Supervised Learning

In [ ]:

In [5]:
```
import pandas as pd
import numpy as np
from sklearn.utils import resample
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split, GridSearchCV, StratifiedKFold
from sklearn.ensemble import RandomForestClassifier, VotingClassifier
from xgboost import XGBClassifier
from lightgbm import LGBMClassifier
from sklearn.metrics import confusion_matrix, classification_report, roc_auc_score,
from imblearn.over_sampling import SMOTE, BorderlineSMOTE, SVMSMOTE, ADASYN

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

import warnings
warnings.filterwarnings('ignore')
```

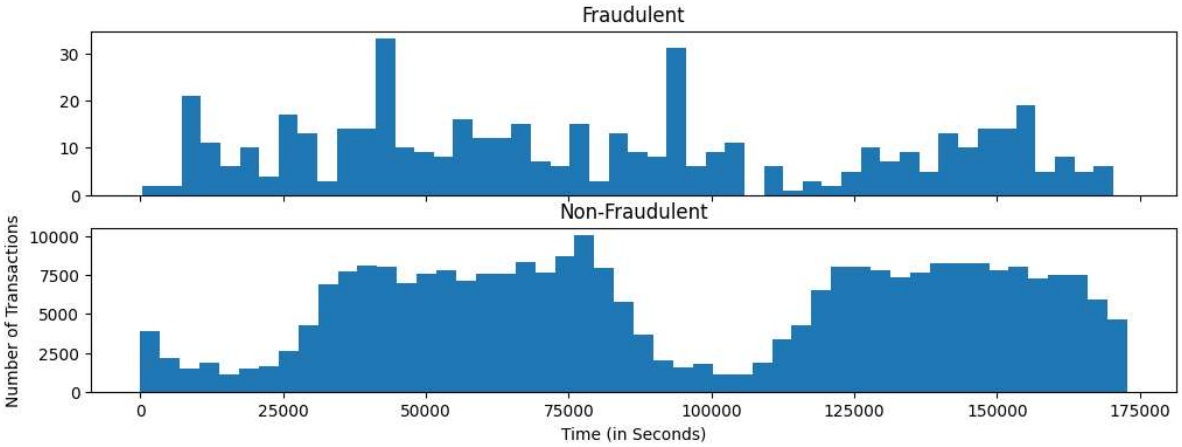
In [6]:
```
df = pd.read_csv("creditcard.csv")
df.head()
```

Out[6]:

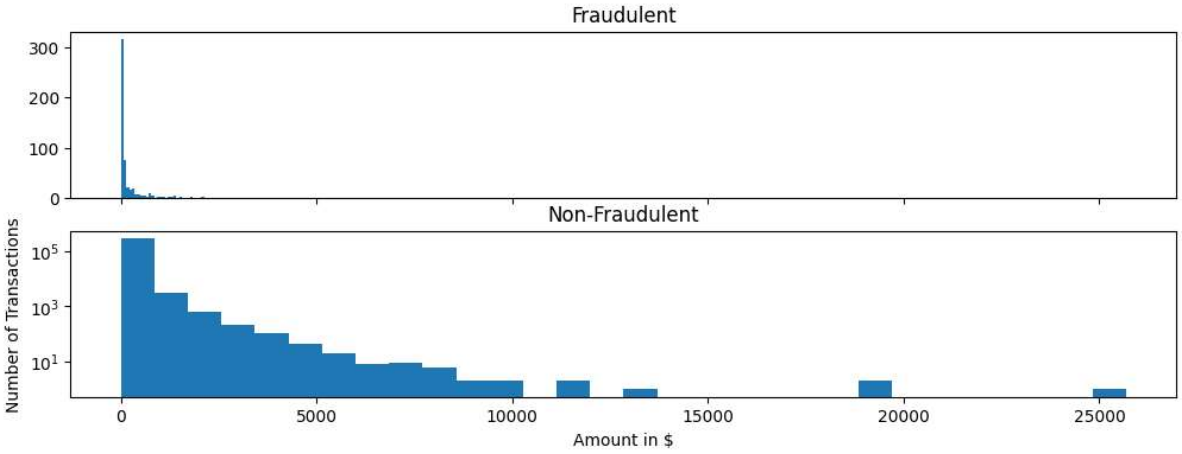
	Time	V1	V2	V3	V4	V5	V6	V7	V8	
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.3
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.2
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.5
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.3
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.8

5 rows × 31 columns

In [7]:
```
fig, (ax1, ax2) = plt.subplots(2,1, sharex = True, figsize = [12,4])

ax1.hist(df.Time[df.Class == 1], bins = 50)
ax1.set_title("Fraudulent")
ax2.hist(df.Time[df.Class == 0], bins = 50)
ax2.set_title("Non-Fraudulent")

plt.xlabel('Time (in Seconds)')
plt.ylabel('Number of Transactions')
plt.show()
```



In [8]:
```
fig, (ax1, ax2) = plt.subplots(2,1, sharex = True, figsize = [12,4])

ax1.hist(df.Amount[df.Class == 1], bins = 30)
ax1.set_title("Fraudulent")
ax2.hist(df.Amount[df.Class == 0], bins = 30)
ax2.set_title("Non-Fraudulent")

plt.xlabel('Amount in $')
plt.ylabel('Number of Transactions')
plt.yscale('log')
plt.show()
```



Amount variable is skewed. So we will standardize it with mean = 0 and sd = 1.

In [9]:
```
df["Normalized_Amount"] = StandardScaler().fit_transform(df['Amount'].values.reshap
#Drop time & amount variable
df = df.drop(['Time', 'Amount'], axis = 1)
df.head()
```

Out[9]:

	V1	V2	V3	V4	V5	V6	V7	V8	V9
0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.363787
1	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.255425
2	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.514654
3	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.387024
4	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.817739

5 rows × 30 columns

In [10]:
```
Class = [len(df.loc[df.Class == 1]), len(df.loc[df.Class == 0])]
pd.Series(Class, index = ['Fraudulent', 'Non-fraudulent'], name = 'target')
```

Out[10]:
```
Fraudulent          492
Non-fraudulent    284315
Name: target, dtype: int64
```

In [11]:
```
#Percentage of minority(fraudulent) class
print('% of Fraudulent Class = {:.3f}%'.format(len(df[df.Class == 1])*100 / len(df)
```

```
% of Fraudulent Class = 0.173%
```

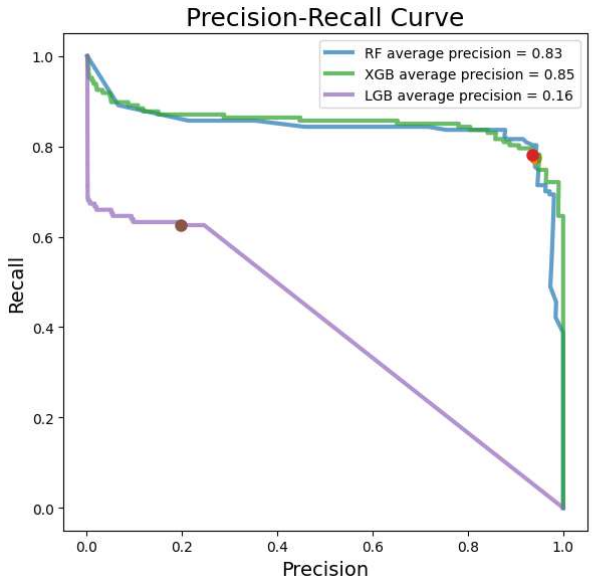
In [12]:
```
def results(balancing_technique):
    print(balancing_technique)
    fig, (ax1, ax2) = plt.subplots(1,2,figsize = (12,6))
    model_name = ["RF", "XGB", "LGB"]
    RFC = RandomForestClassifier(random_state = 0)
    XGBC = XGBClassifier(random_state = 0)
    LGBC = LGBMClassifier(random_state = 0)

    for clf,i in zip([RFC, XGBC, LGBC], model_name):
        model = clf.fit(X_train, y_train)
        y_pred = model.predict(X_test)
        y_pred_prob = model.predict_proba(X_test)[:,1]
        print("#"*25,i,"#"*25)
        print("Training Accuracy = {:.3f}".format(model.score(X_train, y_train)))
        print("Test Accuracy = {:.3f}".format(model.score(X_test, y_test)))
        print("ROC_AUC_score : %.6f" % (roc_auc_score(y_test, y_pred)))
        #Confusion Matrix
        print(confusion_matrix(y_test, y_pred))
        print("-"*15,"CLASSIFICATION REPORT","-"*15)
        print(classification_report(y_test, y_pred))

        #precision-recall curve
        precision, recall, thresholds_pr = precision_recall_curve(y_test, y_pred_pr
        avg_pre = average_precision_score(y_test, y_pred_prob)
        ax1.plot(precision, recall, label = i+ " average precision = {:0.2f}".forma
        ax1.set_xlabel('Precision', fontsize = 14)
        ax1.set_ylabel('Recall', fontsize = 14)
        ax1.set_title('Precision-Recall Curve', fontsize = 18)
        ax1.legend(loc = 'best')
        #find default threshold
        close_default = np.argmin(np.abs(thresholds_pr - 0.5))
        ax1.plot(precision[close_default], recall[close_default], 'o', markersize =
```

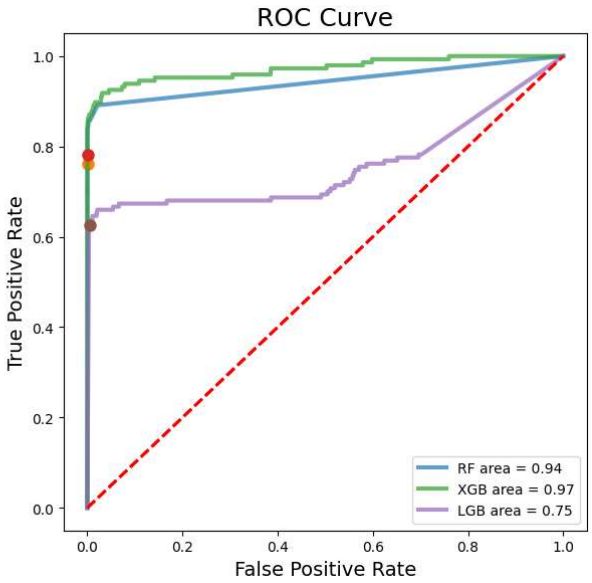
```
        #roc-curve
        fpr, tpr, thresholds_roc = roc_curve(y_test, y_pred_prob)
        roc_auc = auc(fpr,tpr)
        ax2.plot(fpr,tpr, label = i+ " area = {:0.2f}".format(roc_auc), lw = 3, alp
        ax2.plot([0,1], [0,1], 'r', linestyle = "--", lw = 2)
        ax2.set_xlabel("False Positive Rate", fontsize = 14)
        ax2.set_ylabel("True Positive Rate", fontsize = 14)
        ax2.set_title("ROC Curve", fontsize = 18)
        ax2.legend(loc = 'best')
        #find default threshold
        close_default = np.argmin(np.abs(thresholds_roc - 0.5))
        ax2.plot(fpr[close_default], tpr[close_default], 'o', markersize = 8)
        plt.tight_layout()
```

In [13]:
```
X = df.drop(columns = 'Class')
y = df['Class']
#Split data into train and test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_s
```

In [14]:
```
results("Without Balancing")
```

```
Without Balancing
########################## RF ##########################
Training Accuracy = 1.000
Test Accuracy = 1.000
ROC_AUC_score : 0.880911
[[85289     7]
 [   35   112]]
--------------- CLASSIFICATION REPORT ---------------
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     85296
           1       0.94      0.76      0.84       147

    accuracy                           1.00     85443
   macro avg       0.97      0.88      0.92     85443
weighted avg       1.00      1.00      1.00     85443

########################## XGB ##########################
Training Accuracy = 1.000
Test Accuracy = 1.000
ROC_AUC_score : 0.891110
[[85288     8]
 [   32   115]]
--------------- CLASSIFICATION REPORT ---------------
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     85296
           1       0.93      0.78      0.85       147

    accuracy                           1.00     85443
   macro avg       0.97      0.89      0.93     85443
weighted avg       1.00      1.00      1.00     85443

########################## LGB ##########################
Training Accuracy = 0.996
Test Accuracy = 0.995
ROC_AUC_score : 0.810745
[[84924   372]
 [   55    92]]
--------------- CLASSIFICATION REPORT ---------------
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     85296
           1       0.20      0.63      0.30       147

    accuracy                           1.00     85443
   macro avg       0.60      0.81      0.65     85443
weighted avg       1.00      1.00      1.00     85443
```


Precision-Recall Curve
RF average precision = 0.83
XGB average precision = 0.85
LGB average precision = 0.16
Recall
Precision
0.0
0.2
0.4
0.6
0.8
1.0


ROC Curve
RF area = 0.94
XGB area = 0.97
LGB area = 0.75
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0