Time Series Classification of Human Activity Recognition

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Download the AReM data from: [https://archive.ics.uci.edu/ml/datasets/Activity+Recognition+system+based+on+Multisensor+data+fusion- (https://archive.ics.uci.edu/ml/datasets/Activity+Recognition+system+based+on+Multisensor+data+fusion](https://archive.ics.uci.edu/ml/datasets/Activity+Recognition+system+based+on+Multisensor+data+fusion) . The dataset contains 7 folders that represent seven types of activities. In each folder, there are multiple files each of which represents an instant of a human performing an activity. Each file containis 6 time series collected from activities of the same person. There are 88 instances in the dataset, each of which contains 6 time series and each time series has 480 consecutive values.

Keep datasets 1 and 2 in folders bending1 and bending 2, as well as datasets 1, 2, and 3 in other folders as test data and other datasets as train data.

In [96]:

```
#import libraries
import pandas as pd
import numpy as np
import os
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn import metrics
from sklearn import preprocessing
from imblearn.under_sampling import RandomUnderSampler
from sklearn.linear_model import LogisticRegression, LassoCV,LogisticReg
ressionCV
from sklearn.naive_bayes import GaussianNB,MultinomialNB
from sklearn.feature_selection import RFECV, RFE
from sklearn.preprocessing import StandardScaler,label_binarize, normali
ze
from sklearn.model_selection import StratifiedKFold, cross_val_score
from sklearn import metrics
from sklearn.metrics import confusion_matrix,roc_curve, auc,roc_auc_scor
e
import statsmodels.api as sm
from scipy import stats
import warnings
warnings.filterwarnings("ignore")
```

In [97]:

```
cd /Users/sonalisreedhar/Desktop/AReM/AReM
```

```
/Users/sonalisreedhar/Desktop/AReM/AReM
```

In [3]:
```
data_dict = 'AReM/'
prefix = 'dataset'
filetype = '.csv'
classes = ['walking', 'standing', 'sitting', 'lying', 'cycling', 'bendin
g1', 'bending2']
```

In [98]:
```
#variable declarations
data_path = os.getcwd() + '/dataset'

def create_header(names):
    imp_list = []
    for i in range(1, 7):
        for label in names:
            imp_list.append(label + str(i))
    return imp_list


col_headers = create_header(
    ['min', 'max', 'mean', 'median', 'std_dev', '1st_quart', '3rd_quart'
])
col_headers.append('class')
imp_headers = create_header(['median', 'std_dev', '1st_quart'])
imp_headers.append('class')
feature_cols = np.delete(col_headers, 42)
```

Data Splitting and Feature Extraction

(c) i. Different time domain features used in time series classification are: Minimum, Maximum, Standard Deviation, Mean, 1st Quartile, 3rd Quartile

(c) ii. Load Data

In [99]:
```
#read data and split into test and train files
def train_test_split(data_path):

    train_files = []
    test_files = []
    exclude_binding_dataset = ['dataset1.csv', 'dataset2.csv']
    exclude_dataset = ['dataset1.csv', 'dataset2.csv', 'dataset3.csv']
    for act in os.listdir(data_path):
        names = os.listdir(data_path + '/' + act)
        if 'bending' in act:
            train_files = train_files + [
                act + '/' + f for f in names
                if f not in exclude_binding_dataset
            ]
            test_files = test_files + [
                act + '/' + s for s in exclude_binding_dataset
            ]
        else:
            train_files = train_files + [
                act + '/' + f for f in names if f not in exclude_dataset
            ]
            test_files = test_files + [act + '/' + s for s in exclude_da
taset]

    return train_files, test_files


#get time domain featuers for each instance
def get_features(file, split_time_series=None, multi_class = None):
    instance_list = []
    file = data_path + '/' + file
    if 'bending' in file:
        class_type = 1
    else:
        class_type = 0
    df = pd.read_csv(file, header=4, usecols=[*range(1, 7)])
    #df = df.reset_index()
    df.fillna(0, inplace=True)
    #df.fillna(0)
    dflist = [df]
    if split_time_series is not None:
        dflist = np.array_split(df, split_time_series)
    for df in dflist:
        row = []
        stat_df = df.agg(['min', 'max', 'mean', 'median', 'std'])
        #stat_df .head()
        stat_df = stat_df.append(df.quantile(q=0.25))
        stat_df = stat_df.append(df.quantile(q=0.75))
        for col in [stat_df[f] for f in stat_df]:
            for data in col:
                row.append(data)
        row.append(class_type)
        instance_list.append(row)
    return instance_list

def get_instance_frame(file_list,split_size=None):
```

```
    total_instance_frame = pd.DataFrame()
    total_instance_list = []
    for file in file_list:
        instance_features = get_features(file,split_size)
        total_instance_list = total_instance_list + instance_features

    total_instance_frame = pd.DataFrame(total_instance_list, columns=col
_headers)
    return total_instance_frame
```

In [102]:

```
train_files, test_files = train_test_split(data_path)
#train_files = train_files.reset_index()
#test_files = test_files.reset_index()

#print(train_files)
```

(c) iii The three important time domain features selected are median, std deviation and 1st quartile (using feature selection method)

Binary Classification Using Logistic Regression

(d) i. Assume that you want to use the training set to classify bending from other activities, i.e. you have a binary classification problem. Depict scatter plots of the features you specified in 1(c)iii extracted from time series 1, 2, and 6 of each instance, and use color to distinguish bending vs. other activities.

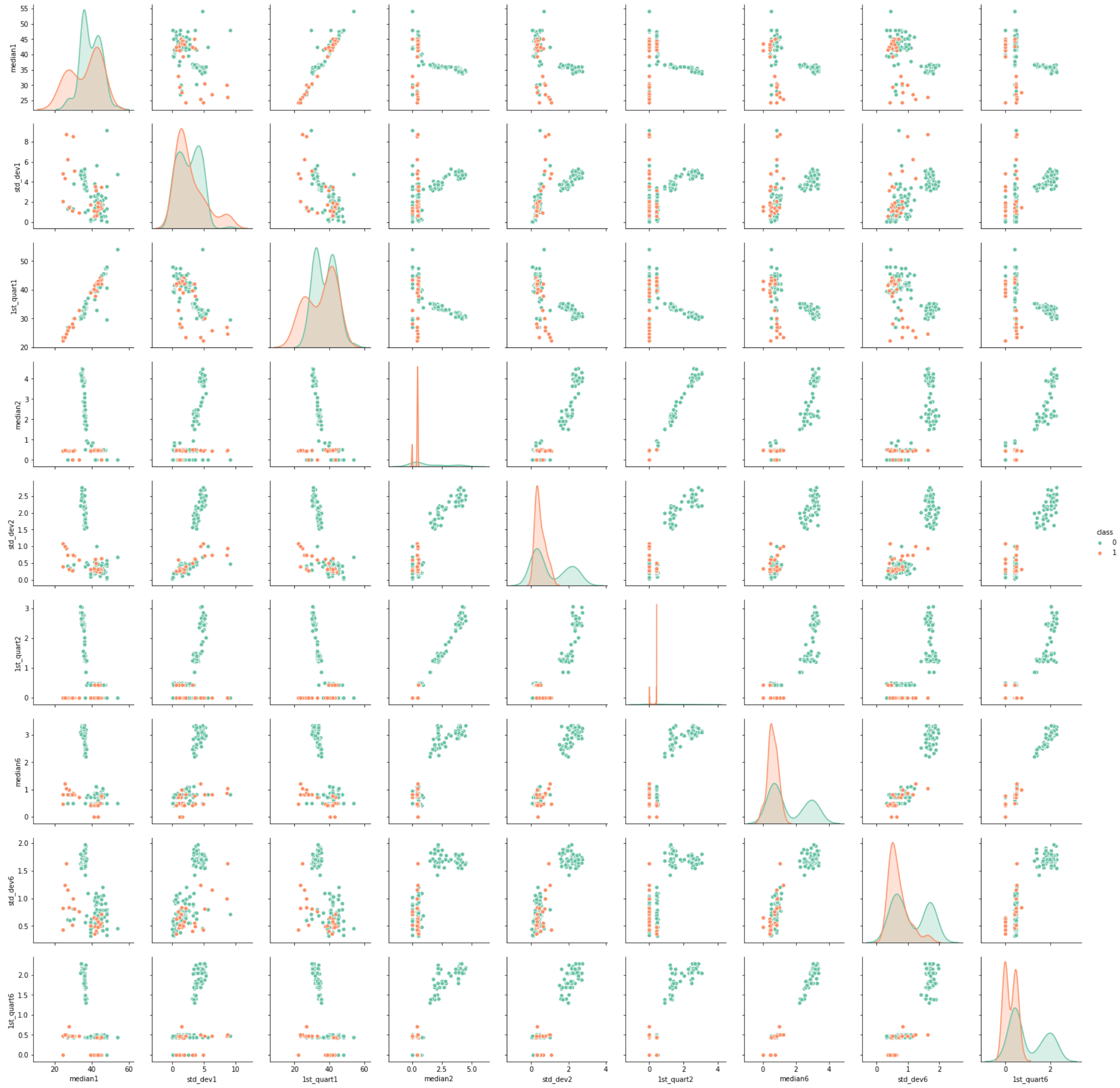
In [100]:
```
total_instance_frame = get_instance_frame(train_files + test_files, 1)
total_selected_frame = total_instance_frame[imp_headers]
scatter_plot = sns.pairplot(data=total_selected_frame, vars= ['median1',
'std_dev1','1st_quart1',
                    'median2','std_dev2','1st_quart2','median6','std_dev6'
,'1st_quart6'], kind='scatter', palette="Set2",hue='class')
```

(d) ii. Break each time series in your training set into two (approximately) equal length time series. Now instead of 6 time series for each of the 88 instances, you have 12 time series for each instance. Repeat the experiment in 1(d)i. Do you see any considerable difference in the results with those of 1(d)i?

