Context

It is important that credit card companies are able to recognize fraudulent credit card transactions so that customers are not charged for items that they did not purchase.

Content

The datasets contains transactions made by credit cards in September 2013 by european cardholders. This dataset presents transactions that occurred in two days, where we have 492 frauds out of 284,807 transactions. The dataset is highly unbalanced, the positive class (frauds) account for 0.172% of all transactions.

It contains only numerical input variables which are the result of a PCA transformation. Unfortunately, due to confidentiality issues, we cannot provide the original features and more background information about the data. Features V1, V2, ... V28 are the principal components obtained with PCA, the only features which have not been transformed with PCA are 'Time' and 'Amount'. Feature 'Time' contains the seconds elapsed between each transaction and the first transaction in the dataset. The feature 'Amount' is the transaction Amount, this feature can be used for example-dependant cost-senstive learning. Feature 'Class' is the response variable and it takes value 1 in case of fraud and 0 otherwise.

Acknowledgements

The dataset has been collected and analysed during a research collaboration of Worldline and the Machine Learning Group (http://mlg.ulb.ac.be (http://mlg.ulb.ac.be)) of ULB (Université Libre de Bruxelles) on big data mining and fraud detection. More details on current and past projects on related topics are available on http://mlg.ulb.ac.be/BruFence (http://mlg.ulb.ac.be/BruFence) and http://mlg.ulb.ac.be/ARTML (http://mlg.ulb.ac.be/ARTML)

Please cite: Andrea Dal Pozzolo, Olivier Caelen, Reid A. Johnson and Gianluca Bontempi. Calibrating Probability with Undersampling for Unbalanced Classification. In Symposium on Computational Intelligence and Data Mining (CIDM), IEEE, 2015

Importing required Libraries

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import StratifiedKFold, train_test_split
from sklearn.metrics import confusion_matrix, cohen_kappa_score, classification_re
port
from sklearn.metrics import r2_score, roc_auc_score
from sklearn.metrics import average_precision_score, auc, roc_curve, precision_rec
all_curve

from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.neural_network import MLPClassifier
from xgboost import XGBClassifier

from sklearn.preprocessing import StandardScaler
import seaborn as sns
from imblearn.over_sampling import SMOTE

import featuretools as ft
import gc

%matplotlib inline
sns.set(style='whitegrid', palette='inferno', font_scale=1.5)

import warnings
warnings.filterwarnings(action="ignore")
```

```
Using TensorFlow backend.
```

In [2]:
```
# load the data
data = pd.read_csv("../input/creditcard.csv")
```

Exploratory Data Analysis

In [3]:
```
# get column names
colNames = data.columns.values
colNames
```

Out[3]:
```
array(['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)
```

In [4]:
```
# get dataframe dimensions
print ("Dimension of dataset:", data.shape)
```

```
Dimension of dataset: (284807, 31)
```

In [5]:
```
# get attribute summaries
print(data.describe())
```

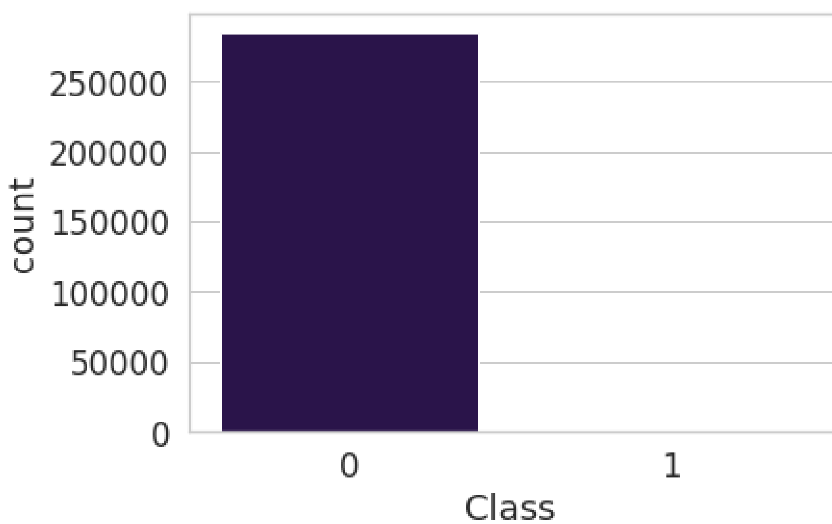
```
                Time            V1      ...            Amount          Class
count  284807.000000  2.848070e+05      ...     284807.000000  284807.000000
mean    94813.859575  3.919560e-15      ...         88.349619       0.001727
std     47488.145955  1.958696e+00      ...        250.120109       0.041527
min         0.000000 -5.640751e+01      ...          0.000000       0.000000
25%     54201.500000 -9.203734e-01      ...          5.600000       0.000000
50%     84692.000000  1.810880e-02      ...         22.000000       0.000000
75%    139320.500000  1.315642e+00      ...         77.165000       0.000000
max    172792.000000  2.454930e+00      ...      25691.160000       1.000000

[8 rows x 31 columns]
```

In [6]:
```
# get class distribution
print ("Normal transaction:", data['Class'][data['Class']==0].count()) #class = 0
print ("Fraudulent transaction:", data['Class'][data['Class']==1].count()) #class
 = 1
```

