EE559 HW3 HW4

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An interesting task in machine learning is classification of time series. In this problem, we will classify the activities of humans based on time series obtained by a Wireless Sensor Network.

¶ (http://localhost:8888/nbconvert/html/Desktop/HW3/Time_Series_HW3_HW4.ipynb download=false#-)

(a) Download the AReM data from: https://archive.ics.uci.edu/ml/datasets/ (https://archive.ics.uci.edu/ml/datasets/) Activity+Recognition+system+based+on+Multisensor+data+fusion+\%28AReM\ %29 . 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.

(b) 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 [1]:
```
#in this step we will merge different datasets to train datasets and test datasets
import pandas as pd
import numpy as np
```

In [2]:
```
import os
path = "/Users/yuxianghou/Desktop/AReM"
files= os.listdir(path) #得到文件夹下的所有文件名称

train_list=[]
test_list=[]
all_list=[]

for file in files:
    if file.startswith("ben"):
        bending_path=path+"/"+str(file)
        bending_files=os.listdir(bending_path)

        for bending_file in bending_files:
            current_path=bending_path+"/"+str(bending_file)
            all_list.append(current_path)

            if bending_file.endswith("1.csv") or bending_file.endswith("2.csv"):
                #then we will save the data
                test_list.append(current_path)
            else:
                train_list.append(current_path)

    if file.endswith("ing"):
        data_path=path+"/"+str(file)
        data_files=os.listdir(data_path)
        for data_file in data_files:
            current_path=data_path+"/"+str(bending_file)
            all_list.append(current_path)

            if data_file=="dataset1.csv" or data_file=="dataset2.csv" or data_file=="dataset3.csv":
                test_list.append(current_path)
            else:
                train_list.append(current_path)
```

In [3]:
```
def get_data_list(alist):
    data_list=[]
    for path in alist:
        data=pd.read_csv(path,header=4)
        data_list.append(data)
    return data_list
```

In [4]:
```
train_data_list=get_data_list(train_list)
test_data_list=get_data_list(test_list)
```

In [5]:
```
train_data=pd.concat(train_data_list)
test_data=pd.concat(test_data_list)
```

In [6]:
```
train_data.head()
```

Out[6]:

	# Columns: time	avg_rss12	var_rss12	avg_rss13	var_rss13	avg_rss23	var_rss23
0	0	42.00	0.71	21.25	0.43	30.00	0.00
1	250	41.50	0.50	20.25	1.48	31.25	1.09
2	500	41.50	0.50	14.25	1.92	33.00	0.00
3	750	40.75	0.83	15.75	0.43	33.00	0.00
4	1000	40.00	0.71	20.00	2.74	32.75	0.43

In [7]:
```
test_data.head()
```

Out[7]:

	# Columns: time	avg_rss12	var_rss12	avg_rss13	var_rss13	avg_rss23	var_rss23
0	0	39.25	0.43	22.75	0.43	33.75	1.3
1	250	39.25	0.43	23.00	0.00	33.00	0.0
2	500	39.25	0.43	23.25	0.43	33.00	0.0
3	750	39.50	0.50	23.00	0.71	33.00	0.0
4	1000	39.50	0.50	24.00	0.00	33.00	0.0

(c) Feature Extraction

Classification of time series usually needs extracting features from them. In this problem, we focus on time-domain features. i. Research what types of time-domain features are usually used in time series classification and list them (examples are minimum, maximum, mean, etc).

My Answer:Mean,max,min, variance, first quartile and third quartile are always useful for the analysis of time series

Extract the time-domain features minimum, maximum, mean, median, stan- dard deviation, first quartile, and third quartile for all of the 6 time series in each instance. You are free to normalize/standardize features or use them directly.2

In [8]:
```
all_data_list=get_data_list(all_list) #then we have all data_list result
```

In [9]:
```
#this is the statistical result

def get_Statistical_result(alist):
    min_=np.min(alist)
    max_=np.max(alist)
    mean_=np.mean(alist)
    median_=np.median(alist)
    std_=np.std(alist)

    first_quartile=np.percentile(alist,25)
    third_quartile=np.percentile(alist,75)

    return [min_,max_,mean_,median_,std_,first_quartile,third_quartile]
```

In [10]:
```
def get_DataMatrix(dataframe_list):

    all_result=[]
    for dataframe in dataframe_list:

        #then the input is the dataframe right now, get the statistical result
        avg_rss12_statis=get_Statistical_result(dataframe["avg_rss12"])
        var_rss12_statis=get_Statistical_result(dataframe["var_rss12"])
        avg_rss13_statis=get_Statistical_result(dataframe["avg_rss13"])
        var_rss13_statis=get_Statistical_result(dataframe["var_rss13"])
        avg_rss23_statis=get_Statistical_result(dataframe["avg_rss23"])
        var_rss23_statis=get_Statistical_result(dataframe["var_rss23"])


        one_result=avg_rss12_statis+var_rss12_statis+avg_rss13_statis+var_rss13_statis+avg_rss23_statis+var_r
ss23_statis
        all_result.append(one_result)
    return all_result
```

In [11]:
```
matrix=get_DataMatrix(all_data_list)
train_matrix=get_DataMatrix(train_data_list)
test_matrix=get_DataMatrix(test_data_list)
columns=["min1","max1","mean1","median1","std1","1st quartile1","3rd quartile1",
         "min2","max2","mean2","median2","std2","1st quartile2","3rd quartile2",
         "min3","max3","mean3","median3","std3","1st quartile3","3rd quartile3",
         "min4","max4","mean4","median4","std4","1st quartile4","3rd quartile4",
         "min5","max5","mean5","median5","std5","1st quartile5","3rd quartile5",
         "min6","max6","mean6","median6","std6","1st quartile6","3rd quartile6"]

Data=pd.DataFrame(matrix,columns=columns)
train_data=pd.DataFrame(train_matrix,columns=columns)
test_data=pd.DataFrame(test_matrix,columns=columns)
```

In [12]:
```
train_data.shape
```

Out[12]: (69, 42)

In [13]:
```
test_data.shape
```

Out[13]: (19, 42)

iii. Use your judgement to select the three most important time-domain features (one option may be min, mean, and max).

According to the above dataframe,I think min,std, and median are the three most important features., because we can know almost surely the situation of one column distribution if we know std, mean, median and std

(d) Binary Classification Using Logistic Regression3

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. (See p. 129 of the textbook).4

In [14]:
```
#according to the above result, then we will pick the series 1 min ,std1,median1 features
new_data=Data[["min1","median1","std1","min2","median2","std2","min6","median6","std6"]]
```

