In [134]: import numpy as np import pandas as pd import seaborn as sb %matplotlib inline import matplotlib.pyplot as plt import sklearn from pandas import Series, DataFrame from pylab import rcParams from sklearn import preprocessing from sklearn.linear_model import LogisticRegression from sklearn.cross_validation import train_test_split from sklearn import metrics from sklearn.metrics import classification report

Out[135]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th	female	38.0	1	0	PC 17599	71.:
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0

In [136]: type(titanic)

Out[136]: pandas.core.frame.DataFrame

In [137]: titanic.isnull().sum()

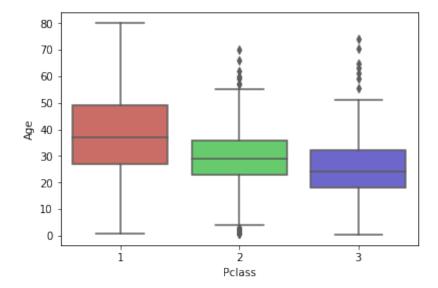
Out[137]: PassengerId 0 Survived 0 Pclass 0 Name 0 Sex 0 177 Age SibSp 0 0 Parch Ticket 0 Fare 0 Cabin 687 Embarked 2 dtype: int64

Out[138]:

	Survived	Pclass	Sex	Age	Parch	Fare	Embarked
0	0	3	male	22.0	0	7.2500	S
1	1	1	female	38.0	0	71.2833	С
2	1	3	female	26.0	0	7.9250	S
3	1	1	female	35.0	0	53.1000	S
4	0	3	male	35.0	0	8.0500	S

```
In [139]: sb.boxplot(x='Pclass', y='Age', data=titanic, palette='hls')
```

Out[139]: <matplotlib.axes._subplots.AxesSubplot at 0x1a1c1875c0>



```
In [140]: def age_approx(cols):
         Age = cols[0]
         Pclass = cols[1]
         if pd.isnull(Age):
               return 37
               elif Pclass == 1:
                    return 29
               else:
                    return 24
               else:
                    return Age
                    titanic['Age'] = titanic[['Age', 'Pclass']].apply(age_approx, axis=1)
                    titanic.isnull().sum()
```

```
Out[140]: Survived 0
Pclass 0
Sex 0
Age 0
Parch 0
Fare 0
Embarked 2
dtype: int64
```

```
In [141]: titanic.dropna(inplace=True)
titanic.isnull().sum()
```

Out[141]: Survived 0
Pclass 0
Sex 0
Age 0
Parch 0
Fare 0
Embarked 0
dtype: int64

```
In [142]: # Now Converting Categorical Variables into Dummy Variables
gender = pd.get_dummies(titanic['Sex'],drop_first=True)
gender.head()
```

Out[142]:

	male
0	1
1	0
2	0
3	0
4	1

```
In [143]: embark = pd.get_dummies(titanic['Embarked'],drop_first=True)
  embark.head()
```

Out[143]:

	Q	s
0	0	1
1	0	0
2	0	1
3	0	1
4	0	1

In [144]: titanic.head()

Out[144]:

	Survived	Pclass	Sex	Age	Parch	Fare	Embarked
0	0	3	male	22.0	0	7.2500	S
1	1	1	female	38.0	0	71.2833	С
2	1	3	female	26.0	0	7.9250	S
3	1	1	female	35.0	0	53.1000	S
4	0	3	male	35.0	0	8.0500	S

In [145]: titanic.drop(['Sex', 'Embarked'],axis=1,inplace=True) titanic.head()

Out[145]:

	Survived	Pclass	Age	Parch	Fare
0	0	3	22.0	0	7.2500
1	1	1	38.0	0	71.2833
2	1	3	26.0	0	7.9250
3	1	1	35.0	0	53.1000
4	0	3	35.0	0	8.0500

In [146]: titanicD = pd.concat([titanic,gender,embark],axis=1) titanicD.head()