- After breaking each time series into two, the scatters plot of different classes look more seperatable

In [33]:
```
total_instance_frame = get_instance_frame(train_files + test_files, 2)
total_selected_frame = total_instance_frame[imp_headers]
scatter_plot = sns.pairplot(data=total_selected_frame, vars= ['median1',
'std_dev1','1st_quart1',
                        'median2','std_dev2','1st_quart2','median6','std_dev6'
,'1st_quart6'], kind='scatter', palette="Set2",hue='class')
plt.figure()
```

Out[33]: <Figure size 432x288 with 0 Axes>



<Figure size 432x288 with 0 Axes>

(d) iii. Break each time series in your training set into l ∈ {1,2,...,20} time series of approximately equal length and use logistic regression 5 to solve the binary classification problem, using time-domain features. Calculate the p-values for your logistic regression parameters and refit a logistic regression model using your pruned set of features. 6 Alternatively, you can use backward selection using sklearn.feature selection or glm in R. Use 5-fold cross-validation to determine the best value of l. Explain what the right way and the wrong way are to perform cross-validation in this problem. 7 Obviously, use the right way! Also, you may encounter the problem of class imbalance, which may make some of your folds not having any instances of the rare class. In such a case, you can use stratified cross validation. Research what it means and use it if needed.

- The right way to perform cross validation is on both L and variable selection. To avoid problem of class balance, we have also used startified cross validation

In [101]:
```
feature_cols = np.delete(col_headers, 42)
best_cv_score = 0
best_l = 0

for l in range(1,10):
    Y_train = train_instance_list = []
    X_train = train_instance_frame = pd.DataFrame()



    train_instance_frame = get_instance_frame(train_files, l)

    Y_train = train_instance_frame['class']
    X_train = train_instance_frame.drop(['class'], axis=1)
    #print(X_train)
    logreg = LogisticRegression()
    for i in range(1,len(X_train.columns)):
        rfe_res = RFE(estimator=logreg, n_features_to_select= i)
        rfe_res.fit(X_train, Y_train)
        cv_score = cross_val_score(rfe_res, X_train, Y_train, cv=5, scor
ing='accuracy')
        mean_score  =  np.mean(cv_score)
        if mean_score > best_cv_score:
            best_cv_score = mean_score
            n_features = i
            best_l = l
            best_features = feature_cols[rfe_res.support_]

print("The best value of L for Logistic Regression is :" , best_l )
print("Optimal cv score for Logistic Regression is :" , best_cv_score)
print("Optimal number of features for Logistic Regression is : " , n_fea
tures)
print("The Optimal features for Logistic Regression are : ", best_featur
es)
```

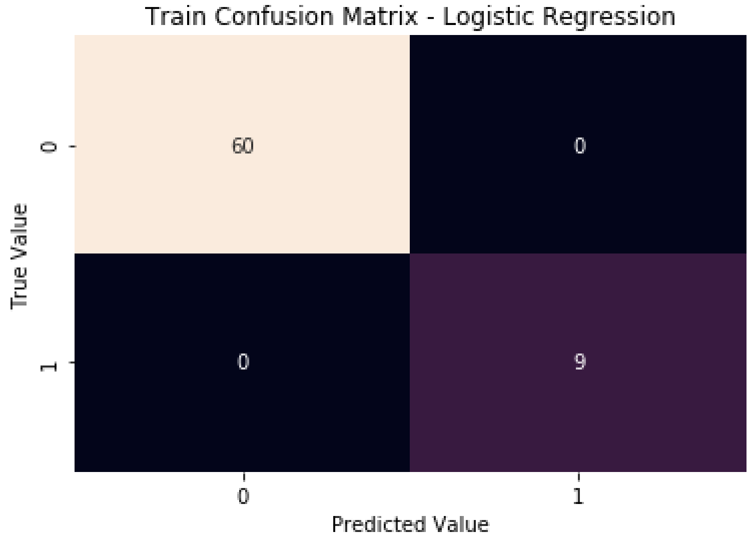
```
The best value of L for Logistic Regression is : 1
Optimal cv score for Logistic Regression is : 0.9428571428571428
Optimal number of features for Logistic Regression is :  9
The Optimal features for Logistic Regression are :  ['mean1' '3rd_quart
1' 'max2' 'median3' 'min5' 'max5' 'mean5' '1st_quart5'
 'max6']
```

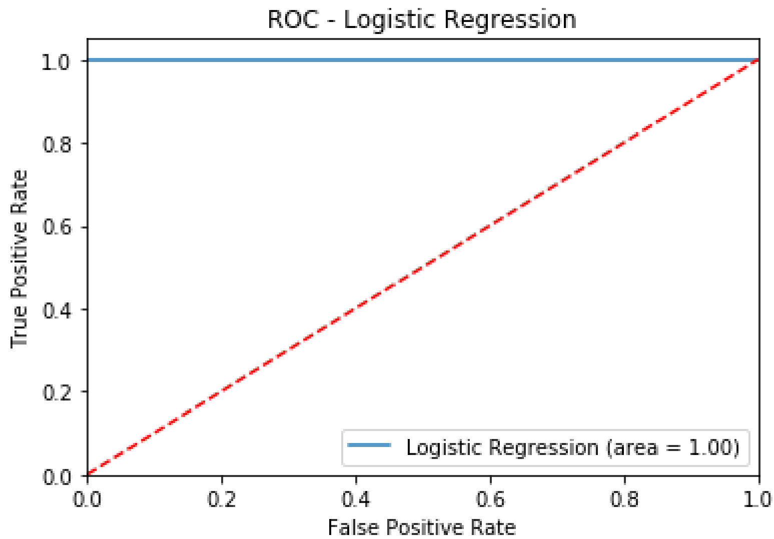
In [88]:
```
X_train.shape
```

Out[88]:
```
(69, 42)
```

(d) iv. Report the confusion matrix and show the ROC and AUC for your classifier on train data. Report the parameters of your logistic regression β i 's as well as the p-values associated with them.

In [53]:
```
train_instance_frame = get_instance_frame(train_files, best_l)
Y_train = train_instance_frame['class']
X_train = train_instance_frame.drop(['class'], axis=1)
X_train = X_train[best_features]
logreg = LogisticRegression()
logreg.fit(X_train, Y_train)
Y_pred = logreg.predict(X_train)

conf_mat = confusion_matrix(Y_train, Y_pred)
ax= plt.subplot()
sns.heatmap(conf_mat, annot=True, cbar= False, ax = ax);
plt.title('Train Confusion Matrix - Logistic Regression')
plt.xlabel('Predicted Value')
plt.ylabel('True Value')
plt.show()

roc_auc = roc_auc_score(Y_train, Y_pred)
fp_rate, tp_rate, thresholds = roc_curve(Y_train, Y_pred)
plt.figure()
plt.plot(fp_rate, tp_rate, label='Logistic Regression (area = %0.2f)' %
roc_auc)
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC - Logistic Regression')
plt.legend(loc="lower right")
plt.show()
```


Train Confusion Matrix - Logistic Regression
60
0
0
9
True Value
Predicted Value
0
1
0
1


ROC - Logistic Regression
True Positive Rate
False Positive Rate
Logistic Regression (area = 1.00)
0.0
0.2
0.4
0.6
0.8
1.0

In [54]:
```
logit_model=sm.Logit(Y_train,X_train)
result=logit_model.fit(maxiter = 21)
result.summary()
```

```
Warning: Maximum number of iterations has been exceeded.
         Current function value: 0.010046
         Iterations: 21
```

Out[54]:

Logit Regression Results

Dep. Variable:	class	**No. Observations:**	69
Model:	Logit	**Df Residuals:**	60
Method:	MLE	**Df Model:**	8
Date:	Sat, 22 Jun 2019	**Pseudo R-squ.:**	0.9741
Time:	19:57:56	**Log-Likelihood:**	-0.69315
converged:	False	**LL-Null:**	-26.718
		LLR p-value:	1.647e-08

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
mean1	-1.5710	5764.138	-0.000	1.000	-1.13e+04	1.13e+04
3rd_quart1	-1.8172	5735.247	-0.000	1.000	-1.12e+04	1.12e+04
max2	-0.4959	3239.569	-0.000	1.000	-6349.934	6348.942
median3	-1.5767	1528.338	-0.001	0.999	-2997.064	2993.911
min5	2.7259	4824.987	0.001	1.000	-9454.075	9459.527
max5	3.6386	3445.513	0.001	0.999	-6749.443	6756.720
mean5	2.1750	2.59e+04	8.39e-05	1.000	-5.08e+04	5.08e+04
1st_quart5	0.4957	1.72e+04	2.89e-05	1.000	-3.36e+04	3.36e+04
max6	-2.1592	4957.298	-0.000	1.000	-9718.284	9713.965

Possibly complete quasi-separation: A fraction 0.99 of observations can be perfectly predicted. This might indicate that there is complete quasi-separation. In this case some parameters will not be identified.