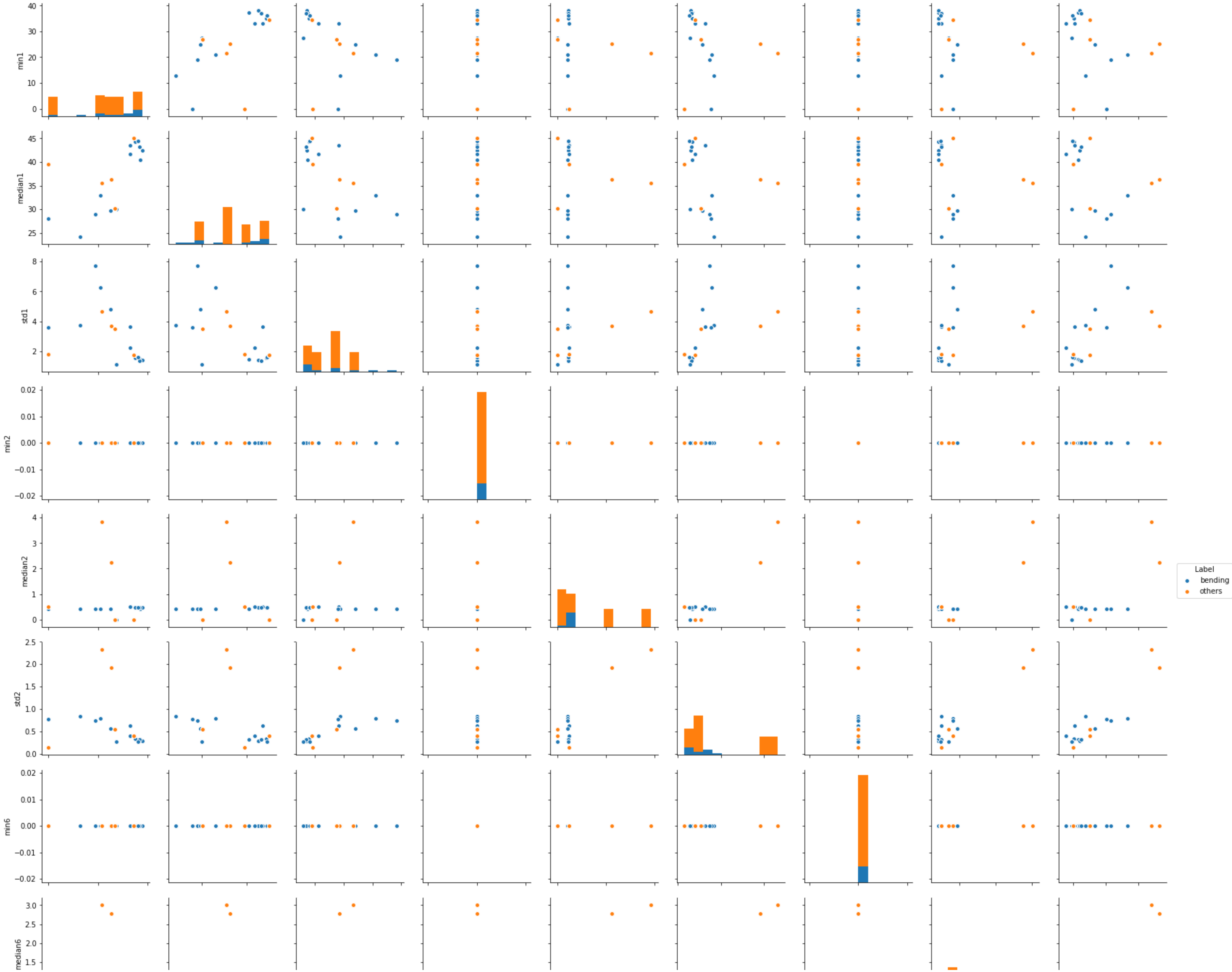
In [15]:
```
label=["bending"]*13+["others"]*75
new_data["Label"]=label
```

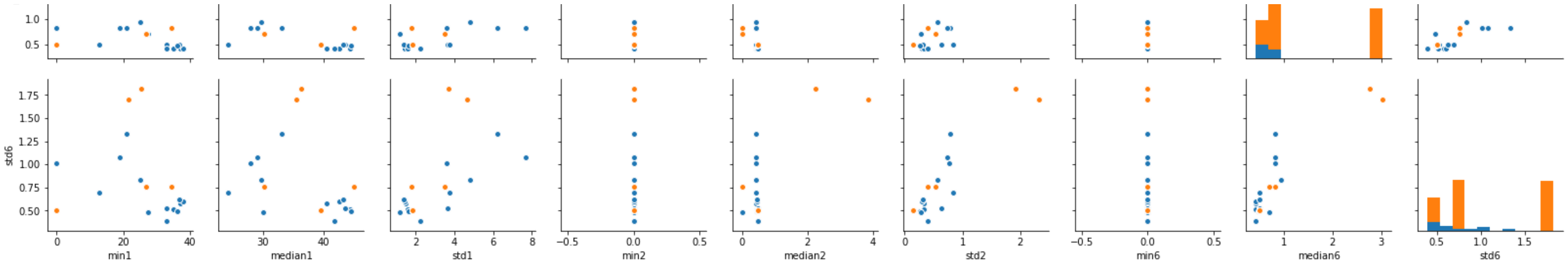
```
/Library/Frameworks/Python.framework/Versions/3.6/lib/python3.6/site-packages/ipykernel_launcher.py:2: Setti
ngWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexing-vie
w-versus-copy
```

In [16]:
```
import matplotlib.pylab as plt
%matplotlib inline
```

In [17]:
```
import seaborn as sns
sns.pairplot(new_data,hue="Label")
```

```
Out[17]: <seaborn.axisgrid.PairGrid at 0x10a89dfd0>
```


min1
median1
std1
min2
median2
std2
min6
median6
Label
bending
others



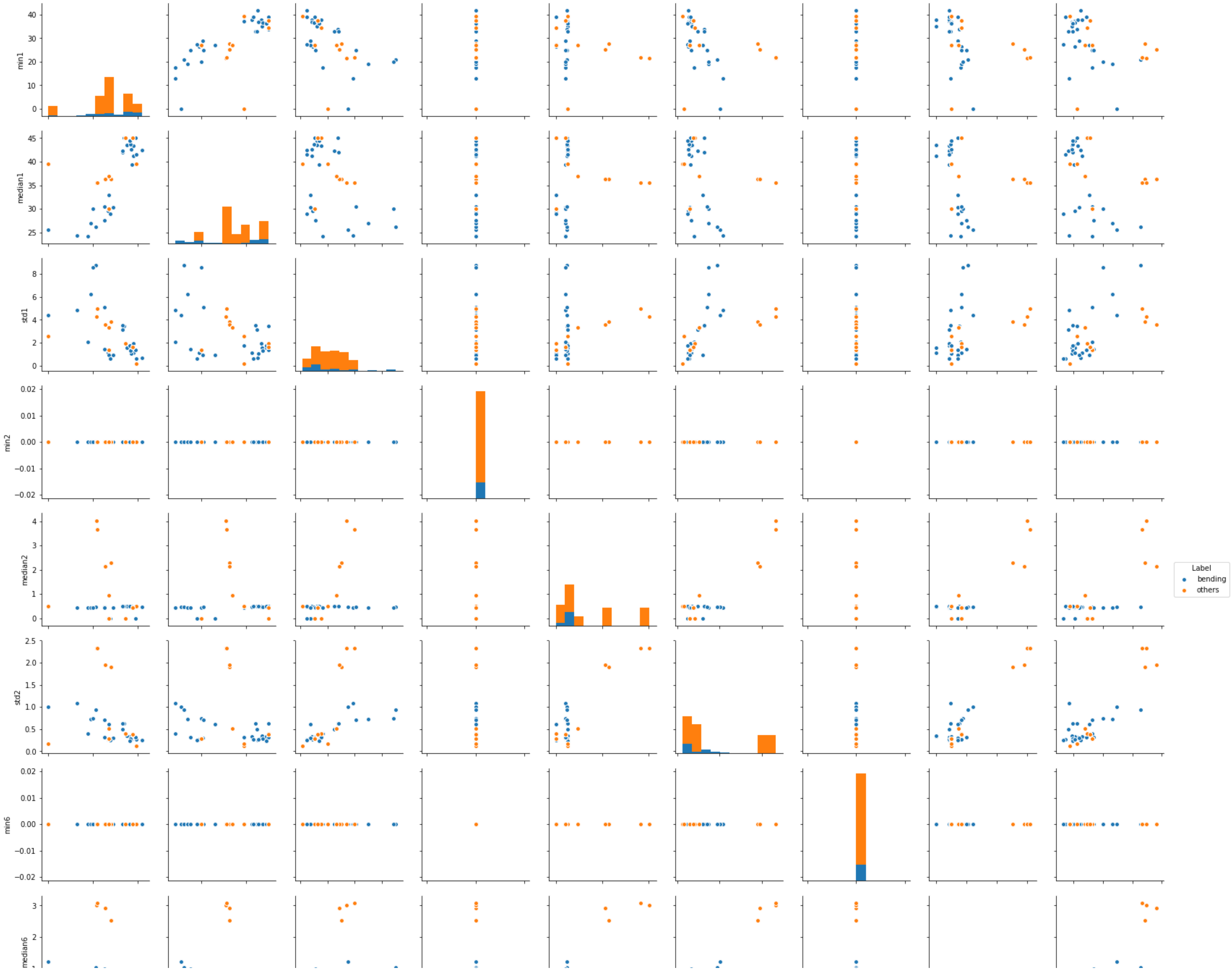
ii. Break each time series in your training set into two (approximately) equal length time series. Now instead of 6 time series for each of the 88 instances, you have 12 time series for each instance. Repeat the experiment in 1(d)i. Do you see any considerable difference in the results with those of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