Out[146]: _____

	Survived	Pclass	Age	Parch	Fare	male	Ø	S
0	0	3	22.0	0	7.2500	1	0	1
1	1	1	38.0	0	71.2833	0	0	0
2	1	3	26.0	0	7.9250	0	0	1
3	1	1	35.0	0	53.1000	0	0	1
4	0	3	35.0	0	8.0500	1	0	1

In [147]: titanicD.corr()

Out[147]:

	Survived	Pclass	Age	Parch	Fare	male	Q	
Survived	1.000000	-0.335549	-0.052051	0.083151	0.255290	-0.541585	0.004536	-
Pclass	-0.335549	1.000000	-0.405549	0.016824	-0.548193	0.127741	0.220558	C
Age	-0.052051	-0.405549	1.000000	-0.170089	0.120938	0.083730	-0.080875	(
Parch	0.083151	0.016824	-0.170089	1.000000	0.217532	-0.247508	-0.081585	(
Fare	0.255290	-0.548193	0.120938	0.217532	1.000000	-0.179958	-0.116684	[-
male	-0.541585	0.127741	0.083730	-0.247508	-0.179958	1.000000	-0.075217	(
Q	0.004536	0.220558	-0.080875	-0.081585	-0.116684	-0.075217	1.000000	-
S	-0.151777	0.076466	0.013598	0.061512	-0.163758	0.121405	-0.499261	1

In [148]: titanicD.drop(['Fare', 'Pclass'],axis=1,inplace=True)
titanicD.head()

Out[148]:

	Survived	Age	Parch	male	Q	S
0	0	22.0	0	1	0	1
1	1	38.0	0	0	0	0
2	1	26.0	0	0	0	1
3	1	35.0	0	0	0	1
4	0	35.0	0	1	0	1

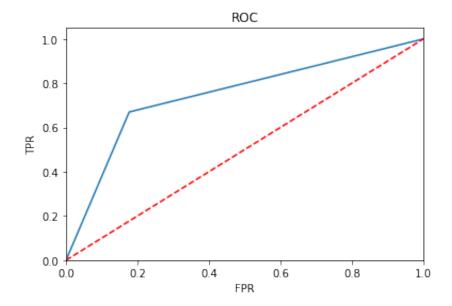
```
In [172]:
          #Using L1
          from sklearn.linear model import LogisticRegression
          from sklearn.metrics import roc auc score
          from sklearn.cross validation import train test split, KFold
          from sklearn.linear model import LinearRegression, Lasso, Ridge
          parameter1 = [0.0001, 0.0002, 0.0005, 0.001, 0.005, 0.01, 0.05, 0.1, 0.5, 1, 10]
          , 100,500,1000]
          auc cv=[]
          for a in parameter1:
              logr=LogisticRegression(C=a,penalty="11",class weight="balanced",r
          andom state=2)
              k = KFold(len(X train), n folds=11)
              score=0
              for train, test in k:
                   logr.fit(X train[train], y train[train])
                   score+=roc auc score(y train,logr.predict(X train))
              auc_cv.append(score/10)
              print('{:.3f}\t {:.5f}\t '.format(a,score/10))
          parameter1=np.array(parameter1)
          auc cv=np.array(auc cv)
          c best=parameter1[auc cv==max(auc cv)][0]
          print("The Value of C Best=",c best)
          y pred= logr.predict(X test)
          from sklearn.metrics import confusion matrix
          cmp = confusion matrix(y test, y pred)
          print("Confusion Matrix \n",cmp)
          0.000
                   0.55000
          0.000
                   0.55000
          0.001
                   0.55000
          0.001
                   0.55000
          0.005
                   0.55000
          0.010
                  0.55000
          0.050
                  0.84868
          0.100
                   0.85166
          0.500
                   0.85166
          1.000
                   0.85187
          10.000
                   0.85429
          100.000 0.85506
          500.000 0.85506
          1000.000
                            0.85506
```