- In the above logit Regression output, coef_ column gives us Beta parameter values and p-values are given by P>|z| column

(d) v. Test the classifier on the test set. Remember to break the time series in your test set into the same number of time series into which you broke your training set. Remember that the classifier has to be tested using the features extracted from the test set. Compare the accuracy on the test set with the cross-validation accuracy you obtained previously.

In [104]:
```
test_instance_frame = get_instance_frame(test_files, best_l)
Y_test = test_instance_frame['class']
X_test = test_instance_frame.drop(['class'], axis=1)
X_test = X_test[best_features]

Y_pred = logreg.predict(X_test)
print("The Test Accuracy is : %d" %metrics.accuracy_score(Y_test, Y_pre
d) )

conf_mat = confusion_matrix(Y_test, Y_pred)
ax= plt.subplot()
sns.heatmap(conf_mat, annot=True, cbar= False, ax = ax);
plt.title('Test Confusion Matrix - Logistic Regression')
plt.xlabel('Predicted Value')
plt.ylabel('True Value')
plt.show()

roc_auc = roc_auc_score(Y_test, Y_pred)
fp_rate, tp_rate, thresholds = roc_curve(Y_test, Y_pred)
plt.figure()
plt.plot(fp_rate, tp_rate, label='Logistic Regression (area = %0.2f)' %
roc_auc)
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC - Logitic Regression')
plt.legend(loc="lower right")
plt.show()
```

```
---------------------------------------------------------------------------
NotFittedError                            Traceback (most recent call last)
<ipython-input-104-000fd84196a4> in <module>
      4 X_test = X_test[best_features]
      5 
----> 6 Y_pred = logreg.predict(X_test)
      7 print("The Test Accuracy is : %d" %metrics.accuracy_score(Y_test, Y_pred) )
      8 

/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/base.py in predict(self, X)
    322             Predicted class label per sample.
    323         """
--> 324         scores = self.decision_function(X)
    325         if len(scores.shape) == 1:
    326             indices = (scores > 0).astype(np.int)

/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/base.py in decision_function(self, X)
    296         if not hasattr(self, 'coef_') or self.coef_ is None:
    297             raise NotFittedError("This %(name)s instance is not fitted "
--> 298                                  "yet" % {'name': type(self).__name__})
    299 
    300         X = check_array(X, accept_sparse='csr')

NotFittedError: This LogisticRegression instance is not fitted yet
```

d (vi) Do your classes seem to be well-separated to cause instability in calculating logistic regression parameters?

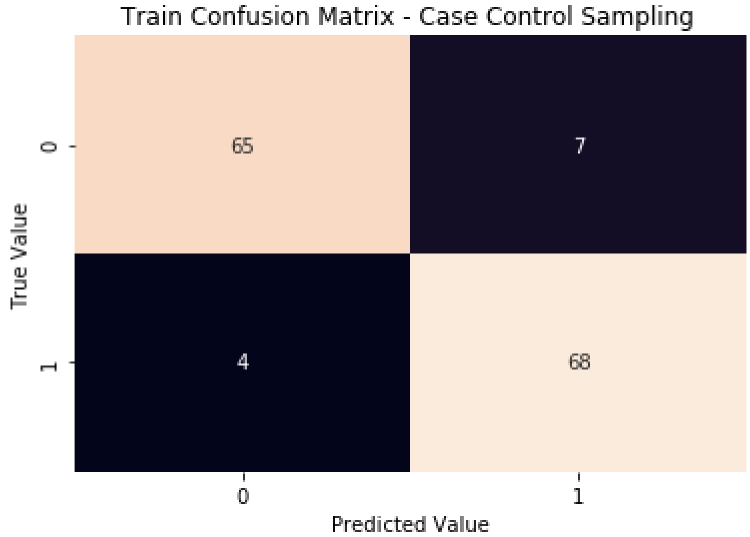
- Yes, from the warning of statsmodel code we find that classes are well-separated thereby resulting in instability in calculating beta and p-values

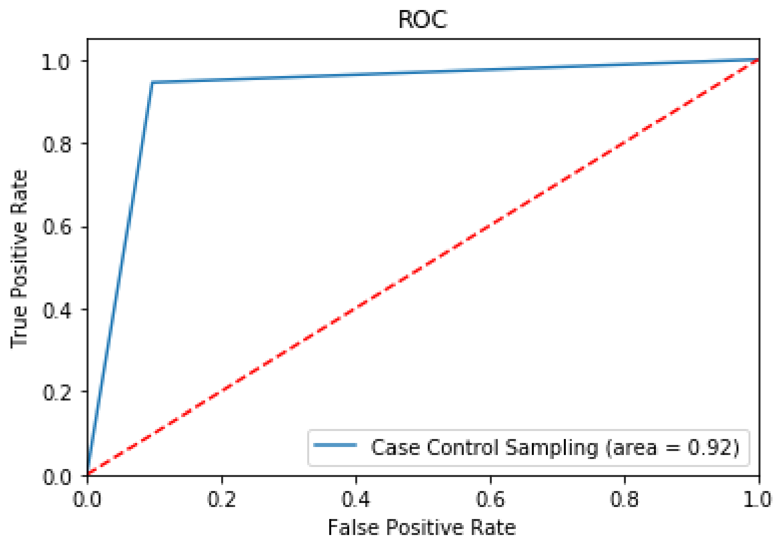
d (vii) From the confusion matrices you obtained, do you see imbalanced classes? If yes, build a logistic regression model based on case-control sampling and adjust its parameters. Report the confusion matrix, ROC, and AUC of the model.

In [56]:
```
feature_cols = np.delete(col_headers, 42)
best_cv_score = 0
best_l = 0
for l in range(1,21):
    Y_train = train_instance_list = []
    X_train = train_instance_frame = pd.DataFrame()
    train_instance_frame = get_instance_frame(train_files, l)

    Y_train = train_instance_frame['class']
    X_train = train_instance_frame.drop(['class'], axis=1)

    rus = RandomUnderSampler()
    X_sampled_train, y_sampled_train = rus.fit_sample(X_train, Y_train)

    logreg = LogisticRegression()
    for i in range(1,len(X_train.columns)):
        rfe_res = RFE(estimator=logreg, n_features_to_select= i)
        rfe_res.fit(X_sampled_train, y_sampled_train)
        cv_score = cross_val_score(rfe_res, X_sampled_train, y_sampled_t
rain, cv=5, scoring='accuracy')
        mean_score  =  np.mean(cv_score)
        if mean_score > best_cv_score:
            best_cv_score = mean_score
            n_features = i
            best_l = l
            best_features = feature_cols[rfe_res.support_]

print("The best value of L for case control sampling is :" , best_l )
print("Optimal CV score for case control sampling is :" , best_cv_score)
print("Optimal number of features for case control sampling : " , n_feat
ures)
print("The Optimal features for for case control sampling are : ", best_
features)
```

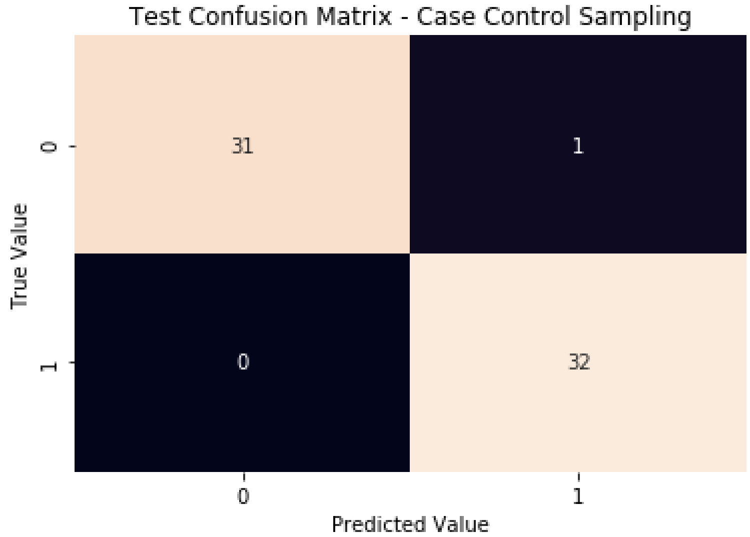
```
The best value of L for case control sampling is : 8
Optimal CV score for case control sampling is : 0.9238095238095239
Optimal number of features for case control sampling :  11
The Optimal features for for case control sampling are :  ['median1' '1
st_quart1' 'max2' 'median2' '1st_quart2' '1st_quart3'
 '3rd_quart3' 'median4' '1st_quart4' 'max5' 'mean5']
```