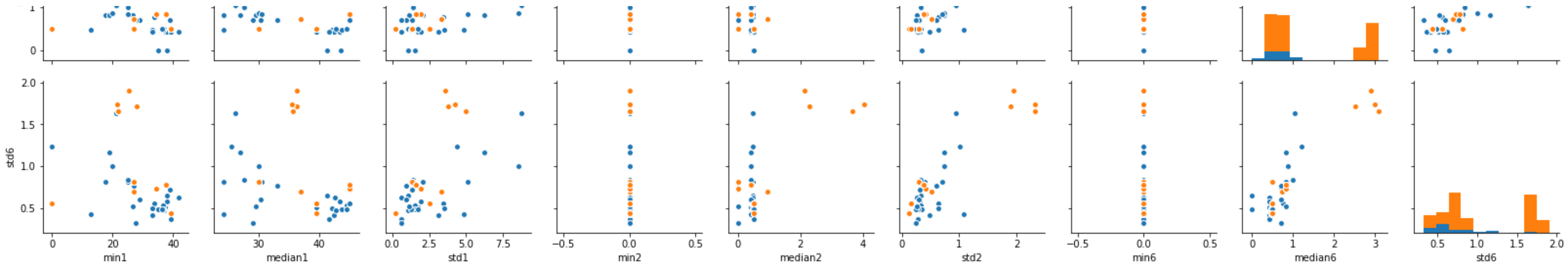
In [18]:
```
def seperate_data():
    new_all_list=[]

    for dataframe in all_data_list:

        first=dataframe[:240]
        second=dataframe[240:]
        new_all_list.append(first)
        new_all_list.append(second)
    return new_all_list

double_dataframe_list=seperate_data()
new_matrix=get_DataMatrix(double_dataframe_list)
double_df=pd.DataFrame(new_matrix,columns=columns)
new_double_df=double_df[["min1","median1","std1","min2","median2","std2","min6","median6","std6"]]

label=["bending"]*26+["others"]*150
new_double_df["Label"]=label
```

```
/Library/Frameworks/Python.framework/Versions/3.6/lib/python3.6/site-packages/ipykernel_launcher.py:18: Sett
ingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexing-vie
w-versus-copy
```

In [19]:
```
sns.pairplot(new_double_df,hue="Label")
```

```
Out[19]: <seaborn.axisgrid.PairGrid at 0x10f909898>
```


min1
median1
std1
min2
median2
std2
min6
median6
Label
bending
others



we can find here there are more data points in each subplot, and some pattern seems become more clearn compared to the patten in (d)(i)

iii

Break each time series in your training set into $l \in \{1, 2, . . . , 20\}$ time series of approximately equal length and use logistic regression5 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 de- termine 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.

In the following, you can see an example of applying Python's Recursive Feature Elimination, which is a backward selection algorithm, to logistic re- gression.

Recursive Feature Elimination from sklearn import datasets from sklearn . feature selection import RFE from sklearn . linear model import LogisticRegression # load the iris datasets dataset = datasets . load iris () # create a base classifier used to evaluate a subset of attributes model = LogisticRegression () # create the RFE model and select 3 attributes rfe =RFE(model, 3) rfe = rfe.fit(dataset.data, dataset.target) # summarize the selection of the attributes print (rfe . support)

In [20]:
```
#break time series into k folder
#the input is a list, then we will split the split into k part
def get_list_split(alist,k):
    split_len=len(alist)//k   #k=10, then every k has 48

    new_list=[]
    for i in range(k):
        split_small_list=alist[(split_len*i):(split_len*(i+1))]
        if i==k-1:
            split_small_list=alist[(split_len*(k-1)):]
        new_list.append(split_small_list)
    return new_list
```

In [21]:
```
def get_train_datasets_labels():
    new_list=[]
    for i in range(len(train_data_list)):
        if i<9:
            train_data_list[i]["Labels"]=["Bedding"]*480
        else:
            train_data_list[i]["Labels"]=["Others"]*480
        new_list.append(train_data_list[i])
    return new_list

new_train_data_list=get_train_datasets_labels()
```

