In [846]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.metrics import balanced_accuracy_score
from sklearn.metrics import accuracy_score
from sklearn.metrics import  classification_report
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
```

Data Preprocessing

In [847]:

```
df = pd.read_csv("train_data.csv")
df.head(3)
```

Out[847]:

	ID	HealthServiceArea	Gender	Race	TypeOfAdmission	CCSProcedureCode	APRS
0	1	New York City	F	Other Race	Newborn	228	
1	2	New York City	M	Black/African American	Newborn	228	
2	3	New York City	M	Other Race	Newborn	220	

In [848]:

```
#Drop the columns ID and HealthServiceArea
df.drop(columns = ['ID','HealthServiceArea'],inplace=True,axis=1)
df.head(3)
```

Out[848]:

	Gender	Race	TypeOfAdmission	CCSProcedureCode	APRSeverityOfIllnessCode	Pa
0	F	Other Race	Newborn	228	1	
1	M	Black/African American	Newborn	228	1	
2	M	Other Race	Newborn	220	1	

EDA (Exploratory Data Analysis

In [849]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 59966 entries, 0 to 59965
Data columns (total 14 columns):
 #   Column                       Non-Null Count  Dtype 
---  ------                       --------------  ----- 
 0   Gender                       59966 non-null  object
 1   Race                         59966 non-null  object
 2   TypeOfAdmission              59966 non-null  object
 3   CCSProcedureCode             59966 non-null  int64 
 4   APRSeverityOfIllnessCode     59966 non-null  int64 
 5   PaymentTypology              59966 non-null  object
 6   BirthWeight                  59966 non-null  int64 
 7   EmergencyDepartmentIndicator 59966 non-null  object
 8   AverageCostInCounty          59966 non-null  int64 
 9   AverageChargesInCounty       59966 non-null  int64 
 10  AverageCostInFacility        59966 non-null  int64 
 11  AverageChargesInFacility     59966 non-null  int64 
 12  AverageIncomeInZipCode       59966 non-null  int64 
 13  LengthOfStay                 59966 non-null  int64 
dtypes: int64(9), object(5)
memory usage: 6.4+ MB
```

The data has categorical columns :
1.Gender
2.Race
3.TypeOfAdmission
4.PaymentTypology
5.Emergency Depearment Indicator
Even though the columns CCSProcedureCode and APRSeverityofIllnessCode are numeric, they seem to be categorical in nature which must be verified

In [850]:

```
df.describe()
```

Out[850]:

	CCSProcedureCode	APRSeverityOfIllnessCode	BirthWeight	AverageCostInCounty	Av
count	59966.000000	59966.000000	59966.000000	59966.000000	
mean	155.404229	1.254594	3336.298903	2372.806690	
std	89.541978	0.546207	446.244475	639.755096	
min	-1.000000	1.000000	2500.000000	712.000000	
25%	115.000000	1.000000	3000.000000	2041.000000	
50%	220.000000	1.000000	3300.000000	2533.000000	
75%	228.000000	1.000000	3600.000000	2785.000000	
max	231.000000	4.000000	7500.000000	3242.000000	

Few observations from the description statistics:
1. The average LengthOfStay(LOS) is 2.53 and the min=1 and max=10
2. The average AverageCostInCounty is 2372 and AvergaeChargesInCounty is 7979 . whats the correlatio between these two ?
It would be interesting to observe the correlation between these and the LengthOfStay(LOS)

Class imbalance investigation

In [851]:

```
#Getting and idea of the LengthOfStay
col_values = df['LengthOfStay'].values
df.groupby(['LengthOfStay']).count()
```

Out[851]:

	Gender	Race	TypeOfAdmission	CCSProcedureCode	APRSeverityOfIllnessCo
LengthOfStay					
1	8895	8895	8895	8895	88
2	25000	25000	25000	25000	250
3	16000	16000	16000	16000	160
4	7504	7504	7504	7504	75
5	1342	1342	1342	1342	13
6	557	557	557	557	5
7	346	346	346	346	3
8	145	145	145	145	1
9	97	97	97	97	
10	80	80	80	80	

The examples with < 4 days is 49895 and 10,071 >=4 days .
1. (< 4 days) => 83.36 %
2. (>=4 days) => 16.64 %
This resembles a good amount of class imbalance . Hence even need to think of decision trees as a mechanism for the same

In [852]:

```
#So lets change the LengthOfStay
def change_los(x):
    if x < 4:
        return 0
    return 1
df['LengthOfStay'] = df['LengthOfStay'].apply(change_los)
```

In [853]:

```
df['LengthOfStay'][0:3]
```

Out[853]:

```
0    0
1    0
2    0
Name: LengthOfStay, dtype: int64
```

In [854]:

```
col_values = df['LengthOfStay'].values
df.groupby(['LengthOfStay']).count()
```

Out[854]:

	Gender	Race	TypeOfAdmission	CCSProcedureCode	APRSeverityOfIllnessCo
LengthOfStay					
0	49895	49895	49895	49895	498
1	10071	10071	10071	10071	1007

So the above change was successful and this confirms our previous undesrtanding that the datasets contains more samples of LOS < 4

NULL values investigation

In [855]:

```
df.isnull().any()
```

Out[855]:

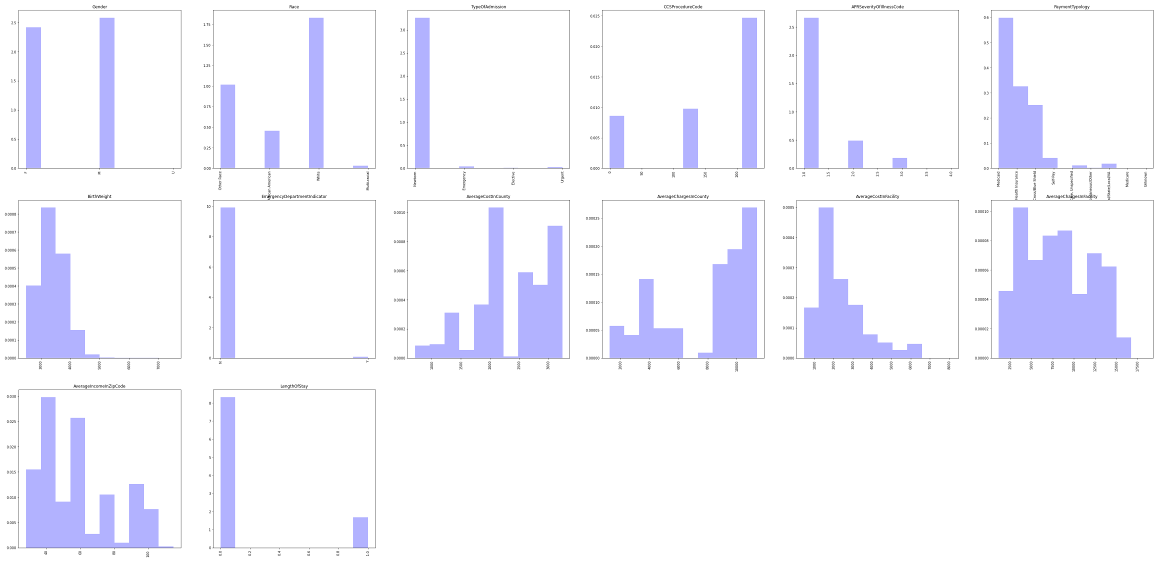
```
Gender                          False
Race                            False
TypeOfAdmission                 False
CCSProcedureCode                False
APRSeverityOfIllnessCode        False
PaymentTypology                 False
BirthWeight                     False
EmergencyDepartmentIndicator    False
AverageCostInCounty             False
AverageChargesInCounty          False
AverageCostInFacility           False
AverageChargesInFacility        False
AverageIncomeInZipCode          False
LengthOfStay                    False
dtype: bool
```

So the dataset doesnot contain any NULL values

**Data visualization, Attribute correlation and dependence

In [856]:

```
plt.figure(figsize=(60,60))
#plt.figure(figsize=(6,6))
for i,col in enumerate(df.columns):
    plt.subplot(6,6,i+1)
    plt.hist(df[col],alpha=0.3, color= 'b',density=True)
    plt.title(col)
    plt.xticks(rotation='vertical')
```



In [857]:

```
df[['Race','Gender']].groupby(['Race']).count()
```

Out[857]:

	Gender
Race	
Black/African American	8183
Multi-racial	526
Other Race	18314
White	32943

In [858]:

```
df[['Race','Gender']].groupby(['Gender']).count()
```

Out[858]:

	Race
Gender	
F	28987
M	30978
U	1

Key takeaways from the sample given:
1.*Definitely the classes are imbalanced with respect to LengthofStay as the measure*
2.*Females are 48.34 % and males form 51.66 % of the samples*
3.*Whites are 54.94% ,30.54% other race and 13.65% Black/African American and remaining Multi racial*

In [859]:

```
df[['Race','TypeOfAdmission']].groupby(['TypeOfAdmission']).count()
```

Out[859]:

	Race
TypeOfAdmission	
Elective	154
Emergency	659
Newborn	58741
Urgent	412

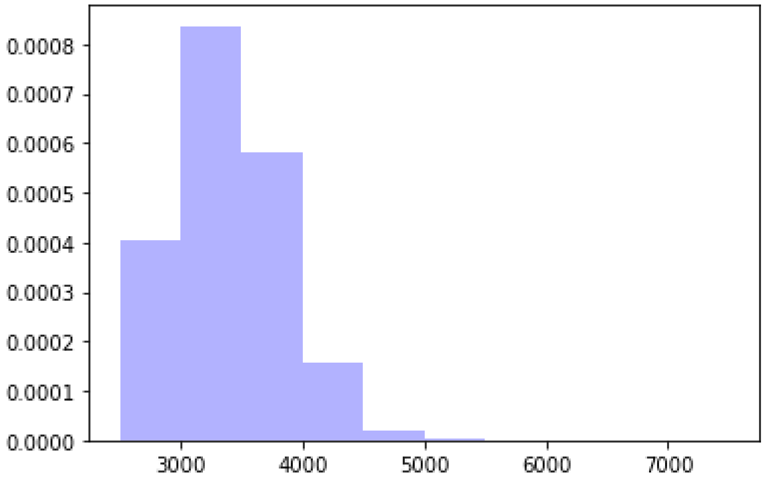
The large number of observations are related to Newborn (97.96%) with next highest being Emergencies followed by Urgent and the Elective samples are very less

In [860]:

```
#Exploring birthweight distribution
plt.hist(df['BirthWeight'],alpha=0.3, color= 'b',density=True)
```

Out[860]:

```
(array([4.03628723e-04, 8.36907581e-04, 5.80362205e-04, 1.55488110e-04,
        2.07450889e-05, 2.10119067e-06, 3.33522329e-07, 3.00170096e-07,
        1.00056699e-07, 3.33522329e-08]),
 array([2500., 3000., 3500., 4000., 4500., 5000., 5500., 6000., 6500.,
        7000., 7500.]),
 <BarContainer object of 10 artists>)
```



In [861]:

```
print("Max=",df['BirthWeight'].max())
print("Min=",df['BirthWeight'].min())
```

```
Max= 7500
Min= 2500
```

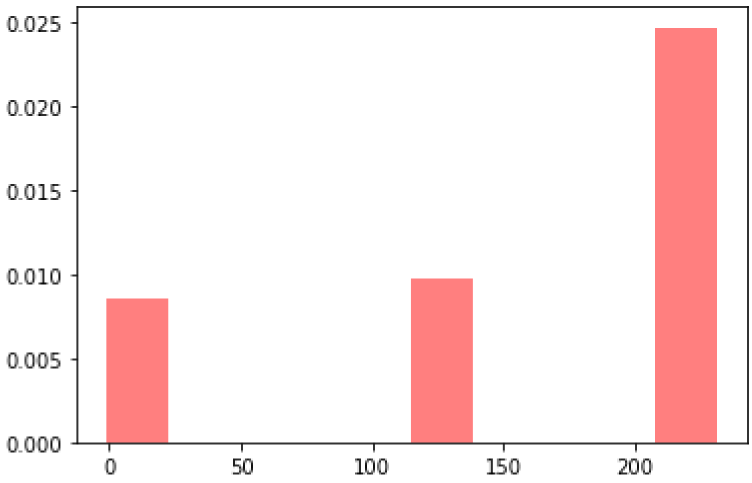
So the birth weight of 7500 looks like an outlier and we cannot assume the distribution is skewed rather anything above 5000 must be assumned to be an outlier condition

In [862]:

```
plt.hist(df['CCSProcedureCode'],alpha=0.5,color='r',density='True')
```

Out[862]:

```
(array([0.00859539, 0.        , 0.        , 0.        , 0.        ,
        0.00979578, 0.        , 0.        , 0.        , 0.02471228]),
 array([ -1. ,  22.2,  45.4,  68.6,  91.8, 115. , 138.2, 161.4, 184.6,
        207.8, 231. ]),
 <BarContainer object of 10 artists>)
```



In [863]:

```
df[['CCSProcedureCode','LengthOfStay']].groupby(['CCSProcedureCode']).count()
```

Out[863]:

CCSProcedureCode	LengthOfStay
-1	769
0	11189
115	13628
216	740
220	10773
228	19886
231	2981

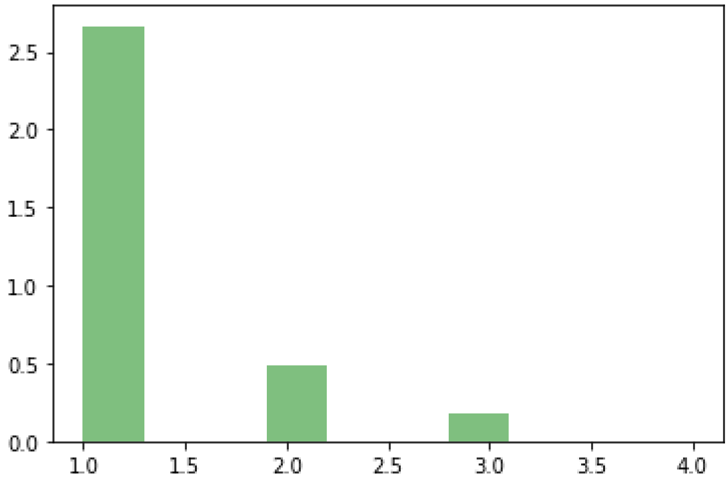
So the CCS procedure code is kind of fixed and we can assume that only specific codes . We can assume its ordinal in nature

In [864]:

```
plt.hist(df['APRSeverityOfIllnessCode'],alpha=0.5,color='g',density='True')
```

Out[864]:

```
(array([2.66556604e+00, 0.00000000e+00, 0.00000000e+00, 4.86942601e-01,
        0.00000000e+00, 0.00000000e+00, 1.80769102e-01, 0.00000000e+00,
        0.00000000e+00, 5.55870549e-05]),
 array([1. , 1.3, 1.6, 1.9, 2.2, 2.5, 2.8, 3.1, 3.4, 3.7, 4. ]),
 <BarContainer object of 10 artists>)
```



In [865]:

```
string='APRSeverityOfIllnessCode'
df[['CCSProcedureCode',string]].groupby([string]).count()
```

Out[865]:

	CCSProcedureCode
APRSeverityOfIllnessCode	
1	47953
2	8760
3	3252
4	1

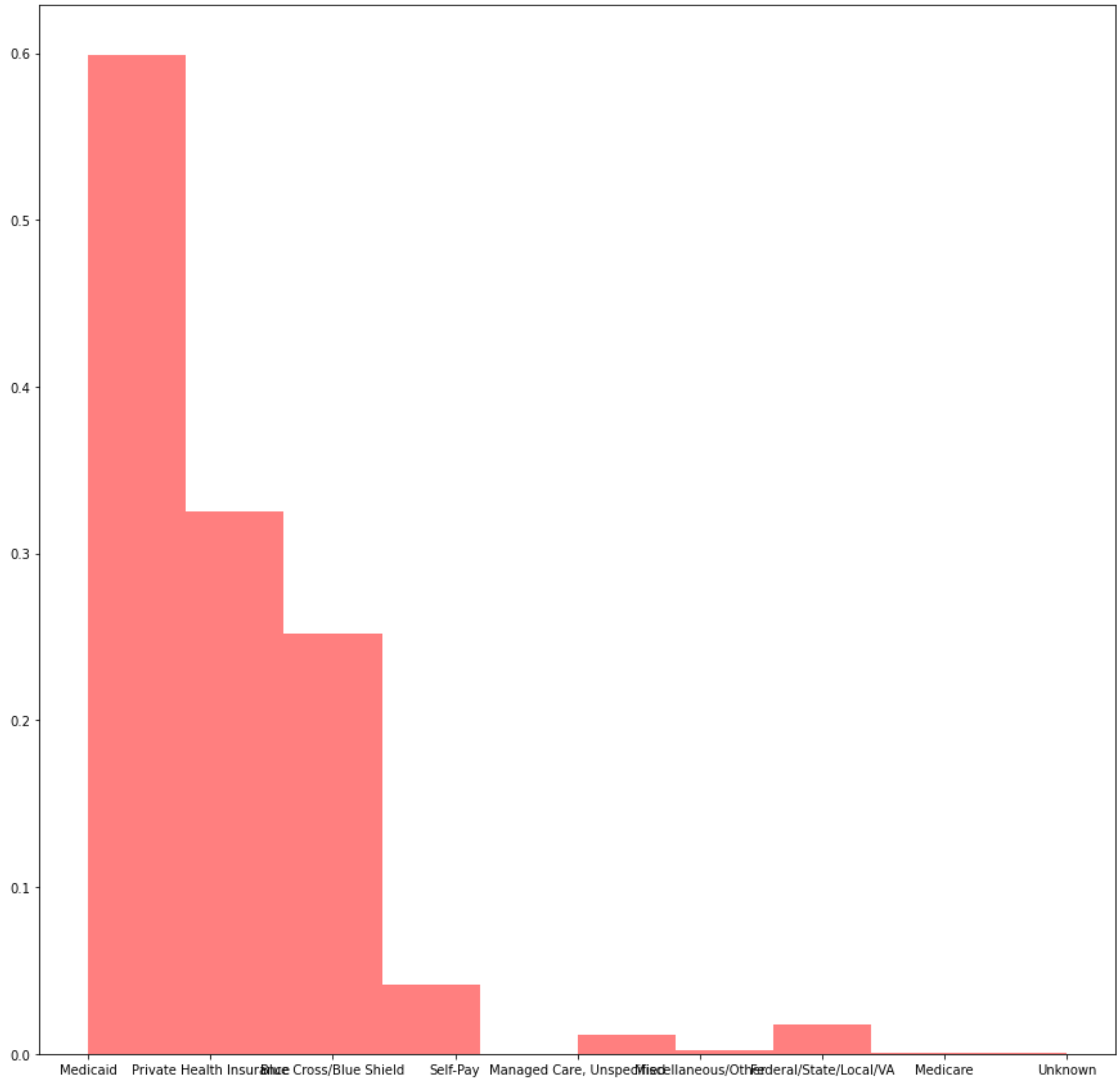
A lot of examples from the training set fall into Category of APRS Severity Illness Code

In [866]:

```
#Exploring Payment Typology
plt.figure(figsize=(15,15))
plt.hist(df['PaymentTypology'],alpha=0.5,color='r',density='True')
```

Out[866]:

```
(array([5.98735117e-01, 3.25351032e-01, 2.51663443e-01, 4.13567688e-02,
        0.00000000e+00, 1.13606043e-02, 2.45972718e-03, 1.76975286e-02,
        9.17186406e-04, 4.58593203e-04]),
 array([0. , 0.8, 1.6, 2.4, 3.2, 4. , 4.8, 5.6, 6.4, 7.2, 8. ]),
 <BarContainer object of 10 artists>)
```



In [867]:

```
string='PaymentTypology'
df[['CCSProcedureCode',string]].groupby([string]).count()
```

Out[867]:

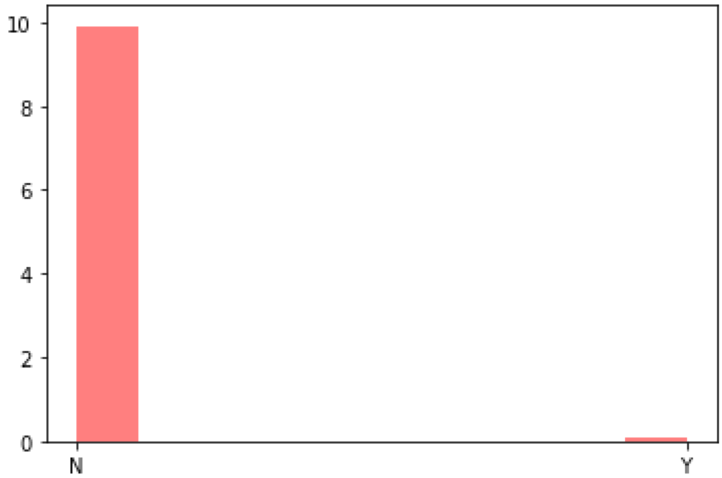
	CCSProcedureCode
PaymentTypology	
Blue Cross/Blue Shield	12073
Federal/State/Local/VA	849
Managed Care, Unspecified	545
Medicaid	28723
Medicare	44
Miscellaneous/Other	118
Private Health Insurance	15608
Self-Pay	1984
Unknown	22

In [868]:

```
plt.hist(df['EmergencyDepartmentIndicator'],alpha=0.5,color='r',density='True')
```

Out[868]:

```
(array([9.91445152, 0.        , 0.        , 0.        , 0.        ,
        0.        , 0.        , 0.        , 0.        , 0.08554848]),
 array([0. , 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1. ]),
 <BarContainer object of 10 artists>)
```



***So the severity code even though specified in numerical attribute its ordinal in nature**
The EmergencyDepartmentIndicator data shows most cases are not emergency in nature

So far in our analysis

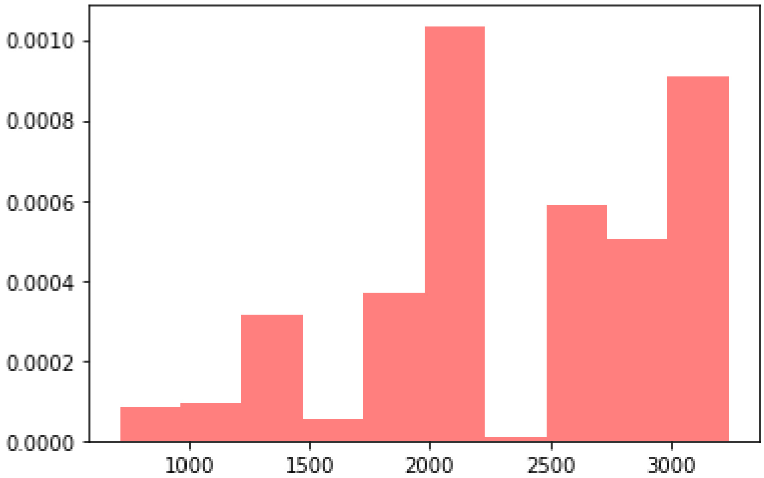
1. Race,Gender,PaymentTypology,TypeOfadmission and EmergencyIndicator are nominal in nature , whereas APRSCode and CCSprocedure code seem to be ordinal in nature
The dataset has class imbalance and also mainly contains data of the newborns and non-emergency cases

In [869]:

```
plt.hist(df['AverageCostInCounty'],alpha=0.5,color='r',density='True')
```

Out[869]:

```
(array([8.41715444e-05, 9.41244835e-05, 3.11836787e-04, 5.42468136e-05,
        3.66413168e-04, 1.03438062e-03, 9.95293908e-06, 5.87816627e-04,
        5.01733591e-04, 9.07892602e-04]),
 array([ 712.,  965., 1218., 1471., 1724., 1977., 2230., 2483., 2736.,
        2989., 3242.]),
 <BarContainer object of 10 artists>)
```

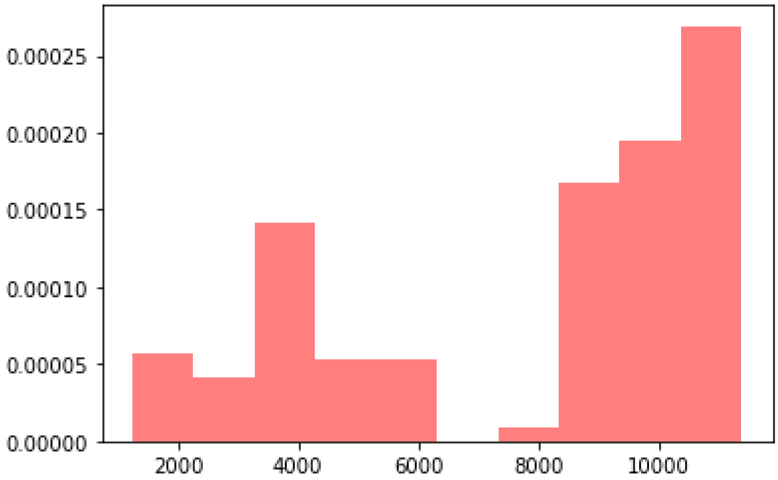


In [870]:

```
plt.hist(df['AverageChargesInCounty'],alpha=0.5,color='r',density='True')
```

Out[870]:

```
(array([5.71442381e-05, 4.09912036e-05, 1.41084090e-04, 5.32128988e-05,
        5.29661620e-05, 0.00000000e+00, 9.44179409e-06, 1.67748112e-04,
        1.94477930e-04, 2.69321419e-04]),
 array([ 1243. ,  2256.8,  3270.6,  4284.4,  5298.2,  6312. ,  7325.8,
         8339.6,  9353.4, 10367.2, 11381. ]),
 <BarContainer object of 10 artists>)
```

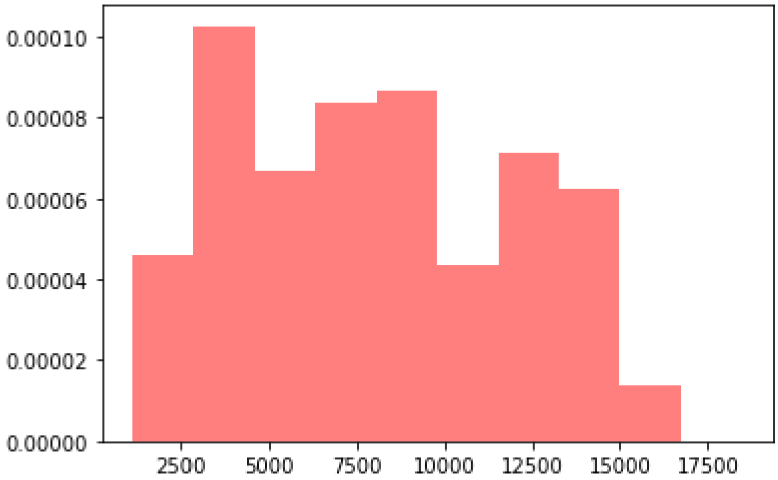


In [871]:

```
plt.hist(df['AverageChargesInFacility'],alpha=0.5,color='r',density='True')
```

Out[871]:

```
(array([4.57617401e-05, 1.02646659e-04, 6.66813927e-05, 8.34959481e-05,
        8.67646438e-05, 4.35601774e-05, 7.12960220e-05, 6.23071087e-05,
        1.39784811e-05, 9.61381095e-09]),
 array([ 1120. ,  2854.6,  4589.2,  6323.8,  8058.4,  9793. , 11527.6,
        13262.2, 14996.8, 16731.4, 18466. ]),
 <BarContainer object of 10 artists>)
```

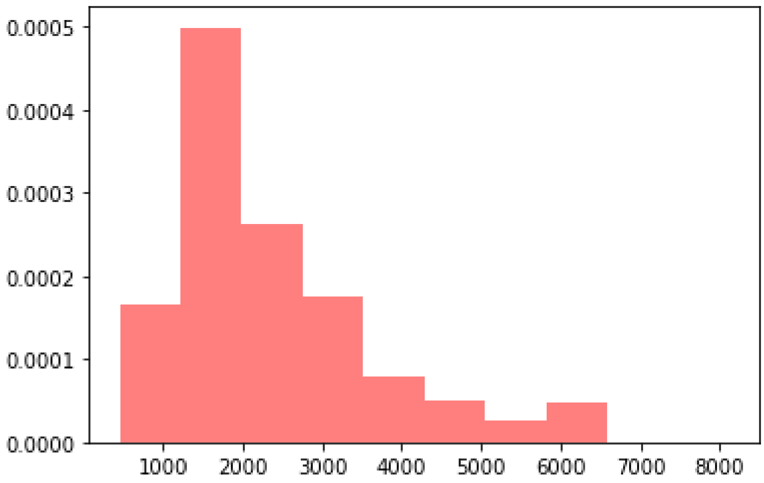


In [872]:

```
plt.hist(df['AverageCostInFacility'],alpha=0.5,color='r',density='True')
```

Out[872]:

```
(array([1.66521597e-04, 4.99129211e-04, 2.61042095e-04, 1.76431004e-04,
        7.82516475e-05, 5.12675698e-05, 2.68098464e-05, 4.65197659e-05,
        0.00000000e+00, 2.17789166e-08]),
 array([ 457. , 1222.7, 1988.4, 2754.1, 3519.8, 4285.5, 5051.2, 5816.9,
        6582.6, 7348.3, 8114. ]),
 <BarContainer object of 10 artists>)
```

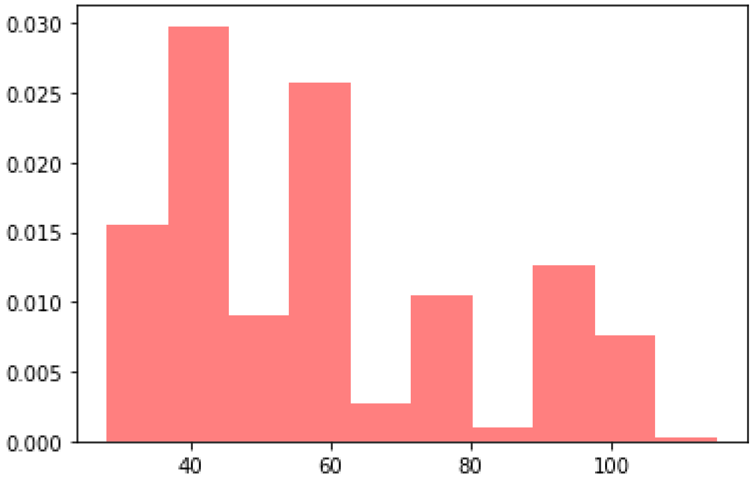


In [873]:

```
plt.hist(df['AverageIncomeInZipCode'],alpha=0.5,color='r',density='True')
```

Out[873]:

```
(array([0.01552987, 0.02981958, 0.00911436, 0.02569847, 0.00274868,
        0.01049829, 0.00100057, 0.01260293, 0.00765185, 0.00027794]),
 array([ 28. ,  36.7,  45.4,  54.1,  62.8,  71.5,  80.2,  88.9,  97.6,
        106.3, 115. ]),
 <BarContainer object of 10 artists>)
```

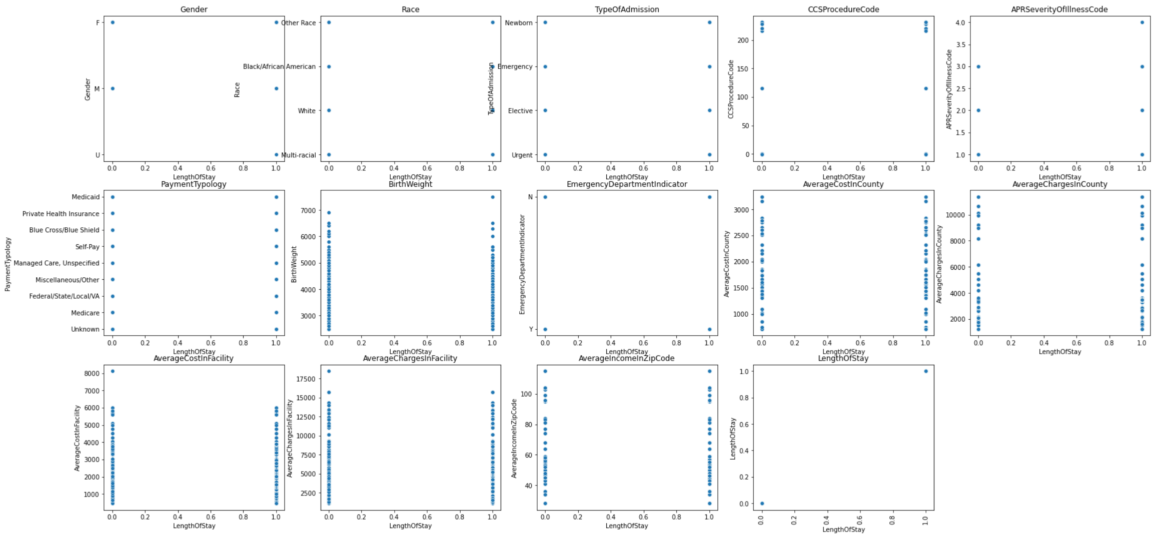


lets focus on now changing the data accordingly and perform scaling etc before we send it to the model

Data Correlation

In [874]:

```
import seaborn as sns
plt.figure(figsize=(30,30))
for i,col in enumerate(df.columns):
    plt.subplot(6,5,i+1)
    sns.scatterplot(data=df,y=col,x='LengthOfStay')
    plt.title(col)
plt.xticks(rotation='vertical')
plt.show()
```



The scatterplot does not reveal any major distribution differences from the attributes influencing LOS

In [875]:

```
string='Race'
df.groupby([string,'LengthOfStay'])['Gender'].count()
```

Out[875]:

```
Race                    LengthOfStay
Black/African American  0               6431
                        1               1752
Multi-racial            0                449
                        1                 77
Other Race              0              15189
                        1               3125
White                   0              27826
                        1               5117
Name: Gender, dtype: int64
```

In [876]:

```
string='Gender'
df.groupby([string,'LengthOfStay'])['Gender'].count()
```

Out[876]:

```
Gender  LengthOfStay
F       0               24449
        1                4538
M       0               25446
        1                5532
U       1                   1
Name: Gender, dtype: int64
```

If its a female , there is 97.85 chance of length of stay being less than 4 days if its a male 82% chance of length stay being less than 4 days

In [877]:

```
string='PaymentTypology'
df.groupby([string,'LengthOfStay'])[string].count()
```

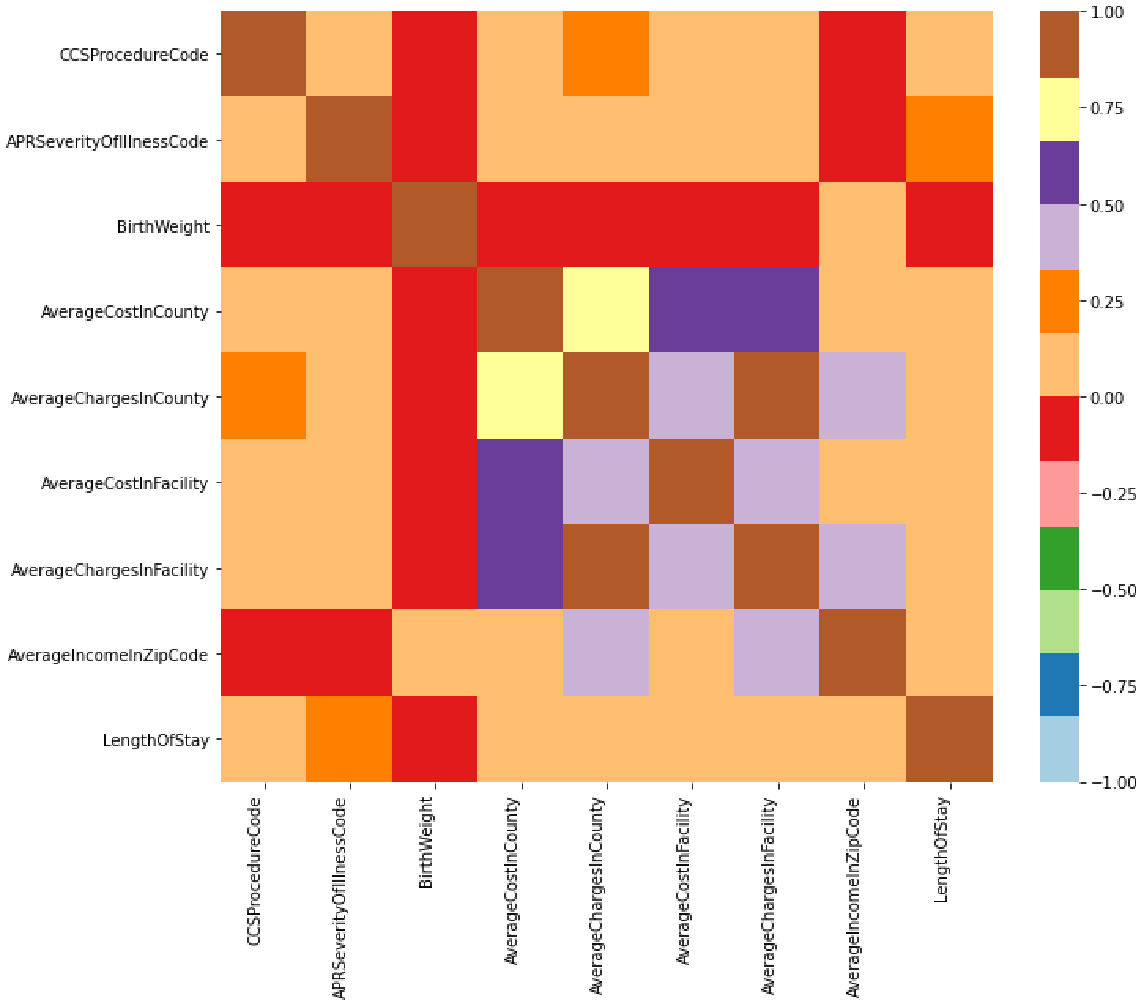
Out[877]:

```
PaymentTypology            LengthOfStay
Blue Cross/Blue Shield     0                9952
                           1                2121
Federal/State/Local/VA     0                 747
                           1                 102
Managed Care, Unspecified  0                 445
                           1                 100
Medicaid                   0               24128
                           1                4595
Medicare                   0                  39
                           1                   5
Miscellaneous/Other        0                  97
                           1                  21
Private Health Insurance   0               12736
                           1                2872
Self-Pay                   0                1739
                           1                 245
Unknown                    0                  12
                           1                  10
Name: PaymentTypology, dtype: int64
```

The next step is to identify the correlation

In [878]:

```
f,ax = plt.subplots(figsize=(11,9))
corr = df.corr()
#print(corr)
ax = sns.heatmap(corr,vmin=-1,vmax=1,center=0,
                cmap='Paired',square=True)
ax.set_xticklabels(ax.get_xticklabels(),rotation=90,horizontalalignment='right');
```



Some observations from the heatmap regarding the relationship between variables :
1.The AverageChargesInCounty and AverageChargesinFacility share a very strong correlation
2.AverageCostInCounty and AverageChargesInCounty share a little higher correlation around 0.75
3.AverageCostinFacility and AverageCostinCounty 0.5
4.AverageChargesinFacility and AverageCostInCounty 0.25
5.The LengthofStay and APRSSeverityOfIllnessCode seem to share some amount +ve correlation aroun 0.25 and all the others
6.share less than 0.25 correlation and BirthWeight seems to have -ve correlation
Ofcourse we have not mapped the relation of other categorical variables yet !!!

Now lets look at the applying logistic Regression model to see the classification model performance :

Step 1: Lets convert the categorical variables using one-hot encoding :

In [879]:

```
#Can we remove the unknown example as it might be an outlier and also unwanted extra co
lun for processing
from sklearn.preprocessing import OneHotEncoder

def convert_to_categorical(df,colname):
    OneHotEncoder_race = OneHotEncoder(handle_unknown='ignore')
    OneHotEncoder_race.fit(df[[colname]])
    one_hot_ = OneHotEncoder_race.transform(df[[colname]]).toarray()
    #print(one_hot_.shape,OneHotEncoder_race.categories_)

    for i in range(len(OneHotEncoder_race.categories_[0])):
        df[colname+'_'+ str(OneHotEncoder_race.categories_[0][i])] = one_hot_[:,i]
    fd = df.drop([colname],axis=1)
    return fd
```

In [880]:

```
df = convert_to_categorical(df,'Gender')
df=convert_to_categorical(df,'Race')
df=convert_to_categorical(df,'TypeOfAdmission')
df=convert_to_categorical(df,'PaymentTypology')
df=convert_to_categorical(df,'EmergencyDepartmentIndicator')
listofzeros= [0]* df.shape[0]
df.insert(21,'PaymentTypology_Department Of Corrections',listofzeros)
df.insert(19,'TypeOfAdmission_Trauma',listofzeros)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 59966 entries, 0 to 59965
Data columns (total 33 columns):
 #   Column                                     Non-Null Count  Dtype  
---  ------                                     --------------  -----  
 0   CCSProcedureCode                           59966 non-null  int64  
 1   APRSeverityOfIllnessCode                   59966 non-null  int64  
 2   BirthWeight                                59966 non-null  int64  
 3   AverageCostInCounty                        59966 non-null  int64  
 4   AverageChargesInCounty                     59966 non-null  int64  
 5   AverageCostInFacility                      59966 non-null  int64  
 6   AverageChargesInFacility                   59966 non-null  int64  
 7   AverageIncomeInZipCode                     59966 non-null  int64  
 8   LengthOfStay                               59966 non-null  int64  
 9   Gender_F                                   59966 non-null  float64
 10  Gender_M                                   59966 non-null  float64
 11  Gender_U                                   59966 non-null  float64
 12  Race_Black/African American                59966 non-null  float64
 13  Race_Multi-racial                          59966 non-null  float64
 14  Race_Other Race                            59966 non-null  float64
 15  Race_White                                 59966 non-null  float64
 16  TypeOfAdmission_Elective                   59966 non-null  float64
 17  TypeOfAdmission_Emergency                  59966 non-null  float64
 18  TypeOfAdmission_Newborn                    59966 non-null  float64
 19  TypeOfAdmission_Trauma                     59966 non-null  int64  
 20  TypeOfAdmission_Urgent                     59966 non-null  float64
 21  PaymentTypology_Blue Cross/Blue Shield     59966 non-null  float64
 22  PaymentTypology_Department Of Corrections  59966 non-null  int64  
 23  PaymentTypology_Federal/State/Local/VA     59966 non-null  float64
 24  PaymentTypology_Managed Care, Unspecified  59966 non-null  float64
 25  PaymentTypology_Medicaid                   59966 non-null  float64
 26  PaymentTypology_Medicare                   59966 non-null  float64
 27  PaymentTypology_Miscellaneous/Other        59966 non-null  float64
 28  PaymentTypology_Private Health Insurance   59966 non-null  float64
 29  PaymentTypology_Self-Pay                   59966 non-null  float64
 30  PaymentTypology_Unknown                    59966 non-null  float64
 31  EmergencyDepartmentIndicator_N             59966 non-null  float64
 32  EmergencyDepartmentIndicator_Y             59966 non-null  float64
dtypes: float64(22), int64(11)
memory usage: 15.1 MB
```

In [881]:

```
df.shape
```

Out[881]:

```
(59966, 33)
```

Splitting the dataset

In [882]:

```
with pd.option_context('mode.chained_assignment',None):
    train_data,test_data = train_test_split(df,test_size=0.2,shuffle=True,random_state=
0)
with pd.option_context('mode.chained_assignment',None):
    train_data,val_data = train_test_split(train_data,test_size=0.25,shuffle=True,rando
m_state=0)
print(train_data.shape,val_data.shape,test_data.shape)
```

```
(35979, 33) (11993, 33) (11994, 33)
```

In [883]:

```
train_X = train_data.drop(['LengthOfStay'],axis=1).to_numpy()
train_y = train_data['LengthOfStay'].to_numpy()

test_X = test_data.drop(['LengthOfStay'],axis=1).to_numpy()
test_y = test_data['LengthOfStay'].to_numpy()

val_X = val_data.drop(['LengthOfStay'],axis=1).to_numpy()
val_y = val_data['LengthOfStay'].to_numpy()
```

In [884]:

```
from sklearn.metrics import f1_score
from sklearn.metrics import *


def print_f1_scores(clf,train_X,train_y,val_X,val_y,tag):
    train_pred = clf.predict(train_X)
    val_pred = clf.predict(val_X)
    train_f1 = balanced_accuracy_score(train_y,train_pred)
    val_f1   = balanced_accuracy_score(val_y,val_pred)

    print("Train   balanced accuracy score:{:.3f}".format(train_f1))
    print("Train            accuracy score:{:.3f}".format(accuracy_score(train_y,train_
pred)))
    print(tag," balanced accuracy score:{:.3f}".format(val_f1))

    print(tag,"          accuracy score:{:.3f}".format(accuracy_score(val_y,val_pred)))

def print_classification_report(model,X,y,tag=" "):
    pred = model.predict(X)
    label_0=tag+"_"+"L0"
    label_1=tag+"_" +"L1"
    label_names = [label_0,label_1]
    print(classification_report(y,pred,target_names=label_names))
```

Logistic Regression, without scaling and regularization

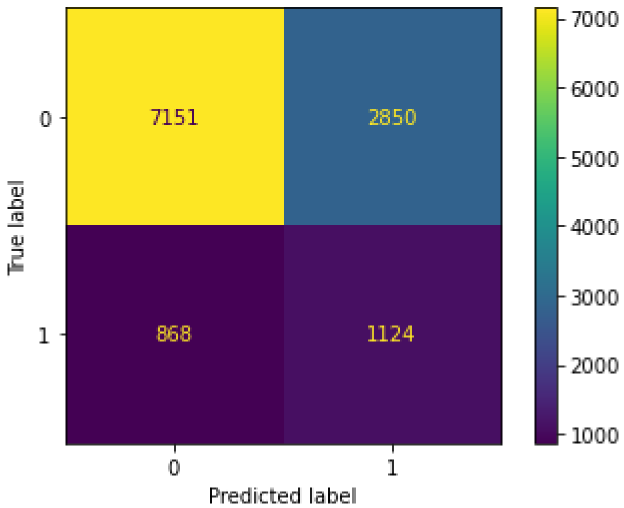
In [885]:

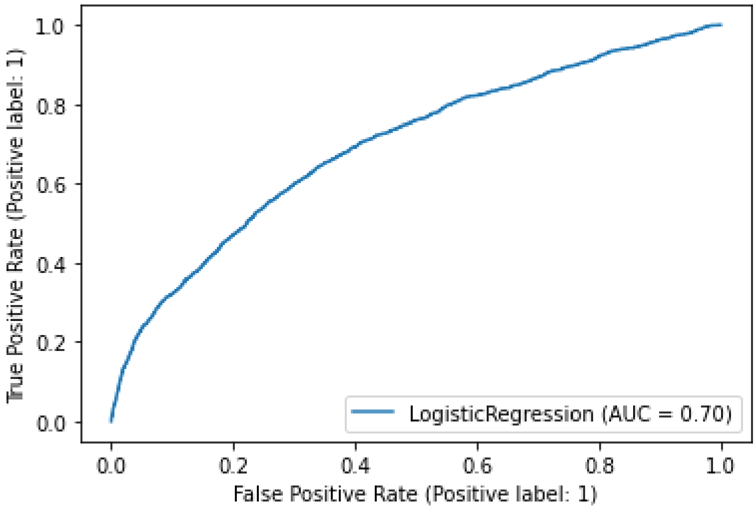
```
#Basic Logistic Regression
from sklearn.metrics import plot_confusion_matrix
clf = LogisticRegression(random_state=0,solver='liblinear',max_iter=1000,class_weight=
'balanced').fit(train_X,train_y.ravel())
plot_confusion_matrix(clf,val_X,val_y)
print_f1_scores(clf,train_X,train_y,val_X,val_y,"Validation")
print_classification_report(clf,val_X,val_y,"validation")
print_f1_scores(clf,train_X,train_y,test_X,test_y,"Test LogReg ")
print_classification_report(clf,test_X,test_y,"Test LogReg ")
plot_roc_curve(clf,test_X,test_y)
```

```
Train   balanced accuracy score:0.648
Train            accuracy score:0.695
Validation  balanced accuracy score:0.640
Validation           accuracy score:0.690
               precision    recall  f1-score   support

validation_L0       0.89      0.72      0.79     10001
validation_L1       0.28      0.56      0.38      1992

     accuracy                           0.69     11993
    macro avg       0.59      0.64      0.59     11993
 weighted avg       0.79      0.69      0.72     11993

Train   balanced accuracy score:0.648
Train            accuracy score:0.695
Test LogReg   balanced accuracy score:0.648
Test LogReg            accuracy score:0.693
                 precision    recall  f1-score   support

Test LogReg _L0       0.89      0.72      0.79      9943
Test LogReg _L1       0.30      0.58      0.39      2051

       accuracy                           0.69     11994
      macro avg       0.59      0.65      0.59     11994
   weighted avg       0.79      0.69      0.73     11994
```

Out[885]:

```
<sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x7fea9b39c2e8>
```





In Summary:
1. The train and validation accuracy score are very close to each other around 0.640 and hence removing any need for regularization and even the test accuracy score is 0.651
2. The precision for label0 is 0.90 and label1 is 0.30 . The precision is low for label1 owing to less class imbalance
3. And the AUC is 0.70 which is like 70%
4. The f1score is low for label1 and around 0.80 for label0

Logistic Regression, Regularized but not scaling

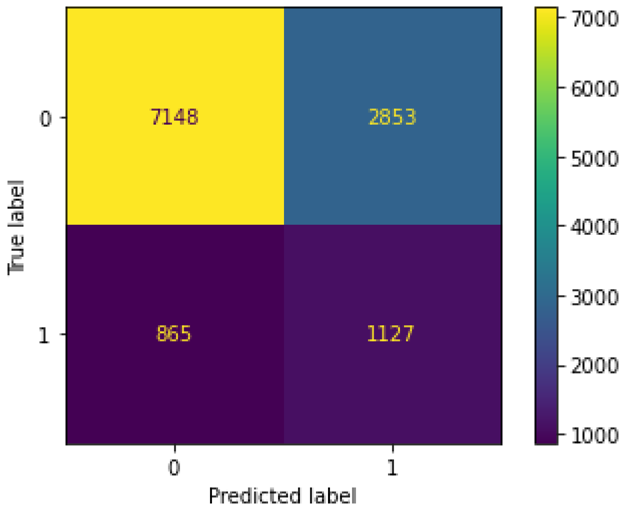
In [886]:

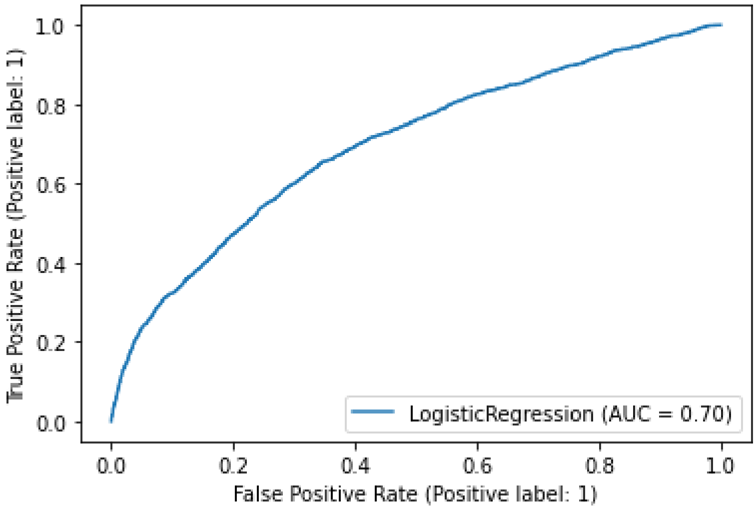
```
clf_l1 = LogisticRegression(penalty='l1',C=0.75,random_state=0,solver='liblinear',max_i
ter=1000,class_weight='balanced').fit(train_X,train_y.ravel())
plot_confusion_matrix(clf_l1,val_X,val_y)
print_f1_scores(clf_l1,train_X,train_y,val_X,val_y,"Validation LogReg L1")
print_classification_report(clf_l1,val_X,val_y,"validation LogReg L1")
print_f1_scores(clf_l1,train_X,train_y,test_X,test_y,"Test LogReg L1")
print_classification_report(clf_l1,test_X,test_y,"Test LogReg L1")
plot_roc_curve(clf_l1,test_X,test_y)
```

```
Train   balanced accuracy score:0.648
Train            accuracy score:0.695
Validation LogReg L1  balanced accuracy score:0.640
Validation LogReg L1           accuracy score:0.690
                         precision    recall  f1-score   support

validation LogReg L1_L0       0.89      0.71      0.79     10001
validation LogReg L1_L1       0.28      0.57      0.38      1992

               accuracy                           0.69     11993
              macro avg       0.59      0.64      0.59     11993
           weighted avg       0.79      0.69      0.72     11993

Train   balanced accuracy score:0.648
Train            accuracy score:0.695
Test LogReg L1  balanced accuracy score:0.650
Test LogReg L1           accuracy score:0.694
                   precision    recall  f1-score   support

Test LogReg L1_L0       0.89      0.72      0.79      9943
Test LogReg L1_L1       0.30      0.58      0.39      2051

         accuracy                           0.69     11994
        macro avg       0.60      0.65      0.59     11994
     weighted avg       0.79      0.69      0.73     11994
```

Out[886]:

```
<sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x7fea9b39c7b8>
```




1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate (Positive label: 1)
LogisticRegression (AUC = 0.70)
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate (Positive label: 1)

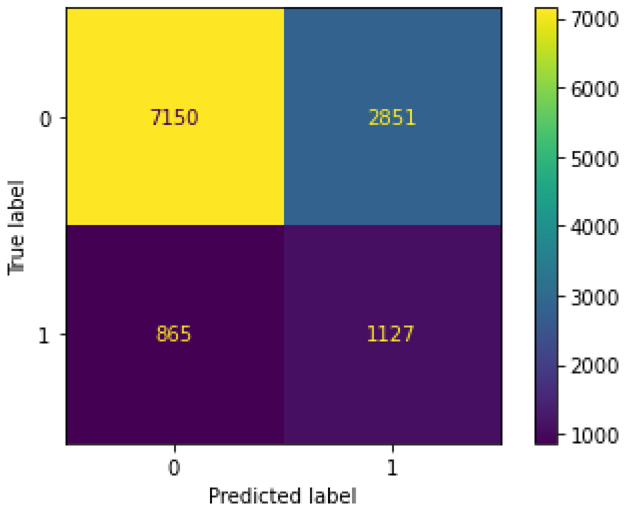
In [887]:

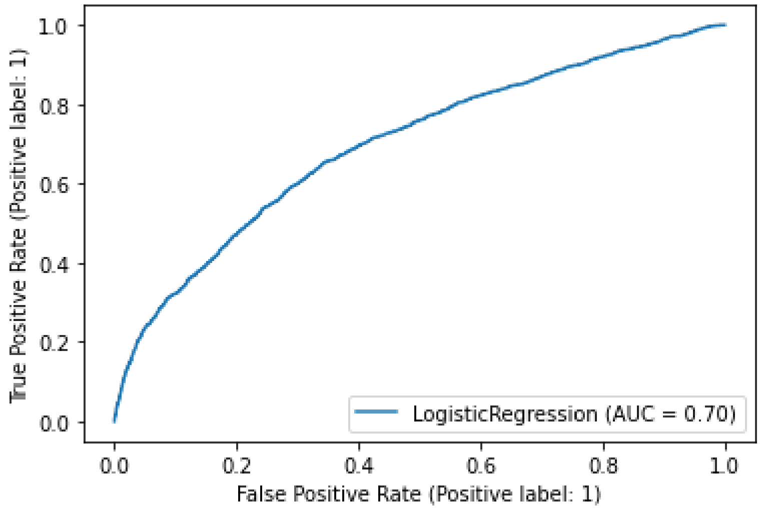
```
clf_l2 = LogisticRegression(penalty='l2',C=0.75,random_state=0,solver='liblinear',max_i
ter=1000,class_weight='balanced').fit(train_X,train_y.ravel())
plot_confusion_matrix(clf_l2,val_X,val_y)
print_f1_scores(clf_l2,train_X,train_y,val_X,val_y,"Validation LogReg L2")
print_classification_report(clf_l2,val_X,val_y,"validation LogReg L2")
print_f1_scores(clf_l2,train_X,train_y,test_X,test_y,"Test LogReg L2")
print_classification_report(clf_l2,test_X,test_y,"Test LogReg L2")
plot_roc_curve(clf_l2,test_X,test_y)
```

```
Train   balanced accuracy score:0.648
Train            accuracy score:0.695
Validation LogReg L2  balanced accuracy score:0.640
Validation LogReg L2           accuracy score:0.690
                         precision    recall  f1-score   support

validation LogReg L2_L0       0.89      0.71      0.79     10001
validation LogReg L2_L1       0.28      0.57      0.38      1992

               accuracy                           0.69     11993
              macro avg       0.59      0.64      0.59     11993
           weighted avg       0.79      0.69      0.72     11993

Train   balanced accuracy score:0.648
Train            accuracy score:0.695
Test LogReg L2  balanced accuracy score:0.650
Test LogReg L2           accuracy score:0.693
                   precision    recall  f1-score   support

Test LogReg L2_L0       0.89      0.72      0.79      9943
Test LogReg L2_L1       0.30      0.58      0.39      2051

         accuracy                           0.69     11994
        macro avg       0.60      0.65      0.59     11994
     weighted avg       0.79      0.69      0.73     11994
```

Out[887]:

```
<sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x7fea9b39c860>
```





Regularization does not help further improve scores as already we observe that both validation and train accuracy and performance metrics are same

**Scaling the attributes and fitting

In [888]:

```
from sklearn.preprocessing import  MinMaxScaler
from sklearn.preprocessing import  StandardScaler
```

In [889]:

```
MinMaxScaler_Train = MinMaxScaler().fit(train_X)
train_X_scale= MinMaxScaler_Train.transform(train_X)
val_X_scale = MinMaxScaler_Train.transform(val_X)
test_X_scale= MinMaxScaler_Train.transform(test_X)
```

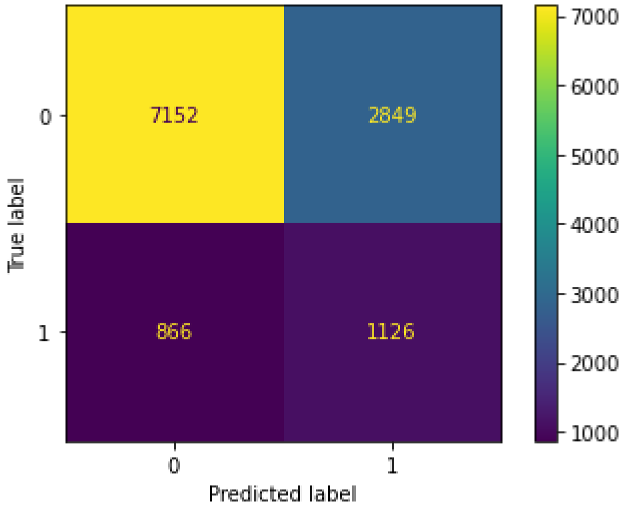
In [890]:

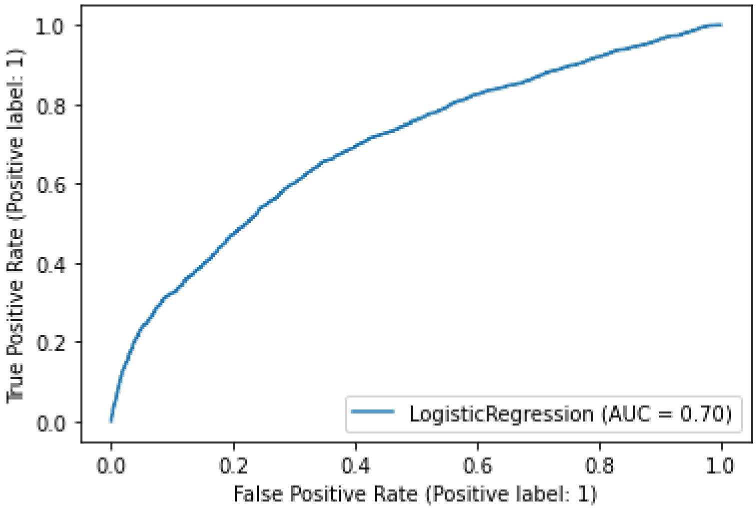
```
clf_scale = LogisticRegression(random_state=0,solver='liblinear',max_iter=1000,class_we
ight='balanced').fit(train_X_scale,train_y.ravel())
plot_confusion_matrix(clf_scale,val_X_scale,val_y)
print_f1_scores(clf_scale,train_X_scale,train_y,val_X_scale,val_y,"Validation LogReg Mi
nMaxScale")
print_classification_report(clf_scale,val_X_scale,val_y,"Validation LogReg MinMaxScale"
)
print_f1_scores(clf_scale,train_X_scale,train_y,test_X_scale,test_y,"Test LogReg MinMax
Scale")
print_classification_report(clf_scale,test_X_scale,test_y,"Test LogReg MinMaxScale")
plot_roc_curve(clf_scale,test_X_scale,test_y)
```

```
Train   balanced accuracy score:0.648
Train            accuracy score:0.696
Validation LogReg MinMaxScale  balanced accuracy score:0.640
Validation LogReg MinMaxScale           accuracy score:0.690
                                  precision    recall  f1-score   support

Validation LogReg MinMaxScale_L0       0.89      0.72      0.79     10001
Validation LogReg MinMaxScale_L1       0.28      0.57      0.38      1992

                        accuracy                           0.69     11993
                       macro avg       0.59      0.64      0.59     11993
                    weighted avg       0.79      0.69      0.72     11993

Train   balanced accuracy score:0.648
Train            accuracy score:0.696
Test LogReg MinMaxScale  balanced accuracy score:0.651
Test LogReg MinMaxScale           accuracy score:0.694
                            precision    recall  f1-score   support

Test LogReg MinMaxScale_L0       0.89      0.72      0.80      9943
Test LogReg MinMaxScale_L1       0.30      0.59      0.40      2051

                  accuracy                           0.69     11994
                 macro avg       0.60      0.65      0.60     11994
              weighted avg       0.79      0.69      0.73     11994
```

Out[890]:

```
<sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x7fea9ac7f630>
```

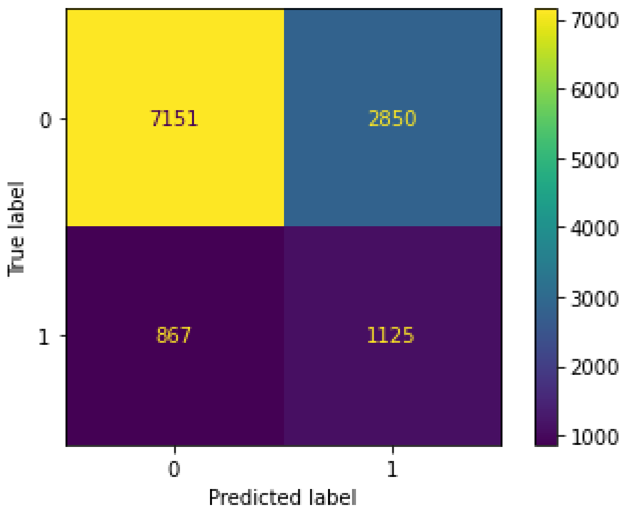


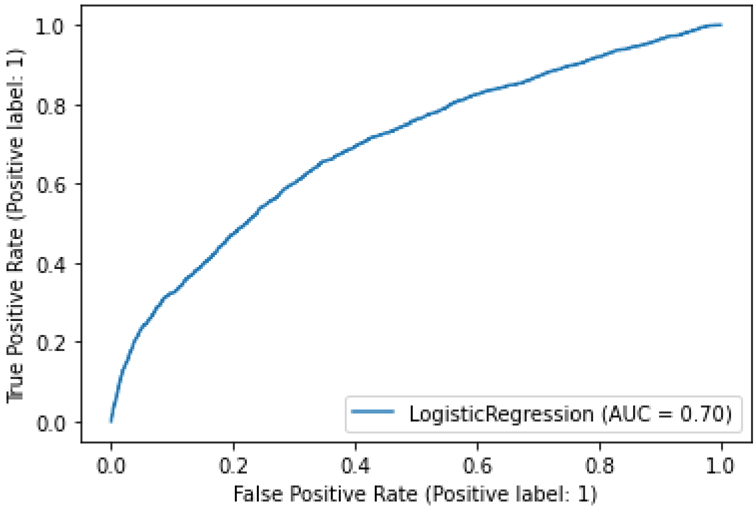

True Positive Rate (Positive label: 1)
1.0
0.8
0.6
0.4
0.2
0.0
LogisticRegression (AUC = 0.70)
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate (Positive label: 1)

In [891]:

```
StandardScaler_Train = StandardScaler().fit(train_X)
train_X_std= StandardScaler_Train.transform(train_X)
val_X_std = StandardScaler_Train.transform(val_X)
test_X_std = StandardScaler_Train.transform(test_X)
clf_std = LogisticRegression(random_state=0,solver='liblinear',max_iter=1000,class_weig
ht='balanced').fit(train_X_std,train_y.ravel())
print_f1_scores(clf_std,train_X_std,train_y,val_X_std,val_y,"Validation LogReg Standard
Scale")
plot_confusion_matrix(clf_std,val_X_std,val_y)
print_classification_report(clf_std,val_X_std,val_y,"Validation LogReg StandardScale")
print_f1_scores(clf_std,train_X_std,train_y,test_X_std,test_y,"Test LogReg StandardScal
e")
print_classification_report(clf_std,test_X_std,test_y,"Test LogReg StandardScale")
plot_roc_curve(clf_std,test_X_std,test_y)
pred_test_y = clf_std.predict(test_X_std)
```

```
Train   balanced accuracy score:0.648
Train            accuracy score:0.696
Validation LogReg StandardScale  balanced accuracy score:0.640
Validation LogReg StandardScale           accuracy score:0.690
                                    precision    recall  f1-score   suppor
t

Validation LogReg StandardScale_L0       0.89      0.72      0.79     1000
1
Validation LogReg StandardScale_L1       0.28      0.56      0.38      199
2

                          accuracy                           0.69     1199
3
                         macro avg       0.59      0.64      0.59     1199
3
                      weighted avg       0.79      0.69      0.72     1199
3

Train   balanced accuracy score:0.648
Train            accuracy score:0.696
Test LogReg StandardScale  balanced accuracy score:0.651
Test LogReg StandardScale           accuracy score:0.694
                              precision    recall  f1-score   support

Test LogReg StandardScale_L0       0.89      0.72      0.80      9943
Test LogReg StandardScale_L1       0.30      0.59      0.40      2051

                    accuracy                           0.69     11994
                   macro avg       0.60      0.65      0.60     11994
                weighted avg       0.79      0.69      0.73     11994
```





The logistic regression Summary :
1.The precision for L0 is good whereas the precision for LOS =1 is not that great with this model.*Primarily this is due to class imbalance*
2. The AUC is around 0.70

Random Forest

Since we saw class imbalance we will look at Random forest and see if they help improve the prediction for the minorty class as well

---

Random forest with max_depth=16

In [892]:

```
from sklearn.ensemble import RandomForestClassifier
rf = RandomForestClassifier(max_depth=16, random_state=0)
rf.fit(train_X, train_y)
print_f1_scores(rf,train_X,train_y,val_X,val_y,  "RF Validation ")
print_f1_scores(rf,train_X,train_y,test_X,test_y,"RF Test ")
print_classification_report(rf, val_X, val_y,tag="RF Validation ")
print_classification_report(rf,test_X,test_y,tag="RF Test ")
```

```
Train   balanced accuracy score:0.689
Train            accuracy score:0.895
RF Validation   balanced accuracy score:0.576
RF Validation            accuracy score:0.844
Train   balanced accuracy score:0.689
Train            accuracy score:0.895
RF Test   balanced accuracy score:0.569
RF Test            accuracy score:0.837
                   precision    recall  f1-score   support

RF Validation _L0       0.86      0.98      0.91     10001
RF Validation _L1       0.61      0.17      0.27      1992

         accuracy                           0.84     11993
        macro avg       0.73      0.58      0.59     11993
     weighted avg       0.82      0.84      0.81     11993

              precision    recall  f1-score   support

 RF Test _L0       0.85      0.98      0.91      9943
 RF Test _L1       0.58      0.16      0.25      2051

    accuracy                           0.84     11994
   macro avg       0.72      0.57      0.58     11994
weighted avg       0.80      0.84      0.80     11994
```

-> The precision is quite good around 0.85 for label 0 and around 0.58 for label 1 which is pretty good .
-> Label0 f1score is higher around 0.91 and around 0.27 for Label1. **Label1's precision has imporved**
-> The balanced accuracy score and accuracy score seem to differ , but we see that with accuracy score of almost 0.844 on validation dataset

Random forest with min_samples_split =4

In [893]:

```
rf = RandomForestClassifier(min_samples_split=4, random_state=0)
rf.fit(train_X, train_y)
print_f1_scores(rf,train_X,train_y, val_X, val_y,"RF Validation ")
print_f1_scores(rf,train_X,train_y,test_X,test_y,"RF Test ")
print_classification_report(rf, val_X, val_y,tag="RF Valdation ")
print_classification_report(rf,test_X,test_y,tag="RF Test ")
```

```
Train   balanced accuracy score:0.812
Train            accuracy score:0.931
RF Validation   balanced accuracy score:0.590
RF Validation            accuracy score:0.825
Train   balanced accuracy score:0.812
Train            accuracy score:0.931
RF Test   balanced accuracy score:0.587
RF Test            accuracy score:0.820
                  precision    recall  f1-score   support

RF Valdation _L0       0.86      0.94      0.90     10001
RF Valdation _L1       0.45      0.24      0.31      1992

        accuracy                           0.83     11993
       macro avg       0.66      0.59      0.61     11993
    weighted avg       0.79      0.83      0.80     11993

              precision    recall  f1-score   support

 RF Test _L0       0.86      0.94      0.90      9943
 RF Test _L1       0.45      0.23      0.31      2051

    accuracy                           0.82     11994
   macro avg       0.65      0.59      0.60     11994
weighted avg       0.79      0.82      0.80     11994
```

Hyperparameter-Tuning using min_samples_splits

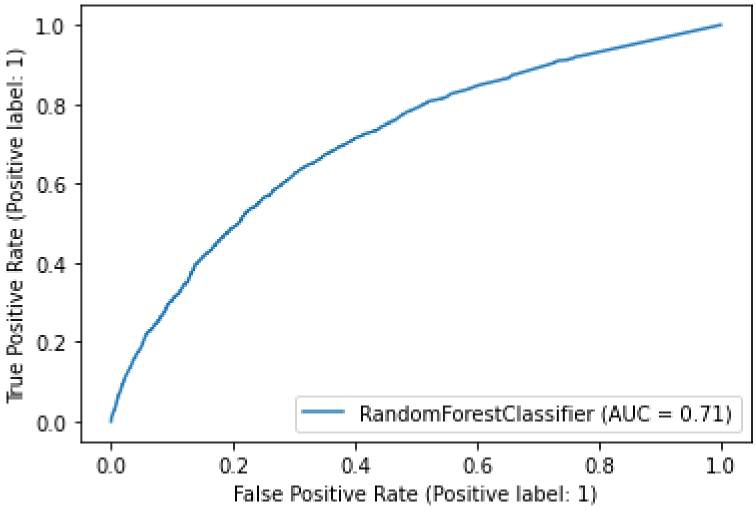
In [894]:

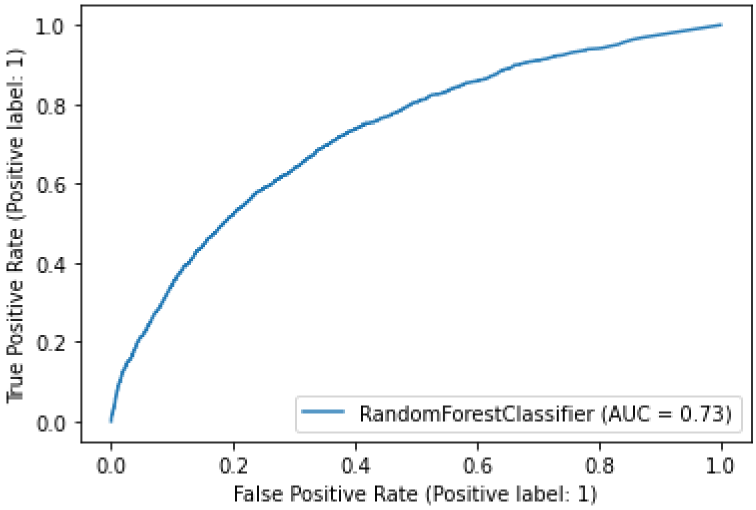
```
from sklearn.metrics import *
train_acc_balanced=list()
val_acc_balanced  =list()
train_acc = list()
val_acc = list()
test_acc = list()
train_class = list()
val_class = list()
for split in [2,4,6,8,10,12,14]:
    rf = RandomForestClassifier(min_samples_split=split, random_state=0)
    rf.fit(train_X, train_y)
    pred_train_y = rf.predict(train_X)
    pred_val_y   = rf.predict(val_X)
    pred_test_y  = rf.predict(test_X)
    train_acc_balanced.append(balanced_accuracy_score(train_y,pred_train_y))
    val_acc_balanced.append(balanced_accuracy_score(val_y,pred_val_y))
    train_acc.append(accuracy_score(train_y,pred_train_y))
    val_acc.append(accuracy_score(val_y,pred_val_y))
    test_acc.append(accuracy_score(test_y,pred_test_y))
    train_class.append(classification_report(train_y,pred_train_y))
    val_class.append(classification_report(val_y,pred_val_y))
    string = "RF Validation " + str(split) + " "
    print_classification_report(rf, val_X, val_y,tag=string)
    string = "RF Test       " + str(split) + " "
    print_classification_report(rf,test_X,test_y,tag=string)
    plot_roc_curve(rf,test_X,test_y)
```

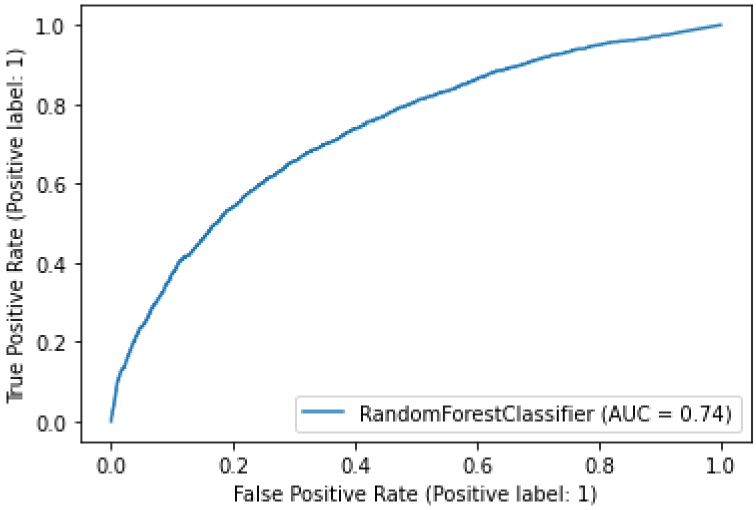
```
                       precision    recall  f1-score   support

  RF Validation 2 _L0       0.86      0.92      0.89     10001
  RF Validation 2 _L1       0.40      0.25      0.31      1992

             accuracy                           0.81     11993
            macro avg       0.63      0.59      0.60     11993
         weighted avg       0.78      0.81      0.80     11993

                       precision    recall  f1-score   support

  RF Test       2 _L0       0.86      0.92      0.89      9943
  RF Test       2 _L1       0.40      0.25      0.31      2051

             accuracy                           0.81     11994
            macro avg       0.63      0.59      0.60     11994
         weighted avg       0.78      0.81      0.79     11994

                       precision    recall  f1-score   support

  RF Validation 4 _L0       0.86      0.94      0.90     10001
  RF Validation 4 _L1       0.45      0.24      0.31      1992

             accuracy                           0.83     11993
            macro avg       0.66      0.59      0.61     11993
         weighted avg       0.79      0.83      0.80     11993

                       precision    recall  f1-score   support

  RF Test       4 _L0       0.86      0.94      0.90      9943
  RF Test       4 _L1       0.45      0.23      0.31      2051

             accuracy                           0.82     11994
            macro avg       0.65      0.59      0.60     11994
         weighted avg       0.79      0.82      0.80     11994

                       precision    recall  f1-score   support

  RF Validation 6 _L0       0.86      0.96      0.91     10001
  RF Validation 6 _L1       0.50      0.22      0.30      1992

             accuracy                           0.83     11993
            macro avg       0.68      0.59      0.60     11993
         weighted avg       0.80      0.83      0.80     11993

                       precision    recall  f1-score   support

  RF Test       6 _L0       0.86      0.96      0.90      9943
  RF Test       6 _L1       0.51      0.22      0.31      2051

             accuracy                           0.83     11994
            macro avg       0.68      0.59      0.60     11994
         weighted avg       0.80      0.83      0.80     11994

                       precision    recall  f1-score   support

  RF Validation 8 _L0       0.86      0.96      0.91     10001
  RF Validation 8 _L1       0.54      0.21      0.30      1992

             accuracy                           0.84     11993
            macro avg       0.70      0.59      0.61     11993
```

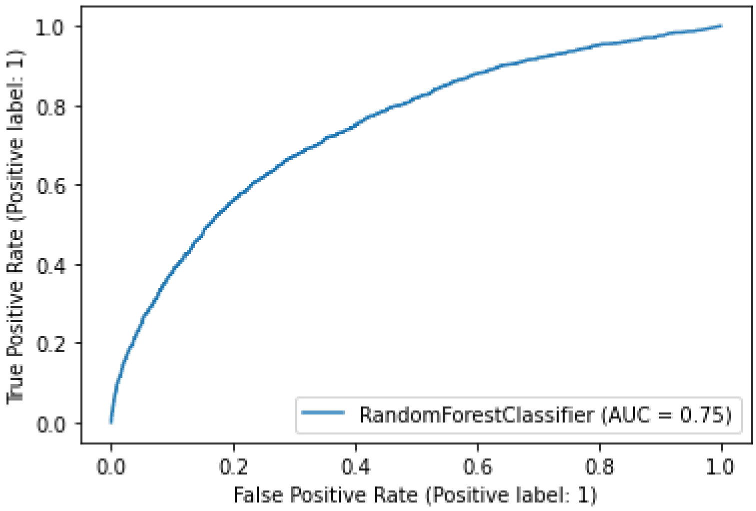
```
       weighted avg       0.81      0.84      0.81     11993

                     precision    recall  f1-score   support

   RF Test       8 _L0       0.85      0.96      0.91      9943
   RF Test       8 _L1       0.53      0.20      0.30      2051

           accuracy                           0.83     11994
          macro avg       0.69      0.58      0.60     11994
       weighted avg       0.80      0.83      0.80     11994

                      precision    recall  f1-score   support

   RF Validation 10 _L0       0.86      0.97      0.91     10001
   RF Validation 10 _L1       0.57      0.20      0.30      1992

            accuracy                           0.84     11993
           macro avg       0.71      0.59      0.60     11993
        weighted avg       0.81      0.84      0.81     11993

                      precision    recall  f1-score   support

   RF Test       10 _L0       0.85      0.97      0.91      9943
   RF Test       10 _L1       0.57      0.20      0.30      2051

            accuracy                           0.84     11994
           macro avg       0.71      0.58      0.60     11994
        weighted avg       0.81      0.84      0.80     11994

                      precision    recall  f1-score   support

   RF Validation 12 _L0       0.86      0.97      0.91     10001
   RF Validation 12 _L1       0.59      0.19      0.29      1992

            accuracy                           0.84     11993
           macro avg       0.72      0.58      0.60     11993
        weighted avg       0.81      0.84      0.81     11993

                      precision    recall  f1-score   support

   RF Test       12 _L0       0.85      0.97      0.91      9943
   RF Test       12 _L1       0.57      0.18      0.28      2051

            accuracy                           0.84     11994
           macro avg       0.71      0.58      0.59     11994
        weighted avg       0.80      0.84      0.80     11994

                      precision    recall  f1-score   support

   RF Validation 14 _L0       0.86      0.98      0.91     10001
   RF Validation 14 _L1       0.62      0.19      0.29      1992

            accuracy                           0.85     11993
           macro avg       0.74      0.58      0.60     11993
        weighted avg       0.82      0.85      0.81     11993

                      precision    recall  f1-score   support

   RF Test       14 _L0       0.85      0.97      0.91      9943
   RF Test       14 _L1       0.60      0.18      0.28      2051
```

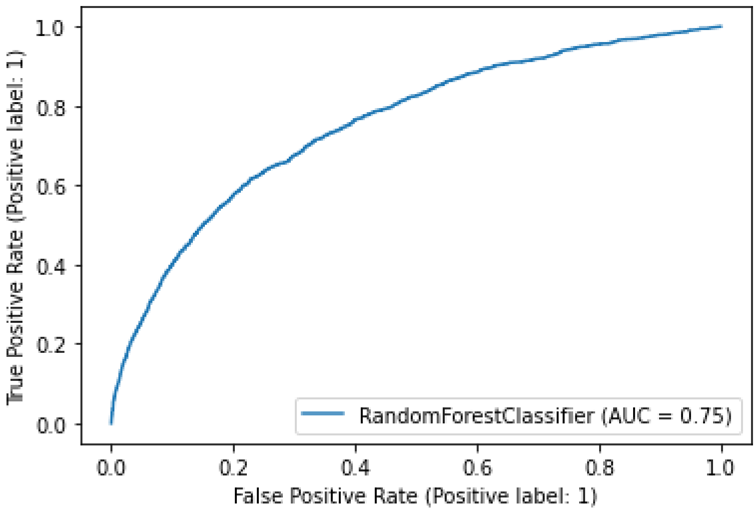
```
    accuracy                           0.84     11994
   macro avg       0.73      0.58      0.60     11994
weighted avg       0.81      0.84      0.80     11994
```

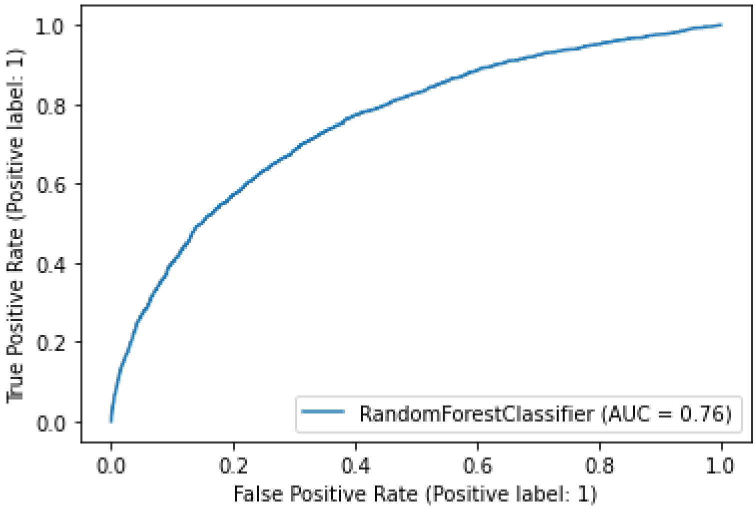


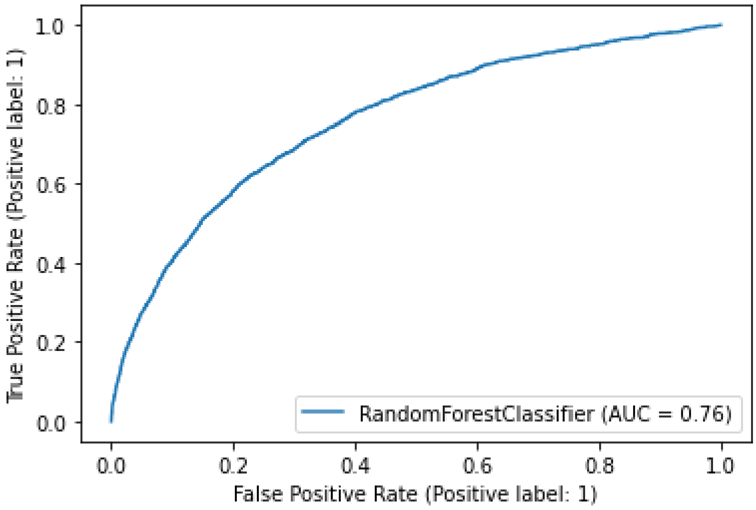



1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate (Positive label: 1)
RandomForestClassifier (AUC = 0.74)
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate (Positive label: 1)


1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate (Positive label: 1)
RandomForestClassifier (AUC = 0.75)
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate (Positive label: 1)


1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate (Positive label: 1)
RandomForestClassifier (AUC = 0.75)
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate (Positive label: 1)

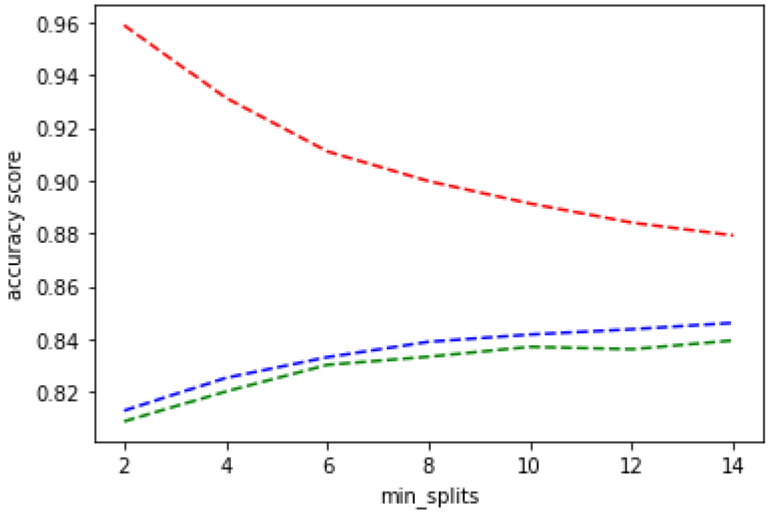




Plot the training and validation accuracy across min splits

In [895]:

```
splits=[2,4,6,8,10,12,14]
plt.plot(splits,train_acc,'r--')
plt.plot(splits,val_acc,'b--')
plt.plot(splits,test_acc,'g--')
plt.xlabel('min_splits')
plt.ylabel('accuracy score')

plt.show()
```



We observe that the label precision goes upto 0.60 at a split of 14 . Lets also observe the RF classifier behavior varying max_depth

---

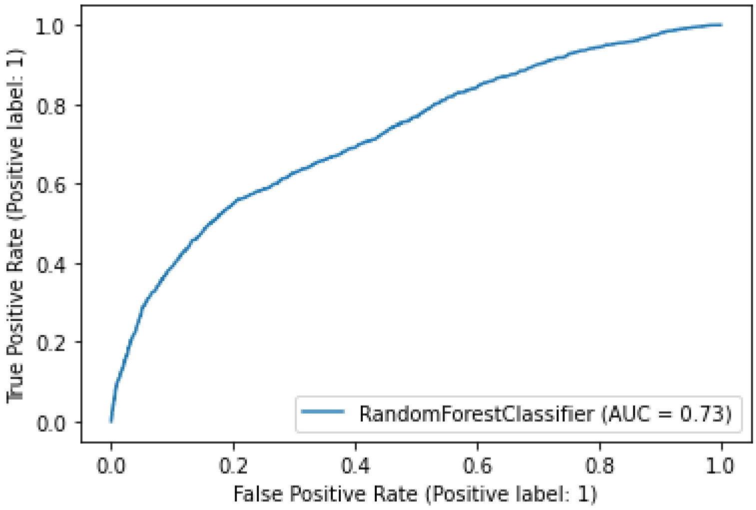
Hyperparameter-Tuning using max_depth

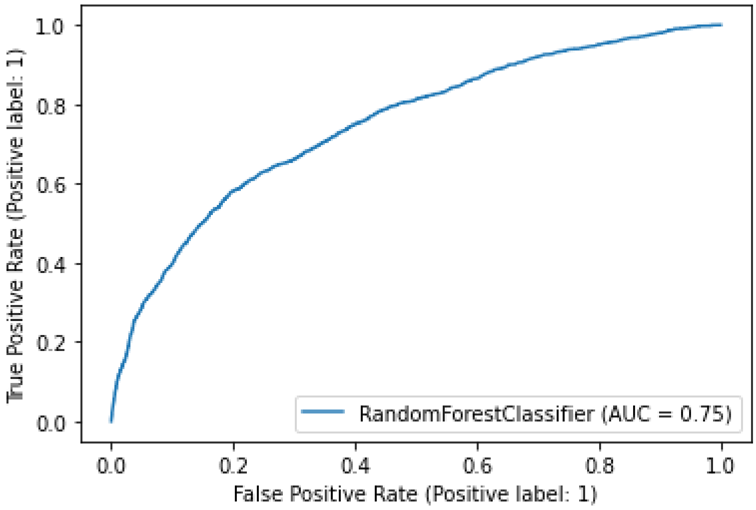
In [896]:

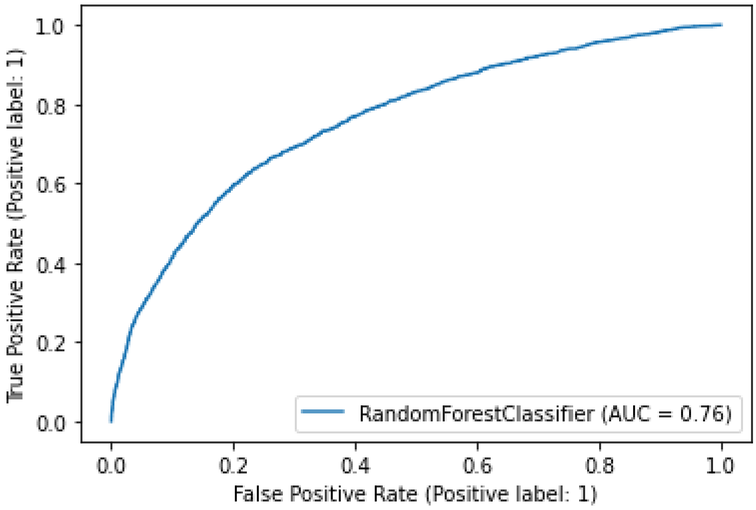
```
from sklearn.metrics import *
train_acc_balanced=list()
val_acc_balanced  =list()
test_acc_balanced = list()
train_acc=list()
val_acc  =list()
train_class = list()
val_class = list()
test_acc = list()
for depth in [4,6,8,10,12,14]:
    rf = RandomForestClassifier(max_depth=depth, random_state=0)
    rf.fit(train_X, train_y)
    pred_train_y = rf.predict(train_X)
    pred_val_y   = rf.predict(val_X)
    pred_test_y   = rf.predict(test_X)
    train_acc_balanced.append(balanced_accuracy_score(train_y,pred_train_y))
    val_acc_balanced.append(balanced_accuracy_score(val_y,pred_val_y))
    test_acc_balanced.append(balanced_accuracy_score(test_y,pred_test_y))
    train_acc.append(accuracy_score(train_y,pred_train_y))
    val_acc.append(accuracy_score(val_y,pred_val_y))
    test_acc.append(accuracy_score(test_y,pred_test_y))
    train_class.append(classification_report(train_y,pred_train_y))
    val_class.append(classification_report(val_y,pred_val_y))
    string = "RF Validation " + str(depth) + " "
    print_classification_report(rf, val_X, val_y,tag=string)
    string = "RF Test       " + str(depth) + " "
    print_classification_report(rf,test_X,test_y,tag=string)
    plot_roc_curve(rf,test_X,test_y)
```

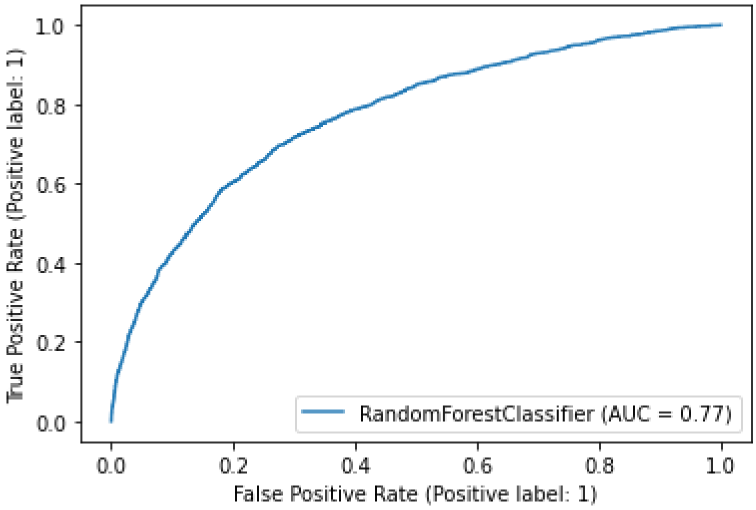
```
                      precision    recall  f1-score   support

RF Validation 4 _L0       0.83      1.00      0.91     10001
RF Validation 4 _L1       1.00      0.00      0.00      1992

           accuracy                           0.83     11993
          macro avg       0.92      0.50      0.46     11993
       weighted avg       0.86      0.83      0.76     11993

                      precision    recall  f1-score   support

RF Test       4 _L0       0.83      1.00      0.91      9943
RF Test       4 _L1       1.00      0.00      0.00      2051

           accuracy                           0.83     11994
          macro avg       0.91      0.50      0.45     11994
       weighted avg       0.86      0.83      0.75     11994

                      precision    recall  f1-score   support

RF Validation 6 _L0       0.84      1.00      0.91     10001
RF Validation 6 _L1       0.79      0.06      0.10      1992

           accuracy                           0.84     11993
          macro avg       0.81      0.53      0.51     11993
       weighted avg       0.83      0.84      0.78     11993

                      precision    recall  f1-score   support

RF Test       6 _L0       0.83      1.00      0.91      9943
RF Test       6 _L1       0.72      0.04      0.08      2051

           accuracy                           0.83     11994
          macro avg       0.78      0.52      0.50     11994
       weighted avg       0.81      0.83      0.77     11994

                      precision    recall  f1-score   support

RF Validation 8 _L0       0.84      0.99      0.91     10001
RF Validation 8 _L1       0.74      0.07      0.13      1992

           accuracy                           0.84     11993
          macro avg       0.79      0.53      0.52     11993
       weighted avg       0.83      0.84      0.78     11993

                      precision    recall  f1-score   support

RF Test       8 _L0       0.84      0.99      0.91      9943
RF Test       8 _L1       0.73      0.07      0.12      2051

           accuracy                           0.84     11994
          macro avg       0.78      0.53      0.52     11994
       weighted avg       0.82      0.84      0.78     11994

                       precision    recall  f1-score   support

RF Validation 10 _L0       0.85      0.99      0.91     10001
RF Validation 10 _L1       0.71      0.11      0.19      1992

            accuracy                           0.84     11993
           macro avg       0.78      0.55      0.55     11993
```

```
      weighted avg       0.83      0.84      0.79     11993

                    precision    recall  f1-score   support

   RF Test       10 _L0       0.84      0.99      0.91      9943
   RF Test       10 _L1       0.70      0.11      0.19      2051

          accuracy                           0.84     11994
         macro avg       0.77      0.55      0.55     11994
      weighted avg       0.82      0.84      0.79     11994

                    precision    recall  f1-score   support

   RF Validation 12 _L0       0.85      0.99      0.91     10001
   RF Validation 12 _L1       0.68      0.14      0.23      1992

          accuracy                           0.85     11993
         macro avg       0.76      0.56      0.57     11993
      weighted avg       0.82      0.85      0.80     11993

                    precision    recall  f1-score   support

   RF Test       12 _L0       0.85      0.99      0.91      9943
   RF Test       12 _L1       0.66      0.14      0.23      2051

          accuracy                           0.84     11994
         macro avg       0.76      0.56      0.57     11994
      weighted avg       0.82      0.84      0.79     11994

                    precision    recall  f1-score   support

   RF Validation 14 _L0       0.85      0.98      0.91     10001
   RF Validation 14 _L1       0.65      0.16      0.25      1992

          accuracy                           0.85     11993
         macro avg       0.75      0.57      0.58     11993
      weighted avg       0.82      0.85      0.80     11993

                    precision    recall  f1-score   support

   RF Test       14 _L0       0.85      0.98      0.91      9943
   RF Test       14 _L1       0.62      0.15      0.24      2051

          accuracy                           0.84     11994
         macro avg       0.74      0.57      0.58     11994
      weighted avg       0.81      0.84      0.80     11994
```

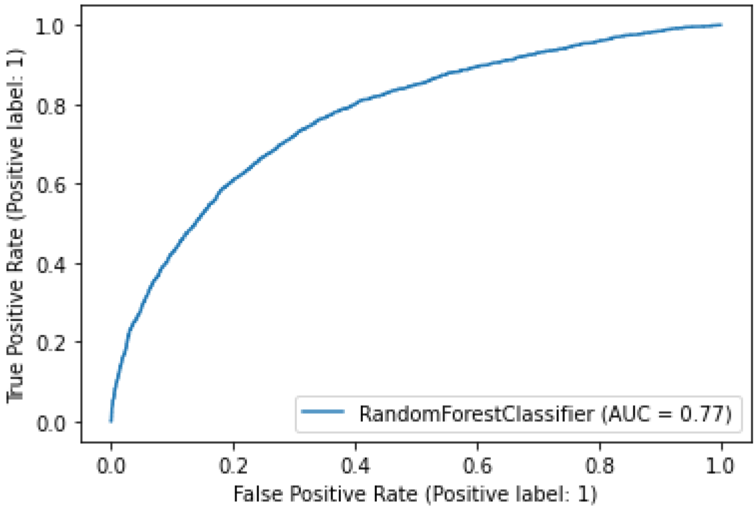

True Positive Rate (Positive label: 1)
1.0
0.8
0.6
0.4
0.2
0.0
RandomForestClassifier (AUC = 0.73)
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate (Positive label: 1)


True Positive Rate (Positive label: 1)
1.0
0.8
0.6
0.4
0.2
0.0
RandomForestClassifier (AUC = 0.75)
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate (Positive label: 1)

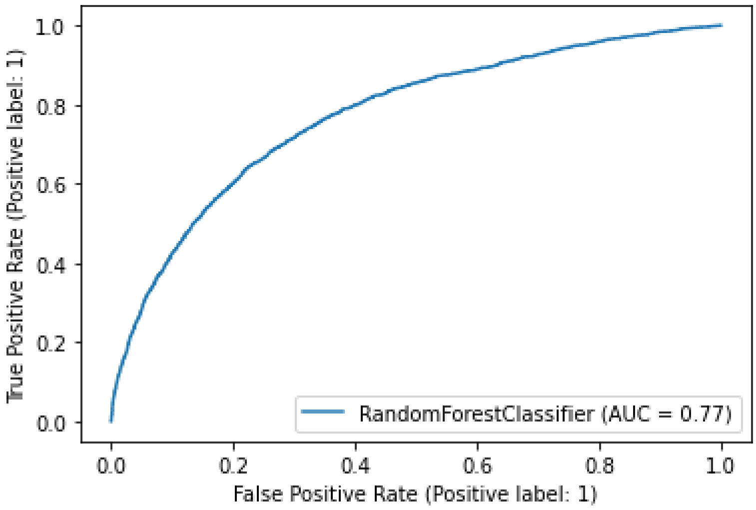

True Positive Rate (Positive label: 1)
1.0
0.8
0.6
0.4
0.2
0.0
RandomForestClassifier (AUC = 0.76)
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate (Positive label: 1)



1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate (Positive label: 1)
RandomForestClassifier (AUC = 0.77)
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate (Positive label: 1)



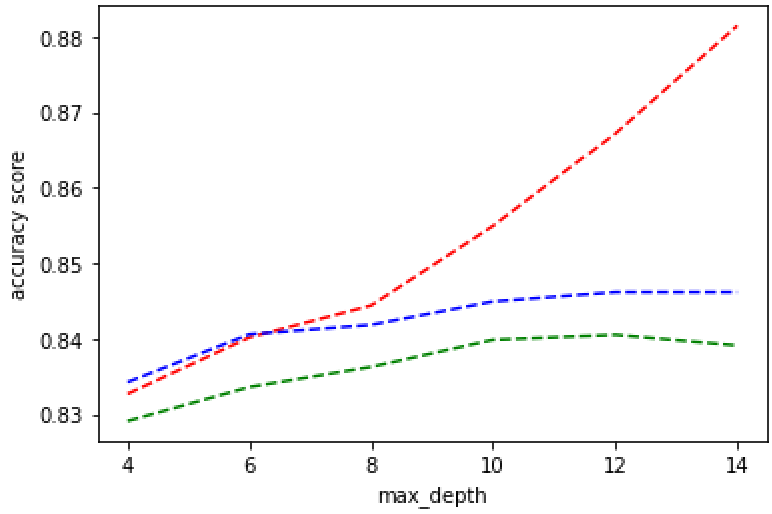
1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate (Positive label: 1)
RandomForestClassifier (AUC = 0.77)
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate (Positive label: 1)



1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate (Positive label: 1)
RandomForestClassifier (AUC = 0.77)
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate (Positive label: 1)

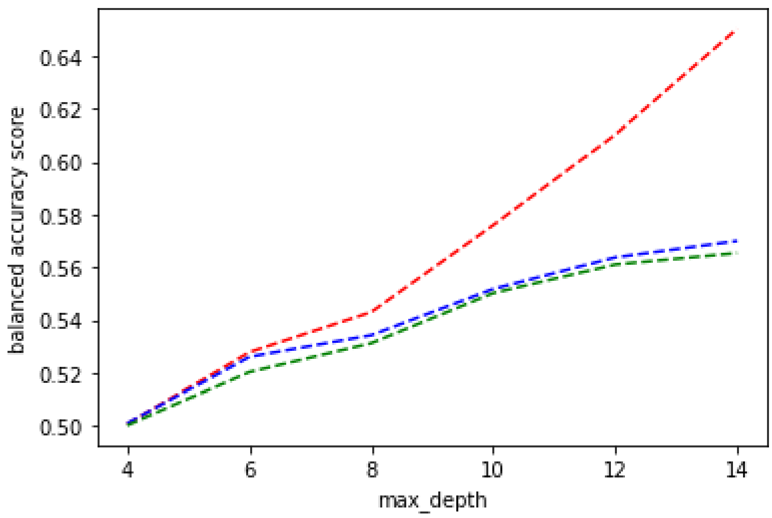
In [897]:

```
depths=[4,6,8,10,12,14]
plt.plot(depths,train_acc,'r--')
#validation accuracy
plt.plot(depths,val_acc,'b--')
#test_acc
plt.plot(depths,test_acc,'g--')
plt.xlabel('max_depth')
plt.ylabel('accuracy score')

plt.show()
```



In [898]:

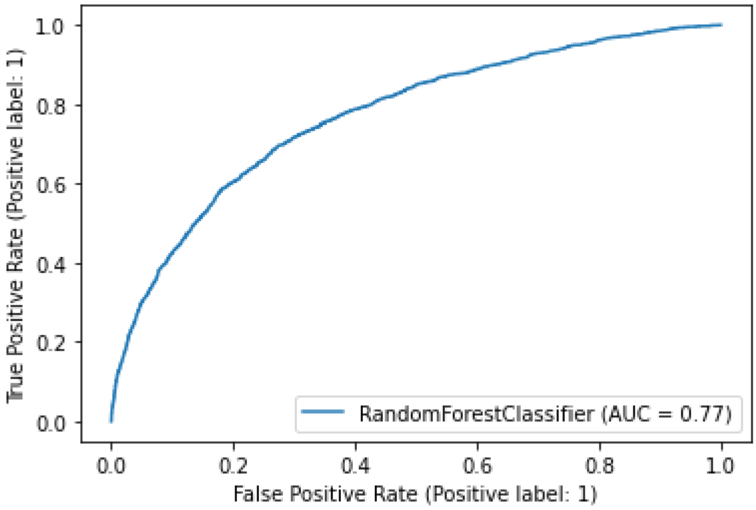
```
depths=[4,6,8,10,12,14]
plt.plot(depths,train_acc_balanced,'r--')
#validation accuracy
plt.plot(depths,val_acc_balanced,'b--')
#test_acc
plt.plot(depths,test_acc_balanced,'g--')
plt.xlabel('max_depth')
plt.ylabel('balanced accuracy score')

plt.show()
```



So at depth 10 we can get a good precision for both the labels around 0.84 and 0.70 for labels 0 and 1 respectively.
We also observe good F1score of 0.91 for label 0 and 0.20 for label1
And also the AUC=0.77 which is slightly also better than the logistic regression fit we saw
Also slightly better than AUC of 0.71 which we see in the case of max_splits tuning

In [899]:

```
rf = RandomForestClassifier(max_depth=10, random_state=0)
rf.fit(train_X, train_y)
pred_test_y = rf.predict(test_X)
plot_roc_curve(rf,test_X,test_y)
pred_test_y = rf.predict(test_X)
```



So we shall choose the randomforest classifier at depth 10 as our model giving slightly better AUC around 0.76

Finally lets generate the prediction

In [900]:

```
#Loading the test data
df_test = pd.read_csv('test_data.csv')
df_test.shape
df_test = df_test.drop(['ID','HealthServiceArea'],axis=1)
df_test =convert_to_categorical(df_test,'Gender')
df_test =convert_to_categorical(df_test,'Race')
df_test =convert_to_categorical(df_test,'TypeOfAdmission')
df_test =convert_to_categorical(df_test,'PaymentTypology')
df_test =convert_to_categorical(df_test,'EmergencyDepartmentIndicator')
df_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 69177 entries, 0 to 69176
Data columns (total 32 columns):
 #   Column                                  Non-Null Count  Dtype
---  ------                                  --------------  -----
 0   CCSProcedureCode                        69177 non-null  int64
 1   APRSeverityOfIllnessCode                69177 non-null  int64
 2   BirthWeight                             69177 non-null  int64
 3   AverageCostInCounty                     69177 non-null  int64
 4   AverageChargesInCounty                  69177 non-null  int64
 5   AverageCostInFacility                   69177 non-null  int64
 6   AverageChargesInFacility                69177 non-null  int64
 7   AverageIncomeInZipCode                  69177 non-null  int64
 8   Gender_F                                69177 non-null  float64
 9   Gender_M                                69177 non-null  float64
 10  Gender_U                                69177 non-null  float64
 11  Race_Black/African American             69177 non-null  float64
 12  Race_Multi-racial                       69177 non-null  float64
 13  Race_Other Race                         69177 non-null  float64
 14  Race_White                              69177 non-null  float64
 15  TypeOfAdmission_Elective                69177 non-null  float64
 16  TypeOfAdmission_Emergency               69177 non-null  float64
 17  TypeOfAdmission_Newborn                 69177 non-null  float64
 18  TypeOfAdmission_Trauma                  69177 non-null  float64
 19  TypeOfAdmission_Urgent                  69177 non-null  float64
 20  PaymentTypology_Blue Cross/Blue Shield  69177 non-null  float64
 21  PaymentTypology_Department of Corrections  69177 non-null  float64
 22  PaymentTypology_Federal/State/Local/VA  69177 non-null  float64
 23  PaymentTypology_Managed Care, Unspecified  69177 non-null  float64
 24  PaymentTypology_Medicaid                69177 non-null  float64
 25  PaymentTypology_Medicare                69177 non-null  float64
 26  PaymentTypology_Miscellaneous/Other     69177 non-null  float64
 27  PaymentTypology_Private Health Insurance  69177 non-null  float64
 28  PaymentTypology_Self-Pay                69177 non-null  float64
 29  PaymentTypology_Unknown                 69177 non-null  float64
 30  EmergencyDepartmentIndicator_N          69177 non-null  float64
 31  EmergencyDepartmentIndicator_Y          69177 non-null  float64
dtypes: float64(24), int64(8)
memory usage: 16.9 MB
```

In [901]:

```
test_pred=rf.predict(df_test.to_numpy())
print(test_pred.shape)
```

```
(69177,)
```

In [902]:

```
unique,counts = np.unique(test_pred,return_counts=True)
print(counts)
```

```
[68436   741]
```

In [903]:

```
f = open('s3785704_predictions.csv','w+')
i=1
length = len(test_pred)
f.write('ID,LengthOfStay\n')
for i in range(0,length):
    if i+1 == length:
        string = str(i+1)+ ',' + str(test_pred[i])
    else:
        string = str(i+1)+ ',' + str(test_pred[i]) + '\n'
    f.write(string)
f.close()
```

In [904]:

```
print("Done")
```

```
Done
```