Q3 part 1

Logistic Regression on Ionosphere Dataset

In [1]:

```
import pandas as pd
import sklearn as sk
from sklearn import model_selection
from matplotlib import pyplot as plt
import numpy as np
from sklearn.metrics import r2_score
from sklearn.linear_model import LogisticRegression
```

In [2]:

```
data = pd.read_csv("F:/assignments/Sem 6 Assignments/ML Assignment 1/Q3/ionosphere_data_k
aggle.csv")
data
```

Out[2]:

	feature1	feature2	feature3	feature4	feature5	feature6	feature7	feature8	feature9	feature10	...	feature26	feature27
0	1	0	0.99539	-0.05889	0.85243	0.02306	0.83398	-0.37708	1.00000	0.03760	...	-0.51171	0.41078
1	1	0	1.00000	-0.18829	0.93035	-0.36156	-0.10868	-0.93597	1.00000	-0.04549	...	-0.26569	-0.20468
2	1	0	1.00000	-0.03365	1.00000	0.00485	1.00000	-0.12062	0.88965	0.01198	...	-0.40220	0.58984
3	1	0	1.00000	-0.45161	1.00000	1.00000	0.71216	-1.00000	0.00000	0.00000	...	0.90695	0.51613
4	1	0	1.00000	-0.02401	0.94140	0.06531	0.92106	-0.23255	0.77152	-0.16399	...	-0.65158	0.13290
...	...	...	...	...	...	...	...	...	...	...	...	...	...
346	1	0	0.83508	0.08298	0.73739	-0.14706	0.84349	-0.05567	0.90441	-0.04622	...	-0.04202	0.83479
347	1	0	0.95113	0.00419	0.95183	-0.02723	0.93438	-0.01920	0.94590	0.01606	...	0.01361	0.93522
348	1	0	0.94701	-0.00034	0.93207	-0.03227	0.95177	-0.03431	0.95584	0.02446	...	0.03193	0.92489
349	1	0	0.90608	-0.01657	0.98122	-0.01989	0.95691	-0.03646	0.85746	0.00110	...	-0.02099	0.89147
350	1	0	0.84710	0.13533	0.73638	-0.06151	0.87873	0.08260	0.88928	-0.09139	...	-0.15114	0.81147

351 rows × 35 columns

Replacing g and b with 1 and 0 in the label column

In [3]:

```
data['label'].replace({'g':1,'b':0},inplace=True)
data
```

Out[3]:

	feature1	feature2	feature3	feature4	feature5	feature6	feature7	feature8	feature9	feature10	...	feature26	feature27
0	1	0	0.99539	-0.05889	0.85243	0.02306	0.83398	-0.37708	1.00000	0.03760	...	-0.51171	0.41078
1	1	0	1.00000	-0.18829	0.93035	-0.36156	-0.10868	-0.93597	1.00000	-0.04549	...	-0.26569	-0.20468
2	1	0	1.00000	-0.03365	1.00000	0.00485	1.00000	-0.12062	0.88965	0.01198	...	-0.40220	0.58984
3	1	0	1.00000	-0.45161	1.00000	1.00000	0.71216	-1.00000	0.00000	0.00000	...	0.90695	0.51613
4	1	0	1.00000	-0.02401	0.94140	0.06531	0.92106	-0.23255	0.77152	-0.16399	...	-0.65158	0.13290
...	...	...	...	...	...	...	...	...	...	...	...	...	...
346	1	0	0.83508	0.08298	0.73739	-0.14706	0.84349	-0.05567	0.90441	-0.04622	...	-0.04202	0.83479
347	1	0	0.95113	0.00419	0.95183	-0.02723	0.93438	-0.01920	0.94590	0.01606	...	0.01361	0.93522
348	1	0	0.94701	-0.00034	0.93207	-0.03227	0.95177	-0.03431	0.95584	0.02446	...	0.03193	0.92489
349	1	0	0.90608	-0.01657	0.98122	-0.01989	0.95691	-0.03646	0.85746	0.00110	...	-0.02099	0.89147
350	1	0	0.84710	0.13533	0.73638	-0.06151	0.87873	0.08260	0.88928	-0.09139	...	-0.15114	0.81147

351 rows × 35 columns

Splitting Dataset into 90% train 10% test

In [4]:

```
train_,test=model_selection.train_test_split(data, test_size=0.1, train_size=0.9)
```

In [5]:

```
stats=pd.DataFrame()
stats["mean"]=train_.mean()
stats["Var"]=train_.var()
stats
```