In [22]:
```
print(new_train_data_list[0])
```

```
     # Columns: time  avg_rss12  var_rss12  avg_rss13  var_rss13  avg_rss23  \
0                  0      42.00       0.71      21.25       0.43      30.00
1                250      41.50       0.50      20.25       1.48      31.25
2                500      41.50       0.50      14.25       1.92      33.00
3                750      40.75       0.83      15.75       0.43      33.00
4               1000      40.00       0.71      20.00       2.74      32.75
5               1250      41.25       0.83      24.25       0.43      31.50
6               1500      42.25       0.43      23.75       0.43      35.25
7               1750      43.50       0.87      21.00       0.00      36.00
8               2000      42.75       0.83      21.25       0.43      36.00
9               2250      43.25       0.43      23.75       0.43      36.00
10              2500      43.25       0.83      24.50       0.50      36.00
11              2750      43.75       0.43      24.25       0.43      36.00
12              3000      44.33       0.47      24.00       0.00      36.00
13              3250      44.50       0.50      24.00       0.00      36.00
14              3500      44.75       0.43      24.00       0.00      36.00
15              3750      45.00       0.00      24.00       0.00      36.25
16              4000      45.00       0.00      23.75       0.43      36.00
17              4250      45.00       0.00      23.25       1.30      36.00
18              4500      45.00       0.00      24.00       0.00      36.50
19              4750      45.00       0.00      21.50       1.50      37.00
20              5000      45.00       0.00      19.50       1.12      37.50
21              5250      45.00       0.00      21.00       0.00      37.00
22              5500      45.00       0.00      22.75       0.83      36.50
23              5750      45.00       0.00      24.00       0.00      36.25
24              6000      45.00       0.00      23.25       0.83      36.75
25              6250      45.00       0.00      23.75       0.43      37.00
26              6500      45.00       0.00      23.50       0.50      37.00
27              6750      45.00       0.00      23.67       0.47      36.00
28              7000      45.00       0.00      24.00       0.00      36.33
29              7250      45.00       0.00      24.00       0.00      36.25
..               ...        ...        ...        ...        ...        ...
450           112500      43.33       0.47      18.00       0.00      36.00
451           112750      43.50       0.50      18.00       0.00      36.00
452           113000      43.50       0.50      19.00       0.71      36.50
453           113250      43.50       0.50      19.00       0.00      36.25
454           113500      43.50       0.50      18.75       0.43      36.00
455           113750      43.25       0.83      18.00       0.00      36.00
456           114000      43.25       0.83      18.50       0.50      36.00
457           114250      43.50       0.50      18.50       0.50      36.00
458           114500      43.25       0.83      19.50       0.50      35.50
459           114750      43.00       0.71      19.75       0.43      36.00
```

460	115000	42.67	0.47	18.25	0.43	36.00
461	115250	43.00	0.00	20.25	0.43	36.00
462	115500	43.00	0.71	20.25	0.43	36.25
463	115750	43.50	0.50	19.33	0.47	36.00
464	116000	43.25	0.83	18.50	0.50	36.00
465	116250	43.00	0.00	18.00	0.00	36.00
466	116500	43.00	1.00	18.25	0.43	36.00
467	116750	43.00	0.71	19.00	0.00	36.00
468	117000	43.00	0.71	19.50	0.50	36.00
469	117250	43.00	0.71	18.25	0.43	36.00
470	117500	43.50	0.50	19.50	0.50	36.00
471	117750	43.50	0.50	19.75	0.43	36.00
472	118000	43.00	0.82	18.33	0.47	36.25
473	118250	43.25	0.83	18.75	0.43	36.00
474	118500	42.75	0.83	18.00	0.00	36.25
475	118750	42.50	0.50	20.00	0.82	36.00
476	119000	42.67	0.47	21.00	0.00	36.33
477	119250	44.33	0.94	21.00	0.00	36.33
478	119500	45.25	0.43	26.75	1.79	36.00
479	119750	47.25	0.83	29.75	0.43	35.25

	var_rss23	Labels
0	0.00	Bedding
1	1.09	Bedding
2	0.00	Bedding
3	0.00	Bedding
4	0.43	Bedding
5	0.87	Bedding
6	1.30	Bedding
7	0.00	Bedding
8	0.00	Bedding
9	0.00	Bedding
10	0.00	Bedding
11	0.00	Bedding
12	0.00	Bedding
13	0.00	Bedding
14	0.00	Bedding
15	0.43	Bedding
16	0.00	Bedding
17	0.00	Bedding
18	0.50	Bedding
19	1.00	Bedding

```
20        1.50  Bedding
21        1.00  Bedding
22        0.50  Bedding
23        0.43  Bedding
24        0.83  Bedding
25        1.00  Bedding
26        1.00  Bedding
27        0.00  Bedding
28        0.47  Bedding
29        0.43  Bedding
..         ...      ...
450       0.00  Bedding
451       0.00  Bedding
452       0.50  Bedding
453       0.43  Bedding
454       0.00  Bedding
455       0.00  Bedding
456       0.00  Bedding
457       0.00  Bedding
458       0.87  Bedding
459       0.00  Bedding
460       0.00  Bedding
461       0.00  Bedding
462       0.43  Bedding
463       0.00  Bedding
464       0.00  Bedding
465       0.00  Bedding
466       0.00  Bedding
467       0.00  Bedding
468       0.00  Bedding
469       0.00  Bedding
470       0.00  Bedding
471       0.00  Bedding
472       0.43  Bedding
473       0.00  Bedding
474       0.43  Bedding
475       0.00  Bedding
476       0.47  Bedding
477       0.47  Bedding
478       0.00  Bedding
479       1.30  Bedding
```

```
[480 rows x 8 columns]
```

In [23]:
```
def get_K_Times_Train_Datasets(k):
    all_list=[]
    for train_data in new_train_data_list:
        alist=[x for x in range(480)]
        list_split=get_list_split(alist,k)

        for i in range(len(list_split)):
            new_train_data=train_data.loc[list_split[i],:]
            all_list.append(new_train_data)
    return all_list
#then we have to consider original datasets bedding situation
```

In [26]:
```
#data preparation,from the above graph, we can find that K=2 is the best model
two_times_list=get_K_Times_Train_Datasets(2)
matrix=get_DataMatrix(two_times_list)
df=pd.DataFrame(matrix,columns=columns)
df["Labels"]=[0]*(9*2)+[1]*(len(two_times_list)-(9*2))
X_train=df.drop("Labels",axis=1)
Y_train=df["Labels"]
min_max_scaler = preprocessing.MinMaxScaler()
X_train_normalized=min_max_scaler.fit_transform(X_train)
```

In [27]:
```
df.head()
```

Out[27]:

	min1	max1	mean1	median1	std1	1st quartile1	3rd quartile1	min2	max2	mean2	...	1st quartile5	3rd quartile5	min6	max6	mean
0	36.50	46.50	44.057167	44.50	1.553724	43.2500	45.00	0.0	1.50	0.381042	...	36.00	37.00	0.0	1.79	0.59825
1	35.00	47.40	43.851833	43.50	1.553920	43.0000	45.00	0.0	1.70	0.471458	...	33.00	36.25	0.0	1.50	0.38833
2	33.75	47.75	43.278875	45.00	3.466111	42.0000	45.25	0.0	3.00	0.673292	...	36.00	37.00	0.0	1.53	0.64095
3	33.00	46.00	41.080750	42.00	3.530103	37.7500	44.50	0.0	2.86	0.718792	...	28.75	33.75	0.0	2.18	0.58608
4	33.00	45.75	41.621208	42.33	3.112140	39.6525	44.25	0.0	2.83	0.623083	...	28.50	31.50	0.0	1.79	0.41908

5 rows × 43 columns

In [28]:
```
def important_feature(alist):
    feature_list=[]
    for i in range(len(alist)):
        if alist[i]==True:
            feature_list.append(columns[i])
    return feature_list
```

In [93]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.feature_selection import RFE
def grid_search_cv():
    res=0
    best_k_number=0
    best_k_feature_number=0
    current_list=[]

    for i in range(1,21):
        k_times_list=get_K_Times_Train_Datasets(i)
        matrix=get_DataMatrix(k_times_list)
        df=pd.DataFrame(matrix,columns=columns)
        df["Labels"]=[0]*(9*i)+[1]*(len(k_times_list)-(9*i))
        X_train=df.drop("Labels",axis=1)
        min_max_scaler = preprocessing.MinMaxScaler()
        X_train_normalized=min_max_scaler.fit_transform(X_train)
        Y_train=df["Labels"]

        cv_score=0
        current_best_k=0
        current_best_feature_number=0

        for j in range(1,43):
            model=LogisticRegression()
            rfe=RFE(model,j)

            rfe.fit(X_train_normalized,Y_train)
            ranking_list=rfe.support_

            feature_list=important_feature(ranking_list)

            new_X_train=df[feature_list]
            Y_train=df["Labels"]

            min_max_scaler = preprocessing.MinMaxScaler()
            new_X_train_normalized=min_max_scaler.fit_transform(new_X_train)

