

In [2]:

In [3]:

```
#save testdata
i=0
for csv in testPath:
    i=i+1
    createVar['testdata'+str(i)]=pd.read_csv(csv,header=None,names=[
        'avg_rss12','var_rss12','avg_rss13',
        'var_rss13','avg_rss23','var_rss23'],
        skiprows=5)
num test = i;
```

In [595]:

```
print("c)i Some popular time-domain features: Mean, Median, Standard Deviation,  
Variance, Root Mean Square, Averaged derivatives, minimum, maximum etc. ")
```

```
c)i Some popular time-domain features: Mean, Median, Standard Deviat  
ion, Variance, Root Mean Square, Averaged derivatives, minimum, maxi  
mum etc.
```

In [5]:

*#c) ii def a function that give a row of 88*42*

```
def give7features(td):
    td_mean = td.mean()
    td_mean_array = np.zeros(shape=(1,6))
    for i in range(6):
        td_mean_array[0,i]=td_mean.iloc[i]

    td_max = td.max()
    td_max_array = np.zeros(shape=(1,6))
    for i in range(6):
        td_max_array[0,i]=td_max.iloc[i]

    td_min = td.min()
    td_min_array = np.zeros(shape=(1,6))
    for i in range(6):
        td_min_array[0,i]=td_min.iloc[i]

    td_median = td.median()
    td_median_array = np.zeros(shape=(1,6))
    for i in range(6):
        td_median_array[0,i]=td_median.iloc[i]

    td_std = td.std()
    td_std_array = np.zeros(shape=(1,6))
    for i in range(6):
        td_std_array[0,i]=td_std.iloc[i]

    td_1stquartile = td.quantile(q=0.25)
    td_1stquartile_array = np.zeros(shape=(1,6))
    for i in range(6):
        td_1stquartile_array[0,i]=td_1stquartile.iloc[i]

    td_3stquartile = td.quantile(q=0.75)
    td_3stquartile_array = np.zeros(shape=(1,6))
    for i in range(6):
        td_3stquartile_array[0,i]=td_3stquartile.iloc[i]

    td_7=np.concatenate((td_min_array,td_max_array,td_mean_array,td_median_array
    ,
                        td_std_array,td_1stquartile_array,td_3stquartile_array)
    ,axis=0)

    #td_7=np.concatenate((td_min_array,td_max_array,td_mean_array,td_median_array,td_std_array,td_1stquartile_array,td_3stquartile_array),axis=1)
    return td_7.reshape([1,42],order='F')
```

```
#stack
dataset=np.empty(shape=[0, 42])
for i in range(num_train):
    i=i+1
    dataset = np.concatenate((dataset,give7features(createVar[ 'traindata'+str(i)
])),axis=0)
for j in range(num_test):
    j=j+1
    dataset = np.concatenate((dataset,give7features(createVar[ 'testdata'+str(j)
])),axis=0)
```

```
#1(c)iii extracted from time series 1, 2, and 6
index_1=[0,1,2,7,8,9,35,36,37]
extracted_1 = dataset[:,index_1]
```

```
temp_class_1 = np.zeros(shape=(1,88))
```

```
#d) i
for i in range(0,9):
    temp_class_1[0,i]=1

#for i in range(69,73):
#    temp_class_1[0,i]=1
temp_class_1 = temp_class_1.T
```

```
new_extrated_class=np.column_stack((extracted_1,temp_class_1))
```

```
new_extrated_trclass = new_extrated_class[0:69]
```

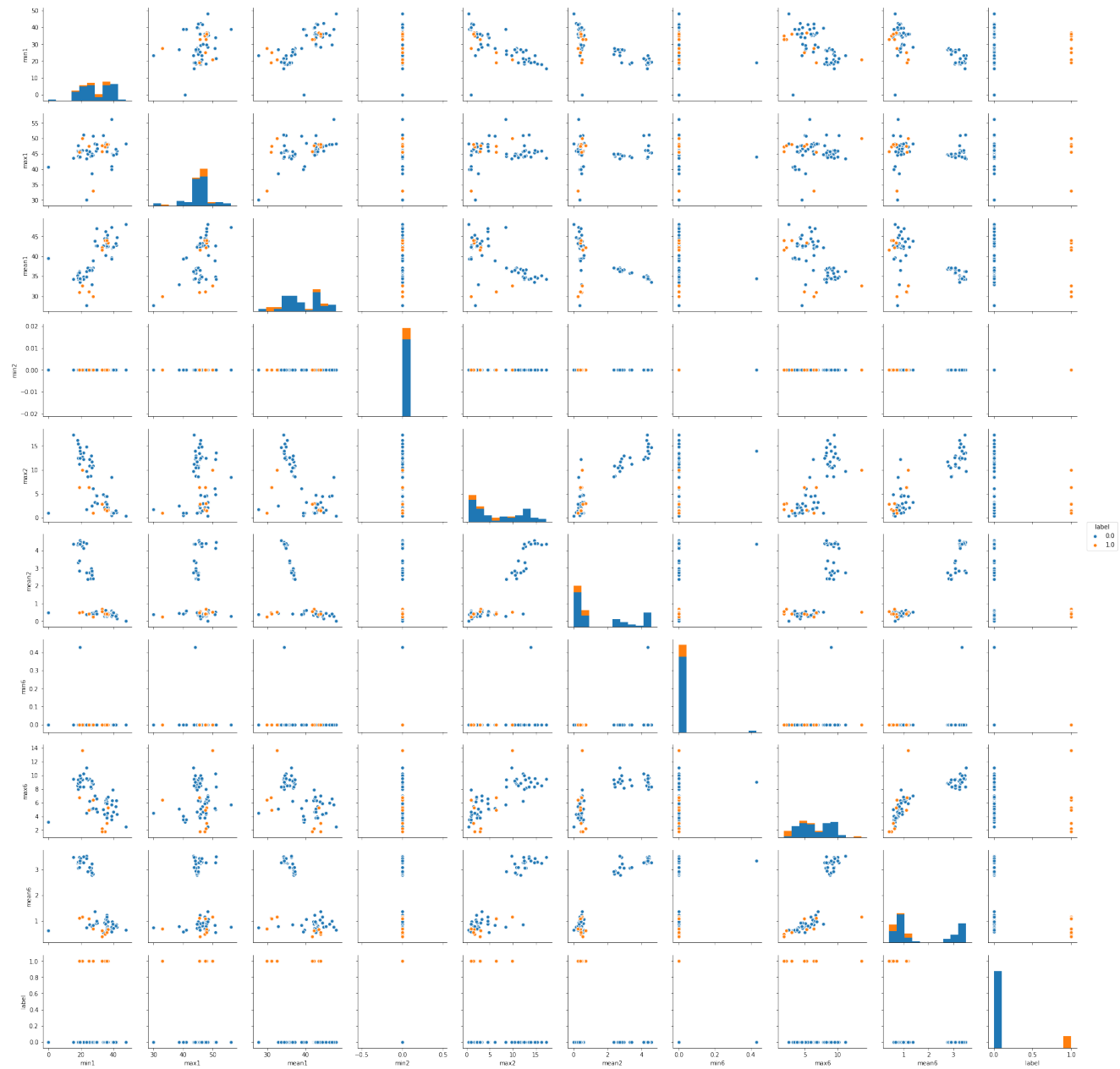
```
df_binary_1 = pd.DataFrame(new_extrated_trclass, columns = ['min1','max1','mean1',  
                  , 'min2','max2','mean2',  
                  , 'min6','max6','mean6'  
                  , 'label'])
```

In [14]:

```
import seaborn as sns
%matplotlib inline
sns.pairplot(df_binary_1, hue="label")
```

Out[14]:

<seaborn.axisgrid.PairGrid at 0x1100e6390>



In [15]:

```
#b) ii split data into n pieces
def splitdata(td,n):
    num_row = td.iloc[:,0].size
    for c in range (n):
        c=c+1
        if(c!=n):
            createVar['traindata_s'+str(c)] = td[int(num_row/n)*(c-1):int(num_row/n)*(c)]
        else:
            createVar['traindata_s'+str(c)] = td[int(num_row/n)*(c-1):]

    tup=(createVar['traindata_s'+str(1)],)
    for c in range (1,n):
        c=c+1
        tup=tup+(createVar['traindata_s'+str(c)],)
    return tup
```

In [16]:

```
for i in range(num_train):
    i=i+1
    createVar['traindata'+str(i)+'1'],createVar['traindata'+str(i)+'2'] = splitdata(createVar['traindata'+str(i)],2)
```

In [17]:

```
#stack2
dataset_2=np.empty(shape=[0, 42])
for i in range(num_train):
    i=i+1
    dataset_2 = np.concatenate((dataset_2,give7features(createVar['traindata'+str(i)+'1'])),axis=0)
    dataset_2 = np.concatenate((dataset_2,give7features(createVar['traindata'+str(i)+'2'])),axis=0)
```

In [18]:

```
index_2=[0,1,2,7,8,9,35,36,37]
extracted_2 = dataset_2[:,index_2]
```

In [19]:

```
temp_class_2 = np.zeros(shape=(1,num_train*2))
```

In [20]:

```
for i in range(0,18):  
    temp_class_2[0,i]=1  
  
#for i in range(69,73):  
#    temp_class_1[0,i]=1  
temp_class_2 = temp_class_2.T
```

In [21]:

```
new_extrated_class_2=np.column_stack((extracted_2,temp_class_2))
```

In [22]:

```
df_binary_2 = pd.DataFrame(new_extrated_class_2,columns = ['min1','max1','mean1'  
, 'min2', 'max2', 'mean2',  
                                                         'min6', 'max6', 'mean6'  
, 'label'])
```

In [23]:

```
df_binary_2.shape
```

Out[23]:

```
(138, 10)
```

In [24]:

```
sns.pairplot(df_binary_2, hue="label")
```

Out[24]:

```
<seaborn.axisgrid.PairGrid at 0x1a202a9320>
```



In [25]:

```
print("Compared to d) i, the number of data increase but so as the noise")
```

Compared to d) i, the number of data increase but so as the noise

In [26]:

```
#d) iii every traindata need a empty array to store 42-feartures, n pieces n*42
for i in range(20):
    i=i+1
    createVar[ 'dataset_'+str(i)]=np.empty(shape=[0, 42])
```


In [27]:

```
#split every train data(from traindata1 to traindata69) into n pieces, save into p1 to p69, each pi have n dataframes. p are tuples
def finaldata(n):
    for i in range(num_train):
        i=i+1
        createVar['p'+str(i)]= splitdata(createVar['traindata'+str(i)],n)

    for i in range(num_train):
        i=i+1
        for j in range(n):
            j=j+1
            createVar['dataset_'+str(n)] = np.concatenate((createVar['dataset_'+str(n)],
                                                                give7features(createV
ar['p'+str(i)][j-1])),axis=0)
```

In [28]:

```
for i in range(20):
    i=i+1
    finaldata(i)
```

In [29]:

```
dataset_20.shape
```

Out[29]:

```
(1380, 42)
```

In [30]:

```
#extract features
from sklearn.feature_selection import RFE
from sklearn.linear_model import LogisticRegression
def featureExtract(x,y,f):
    index=[]
    model = LogisticRegression( )
    rfe = RFE(model,f)

    rfe = rfe.fit(x,y)
    x=rfe.support_
    for i in range(f):
        index.append(np.where(x==True)[0][i])
    return index
```

```
for i in range(20):
    i=i+1
    createVar['y_'+str(i)]= np.zeros(shape=(1,69*i))
for i in range(20):
    i=i+1
    for j in range(0,9*i):
        createVar['y_'+str(i)][0,j]=1
for i in range(20):
    i=i+1
    createVar['y_'+str(i)] = createVar['y_'+str(i)].T
```

```
print("fit all features")
from sklearn.linear_model import LogisticRegression

from sklearn.metrics import accuracy_score
acc_42 = list()
for i in range(20):
    i=i+1
    createVar['clf_'+str(i)] = LogisticRegression(random_state = 0)
    createVar['clf_'+str(i)].fit(createVar['dataset_'+str(i)],createVar['y_'+str(i)].ravel())
    createVar['y_pred_'+str(i)] = createVar['clf_'+str(i)].predict(createVar['dataset_'+str(i)])
    createVar['test_acc_'+str(i)] = accuracy_score(createVar['y_'+str(i)],createVar['y_pred_'+str(i)])
    acc_42.append(createVar['test_acc_'+str(i)])
```

In [597]:

```

the predicted class for training set when l = 1 is:
[1. 0. 1. 1. 0. 1. 0. 1. 1. 0. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
. 0.
 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
. 0.
 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
train accuracy when l = 1 is:
0.9420289855072463
the predicted class for training set when l = 2 is:
[0. 1. 0. 0. 1. 0. 0. 0. 0. 0. 1. 1. 0. 0. 1. 1. 1. 0. 0. 0. 0. 0. 0. 0.