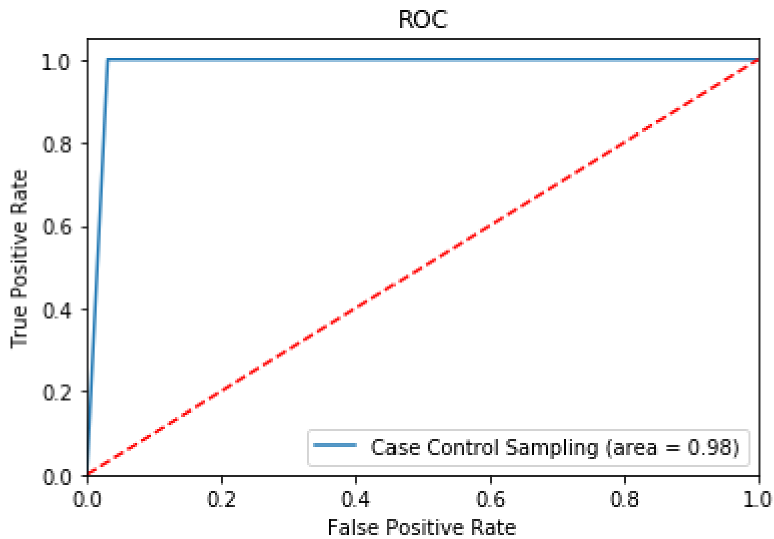
In [58]:
```
train_files, test_files = train_test_split(data_path)

train_instance_frame = get_instance_frame(train_files, best_l)
Y_train = train_instance_frame['class']
X_train = train_instance_frame.drop(['class'], axis=1)
X_train = X_train[best_features]

X_sampled_train, y_sampled_train =  RandomUnderSampler().fit_sample(X_tr
ain, Y_train)

logreg = LogisticRegression()
logreg.fit(X_sampled_train, y_sampled_train)
Y_pred = logreg.predict(X_sampled_train)

conf_mat = confusion_matrix(y_sampled_train, Y_pred)
ax= plt.subplot()
sns.heatmap(conf_mat, annot=True, cbar= False, ax = ax);
plt.title('Train Confusion Matrix - Case Control Sampling ')
plt.xlabel('Predicted Value')
plt.ylabel('True Value')
plt.show()

roc_auc = roc_auc_score(y_sampled_train, Y_pred)
fpr, tpr, thresholds = roc_curve(y_sampled_train, Y_pred)
plt.figure()
plt.plot(fpr, tpr, label='Case Control Sampling (area = %0.2f)' % roc_au
c)
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC')
plt.legend(loc="lower right")
plt.show()
```


Train Confusion Matrix - Case Control Sampling
True Value
Predicted Value
65
7
4
68
0
1
0
1


ROC
True Positive Rate
False Positive Rate
Case Control Sampling (area = 0.92)
0.0
0.2
0.4
0.6
0.8
1.0

In [59]:
```
train_files, test_files = train_test_split(data_path)

test_instance_frame = get_instance_frame(test_files, best_l)
Y_test = test_instance_frame['class']
X_test = test_instance_frame.drop(['class'], axis=1)
X_test = X_test[best_features]

X_sampled_test, y_sampled_test =  RandomUnderSampler().fit_sample(X_test
, Y_test)

Y_pred = logreg.predict(X_sampled_test)

conf_mat = confusion_matrix(y_sampled_test, Y_pred)
ax= plt.subplot()
sns.heatmap(conf_mat, annot=True, cbar= False, ax = ax);
plt.title('Test Confusion Matrix - Case Control Sampling')
plt.xlabel('Predicted Value')
plt.ylabel('True Value')
plt.show()

roc_auc = roc_auc_score(y_sampled_test, Y_pred)
fpr, tpr, thresholds = roc_curve(y_sampled_test, Y_pred)
plt.figure()
plt.plot(fpr, tpr, label='Case Control Sampling (area = %0.2f)' % roc_au
c)
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC')
plt.legend(loc="lower right")
plt.show()
```





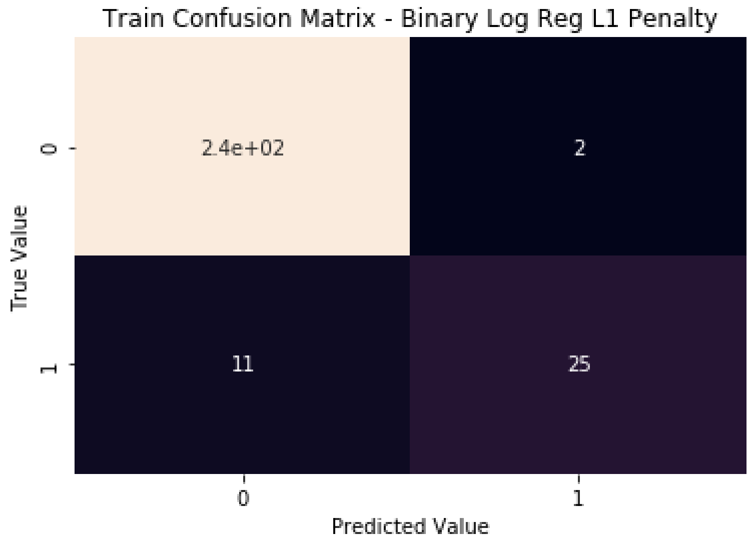
Binary Classification Using L 1 -penalized logistic regression

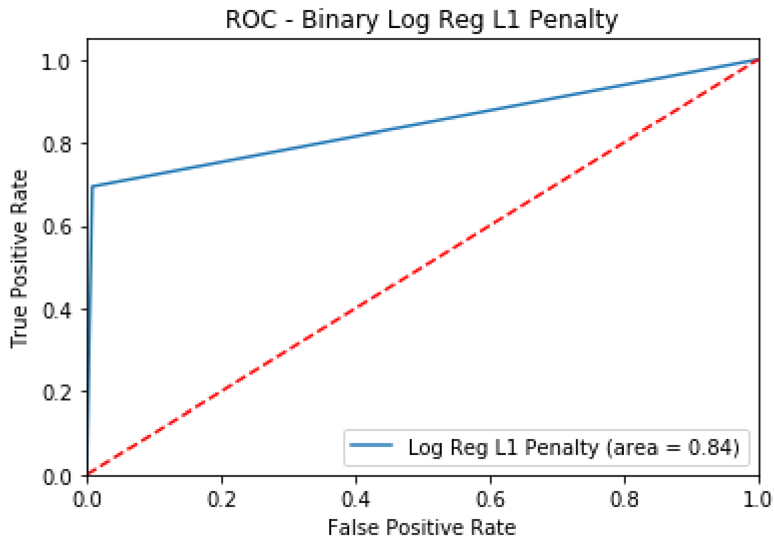
e (i) Repeat 1(d)iii using L 1 -penalized logistic regression, 8 i.e. instead of using p-values for variable selection, use L 1 regularization. Note that in this problem,you have to cross-validate for both l, the number of time series into which you break each of your instances, and λ, the weight of L 1 penalty in your logistic regression objective function (or C, the budget). Packages usually perform cross-validation for λ automatically.

In [60]:
```
train_files, test_files = train_test_split(data_path)

best_l = 0
best_cv_score = 0
for l in range(1,21):
    Y_train = []
    X_train = pd.DataFrame()
    train_instance_frame = get_instance_frame(train_files, l)
    Y_train = train_instance_frame['class']
    X_train = train_instance_frame.drop(['class'], axis=1)

    #normalization
    scalar = StandardScaler()
    X_train  = scalar.fit_transform(X_train)

    lasso = LogisticRegressionCV(penalty = 'l1',cv=StratifiedKFold(5),so
lver='saga')
    lasso = lasso.fit(X_train, Y_train)
    cv_score = cross_val_score(lasso, X_train, Y_train, cv=StratifiedKFo
ld(5), scoring='accuracy')
    mean_score  =  np.mean(cv_score)
    if mean_score > best_cv_score:
        best_cv_score = mean_score
        best_l = l
        best_C = lasso.C_[0]

print("The best L-value for binary Log Reg L1 Penalty is : ", best_l )
print("The best C-value for binary Log Reg L1 Penalty : " ,best_C )
print("Optimal CV score for binary Log Reg L1 Penalty: " ,  best_cv_scor
e)
```

```
The best L-value for binary Log Reg L1 Penalty is :  4
The best C-value for binary Log Reg L1 Penalty :  0.3593813663804626
Optimal CV score for binary Log Reg L1 Penalty:  0.895064935064935
```