Out[5]:

	mean	Var
feature1	0.892063	0.096593
feature2	0.000000	0.000000
feature3	0.642893	0.238592
feature4	0.051843	0.192843
feature5	0.608174	0.254543
feature6	0.123541	0.213319
feature7	0.555684	0.226843
feature8	0.118215	0.278598
feature9	0.501287	0.260881
feature10	0.189137	0.244225
feature11	0.471601	0.309997
feature12	0.171377	0.239788
feature13	0.395721	0.388738

	mean	Var
feature14	0.110508	0.245293
feature15	0.333867	0.430329
feature16	0.075898	0.210811
feature17	0.366644	0.385899
feature18	0.004513	0.249589
feature19	0.348317	0.394385
feature20	-0.008207	0.274522
feature21	0.336343	0.364187
feature22	0.024012	0.267117
feature23	0.361513	0.361545
feature24	-0.051329	0.277417
feature25	0.378971	0.336360
feature26	-0.058471	0.261215
feature27	0.540448	0.263351
feature28	-0.065516	0.304881
feature29	0.370661	0.326723
feature30	-0.005855	0.253571
feature31	0.340722	0.326127
feature32	-0.000377	0.264168
feature33	0.354652	0.264820
feature34	0.014154	0.222551
label	0.638095	0.231665

In [6]:

```
stats['Var'].nlargest(5)
```

Out[6]:

```
feature15    0.430329
feature19    0.394385
feature13    0.388738
feature17    0.385899
feature21    0.364187
Name: Var, dtype: float64
```

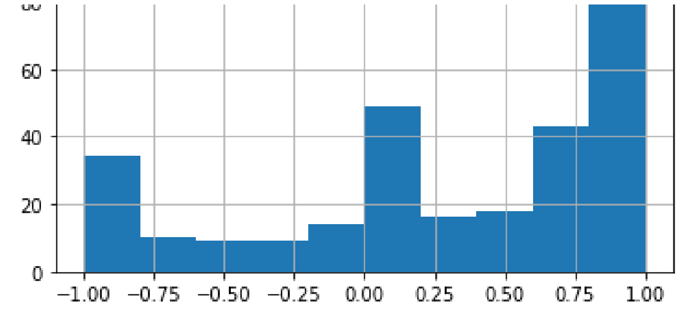
Plotting Histograms of the Features with the highest variances (top 5)

In [7]:

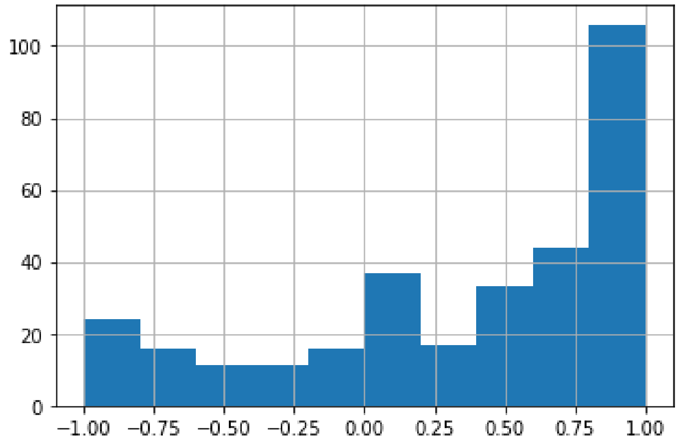
```
train_.hist(column='feature15')
train_.hist(column='feature19')
train_.hist(column='feature13')
train_.hist(column='feature17')
train_.hist(column='feature21')
```

Out[7]:

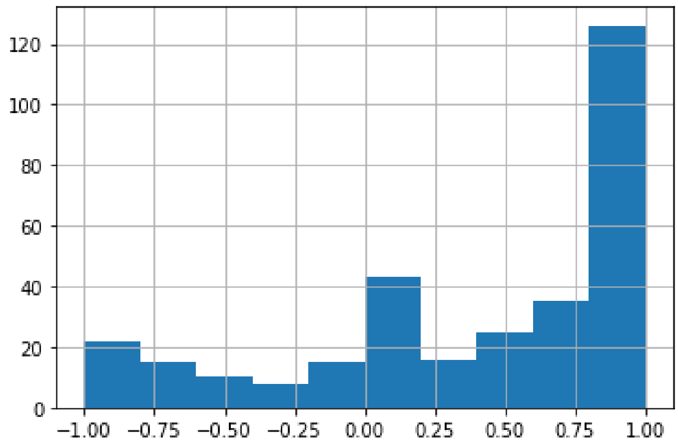
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x0000027AC8F32EC8>]],
      dtype=object)
```



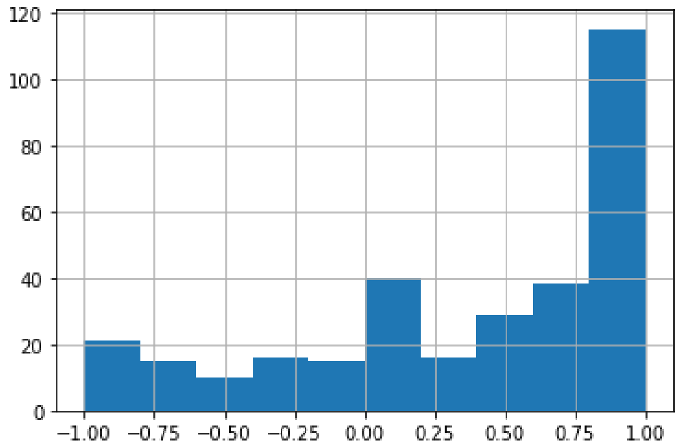
feature19



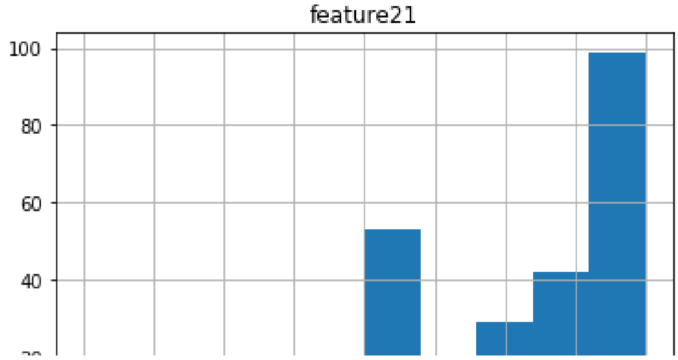
feature13

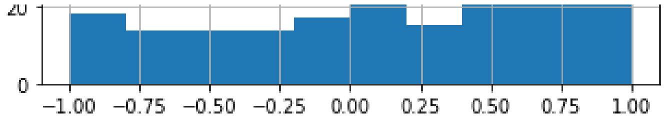


feature17



feature21





In [8]:

```
reg=LogisticRegression(penalty='none',max_iter=1000)
kf=model_selection.KFold(n_splits=5)
# train=kf.get_n_splits(train_)
# print(train_.shape)
# print(y.shape)
y1=test['label']
new_test=test.drop(['label'],axis=1)
new_test=np.array(new_test)
from sklearn.metrics import precision_recall_fscore_support
from sklearn.metrics import accuracy_score

y = train_['label']
new_train = train_.drop(['label'], axis=1)
# print(train_.shape)
# print(y.shape)
stats1=[]
for train_index, test_index in kf.split(train_):
    rmse=[]

#     print("TRAIN:", train_index, "TEST:", test_index)
    x_train, x_test = new_train.iloc[train_index], new_train.iloc[test_index]
    y_train, y_test = y.iloc[train_index], y.iloc[test_index]
#     print(y_test.shape)
    reg.fit(x_train,y_train)
    ac=accuracy_score(reg.predict(new_test), y1)

    stats1.append(list(precision_recall_fscore_support(reg.predict(new_test), y1, averag
e='micro')))
    stats1[-1].append(ac)

# y=test['label']
# new_test=test.drop(['label'],axis=1)
# new_test=np.array(new_test)
# from sklearn.metrics import precision_recall_fscore_support
stats1=pd.DataFrame(stats1)
stats1.columns =['Precision', 'Recall', 'F1-Score', 'Support','Accuracy']
stats1=stats1.drop(['Support'],axis=1)
print("Logistic Regression Stats without PCA")
print(stats1)
```

```
Logistic Regression Stats without PCA
   Precision    Recall  F1-Score  Accuracy
0   0.861111  0.861111  0.861111  0.861111
1   0.861111  0.861111  0.861111  0.861111
2   0.861111  0.861111  0.861111  0.861111
3   0.888889  0.888889  0.888889  0.888889
4   0.861111  0.861111  0.861111  0.861111
```

PCA for dimensionality reduction

In [9]:

```
from sklearn.decomposition import PCA
kf=model_selection.KFold(n_splits=5)
# train=kf.get_n_splits(train_)
# print(train_.shape)
# print(y.shape)
for val in range(90,100,1):
    pca = PCA(val/100)
    y1=test['label']
    new_test=test.drop(['label'],axis=1)
    new_test=np.array(new_test)
    # print(new_test.shape)
```

```python
    y = train_['label']
    new_train = train_.drop(['label'], axis=1)
    # print(train_.shape)
    # print(y.shape)
    stats1=[]
    ind=0
    for train_index, test_index in kf.split(train_):
        x_train, x_test = new_train.iloc[train_index], new_train.iloc[test_index]
        y_train, y_test = y.iloc[train_index], y.iloc[test_index]
    #     print(y_test.shape)

    #     components=pca.fit_transform(x_train)
    #     pca.fit(x_train)
    #     x_train= pca.transform(x_train)
    #     pca.fit(x_train)
    #     x_train= pca.transform(x_train)
        pca.fit(x_train)
        x_train= pca.transform(x_train)
        new_test1=pca.transform(new_test)
    #     ind=10
    #     y_train=y_train.values.reshape(-1, 1)
    #     y_test=y_test.values.reshape(-1, 1)
    #     print(y_test.shape)
    #     y_train=pca.transform(y_train)
    #     y_test=pca.transform(y_test)
        reg=LogisticRegression(penalty='none',max_iter=1000)
        reg.fit(x_train,y_train)
        ac=accuracy_score(reg.predict(new_test1), y1)

        stats1.append(list(precision_recall_fscore_support(reg.predict(new_test1), y1, average='micro')))
        stats1[-1].append(ac)

    # y=test['label']
    # new_test=test.drop(['label'],axis=1)
    # new_test=np.array(new_test)
    # from sklearn.metrics import precision_recall_fscore_support
    stats1=pd.DataFrame(stats1)
    stats1.columns =['Precision', 'Recall', 'F1-Score', 'Support','Accuracy']
    stats1=stats1.drop(['Support'],axis=1)
    print("Logistic Regression Stats with PCA with variance", val/100)
    print(stats1)
    print()
```

```
Logistic Regression Stats with PCA with variance 0.9
   Precision    Recall  F1-Score  Accuracy
0   0.861111  0.861111  0.861111  0.861111
1   0.861111  0.861111  0.861111  0.861111
2   0.861111  0.861111  0.861111  0.861111
3   0.888889  0.888889  0.888889  0.888889
4   0.888889  0.888889  0.888889  0.888889

Logistic Regression Stats with PCA with variance 0.91
   Precision    Recall  F1-Score  Accuracy
0   0.861111  0.861111  0.861111  0.861111
1   0.861111  0.861111  0.861111  0.861111
2   0.861111  0.861111  0.861111  0.861111
3   0.888889  0.888889  0.888889  0.888889
4   0.888889  0.888889  0.888889  0.888889

Logistic Regression Stats with PCA with variance 0.92
   Precision    Recall  F1-Score  Accuracy
0   0.916667  0.916667  0.916667  0.916667
1   0.861111  0.861111  0.861111  0.861111
2   0.861111  0.861111  0.861111  0.861111
3   0.888889  0.888889  0.888889  0.888889
4   0.916667  0.916667  0.916667  0.916667

Logistic Regression Stats with PCA with variance 0.93
   Precision    Recall  F1-Score  Accuracy
0   0.888889  0.888889  0.888889  0.888889
1   0.861111  0.861111  0.861111  0.861111
```

```
2    0.861111  0.861111  0.861111  0.861111
3    0.916667  0.916667  0.916667  0.916667
4    0.916667  0.916667  0.916667  0.916667

Logistic Regression Stats with PCA with variance 0.94
   Precision     Recall  F1-Score  Accuracy
0    0.916667  0.916667  0.916667  0.916667
1    0.888889  0.888889  0.888889  0.888889
2    0.888889  0.888889  0.888889  0.888889
3    0.916667  0.916667  0.916667  0.916667
4    0.916667  0.916667  0.916667  0.916667

Logistic Regression Stats with PCA with variance 0.95
   Precision     Recall  F1-Score  Accuracy
0    0.916667  0.916667  0.916667  0.916667
1    0.916667  0.916667  0.916667  0.916667
2    0.888889  0.888889  0.888889  0.888889
3    0.944444  0.944444  0.944444  0.944444
4    0.916667  0.916667  0.916667  0.916667

Logistic Regression Stats with PCA with variance 0.96
   Precision     Recall  F1-Score  Accuracy
0    0.916667  0.916667  0.916667  0.916667
1    0.916667  0.916667  0.916667  0.916667
2    0.888889  0.888889  0.888889  0.888889
3    0.916667  0.916667  0.916667  0.916667
4    0.916667  0.916667  0.916667  0.916667

Logistic Regression Stats with PCA with variance 0.97
   Precision     Recall  F1-Score  Accuracy
0    0.916667  0.916667  0.916667  0.916667
1    0.888889  0.888889  0.888889  0.888889
2    0.888889  0.888889  0.888889  0.888889
3    0.916667  0.916667  0.916667  0.916667
4    0.916667  0.916667  0.916667  0.916667

Logistic Regression Stats with PCA with variance 0.98
   Precision     Recall  F1-Score  Accuracy
0    0.888889  0.888889  0.888889  0.888889
1    0.888889  0.888889  0.888889  0.888889
2    0.916667  0.916667  0.916667  0.916667
3    0.916667  0.916667  0.916667  0.916667
4    0.888889  0.888889  0.888889  0.888889

Logistic Regression Stats with PCA with variance 0.99
   Precision     Recall  F1-Score  Accuracy
0    0.888889  0.888889  0.888889  0.888889
1    0.861111  0.861111  0.861111  0.861111
2    0.916667  0.916667  0.916667  0.916667
3    0.888889  0.888889  0.888889  0.888889
4    0.833333  0.833333  0.833333  0.833333
```

The best model among the 5 folds is determined using the accuracy, higher the accuracy, better is the model. Again, F1 Score/Accuracy is first reported on the validation set and testing is done on the 10% test dataset

Logistic Regression w/o penalty

In [10]:

```
reg=LogisticRegression(penalty='none',max_iter=1000)
kf=model_selection.KFold(n_splits=5)
# train=kf.get_n_splits(train_)
# print(train_.shape)
# print(y.shape)
```

```
# y1=test['label']
# new_test=test.drop(['label'],axis=1)
# new_test=np.array(new_test)
from sklearn.metrics import precision_recall_fscore_support
from sklearn.metrics import accuracy_score

y = train_['label']
new_train = train_.drop(['label'], axis=1)
# print(train_.shape)
# print(y.shape)
stats1=[]
best_accuracy=0
for train_index, test_index in kf.split(train_):
    rmse=[]

#     print("TRAIN:", train_index, "TEST:", test_index)
    x_train, x_test = new_train.iloc[train_index], new_train.iloc[test_index]
    y_train, y_test = y.iloc[train_index], y.iloc[test_index]
#     print(y_test.shape)
    reg.fit(x_train,y_train)
    ac=accuracy_score(reg.predict(x_test), y_test)

    stats1.append(list(precision_recall_fscore_support(reg.predict(x_test), y_test, aver
age='micro')))
    stats1[-1].append(ac)
    if(ac>best_accuracy):
        best_model_nopenalty=reg
        best_accuracy=ac

# y=test['label']
# new_test=test.drop(['label'],axis=1)
# new_test=np.array(new_test)
# from sklearn.metrics import precision_recall_fscore_support
stats1=pd.DataFrame(stats1)
stats1.columns =['Precision', 'Recall', 'F1-Score', 'Support','Accuracy']
stats1=stats1.drop(['Support'],axis=1)
print("Logistic Regression Stats without Penalty")
print(stats1)
```

```
Logistic Regression Stats without Penalty
   Precision    Recall  F1-Score  Accuracy
0   0.841270  0.841270  0.841270  0.841270
1   0.873016  0.873016  0.873016  0.873016
2   0.888889  0.888889  0.888889  0.888889
3   0.936508  0.936508  0.936508  0.936508
4   0.888889  0.888889  0.888889  0.888889
```

In [11]:

```
y=test['label']
y_numpy=np.array(y)
new_test=test.drop(['label'],axis=1)
new_test=np.array(new_test)
ac=accuracy_score(best_model_nopenalty.predict(new_test), y)
fscore=precision_recall_fscore_support(best_model_nopenalty.predict(new_test), y, averag
e='micro')
print("Testing Best Model with no Penalty")
print("Accuracy=",ac)
print("Precision=",fscore[0])
print("Recall=",fscore[1])
print("F1-Score=",fscore[2])
```

```
Testing Best Model with no Penalty
Accuracy= 0.8611111111111112
Precision= 0.8611111111111112
Recall= 0.8611111111111112
F1-Score= 0.8611111111111112
```

Logistic Regression with L1 penalty

In [12]:

```
reg=LogisticRegression(penalty='l1',max_iter=1000,solver='liblinear')
kf=model_selection.KFold(n_splits=5)
# train=kf.get_n_splits(train_)
# print(train_.shape)
# print(y.shape)
# y1=test['label']
# new_test=test.drop(['label'],axis=1)
# new_test=np.array(new_test)
from sklearn.metrics import precision_recall_fscore_support
from sklearn.metrics import accuracy_score

y = train_['label']
new_train = train_.drop(['label'], axis=1)
# print(train_.shape)
# print(y.shape)
stats1=[]
best_accuracy=0
for train_index, test_index in kf.split(train_):
    rmse=[]

#     print("TRAIN:", train_index, "TEST:", test_index)
    x_train, x_test = new_train.iloc[train_index], new_train.iloc[test_index]
    y_train, y_test = y.iloc[train_index], y.iloc[test_index]
#     print(y_test.shape)
    reg.fit(x_train,y_train)
    ac=accuracy_score(reg.predict(x_test), y_test)

    stats1.append(list(precision_recall_fscore_support(reg.predict(x_test), y_test, aver
age='micro')))
    stats1[-1].append(ac)
    if(ac>best_accuracy):
        best_model_l1=reg
        best_accuracy=ac

# y=test['label']
# new_test=test.drop(['label'],axis=1)
# new_test=np.array(new_test)
# from sklearn.metrics import precision_recall_fscore_support
stats1=pd.DataFrame(stats1)
stats1.columns =['Precision', 'Recall', 'F1-Score', 'Support','Accuracy']
stats1=stats1.drop(['Support'],axis=1)
print("Logistic Regression Stats L1")
print(stats1)
```

```
Logistic Regression Stats L1
   Precision    Recall  F1-Score  Accuracy
0   0.873016  0.873016  0.873016  0.873016
1   0.857143  0.857143  0.857143  0.857143
2   0.888889  0.888889  0.888889  0.888889
3   0.904762  0.904762  0.904762  0.904762
4   0.841270  0.841270  0.841270  0.841270
```

In [13]:

```
y=test['label']
y_numpy=np.array(y)
new_test=test.drop(['label'],axis=1)
new_test=np.array(new_test)
ac=accuracy_score(best_model_l1.predict(new_test), y)
fscore=precision_recall_fscore_support(best_model_l1.predict(new_test), y, average='micr
o')
print("Testing Best Model with L1 Penalty")
print("Accuracy=",ac)
print("Precision=",fscore[0])
print("Recall=",fscore[1])
print("F1-Score=",fscore[2])
```

```
Testing Best Model with L1 Penalty
Accuracy= 0.9166666666666666
Precision= 0.9166666666666666
Recall= 0.9166666666666666
```