The Value of C Best= 100.0

Confusion Matrix

[[135 29] [34 69]]

```
In [173]: from sklearn.metrics import roc_auc_score
    from sklearn.metrics import roc_curve
    from sklearn.metrics import roc_curve, auc
    fpr, tpr, thresholds = roc_curve(y_test, y_pred)
    plt.figure()
    plt.plot(fpr, tpr, label='Logistic Regression (area = %0.2f)' % max(au c_cv))
    plt.plot([0, 1], [0, 1], 'r--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('FPR')
    plt.ylabel('TPR')
    plt.title('ROC')
    plt.show()
    print("AUC Ridge = ",max(auc_cv)*100)
```

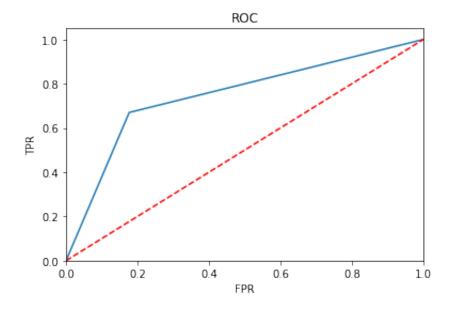


AUC Ridge = 85.5055071511

```
In [174]:
          #Using L2
          parameter1 = [0.0001, 0.0002, 0.0005, 0.001, 0.005, 0.01, 0.05, 0.1, 0.5, 1, 10]
          , 100,500,1000]
          auc_cv 1=[]
          for a in parameter1:
               logreg=LogisticRegression(C=a,penalty="12",class weight="balanced"
          ,random state=2)
              k = KFold(len(X train), n folds=10)
               score=0
               for train, test in k:
                   logreg.fit(X_train[train], y_train[train])
                   score+=roc auc score(y train,logreg.predict(X train))
               auc cv 1.append(score/10)
              print('{:.3f}\t {:.5f}\t '.format(a,score/10))
          parameter1=np.array(parameter1)
          auc cv 1=np.array(auc cv 1)
          c best=parameter1[auc cv 1==max(auc cv 1)][0]
          print("The Value of C Best=",c_best)
          y pred= logreg.predict(X test)
          from sklearn.metrics import confusion matrix
          cmp = confusion matrix(y test, y pred)
          print("Confusion Matrix \n",cmp)
```

```
0.000
         0.50798
0.000
         0.51417
0.001
         0.53075
0.001
         0.58308
0.005
         0.76934
0.010
         0.76971
0.050
        0.77216
0.100
         0.77411
0.500
         0.77424
1.000
         0.77424
10.000
        0.77463
100.000 0.77593
500.000 0.77593
1000.000
                 0.77593
The Value of C Best= 100.0
Confusion Matrix
 [[135 29]
 [ 34 69]]
```

```
In [175]: from sklearn.metrics import roc_auc_score
    from sklearn.metrics import roc_curve
    from sklearn.metrics import roc_curve, auc
    fpr, tpr, thresholds = roc_curve(y_test, y_pred)
    plt.plot(fpr, tpr, label='Logistic Regression (area = %0.2f)' % max
    (auc_cv_1))
    plt.plot([0, 1], [0, 1], 'r--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.ylim([0.0, 1.05])
    plt.ylabel('TPR')
    plt.title('ROC')
    plt.show()
    print("AUC Lasso = ",max(auc_cv_1)*100)
```



AUC Lasso = 77.5926352129

In [176]: print(classification report(y test, y pred))

support	f1-score	recall	precision	
164	0.81	0.82	0.80	0
103	0.69	0.67	0.70	1
267	0.76	0.76	0.76	avg / total

In [177]: import pandas as pd titanic3 = [['AUC Ridge ',max(auc_cv)*100],['AUC Lasso ',max(auc_cv_1) *100]] df = pd.DataFrame(titanic3,columns=['Loss Method','Accuracy']) print(df)

```
Loss Method Accuracy
0 AUC Ridge 85.505507
1 AUC Lasso 77.592635
```

In [79]: # From the above analysis in the table, we see that L1 Loss method has high accuracy as compared to L2 Loss method.