            Log=linear_model.LogisticRegression()
            scores = cross_val_score(Log,new_X_train_normalized ,Y_train, cv=5)
            avg_scores=np.mean(scores)
            #print("When Time Series ="+str(i)+",Feature number equals ="+str(j)+" CV scores is"+str(avg_scor
```

```
es))

            if avg_scores>res:
                res=avg_scores
                best_k_number=i
                best_k_feature_number=j
            if avg_scores>cv_score:
                cv_score=avg_scores
                current_best_k=i
                current_best_feature_number=j
        current_list.append((current_best_k,current_best_feature_number))



    return current_list
alist=grid_search_cv()
```

From the Above result, we can find that when Time Series number=6, and the feature number equals to 9, The cross validation result is the highest with 95.40% accuracy

In [30]:
```
#save it to the csv file

six_times_list=get_K_Times_Train_Datasets(6)
matrix=get_DataMatrix(six_times_list)
df=pd.DataFrame(matrix,columns=columns)
df["Labels"]=[0]*(9*6)+[1]*(len(six_times_list)-(9*6))

X_train=df.drop("Labels",axis=1)
min_max_scaler = preprocessing.MinMaxScaler()
X_train_normalized=min_max_scaler.fit_transform(X_train)
Y_train=df["Labels"]

model=LogisticRegression()
rfe=RFE(model,9)
rfe.fit(X_train_normalized,Y_train)
ranking_list=rfe.support_
feature_list=important_feature(ranking_list)
best_model=df[feature_list]
best_model["Labels"]=Y_train
best_model.to_csv("Best_Model.csv")
```

```
/Library/Frameworks/Python.framework/Versions/3.6/lib/python3.6/site-packages/ipykernel_launcher.py:19: Sett
ingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexing-vie
w-versus-copy
```

In [31]:
```
best_model.shape
```

Out[31]:
```
(414, 10)
```

In [32]:
```
best_model.head()
```

Out[32]:

	min2	1st quartile2	1st quartile3	median4	1st quartile4	min5	max5	mean5	3rd quartile5	Labels
0	0.0	0.0	22.1875	0.215	0.0	30.0	37.50	35.906250	36.5000	0
1	0.0	0.0	22.5000	0.470	0.0	33.0	38.50	36.791500	37.5000	0
2	0.0	0.0	20.2500	0.485	0.0	32.5	38.33	36.182875	37.6900	0
3	0.0	0.0	20.1875	0.470	0.0	29.0	37.00	33.245625	35.7525	0
4	0.0	0.0	20.1875	0.430	0.0	30.0	38.25	35.385875	37.0000	0

In [33]:
```
#make the plot of ROC and AUC curve
from sklearn import metrics
X_train=best_model.drop("Labels",axis=1)
X_train=np.array(X_train)
Y_train=list(best_model["Labels"])

model=LogisticRegression()
model.fit(X_train,Y_train)
probs=model.predict_proba(X_train)
```

In [34]:
```
preds = probs[:,1]
fpr, tpr, threshold = metrics.roc_curve(Y_train, preds)
roc_auc = metrics.auc(fpr, tpr)
```

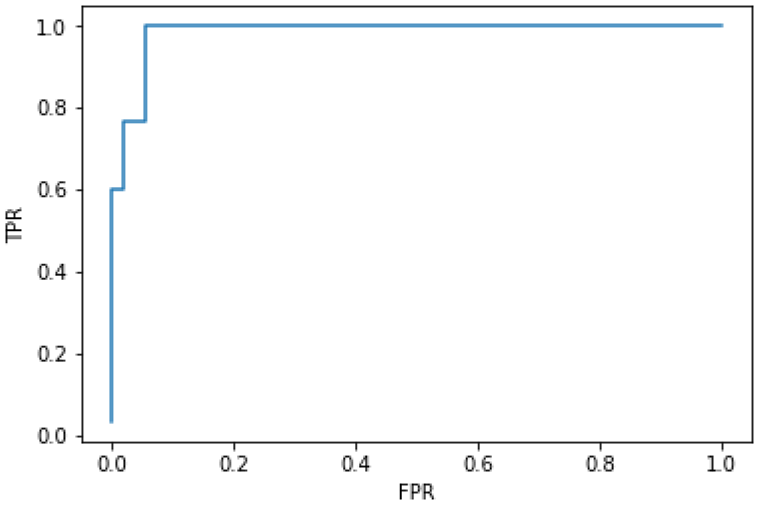
In [35]:
```
print(roc_auc) #So the AUC curve result is 98.3%
```

```
0.9839506172839506
```

In [36]:
```
df = pd.DataFrame(dict(fpr = fpr, tpr = tpr))
```

In [37]:
```
plt.plot(fpr,tpr)
plt.xlabel("FPR")
plt.ylabel("TPR")
```

Out[37]: Text(0,0.5,'TPR')



from here we can find the best model is 6 times series and the Number of features equals to 9,we will save it

P_value calcualtion

Method-calcuate P value by using the code

fit<- glm(Labels~. ,data=Best_Model,family = binomial())

summary(fit) in R

Coefficients: Estimate Std. Error z value Pr(>|z|) (Intercept) 25.2657 9.2451 2.733 0.006278 ** min2 28.3598 4869.4543 0.006 0.995353 `1st quartile2` 8.4463 5.0186 1.683 0.092377 . `1st quartile3` 1.1611 0.3363 3.452 0.000556 *** median4 -11.2355 6.0051 -1.871 0.061347 . `1st quartile4` 25.0989 8.4415 2.973 0.002946 ** min5 -1.4364 0.6474 -2.219 0.026505 * max5 -1.8947 0.6016 -3.149 0.001637 ** mean5 6.9458 3.2256 2.153 0.031293 * `3rd quartile5` -5.5669 2.8060 -1.984 0.047267 *

Explain what the right way and the wrong way are to perform cross-validation in this problem

Correct Way:According to the above experiment,we can find that the correct procedure to choose the cross validation result is set different parameters, and then use cross-validation to guide us to pick the correct parameters.

In [38]:
```
from sklearn.metrics import confusion_matrix
```

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

In [39]:
```
data=pd.read_csv("Best_Model.csv")
```

In [40]:
```
data.head()
```

Out[40]:

	Unnamed: 0	min2	1st quartile2	1st quartile3	median4	1st quartile4	min5	max5	mean5	3rd quartile5	Labels
0	0	0.0	0.0	22.1875	0.215	0.0	30.0	37.50	35.906250	36.5000	0
1	1	0.0	0.0	22.5000	0.470	0.0	33.0	38.50	36.791500	37.5000	0
2	2	0.0	0.0	20.2500	0.485	0.0	32.5	38.33	36.182875	37.6900	0
3	3	0.0	0.0	20.1875	0.470	0.0	29.0	37.00	33.245625	35.7525	0
4	4	0.0	0.0	20.1875	0.430	0.0	30.0	38.25	35.385875	37.0000	0

In [41]:
```
train_x=data.drop("Labels",axis=1)
train_y=data["Labels"]