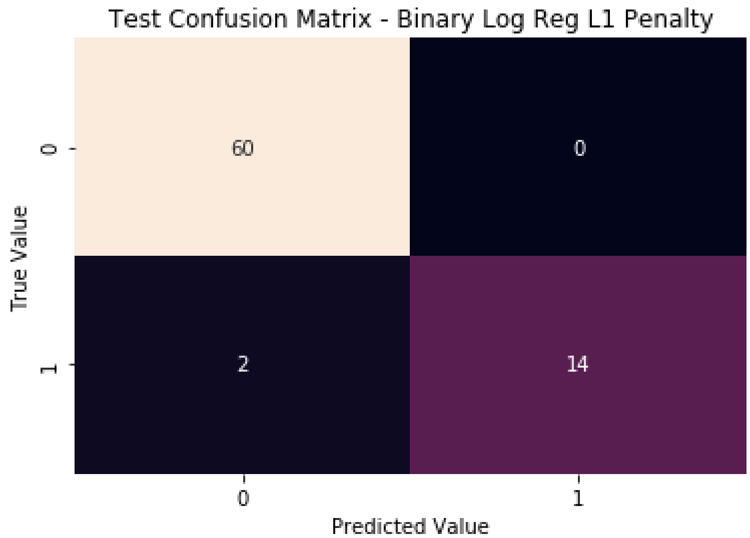
In [61]:
```
#perform binary L 1 -penalized logistic regression on train data using b
est L value and c-value obtained above
train_files, test_files = train_test_split(data_path)

train_instance_frame = get_instance_frame(train_files, best_l)
Y_train = train_instance_frame['class']
X_train = train_instance_frame.drop(['class'], axis=1)

#normalization
scalar = StandardScaler()
X_train  = scalar.fit_transform(X_train)

lasso = LogisticRegression(penalty = 'l1', C = best_C, solver='liblinea
r')
lasso = lasso.fit(X_train, Y_train)
Y_pred = lasso.predict(X_train)
conf_matrix = confusion_matrix(Y_train, Y_pred)

ax= plt.subplot()
sns.heatmap(conf_matrix, annot=True, cbar= False, ax = ax);
plt.title('Train Confusion Matrix - Binary Log Reg L1 Penalty')
plt.xlabel('Predicted Value')
plt.ylabel('True Value')
plt.show()

roc_auc = roc_auc_score(Y_train, Y_pred)
fpr, tpr, thresholds = roc_curve(Y_train, Y_pred)
plt.figure()
plt.plot(fpr, tpr, label='Log Reg L1 Penalty (area = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC - Binary Log Reg L1 Penalty')
plt.legend(loc="lower right")
plt.show()
```

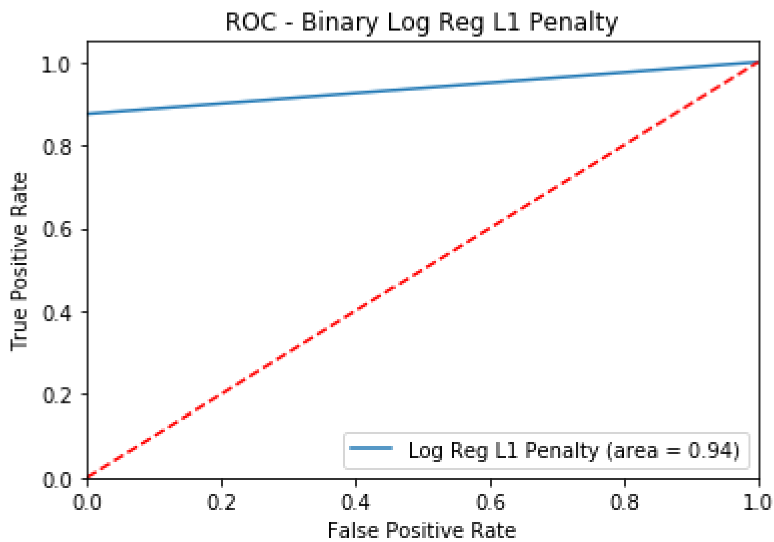

Train Confusion Matrix - Binary Log Reg L1 Penalty
2.4e+02
2
11
25
0
1
True Value
0
1
Predicted Value


ROC - Binary Log Reg L1 Penalty
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
Log Reg L1 Penalty (area = 0.84)

In [62]:
```
#perform binary L 1 -penalized logistic regression on test data using be
st L value and c-value obtained above
train_files, test_files = train_test_split(data_path)

test_instance_frame = get_instance_frame(test_files, best_l)
Y_test = test_instance_frame['class']
X_test = test_instance_frame.drop(['class'], axis=1)

scalar = StandardScaler()
X_test  = scalar.fit_transform(X_test)

Y_pred = lasso.predict(X_test)

accuracy = metrics.accuracy_score(Y_test, Y_pred)
print("Test Error rate for Binary Log Reg L1 penalty is : ", 1-accuracy
)

conf_matrix = confusion_matrix(Y_test, Y_pred)
ax= plt.subplot()
sns.heatmap(conf_matrix, annot=True, cbar= False, ax = ax);
plt.title('Test Confusion Matrix - Binary Log Reg L1 Penalty')
plt.xlabel('Predicted Value')
plt.ylabel('True Value')
plt.show()

roc_auc = roc_auc_score(Y_test, Y_pred)
fpr, tpr, thresholds = roc_curve(Y_test, Y_pred)
plt.figure()
plt.plot(fpr, tpr, label='Log Reg L1 Penalty (area = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC - Binary Log Reg L1 Penalty')
plt.legend(loc="lower right")
plt.show()
```

```
Test Error rate for Binary Log Reg L1 penalty is :  0.02631578947368418
```





e (iii) Compare the L 1 -penalized with variable selection using p-values. Which one performs better? Which one is easier to implement?

- Logistic Regression with variable selection will perform better as it has higher CV than l1 penalized. However, l1 penalized regression is easier to implement as it avoids variable selection loop thereby reducing computational load

Multi-class Classification

(i). Find the best l in the same way as you found it in 1(e)i to build an L 1 -penalized multinomial regression model to classify all activities in your training set. Report your test error. Research how confusion matrices and ROC curves are defined for multiclass classification and show them for this problem if possible.

In [78]:
```
#get time domain featuers for each instance
multi_class_labels = ['bending1', 'bending2','cycling','lying', 'sittin
g', 'standing', 'walking']

def get_features_multi_class(file, split_time_series=None):
    instance_list = []
    class_type = file.split('/')[0]
    file = data_path + '/' + file
    df = pd.read_csv(file, header=4, usecols=[*range(1, 7)])
    df.fillna(0, inplace=True)
    dflist = [df]
    if split_time_series is not None:
        dflist = np.array_split(df, split_time_series)
    for df in dflist:
        row = []
        stat_df = df.agg(['min', 'max', 'mean', 'median', 'std'])
        stat_df = stat_df.append(df.quantile(q=0.25))
        stat_df = stat_df.append(df.quantile(q=0.75))
        for col in [stat_df[f] for f in stat_df]:
            for data in col:
                row.append(data)
        row.append(class_type)
        instance_list.append(row)
    return instance_list


def get_multi_class_instance_frame(file_list, split_size=None):
    total_instance_frame = pd.DataFrame()
    total_instance_list = []
    for file in file_list:
        instance_features = get_features_multi_class(file,split_size)
        total_instance_list = total_instance_list + instance_features

    total_instance_frame = pd.DataFrame(
        total_instance_list, columns=col_headers)
    return total_instance_frame
```

In [79]:
```
def multiclass_roc(y_true, y_pred):
    '''
        This function plots ROC curve with AUC for
        multiclass classification
    '''
    multi_class_labels = ['bending1', 'bending2','cycling', 'lying','sit
ting', 'standing', 'walking']
    lw=2
    fpr = tpr = roc_auc = dict()
    colors = ['purple','brown','blue','green','yellow','orange','red']
    for i in range(0,7):
        fpr, tpr, _ = roc_curve(y_true[:, i], y_pred[:, i])
        roc_auc = auc(fpr, tpr)
        plt.plot(fpr, tpr, color=colors[i],
             lw=lw, label=f'ROC curve for {multi_class_labels[i]} (area
 = %0.2f)' %roc_auc)
    plt.plot([0, 1], [0, 1],'r--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('ROC Curve')
    plt.legend(loc="lower right")
    plt.show()
```

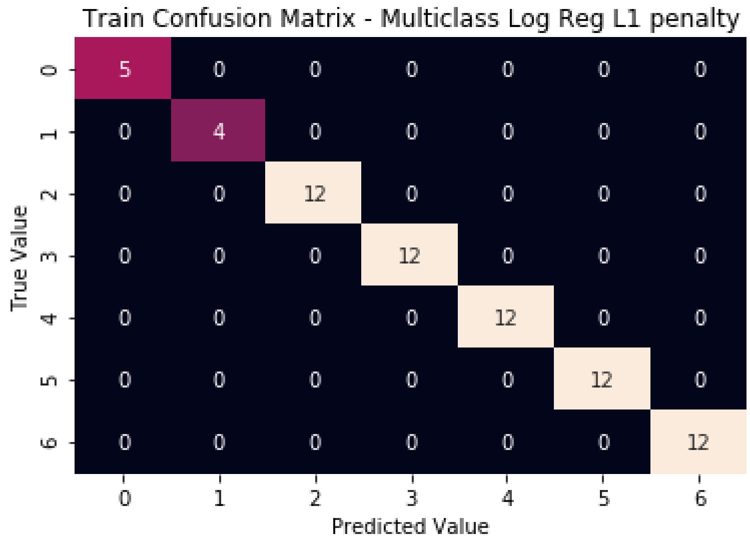
In [80]:

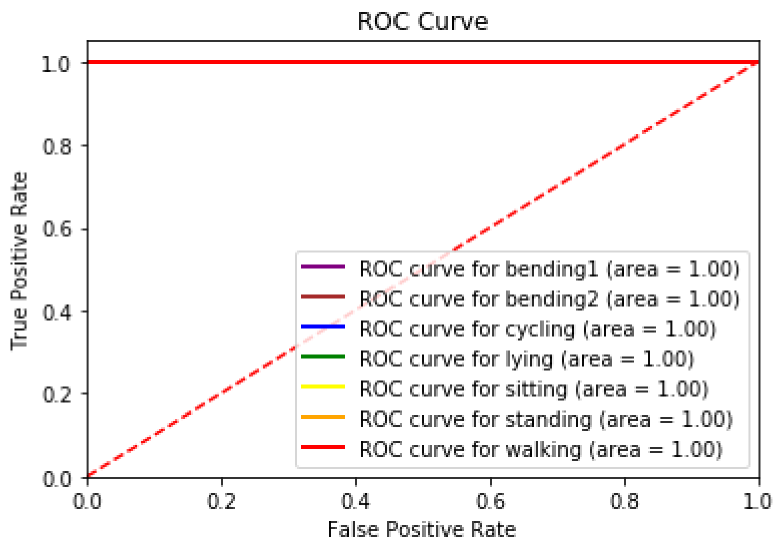
```
#perform L1-penalized multiclass logistic regression to find best L valu
e

train_files, test_files = train_test_split(data_path)

best_l = 0
best_cv_score = 0
for l in range(1, 21):
    Y_train = []
    X_train = pd.DataFrame()
    train_instance_frame = get_multi_class_instance_frame(train_files, l
)
    Y_train = train_instance_frame['class']
    X_train = train_instance_frame.drop(['class'], axis=1)

    #normalization
    scalar = StandardScaler()
    X_test  = scalar.fit_transform(X_test)

    multi_lasso = LogisticRegressionCV(
        penalty='l1',
        multi_class='multinomial',
        cv=3,
        solver='saga')
    multi_lasso = multi_lasso.fit(X_train, Y_train)
    cv_score = cross_val_score(
        multi_lasso, X_train, Y_train, cv=3, scoring='accuracy')
    mean_score = np.mean(cv_score)
    if mean_score > best_cv_score:
        best_cv_score = mean_score
        best_l = l
        best_C = multi_lasso.C_[0]

print("The best L-value Multiclass Log Reg L1 penalty is : ", best_l )
print("The best C-value Multiclass Log Reg L1 penalty is : " ,best_C )
print("Optimal CV score Multiclass Log Reg L1 penalty is: " ,  best_cv_s
core)
```

```
The best L-value Multiclass Log Reg L1 penalty is :  1
The best C-value Multiclass Log Reg L1 penalty is :  166.81005372000558
Optimal CV score Multiclass Log Reg L1 penalty is:  0.85677426438296
```

Note: We have used cv = 3 to avoid number of samples warning resulting from limited samples in bending1 and bending2 dataset

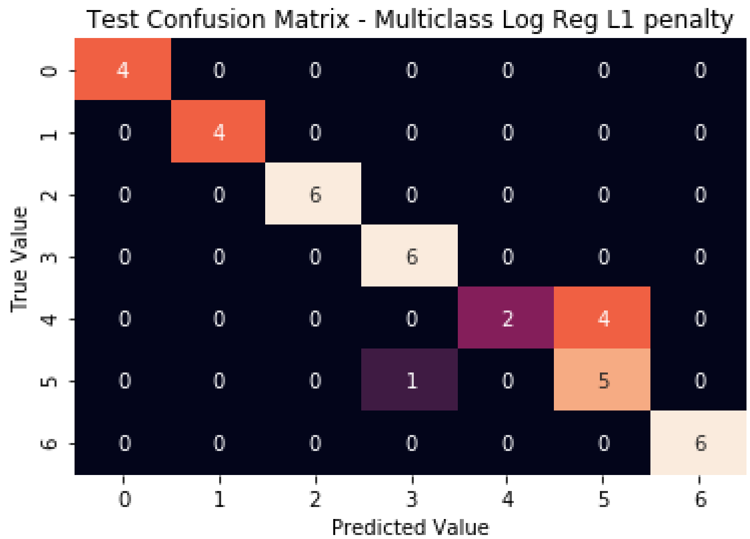
In [81]:
```
#perform L1-penalized multiclass logistic regression on train data using
best L value and C value obtained from above

train_files, test_files = train_test_split(data_path)

train_instance_frame = get_multi_class_instance_frame(train_files, best_
l)
Y_train = train_instance_frame['class']
X_train = train_instance_frame.drop(['class'], axis=1)

#normalization
scalar = StandardScaler()
X_train  = scalar.fit_transform(X_train)
multi_lasso = LogisticRegression(penalty = 'l1', C = best_C, multi_class
='multinomial', solver='saga')
multi_lasso = multi_lasso.fit(X_train, Y_train)
Y_pred = multi_lasso.predict(X_train)

conf_matrix = confusion_matrix(Y_train, Y_pred)
ax= plt.subplot()
sns.heatmap(conf_matrix, annot=True, cbar= False, ax = ax);
plt.title('Train Confusion Matrix - Multiclass Log Reg L1 penalty')
plt.xlabel('Predicted Value')
plt.ylabel('True Value')
plt.show()

Y_train = label_binarize(Y_train, classes= multi_class_labels)
Y_pred = label_binarize(Y_pred, classes= multi_class_labels)
multiclass_roc(Y_train, Y_pred)
```

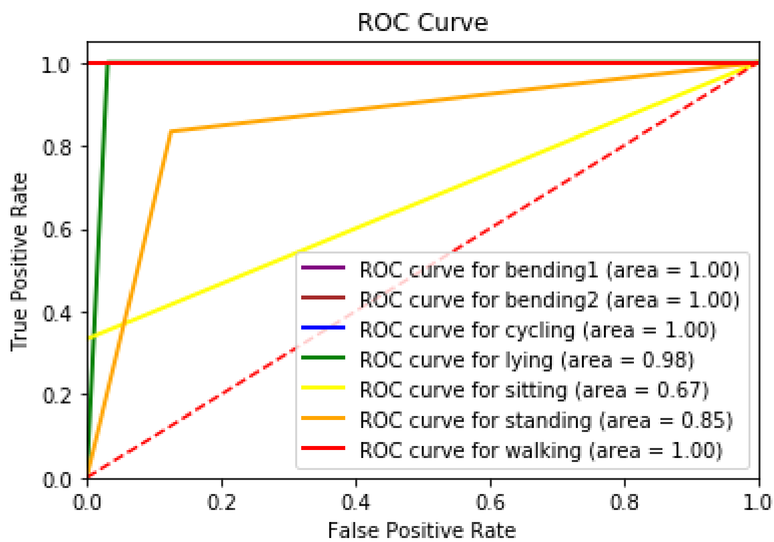

Train Confusion Matrix - Multiclass Log Reg L1 penalty
True Value
Predicted Value


ROC Curve
True Positive Rate
False Positive Rate
ROC curve for bending1 (area = 1.00)
ROC curve for bending2 (area = 1.00)
ROC curve for cycling (area = 1.00)
ROC curve for lying (area = 1.00)
ROC curve for sitting (area = 1.00)
ROC curve for standing (area = 1.00)
ROC curve for walking (area = 1.00)

In [83]:
```
#perform L1-penalized multiclass logistic regression (L1 penalty)on test
data using best L value

test_instance_frame = get_multi_class_instance_frame(test_files, best_l)
Y_test = test_instance_frame['class']
X_test = test_instance_frame.drop(['class'], axis=1)

#normalization
scalar = StandardScaler()
X_test  = scalar.fit_transform(X_test)
Y_pred = multi_lasso.predict(X_test)

accuracy = metrics.accuracy_score(Y_test, Y_pred)
print("Test Error rate for multi-class Log Reg L1 penalty is : ", 1-accu
racy )
conf_matrix = confusion_matrix(Y_test, Y_pred)
ax= plt.subplot()
sns.heatmap(conf_matrix, annot=True, cbar= False, ax = ax);
plt.title('Test Confusion Matrix - Multiclass Log Reg L1 penalty')
plt.xlabel('Predicted Value')
plt.ylabel('True Value')
plt.show()

Y_test = label_binarize(Y_test, classes= multi_class_labels)
Y_pred = label_binarize(Y_pred, classes= multi_class_labels)
multiclass_roc(Y_test, Y_pred)
```

```
Test Error rate for multi-class Log Reg L1 penalty is :  0.131578947368
42102
```



