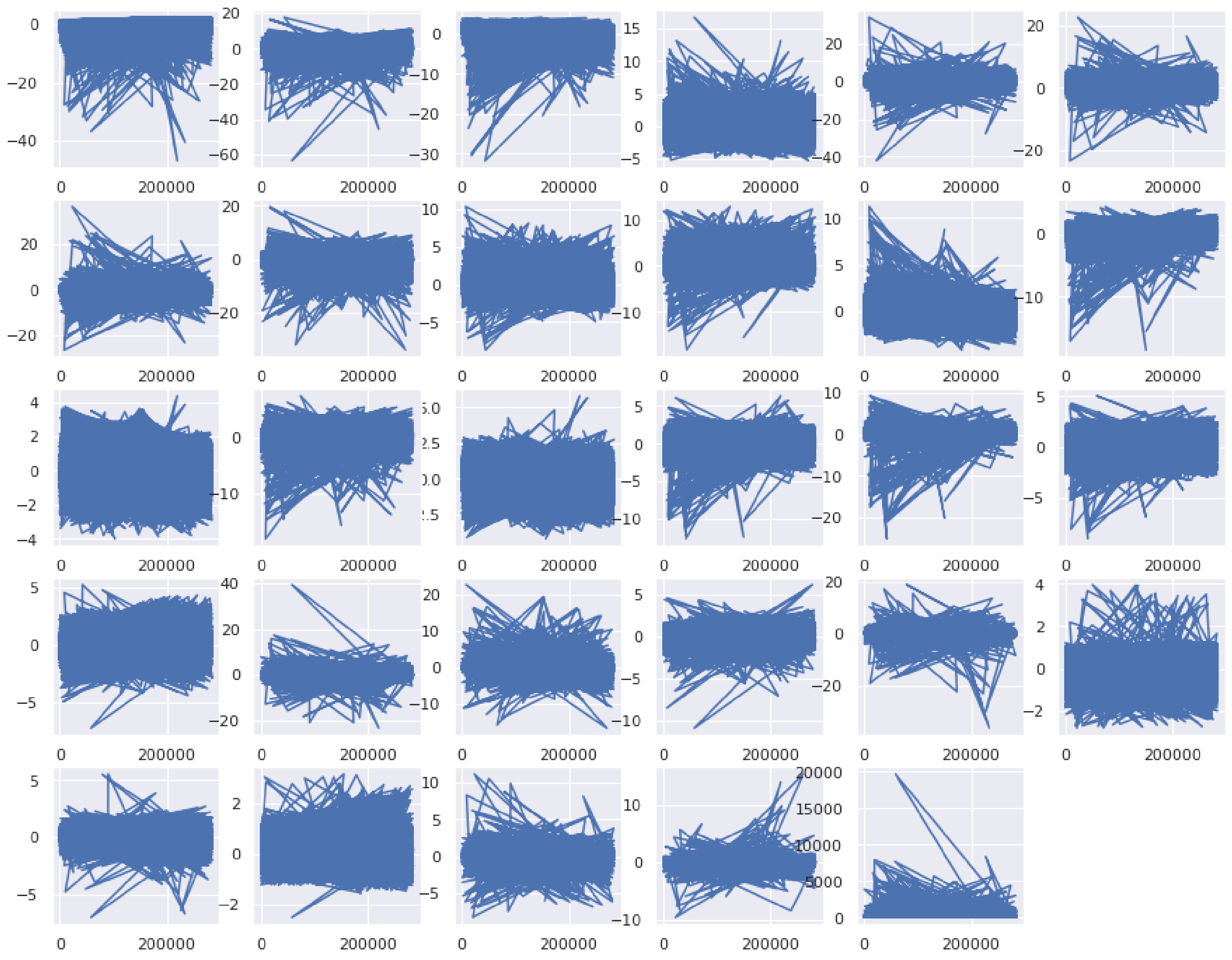
```
# determine the number of fraud cases
fraud = data[data['Class'] == 1]
valid = data[data['Class'] == 0]

outlier_fraction = len(fraud) / float(len(valid))
print(outlier_fraction)

print('Fraud Cases: {}'.format(len(fraud)))
print('Valid Cases: {}'.format(len(valid)))
```

```
0.0015296972254457222
Fraud Cases: 87
Valid Cases: 56874
```