min_max_scaler = preprocessing.MinMaxScaler()
train_x_norm=min_max_scaler.fit_transform(train_x)

model=LogisticRegression()
model.fit(train_x_norm,train_y)
predict=model.predict(train_x_norm)

print(confusion_matrix(predict,train_y))
```

```
[[ 49   0]
 [  5 360]]
```

Coefficients: Estimate Std. Error z value Pr(>|z|) (Intercept) 25.2657 9.2451 2.733 0.006278 ** min2 28.3598 4869.4543 0.006 0.995353 `1st quartile2` 8.4463 5.0186 1.683 0.092377 . `1st quartile3` 1.1611 0.3363 3.452 0.000556 *** median4 -11.2355 6.0051 -1.871 0.061347 . `1st quartile4` 25.0989 8.4415 2.973 0.002946 ** min5 -1.4364 0.6474 -2.219 0.026505 * max5 -1.8947 0.6016 -3.149 0.001637 ** mean5 6.9458 3.2256 2.153 0.031293 * `3rd quartile5` -5.5669 2.8060 -1.984 0.047267 *

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 [42]:
```
#then we can know the test datasets also need to have time series=6, and K=9.
train_data=pd.read_csv("Best_Model.csv")
```

In [43]:
```
def get_test_datasets_labels():
    new_list=[]
    for i in range(len(test_data_list)):
        if i<4:
            test_data_list[i]["Labels"]=["Bedding"]*480
        else:
            test_data_list[i]["Labels"]=["Others"]*480
        new_list.append(train_data_list[i])
    return new_list
new_test_data_list=get_test_datasets_labels()
```

In [44]:
```
def get_K_Times_Test_Datasets(k):
    all_list=[]
    for test_data in new_test_data_list:
        alist=[x for x in range(480)]
        list_split=get_list_split(alist,k)

        for i in range(len(list_split)):
            new_test_data=test_data.loc[list_split[i],:]
            all_list.append(new_test_data)
    return all_list
```

In [45]:
```
#then we will get the whole test datasets
six_times_test_list=get_K_Times_Train_Datasets(6)
matrix=get_DataMatrix(six_times_test_list)
df=pd.DataFrame(matrix,columns=columns)
df["Labels"]=[0]*(9*6)+[1]*(len(six_times_test_list)-(9*6))
```

In [46]:
```
train_data=train_data.drop("Unnamed: 0",axis=1)
```

In [47]:
```
clean_feature=list(train_data.columns)
```

In [48]:
```
test_data=df[clean_feature]
```

In [49]:
```
print(train_data.shape)
print(test_data.shape)
```

```
(414, 10)
(414, 10)
```

In [50]:
```
from sklearn.metrics import confusion_matrix
train_x=train_data.drop("Labels",axis=1)
train_y=train_data["Labels"]

test_x=test_data.drop("Labels",axis=1)
test_y=test_data["Labels"]

min_max_scaler = preprocessing.MinMaxScaler()
train_x_normalized=min_max_scaler.fit_transform(train_x)
test_x_normalized=min_max_scaler.fit_transform(test_x)


Log=LogisticRegression()
Log.fit(train_x_normalized,train_y)
predict=Log.predict(test_x)
matrix=confusion_matrix(predict,test_y)
accuracy=(matrix[0][0]+matrix[1][1])/(matrix[0][0]+matrix[0][1]+matrix[1][0]+matrix[1][1])
print(matrix)
print("The test datasets accuracy score is: "+str(accuracy))
```

```
[[ 54 360]
 [  0   0]]
The test datasets accuracy score is: 0.13043478260869565
```

From above we can find that the test dataset accuracy is only 13.0%, which are much lower than the cross validation score in test datasets

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

No, the datasets most of data are others and just a few data are bending. Which caused some imbalance datasets, THen we will use the oversampling tech to solve this problem

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 [51]:
```
from sklearn.model_selection import train_test_split
from sklearn.metrics import recall_score
from imblearn.over_sampling import SMOTE
```

In [52]:
```
train_features=train_data.drop("Labels",axis=1)
train_target=train_data["Labels"]

test_features=test_data.drop("Labels",axis=1)
test_target=test_data["Labels"]
```

In [53]:
```
x_train, x_val, y_train, y_val = train_test_split(train_features, train_target,
                                                    test_size = .1,
                                                    random_state=12)
```

In [54]:
```
sm = SMOTE(random_state=12, ratio = 1.0)
x_train_res, y_train_res = sm.fit_sample(x_train, y_train)
```

```
/Library/Frameworks/Python.framework/Versions/3.6/lib/python3.6/site-packages/sklearn/utils/deprecation.py:7
7: DeprecationWarning: Function _ratio_float is deprecated; Use a float for 'ratio' is deprecated from versi
on 0.2. The support will be removed in 0.4. Use a dict, str, or a callable instead.
  warnings.warn(msg, category=DeprecationWarning)
```

In [55]:
```
log=LogisticRegression()
log.fit(x_train_res,y_train_res)
```

Out[55]:
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)
```

In [56]:
```
print(log.score(x_val,y_val))
print(recall_score(y_val, log.predict(x_val)))
```

```
0.9523809523809523
0.9375
```

In [57]:
```
matrix=confusion_matrix(log.predict(x_val),y_val)
```

In [58]:
```
print(matrix)
accuracy=(matrix[0][0]+matrix[1][1])/(matrix[0][0]+matrix[0][1]+matrix[1][0]+matrix[1][1])
print("The test datasets accuracy score is: "+str(accuracy))
```

```
[[10  2]
 [ 0 30]]
The test datasets accuracy score is: 0.9523809523809523
```

After oversampling, we can find that accuracy greatly improved from 47.3% to 95.2%

(e) Binary Classification Using L1-penalized logistic regression

i. Repeat 1(d)iii using L1-penalized logistic regression,8 i.e. instead of using p- values for variable selection, use L1 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 L1 penalty in your logistic regression objective function (or C, the budget). Packages usually perform cross-validation for λ automatically.9

In [94]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.feature_selection import RFE
def logistic_grid_search_cv():
    res=0
    best_k_number=0
    best_lambda=0
    current_list=[]

    #i is the number of Time Seires, J is the number of Lambda we choose
    for i in range(1,21):
        k_times_list=get_K_Times_Train_Datasets(i)
        matrix=get_DataMatrix(k_times_list)
        df=pd.DataFrame(matrix,columns=columns)
        df["Labels"]=[0]*(9*i)+[1]*(len(k_times_list)-(9*i))