```
F1-Score= 0.9166666666666666
```

Logistic Regression with L2

In [14]:

```
reg=LogisticRegression(penalty='l2',max_iter=1000,solver='liblinear')
kf=model_selection.KFold(n_splits=5)
# train=kf.get_n_splits(train_)
# print(train_.shape)
# print(y.shape)
# y1=test['label']
# new_test=test.drop(['label'],axis=1)
# new_test=np.array(new_test)
from sklearn.metrics import precision_recall_fscore_support
from sklearn.metrics import accuracy_score

y = train_['label']
new_train = train_.drop(['label'], axis=1)
# print(train_.shape)
# print(y.shape)
stats1=[]
best_accuracy=0
for train_index, test_index in kf.split(train_):
    rmse=[]

#     print("TRAIN:", train_index, "TEST:", test_index)
    x_train, x_test = new_train.iloc[train_index], new_train.iloc[test_index]
    y_train, y_test = y.iloc[train_index], y.iloc[test_index]
#     print(y_test.shape)
    reg.fit(x_train,y_train)
    ac=accuracy_score(reg.predict(x_test), y_test)

    stats1.append(list(precision_recall_fscore_support(reg.predict(x_test), y_test, aver
age='micro')))
    stats1[-1].append(ac)
    if(ac>best_accuracy):
        best_model_l2=reg
        best_accuracy=ac
#         print("YAY")

# y=test['label']
# new_test=test.drop(['label'],axis=1)
# new_test=np.array(new_test)
# from sklearn.metrics import precision_recall_fscore_support
stats1=pd.DataFrame(stats1)
stats1.columns =['Precision', 'Recall', 'F1-Score', 'Support','Accuracy']
stats1=stats1.drop(['Support'],axis=1)
print("Logistic Regression Stats L2")
print(stats1)
```

```
Logistic Regression Stats L2
   Precision    Recall  F1-Score  Accuracy
0   0.841270  0.841270  0.841270  0.841270
1   0.841270  0.841270  0.841270  0.841270
2   0.873016  0.873016  0.873016  0.873016
3   0.888889  0.888889  0.888889  0.888889
4   0.873016  0.873016  0.873016  0.873016
```

In [15]:

```
y=test['label']
y_numpy=np.array(y)
new_test=test.drop(['label'],axis=1)
new_test=np.array(new_test)
ac=accuracy_score(best_model_l2.predict(new_test), y)
fscore=precision_recall_fscore_support(best_model_l2.predict(new_test), y, average='micr
o')
print("Testing Best Model with L2 Penalty")
```

```
print("Accuracy=",ac)
print("Precision=",fscore[0])
print("Recall=",fscore[1])
print("F1-Score=",fscore[2])
```

```
Testing Best Model with L2 Penalty
Accuracy= 0.9166666666666666
Precision= 0.9166666666666666
Recall= 0.9166666666666666
F1-Score= 0.9166666666666666
```

Introduction of L1 and L2 penalty has improved the accuracy/F1 Score.

In [16]:

```
print(best_model_nopenalty)
print(best_model_l1)
print(best_model_l2)
```

```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=1000,
                   multi_class='auto', n_jobs=None, penalty='none',
                   random_state=None, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=1000,
                   multi_class='auto', n_jobs=None, penalty='l1',
                   random_state=None, solver='liblinear', tol=0.0001, verbose=0,
                   warm_start=False)
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=1000,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=None, solver='liblinear', tol=0.0001, verbose=0,
                   warm_start=False)
```

Plotting ROC-AUC curve for the three best models

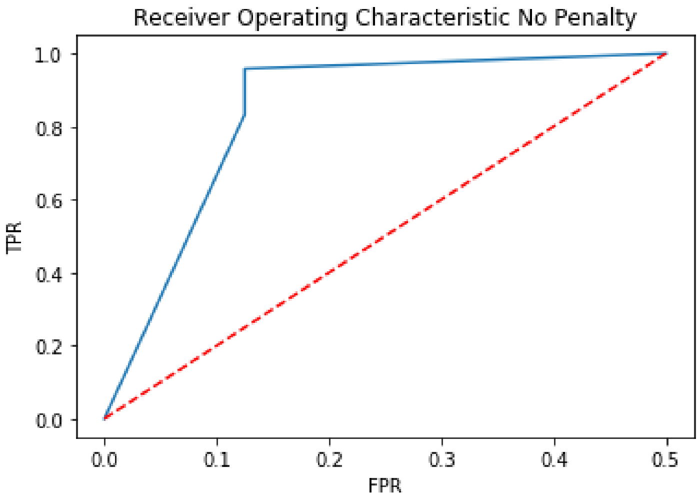
In [17]:

```
y=test['label']
y_numpy=np.array(y)
new_test=test.drop(['label'],axis=1)
new_test=np.array(new_test)
probab_l2=best_model_l2.predict_proba(new_test)
probab_l1=best_model_l1.predict_proba(new_test)
probab_no=best_model_nopenalty.predict_proba(new_test)

#second column is 1 first column is 0
curve_no_x=[]
curve_no_y=[]
curve_l1_x=[]
curve_l1_y=[]
curve_l2_x=[]
curve_l2_y=[]
# print(y)
for i in range (0,110,10):
    threshold=i/100
    predicted=[]
#     print(threshold)
    for j in probab_no:
        if(j[1]>threshold):
            predicted.append(1)
        else:
            predicted.append(0)
#     print(predicted)
    tpr=0
    fpr=0
    for j in range(len(predicted)):
        if(predicted[j]==y_numpy[j] and y_numpy[j]==1):
```

```
            tpr+=1
        if(predicted[j]!=y_numpy[j] and predicted[j]==1):
            fpr+=1
    tpr=tpr/sum(y_numpy)
    fpr=fpr/sum(y_numpy)
    curve_no_x.append(fpr)
    curve_no_y.append(tpr)

plt.plot(curve_no_x,curve_no_y)
plt.plot([0, max(curve_no_x)], [0, max(curve_no_y)],'r--')
plt.title('Receiver Operating Characteristic No Penalty')
plt.ylabel('TPR')
plt.xlabel('FPR')
```

Out[17]:

```
Text(0.5, 0, 'FPR')
```

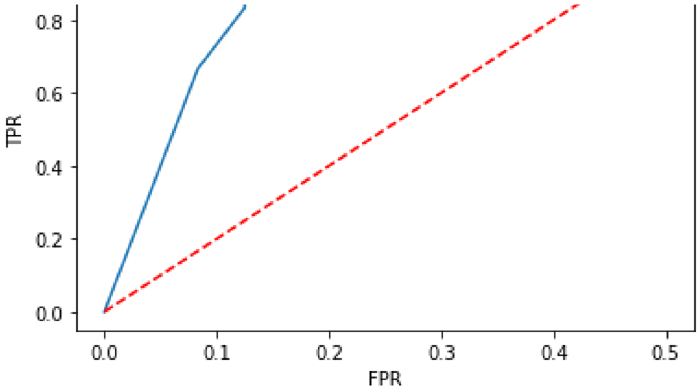


In [18]:

```
for i in range (0,110,10):
    threshold=i/100
    predicted=[]
#     print(threshold)
    for j in probab_l1:
        if(j[1]>threshold):
            predicted.append(1)
        else:
            predicted.append(0)
#     print(predicted)
    tpr=0
    fpr=0
    for j in range(len(predicted)):
        if(predicted[j]==y_numpy[j] and predicted[j]==1):
            tpr+=1
        if(predicted[j]!=y_numpy[j] and predicted[j]==1):
            fpr+=1
    tpr=tpr/sum(y_numpy)
    fpr=fpr/sum(y_numpy)
    curve_l1_x.append(fpr)
    curve_l1_y.append(tpr)

plt.plot(curve_l1_x,curve_l1_y)
plt.plot([0, max(curve_l1_x)], [0, max(curve_l1_y)],'r--')
plt.title('Receiver Operating Characteristic L1')
plt.ylabel('TPR')
plt.xlabel('FPR')
```

Out[18]:

```
Text(0.5, 0, 'FPR')
```

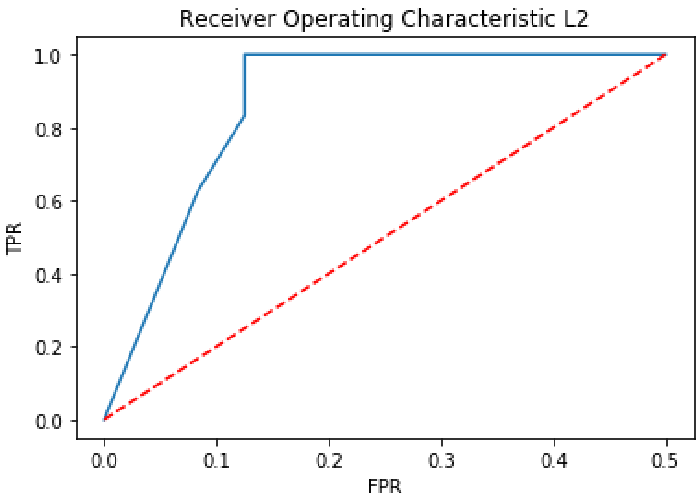


In [19]:

```
for i in range (0,110,10):
    threshold=i/100
    predicted=[]
#     print(threshold)
    for j in probab_l2:
        if(j[1]>threshold):
            predicted.append(1)
        else:
            predicted.append(0)
#     print(predicted)
    tpr=0
    fpr=0
    for j in range(len(predicted)):
        if(predicted[j]==y_numpy[j] and y_numpy[j]==1):
            tpr+=1
        if(predicted[j]!=y_numpy[j] and predicted[j]==1):
            fpr+=1
    tpr=tpr/sum(y_numpy)
    fpr=fpr/sum(y_numpy)
    curve_l2_x.append(fpr)
    curve_l2_y.append(tpr)

plt.plot(curve_l2_x,curve_l2_y)
plt.plot([0, max(curve_l2_x)], [0, max(curve_l2_y)],'r--')
plt.title('Receiver Operating Characteristic L2')
plt.ylabel('TPR')
plt.xlabel('FPR')
```

Out[19]:

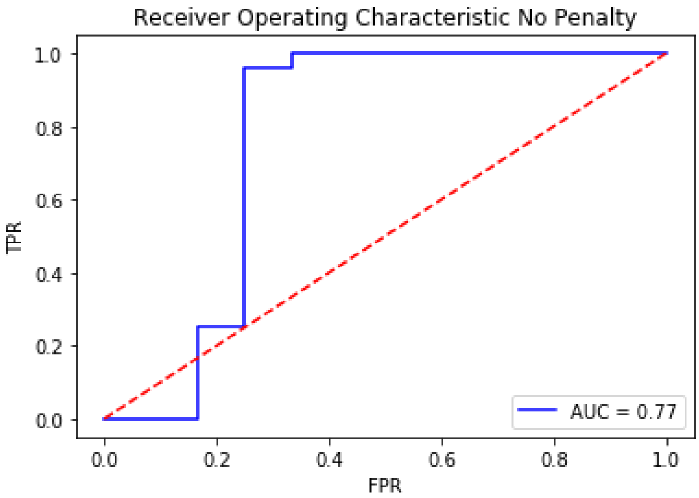
```
Text(0.5, 0, 'FPR')
```



In [20]:

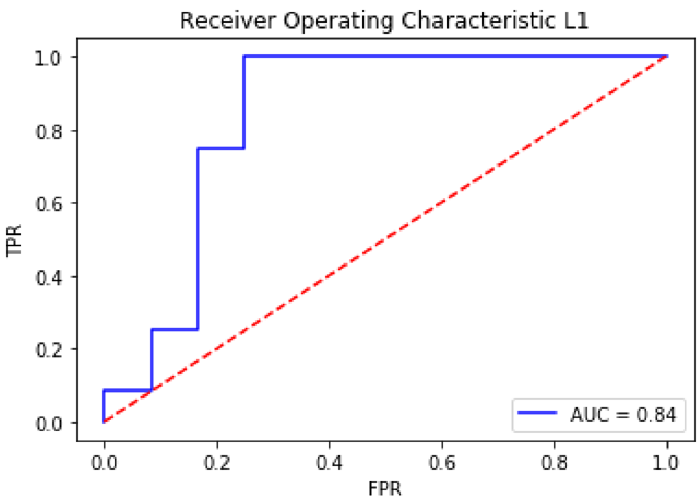
```
import sklearn.metrics as metrics
preds = probab_no[:,1]
fpr, tpr, threshold = metrics.roc_curve(y_numpy, preds)
roc_auc = metrics.auc(fpr, tpr)
plt.title('Receiver Operating Characteristic No Penalty')
```

```
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.ylabel('TPR')
plt.xlabel('FPR')
plt.show()
```



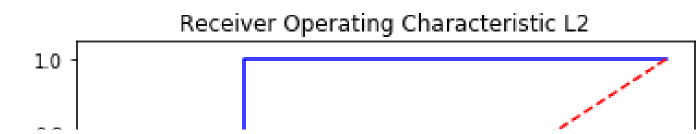
In [21]:

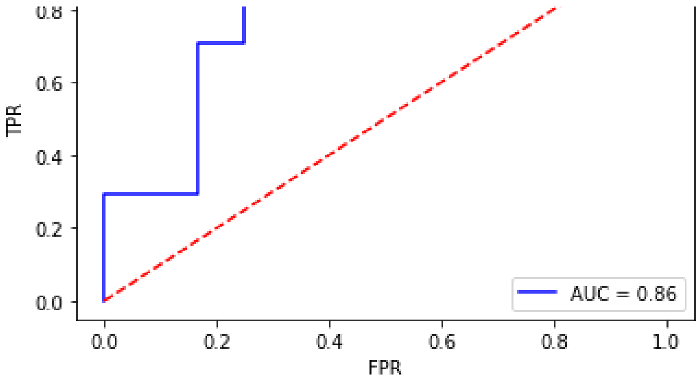
```
preds = probab_l1[:,1]
fpr, tpr, threshold = metrics.roc_curve(y_numpy, preds)
roc_auc = metrics.auc(fpr, tpr)
plt.title('Receiver Operating Characteristic L1')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.ylabel('TPR')
plt.xlabel('FPR')
plt.show()
```



In [22]:

```
preds = probab_l2[:,1]
fpr, tpr, threshold = metrics.roc_curve(y_numpy, preds)
roc_auc = metrics.auc(fpr, tpr)
plt.title('Receiver Operating Characteristic L2')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.ylabel('TPR')
plt.xlabel('FPR')
plt.show()
```





The difference between the inbuilt and implemented versions of the ROC-AUC curve is the resolution. I have implemented the curve for only 11 points of threshold, which is much lesser than the inbuilt version. Increasing the resolution results in the plots being similar.