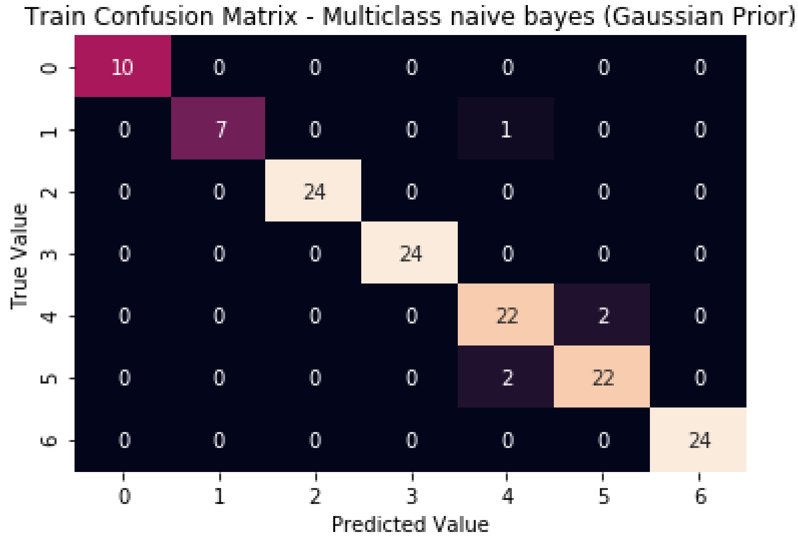


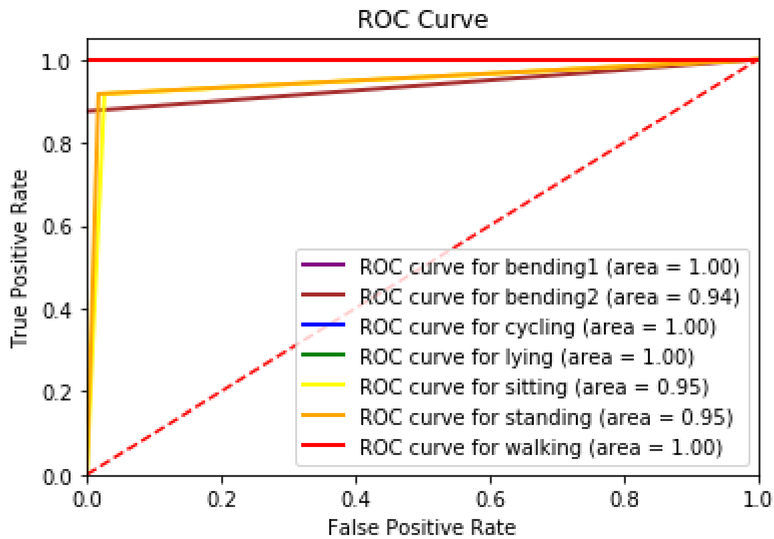
e (ii) Repeat 1(f)i using a Naive Bayes' classifier. Use both Gaussian and Multi-nomial priors and compare the results.

In [82]:
```
#perform multi-class Naive Bayes(Gaussian Prior) to find best L
train_files, test_files = train_test_split(data_path)

best_l = 0
best_cv_score = 0
for l in range(1, 21):
    train_instance_frame = get_multi_class_instance_frame(train_files, l
)
    Y_train = train_instance_frame['class']
    X_train = train_instance_frame.drop(['class'], axis=1)
    nbgaussian = GaussianNB()
    nbgaussian = nbgaussian.fit(X_train, Y_train)
    cv_score = cross_val_score(
        nbgaussian, X_train, Y_train, cv=3, scoring='accuracy')
    mean_score = np.mean(cv_score)
    if mean_score > best_cv_score:
        best_cv_score = mean_score
        best_l = l

print("The best L-value for multiclass naive bayes (Gaussian Prior) is :
", best_l)
print("Optimal CV score for multiclass naive bayes (Gaussian Prior) is:
 ", best_cv_score)
```

```
The best L-value for multiclass naive bayes (Gaussian Prior) is :  2
Optimal CV score for multiclass naive bayes (Gaussian Prior) is:  0.796
8787473875355
```

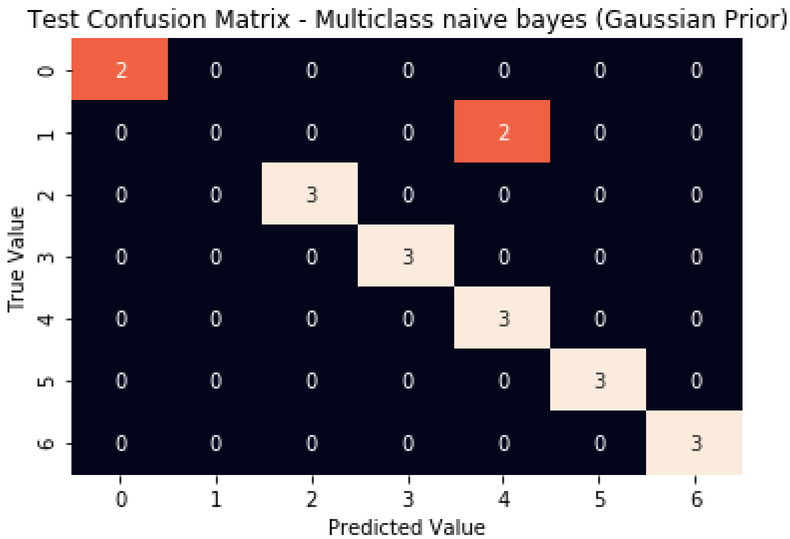
In [84]:
```
#perform multiclass naive bayes (Gaussian Prior) on train data using bes
t L value obtained from above
train_files, test_files = train_test_split(data_path)

train_instance_frame = get_multi_class_instance_frame(train_files, best_
l)
Y_train = train_instance_frame['class']
X_train = train_instance_frame.drop(['class'], axis=1)

nbgaussian = GaussianNB()
nbgaussian = nbgaussian.fit(X_train, Y_train)

Y_pred = nbgaussian.predict(X_train)
conf_matrix = confusion_matrix(Y_train, Y_pred)
ax= plt.subplot()
sns.heatmap(conf_matrix, annot=True, cbar= False, ax = ax);
plt.title('Train Confusion Matrix - Multiclass naive bayes (Gaussian Pri
or)')
plt.xlabel('Predicted Value')
plt.ylabel('True Value')
plt.show()

Y_train = label_binarize(Y_train, classes= multi_class_labels)
Y_pred = label_binarize(Y_pred, classes= multi_class_labels)
multiclass_roc(Y_train, Y_pred)
```

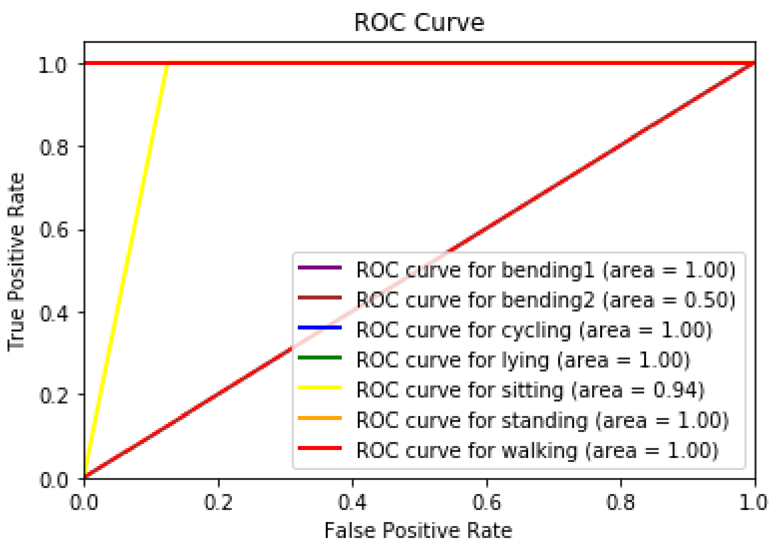

Train Confusion Matrix - Multiclass naive bayes (Gaussian Prior)
True Value
Predicted Value
0
1
2
3
4
5
6
10
7
1
24
24
22
2
2
22
24


ROC Curve
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
ROC curve for bending1 (area = 1.00)
ROC curve for bending2 (area = 0.94)
ROC curve for cycling (area = 1.00)
ROC curve for lying (area = 1.00)
ROC curve for sitting (area = 0.95)
ROC curve for standing (area = 0.95)
ROC curve for walking (area = 1.00)

In [70]:
```
train_files, test_files = train_test_split(data_path)

#perform multiclass naive bayes (Gaussian Prior) on test data using best
L value

test_instance_frame = get_multi_class_instance_frame(test_files, best_l)
Y_test = test_instance_frame['class']
X_test = test_instance_frame.drop(['class'], axis=1)

Y_pred = nbgaussian.predict(X_test)

accuracy = metrics.accuracy_score(Y_test, Y_pred)
print("Test Error rate for multiclass naive bayes(Gaussian Prior) is : "
, 1-accuracy )
conf_matrix = confusion_matrix(Y_test, Y_pred)
ax= plt.subplot()
sns.heatmap(conf_matrix, annot=True, cbar= False, ax = ax);
plt.title('Test Confusion Matrix - Multiclass naive bayes (Gaussian Prio
r)')
plt.xlabel('Predicted Value')
plt.ylabel('True Value')
plt.show()

Y_test = label_binarize(Y_test, classes= multi_class_labels)
Y_pred = label_binarize(Y_pred, classes= multi_class_labels)
multiclass_roc(Y_test, Y_pred)
```

```
Test Error rate for multiclass naive bayes(Gaussian Prior) is :  0.1052
6315789473684
```