        X_train=df.drop("Labels",axis=1)
        min_max_scaler = preprocessing.MinMaxScaler()
        X_train_normalized=min_max_scaler.fit_transform(X_train)
        Y_train=df["Labels"]

        cv_score=0
        current_best_k=0
        current_best_feature_number=0


        for j in np.arange(1,100):
            model=LogisticRegression(penalty="l1",C=1/j)
            scores = cross_val_score(model,X_train_normalized ,Y_train, cv=5)
            avg_scores=np.mean(scores)
            #print("When Time Series ="+str(i)+", Lasso Regualize Lambda ="+str(j)+" CV scores is"+str(avg_sc
ores))

            if avg_scores>res:
                res=avg_scores
                best_k_number=i
                best_lambda=j

    current_list.append((res,best_k_number,best_lambda))
```

```
    return current_list

Lasso_Res=logistic_grid_search_cv()
print(Lasso_Res)
```

```
[(0.9857142857142858, 1, 1)]
```

ii. Compare the L1-penalized with variable selection using p-values. Which one performs better? Which one is easier to implement?

From The above result, we can find that L1 Regualizer is much easier to implement because it did not have the process of feature selection, it can Automatically select the feature. Also The best Accuracy score is 98.7% which is higher than the RTF best Accuracy is 95.4%

(f) Multi-class Classification (The Realistic Case)

i. Find the best l in the same way as you found it in 1(e)i to build an L1- penalized multinomial regression model to classify all activities in your train- ing set.10 Report your test error. Research how confusion matrices and ROC curves are defined for multiclass classification and show them for this problem if possible.11

In [60]:
```
#The first step is that we will construct the matrix, And then give them differenct names, seven names totall
y
```

In [69]:
```
train_data=pd.DataFrame(train_matrix,columns=columns)
test_data=pd.DataFrame(test_matrix,columns=columns)
```

In [70]:
```
train_data.shape
```

Out[70]:
```
(69, 42)
```

In [71]:
```
test_data.shape
```
Out[71]: (19, 42)

In [72]:
```
train_data.head()
```
Out[72]:

	min1	max1	mean1	median1	std1	1st quartile1	3rd quartile1	min2	max2	mean2	...	std5	1st quartile5	3rd quartile5	min6	max
0	35.00	47.40	43.954500	44.33	1.557210	43.00	45.00	0.0	1.70	0.426250	...	1.997520	35.3625	36.50	0.0	1.79
1	33.00	47.75	42.179812	43.50	3.666840	39.15	45.00	0.0	3.00	0.696042	...	3.845436	30.4575	36.33	0.0	2.18
2	33.00	45.75	41.678063	41.75	2.241152	41.33	42.75	0.0	2.83	0.535979	...	2.408514	28.4575	31.25	0.0	1.79
3	37.00	48.00	43.454958	43.25	1.384653	42.50	45.00	0.0	1.58	0.378083	...	2.486268	22.2500	24.00	0.0	5.26
4	36.25	48.00	43.969125	44.50	1.616677	43.31	44.67	0.0	1.50	0.413125	...	3.314843	20.5000	23.75	0.0	2.96

5 rows × 42 columns

In [73]:
```
#give the columns name to the train data frame

labels=[1]*9+[2]*12+[3]*12+[4]*12+[5]*12+[6]*12
train_data["Labels"]=labels
```

In [95]:
```
def multi_logistic_grid_search_cv():
    res=0
    best_k_number=0
    best_lambda=0
    current_list=[]

    #i is the number of Time Seires, J is the number of Lambda we choose
    for i in range(1,21):
        k_times_list=get_K_Times_Train_Datasets(i)
        matrix=get_DataMatrix(k_times_list)
        df=pd.DataFrame(matrix,columns=columns)
        df["Labels"]=[1]*(9*i)+[2]*(12*i)+[3]*(12*i)+[4]*(12*i)+[5]*(12*i)+[6]*(12*i)

        X_train=df.drop("Labels",axis=1)
        min_max_scaler = preprocessing.MinMaxScaler()
        X_train_normalized=min_max_scaler.fit_transform(X_train)
        Y_train=df["Labels"]

        cv_score=0
        current_best_k=0
        current_best_feature_number=0


        for j in range(1,100):
            model=LogisticRegression(penalty="l1",C=1/j)
            scores = cross_val_score(model,X_train_normalized ,Y_train, cv=5)
            avg_scores=np.mean(scores)
            #print("When Time Series ="+str(i)+", Lasso Regualize Lambda ="+str(j)+" CV scores is"+str(avg_sc
ores))

            if avg_scores>res:
                res=avg_scores
                best_k_number=i
                best_lambda=j

    current_list.append((res,best_k_number,best_lambda))



    return current_list
```

```
multi_logisitc=multi_logistic_grid_search_cv()
```

From the above result, we can find that the best result of Multi class logistic regression result is Time Series=1, and the Lambda=1 , Accuracy result is 96.6%

make the ROC and AUC curve

The way to do Mutiple class classification is that we will do it seperately. Each one get AUC and ROC curve

In [75]:
```
k_times_list=get_K_Times_Train_Datasets(1)
matrix=get_DataMatrix(k_times_list)
df=pd.DataFrame(matrix,columns=columns)
df["Labels"]=[0]*(9*1)+[1]*(12*1)+[2]*(12*1)+[3]*(12*1)+[4]*(12*1)+[5]*(12*1)
```

Plot Multiple class ROC and AUC curve

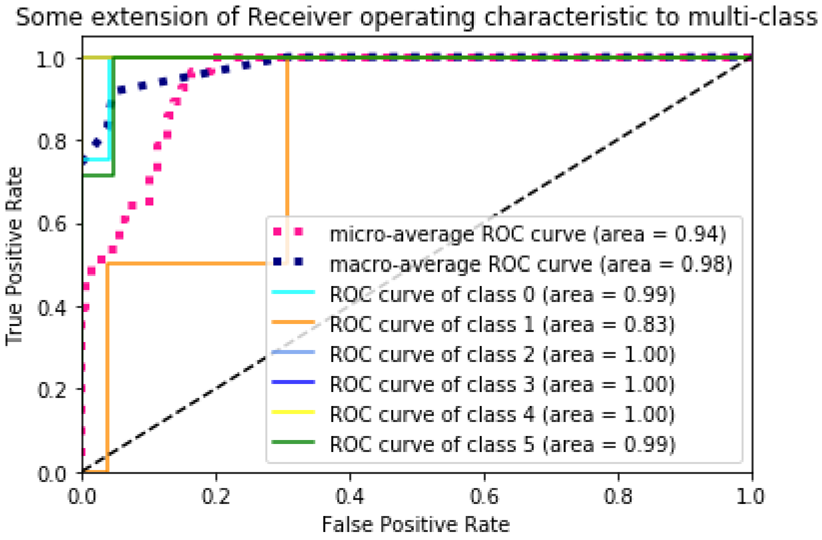
In [76]:
```
import numpy as np
import matplotlib.pyplot as plt
from itertools import cycle

from sklearn import svm, datasets
from sklearn.metrics import roc_curve, auc
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import label_binarize
from sklearn.multiclass import OneVsRestClassifier
from scipy import interp

# Import some data to play with
X = np.array(df.drop("Labels",axis=1))
y = list(df["Labels"])

# Binarize the output
y = label_binarize(y, classes=[0, 1, 2,3,4,5])
n_classes = y.shape[1]

# Add noisy features to make the problem harder
random_state = np.random.RandomState(0)
n_samples, n_features = X.shape
X = np.c_[X, random_state.randn(n_samples, 200 * n_features)]

# shuffle and split training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=.4,
                                                    random_state=0)

# Learn to predict each class against the other
classifier = OneVsRestClassifier(svm.SVC(kernel='linear', probability=True,
                                 random_state=random_state))
y_score = classifier.fit(X_train, y_train).decision_function(X_test)

# Compute ROC curve and ROC area for each class
fpr = dict()
tpr = dict()
roc_auc = dict()
for i in range(n_classes):
    fpr[i], tpr[i], _ = roc_curve(y_test[:, i], y_score[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])
```

```
# Compute micro-average ROC curve and ROC area
fpr["micro"], tpr["micro"], _ = roc_curve(y_test.ravel(), y_score.ravel())
roc_auc["micro"] = auc(fpr["micro"], tpr["micro"])
```

In [78]:
```
y_score = classifier.fit(X_train, y_train).decision_function(X_test)


# Compute ROC curve and ROC area for each class
fpr = dict()
tpr = dict()
roc_auc = dict()
for i in range(n_classes):
    fpr[i], tpr[i], _ = roc_curve(y_test[:, i], y_score[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

# Compute micro-average ROC curve and ROC area
fpr["micro"], tpr["micro"], _ = roc_curve(y_test.ravel(), y_score.ravel())
roc_auc["micro"] = auc(fpr["micro"], tpr["micro"])
```

In [82]:
```
import numpy as np
import matplotlib.pyplot as plt
from itertools import cycle

from sklearn import svm, datasets
from sklearn.metrics import roc_curve, auc
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import label_binarize
from sklearn.multiclass import OneVsRestClassifier
from scipy import interp
```

In [87]:
```
all_fpr = np.unique(np.concatenate([fpr[i] for i in range(n_classes)]))

# Then interpolate all ROC curves at this points
mean_tpr = np.zeros_like(all_fpr)
for i in range(n_classes):
    mean_tpr += interp(all_fpr, fpr[i], tpr[i])

# Finally average it and compute AUC
mean_tpr /= n_classes

fpr["macro"] = all_fpr
tpr["macro"] = mean_tpr
roc_auc["macro"] = auc(fpr["macro"], tpr["macro"])

# Plot all ROC curves
plt.figure()
plt.plot(fpr["micro"], tpr["micro"],
         label='micro-average ROC curve (area = {0:0.2f})'
               ''.format(roc_auc["micro"]),
         color='deeppink', linestyle=':', linewidth=4)

plt.plot(fpr["macro"], tpr["macro"],
         label='macro-average ROC curve (area = {0:0.2f})'
               ''.format(roc_auc["macro"]),
         color='navy', linestyle=':', linewidth=4)

colors = cycle(['aqua', 'darkorange', 'cornflowerblue',"blue","yellow","green"])
for i, color in zip(range(n_classes), colors):
    plt.plot(fpr[i], tpr[i], color=color, #lw=lw,
             label='ROC curve of class {0} (area = {1:0.2f})'
             ''.format(i, roc_auc[i]))

plt.plot([0, 1], [0, 1], 'k--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Some extension of Receiver operating characteristic to multi-class')
plt.legend(loc="lower right")
plt.show()
```



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

Gaussian Naive Bayes

In [88]:
```
from sklearn.naive_bayes import GaussianNB
```

In [89]:
```
def multi_Gau_NB_grid_search_cv():
    res=0
    best_k_number=0
    current_list=[]

    #i is the number of Time Seires, J is the number of Lambda we choose
    for i in range(1,21):
        k_times_list=get_K_Times_Train_Datasets(i)
        matrix=get_DataMatrix(k_times_list)
        df=pd.DataFrame(matrix,columns=columns)
        df["Labels"]=[1]*(9*i)+[2]*(12*i)+[3]*(12*i)+[4]*(12*i)+[5]*(12*i)+[6]*(12*i)

        X_train=df.drop("Labels",axis=1)
        min_max_scaler = preprocessing.MinMaxScaler()
        X_train_normalized=min_max_scaler.fit_transform(X_train)
        Y_train=df["Labels"]

        cv_score=0
        current_best_k=0
        current_best_feature_number=0



        model=GaussianNB()
        scores = cross_val_score(model,X_train ,Y_train, cv=5)
        avg_scores=np.mean(scores)
        print("When Time Series = "+str(i)+" CV scores is:"+str(avg_scores))

        if avg_scores>res:
            res=avg_scores
            best_k_number=i

    current_list.append((res,best_k_number))


    return current_list

Gau_NB_res=multi_Gau_NB_grid_search_cv()
```

```
When Time Series = 1 CV scores is:1.0
When Time Series = 2 CV scores is:1.0
When Time Series = 3 CV scores is:1.0
When Time Series = 4 CV scores is:0.9923076923076923
When Time Series = 5 CV scores is:0.9739130434782609
When Time Series = 6 CV scores is:0.9753086419753085
When Time Series = 7 CV scores is:0.9773195876288661
When Time Series = 8 CV scores is:0.9706422018348624
When Time Series = 9 CV scores is:0.9719008264462812
When Time Series = 10 CV scores is:0.9710144927536233
When Time Series = 11 CV scores is:0.9652796420581655
When Time Series = 12 CV scores is:0.969699648820297
When Time Series = 13 CV scores is:0.9696754754880421
When Time Series = 14 CV scores is:0.9622402159244265
When Time Series = 15 CV scores is:0.9623188405797102
When Time Series = 16 CV scores is:0.9598408035452461
When Time Series = 17 CV scores is:0.9632521676413865
When Time Series = 18 CV scores is:0.9603336815985373
When Time Series = 19 CV scores is:0.9493005269420364
When Time Series = 20 CV scores is:0.9543478260869565
```

For the above result, we can find that The Gaussian Naive Bayes result are 100% percent Accuracy

Multinomial Naive Bayes

In [90]:
```
from sklearn.naive_bayes import MultinomialNB
```

In [96]:
```
def multi_Mul_NB_grid_search_cv():
    res=0
    best_k_number=0
    best_lambda=0
    current_list=[]

    #i is the number of Time Seires, J is the number of Lambda we choose
    for i in range(1,21):
        k_times_list=get_K_Times_Train_Datasets(i)
        matrix=get_DataMatrix(k_times_list)
        df=pd.DataFrame(matrix,columns=columns)
        df["Labels"]=[1]*(9*i)+[2]*(12*i)+[3]*(12*i)+[4]*(12*i)+[5]*(12*i)+[6]*(12*i)

        X_train=df.drop("Labels",axis=1)
        min_max_scaler = preprocessing.MinMaxScaler()
        X_train_normalized=min_max_scaler.fit_transform(X_train)
        Y_train=df["Labels"]

        cv_score=0
        current_best_k=0
        current_best_feature_number=0


        for j in np.arange(1,10):
            model=MultinomialNB(alpha=j)
            scores = cross_val_score(model,X_train_normalized ,Y_train, cv=5)
            avg_scores=np.mean(scores)
            #print("When Time Series ="+str(i)+", Mutli NB Alpha ="+str(j)+" CV scores is"+str(avg_scores))

            if avg_scores>res:
                res=avg_scores
                best_k_number=i
                best_lambda=j

    current_list.append((res,best_k_number,best_lambda))



    return current_list

Mul_NB_res=multi_Mul_NB_grid_search_cv()
```

In [92]:
```
print(Mul_NB_res)
```

```
[(0.9639120372487856, 7, 2)]
```

From the above result,we can find that the Mul-NB has the 96.3% accuracy when Time Series=7, alpha=2

iii. Which method is better for multi-class classification in this problem?

From this problem, we can find Gaussian Naive Bayes is best in this problem because it has 100% accuracy