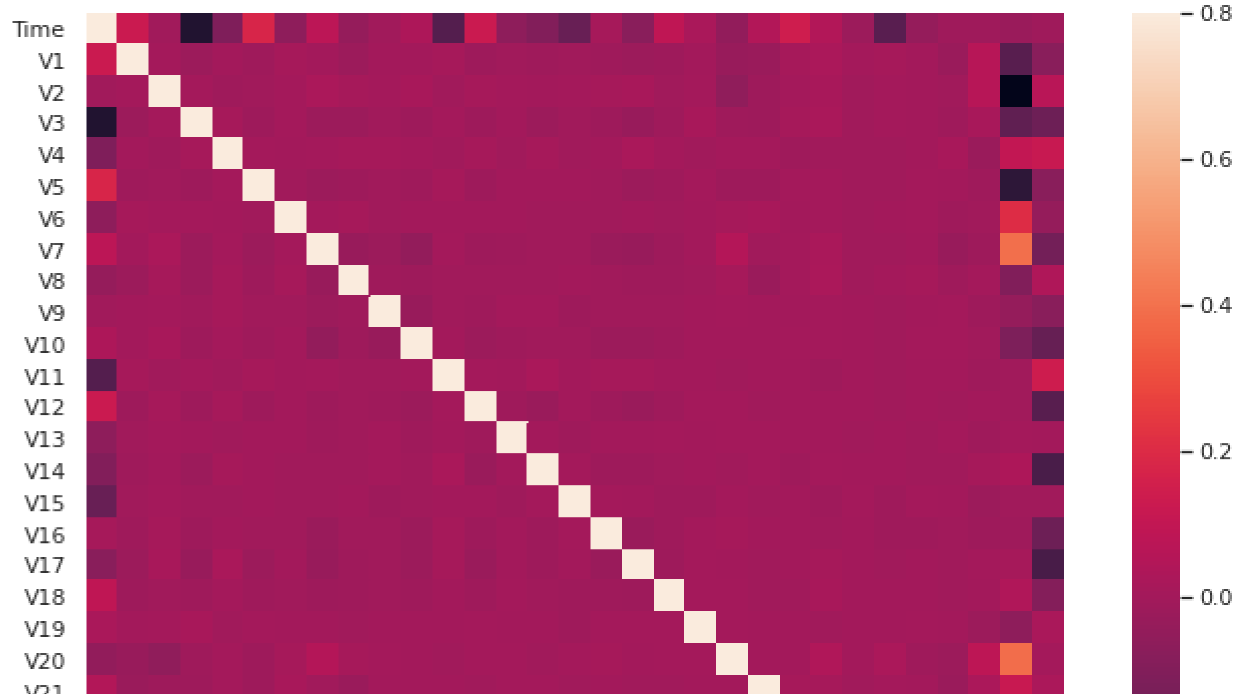
```
# plot the histogram of each parameter
data.hist(figsize = (20, 20))
plt.show()
```



```
#Plotting the variables using subplots
fig = plt.figure(figsize = (15, 12))

plt.subplot(5, 6, 1) ; plt.plot(data.V1) ; plt.subplot(5, 6, 15) ; plt.plot(data.V15)
plt.subplot(5, 6, 2) ; plt.plot(data.V2) ; plt.subplot(5, 6, 16) ; plt.plot(data.V16)
plt.subplot(5, 6, 3) ; plt.plot(data.V3) ; plt.subplot(5, 6, 17) ; plt.plot(data.V17)
plt.subplot(5, 6, 4) ; plt.plot(data.V4) ; plt.subplot(5, 6, 18) ; plt.plot(data.V18)
plt.subplot(5, 6, 5) ; plt.plot(data.V5) ; plt.subplot(5, 6, 19) ; plt.plot(data.V19)
plt.subplot(5, 6, 6) ; plt.plot(data.V6) ; plt.subplot(5, 6, 20) ; plt.plot(data.V20)
plt.subplot(5, 6, 7) ; plt.plot(data.V7) ; plt.subplot(5, 6, 21) ; plt.plot(data.V21)
plt.subplot(5, 6, 8) ; plt.plot(data.V8) ; plt.subplot(5, 6, 22) ; plt.plot(data.V22)
plt.subplot(5, 6, 9) ; plt.plot(data.V9) ; plt.subplot(5, 6, 23) ; plt.plot(data.V23)
plt.subplot(5, 6, 10) ; plt.plot(data.V10) ; plt.subplot(5, 6, 24) ; plt.plot(data.V24)
plt.subplot(5, 6, 11) ; plt.plot(data.V11) ; plt.subplot(5, 6, 25) ; plt.plot(data.V25)
plt.subplot(5, 6, 12) ; plt.plot(data.V12) ; plt.subplot(5, 6, 26) ; plt.plot(data.V26)
plt.subplot(5, 6, 13) ; plt.plot(data.V13) ; plt.subplot(5, 6, 27) ; plt.plot(data.V27)
plt.subplot(5, 6, 14) ; plt.plot(data.V14) ; plt.subplot(5, 6, 28) ; plt.plot(data.V28)
plt.subplot(5, 6, 29) ; plt.plot(data.Amount)
plt.show()
```



```
# correlation matrix
corrmat = data.corr()
fig = plt.figure(figsize = (12, 9))

sns.heatmap(corrmat, vmax = .8, square = True)
plt.show()
```



```
!pip install catboost
```

```
Collecting catboost
  Downloading https://files.pythonhosted.org/packages/b2/aa/e61819d04ef2bbee778bf4b3a
     |████████████████████████████████| 64.8MB 59kB/s
Requirement already satisfied: six in /usr/local/lib/python3.6/dist-packages (from ca
Requirement already satisfied: scipy in /usr/local/lib/python3.6/dist-packages (from
Requirement already satisfied: graphviz in /usr/local/lib/python3.6/dist-packages (fr
Requirement already satisfied: pandas>=0.24.0 in /usr/local/lib/python3.6/dist-packag
Requirement already satisfied: matplotlib in /usr/local/lib/python3.6/dist-packages (
Requirement already satisfied: numpy>=1.16.0 in /usr/local/lib/python3.6/dist-package
Requirement already satisfied: plotly in /usr/local/lib/python3.6/dist-packages (from
Requirement already satisfied: python-dateutil>=2.6.1 in /usr/local/lib/python3.6/dis
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.6/dist-pac
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /usr/local
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: retrying>=1.3.3 in /usr/local/lib/python3.6/dist-packa
Installing collected packages: catboost
Successfully installed catboost-0.23.2
```

Load Packages

```
import pandas as pd
import numpy as np
import matplotlib
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import plotly.graph_objs as go
import plotly.figure_factory as ff
from plotly import tools
from plotly.offline import download_plotlyjs, init_notebook_mode, plot, iplot
init_notebook_mode(connected=True)
```

```
import gc
from datetime import datetime
from sklearn.model_selection import train_test_split
from sklearn.model_selection import KFold
from sklearn.metrics import roc_auc_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import AdaBoostClassifier
from catboost import CatBoostClassifier
from sklearn import svm
import lightgbm as lgb
from lightgbm import LGBMClassifier
import xgboost as xgb

pd.set_option('display.max_columns', 100)


RFC_METRIC = 'gini'  #metric used for RandomForrestClassifier
NUM_ESTIMATORS = 100 #number of estimators used for RandomForrestClassifier
NO_JOBS = 4 #number of parallel jobs used for RandomForrestClassifier


#TRAIN/VALIDATION/TEST SPLIT
#VALIDATION
VALID_SIZE = 0.20 # simple validation using train_test_split
TEST_SIZE = 0.20 # test size using_train_test_split

#CROSS-VALIDATION
NUMBER_KFOLDS = 5 #number of KFolds for cross-validation



RANDOM_STATE = 2018

MAX_ROUNDS = 1000 #lgb iterations
EARLY_STOP = 50 #lgb early stop
OPT_ROUNDS = 1000  #To be adjusted based on best validation rounds
VERBOSE_EVAL = 50 #Print out metric result

IS_LOCAL = False

import os

if (IS_LOCAL):
    PATH="../input/credit-card-fraud-detection"
else:
    PATH="../input"
```

```
data = pd.read_csv("creditcard.csv")
```

```
print("Credit Card Fraud Detection data -  rows:",data.shape[0]," columns:", data.shape[1]
Credit Card Fraud Detection data -  rows: 284807  columns: 31
```

```
#Check missing data
total = data.isnull().sum().sort_values(ascending = False)
percent = (data.isnull().sum()/data.isnull().count()*100).sort_values(ascending = False)
pd.concat([total, percent], axis=1, keys=['Total', 'Percent']).transpose()
```

	Class	V14	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V15
Total	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Percent	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

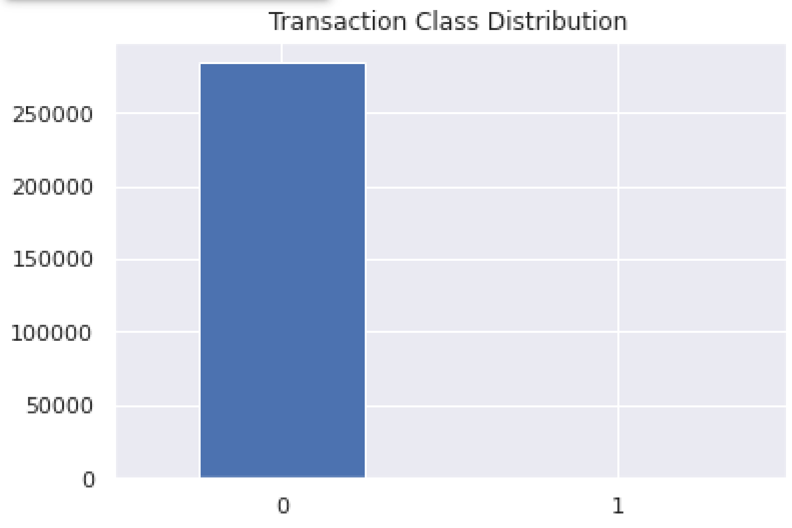
ANOMALY DETECTION

Exploratory Data Analysis

```
count_classes = pd.value_counts(data['Class'], sort = True)
count_classes.plot(kind = 'bar', rot=0)
plt.title("Transaction Class Distribution")
plt.xticks(range(2), LABELS)
plt.xlabel("Class")
plt.ylabel("Frequency");
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-31-94e0c4ced588> in <module>()
      2 count_classes.plot(kind = 'bar', rot=0)
      3 plt.title("Transaction Class Distribution")
----> 4 plt.xticks(range(2), LABELS)
      5 plt.xlabel("Class")
      6 plt.ylabel("Frequency");

NameError: name 'LABELS' is not defined
```

SEARCH STACK OVERFLOW



```
Fraud = data[data['Class']==1]
```

```
Normal = data[data['Class']==0]
```

```
Fraud.shape
```

```
(492, 31)
```

```
Normal.shape
```

```
(284315, 31)
```

How different are the amount of money used in different transaction classes?

```
Fraud.Amount.describe()
```

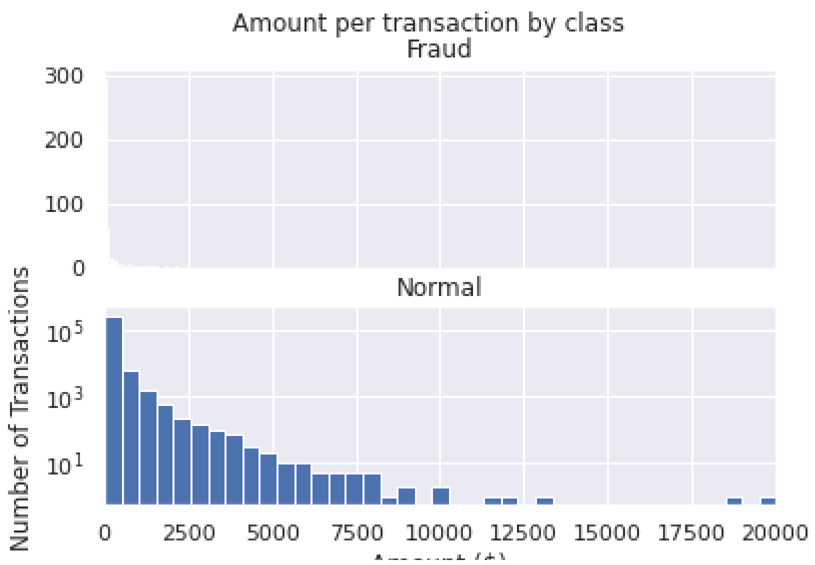
```
count     492.000000
mean      122.211321
std       256.683288
min         0.000000
25%         1.000000
50%         9.250000
75%       105.890000
max      2125.870000
Name: Amount, dtype: float64
```

```
Normal.Amount.describe()
```

```
count    284315.000000
mean         88.291022
std         250.105092
min           0.000000
25%           5.650000
50%          22.000000
75%          77.050000
max       25691.160000
Name: Amount, dtype: float64
```

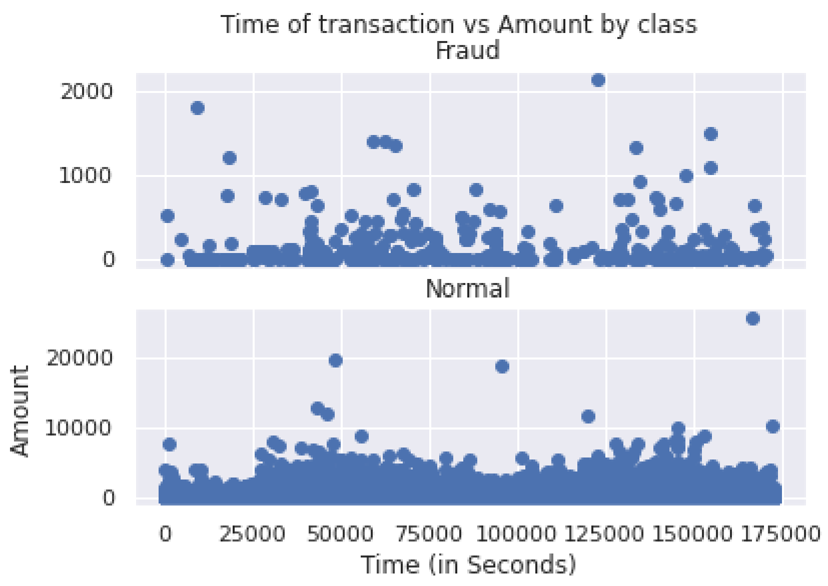
Let's have a more graphical representation of the data

```
f, (ax1, ax2) = plt.subplots(2, 1, sharex=True)
f.suptitle('Amount per transaction by class')
bins = 50
ax1.hist(Fraud.Amount, bins = bins)
ax1.set_title('Fraud')
ax2.hist(Normal.Amount, bins = bins)
ax2.set_title('Normal')
plt.xlabel('Amount ($)')
plt.ylabel('Number of Transactions')
plt.xlim((0, 20000))
plt.yscale('log')
plt.show();
```



Do fraudulent transactions occur more often during certain time frame ? Let us find out with a visual representation.

```
f, (ax1, ax2) = plt.subplots(2, 1, sharex=True)
f.suptitle('Time of transaction vs Amount by class')
ax1.scatter(Fraud.Time, Fraud.Amount)
ax1.set_title('Fraud')
ax2.scatter(Normal.Time, Normal.Amount)
ax2.set_title('Normal')
plt.xlabel('Time (in Seconds)')
plt.ylabel('Amount')
plt.show()
```



Organizing the Data

```
data = pd.read_csv("creditcard.csv")
```

```
# get the columns from the dataframe
columns = data.columns.tolist()
```

```
# filter the columns to remove the data we do not want
columns = [c for c in columns if c not in ['Class']]

# store the variable we will be predicting on which is class
target = 'Class'

# X includes everything except our class column
X = data[columns]
# Y includes all the class labels for each sample
# this is also one-dimensional
Y = data[target]

# print the shapes of X and Y
print(X.shape)
print(Y.shape)
```

```
(284807, 30)
(284807,)
```

Applying Algorithms

```
from sklearn.metrics import classification_report, accuracy_score
from sklearn.ensemble import IsolationForest
from sklearn.neighbors import LocalOutlierFactor
```

```
# define a random state
state = 1

# define the outlier detection methods
classifiers = {
    # contamination is the number of outliers we think there are
    'Isolation Forest': IsolationForest(max_samples = len(X),
                                       contamination = outlier_fraction,
                                       random_state = state),
    # number of neighbors to consider, the higher the percentage of outliers the higher yo
    'Local Outlier Factor': LocalOutlierFactor(
    n_neighbors = 20,
    contamination = outlier_fraction)
}
```

Fit the Model - (please wait the process will take few minutes for output)

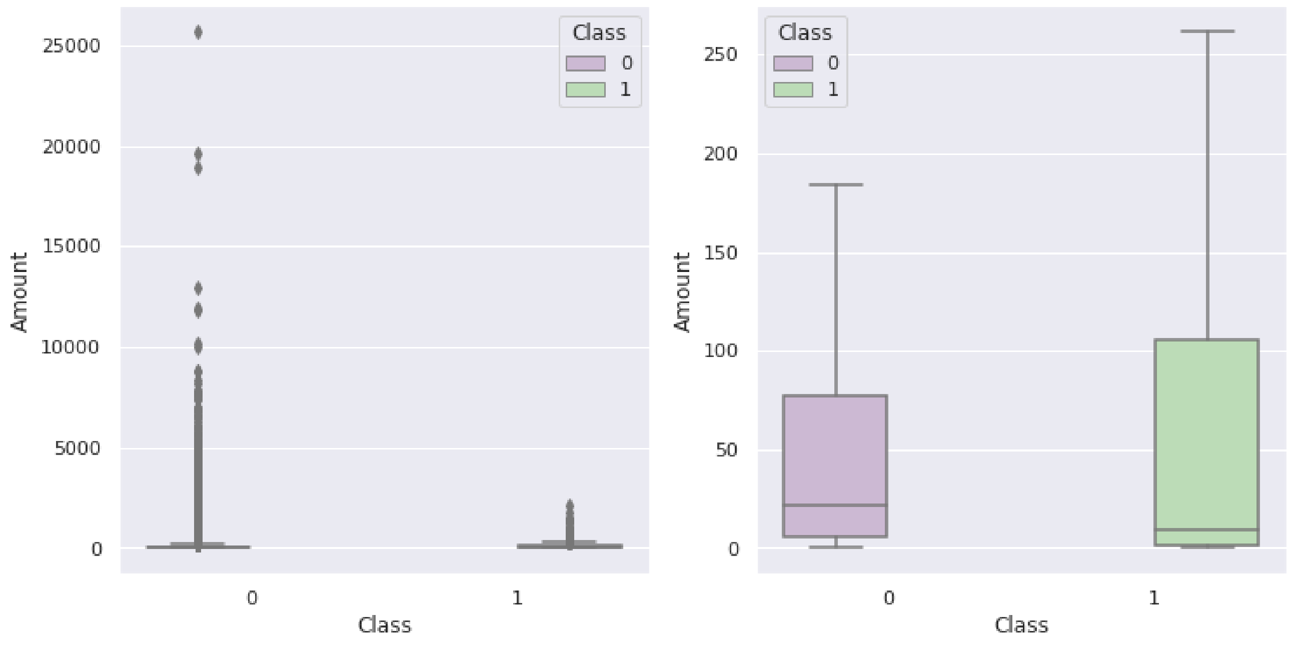
```
n_outliers = len(fraud)

for i, (clf_name, clf) in enumerate(classifiers.items()):
    # fit the data and tag outliers
    if clf_name == 'Local Outlier Factor':
        y_pred = clf.fit_predict(data)
        scores_pred = clf.negative_outlier_factor_
    else:
        clf.fit(data)
        scores_pred = clf.decision_function(data)
        y_pred = clf.predict(data)

    # reshape the prediction values to 0 for valid and 1 for fraud
    y_pred[y_pred == 1] = 0
    y_pred[y_pred == -1] = 1

    # calculate the number of errors
    n_errors = (y_pred != Y).sum()

    # classification matrix
    print('{}: {}'.format(clf_name, n_errors))
    print(accuracy_score(Y, y_pred))
    print(classification_report(Y, y_pred))
```

```
Isolation Forest: 558
0.9980407784921017
              precision    recall  f1-score   support

           0       1.00      1.00      1.00    284315
           1       0.42      0.38      0.40       492

    accuracy                           1.00    284807
   macro avg       0.71      0.69      0.70    284807
weighted avg       1.00      1.00      1.00    284807

Local Outlier Factor: 880
0.9969101883029561
              precision    recall  f1-score   support

           0       1.00      1.00      1.00    284315
           1       0.06      0.05      0.05       492

    accuracy                           1.00    284807
   macro avg       0.53      0.52      0.53    284807
weighted avg       1.00      1.00      1.00    284807
```

Transactions amount

Box Model - Data Analytics

```
fig, (ax1, ax2) = plt.subplots(ncols=2, figsize=(12,6))
s = sns.boxplot(ax = ax1, x="Class", y="Amount", hue="Class",data=data, palette="PRGn",sho
s = sns.boxplot(ax = ax2, x="Class", y="Amount", hue="Class",data=data, palette="PRGn",sho
plt.show();
```



```
tmp = data[['Amount','Class']].copy()
class_0 = tmp.loc[tmp['Class'] == 0]['Amount']
class_1 = tmp.loc[tmp['Class'] == 1]['Amount']
class_0.describe()
```

```
count    284315.000000
mean         88.291022
std         250.105092
min           0.000000
25%           5.650000
50%          22.000000
75%          77.050000
max       25691.160000
Name: Amount, dtype: float64
```

```
class_1.describe()
```

```
count     492.000000
mean      122.211321
std       256.683288
min         0.000000
25%         1.000000
50%         9.250000
75%       105.890000
max      2125.870000
Name: Amount, dtype: float64
```

Features correlation

```
data = pd.read_csv("creditcard.csv")
```

```
plt.figure(figsize = (14,14))
plt.title('Credit Card Transactions features correlation plot (Pearson)')
corr = data.corr()
corr = data.corr()
sns.heatmap(corr,xticklabels=corr.columns,yticklabels=corr.columns,linewidths=.1,cmap="Red
plt.show()
```

As expected, there is no notable correlation between features V1-V28. There are certain correlations between some of these features and Time (inverse correlation with V3) and Amount (direct correlation with V7 and V20, inverse correlation with V1 and V5).

Let's plot the correlated and inverse correlated values on the same graph.

Let's start with the direct correlated values: {V20;Amount} and {V7;Amount}.

```
s = sns.lmplot(x='V20', y='Amount',data=data, hue='Class', fit_reg=True,scatter_kws={'s':2
s = sns.lmplot(x='V7', y='Amount',data=data, hue='Class', fit_reg=True,scatter_kws={'s':2}
plt.show()
```

We can confirm that the two couples of features are correlated (the regression lines for Class = 0 have a positive slope, whilst the regression line for Class = 1 have a smaller positive slope).

Let's plot now the inverse correlated values.

```
s = sns.lmplot(x='V2', y='Amount',data=data, hue='Class', fit_reg=True,scatter_kws={'s':2}
s = sns.lmplot(x='V5', y='Amount',data=data, hue='Class', fit_reg=True,scatter_kws={'s':2}
plt.show()
plt.show()
```

We can confirm that the two couples of features are inverse correlated (the regression lines for Class = 0 have a negative slope while the regression lines for Class = 1 have a very small negative slope).

Features density plot

```
var = data.columns.values

i = 0
t0 = data.loc[data['Class'] == 0]
t1 = data.loc[data['Class'] == 1]
```

```
sns.set_style('whitegrid')
plt.figure()
fig, ax = plt.subplots(8,4,figsize=(16,28))

for feature in var:
    i += 1
    plt.subplot(8,4,i)
    sns.kdeplot(t0[feature], bw=0.5,label="Class = 0")
    sns.kdeplot(t1[feature], bw=0.5,label="Class = 1")
    plt.xlabel(feature, fontsize=12)
    locs, labels = plt.xticks()
    plt.tick_params(axis='both', which='major', labelsize=12)
plt.show();
```

For some of the features we can observe a good selectivity in terms of distribution for the two values of Class: V4, V11 have clearly separated distributions for Class values 0 and 1, V12, V14, V18 are partially separated, V1, V2, V3, V10 have a quite distinct profile, whilst V25, V26, V28 have similar profiles for the two values of Class.

In general, with just few exceptions (Time and Amount), the features distribution for legitimate transactions (values of Class = 0) is centered around 0, sometime with a long queue at one of the extremities. In the same time, the fraudulent transactions (values of Class = 1) have a skewed (asymmetric) distribution.

Predictive models - (please wait the process will take few minutes for output)

1.RandomForrestClassifier 2.AdaBoostClassifier 3.CatBoostClassifier ![alt text](![alt text](alt text))

```
target = 'Class'
predictors = ['Time', 'V1', 'V2', 'V3', 'V4', 'V5', 'V6', 'V7', 'V8', 'V9', 'V10',\
       'V11', 'V12', 'V13', 'V14', 'V15', 'V16', 'V17', 'V18', 'V19',\
       'V20', 'V21', 'V22', 'V23', 'V24', 'V25', 'V26', 'V27', 'V28',\
       'Amount']
```

```
#Split data in train, test and validation set
train_df, test_df = train_test_split(data, test_size=TEST_SIZE, random_state=RANDOM_STATE,
train_df, valid_df = train_test_split(train_df, test_size=VALID_SIZE, random_state=RANDOM_
```

1.RandomForestClassifier

model parameters Let's set the parameters for the model.

Let's run a model using the training set for training. Then, we will use the validation set for validation.

We will use as validation criterion GINI, which formula is GINI = 2 * (AUC) - 1, where AUC is the Receiver Operating Characteristic - Area Under Curve (ROC-AUC) [4]. Number of estimators is set to 100 and number of parallel jobs is set to 4.

We start by initializing the RandomForestClassifier.

```
clf = RandomForestClassifier(n_jobs=NO_JOBS,
                             random_state=RANDOM_STATE,
                             criterion=RFC_METRIC,
                             n_estimators=NUM_ESTIMATORS,
                             verbose=False)
```

```
clf.fit(train_df[predictors], train_df[target].values)
```

```
preds = clf.predict(valid_df[predictors])
```

```
tmp = pd.DataFrame({'Feature': predictors, 'Feature importance': clf.feature_importances_}
tmp = tmp.sort_values(by='Feature importance',ascending=False)
plt.figure(figsize = (7,4))
plt.title('Features importance',fontsize=14)
s = sns.barplot(x='Feature',y='Feature importance',data=tmp)
s.set_xticklabels(s.get_xticklabels(),rotation=90)
plt.show()
```

The most important features are V17, V12, V14, V10, V11, V16.

```
#Confusion matrix
cm = pd.crosstab(valid_df[target].values, preds, rownames=['Actual'], colnames=['Predicted
fig, (ax1) = plt.subplots(ncols=1, figsize=(5,5))
sns.heatmap(cm,
            xticklabels=['Not Fraud', 'Fraud'],
            yticklabels=['Not Fraud', 'Fraud'],
            annot=True,ax=ax1,
            linewidths=.2,linecolor="Darkblue", cmap="Blues")
plt.title('Confusion Matrix', fontsize=14)
plt.show()
```

```
#Area under curve
roc_auc_score(valid_df[target].values, preds)
```

ROC-AUC score obtained with RandomForrestClassifier is 0.85

2.AdaBoostClassifier

AdaBoostClassifier stands for Adaptive Boosting Classifier

```
clf = AdaBoostClassifier(random_state=RANDOM_STATE,
                         algorithm='SAMME.R',
                         learning_rate=0.8,
                             n_estimators=NUM_ESTIMATORS)
```

```
clf.fit(train_df[predictors], train_df[target].values)
```

```
preds = clf.predict(valid_df[predictors])
```

```
tmp = pd.DataFrame({'Feature': predictors, 'Feature importance': clf.feature_importances_}
tmp = tmp.sort_values(by='Feature importance',ascending=False)
plt.figure(figsize = (7,4))
plt.title('Features importance',fontsize=14)
s = sns.barplot(x='Feature',y='Feature importance',data=tmp)
s.set_xticklabels(s.get_xticklabels(),rotation=90)
plt.show()
```

```
#Confusion Matrix
cm = pd.crosstab(valid_df[target].values, preds, rownames=['Actual'], colnames=['Predicted
fig, (ax1) = plt.subplots(ncols=1, figsize=(5,5))
sns.heatmap(cm,
            xticklabels=['Not Fraud', 'Fraud'],
            yticklabels=['Not Fraud', 'Fraud'],
            annot=True,ax=ax1,
            linewidths=.2,linecolor="Darkblue", cmap="Blues")
plt.title('Confusion Matrix', fontsize=14)
plt.show()
```

```
#Area under curve
roc_auc_score(valid_df[target].values, preds)
```

ROC-AUC score obtained with AdaBoostClassifier is 0.83

3.CatBoostClassifier

CatBoostClassifier is a gradient boosting for decision trees algorithm with support for handling categorical data

```
clf = CatBoostClassifier(iterations=500,
                             learning_rate=0.02,
                             depth=12,
                             eval_metric='AUC',
                             random_seed = RANDOM_STATE,
                             bagging_temperature = 0.2,
                             od_type='Iter',
                             metric_period = VERBOSE_EVAL,
                             od_wait=100)
```

```
clf.fit(train_df[predictors], train_df[target].values,verbose=True)
```

```
preds = clf.predict(valid_df[predictors])
```

```
tmp = pd.DataFrame({'Feature': predictors, 'Feature importance': clf.feature_importances_}
tmp = tmp.sort_values(by='Feature importance',ascending=False)
plt.figure(figsize = (7,4))
plt.title('Features importance',fontsize=14)
s = sns.barplot(x='Feature',y='Feature importance',data=tmp)
s.set_xticklabels(s.get_xticklabels(),rotation=90)
plt.show()
```

```
#Confusion Matrix
cm = pd.crosstab(valid_df[target].values, preds, rownames=['Actual'], colnames=['Predicted
fig, (ax1) = plt.subplots(ncols=1, figsize=(5,5))
sns.heatmap(cm,
            xticklabels=['Not Fraud', 'Fraud'],
            yticklabels=['Not Fraud', 'Fraud'],
            annot=True,ax=ax1,
            linewidths=.2,linecolor="Darkblue", cmap="Blues")
plt.title('Confusion Matrix', fontsize=14)
plt.show()
```

```
#Area Under Curve
roc_auc_score(valid_df[target].values, preds)
```

ROC-AUC score obtained with CatBoostClassifier is 0.86

Training and validation using cross-validation Let's use now cross-validation. We will use cross-validation (KFolds) with 5 folds. Data is divided in 5 folds and, by rotation, we are training using 4 folds (n-1) and validate using the 5th (nth) fold.

Test set is calculated as an average of the predictions

```
kf = KFold(n_splits = NUMBER_KFOLDS, random_state = RANDOM_STATE, shuffle = True)

# Create arrays and dataframes to store results
oof_preds = np.zeros(train_df.shape[0])
test_preds = np.zeros(test_df.shape[0])
feature_importance_df = pd.DataFrame()
n_fold = 0
for train_idx, valid_idx in kf.split(train_df):
    train_x, train_y = train_df[predictors].iloc[train_idx],train_df[target].iloc[train_id
    valid_x, valid_y = train_df[predictors].iloc[valid_idx],train_df[target].iloc[valid_id

    evals_results = {}
    model =  LGBMClassifier(
                  nthread=-1,
                  n_estimators=2000,
                  learning_rate=0.01,
                  num_leaves=80,
                  colsample_bytree=0.98,
                  subsample=0.78,
                  reg_alpha=0.04,
                  reg_lambda=0.073,
                  subsample_for_bin=50,
                  boosting_type='gbdt',
                  is_unbalance=False,
                  min_split_gain=0.025,
                  min_child_weight=40,
                  min_child_samples=510,
                  objective='binary',
                  metric='auc',
                  silent=-1,
                  verbose=-1,
                  feval=None)
    model.fit(train_x, train_y, eval_set=[(train_x, train_y), (valid_x, valid_y)],
                eval_metric= 'auc', verbose= VERBOSE_EVAL, early_stopping_rounds= EARLY_ST

    oof_preds[valid_idx] = model.predict_proba(valid_x, num_iteration=model.best_iteration
    test_preds += model.predict_proba(test_df[predictors], num_iteration=model.best_iterat
    fold_importance_df = pd.DataFrame()
    fold_importance_df["feature"] = predictors
    fold_importance_df["importance"] = clf.feature_importances_
    fold_importance_df["fold"] = n_fold + 1

    feature_importance_df = pd.concat([feature_importance_df, fold_importance_df], axis=0)
    print('Fold %2d AUC : %.6f' % (n_fold + 1, roc_auc_score(valid_y, oof_preds[valid_idx]
    del model, train_x, train_y, valid_x, valid_y
    gc.collect()
    n_fold = n_fold + 1
train_auc_score = roc_auc_score(train_df[target], oof_preds)
print('Full AUC score %.6f' % train_auc_score)
```

We investigated the data, checking for data unbalancing, visualizing the features and understanding the relationship between different features. We then investigated two predictive models. The data was split in 3 parts, a train set, a validation set and a test set. For the first three models, we only used the train and test set.

We started with RandomForrestClassifier, for which we obtained an AUC scode of 0.85 when predicting the target for the test set.

We followed with an AdaBoostClassifier model, with lower AUC score (0.83) for prediction of the test set target values.

We then followed with an CatBoostClassifier, with the AUC score after training 500 iterations 0.86. For the test set, the score obtained was 0.946. With the cross-validation, we obtained an

AUC score for the test prediction of 0.93.

Note:Please note that the Data Set when it is uploaded then only it will work