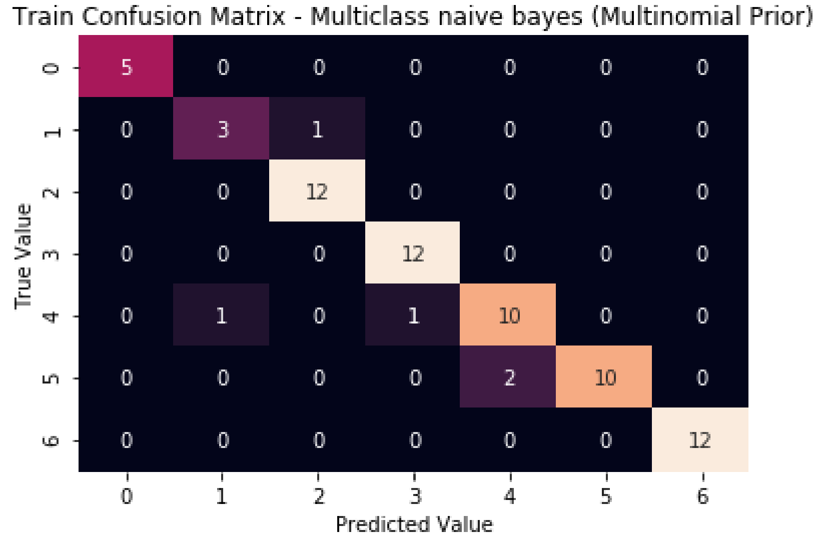


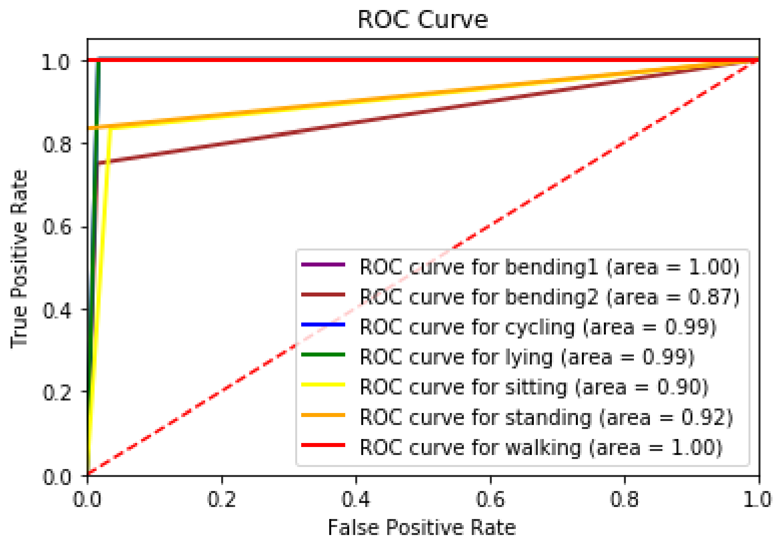


In [103]:
```
train_files, test_files = train_test_split(data_path)

#perfor multi-class Naive Bayes(Multinomial Prior) to find best L
best_l = 0
best_cv_score = 0
for l in range(1,21):
    train_instance_frame = get_multi_class_instance_frame(train_files, l
)
    Y_train = train_instance_frame['class']
    X_train = train_instance_frame.drop(['class'], axis=1)
    nbmultinomial = MultinomialNB()
    #X_train.dropna()
    #print(X_train)
    nbmultinomial = nbmultinomial.fit(X_train, Y_train)
    cv_score = cross_val_score(nbmultinomial, X_train, Y_train, cv = 3,
scoring='accuracy')
    mean_score  =  np.mean(cv_score)
    if mean_score > best_cv_score:
        best_cv_score = mean_score
        best_l = l

print("The best L-value for multiclass naive bayes (Multinomial Prior) i
s : ", best_l )
print("Optimal CV score for multiclass naive bayes (Multinomial Prior) i
s: " ,  best_cv_score)
```

```
The best L-value for multiclass naive bayes (Multinomial Prior) is :  1
Optimal CV score for multiclass naive bayes (Multinomial Prior) is:  0.
8416227492314449
```

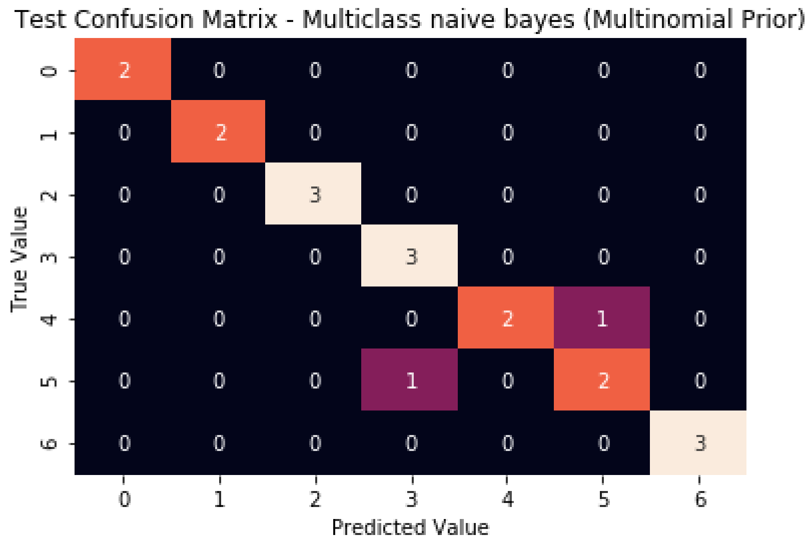
In [86]:
```
#perform multi-class Naive Bayes(Multinomial Prior) on train data using
 best L value
train_files, test_files = train_test_split(data_path)
best_l = 1
train_instance_frame = get_multi_class_instance_frame(train_files, best_
l)
Y_train = train_instance_frame['class']
X_train = train_instance_frame.drop(['class'], axis=1)

nbmultinomial = MultinomialNB()
#X_train_norm=normalize(X_train)
#Y_train_norm=normalize(Y_train)
nbmultinomial = nbmultinomial.fit(X_train, Y_train)

Y_pred = nbmultinomial.predict(X_train)

conf_matrix = confusion_matrix(Y_train, Y_pred)
ax= plt.subplot()
sns.heatmap(conf_matrix, annot=True, cbar= False, ax = ax);
plt.title('Train Confusion Matrix - Multiclass naive bayes (Multinomial
 Prior)')
plt.xlabel('Predicted Value')
plt.ylabel('True Value')
plt.show()

Y_train = label_binarize(Y_train, classes= multi_class_labels)
Y_pred = label_binarize(Y_pred, classes= multi_class_labels)
multiclass_roc(Y_train, Y_pred)
```

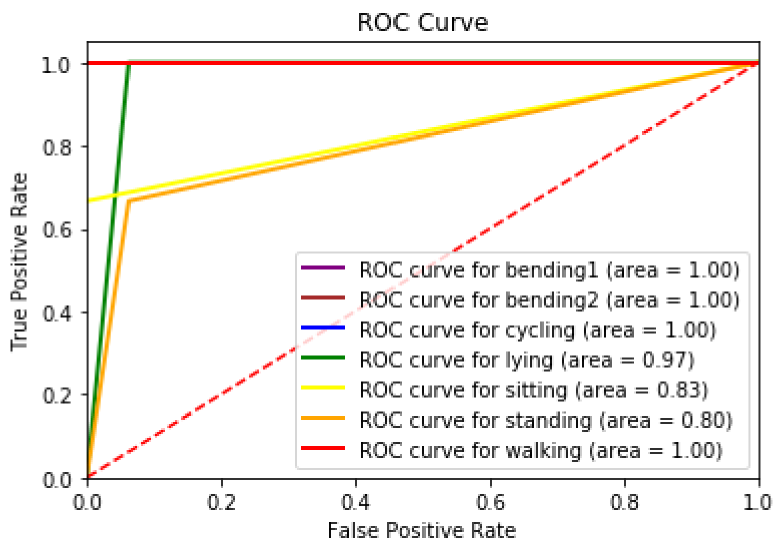

Train Confusion Matrix - Multiclass naive bayes (Multinomial Prior)
True Value
Predicted Value
0 1 2 3 4 5 6
5 0 0 0 0 0 0
0 3 1 0 0 0 0
0 0 12 0 0 0 0
0 0 0 12 0 0 0
0 1 0 1 10 0 0
0 0 0 0 2 10 0
0 0 0 0 0 0 12


ROC Curve
True Positive Rate
False Positive Rate
ROC curve for bending1 (area = 1.00)
ROC curve for bending2 (area = 0.87)
ROC curve for cycling (area = 0.99)
ROC curve for lying (area = 0.99)
ROC curve for sitting (area = 0.90)
ROC curve for standing (area = 0.92)
ROC curve for walking (area = 1.00)

In [87]:
```
#perform multi-class Naive Bayes(Multinomial Prior) on test data using b
est L value

train_files, test_files = train_test_split(data_path)
test_instance_frame = get_multi_class_instance_frame(test_files, best_l)
Y_test = test_instance_frame['class']
X_test = test_instance_frame.drop(['class'], axis=1)

Y_pred = nbmultinomial.predict(X_test)
conf_matrix = confusion_matrix(Y_test, Y_pred)

accuracy = metrics.accuracy_score(Y_test, Y_pred)
print("Test Error rate for multiclass naive bayes(Multinomial Prior) is
 : ", 1-accuracy )
ax= plt.subplot()
sns.heatmap(conf_matrix, annot=True, cbar= False, ax = ax);
plt.title('Test Confusion Matrix - Multiclass naive bayes (Multinomial P
rior)')
plt.xlabel('Predicted Value')
plt.ylabel('True Value')
plt.show()

Y_test = label_binarize(Y_test, classes= multi_class_labels)
Y_pred = label_binarize(Y_pred, classes= multi_class_labels)
multiclass_roc(Y_test, Y_pred)
```

```
Test Error rate for multiclass naive bayes(Multinomial Prior) is :  0.1
0526315789473684
```





e (iii) Which method is better for multi-class classification in this problem?

- After comparation, we observe that L1-norm logistic regression has the best performance here with this dataset.

In [ ]: