Oversamplaing and Undersampling Techniques

Explaining techniques to handle imbalanced Dataset

In [29]:

```
import os
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
import warnings
from imblearn.over_sampling import SMOTE
from imblearn.pipeline import make_pipeline
from pylab import rcParams
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
from sklearn.metrics import precision_score, recall_score, confusion_matrix
from sklearn.metrics import f1_score, roc_auc_score, roc_curve
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
os.chdir('/Users/subham/Desktop/SMOTE')
```

In [30]:

```
%matplotlib inline
np.random.seed(27)
rcParams['figure.figsize'] = 10, 6
warnings.filterwarnings('ignore')
sns.set(style="darkgrid")
```

In [31]:

```
def generate_model_report(y_actual, y_predicted):
    print("Accuracy = " , accuracy_score(y_actual, y_predicted))
    print("Precision = " ,precision_score(y_actual, y_predicted))
    print("Recall = " ,recall_score(y_actual, y_predicted))
    print("F1 Score = " ,f1_score(y_actual, y_predicted))
    pass
```

In [32]:

```
def generate_auc_roc_curve(clf, X_test):
    y_pred_proba = clf.predict_proba(X_test)[:, 1]
    fpr, tpr, thresholds = roc_curve(Y_test,  y_pred_proba)
    auc = roc_auc_score(Y_test, y_pred_proba)
    plt.plot(fpr,tpr,label="AUC ROC Curve with Area Under the curve ="+str(auc))
    plt.legend(loc=4)
    plt.show()
    pass
```

In [33]:

```
df = pd.read_csv('data.csv')
```

In [34]:

```
df.tail()
```

Out[34]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	V22
284802	172786.0	-11.881118	10.071785	-9.834783	-2.066656	-5.364473	-2.606837	-4.918215	7.305334	1.914428	...	0.213454	0.111864

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	V22
284803	172787.0	-0.732789	-0.055080	2.035030	-0.738589	0.868229	1.058415	0.024330	0.294869	0.584800	...	0.214205	0.924384
284804	172788.0	1.919565	-0.301254	-3.249640	-0.557828	2.630515	3.031260	-0.296827	0.708417	0.432454	...	0.232045	0.578229
284805	172788.0	-0.240440	0.530483	0.702510	0.689799	-0.377961	0.623708	-0.686180	0.679145	0.392087	...	0.265245	0.800049
284806	172792.0	-0.533413	-0.189733	0.703337	-0.506271	-0.012546	-0.649617	1.577006	-0.414650	0.486180	...	0.261057	0.643078

5 rows × 31 columns

In [35]:

```
X = df.loc[:, df.columns!='Class']
```

In [36]:

```
Y = df.loc[:, df.columns=='Class']
```

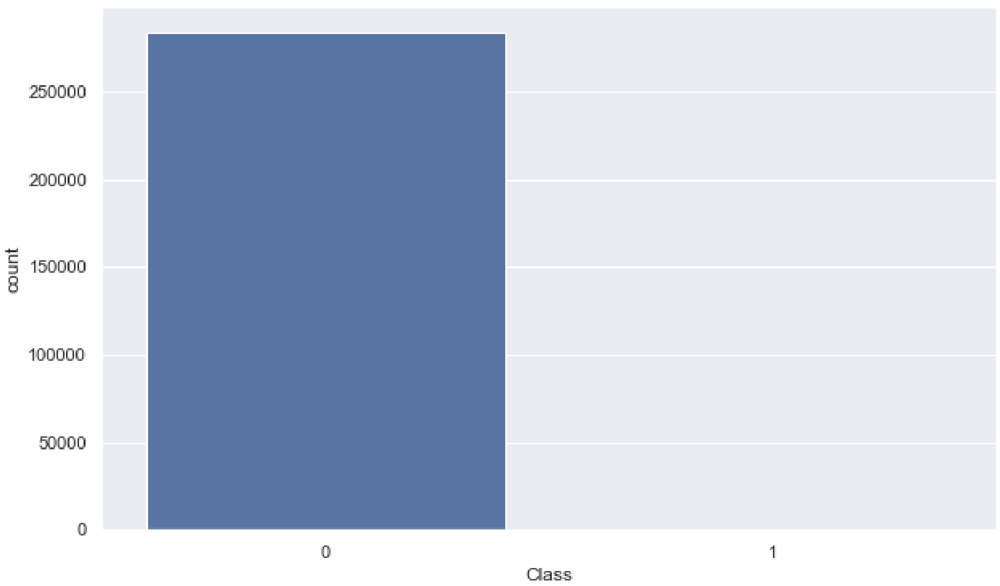
In [37]:

```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y,test_size=0.33,random_state=42)
```

In [38]:

```
ax = sns.countplot(x=df['Class'], data=df)
print(df['Class'].value_counts())
```

```
0    284315
1       492
Name: Class, dtype: int64
```



Observation :

- Imbalanced Dataset

In [39]:

```
print(X_train.shape,Y_train.shape)
print(X_test.shape,Y_test.shape)
```

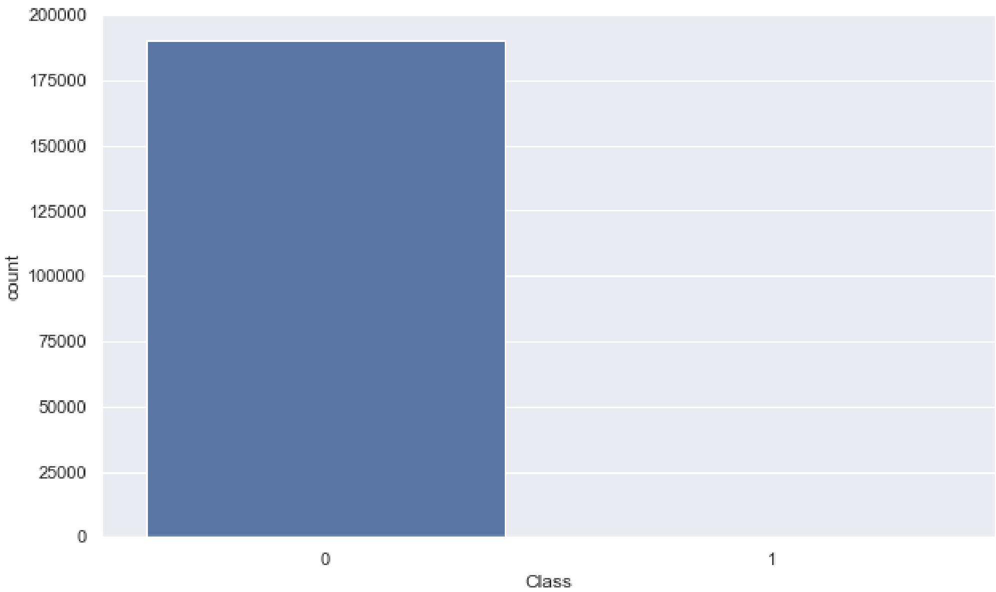
```
(190820, 30) (190820, 1)
(93987, 30) (93987, 1)
```

Let's check imbalance in the train labels too

In [40]:

```
ax = sns.countplot(x=Y_train['Class'], data=Y_train)
print(Y_train['Class'].value_counts())
```

```
0    190477
1       343
Name: Class, dtype: int64
```



Let's train a model

In [41]:

```
clf = LogisticRegression().fit(X_train, Y_train)
```

In [42]:

```
Y_Test_Pred = clf.predict(X_test)
```

In [43]:

```
pd.crosstab(Y_Test_Pred, Y_test['Class'], rownames=['Predicted'], colnames=['Actual'])
```

Out[43]:

Actual	0	1
Predicted		
0	93792	47
1	46	102

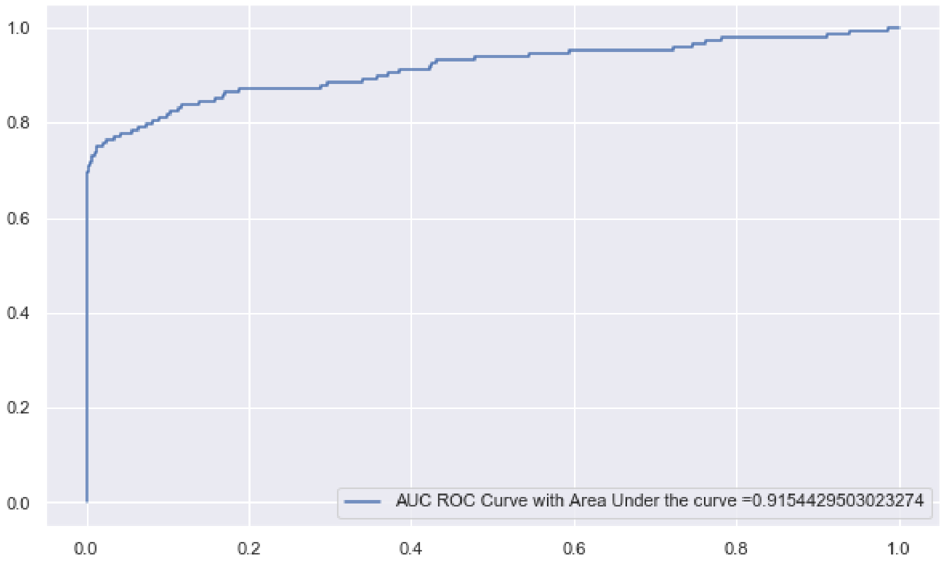
In [44]:

```
generate_model_report(Y_test, Y_Test_Pred)
```

```
Accuracy =  0.9990105014523285
Precision =  0.6891891891891891
Recall =  0.6845637583892618
F1 Score =  0.6868686868686869
```

In [22]:

```
generate_auc_roc_curve(clf, X_test)
```



Results are not bad at all.

Performing some tuning of class weights

In [45]:

```
weights = np.linspace(0.05, 0.95, 20)
gsc = GridSearchCV(
    estimator=LogisticRegression(),
    param_grid={
        'class_weight': [{0: x, 1: 1.0-x} for x in weights]
    },
    scoring='f1',
    cv=5
)

grid_result = gsc.fit(X_train, Y_train)
print("Best parameters : %s" % grid_result.best_params_)
```

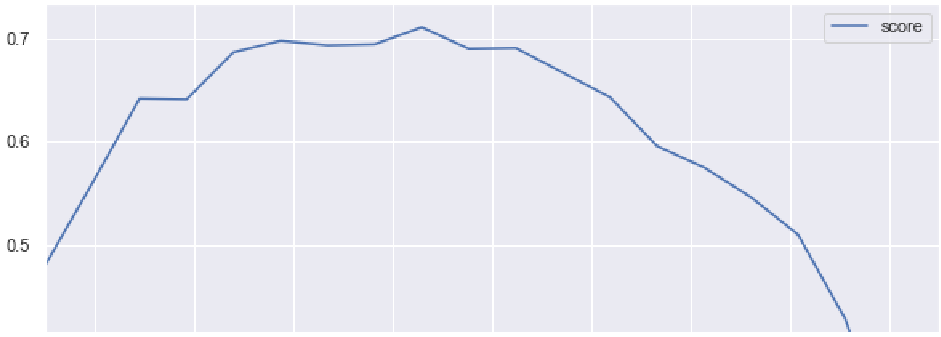
```
Best parameters : {'class_weight': {0: 0.4289473684210526, 1: 0.5710526315789475}}
```

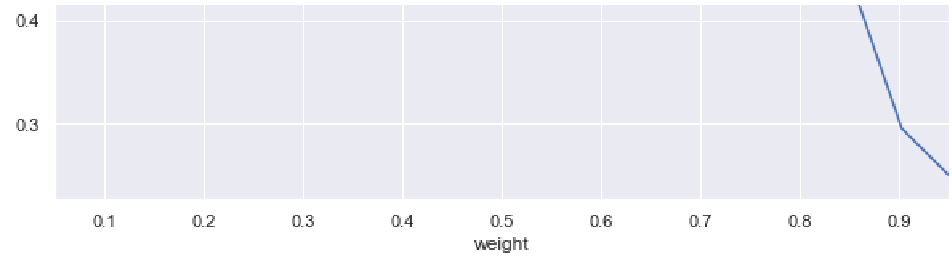
In [48]:

```
data_out = pd.DataFrame({'score': grid_result.cv_results_['mean_test_score'],'weight': weights })
data_out.plot(x='weight')
```

Out[48]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x119bcab50>
```





In [49]:

```
clf = LogisticRegression(**grid_result.best_params_).fit(X_train, Y_train)
Y_Test_Pred = clf.predict(X_test)
```

In [51]:

```
pd.crosstab(Y_Test_Pred, Y_test['Class'], rownames=['Predicted'], colnames=['Actual'])
```

Out[51]:

Actual	**0**	**1**
Predicted		
0	93802	59
1	36	90

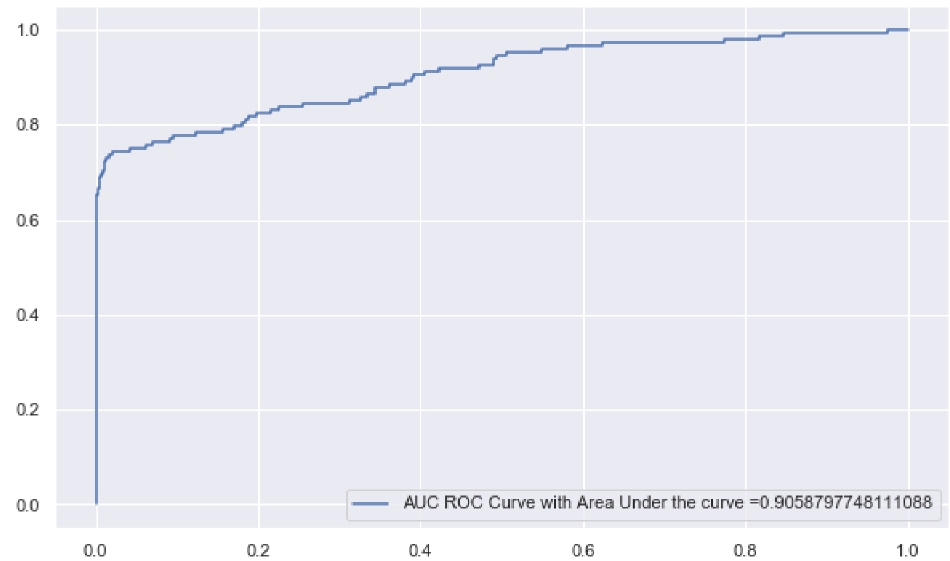
In [52]:

```
generate_model_report(Y_test, Y_Test_Pred)
```

```
Accuracy =  0.9989892219136689
Precision =  0.7142857142857143
Recall =  0.6040268456375839
F1 Score =  0.6545454545454547
```

In [53]:

```
generate_auc_roc_curve(clf, X_test)
```



Let's try using class_weight='balanced'

- wj = n/k*nj , where wj is weight to class j, n is the number of observations, nj is the number of observations in class j, k is the total number of classes.

In [54]:

```
clf = LogisticRegression(class_weight='balanced').fit(X_train, Y_train)
Y_Test_Pred = clf.predict(X_test)
```

In [55]:

```
pd.crosstab(Y_Test_Pred, Y_test['Class'], rownames=['Predicted'], colnames=['Actual'])
```

Out[55]:

Actual	0	1
Predicted		
0	90726	12
1	3112	137

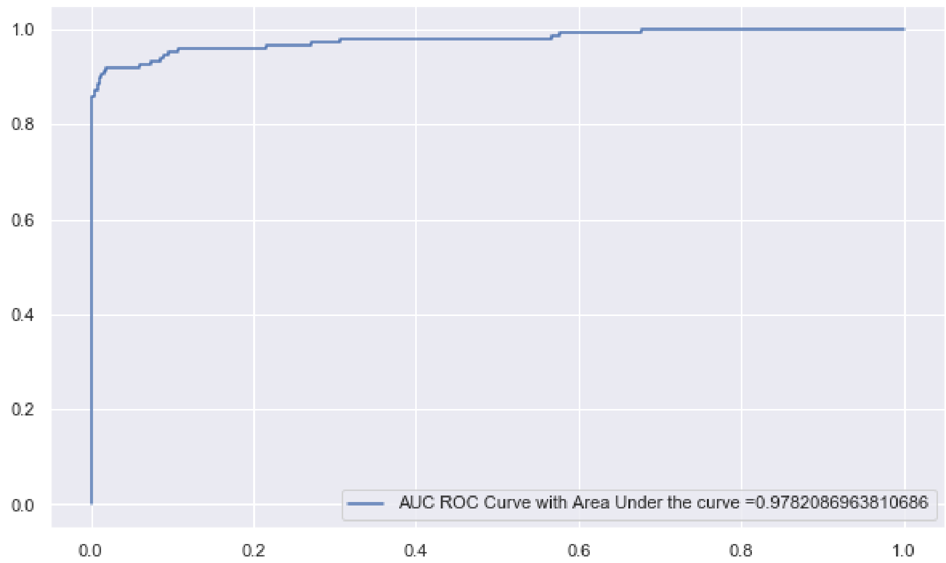
In [56]:

```
generate_model_report(Y_test, Y_Test_Pred)
```

```
Accuracy =  0.9667613606137019
Precision =  0.04216682056017236
Recall =  0.9194630872483222
F1 Score =  0.08063566804002353
```

In [57]:

```
generate_auc_roc_curve(clf, X_test)
```



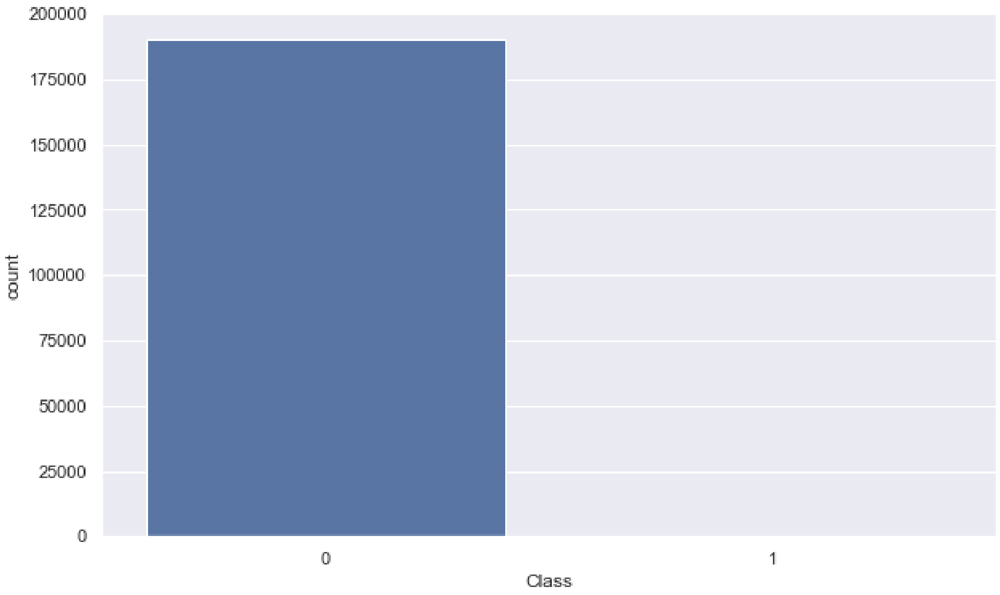
F1 score has dropped drastically since precision has dropped

Let's try the SMOTE technique

In [58]:

```
ax = sns.countplot(x=Y_train['Class'], data=Y_train)
print(Y_train['Class'].value_counts())
```

```
0    190477
1       343
Name: Class, dtype: int64
```



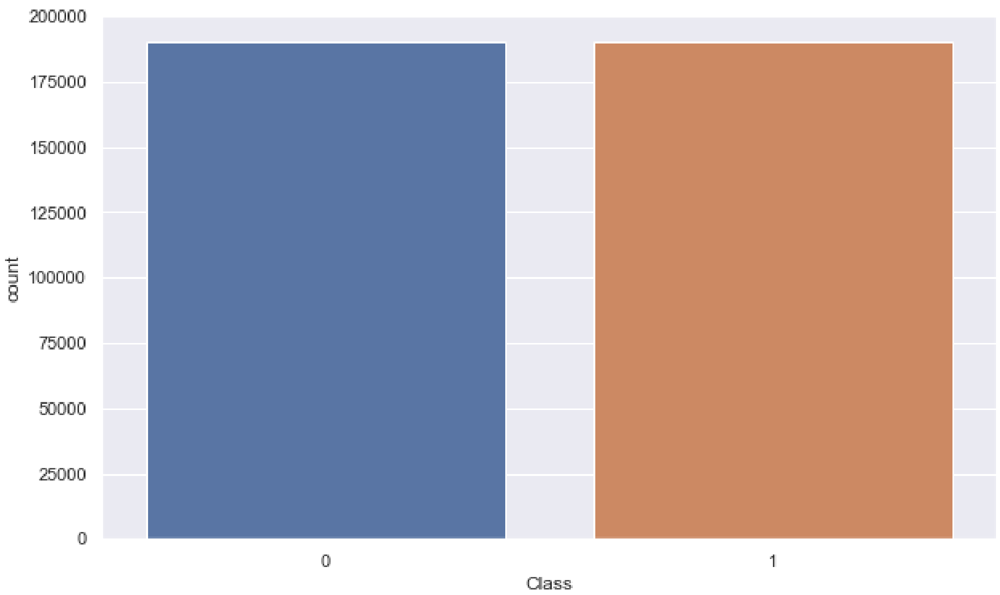
In [60]:

```
sm = SMOTE(random_state=12, sampling_strategy='auto')
x_train_res, y_train_res = sm.fit_sample(X_train, Y_train)
```

In [61]:

```
ax = sns.countplot(x=y_train_res['Class'], data=y_train_res)
print(y_train_res['Class'].value_counts())
```

```
1    190477
0    190477
Name: Class, dtype: int64
```



In [62]:

```
clf = LogisticRegression().fit(x_train_res, y_train_res)
```

In [63]:

```
Y_Test_Pred = clf.predict(X_test)
```

In [65]:

```
pd.crosstab(Y_Test_Pred, Y_test['Class'], rownames=['Predicted'], colnames=['Actual'])
```

Out[65]:

Actual	0	1
Predicted		
0	92202	15
1	1636	134

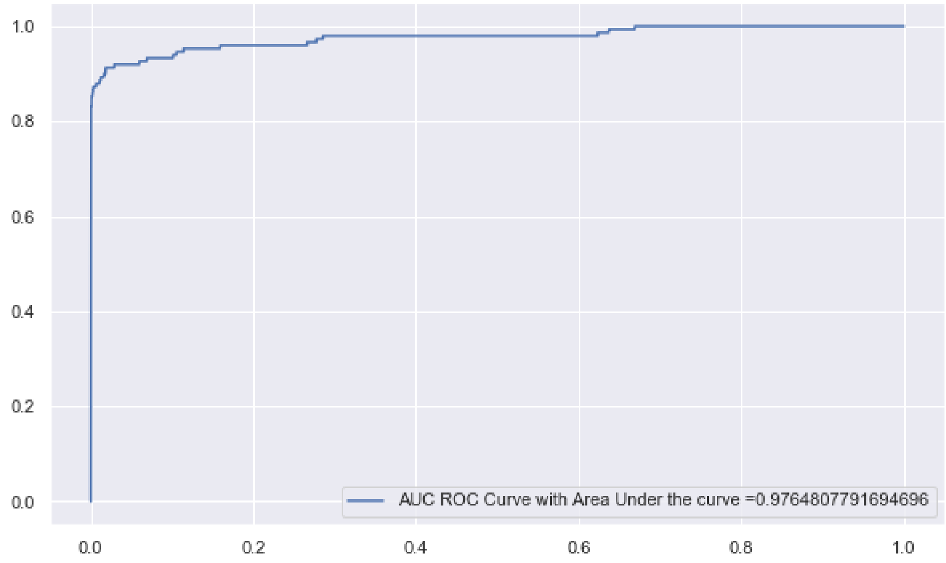
In [66]:

```
generate_model_report(Y_test, Y_Test_Pred)
```

```
Accuracy =  0.9824337408364987
Precision =  0.07570621468926554
Recall =  0.8993288590604027
F1 Score =  0.13965607087024492
```

In [67]:

```
generate_auc_roc_curve(clf, X_test)
```



The F1 Score is very low.

In [97]:

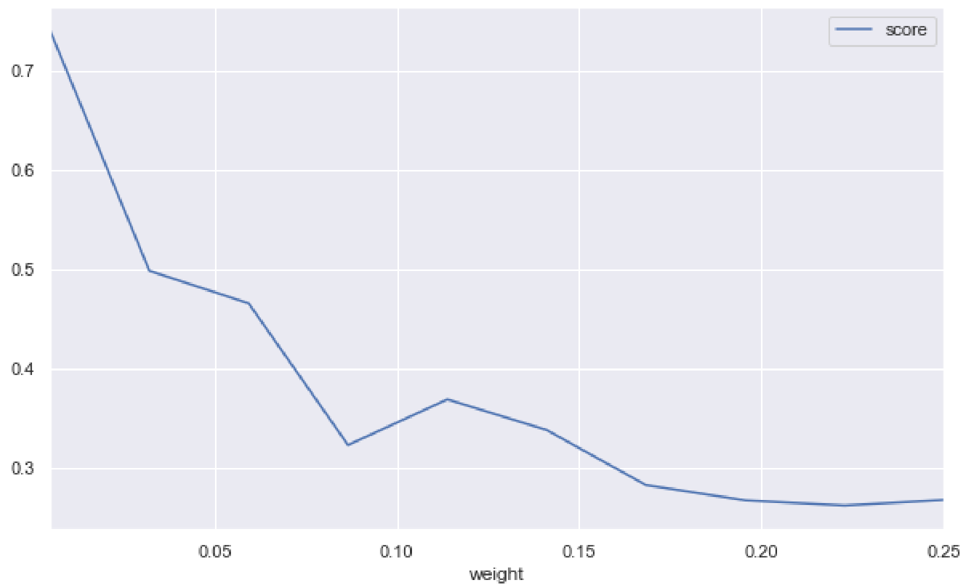
```
pipe = make_pipeline(
    SMOTE(),
    LogisticRegression()
)

weights = np.linspace(0.005, 0.25, 10)

gsc = GridSearchCV(
    estimator=pipe,
    param_grid={
        'smote__sampling_strategy': weights
    },
    scoring='f1',
    cv=3
)
grid_result = gsc.fit(X_train, Y_train)

print("Best parameters : %s" % grid_result.best_params_)
weight_f1_score_df = pd.DataFrame({ 'score': grid_result.cv_results_['mean_test_score'],
```

```
                                  'weight': weights })
weight_f1_score_df.plot(x='weight')
```

```
Best parameters : {'smote__sampling_strategy': 0.005}
```

Out[97]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1a3bd44890>
```



In [98]:

```
pipe = make_pipeline(
    SMOTE(sampling_strategy=0.005),
    LogisticRegression()
)

pipe.fit(X_train, Y_train)

Y_Test_Pred = pipe.predict(X_test)
```

In [99]:

```
pd.crosstab(Y_Test_Pred, Y_test['Class'],
            rownames=['Predicted'], colnames=['Actual'])
```

Out[99]:

Actual	0	1
Predicted		
0	93761	37
1	77	112

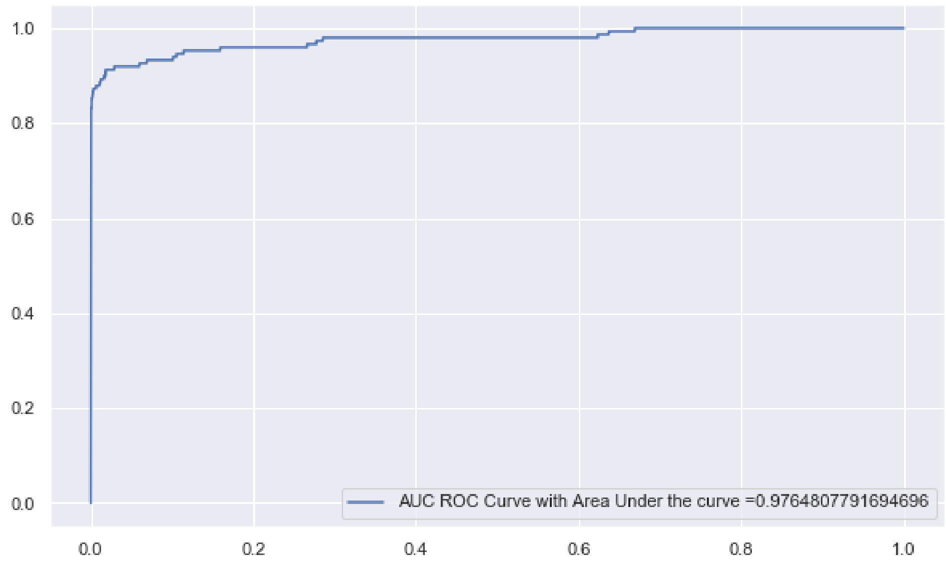
In [100]:

```
generate_model_report(Y_test, Y_Test_Pred)
```

```
Accuracy =  0.9987870662964027
Precision =  0.5925925925925926
Recall =  0.7516778523489933
F1 Score =  0.6627218934911243
```

In [96]:

```
generate_auc_roc_curve(clf, X_test)
```



UNDERSAMPLING

In [102]:

```
minority_class_len = len(df[df['Class'] == 1])
print(minority_class_len)
```

```
492
```

In [104]:

```
majority_class_len = len(df[df['Class'] == 0])
print(majority_class_len)
```

```
284315
```

In [105]:

```
majority_class_indices = df[df['Class'] == 0].index
```

In [106]:

```
## Undersampling
random_majority_indices = np.random.choice(majority_class_indices,minority_class_len,replace=False
)
print(len(random_majority_indices))
```

```
492
```

In [108]:

```
minority_class_indices = df[df['Class'] == 1].index
```

In [109]:

```
under_sample_indices = np.concatenate([minority_class_indices,random_majority_indices])
```

In [110]:

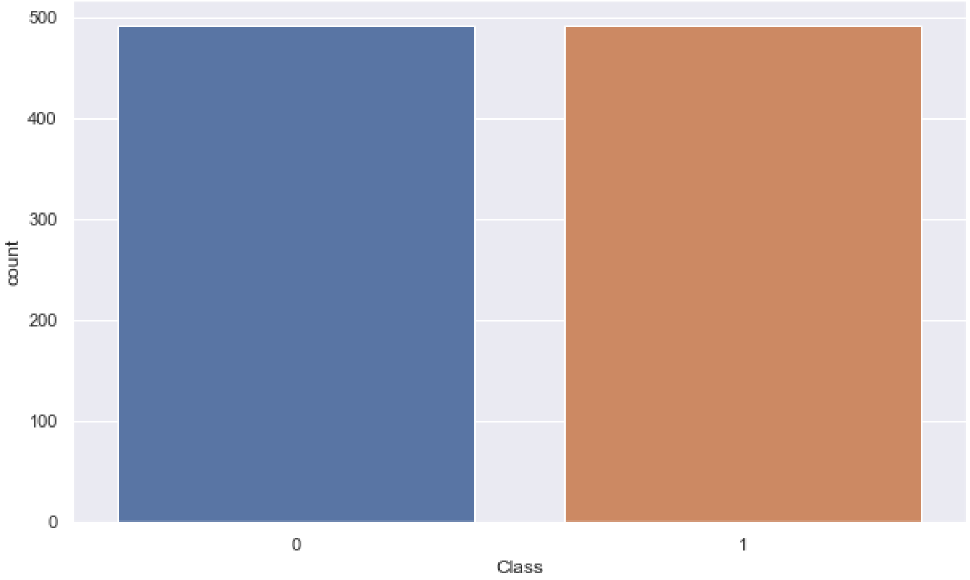
```
under_sample = df.loc[under_sample_indices]
```

In [111]:

```
sns.countplot(x='Class', data=under_sample)
```

Out[111]:

<matplotlib.axes._subplots.AxesSubplot at 0x1a390b2f50>



In [112]:

```
X = under_sample.loc[:, df.columns!='Class']
Y = under_sample.loc[:, df.columns=='Class']
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.33, random_state=42)
clf = LogisticRegression().fit(X_train, Y_train)
Y_Test_Pred = clf.predict(X_test)
```

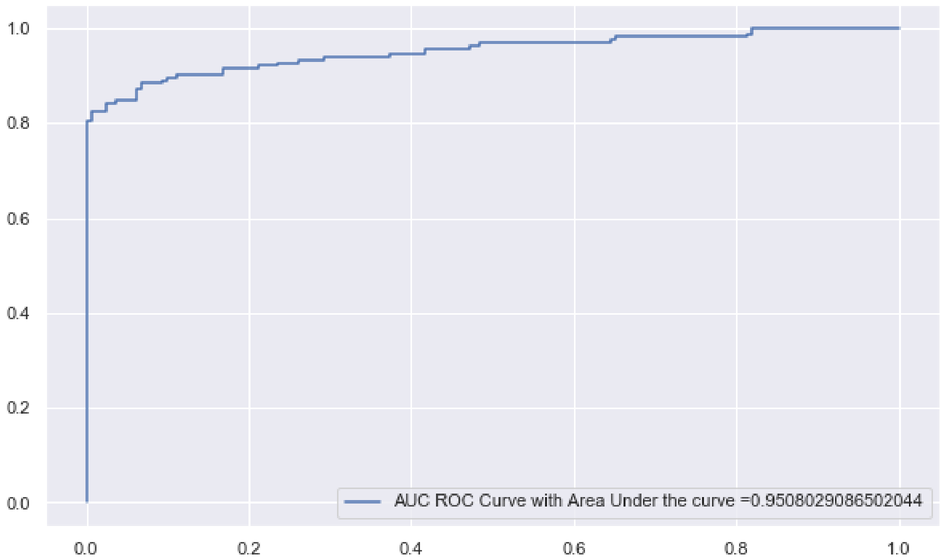
In [113]:

```
generate_model_report(Y_test, Y_Test_Pred)
```

```
Accuracy =  0.8984615384615384
Precision =  0.9337748344370861
Recall =  0.8597560975609756
F1 Score =  0.8952380952380953
```

In [114]:

```
generate_auc_roc_curve(clf, X_test)
```



In [ ]:

```

```