```
Normal transaction: 284315
Fraudulent transaction: 492
```

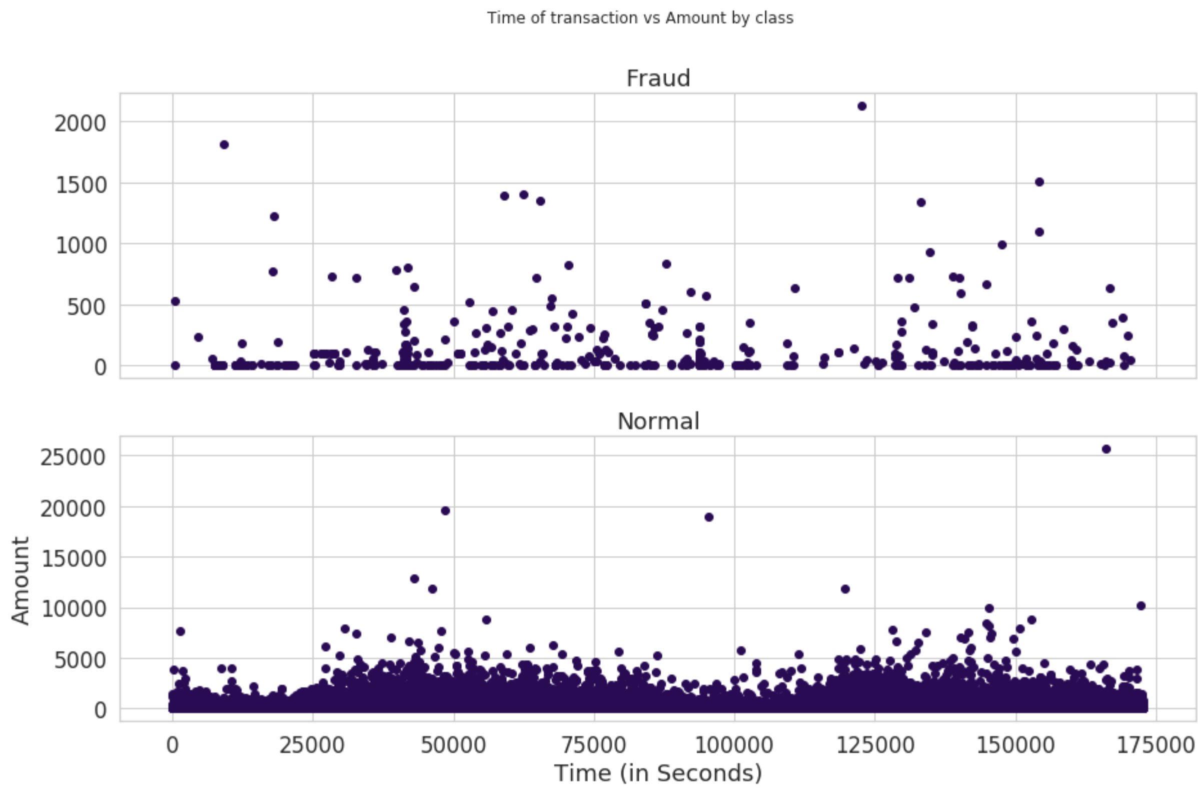
In [7]:
```
sns.countplot(data['Class'])
```

Out[7]: <matplotlib.axes._subplots.AxesSubplot at 0x7f45cb151d30>



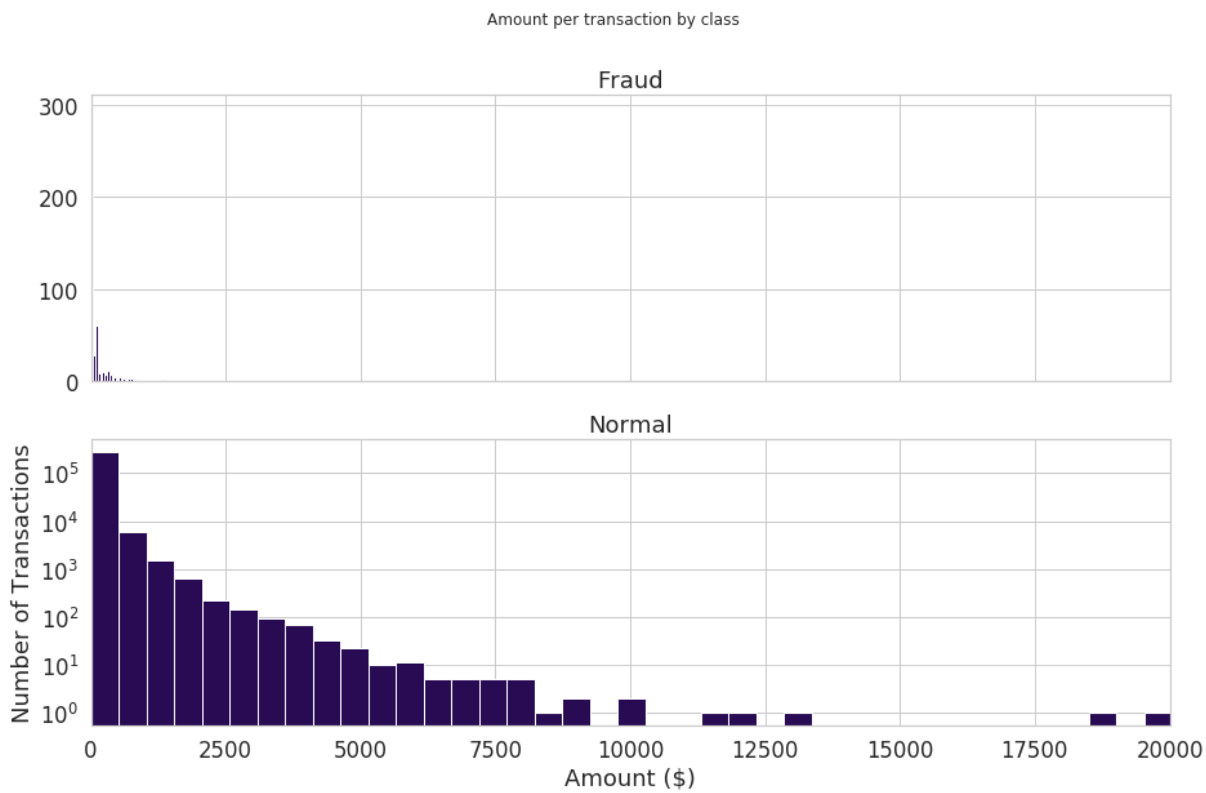
In [8]:
```
# separate classes into different datasets
normal_class = data.query('Class == 0')
fraudulent_class = data.query('Class == 1')

# randomize the datasets
normal_class = normal_class.sample(frac=1,random_state=1210)
fraudulent_class = fraudulent_class.sample(frac=1,random_state=1210)
```

In [9]:
```
f, (ax1, ax2) = plt.subplots(2, 1, sharex=True, figsize=(15,9))
f.suptitle('Time of transaction vs Amount by class')

ax1.scatter(fraudulent_class.Time, fraudulent_class.Amount)
ax1.set_title('Fraud')

ax2.scatter(normal_class.Time, normal_class.Amount)
ax2.set_title('Normal')

plt.xlabel('Time (in Seconds)')
plt.ylabel('Amount')
plt.show()
```



The above graph shows that Time is irrelevent for detecting fraudulent transactions

In [10]:
```
f, (ax1, ax2) = plt.subplots(2, 1, sharex=True, figsize=(15,9))
f.suptitle('Amount per transaction by class')

bins = 50

ax1.hist(fraudulent_class.Amount, bins = bins)
ax1.set_title('Fraud')

ax2.hist(normal_class.Amount, bins = bins)
ax2.set_title('Normal')

plt.xlabel('Amount ($)')
plt.ylabel('Number of Transactions')
plt.xlim((0, 20000))
plt.yscale('log')
plt.show();
```



The above graph shows that most of the fraudulent transactions are of very low amount

In [11]:
```
data = data.drop(['Time'], axis=1)
data['Amount'] = StandardScaler().fit_transform(data['Amount'].values.reshape(-1,
1))
```

In [12]:
```
# separate classes into different datasets
normal_class = data.query('Class == 0')
fraudulent_class = data.query('Class == 1')

# randomize the datasets
normal_class = normal_class.sample(frac=1,random_state=1210)
fraudulent_class = fraudulent_class.sample(frac=1,random_state=1210)
```

Oversampling to deal with class imbalance

The examples of the majority class, in this case the normal transactions, drastically outnumber the incidences of fraudulent transactions in our dataset. One of the strategies employed in the data science community is to generate synthetic data points for under-represented class to improve the learning function.

In [13]:
```
X = data.drop(['Class'], axis = 1)

y = data['Class']
```

In [14]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_st
ate=1210)
```

In [15]:
```
X_train.head()
```

Out[15]:

	V1	V2	V3	V4	V5	V6	V7	V8
173987	2.127226	-1.643078	-1.159414	-1.518021	-1.149425	-0.442776	-0.984404	-0.202669
77761	1.177903	-0.929866	0.319984	-0.498674	-1.066237	-0.232614	-0.642941	0.128873
91298	1.221186	-0.295558	0.410340	-0.284122	-0.590148	-0.096934	-0.554816	0.273252
221298	2.048182	0.638386	-2.351720	0.774162	0.583337	-1.801964	0.422012	-0.450297
24116	1.253101	-0.328803	0.724816	0.754850	-0.758306	0.096501	-0.513748	0.000848

In [16]:
```
gc.collect()
```

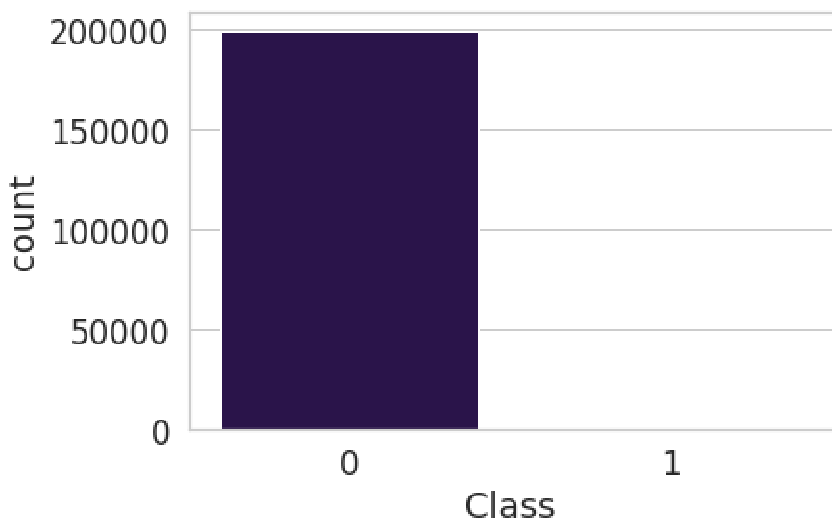
Out[16]: 8295

In [17]:
```
def score(model, test = X_test, y_true = y_test):

    pred = model.predict(test)

    print('Average precision-recall score RF:\t', round(average_precision_score(y_
true, pred),4)*100)
    print()
    print("Cohen's Kappa Score:\t",round(cohen_kappa_score(y_true,pred),4)*100)
    print()
    print("R-Squared Score:\t",round(r2_score(y_true,pred),4)*100)
    print()
    print("Area Under ROC Curve:\t",round(roc_auc_score(y_true,pred),4)*100)
    print()
    print(classification_report(y_true,pred))


    precision, recall, _ = precision_recall_curve(y_true, pred)

    plt.step(recall, precision, color='b', alpha=0.2, where='post')

    plt.fill_between(recall, precision, step='post', alpha=0.2, color='b')

    plt.xlabel('Recall')
    plt.ylabel('Precision')
    plt.ylim([0.0, 1.05])
    plt.xlim([0.0, 1.0])
    plt.title('2-class Precision-Recall curve: AP={0:0.2f}'.format(average_precisi
on_score(y_true, pred)))



    fpr_rf, tpr_rf, _ = roc_curve(y_true, pred)
    roc_auc_rf = auc(fpr_rf, tpr_rf)
    plt.figure(figsize=(8,8))
    plt.xlim([-0.01, 1.00])
    plt.ylim([-0.01, 1.01])
    plt.step(fpr_rf, tpr_rf, lw=1, label='{} curve (AUC = {:0.2f})'.format('RF',ro
c_auc_rf))
    #plt.fill_between(fpr_rf, tpr_rf, step='post', alpha=0.2, color='b')


    plt.xlabel('False Positive Rate', fontsize=16)
    plt.ylabel('True Positive Rate', fontsize=16)
    plt.title('ROC curve', fontsize=16)
    plt.legend(loc='lower right', fontsize=13)
    plt.plot([0, 1], [0, 1], color='navy', lw=1, linestyle='--')
    plt.axes().set_aspect('equal')
    plt.show()
```

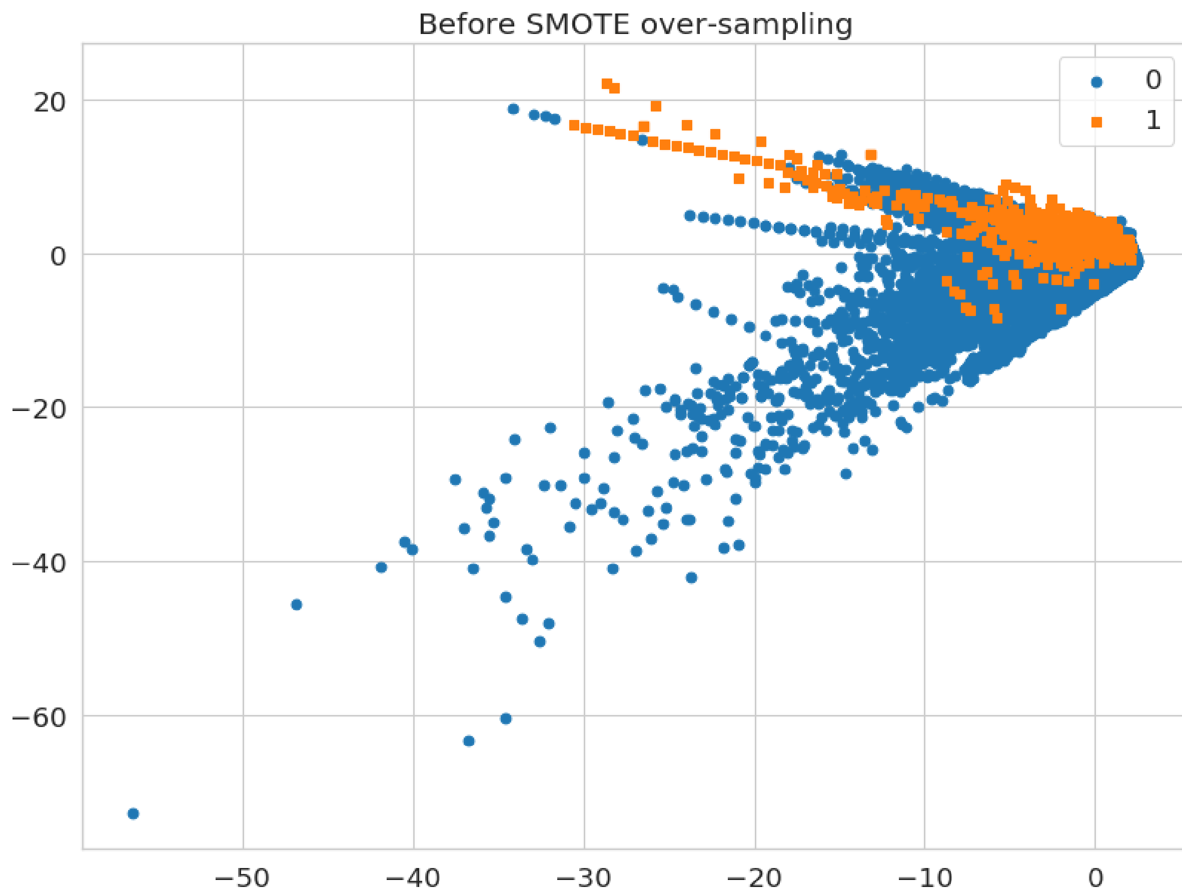
In [18]:
```
def plot_2d_space(X, y, label='Classes'):
    colors = ['#1F77B4', '#FF7F0E']
    markers = ['o', 's']
    plt.figure(figsize=(12, 9), dpi=80)
    for l, c, m in zip(np.unique(y), colors, markers):
        plt.scatter(X[y==l, 0], X[y==l, 1], c=c, label=l, marker=m)
    plt.title(label)
    plt.legend(loc='upper right')
    plt.show()
```

In [19]:
```
#np.unique(y_train, return_counts= True)
sns.countplot(y_train)
```

Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0x7f45c5b54710>

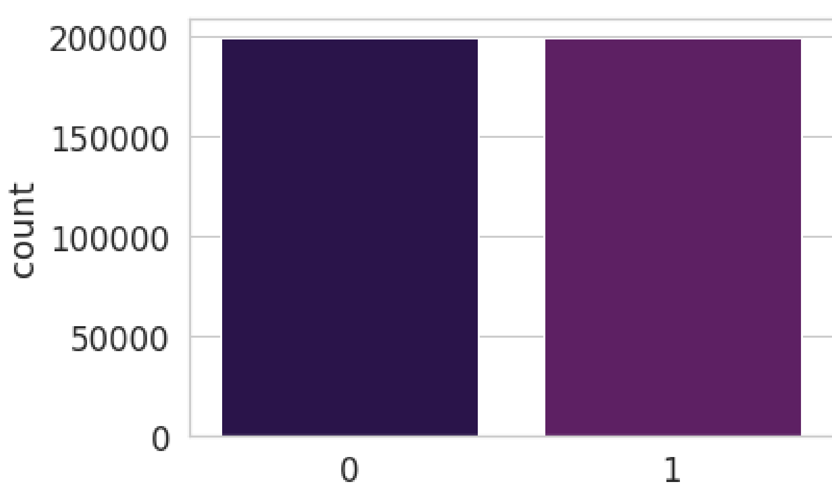


In [20]:
```
plot_2d_space(np.array(X), np.array(y), 'Before SMOTE over-sampling')
```

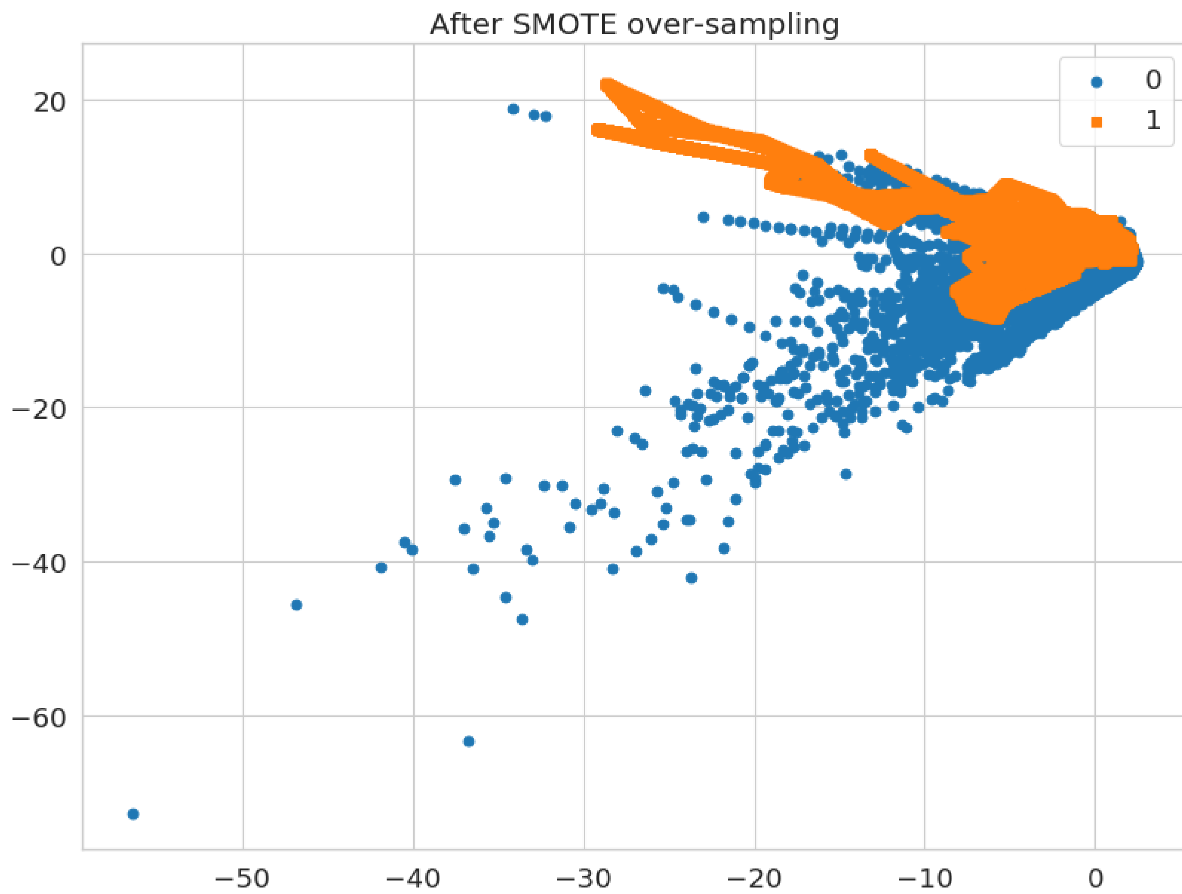


In [21]:
```
smote = SMOTE(ratio='minority', random_state=1210)
X_sm, y_sm = smote.fit_sample(X_train, y_train)

#np.unique(y_sm, return_counts= True)
sns.countplot(y_sm)
```

Out[21]: <matplotlib.axes._subplots.AxesSubplot at 0x7f45bab55fd0>



In [22]:
```
plot_2d_space(X_sm, y_sm, 'After SMOTE over-sampling')
```

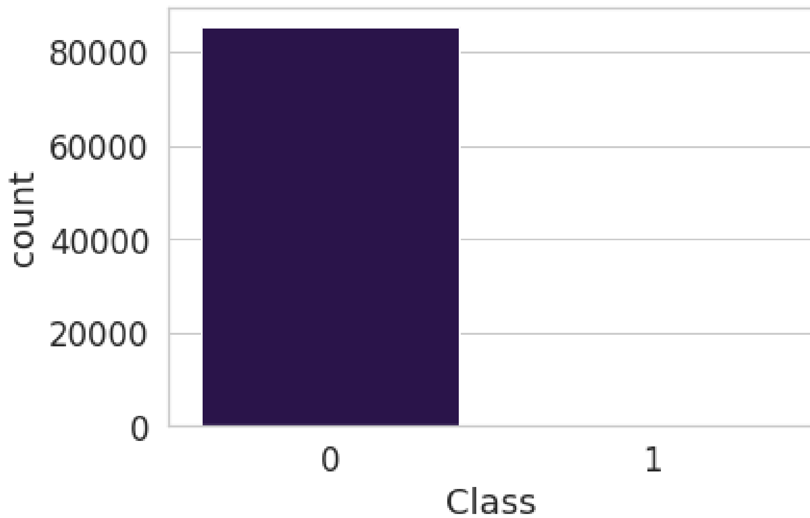


Time to train and test the performance of various models

In [23]:
```
# See category counts for test data
category, records = np.unique(y_test, return_counts= True)
cat_counts = dict(zip(category,records))

print(cat_counts)
sns.countplot(y_test)
```

```
{0: 85319, 1: 124}
```

Out[23]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f45c5a24518>
```



Random Forest Classifier

In [24]:
```
rf_model = RandomForestClassifier(n_estimators=500,verbose=1,n_jobs=8)
```

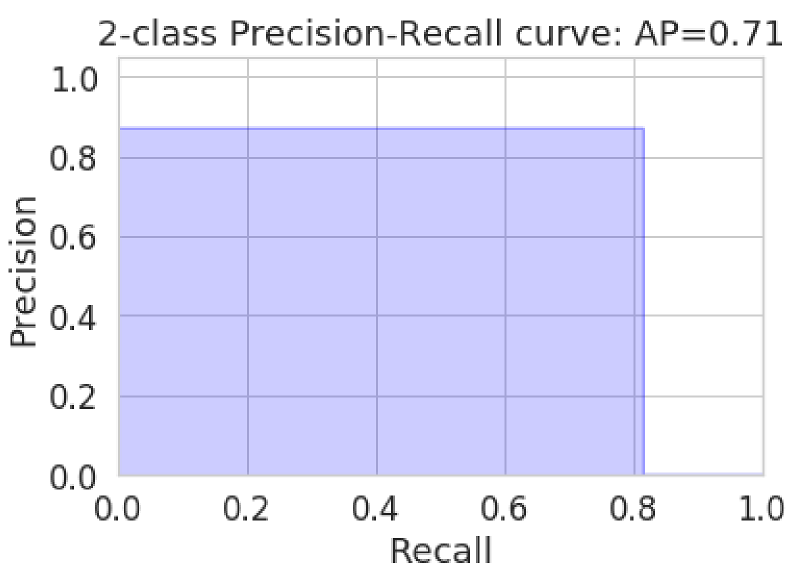
In [25]:
```
rf_model.fit(X_sm,y_sm)
```

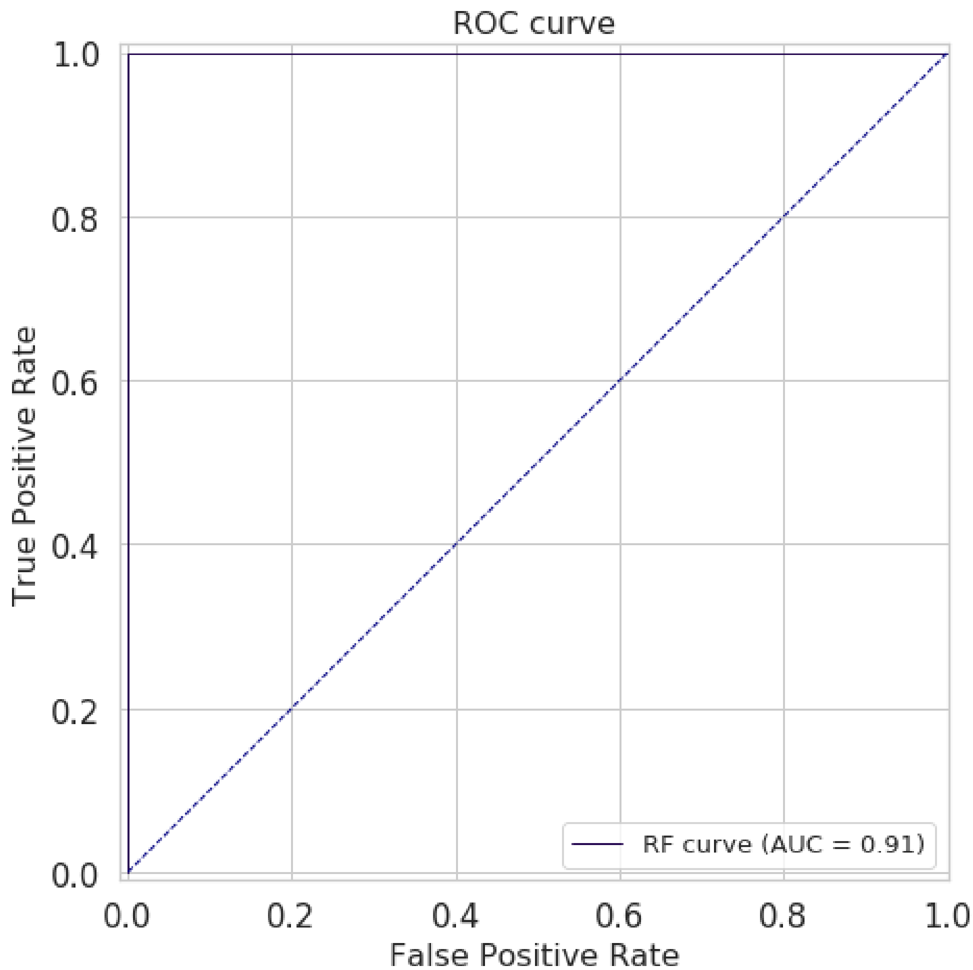
```
[Parallel(n_jobs=8)]: Using backend ThreadingBackend with 8 concurrent workers.
[Parallel(n_jobs=8)]: Done  34 tasks      | elapsed:   53.1s
[Parallel(n_jobs=8)]: Done 184 tasks      | elapsed:  4.4min
[Parallel(n_jobs=8)]: Done 434 tasks      | elapsed: 10.3min
[Parallel(n_jobs=8)]: Done 500 out of 500 | elapsed: 11.7min finished
```

Out[25]:
```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                       max_depth=None, max_features='auto', max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=500, n_jobs=8,
                       oob_score=False, random_state=None, verbose=1,
                       warm_start=False)
```

In [26]:
```
score(rf_model)
```

```
[Parallel(n_jobs=8)]: Using backend ThreadingBackend with 8 concurrent workers.
[Parallel(n_jobs=8)]: Done  34 tasks      | elapsed:    0.2s
[Parallel(n_jobs=8)]: Done 184 tasks      | elapsed:    0.9s
[Parallel(n_jobs=8)]: Done 434 tasks      | elapsed:    2.0s
[Parallel(n_jobs=8)]: Done 500 out of 500 | elapsed:    2.3s finished

Average precision-recall score RF:       70.95

Cohen's Kappa Score:     84.14

R-Squared Score:         69.31

Area Under ROC Curve:    90.72

              precision    recall  f1-score   support

           0       1.00      1.00      1.00     85319
           1       0.87      0.81      0.84       124

   micro avg       1.00      1.00      1.00     85443
   macro avg       0.94      0.91      0.92     85443
weighted avg       1.00      1.00      1.00     85443
```





XGBoost Classifier

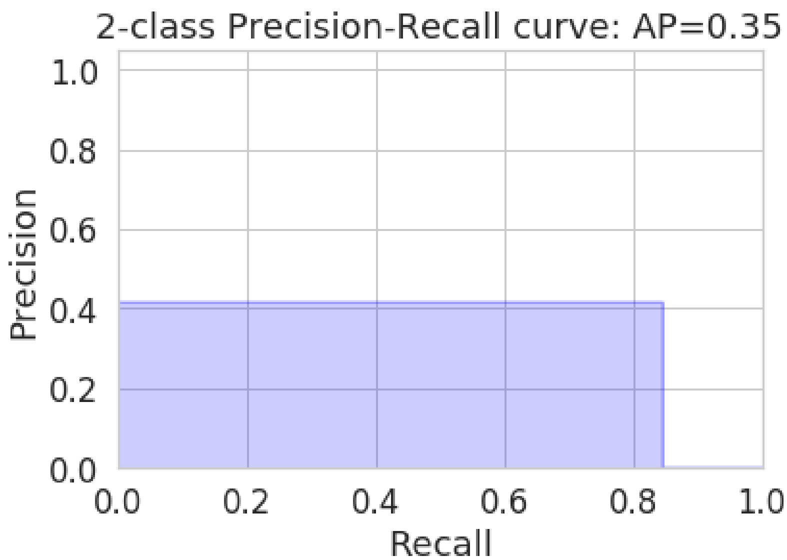
In [27]:
```
xgb_model = XGBClassifier(n_estimators=500, n_jobs=8)

xgb_model.fit(X_sm,y_sm)
```

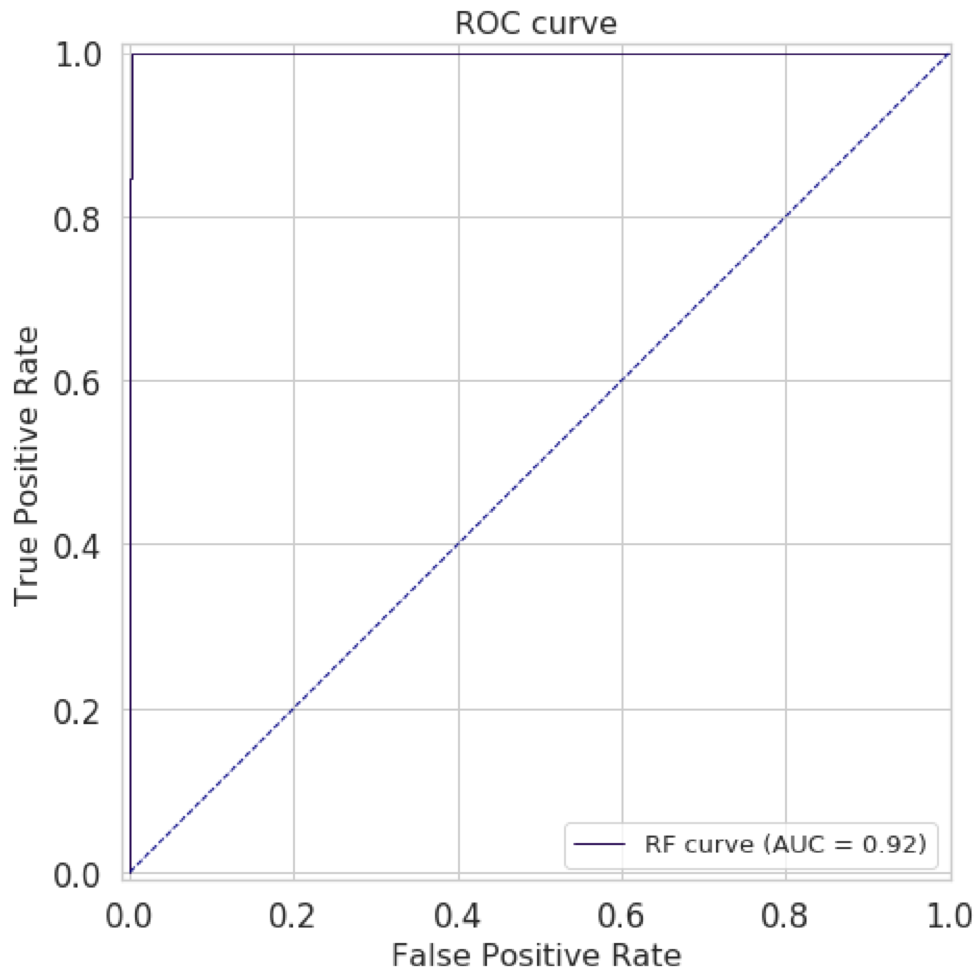
Out[27]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
       colsample_bytree=1, gamma=0, learning_rate=0.1, max_delta_step=0,
       max_depth=3, min_child_weight=1, missing=None, n_estimators=500,
       n_jobs=8, nthread=None, objective='binary:logistic', random_state=0,
       reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
       silent=True, subsample=1)
```

In [28]:

```
score(xgb_model, test= np.array(X_test))
```

```
Average precision-recall score RF:       35.449999999999996

Cohen's Kappa Score:      55.910000000000004

R-Squared Score:          -33.26

Area Under ROC Curve:     92.25

              precision    recall  f1-score   support

           0       1.00      1.00      1.00     85319
           1       0.42      0.85      0.56       124

   micro avg       1.00      1.00      1.00     85443
   macro avg       0.71      0.92      0.78     85443
weighted avg       1.00      1.00      1.00     85443
```





Logistic Regression

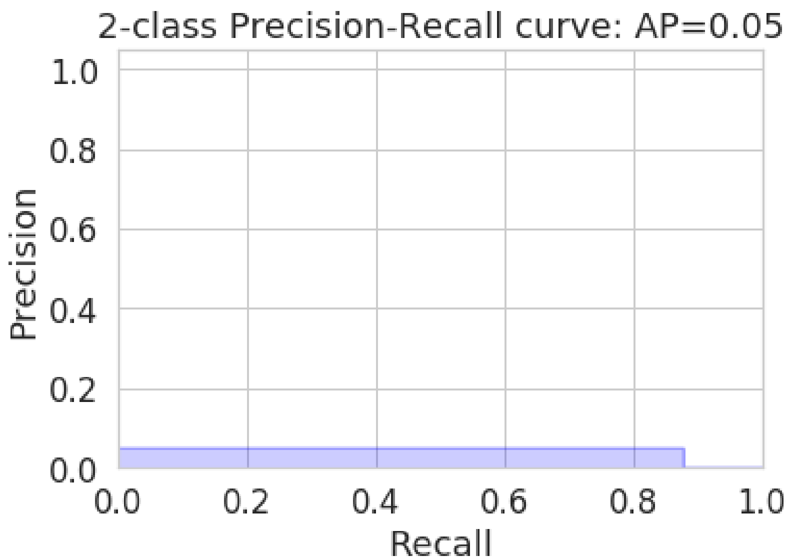
In [29]:
```
lr_model = LogisticRegression(max_iter=1000)

lr_model.fit(X_sm,y_sm)
```

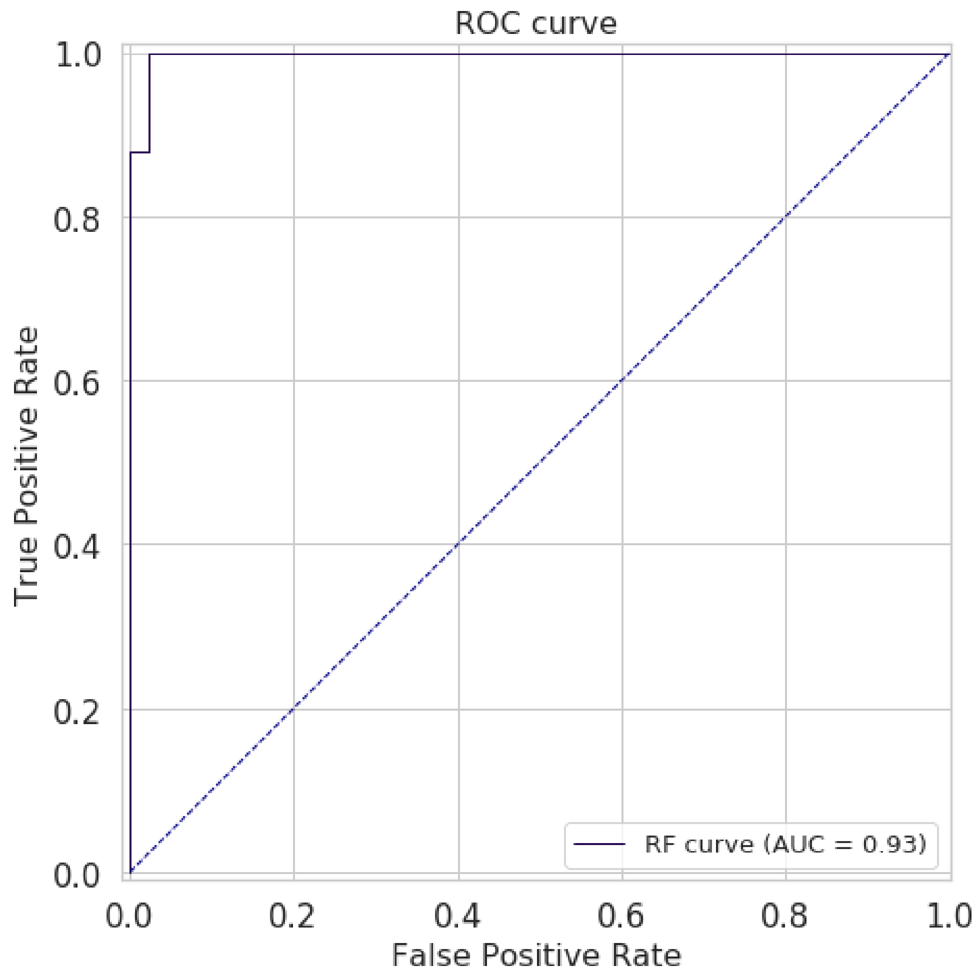
Out[29]:
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=1000, multi_class='warn',
          n_jobs=None, penalty='l2', random_state=None, solver='warn',
          tol=0.0001, verbose=0, warm_start=False)
```

In [30]:
```
score(lr_model)
```

```
Average precision-recall score RF:       4.6

Cohen's Kappa Score:      9.59

R-Squared Score:          -1513.63

Area Under ROC Curve:     92.78999999999999
```

	precision	recall	f1-score	support
0	1.00	0.98	0.99	85319
1	0.05	0.88	0.10	124
micro avg	0.98	0.98	0.98	85443
macro avg	0.53	0.93	0.54	85443
weighted avg	1.00	0.98	0.99	85443





Light GBM

In [31]:
```
import lightgbm
```

In [32]:
```
lgbm = lightgbm.LGBMClassifier(n_estimators=1000, verbose=1)
```

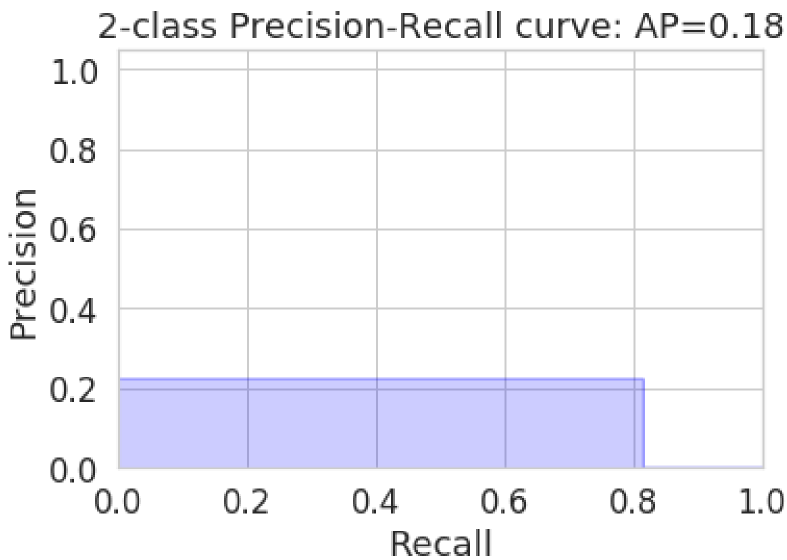
In [33]:
```
lgbm.fit(X_sm, y_sm)
```

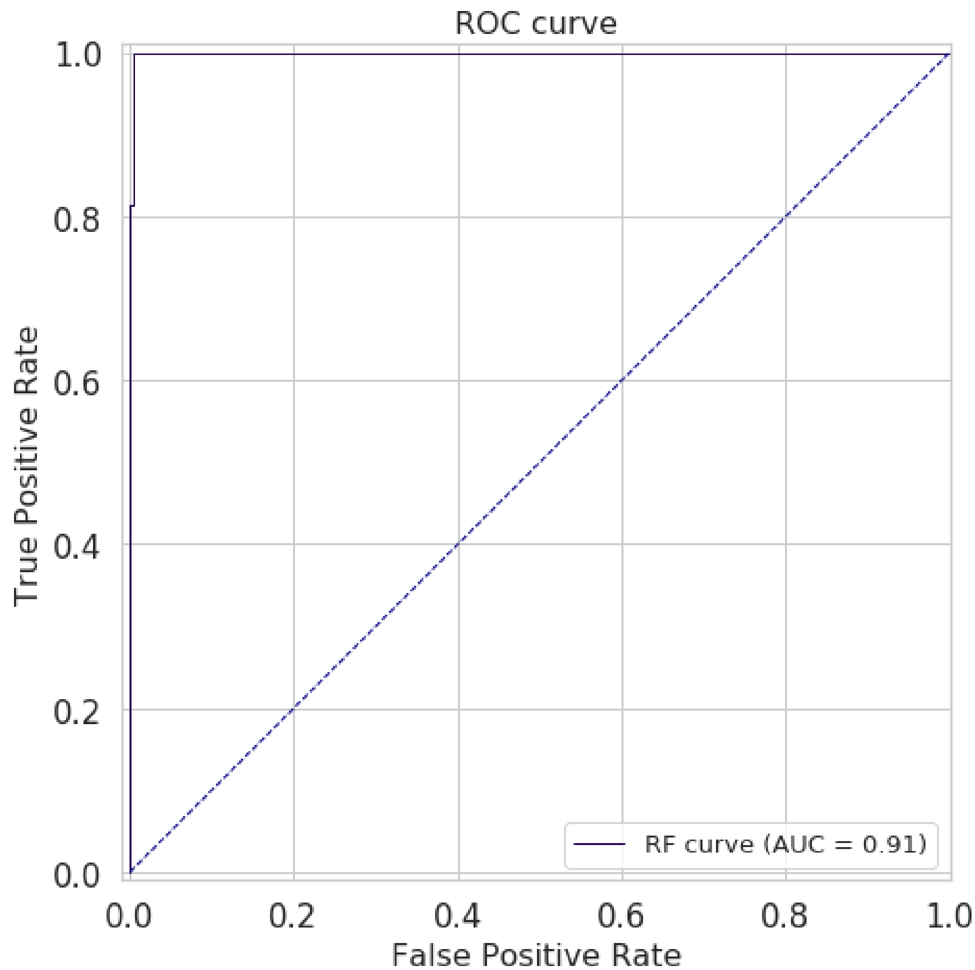
Out[33]:
```
LGBMClassifier(boosting_type='gbdt', class_weight=None, colsample_bytree=1.0,
               importance_type='split', learning_rate=0.1, max_depth=-1,
               min_child_samples=20, min_child_weight=0.001, min_split_gain=0.0,
               n_estimators=1000, n_jobs=-1, num_leaves=31, objective=None,
               random_state=None, reg_alpha=0.0, reg_lambda=0.0, silent=True,
               subsample=1.0, subsample_for_bin=200000, subsample_freq=0,
               verbose=1)
```

In [34]:
```
score(lgbm)
```

```
Average precision-recall score RF:       18.27

Cohen's Kappa Score:     34.98

R-Squared Score:         -201.24

Area Under ROC Curve:    90.52
```

	precision	recall	f1-score	support
0	1.00	1.00	1.00	85319
1	0.22	0.81	0.35	124
micro avg	1.00	1.00	1.00	85443
macro avg	0.61	0.91	0.67	85443
weighted avg	1.00	1.00	1.00	85443





We can see that SMOTE doesn't give us very good results no matter which algorithm we try. I believe this is because we don't have enough **actual** fraudulent samples and the patterns just get lost in between so many non-fraudulent transaction samples.

Time to try Random Under-Sampling

In [35]:
```
normal_class.head(3)
```

Out[35]:

	V1	V2	V3	V4	V5	V6	V7	V8
50830	-2.451616	1.973770	0.902784	1.595978	-1.805211	0.841257	-1.597407	2.246228
179064	0.421688	0.945353	-1.211215	1.097346	0.487790	-0.288520	0.788650	-0.491782
10158	-0.611302	0.557936	2.105733	-0.156311	0.185058	1.391241	-0.391631	0.338555

In [36]:
```
fraudulent_class.head(3)
```

Out[36]:

	V1	V2	V3	V4	V5	V6	V7	V8
81186	-4.384221	3.264665	-3.077158	3.403594	-1.938075	-1.221081	-3.310317	-1.111975
226877	-6.423306	1.658515	-5.866440	2.052064	-0.615817	-3.372266	-5.036556	2.643106
42009	-2.740483	3.658095	-4.110636	5.340242	-2.666775	-0.092782	-4.388699	-0.280133

In [37]:
```
resampled = normal_class.sample(n=int(len(fraudulent_class)*3), random_state=1210)
```

In [38]:
```
len(resampled)
```

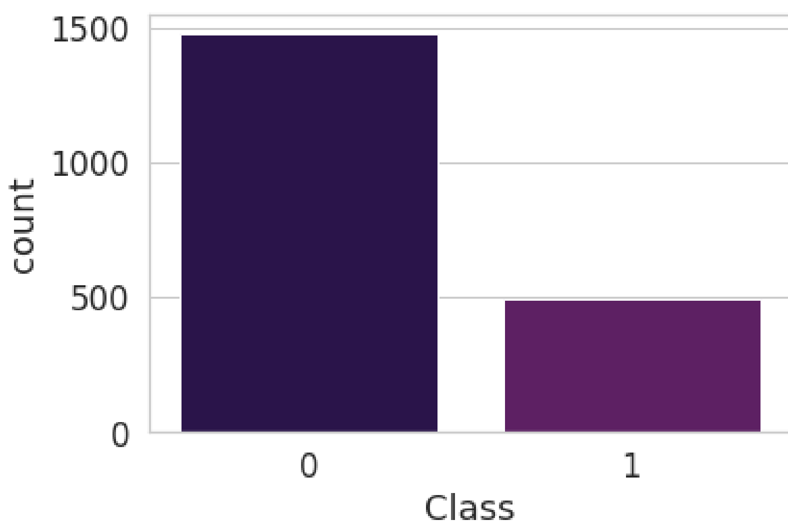
Out[38]: 1476

In [39]:
```
data = pd.concat([fraudulent_class,resampled])
```

In [40]:
```
X_tr, X_te, y_tr, y_te = train_test_split(data.drop('Class',axis=1), data['Class'
], test_size=0.2, random_state=1210)
```

In [41]:
```
sns.countplot(data['Class'])
```

Out[41]: <matplotlib.axes._subplots.AxesSubplot at 0x7f45b86e4da0>



In [42]:

```
score(RandomForestClassifier(n_estimators=500,random_state=1210).fit(X_tr,y_tr),te
st=X_te, y_true=y_te)
```

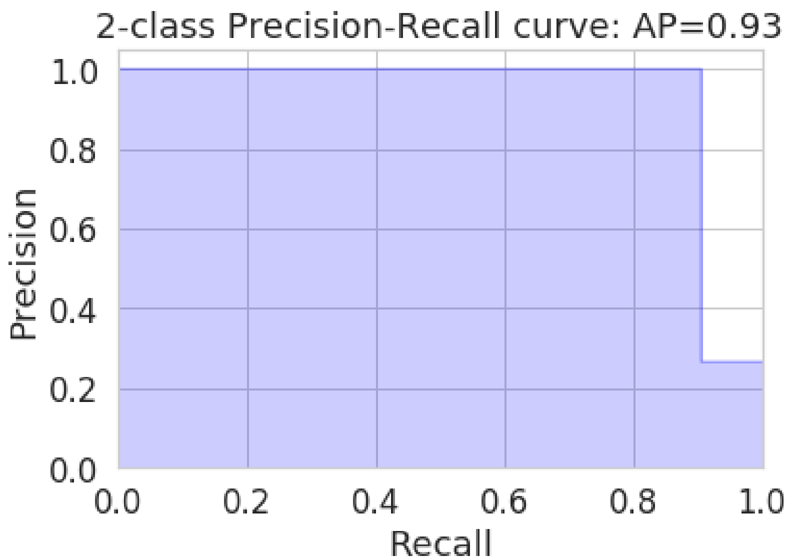
Average precision-recall score RF: 93.01

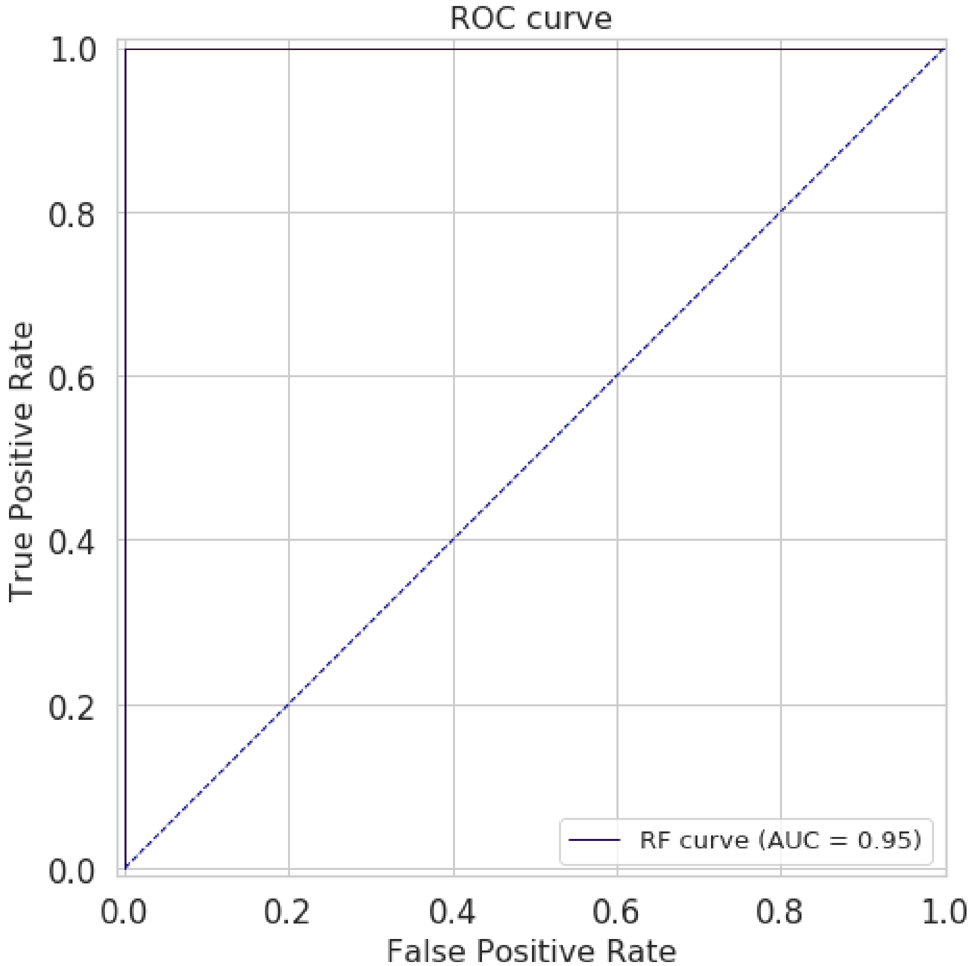
Cohen's Kappa Score: 93.31

R-Squared Score: 87.02

Area Under ROC Curve: 95.24000000000001

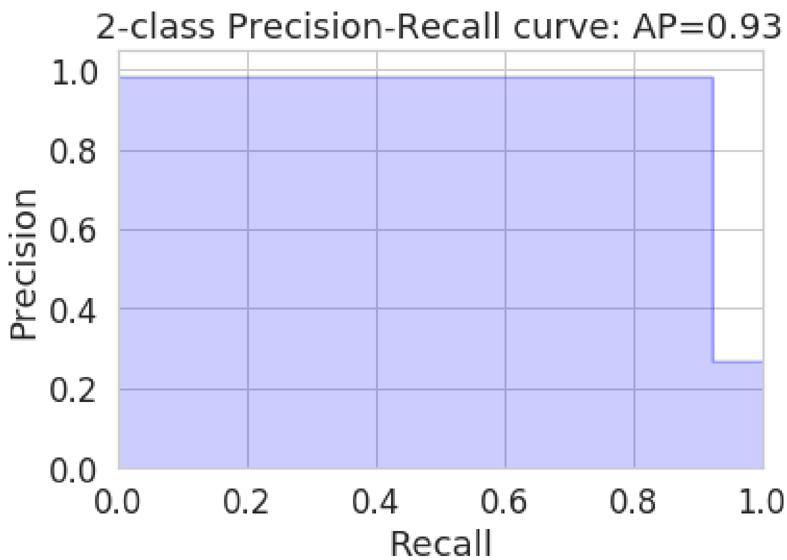
	precision	recall	f1-score	support
0	0.97	1.00	0.98	289
1	1.00	0.90	0.95	105
micro avg	0.97	0.97	0.97	394
macro avg	0.98	0.95	0.97	394
weighted avg	0.98	0.97	0.97	394

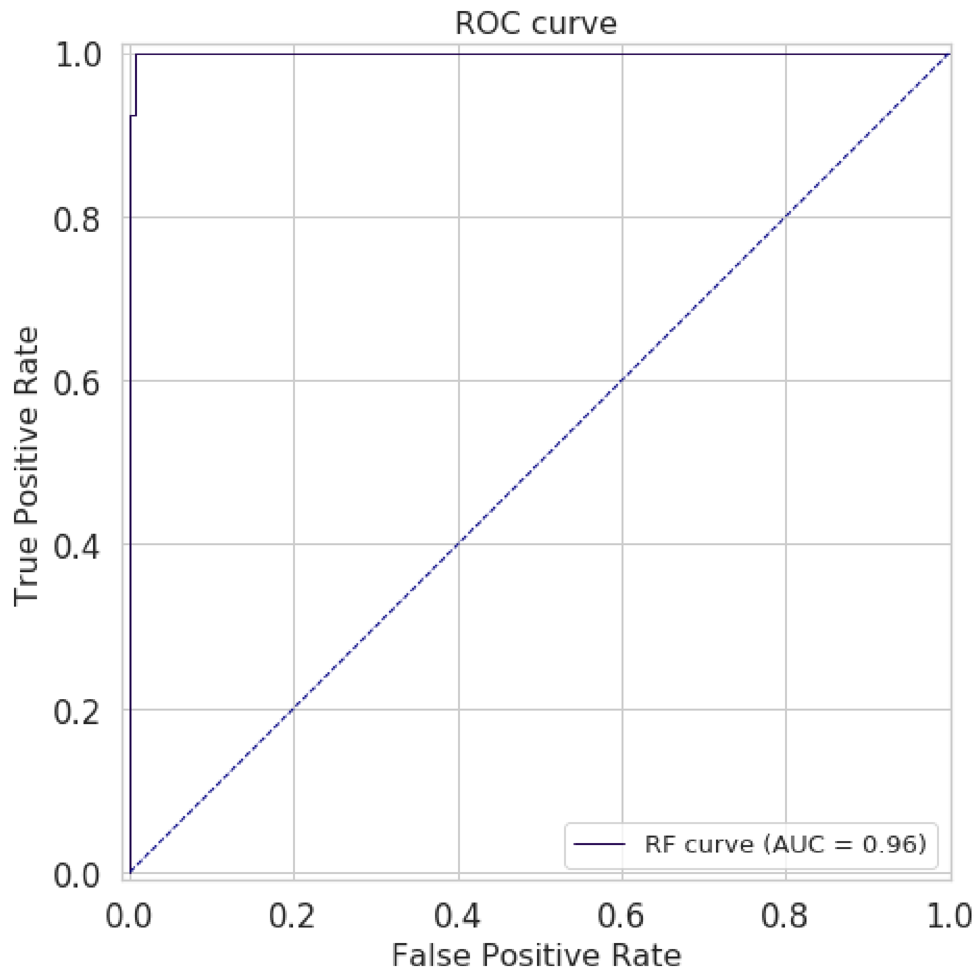



ROC curve
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
RF curve (AUC = 0.95)

In [43]:
```
score(lightgbm.LGBMClassifier(n_estimators=5000, random_state=1210).fit(X_tr,y_tr
),test=X_te, y_true=y_te)
```

```
Average precision-recall score RF:       92.55

Cohen's Kappa Score:     93.39

R-Squared Score:         87.02

Area Under ROC Curve:    95.84

              precision    recall  f1-score   support

           0       0.97      0.99      0.98       289
           1       0.98      0.92      0.95       105

   micro avg       0.97      0.97      0.97       394
   macro avg       0.98      0.96      0.97       394
weighted avg       0.97      0.97      0.97       394
```





Results

The best results are 92% Recall, 97% Precision with Area Under Precision-Recall Curve = 91.64%