```



```
train accuracy when l = 10 is:
0.9130434782608695
```

the predicted class for training set when $l = 11$ is:

[illegible]

[illegible]


```
[1. 0. 1. ... 0. 0. 0.]
train accuracy when l = 15is:
0.9130434782608695
the predicted class for training set when l = 16 is:
[1. 0. 0. ... 0. 0. 0.]
train accuracy when l = 16is:
0.9021739130434783
the predicted class for training set when l = 17 is:
[1. 0. 0. ... 0. 0. 0.]
train accuracy when l = 17is:
0.9053708439897699
the predicted class for training set when l = 18 is:
[1. 0. 0. ... 0. 0. 0.]
train accuracy when l = 18is:
0.9017713365539453
the predicted class for training set when l = 19 is:
[1. 0. 0. ... 0. 0. 0.]
train accuracy when l = 19is:
0.9099923722349351
the predicted class for training set when l = 20 is:
[1. 0. 0. ... 0. 0. 0.]
train accuracy when l = 20is:
0.913768115942029
```

In [34]:

```
print("the accuracy is max when l = "+str(acc_42.index(max(acc_42))+1))
print("which is " +str(max(acc_42)))
```

```
the accuracy is max when l = 1
which is 1.0
```

In [35]:

```
import rpy2.robj as ro
from rpy2.robj import pandas2ri
f=ro.r['glm']
```

In [36]:

```
for i in range(20):
    i=i+1
    createVar['new_dataset_'+str(i)]=np.column_stack((createVar['dataset_'+str(i)
]),createVar['y_'+str(i)]))
    createVar['df_bi_'+str(i)] = pd.DataFrame(createVar['new_dataset_'+str(i)],c
olumns = ['min1','max1',
'mean1','median1','std1',
'one_quartile1','th_quartile1',
'min2','max2','mean2','medi
an2','std2','one_quartile2','th_quartile2',
'min3','max3','mean3','medi
an3','std3','one_quartile3','th_quartile3',
'min4','max4','mean4','medi
an4','std4','one_quartile4','th_quartile4',
'min5','max5','mean5','medi
an5','std5','one_quartile5','th_quartile5',
'min6','max6','mean6','medi
an6','std6','one_quartile6','th_quartile6',
'label'])
```

In [37]:

```
df_bi_1.shape
```

Out[37]:

```
(69, 43)
```

In [38]:

```
pandas2ri.activate()
for i in range(20):
    i=i+1
    feature=createVar['df_bi_'+str(i)].columns[0:42]
    mylogit = f(formula="label~(min1+max1+mean1+median1+std1+one_quartile1+th_qu
artile1+min2+max2+mean2+median2+std2+one_quartile2+th_quartile2+min3+max3+mean3+
median3+std3+one_quartile3+th_quartile3+min4+max4+mean4+median4+std4+one_quartil
e4+th_quartile4+min5+max5+mean5+median5+std5+one_quartile5+th_quartile5+min6+max
6+mean6+median6+std6+one_quartile6+th_quartile6)",data=createVar['df_bi_'+str(i)
],family=ro.r('binomial(link="logit")'))
    print("p values when for all features when l = " +str(i))
    print(ro.r.summary(mylogit)[-6])
```

p values when for all features when l = 1

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-55.3749022	1722887.96	-3.214074e-05	0.9999744
min1	-0.1770208	23016.98	-7.690878e-06	0.9999939
max1	-6.7758958	97554.17	-6.945777e-05	0.9999446
mean1	40.7412300	1069233.40	3.810321e-05	0.9999696

median1	1.7412045	232545.55	7.487585e-06	0.9999940
std1	14.4090250	434499.08	3.316238e-05	0.9999735
one_quartile1	-14.3532758	406773.96	-3.528563e-05	0.9999718
th_quartile1	-23.7116311	544872.45	-4.351776e-05	0.9999653
max2	-8.6067826	125244.28	-6.871997e-05	0.9999452
mean2	10.9098357	2624698.26	4.156606e-06	0.9999967
median2	35.6546290	967273.90	3.686094e-05	0.9999706
std2	137.8060698	2342352.03	5.883235e-05	0.9999531
one_quartile2	46.9130737	1004843.26	4.668696e-05	0.9999627
th_quartile2	-77.9110596	1195469.41	-6.517194e-05	0.9999480
min3	-7.6102654	52498.62	-1.449613e-04	0.9998843
max3	-1.1958961	83694.94	-1.428875e-05	0.9999886
mean3	14.3792237	739885.26	1.943440e-05	0.9999845
median3	32.5222711	258507.59	1.258078e-04	0.9998996
std3	-20.7636380	1005973.36	-2.064035e-05	0.9999835
one_quartile3	-35.1473335	422555.21	-8.317808e-05	0.9999336
th_quartile3	-12.4252665	430044.39	-2.889299e-05	0.9999769
max4	16.3922563	126039.45	1.300566e-04	0.9998962
mean4	-73.7168854	2577899.06	-2.859572e-05	0.9999772
median4	-84.7028816	2585280.66	-3.276351e-05	0.9999739
std4	17.4110613	2033433.99	8.562393e-06	0.9999932
one_quartile4	70.0897147	973654.75	7.198621e-05	0.9999426
th_quartile4	-44.4164349	1274446.95	-3.485154e-05	0.9999722
min5	-5.9160312	78212.43	-7.564055e-05	0.9999396
max5	11.8466963	79491.35	1.490313e-04	0.9998811
mean5	-59.7823369	1408414.17	-4.244656e-05	0.9999661
median5	17.2175198	293794.67	5.860392e-05	0.9999532
std5	-36.1585384	483756.04	-7.474540e-05	0.9999404
one_quartile5	5.9948190	557581.49	1.075147e-05	0.9999914
th_quartile5	36.4839887	521836.35	6.991462e-05	0.9999442
min6	18.0679010	1339328.56	1.349027e-05	0.9999892
max6	5.4455133	170732.02	3.189509e-05	0.9999746
mean6	426.3700413	2571370.20	1.658143e-04	0.9998677
median6	-38.1667300	2598463.04	-1.468819e-05	0.9999883
std6	-390.6254724	1970851.22	-1.982014e-04	0.9998419
one_quartile6	-250.0942302	1126295.86	-2.220502e-04	0.9998228
th_quartile6	39.1767540	1556602.07	2.516812e-05	0.9999799

p values when for all features when $l = 2$

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	26.846777	910336.83	2.949104e-05	0.9999765
min1	-6.110295	13321.85	-4.586672e-04	0.9996340
max1	7.415199	131445.08	5.641291e-05	0.9999550
mean1	-33.690139	333034.44	-1.011611e-04	0.9999193
median1	-7.216812	152462.99	-4.733484e-05	0.9999622
std1	-14.617440	266403.68	-5.486951e-05	0.9999562
one_quartile1	19.379003	211320.83	9.170418e-05	0.9999268
th_quartile1	12.599653	90357.60	1.394421e-04	0.9998887
min2	-235.143243	2109091.59	-1.114903e-04	0.9999110
max2	41.681148	204275.25	2.040440e-04	0.9998372
mean2	-341.418002	1911894.13	-1.785758e-04	0.9998575
median2	112.366444	689823.94	1.628915e-04	0.9998700
std2	-587.867915	2032846.50	-2.891846e-04	0.9997693

one_quartile2	-25.541117	617691.63	-4.134930e-05	0.9999670
th_quartile2	366.946372	875370.91	4.191896e-04	0.9996655
min3	-7.289138	56526.32	-1.289512e-04	0.9998971
max3	23.563071	83600.99	2.818516e-04	0.9997751
mean3	-105.062579	761691.26	-1.379333e-04	0.9998899
median3	18.465686	311419.93	5.929513e-05	0.9999527
std3	-69.447415	407485.26	-1.704293e-04	0.9998640
one_quartile3	22.411327	298350.04	7.511756e-05	0.9999401
th_quartile3	40.098593	171173.00	2.342577e-04	0.9998131
min4	472.367238	1324124.40	3.567393e-04	0.9997154
max4	-2.359768	103214.05	-2.286286e-05	0.9999818
mean4	-300.334230	1663881.32	-1.805022e-04	0.9998560
median4	-185.382749	964997.21	-1.921070e-04	0.9998467
std4	88.350440	1113176.73	7.936785e-05	0.9999367
one_quartile4	172.640582	338226.54	5.104288e-04	0.9995927
th_quartile4	115.675588	438149.74	2.640093e-04	0.9997894
min5	-14.001666	45445.58	-3.080974e-04	0.9997542
max5	35.274906	104045.52	3.390334e-04	0.9997295
mean5	5.571041	547296.07	1.017921e-05	0.9999919
median5	-15.665552	131198.43	-1.194035e-04	0.9999047
std5	-111.572321	327694.05	-3.404771e-04	0.9997283
one_quartile5	-29.875917	198612.08	-1.504235e-04	0.9998800
th_quartile5	32.091090	291139.33	1.102259e-04	0.9999121
min6	-261.978519	2512067.16	-1.042880e-04	0.9999168
max6	-14.431041	350037.57	-4.122712e-05	0.9999671
mean6	-184.694292	1658948.13	-1.113322e-04	0.9999112
median6	90.031582	880805.80	1.022150e-04	0.9999184
std6	3.977006	2354823.52	1.688877e-06	0.9999987
one_quartile6	46.143975	524567.17	8.796581e-05	0.9999298
th_quartile6	106.015729	846227.29	1.252804e-04	0.9999000

p values when for all features when l = 3

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	1294.59724	287339.518	4.505462e-03	0.9964052
min1	-21.66935	6700.080	-3.234193e-03	0.9974195
max1	30.29387	10091.583	3.001895e-03	0.9976048
mean1	-165.59296	95012.439	-1.742856e-03	0.9986094
median1	60.85039	30995.180	1.963221e-03	0.9984336
std1	-182.86851	49631.624	-3.684516e-03	0.9970602
one_quartile1	-24.23158	40251.347	-6.020066e-04	0.9995197
th_quartile1	50.95557	28357.317	1.796911e-03	0.9985663
min2	87.60733	613193.696	1.428706e-04	0.9998860
max2	244.48370	26931.458	9.077997e-03	0.9927569
mean2	401.02554	283137.914	1.416361e-03	0.9988699
median2	-195.45039	118923.769	-1.643493e-03	0.9986887
std2	-3204.84039	301484.455	-1.063020e-02	0.9915185
one_quartile2	-325.52528	104597.783	-3.112162e-03	0.9975169
th_quartile2	588.11275	118328.267	4.970180e-03	0.9960344
min3	-40.11154	11327.613	-3.541041e-03	0.9971747
max3	79.51700	16091.539	4.941541e-03	0.9960572
mean3	214.16904	95254.098	2.248397e-03	0.9982060
median3	-123.71181	16050.815	-7.707509e-03	0.9938504
std3	-19.02835	62662.598	-3.036637e-04	0.9997577

one_quartile3	-57.59689	38890.464	-1.481003e-03	0.9988183
th_quartile3	-27.77979	50028.595	-5.552782e-04	0.9995570
min4	29.14211	388504.478	7.501101e-05	0.9999401
max4	30.08913	15591.135	1.929887e-03	0.9984602
mean4	-1407.08972	332716.581	-4.229094e-03	0.9966257
median4	-788.21972	115741.516	-6.810173e-03	0.9945663
std4	968.03914	159691.645	6.061927e-03	0.9951633
one_quartile4	988.07821	128876.692	7.666850e-03	0.9938828
th_quartile4	357.00248	137566.302	2.595130e-03	0.9979294
min5	-31.73682	5639.021	-5.628072e-03	0.9955095
max5	140.27468	19124.133	7.334956e-03	0.9941476
mean5	-637.92548	95921.428	-6.650500e-03	0.9946937
median5	96.81822	38901.444	2.488808e-03	0.9980142
std5	-549.40375	78569.399	-6.992592e-03	0.9944208
one_quartile5	136.71960	21575.458	6.336811e-03	0.9949440
th_quartile5	310.14145	40291.635	7.697416e-03	0.9938584
min6	-690.15394	238930.865	-2.888509e-03	0.9976953
max6	11.81975	28173.484	4.195345e-04	0.9996653
mean6	-778.32178	185390.316	-4.198287e-03	0.9966503
median6	-116.55872	146662.845	-7.947392e-04	0.9993659
std6	-1300.29432	349106.205	-3.724638e-03	0.9970282
one_quartile6	182.57126	83311.130	2.191439e-03	0.9982515
th_quartile6	1320.86339	167516.729	7.884964e-03	0.9937088

p values when for all features when l = 4

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	140.409767	257870.433	5.444973e-04	0.9995656
min1	-57.782258	8698.569	-6.642731e-03	0.9946999
max1	100.833452	14020.975	7.191615e-03	0.9942620
mean1	-432.871595	150422.115	-2.877712e-03	0.9977039
median1	34.846912	82897.569	4.203611e-04	0.9996646
std1	-638.783997	93178.744	-6.855469e-03	0.9945302
one_quartile1	-9.642309	22843.434	-4.221042e-04	0.9996632
th_quartile1	330.936138	47365.301	6.986890e-03	0.9944253
min2	303.938593	15836155.923	1.919270e-05	0.9999847
max2	-46.523695	21265.796	-2.187724e-03	0.9982545
mean2	1280.760830	442375.457	2.895190e-03	0.9976900
median2	-140.606974	145920.171	-9.635883e-04	0.9992312
std2	278.361410	318607.775	8.736805e-04	0.9993029
one_quartile2	-419.432636	187596.511	-2.235823e-03	0.9982161
th_quartile2	-566.963578	151791.717	-3.735142e-03	0.9970198
min3	-114.301582	13787.871	-8.290010e-03	0.9933856
max3	46.937230	9908.741	4.736952e-03	0.9962205
mean3	274.205983	86919.115	3.154726e-03	0.9974829
median3	48.276813	17567.713	2.748042e-03	0.9978074
std3	-146.361663	54853.616	-2.668223e-03	0.9978711
one_quartile3	-155.883321	24675.617	-6.317302e-03	0.9949596
th_quartile3	-135.792251	57529.166	-2.360407e-03	0.9981167
min4	422.915083	30197625.548	1.400491e-05	0.9999888
max4	57.070410	31464.268	1.813817e-03	0.9985528
mean4	-1586.411268	291172.628	-5.448353e-03	0.9956529
median4	-315.103468	113048.693	-2.787325e-03	0.9977760
std4	225.271588	122291.263	1.842091e-03	0.9985302

one_quartile4	612.910776	118658.013	5.165355e-03	0.9958787
th_quartile4	524.583197	113974.790	4.602625e-03	0.9963276
min5	-48.586751	15773.403	-3.080296e-03	0.9975423
max5	114.816522	12649.261	9.076935e-03	0.9927578
mean5	-402.053766	64254.419	-6.257216e-03	0.9950075
median5	93.767552	19427.927	4.826431e-03	0.9961491
std5	-483.209300	100484.254	-4.808806e-03	0.9961631
one_quartile5	29.183659	42688.167	6.836475e-04	0.9994545
th_quartile5	259.787258	36481.239	7.121119e-03	0.9943182
min6	192.989095	15645079.812	1.233545e-05	0.9999902
max6	-2.354802	36015.969	-6.538217e-05	0.9999478
mean6	-453.078494	467751.535	-9.686307e-04	0.9992271
median6	60.340029	87503.363	6.895738e-04	0.9994498
std6	-309.025944	181043.552	-1.706915e-03	0.9986381
one_quartile6	232.525027	155556.402	1.494796e-03	0.9988073
th_quartile6	343.554445	184689.471	1.860173e-03	0.9985158

p values when for all features when l = 5

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	12.61898908	4.5716281	2.7602833828	0.0057751242
min1	-0.20017550	0.4195539	-0.4771151362	0.6332801369
max1	0.31966032	0.4847796	0.6593931221	0.5096433576
mean1	-2.33587928	2.9021966	-0.8048659575	0.4208970349
median1	0.62042993	0.9358734	0.6629421783	0.5073675870
std1	-1.23748849	2.5001206	-0.4949715149	0.6206202278
one_quartile1	0.76363167	0.8558066	0.8922947124	0.3722349877
th_quartile1	0.09541636	1.3360311	0.0714177664	0.9430652702
min2	-41.34723442	7701.2661787	-0.0053688878	0.9957162679
max2	2.23920090	1.1019153	2.0320989818	0.0421436365
mean2	-11.83243726	11.3712186	-1.0405601789	0.2980797207
median2	2.77091537	3.7400040	0.7408856617	0.4587627699
std2	-18.51154338	9.5974012	-1.9288079094	0.0537547136
one_quartile2	-2.23930494	4.0572074	-0.5519325719	0.5809945513
th_quartile2	8.50211151	4.3284914	1.9642205005	0.0495045264
min3	-1.40298339	0.3685695	-3.8065643230	0.0001409107
max3	1.26640423	0.4556227	2.7795022975	0.0054442268
mean3	1.00011652	1.9325027	0.5175239807	0.6047904331
median3	0.88785598	0.9002641	0.9862172258	0.3240265281
std3	-5.06551007	1.5921679	-3.1815176086	0.0014650562
one_quartile3	-2.23173831	0.9204363	-2.4246525914	0.0153230423
th_quartile3	0.14821868	0.7932121	0.1868588155	0.8517713309
min4	-2.38487041	5421.2498394	-0.0004399115	0.9996490014
max4	0.59534425	0.9023913	0.6597406972	0.5094202453
mean4	-2.76802145	10.7480654	-0.2575367146	0.7967644767
median4	-7.47313027	5.0756093	-1.4723612126	0.1409233615
std4	0.52222361	7.0648464	0.0739186080	0.9410751493
one_quartile4	2.54748693	3.6056005	0.7065361131	0.4798548030
th_quartile4	4.16209314	5.0056211	0.8314838616	0.4057003414
min5	-1.27209034	0.3961613	-3.2110413836	0.0013225489
max5	1.74629950	0.5745337	3.0395073239	0.0023696544
mean5	-0.71618862	2.5459420	-0.2813059419	0.7784757533
median5	-0.02837379	1.0327861	-0.0274730579	0.9780824285
std5	-9.07106898	2.5729276	-3.5255827050	0.0004225522

one_quartile5	-1.78695973	1.2558020	-1.4229629230	0.1547469038
th_quartile5	2.70986575	1.1669066	2.3222645418	0.0202186956
min6	-4.50350612	4793.7830004	-0.0009394472	0.9992504297
max6	-0.73692420	0.7989413	-0.9223758829	0.3563325450
mean6	-11.55173474	11.7079336	-0.9866587130	0.3238099767
median6	3.60560721	4.8103548	0.7495512017	0.4535250502
std6	2.00404520	8.3918500	0.2388085113	0.8112540701
one_quartile6	1.89773416	4.2019846	0.4516280637	0.6515369493
th_quartile6	3.74254246	4.1318953	0.9057689430	0.3650581626

p values when for all features when l = 6

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	2.57393348	2.8812087	0.893351979	0.371668710
min1	-0.03804819	0.2483760	-0.153187879	0.878250116
max1	-0.34686221	0.3622869	-0.957424232	0.338353172
mean1	3.04795162	2.0570990	1.481674704	0.138426871
median1	-0.93669285	0.5674171	-1.650801216	0.098779172
std1	0.68593545	1.1604228	0.591108202	0.554447925
one_quartile1	-0.68549130	0.7015796	-0.977068415	0.328535283
th_quartile1	-1.35040606	0.8427316	-1.602415294	0.109063805
min2	-40.39482282	5994.1745542	-0.006739013	0.994623086
max2	2.18048423	0.8395033	2.597350407	0.009394603
mean2	-5.88437360	6.6612440	-0.883374571	0.377033925
median2	-0.81068537	2.4353134	-0.332887491	0.739219212
std2	-15.55648008	7.0889992	-2.194453636	0.028202814
one_quartile2	-3.02874648	2.7287263	-1.109948798	0.267021091
th_quartile2	7.12428939	2.8312955	2.516264864	0.011860601
min3	-0.45018046	0.1990660	-2.261463220	0.023730588
max3	0.47822629	0.2676954	1.786457166	0.074025267
mean3	0.29746312	1.4795747	0.201046369	0.840662317
median3	0.02383371	0.4959706	0.048054678	0.961672666
std3	-1.77786046	1.0531263	-1.688173949	0.091377842
one_quartile3	-0.69107865	0.5193022	-1.330783292	0.183260327
th_quartile3	0.10745479	0.7278365	0.147635896	0.882630125
min4	-18.27967488	5355.3043479	-0.003413377	0.997276524
max4	1.71187716	0.6443649	2.656688981	0.007891221
mean4	15.76906444	7.2876061	2.163819537	0.030478202
median4	-7.73247019	3.3457720	-2.311116872	0.020826400
std4	-11.84973893	5.1328987	-2.308586179	0.020966556
one_quartile4	-7.00336975	2.5941629	-2.699664649	0.006940940
th_quartile4	-2.98239020	2.5409577	-1.173726818	0.240504465
min5	-0.37985617	0.2205133	-1.722600187	0.084960851
max5	0.66834003	0.3575744	1.869093683	0.061609782
mean5	-0.51867474	1.8660650	-0.277951052	0.781049933
median5	-0.08996819	0.6119155	-0.147027136	0.883110602
std5	-2.46348086	1.4096159	-1.747625653	0.080528870
one_quartile5	-0.36220591	0.6416996	-0.564447789	0.572449424
th_quartile5	1.17491420	0.8401405	1.398473470	0.161970934
min6	-38.16801696	4576.0190194	-0.008340878	0.993345019
max6	0.90700766	0.7802523	1.162454304	0.245050976
mean6	3.45648873	7.0094003	0.493121892	0.621926463
median6	-0.17936348	3.2848661	-0.054602981	0.956454764
std6	-12.30323518	6.4582131	-1.905052533	0.056773243

one_quartile6	-3.40344036	3.1168645	-1.091943652	0.274857869
th_quartile6	1.79450584	3.0057819	0.597017984	0.550495374

p values when for all features when l = 7

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	3.64803580	2.4137207	1.511374442	0.1306930774
min1	-0.21048906	0.2524395	-0.833819876	0.4043824931
max1	0.32406797	0.2275744	1.424008968	0.1544438759
mean1	0.28596063	1.3654910	0.209419633	0.8341206673
median1	0.40954415	0.4983880	0.821737592	0.4112262590
std1	-1.00340220	0.9189858	-1.091858216	0.2748954259
one_quartile1	-0.76342764	0.5157892	-1.480115610	0.1388423965
th_quartile1	-0.42483136	0.6671234	-0.636810804	0.5242480876
min2	-40.25621225	4687.4391934	-0.008588103	0.9931477692
max2	1.69307208	0.7385235	2.292509517	0.0218762590
mean2	-8.56940555	6.6952483	-1.279923493	0.2005720445
median2	1.91459939	2.8977877	0.660710729	0.5087978422
std2	-12.43785010	6.1877252	-2.010084420	0.0444222547
one_quartile2	-0.15497790	2.5193572	-0.061514858	0.9509491817
th_quartile2	5.17561679	2.1974830	2.355247718	0.0185103614
min3	-0.57803790	0.1809911	-3.193736107	0.0014044444
max3	0.52402764	0.2272660	2.305789800	0.0211223804
mean3	0.94511562	1.2244777	0.771852062	0.4402020527
median3	0.40846588	0.4630894	0.882045435	0.3777522379
std3	-2.23453497	0.8833742	-2.529545141	0.0114210481
one_quartile3	-1.29192720	0.5476611	-2.358990166	0.0183247413
th_quartile3	-0.17651036	0.4842801	-0.364479911	0.7154996722
min4	-43.40339772	4896.1679589	-0.008864769	0.9929270304
max4	1.09050323	0.4928897	2.212469170	0.0269342642
mean4	5.03288605	6.7595257	0.744562007	0.4565365431
median4	-6.22188082	2.9904454	-2.080586683	0.0374717539
std4	-5.25072111	4.2581811	-1.233090122	0.2175421424
one_quartile4	-0.28395064	2.0653886	-0.137480492	0.8906510111
th_quartile4	-0.01298733	2.2682718	-0.005725648	0.9954316189
min5	-0.69664733	0.1928977	-3.611486490	0.0003044469
max5	1.17031787	0.3100750	3.774305752	0.0001604539
mean5	-1.35638802	1.3501909	-1.004589823	0.3150943997
median5	-0.10761830	0.5500799	-0.195641222	0.8448909936
std5	-4.28216659	1.1071061	-3.867891717	0.0001097804
one_quartile5	-0.18661326	0.6231256	-0.299479365	0.7645743146
th_quartile5	1.63989670	0.5202742	3.151985551	0.0016216430
min6	-32.61520278	3501.2348591	-0.009315343	0.9925675393
max6	-0.01898734	0.6228276	-0.030485705	0.9756796936
mean6	-9.77345942	6.1338978	-1.593352167	0.1110812099
median6	4.79591075	2.7361671	1.752784307	0.0796390378
std6	-0.79270233	4.9932965	-0.158753307	0.8738632380
one_quartile6	3.27768483	2.3855962	1.373947896	0.1694578588
th_quartile6	2.36538090	2.3914203	0.989111315	0.3226086822

p values when for all features when l = 8

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	1.20203724	1.9539911	0.615170278	0.5384422738
min1	-0.41857579	0.1827986	-2.289819085	0.0220318063

max1	0.39130213	0.3036006	1.288871487	0.1974427683
mean1	1.03018620	1.3396873	0.768975108	0.4419080877
median1	-0.45558834	0.4445099	-1.024922882	0.3053995767
std1	-1.89204106	1.1106807	-1.703496900	0.0884751177
one_quartile1	-0.68372351	0.4446250	-1.537753061	0.1241090044
th_quartile1	-0.12085975	0.5849152	-0.206627808	0.8363005414
min2	-36.90960790	4571.6688062	-0.008073552	0.9935583071
max2	0.57984018	0.6351158	0.912967656	0.3612595525
mean2	-8.85632958	5.5593762	-1.593043769	0.1111503725
median2	0.97547284	2.1036347	0.463708288	0.6428567582
std2	-3.48029940	4.8834605	-0.712670741	0.4760495258
one_quartile2	0.15363970	1.9917252	0.077139007	0.9385129625
th_quartile2	4.92636863	2.0565396	2.395465045	0.0165992969
min3	-0.50638087	0.1609862	-3.145492587	0.0016580740
max3	0.42991498	0.1993663	2.156407499	0.0310518596
mean3	0.40187858	1.2187584	0.329744266	0.7415932033
median3	-0.76200347	0.3942891	-1.932600830	0.0532853901
std3	-1.47744141	0.8094803	-1.825172691	0.0679749734
one_quartile3	-0.12185551	0.4372925	-0.278659035	0.7805065033
th_quartile3	0.45931024	0.5682041	0.808354331	0.4188866343
min4	-24.07281959	4009.8699525	-0.006003392	0.9952100153
max4	0.84875240	0.4540431	1.869321154	0.0615781468
mean4	6.08617791	5.6240684	1.082166413	0.2791785897
median4	-6.25272320	2.2334432	-2.799589097	0.0051167694
std4	-5.98684611	3.6787185	-1.627427080	0.1036464241
one_quartile4	-2.25000834	1.8788010	-1.197576705	0.2310818495
th_quartile4	0.47794338	1.8502925	0.258306938	0.7961700319
min5	-0.33819643	0.1636411	-2.066696487	0.0387627624
max5	1.00848460	0.2850153	3.538352365	0.0004026324
mean5	-1.94135116	1.2340495	-1.573154972	0.1156829388
median5	0.47833862	0.4298961	1.112684123	0.2658441167
std5	-2.94607002	0.9403106	-3.133081789	0.0017298123
one_quartile5	0.03542295	0.5040357	0.070278646	0.9439718787
th_quartile5	1.11170220	0.5324899	2.087743124	0.0368210126
min6	1.08097811	4.6071673	0.234629662	0.8144961855
max6	0.31421532	0.5204802	0.603702717	0.5460413072
mean6	-1.56341268	5.7303150	-0.272831889	0.7849824453
median6	2.94640528	2.3860959	1.234822665	0.2168965100
std6	-3.60452477	4.0182782	-0.897032162	0.3697017555
one_quartile6	-1.43734267	2.0013087	-0.718201389	0.4726331214
th_quartile6	0.14868243	2.2629661	0.065702453	0.9476147192

p values when for all features when l = 9

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	1.995914758	1.6388463	1.21787793	0.2232703641
min1	-0.382154888	0.2239815	-1.70618914	0.0879728692
max1	0.602911572	0.3114670	1.93571554	0.0529025504
mean1	-1.452489605	1.5357792	-0.94576720	0.3442673394
median1	-0.359023428	0.4492178	-0.79921905	0.4241634090
std1	-2.562333410	1.1869041	-2.15883784	0.0308627494
one_quartile1	-0.149611739	0.5089787	-0.29394496	0.7687999608
th_quartile1	1.530281536	0.7369926	2.07638657	0.0378582127
min2	-38.071425817	3803.0988314	-0.01001063	0.9920128041

max2	1.331563078	0.6942983	1.91785457	0.0551294544
mean2	-5.122881943	4.8595652	-1.05418524	0.2917981170
median2	-1.799094184	1.9405931	-0.92708470	0.3538825591
std2	-8.516016770	5.0311884	-1.69264518	0.0905230256
one_quartile2	-1.263493745	2.0169740	-0.62643036	0.5310327044
th_quartile2	4.172222267	1.8637107	2.23866410	0.0251777800
min3	-0.564936995	0.1688417	-3.34595711	0.0008199908
max3	0.513180738	0.2047325	2.50659190	0.0121901365
mean3	0.818452078	1.0516725	0.77823857	0.4364283800
median3	-0.009488738	0.3365537	-0.02819383	0.9775075563
std3	-2.136847285	0.7294572	-2.92936626	0.0033965394
one_quartile3	-0.927979299	0.3934811	-2.35838337	0.0183547263
th_quartile3	0.047473762	0.4287094	0.11073645	0.9118253378
min4	-37.250342493	3418.0516424	-0.01089812	0.9913047291
max4	1.276837109	0.4290652	2.97585791	0.0029217020
mean4	7.900145288	4.8282096	1.63624737	0.1017878252
median4	-4.503014275	2.0145089	-2.23529134	0.0253982285
std4	-8.724024619	3.6595049	-2.38393576	0.0171285920
one_quartile4	-2.550086491	1.6891318	-1.50970248	0.1311193579
th_quartile4	-1.261824514	1.6514868	-0.76405367	0.4448352597
min5	-0.248491362	0.1670656	-1.48738760	0.1369124698
max5	0.570976723	0.2662116	2.14482308	0.0319669953
mean5	-0.653328668	1.2553922	-0.52041796	0.6027722948
median5	0.316236149	0.4082157	0.77467901	0.4385293591
std5	-1.886639199	0.8726587	-2.16194389	0.0306225017
one_quartile5	-0.213638256	0.4615489	-0.46287247	0.6434557842
th_quartile5	0.551779519	0.5187260	1.06372063	0.2874552755
min6	1.737585275	6.4970527	0.26744208	0.7891288066
max6	0.725795510	0.5135757	1.41322018	0.1575909942
mean6	-0.762598458	4.8506154	-0.15721685	0.8750739512
median6	1.820393644	1.9507448	0.93317878	0.3507276679
std6	-5.654386461	3.8090958	-1.48444321	0.1376913776
one_quartile6	-2.610808581	1.6811927	-1.55295022	0.1204350268
th_quartile6	0.954187597	1.7436732	0.54722846	0.5842217877

p values when for all features when l = 10

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	3.12525725	1.5233152	2.05161558	4.020704e-02
min1	-0.35359347	0.1402096	-2.52189244	1.167254e-02
max1	0.18139334	0.2193397	0.82699738	4.082385e-01
mean1	0.31263149	0.9513165	0.32863038	7.424351e-01
median1	0.03957648	0.3082987	0.12837059	8.978557e-01
std1	-1.25347953	0.7173331	-1.74741636	8.056514e-02
one_quartile1	-0.45236804	0.3518484	-1.28569020	1.985512e-01
th_quartile1	-0.01155384	0.4049352	-0.02853255	9.772374e-01
min2	-2.34042266	2.3653803	-0.98944879	3.224436e-01
max2	1.04181236	0.5404184	1.92778859	5.388143e-02
mean2	2.91666694	5.0184224	0.58119200	5.611111e-01
median2	-2.42695389	1.8402915	-1.31878773	1.872401e-01
std2	-8.77640147	4.0204819	-2.18292279	2.904150e-02
one_quartile2	-3.37591206	1.8153778	-1.85961959	6.293937e-02
th_quartile2	1.70217330	1.7531683	0.97091265	3.315918e-01
min3	-0.59939228	0.1442275	-4.15588161	3.240356e-05

max3	0.88554225	0.1863187	4.75283626	2.005828e-06
mean3	-1.27975770	0.9803677	-1.30538535	1.917617e-01
median3	0.30192730	0.3101284	0.97355590	3.302771e-01
std3	-2.92056228	0.7097997	-4.11462902	3.878026e-05
one_quartile3	-0.37875621	0.3362215	-1.12650790	2.599506e-01
th_quartile3	0.99289716	0.4274673	2.32274416	2.019290e-02
min4	-31.99121633	2453.7140838	-0.01303787	9.895976e-01
max4	0.75796907	0.4382787	1.72942242	8.373352e-02
mean4	2.22620437	4.2221254	0.52727102	5.980054e-01
median4	-1.61871478	1.7618616	-0.91875251	3.582250e-01
std4	-4.03866338	3.4332285	-1.17634565	2.394568e-01
one_quartile4	-2.53964771	1.5750305	-1.61244346	1.068655e-01
th_quartile4	-0.50299371	1.4071691	-0.35745080	7.207544e-01
min5	-0.44837187	0.1660823	-2.69969654	6.940275e-03
max5	0.53457217	0.2093461	2.55353249	1.066363e-02
mean5	0.87189560	1.1488914	0.75890164	4.479114e-01
median5	0.33034169	0.3870662	0.85345011	3.934097e-01
std5	-1.80712047	0.7741206	-2.33441720	1.957389e-02
one_quartile5	-0.61021564	0.4111032	-1.48433680	1.377196e-01
th_quartile5	-0.35109784	0.5105734	-0.68765397	4.916707e-01
min6	-0.29063887	3.3801319	-0.08598448	9.314788e-01
max6	0.92675260	0.5025808	1.84398734	6.518499e-02
mean6	1.47476637	4.8626164	0.30328659	7.616715e-01
median6	-0.77434405	1.7414290	-0.44466013	6.565654e-01
std6	-8.55639140	3.5993443	-2.37720835	1.744423e-02
one_quartile6	-2.56701711	1.9075571	-1.34570918	1.783963e-01
th_quartile6	1.95197129	1.7107852	1.14097975	2.538783e-01

p values when for all features when l = 11

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	2.09419806	1.3540767	1.54658746	0.1219627547
min1	-0.24379140	0.1678456	-1.45247382	0.1463699040
max1	0.13343097	0.2938260	0.45411557	0.6497456492
mean1	0.94600557	1.2026990	0.78656883	0.4315343147
median1	-0.13616244	0.3859409	-0.35280641	0.7242335762
std1	-0.53699959	0.9783141	-0.54890306	0.5830719760
one_quartile1	-0.46627569	0.3281744	-1.42081676	0.1553700380
th_quartile1	-0.47447619	0.5420800	-0.87528817	0.3814171285
min2	-4.38885098	2.8908605	-1.51818151	0.1289686475
max2	1.80283036	0.5914194	3.04831103	0.0023013160
mean2	-3.77327438	4.4331619	-0.85114744	0.3946874563
median2	-0.82719092	1.5443656	-0.53561859	0.5922221793
std2	-10.30714767	3.7493947	-2.74901643	0.0059774391
one_quartile2	-1.61246601	1.6905063	-0.95383617	0.3401665780
th_quartile2	4.02554823	1.6892155	2.38308739	0.0171681183
min3	-0.52916007	0.1361486	-3.88663605	0.0001016430
max3	0.55240668	0.1654982	3.33784038	0.0008443224
mean3	-1.01209865	0.9494561	-1.06597732	0.2864338937
median3	-0.14130098	0.2868395	-0.49261340	0.6222857795
std3	-2.33177012	0.6966455	-3.34714005	0.0008164995
one_quartile3	-0.08503818	0.3229456	-0.26332048	0.7923035784
th_quartile3	1.12850957	0.4745134	2.37824571	0.0173952304
min4	-32.65508222	1985.6072773	-0.01644589	0.9868786684

max4	1.04641264	0.4004969	2.61278558	0.0089807626
mean4	0.67189954	3.8186133	0.17595380	0.8603302358
median4	-2.17916217	1.5133191	-1.43998857	0.1498706326
std4	-4.93532303	2.8911393	-1.70705129	0.0878125196
one_quartile4	-1.16359316	1.4362936	-0.81013601	0.4178620114
th_quartile4	0.53789152	1.3160202	0.40872588	0.6827408398
min5	-0.22718254	0.1561422	-1.45497181	0.1456770653
max5	0.72224201	0.2461096	2.93463524	0.0033393999
mean5	-1.42929270	1.2797043	-1.11689295	0.2640400979
median5	0.17922332	0.3983397	0.44992580	0.6527639418
std5	-1.65256415	0.8675678	-1.90482431	0.0568029131
one_quartile5	0.42253617	0.4108218	1.02851443	0.3037079060
th_quartile5	0.66582345	0.5400545	1.23288196	0.2176198056
min6	-3.87244127	2.8265523	-1.37002285	0.1706797702
max6	0.37187191	0.4735026	0.78536401	0.4322401746
mean6	-0.26903727	3.9416267	-0.06825539	0.9455823353
median6	0.12535598	1.4423600	0.08691033	0.9307427868
std6	-3.50857283	3.0356593	-1.15578609	0.2477686642
one_quartile6	0.89666276	1.6519338	0.54279581	0.5872704012
th_quartile6	0.26823799	1.4156008	0.18948703	0.8497111172

p values when for all features when l = 12

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	3.522117584	1.2241486	2.87719771	0.0040122412
min1	-0.259406992	0.1414328	-1.83413544	0.0666338925
max1	0.012403738	0.2024010	0.06128299	0.9511338383
mean1	0.334534710	0.8880594	0.37670308	0.7063942768
median1	-0.355201044	0.3250208	-1.09285637	0.2744568681
std1	-0.787435444	0.7754312	-1.01548070	0.3098767441
one_quartile1	-0.254861205	0.3141278	-0.81132978	0.4171763105
th_quartile1	0.261589656	0.4301083	0.60819483	0.5430582644
min2	-0.844784363	1.9848516	-0.42561588	0.6703877663
max2	1.299337874	0.5895023	2.20412693	0.0275154190
mean2	-4.659641426	3.9947329	-1.16644630	0.2434340476
median2	1.285600932	1.4116741	0.91069241	0.3624574645
std2	-6.714384740	3.4904252	-1.92365809	0.0543974547
one_quartile2	-1.563281119	1.5549978	-1.00532692	0.3147394578
th_quartile2	2.474668505	1.4667096	1.68722456	0.0915601798
min3	-0.493331162	0.1383102	-3.56684682	0.0003613025
max3	0.498127467	0.1656167	3.00771287	0.0026322171
mean3	0.395385199	0.8307767	0.47592235	0.6341297007
median3	0.107202753	0.2580153	0.41548994	0.6777832783
std3	-1.642749627	0.5828700	-2.81838074	0.0048266538
one_quartile3	-0.577868950	0.2887003	-2.00162261	0.0453253352
th_quartile3	-0.004304513	0.3489054	-0.01233719	0.9901565944
min4	-31.828528856	1807.4294460	-0.01760983	0.9859501131
max4	1.167151612	0.3935438	2.96574788	0.0030194791
mean4	3.848900422	3.8835366	0.99108127	0.3216458979
median4	-1.137787297	1.4789609	-0.76931532	0.4417061450
std4	-6.762959117	2.7983694	-2.41674992	0.0156597721
one_quartile4	-3.649776609	1.4338417	-2.54545291	0.0109136082
th_quartile4	-0.793806422	1.2621857	-0.62891411	0.5294052874
min5	-0.189113689	0.1406282	-1.34477775	0.1786970190

max5	0.437413128	0.2150976	2.03355658	0.0419963239
mean5	-0.245887089	1.1533293	-0.21319765	0.8311728026
median5	-0.068838853	0.3706220	-0.18573869	0.8526496832
std5	-0.612516220	0.6895325	-0.88830659	0.3743758582
one_quartile5	0.292493298	0.3585288	0.81581531	0.4146057783
th_quartile5	0.071721487	0.4684801	0.15309399	0.8783241517
min6	-4.883146697	2.4315068	-2.00828009	0.0446135367
max6	0.523730146	0.4436611	1.18047342	0.2378119778
mean6	2.376064737	3.6006099	0.65990619	0.5093140342
median6	-0.187628026	1.3846604	-0.13550473	0.8922128263
std6	-5.625070093	2.9610406	-1.89969366	0.0574733329
one_quartile6	-1.931300703	1.5962896	-1.20986860	0.2263293171
th_quartile6	0.228500587	1.3463021	0.16972460	0.8652267230

p values when for all features when l = 13

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	2.91224490	1.2102071	2.40640218	1.611052e-02
min1	-0.29271332	0.1573683	-1.86005314	6.287801e-02
max1	0.32497116	0.2693070	1.20669417	2.275499e-01
mean1	0.59937037	1.0718265	0.55920465	5.760221e-01
median1	-0.15373491	0.3645695	-0.42168885	6.732521e-01
std1	-1.26195397	0.8523221	-1.48060685	1.387114e-01
one_quartile1	-0.63116745	0.3507700	-1.79937704	7.195906e-02
th_quartile1	-0.09808047	0.5012321	-0.19567875	8.448616e-01
min2	-3.97469018	2.2179567	-1.79205043	7.312489e-02
max2	0.71038725	0.5441698	1.30545136	1.917392e-01
mean2	-2.14308010	4.2800635	-0.50071222	6.165737e-01
median2	-0.53798314	1.6138563	-0.33335256	7.388682e-01
std2	-4.30915249	3.3194446	-1.29815466	1.942342e-01
one_quartile2	-0.49864927	1.6099030	-0.30973871	7.567597e-01
th_quartile2	1.65983655	1.4030235	1.18304258	2.367923e-01
min3	-0.61243281	0.1381234	-4.43395303	9.252079e-06
max3	0.74627638	0.1816434	4.10846904	3.982906e-05
mean3	-0.63594498	0.9376685	-0.67821942	4.976326e-01
median3	0.23330840	0.2588153	0.90144757	3.673504e-01
std3	-3.05593924	0.6575534	-4.64743910	3.360813e-06
one_quartile3	-0.66952216	0.3226633	-2.07498683	3.798776e-02
th_quartile3	0.87481111	0.3970150	2.20347097	2.756157e-02
min4	-35.57793304	1749.3936762	-0.02033729	9.837743e-01
max4	1.38210741	0.4225180	3.27112078	1.071221e-03
mean4	-4.06838464	3.7549727	-1.08346584	2.786017e-01
median4	0.19230980	1.6115307	0.11933362	9.050110e-01
std4	-4.16062755	2.7625629	-1.50607524	1.320479e-01
one_quartile4	-0.60481162	1.4491858	-0.41734580	6.764255e-01
th_quartile4	1.32635624	1.2030003	1.10254027	2.702269e-01
min5	-0.38272959	0.1555479	-2.46052486	1.387340e-02
max5	0.40430838	0.2121960	1.90535326	5.673417e-02
mean5	0.69511958	1.1386046	0.61050129	5.415298e-01
median5	0.01870752	0.3288786	0.05688276	9.546386e-01
std5	-1.95219369	0.7477266	-2.61083903	9.032040e-03
one_quartile5	-0.77045382	0.3825066	-2.01422346	4.398608e-02
th_quartile5	0.33045196	0.4598082	0.71867343	4.723422e-01
min6	0.35974669	1.8927653	0.19006408	8.492589e-01

max6	0.59702628	0.5057153	1.18055798	2.377784e-01
mean6	-1.51818757	3.7535035	-0.40447213	6.858656e-01
median6	0.42294296	1.4644833	0.28880014	7.727343e-01
std6	-3.91188406	2.9884115	-1.30901789	1.905283e-01
one_quartile6	-1.72078310	1.4584317	-1.17988596	2.380456e-01
th_quartile6	1.72140336	1.3666823	1.25954902	2.078321e-01

p values when for all features when l = 14

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	2.82182647	1.1338297	2.48875697	1.281906e-02
min1	-0.30757564	0.1787422	-1.72077771	8.529117e-02
max1	0.23543607	0.2428035	0.96965685	3.322176e-01
mean1	0.20771002	0.9588522	0.21662361	8.285017e-01
median1	-0.22594638	0.2985407	-0.75683604	4.491481e-01
std1	-1.43212174	0.8299158	-1.72562293	8.441527e-02
one_quartile1	-0.42227056	0.3405990	-1.23978808	2.150538e-01
th_quartile1	0.26001885	0.4316036	0.60244825	5.468758e-01
min2	-4.01669053	1.9402462	-2.07019630	3.843397e-02
max2	1.78894170	0.5913738	3.02506084	2.485831e-03
mean2	-3.83231492	3.9633302	-0.96694313	3.335725e-01
median2	-0.28415413	1.3248182	-0.21448537	8.301686e-01
std2	-9.76619007	3.3886239	-2.88205197	3.950946e-03
one_quartile2	-1.38114783	1.5214572	-0.90777960	3.639947e-01
th_quartile2	3.78181409	1.5326671	2.46747258	1.360706e-02
min3	-0.53134779	0.1259301	-4.21938810	2.449663e-05
max3	0.56255122	0.1661692	3.38541229	7.107142e-04
mean3	0.49763456	0.7791942	0.63865282	5.230488e-01
median3	-0.04923073	0.2278267	-0.21608844	8.289188e-01
std3	-1.61357026	0.5005460	-3.22362039	1.265811e-03
one_quartile3	-0.54590883	0.2709378	-2.01488622	4.391657e-02
th_quartile3	0.02630419	0.3282557	0.08013325	9.361313e-01
min4	-4.80906307	3.5867794	-1.34077470	1.799936e-01
max4	1.05999496	0.3901462	2.71691747	6.589304e-03
mean4	2.36878848	3.1918932	0.74212648	4.580107e-01
median4	-1.49556133	1.2220502	-1.22381333	2.210227e-01
std4	-6.47086076	2.5253538	-2.56235806	1.039641e-02
one_quartile4	-2.37309632	1.2590236	-1.88487046	5.944733e-02
th_quartile4	0.16620294	1.0606315	0.15670186	8.754798e-01
min5	-0.19506431	0.1584658	-1.23095557	2.183395e-01
max5	1.02663177	0.2250625	4.56153988	5.077983e-06
mean5	-2.45444142	1.0163442	-2.41497074	1.573647e-02
median5	0.85221423	0.3276590	2.60091850	9.297454e-03
std5	-1.98286515	0.7211637	-2.74953536	5.967982e-03
one_quartile5	0.33276443	0.3538886	0.94030829	3.470594e-01
th_quartile5	0.73460028	0.3868128	1.89911048	5.754995e-02
min6	-2.10083816	1.6555596	-1.26895955	2.044555e-01
max6	0.99298452	0.4865651	2.04080523	4.127019e-02
mean6	-1.17596517	3.5579970	-0.33051326	7.410122e-01
median6	-0.26186112	1.3907303	-0.18829037	8.506490e-01
std6	-6.14324655	2.7380399	-2.24366586	2.485391e-02
one_quartile6	-0.91631051	1.4125626	-0.64868664	5.165409e-01
th_quartile6	1.47181337	1.2625074	1.16578596	2.437010e-01

p values when for all features when l = 15

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	2.904352198	1.0446292	2.78027097	5.431356e-03
min1	-0.411919831	0.1969360	-2.09164305	3.647046e-02
max1	0.680908569	0.3122953	2.18033530	2.923262e-02
mean1	-1.058166398	1.2129594	-0.87238402	3.829989e-01
median1	0.147288763	0.3361827	0.43812114	6.612985e-01
std1	-2.279160698	0.9697699	-2.35020767	1.876294e-02
one_quartile1	-0.330586323	0.3521790	-0.93868833	3.478908e-01
th_quartile1	0.736735034	0.5405784	1.36286436	1.729253e-01
min2	-3.121065004	1.7590937	-1.77424605	7.602246e-02
max2	1.709936289	0.6069138	2.81742841	4.840991e-03
mean2	-0.870630234	3.9737476	-0.21909550	8.265757e-01
median2	0.469749129	1.3404571	0.35043950	7.260089e-01
std2	-9.324912376	3.3986392	-2.74371945	6.074743e-03
one_quartile2	-3.555086917	1.5562857	-2.28434082	2.235151e-02
th_quartile2	1.401824109	1.4168721	0.98937941	3.224775e-01
min3	-0.549674331	0.1241606	-4.42712453	9.549760e-06
max3	0.451533081	0.1723475	2.61989937	8.795572e-03
mean3	0.487085940	0.8281229	0.58818075	5.564110e-01
median3	0.009976968	0.2410543	0.04138888	9.669859e-01
std3	-2.092810335	0.5648522	-3.70505836	2.113421e-04
one_quartile3	-0.748269778	0.2772598	-2.69880349	6.958925e-03
th_quartile3	0.259465804	0.3401333	0.76283560	4.455614e-01
min4	-33.914909807	1459.1517652	-0.02324289	9.814565e-01
max4	1.359058962	0.3577456	3.79895379	1.453082e-04
mean4	3.156809125	3.3986331	0.92884669	3.529685e-01
median4	-1.092107643	1.3510726	-0.80832641	4.189027e-01
std4	-7.653690528	2.5551994	-2.99533979	2.741393e-03
one_quartile4	-4.120191170	1.3675757	-3.01277000	2.588750e-03
th_quartile4	0.322302720	1.0065264	0.32021287	7.488070e-01
min5	-0.141379064	0.1488449	-0.94984147	3.421928e-01
max5	0.569102877	0.2169124	2.62365357	8.699222e-03
mean5	-0.586522076	1.0288161	-0.57009417	5.686138e-01
median5	0.537012912	0.2885671	1.86096373	6.274930e-02
std5	-0.778070096	0.6723665	-1.15721124	2.471861e-01
one_quartile5	-0.043670822	0.3439120	-0.12698254	8.989542e-01
th_quartile5	-0.014093202	0.4135818	-0.03407598	9.728166e-01
min6	-3.467956449	1.6201899	-2.14046289	3.231738e-02
max6	1.047618146	0.4586592	2.28408832	2.236634e-02
mean6	10.009879542	3.4874954	2.87022016	4.101861e-03
median6	-2.500967435	1.3340445	-1.87472560	6.083048e-02
std6	-9.892313789	2.8053354	-3.52624997	4.214889e-04
one_quartile6	-4.469886105	1.5077036	-2.96469822	3.029800e-03
th_quartile6	-2.178699470	1.2692939	-1.71646569	8.607684e-02

p values when for all features when l = 16

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	3.39982481	1.0095284	3.36773557	7.578825e-04
min1	-0.39691592	0.1627760	-2.43841785	1.475171e-02
max1	0.23804543	0.2872731	0.82863818	4.073092e-01
mean1	0.69586120	1.0077426	0.69051484	4.898705e-01
median1	-0.10655118	0.2939041	-0.36253720	7.169506e-01

std1	-1.50508890	0.8812654	-1.70787240	8.766002e-02
one_quartile1	-0.65238261	0.3258890	-2.00185518	4.530031e-02
th_quartile1	-0.02835256	0.4400501	-0.06443030	9.486276e-01
min2	-3.71521882	1.6198234	-2.29359504	2.181377e-02
max2	0.44107631	0.5345281	0.82516954	4.092753e-01
mean2	4.95184907	3.8872209	1.27387899	2.027063e-01
median2	-0.50296172	1.1431376	-0.43998355	6.599490e-01
std2	-3.55657423	2.9089314	-1.22263944	2.214659e-01
one_quartile2	-2.84189705	1.5137704	-1.87736338	6.046831e-02
th_quartile2	-1.66019070	1.4114003	-1.17627207	2.394862e-01
min3	-0.53060043	0.1324082	-4.00730855	6.141461e-05
max3	0.73013305	0.1677028	4.35373230	1.338391e-05
mean3	-1.32880086	0.8368872	-1.58778977	1.123339e-01
median3	0.48519334	0.2351768	2.06310043	3.910309e-02
std3	-2.52636409	0.5825632	-4.33663491	1.446806e-05
one_quartile3	-0.30349798	0.2780099	-1.09168031	2.749736e-01
th_quartile3	0.89080198	0.3621878	2.45950284	1.391296e-02
min4	-32.36721292	1443.5419018	-0.02242208	9.821113e-01
max4	1.35419680	0.3466036	3.90704746	9.343081e-05
mean4	-1.69837802	3.1627077	-0.53700127	5.912667e-01
median4	-0.63026694	1.2081333	-0.52168657	6.018886e-01
std4	-5.40486055	2.2409551	-2.41185578	1.587156e-02
one_quartile4	-1.11225120	1.2249194	-0.90801991	3.638677e-01
th_quartile4	1.01477979	0.9572430	1.06010677	2.890960e-01
min5	-0.10517219	0.1613127	-0.65197725	5.144158e-01
max5	0.73206580	0.2077232	3.52423697	4.247042e-04
mean5	-1.78549436	1.0452707	-1.70816449	8.760583e-02
median5	0.44439348	0.2853926	1.55713048	1.194395e-01
std5	-1.16971846	0.6439345	-1.81651764	6.929100e-02
one_quartile5	0.47818274	0.3676334	1.30070552	1.933593e-01
th_quartile5	0.51907458	0.3944179	1.31605229	1.881565e-01
min6	-1.37568382	1.2692798	-1.08383026	2.784401e-01
max6	0.93292705	0.4363998	2.13778071	3.253455e-02
mean6	1.88393113	3.3948089	0.55494468	5.789325e-01
median6	-0.77733517	1.1988025	-0.64842636	5.167092e-01
std6	-6.90882630	2.5269503	-2.73405709	6.255920e-03
one_quartile6	-2.27033501	1.3921067	-1.63086281	1.029193e-01
th_quartile6	0.77666699	1.1249230	0.69041789	4.899314e-01

p values when for all features when l = 17

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	3.15378369	0.9589294	3.28885924	0.0010059432
min1	-0.41541244	0.1582195	-2.62554507	0.0086510355
max1	0.57073083	0.2731196	2.08967399	0.0366470955
mean1	-1.19232341	0.9053031	-1.31704332	0.1878241034
median1	0.20411738	0.2747437	0.74293737	0.4575195969
std1	-2.18397822	0.8360503	-2.61225703	0.0089946602
one_quartile1	-0.16569844	0.2938132	-0.56395855	0.5727823435
th_quartile1	0.75086324	0.4268429	1.75910920	0.0785589623
min2	-2.21753814	1.5658057	-1.41622815	0.1567087175
max2	0.49855251	0.6026720	0.82723683	0.4081028424
mean2	1.36776096	4.0466855	0.33799537	0.7353666797
median2	-0.21303928	1.2770264	-0.16682449	0.8675081513

std2	-4.30500600	3.1576550	-1.36335540	0.1727705311
one_quartile2	-2.37006144	1.5147918	-1.56461198	0.1176739185
th_quartile2	0.07412798	1.3912319	0.05328226	0.9575070131
min3	-0.50570985	0.1305832	-3.87270361	0.0001076347
max3	0.56862034	0.1668100	3.40879062	0.0006525154
mean3	-0.01382535	0.7815411	-0.01768986	0.9858862684
median3	0.24158715	0.2323803	1.03961987	0.2985165409
std3	-1.98143237	0.5318627	-3.72545843	0.0001949606
one_quartile3	-0.57378502	0.2601748	-2.20538274	0.0274272485
th_quartile3	0.23646575	0.3021460	0.78262086	0.4338497899
min4	-3.85015117	3.4948124	-1.10167607	0.2706025254
max4	1.15675564	0.3635767	3.18159977	0.0014646407
mean4	-3.63875957	3.2263204	-1.12783577	0.2593892850
median4	0.60149902	1.2654920	0.47530842	0.6345671608
std4	-2.90794326	2.3533445	-1.23566409	0.2165834525
one_quartile4	-0.15775285	1.2313219	-0.12811666	0.8980566552
th_quartile4	0.67911250	0.9707736	0.69955803	0.4842033620
min5	-0.28804651	0.1463273	-1.96850900	0.0490095014
max5	0.73013713	0.2281708	3.19995858	0.0013744734
mean5	-0.85842709	1.0535662	-0.81478230	0.4151969332
median5	-0.16816026	0.3071936	-0.54740800	0.5840984593
std5	-1.45560288	0.6788067	-2.14435537	0.0320044237
one_quartile5	0.35002727	0.3442412	1.01680811	0.3092447240
th_quartile5	0.51057354	0.3970910	1.28578464	0.1985182328
min6	-1.74189258	1.2991318	-1.34081284	0.1799812261
max6	0.57091512	0.4596862	1.24196717	0.2142486739
mean6	0.73206910	3.2170459	0.22755942	0.8199887730
median6	-0.07254759	1.2168061	-0.05962132	0.9524572374
std6	-4.86755472	2.5904271	-1.87905488	0.0602369998
one_quartile6	-1.70723070	1.3036590	-1.30956843	0.1903418744
th_quartile6	0.87500768	1.0253049	0.85341219	0.3934307653

p values when for all features when l = 18

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	2.78613624	0.9034177	3.08399568	0.0020424056
min1	-0.21019455	0.1329442	-1.58107303	0.1138613415
max1	0.28784558	0.2671138	1.07761405	0.2812060286
mean1	0.02765776	0.8866222	0.03119453	0.9751144034
median1	0.04664678	0.2652142	0.17588339	0.8603855521
std1	-0.77733762	0.7855621	-0.98953044	0.3224036859
one_quartile1	-0.23221947	0.2589497	-0.89677439	0.3698393154
th_quartile1	-0.13105700	0.4238426	-0.30921149	0.7571606532
min2	-2.52926195	1.3254012	-1.90829910	0.0563525696
max2	0.87068563	0.5000189	1.74130548	0.0816300459
mean2	1.74689112	3.2361567	0.53980424	0.5893320400
median2	-1.81663616	1.1014773	-1.64927247	0.0990918267
std2	-5.66719115	2.6950556	-2.10281044	0.0354823429
one_quartile2	-2.26177329	1.2794427	-1.76778000	0.0770976894
th_quartile2	1.02964461	1.1294534	0.91163091	0.3619630469
min3	-0.49866583	0.1201120	-4.15167344	0.0000330053
max3	0.60350006	0.1609498	3.74961668	0.0001771051
mean3	-0.25697481	0.7172710	-0.35826740	0.7201432122
median3	0.16894689	0.2271864	0.74364869	0.4570890390

std3	-1.90886550	0.5211784	-3.66259506	0.0002496731
one_quartile3	-0.37000835	0.2151776	-1.71954898	0.0855144569
th_quartile3	0.32253862	0.2893898	1.11454736	0.2650444371
min4	-4.82808485	2.7822029	-1.73534606	0.0826795284
max4	1.19962363	0.3746075	3.20234828	0.0013631209
mean4	4.00799862	2.6767094	1.49736038	0.1342995115
median4	-2.81492617	1.0866045	-2.59057094	0.0095816869
std4	-6.90342080	2.2938142	-3.00958151	0.0026160787
one_quartile4	-1.70781364	1.0555303	-1.61796746	0.1056696099
th_quartile4	-0.11056864	0.8057500	-0.13722450	0.8908533481
min5	0.04379656	0.1526507	0.28690711	0.7741834490
max5	0.69524107	0.2207096	3.15002691	0.0016325543
mean5	-2.47050193	0.8978573	-2.75155287	0.0059313445
median5	0.75632845	0.2747474	2.75281357	0.0059085532
std5	-1.00545491	0.6243634	-1.61036813	0.1073175145
one_quartile5	0.54028130	0.3002087	1.79968589	0.0719102509
th_quartile5	0.67225214	0.3248124	2.06966296	0.0384839178
min6	-0.85913518	1.1486059	-0.74798080	0.4544717410
max6	0.44295274	0.4131915	1.07202783	0.2837075308
mean6	0.98087913	2.8351463	0.34597125	0.7293643179
median6	-0.34527765	0.9580512	-0.36039582	0.7185511526
std6	-3.13541230	2.2268505	-1.40800305	0.1591301665
one_quartile6	-0.98833875	1.1524864	-0.85757086	0.3911294715
th_quartile6	0.02836561	0.9618938	0.02948934	0.9764743208

p values when for all features when l = 19

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	3.45548547	0.8968469	3.8529266	1.167144e-04
min1	-0.30877975	0.1498441	-2.0606737	3.933418e-02
max1	0.55771328	0.2763215	2.0183491	4.355492e-02
mean1	-1.13837041	0.8765226	-1.2987348	1.940350e-01
median1	-0.26229198	0.2762285	-0.9495473	3.423424e-01
std1	-1.65024206	0.7435097	-2.2195301	2.645069e-02
one_quartile1	0.07773151	0.2602111	0.2987248	7.651500e-01
th_quartile1	0.82888415	0.3960745	2.0927482	3.637164e-02
min2	-3.19965157	1.3510619	-2.3682494	1.787249e-02
max2	0.61588463	0.5190295	1.1866082	2.353822e-01
mean2	4.48804488	3.1780517	1.4122001	1.578911e-01
median2	-0.97763742	1.0443863	-0.9360880	3.492279e-01
std2	-5.50580396	2.6663857	-2.0648940	3.893303e-02
one_quartile2	-3.29233851	1.2675468	-2.5974097	9.392981e-03
th_quartile2	-0.95005319	1.1402310	-0.8332112	4.047256e-01
min3	-0.49805191	0.1220865	-4.0795000	4.513267e-05
max3	0.56033092	0.1544737	3.6273542	2.863404e-04
mean3	-0.64155707	0.7179909	-0.8935449	3.715654e-01
median3	0.14794067	0.2075016	0.7129617	4.758694e-01
std3	-1.98241339	0.5040688	-3.9328227	8.395415e-05
one_quartile3	-0.24113634	0.2309417	-1.0441436	2.964189e-01
th_quartile3	0.61499208	0.3005490	2.0462292	4.073382e-02
min4	-3.53498741	2.2948154	-1.5404235	1.234572e-01
max4	1.53805583	0.3451323	4.4564238	8.333822e-06
mean4	-0.46191756	2.4603731	-0.1877429	8.510782e-01
median4	-0.33519045	0.9951374	-0.3368283	7.362463e-01

std4	-6.57693954	2.0081920	-3.2750551	1.056414e-03
one_quartile4	-2.08048468	0.9956236	-2.0896296	3.665108e-02
th_quartile4	0.98560101	0.7608723	1.2953567	1.951972e-01
min5	-0.33431769	0.1426079	-2.3443135	1.906214e-02
max5	0.53814346	0.2125941	2.5313193	1.136344e-02
mean5	0.33765735	0.9222185	0.3661360	7.142636e-01
median5	0.17642757	0.2788659	0.6326611	5.269550e-01
std5	-1.48169357	0.6376608	-2.3236393	2.014484e-02
one_quartile5	-0.38826934	0.3032181	-1.2804951	2.003711e-01
th_quartile5	-0.04550321	0.3656262	-0.1244528	9.009568e-01
min6	-2.54389906	1.1819625	-2.1522671	3.137633e-02
max6	1.03672516	0.4335977	2.3909837	1.680330e-02
mean6	0.86549868	2.8018034	0.3089077	7.573917e-01
median6	-0.26125155	1.0402582	-0.2511411	8.017050e-01
std6	-6.49851850	2.3910281	-2.7178763	6.570240e-03
one_quartile6	-1.81634010	1.1658443	-1.5579611	1.192425e-01
th_quartile6	0.88235612	0.9656019	0.9137887	3.608279e-01

p values when for all features when l = 20

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	3.15789080	0.8564960	3.6869883	2.269238e-04
min1	-0.59349891	0.2418174	-2.4543270	1.411485e-02
max1	0.86374044	0.3007262	2.8721820	4.076481e-03
mean1	-1.20725992	1.1905338	-1.0140493	3.105592e-01
median1	0.12667870	0.3383544	0.3743965	7.081093e-01
std1	-2.94077313	0.9617952	-3.0575876	2.231264e-03
one_quartile1	-0.34961042	0.3624966	-0.9644516	3.348196e-01
th_quartile1	0.93556506	0.4803269	1.9477672	5.144282e-02
min2	-1.78849141	1.2505777	-1.4301322	1.526791e-01
max2	1.03111895	0.5927190	1.7396422	8.192186e-02
mean2	1.99063618	3.8785456	0.5132430	6.077814e-01
median2	-2.26759035	1.2828202	-1.7676603	7.711772e-02
std2	-6.32748221	2.8506652	-2.2196512	2.644246e-02
one_quartile2	-2.54485520	1.4627267	-1.7398023	8.189374e-02
th_quartile2	1.11168020	1.2218164	0.9098586	3.628971e-01
min3	-0.66568069	0.1354952	-4.9129453	8.971833e-07
max3	0.93422352	0.1808918	5.1645421	2.410282e-07
mean3	-1.64920383	0.8416012	-1.9596026	5.004226e-02
median3	0.53423513	0.2462465	2.1695139	3.004369e-02
std3	-3.23494857	0.5845175	-5.5343916	3.123106e-08
one_quartile3	-0.38563634	0.2405462	-1.6031695	1.088972e-01
th_quartile3	1.18334386	0.3502526	3.3785438	7.287083e-04
min4	-5.05053824	2.2688624	-2.2260222	2.601269e-02
max4	1.58806206	0.3919960	4.0512201	5.095125e-05
mean4	3.07946843	2.7344670	1.1261677	2.600945e-01
median4	-2.12427189	1.0951620	-1.9396874	5.241769e-02
std4	-8.68117526	2.2690371	-3.8259293	1.302797e-04
one_quartile4	-3.02834322	1.1348971	-2.6683856	7.621672e-03
th_quartile4	0.27030495	0.8314504	0.3251005	7.451050e-01
min5	-0.02318920	0.1543870	-0.1502018	8.806054e-01
max5	0.27474047	0.2196353	1.2508939	2.109732e-01
mean5	0.17765522	0.9463956	0.1877177	8.510979e-01
median5	0.03284379	0.3022085	0.1086792	9.134569e-01

std5	0.11113492	0.6540200	0.1699259	8.650684e-01
one_quartile5	0.17308849	0.3080325	0.5619163	5.741730e-01
th_quartile5	-0.36550971	0.3463258	-1.0553928	2.912457e-01
min6	-2.03074430	1.1026779	-1.8416478	6.552668e-02
max6	0.41482600	0.4417317	0.9390904	3.476843e-01
mean6	6.57153319	3.2833001	2.0015025	4.533827e-02
median6	-0.89868301	1.1036720	-0.8142664	4.154924e-01
std6	-5.67366901	2.3259591	-2.4392815	1.471650e-02
one_quartile6	-3.03514166	1.3062496	-2.3235541	2.014940e-02
th_quartile6	-1.52913766	1.0653351	-1.4353584	1.511850e-01

In [39]:

```
#index_2=[0,1,2,7,8,9,35,36,37]
for i in range(20):
    i=i+1
    createVar['pse_9'+str(i)] = createVar['dataset_'+str(i)][:,index_2]
    createVar['pse_new_dataset_'+str(i)]=np.column_stack((createVar['pse_9'+str(i)],createVar['y_'+str(i)]))
    createVar['pse_df_bi_'+str(i)] = pd.DataFrame(createVar['pse_new_dataset_'+str(i)],
                                                    columns = ['min1','max1','mean1','min2','max2','mean2',
                                                                'min6','max6','mean6','label'])
```

In [40]:

```
pse_acc_9 = list()
for i in range(20):
    i=i+1
    createVar['pse_clf_'+str(i)] = LogisticRegression(random_state = 0)
    createVar['pse_clf_'+str(i)].fit( createVar['pse_9'+str(i)],createVar['y_'+str(i)].ravel())
    createVar['pse_y_pred_'+str(i)]= createVar['pse_clf_'+str(i)].predict(createVar['pse_9'+str(i)])
    createVar['pse_test_acc_'+str(i)]=accuracy_score(createVar['y_'+str(i)],createVar['pse_y_pred_'+str(i)])
    pse_acc_9.append(createVar['pse_test_acc_'+str(i)])
```

In [41]:

```
for i in range (20):
    i=i+1
    print("use the selected 9 features in d)i, the predicted class for training set when l = "+str(i)+"is:")
    print( createVar['pse_y_pred_'+str(i)])
    print( "test accuracy when l = "+str(i)+"is:")
    print( createVar['pse_test_acc_'+str(i)])
```

use the selected 9 features in d)i, the predicted class for training set when l = 1is:

[illegible]

[illegible]

In [42]:

```
print("Using the selected 9 features, the accuracy is max when l = "+str(pse_acc_9 .index(max(pse_acc_9 ))+1))
print("which is " +str(max(pse_acc_9 )))
```

Using the selected 9 features, the accuracy is max when l = 1
which is 0.8840579710144928

In [44]:

```
from sklearn.model_selection import StratifiedKFold
from sklearn.metrics import f1_score
```

In [601]:

```
import warnings
warnings.filterwarnings('ignore')
```

In [602]:

```
#assuem select 10 features, use cv to determine the best l with best 10 features
score_report = list()
for l in range(20):
    l=l+1
    train_X = createVar['df_bi_'+str(l)].iloc[:,0:-1]
    train_Y = createVar['df_bi_'+str(l)]['label']
    model=LogisticRegression()
    cv=StratifiedKFold(n_splits=5,shuffle=False)
    scorelist = list()
    k=0
    for train_id, cv_id in cv.split(train_X,train_Y):
        k=k+1
        createVar['train_id_'+str(l)+'_'+str(k)]=train_id
        x_train_k, X_cv = train_X.loc[train_id], train_X.loc[cv_id]
        y_train_k, y_cv = train_Y.loc[train_id], train_Y.loc[cv_id]
        rfe=RFE(model,10)
        rfe=rfe.fit(x_train_k,y_train_k)
        createVar['sf_list_'+str(l)+'_'+str(k)]=list()
        for i in range(len(rfe.support_)):
            if rfe.support_[i]==True:
                createVar['sf_list_'+str(l)+'_'+str(k)].append(i)
        y_predict=model.fit(x_train_k[x_train_k.columns[ createVar['sf_list_'+str(l)+'_'+str(k)]]],
                                y_train_k).predict(X_cv[X_cv.columns[ createVar['sf_list_'+str(l)+'_'+str(k)]]])
        scorelist.append(f1_score(y_cv, y_predict,average = 'weighted'))
    #print(l,scorelist)
    score_report.append(scorelist)
```


In [603]:

```
idx=0
mx=0
for i in range(20):
    a = np.mean(score_report[i])
    if mx < a :
        mx=a
        idx=i
    else:
        continue
```

In [604]:

```
idx2=0
mx=0
for i in range(5):
    a=score_report[idx][i]
    if mx < a :
        mx=a
        idx2=i
    else:
        continue
```

In [606]:

```
print("by using 5-folds, the accuracy reach max when l =" +str(idx+1))
```

by using 5-folds, the accuracy reach max when l =1

In [639]:

```
score_report[0]
```

Out[639]:

```
[0.9180952380952382,
 0.6938775510204083,
 0.8571428571428571,
 0.9180952380952382,
 0.8776223776223776]
```

In [608]:

```
for i in range(5):
    i=i+1
    print(createVar['signif_list_'+str(1)+'_'+str(i)])
```

```
[6, 8, 14, 15, 18, 20, 29, 32, 33, 34]
[0, 3, 6, 8, 14, 15, 19, 20, 29, 33]
[6, 8, 14, 19, 20, 22, 28, 29, 31, 33]
[6, 14, 15, 18, 19, 20, 28, 29, 33, 36]
[1, 6, 8, 14, 15, 19, 20, 28, 29, 33]
```

In [609]:

```
idx2=idx2+1
idx=idx+1
```

In [610]:

```
best_features=createVar['signif_list_'+str(idx)+'_'+str(idx2)]
```

In [611]:

```
best_features
```

Out[611]:

```
[6, 8, 14, 15, 18, 20, 29, 32, 33, 34]
```

In [54]:

```
col=['min1','max1','mean1','median1','std1','one_quartile1','th_quartile1',
                                          'min2','max2','mean2','medi
an2','std2','one_quartile2','th_quartile2',
                                          'min3','max3','mean3','medi
an3','std3','one_quartile3','th_quartile3',
                                          'min4','max4','mean4','medi
an4','std4','one_quartile4','th_quartile4',
                                          'min5','max5','mean5','medi
an5','std5','one_quartile5','th_quartile5',
                                          'min6','max6','mean6','medi
an6','std6','one_quartile6','th_quartile6',
                                          ]
```

In [614]:

```
print("the best features are:")
for i in range(10):
    print(col[best_features[i]])
```

the best features are:

```
th_quartile1
max2
min3
max3
std3
th_quartile3
max5
std5
one_quartile5
th_quartile5
```

In [619]:

```
# extract best_features from the best 1
```

```
df_10 = dataset_1[:,best_features]
df_new_dataset_10 = np.column_stack((df_10 ,y_1))
df_b_10 = pd.DataFrame(df_new_dataset_10,columns = ['th_quartile1','max2','min3'
, 'max3','std3','th_quartile3',
                                                    'max5','std5','one_quartile5'
, 'th_quartile5','label'])

acc_10 = list()

clf = LogisticRegression(random_state = 0)
clf.fit(df_10,y_1.ravel())
y_pred_10= clf.predict(df_10)
acc_10 =accuracy_score(y_1,y_pred_10)
```

In [620]:

```
print("the accuracy of the moldel when train acuuracy is maximum is: "+str(acc_10))
```

the accuracy of the moldel when train acuuracy is maximum is: 0.9420
289855072463

```
print("the predicted classification is:")
print(y_pred_10)
```

In [622]:

Apparently, the accuracy calculated by the right way is bigger than which calculated by the wrong way. Thus we can't determine how many features and what features before using cross validation to determine the best 1, we should use cross validation to find the best features.

```
#d)iv every testdata need a empty array to store 42-feartures, n pieces n*42
for i in range(20):
    i=i+1
    createVar[ 'dataset2_'+str(i) ]=np.empty(shape=[0, 42])
```

```
#split every test data(from 1 to 19) into n pieces, save into q1 to q19, each qi
have n dataframes. q are tuples
def finaldata2(n):
    for i in range(num_test):
        i=i+1
        createVar['q'+str(i)]= splitdata(createVar['testdata'+str(i)],n)

    for i in range(num_test):
        i=i+1
        for j in range(n):
            j=j+1
            createVar['dataset2_'+str(n)] = np.concatenate((createVar['dataset2_
'+str(n)],

                                                                    give7features(create
Var['q'+str(i)][j-1])),axis=0)
```

In [62]:

```
for i in range(20):  
    i=i+1  
    finaldata2(i)
```

In [625]:

```
t_1= np.zeros(shape=(1,19))  
for i in range(0,4):  
    t_1[0,i]=1  
t_1 = t_1.T
```

In [624]:

```
from sklearn.metrics import confusion_matrix  
print("the confusion matrix for train data:")  
confusion_matrix(y_1, y_pred_10)
```

the confusion matrix for train data:

Out[624]:

```
array([[59,  1],  
       [ 3,  6]])
```

In [627]:

```
print("the confusion matrix for test data:")  
confusion_matrix(t_1, clf.fit(df_10,y_1.ravel()).predict(dataset2_1[:,best_features]))
```

the confusion matrix for test data:

Out[627]:

```
array([[15,  0],  
       [ 0,  4]])
```

In [628]:

```
from ggplot import *  
from sklearn import metrics
```

In [629]:

```
probs = clf.predict_proba(df_10)  
preds = probs[:,1]  
fpr, tpr, threshold = metrics.roc_curve(y_1, preds)  
roc_auc = metrics.auc(fpr, tpr)
```

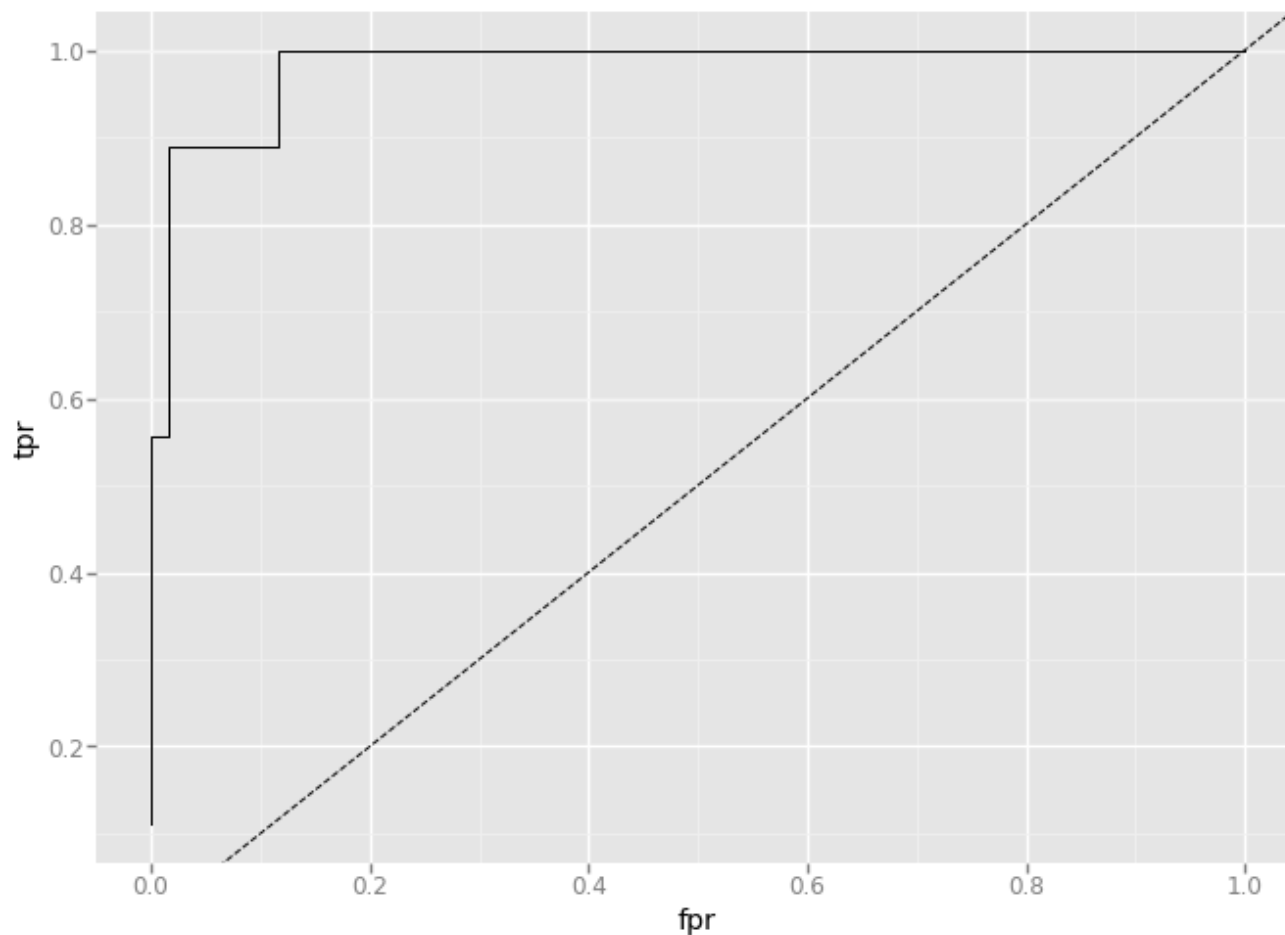
In [630]:

```
df = pd.DataFrame(dict(fpr = fpr, tpr = tpr))
```

In [635]:

```
print("ROC for train data:")  
ggplot(df, aes(x = 'fpr', y = 'tpr')) + geom_line() + geom_abline(linetype = 'dashed')
```

ROC for train data:



Out[635]:

<ggplot: (7024630571)>

In [636]:

```
from sklearn.metrics import roc_auc_score  
auc=roc_auc_score(y_1, clf.decision_function(df_10))  
print("auc for train data is "+str(auc))
```

auc for train data is 0.9814814814814814

In [70]:

```
df_2_dataset_10 = np.column_stack((df_10 ,y_1))
df_b2_10 = pd.DataFrame(df_2_dataset_10,columns = ['th_quartile1','max2','min3',
'max3','std3',
'th_quartile3','max5','std5',
'one_quartile5','th_quartile5','label'])
```

In [71]:

```
print("Refit with pruned set of features:")
```

```
import statsmodels.api as sm
y=df_b_10['label']
x=pd.DataFrame(df_b_10,columns=['th_quartile1','max2','min3','max3','std3','th_q
uartile3',
'max5','std5','one_quartile5','th_quartile5'])

logit_model=sm.Logit(y,x)
result=logit_model.fit()
print("summary",result.summary2())
```

Refit with pruned set of features:

Optimization terminated successfully.

Current function value: 0.097756

Iterations 13

```
summary                                Results: Logit
=====
Model:                                Logit                No. Iterations:    13.0000
Dependent Variable: label              Pseudo R-squared:  0.748
Date: 2018-07-01 12:56 AIC:              33.4903
No. Observations: 69                  BIC:              55.8314
Df Model: 9                          Log-Likelihood:   -6.7452
Df Residuals: 59                     LL-Null:         -26.718
Converged: 1.0000                     Scale:           1.0000
-----
              Coef.  Std.Err.  z      P>|z|    [0.025  0.975]
-----
th_quartile1   -0.9523    0.6642 -1.4337  0.1516  -2.2541  0.3495
max2           -1.2553    1.1157 -1.1252  0.2605  -3.4420  0.9313
min3           -0.6225    0.4145 -1.5017  0.1332  -1.4350  0.1900
max3            1.7732    1.2262  1.4461  0.1482  -0.6301  4.1766
std3           -0.2923    1.3474 -0.2169  0.8283  -2.9332  2.3486
th_quartile3   -2.5766    1.9900 -1.2948  0.1954  -6.4769  1.3237
max5            0.9950    0.5591  1.7795  0.0752  -0.1009  2.0909
std5            0.9397    4.5550  0.2063  0.8365  -7.9878  9.8673
one_quartile5   0.7845    2.3130  0.3391  0.7345  -3.7490  5.3180
th_quartile5   -0.1483    1.8827 -0.0787  0.9372  -3.8383  3.5418
=====
```

In [637]:

```
#d)v
x_test = dataset2_1[:,best_features]
clf.fit(df_10,y_1.ravel())
y_pr=clf.predict(x_test)
test_acc=accuracy_score(t_1,y_pr)
print("the predicted result in test set are " ,y_pr)
```

```
the predicted result in test set are [1. 1. 1. 1. 0. 0. 0. 0. 0. 0.
0. 0. 0. 0. 0. 0. 0. 0. 0.]
```

In [641]:

```
print("test accuracy is: ",test_acc)
print("test accuracy is bigger than the max cross validation accuracy which is "
+str(max(score_report[0])))
```

```
test accuracy is: 1.0
test accuracy is bigger than the max cross validation accuracy which
is 0.9180952380952382
```

In [74]:

```
#d)vi
print("if i choose 10 features, no well-separated occurred")
```

```
if i choose 10 features, no well-separated occurred
```

In [643]:

```
#d)vii
print("the confusion matrix from train data:")
print(confusion_matrix(y_1, y_pred_10))
print("it's imbalanced due to the class'0' is even more than 5 times of class'1'
")
```

```
the confusion matrix from train data:
[[59  1]
 [ 3  6]]
it's imbalanced due to the class'0' is even more than 5 times of cla
ss'1'
```

In [644]:

```
from sklearn.model_selection import train_test_split
from sklearn.metrics import recall_score
from imblearn.over_sampling import SMOTE
```

In [645]:

```
xt, xv, yt,yv =train_test_split(df_10,y_1,test_size =.1,random_state=12)
```



```
sm=SMOTE(random_state=12,ratio=1.0)
xt_r,yt_r=sm.fit_sample(xt,yt.ravel())
```

```
log2=LogisticRegression()  
log2.fit(xt_r,yt_r)
```

```
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)
```

```
print("test accuracy when applying SMOTE is: ",accuracy_score(y_1,log2.predict(d
f_10)))
```

In [649]:

```
print("the confusion matrix from train data after SMOTE:")
confusion_matrix(y_1, log2.predict(df_10))
```

Out[649]:

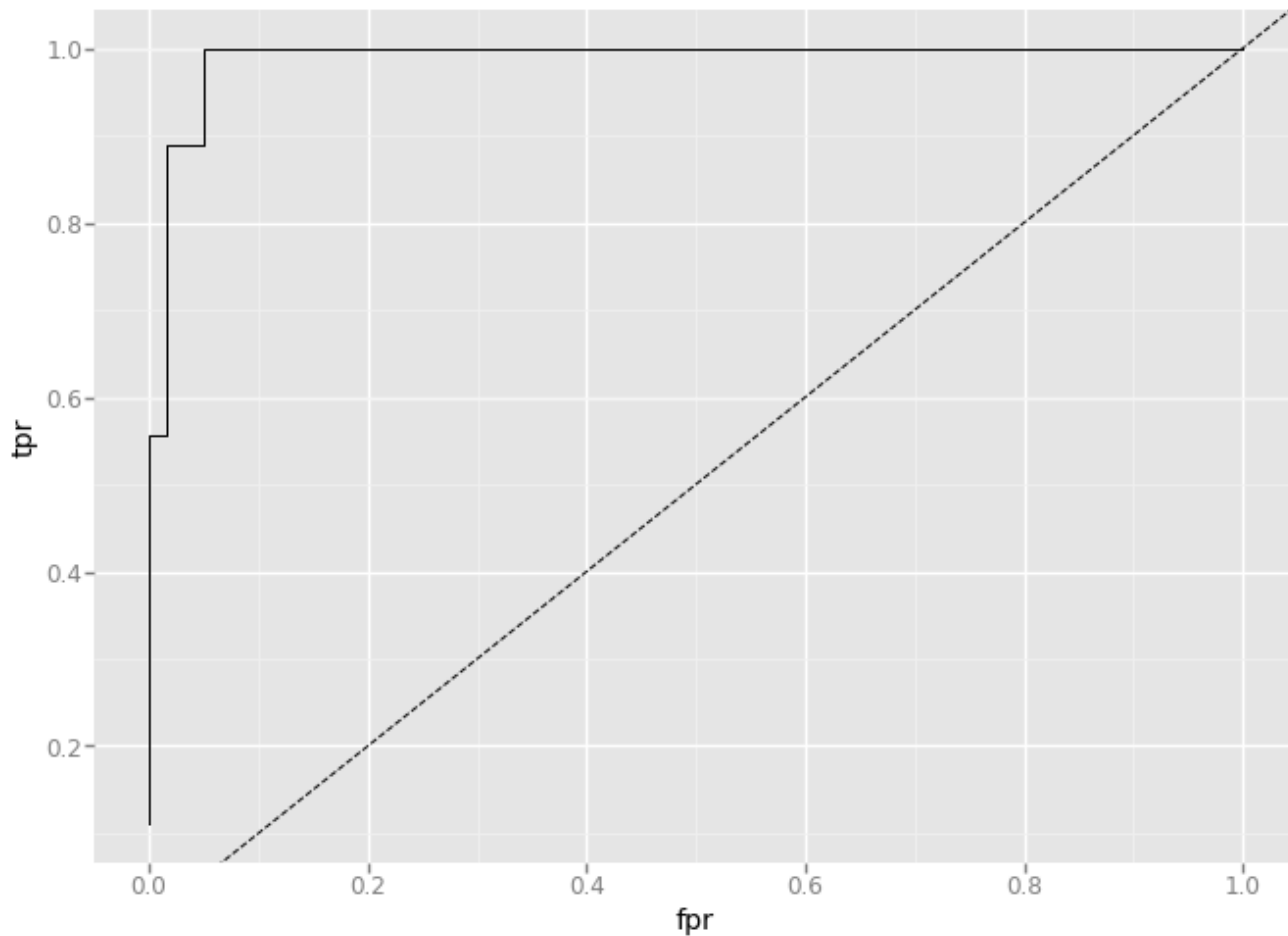
```
array([[57, 3],
       [ 0, 9]])
```

```
log2.predict(dataset2_1[:,best_features])
```

[illegible]

In [651]:

```
probs = log2.predict_proba(dataset_1[:,best_features])
preds = probs[:,1]
fpr, tpr, threshold = metrics.roc_curve(y_1, preds)
roc_auc = metrics.auc(fpr, tpr)
df = pd.DataFrame(dict(fpr = fpr, tpr = tpr))
ggplot(df, aes(x = 'fpr', y = 'tpr')) + geom_line() + geom_abline(linetype = 'dashed')
```



Out[651]:

<ggplot: (7565875895)>

In [653]:

```
auc2=roc_auc_score(y_1, log2.decision_function(df_10))
print("auc after SMOTE is "+str(auc2))
```

auc after SMOTE is 0.9888888888888888

In [95]:

```
#e)i
from sklearn import preprocessing
import numpy as np
for i in range(20):
    i=i+1
    createVar[ 'dataset_norm_'+str(i)] = preprocessing.scale(createVar[ 'dataset_'
+str(i)])
```

In [160]:

```
for i in range(20):
    i=i+1
    createVar[ 'dataset2_norm_'+str(i)] = preprocessing.scale(createVar[ 'dataset2
_'+str(i)])
```

In [189]:

```
for i in range(20):
    i=i+1
    createVar[ 't_'+str(i)] = np.zeros(shape=(1,19*i))
for i in range(20):
    i=i+1
    for j in range(0,4*i):
        createVar[ 't_'+str(i)][0,j]=1
for i in range(20):
    i=i+1
    createVar[ 't_'+str(i)] = createVar[ 't_'+str(i)].T
```

In [654]:

```
from sklearn.cross_validation import train_test_split
from sklearn.cross_validation import train_test_split,KFold
from sklearn.linear_model import LinearRegression, Lasso, Ridge
```

In [289]:

```
from sklearn.linear_model import LogisticRegressionCV
from sklearn.model_selection import cross_validate
from sklearn.cross_validation import cross_val_score
from sklearn import model_selection
```

In [655]:

```
score_report = list()
for l in range(20):
    l=l+1
    train_X = createVar['dataset_norm_'+str(l)]
    train_Y = createVar['y_'+str(l)]
    model=LogisticRegressionCV(penalty='l1', solver='liblinear',max_iter=200)
    scores = model_selection.cross_val_score(model, train_X,train_Y.ravel(), cv=
5)
    score_report.append(np.mean(scores))
```

In [657]:

```
score_report
```

Out[657]:

```
[0.8703296703296702,
 0.8341269841269842,
 0.8696864111498257,
 0.855064935064935,
 0.8376811594202899,
 0.8382603585071996,
 0.838659793814433,
 0.8514004914004915,
 0.8340903225806452,
 0.8565217391304347,
 0.8550975949808295,
 0.8527053669222344,
 0.8561638733705772,
 0.8509160835425458,
 0.8492753623188406,
 0.852373508844097,
 0.855100927441353,
 0.8478138359891177,
 0.8504832670594723,
 0.8550724637681159]
```

In [658]:

```
print("Using L1-penalized logistic regression, the best l is: ",score_report.ind
ex(max(score_report))+1)
```

Using L1-penalized logistic regression, the best l is: 1

In [659]:

```
train_X = createVar['dataset_'+str(score_report.index(max(score_report))+1)]
train_Y = createVar['y_'+str(score_report.index(max(score_report))+1)]
model=LogisticRegressionCV(penalty='l1', solver='liblinear')
y_pred=model.fit(train_X ,train_Y.ravel()).predict(createVar['dataset2_'+
                                                             str(score_report.in
dex(max(score_report))+1)])
print("The accuracy when use L1 penalty to classify 2 classes is :",
      accuracy_score( createVar['t_'+str(score_report.index(max(score_report))+1
)], y_pred))
```

The accuracy when use L1 penalty to classify 2 classes is : 1.0

In [660]:

```
print("Compared to p-value selection, L1 perform better. Because in previous met
hod, it is almost impossible to do cross validation for all possible combination
s of different amount of features, however, using L1, it can somehow check all p
ossibilities and give the same result as p-value do.")
```

Compared to p-value selection, L1 perform better. Because in previous method, it is almost impossible to do cross validation for all possible combinations of different amount of features, however, using L1, it can somehow check all possibilities and give the same result as p-value do.

In [370]:

```
for i in range(69):
    i=i+1
    createVar['ym_'+str(i)]= np.zeros(shape=(1,69*i))
for i in range(20):
    i=i+1
    for j in range(0,5*i):
        createVar['ym_'+str(i)][0,j]=1
    for j in range(5*i,9*i):
        createVar['ym_'+str(i)][0,j]=2
    for j in range(9*i,21*i):
        createVar['ym_'+str(i)][0,j]=3
    for j in range(21*i,33*i):
        createVar['ym_'+str(i)][0,j]=4
    for j in range(33*i,45*i):
        createVar['ym_'+str(i)][0,j]=5
    for j in range(45*i,57*i):
        createVar['ym_'+str(i)][0,j]=6
    for j in range(57*i,69*i):
        createVar['ym_'+str(i)][0,j]=7
for i in range(20):
    i=i+1
    createVar['ym_'+str(i)] = createVar['ym_'+str(i)].T
```

In [371]:

```
for i in range(20):
    i=i+1
    createVar['tm_'+str(i)]= np.zeros(shape=(1,19*i))
for i in range(20):
    i=i+1
    for j in range(0,2*i):
        createVar['tm_'+str(i)][0,j]=1
    for j in range(2*i,4*i):
        createVar['tm_'+str(i)][0,j]=2
    for j in range(4*i,7*i):
        createVar['tm_'+str(i)][0,j]=3
    for j in range(7*i,10*i):
        createVar['tm_'+str(i)][0,j]=4
    for j in range(10*i,13*i):
        createVar['tm_'+str(i)][0,j]=5
    for j in range(13*i,16*i):
        createVar['tm_'+str(i)][0,j]=6
    for j in range(16*i,19*i):
        createVar['tm_'+str(i)][0,j]=7
for i in range(20):
    i=i+1
    createVar['tm_'+str(i)] = createVar['tm_'+str(i)].T
```

In [530]:

```
score_report2 = list()
for l in range(20):
    l=l+1
    train_X = createVar['dataset_norm_'+str(l)]
    train_Y = createVar['ym_'+str(l)]
    model2=LogisticRegressionCV(penalty='l1', solver='saga',multi_class='multino
mial')
    scores = model_selection.cross_val_score(model, train_X,train_Y.ravel(), cv=
4)
    score_report2.append(np.mean(scores))
    print (l)
```

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20

In [661]:

```
score_report2
```

Out[661]:

```
[0.5081699346405228,  
 0.49264705882352944,  
 0.4686085972850679,  
 0.4891304347826087,  
 0.5333132852178563,  
 0.475658140403286,  
 0.4223829201101928,  
 0.5072463768115941,  
 0.47336641852770883,  
 0.4825077295335394,  
 0.4545182400445559,  
 0.4070048309178744,  
 0.40251984126984125,  
 0.4202573642879188,  
 0.4280177187153932,  
 0.4003623188405797,  
 0.4058415174943698,  
 0.4266958821698994,  
 0.4698198702170508,  
 0.40072463768115946]
```

In [662]:

```
print("Using L1-penalized logistic regression to classifiy 6 classes, the best l  
is: ",score_report2.index(max(score_report2))+1)
```

```
Using L1-penalized logistic regression to classifiy 6 classes, the b  
est l is: 5
```


In [683]:

```
train_X = createVar['dataset_'+str(score_report2.index(max(score_report2))+1)]
train_Y = createVar['ym_'+str(score_report2.index(max(score_report2))+1)]

model2=LogisticRegressionCV(penalty='l1', solver='saga',multi_class='multinomial')

y_true= createVar['tm_'+str(score_report2.index(max(score_report2))+1)]
y_pred=model2.fit(train_X ,train_Y.ravel()).predict(createVar['dataset2_'+str(score_report2.index(max(score_report2))+1)])
y_score=model2.predict_proba(createVar['dataset2_'+str(score_report2.index(max(score_report2))+1)]))

print("The accuracy when use L1 penalty to classify 6 classes is :",accuracy_score(y_true, y_pred))

from sklearn.metrics import classification_report
print ("classification_report(left: labels):")
print (confusion_matrix(y_true,y_pred))
```

The accuracy when use L1 penalty to classify 6 classes is : 0.7473684210526316

classification_report(left: labels):

```
[[ 6  1  3  0  0  0  0]
 [ 1  3  2  0  3  0  1]
 [ 0  0 15  0  0  0  0]
 [ 0  0  0 12  1  2  0]
 [ 0  0  0  2 11  2  0]
 [ 0  0  0  2  4  9  0]
 [ 0  0  0  0  0  0 15]]
```

In [664]:

```
n_classes=7
from scipy import interp
from sklearn.metrics import roc_curve, auc
```

In [701]:

```
from sklearn.preprocessing import label_binarize
y = label_binarize(y_true, classes=[1,2,3,4,5,6,7])
fpr["micro"], tpr["micro"], _ = roc_curve(y.ravel(), y_score.ravel())
roc_auc["micro"] = auc(fpr["micro"], tpr["micro"])

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])

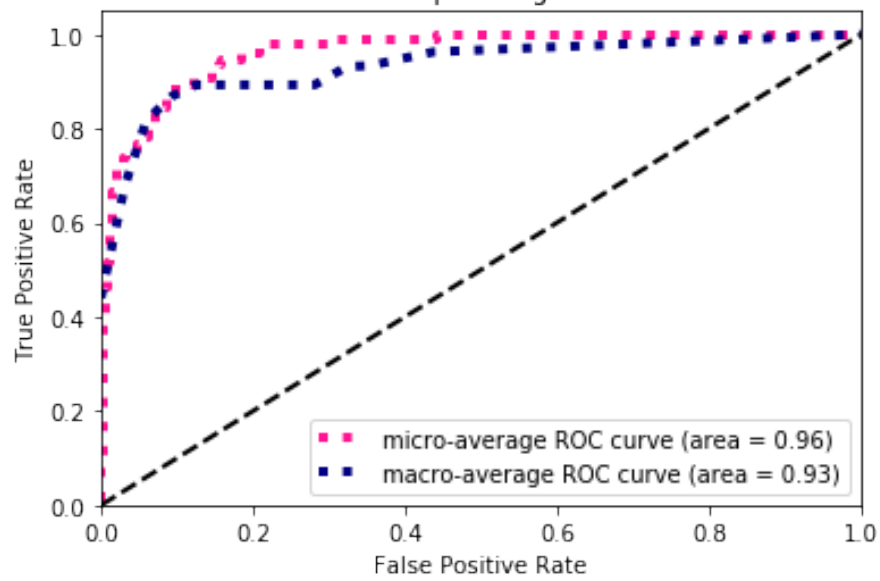
# Finally average it and compute AUC
mean_tpr /= n_classes

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)
plt.plot([0, 1], [0, 1], 'k--', lw=lw)
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()
```

Some extension of Receiver operating characteristic to multi-class



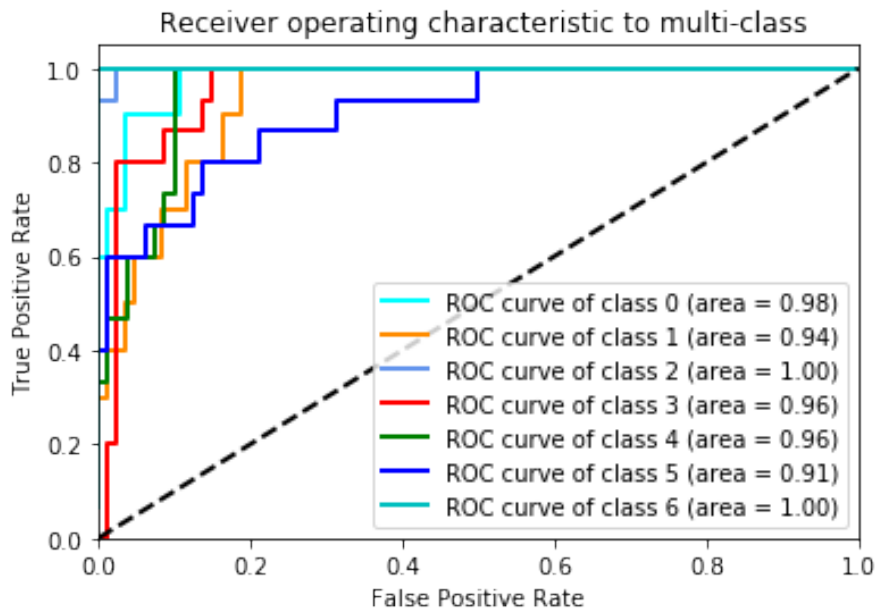
In [685]:

```
from sklearn.metrics import roc_curve, auc
from itertools import cycle
import matplotlib.pyplot as plt

fpr = dict()
tpr = dict()
roc_auc = dict()
for i in range(7):
    fpr[i], tpr[i], _ = roc_curve(y[:, i], y_score[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

lw=2
colors = cycle(['aqua', 'darkorange', 'cornflowerblue', 'r', 'g', 'b', 'c'])
for i, color in zip(range(7), 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--', lw=lw)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title(' Receiver operating characteristic to multi-class')
plt.legend(loc="lower right")
plt.show()
```



In [686]:

```
score_report3 = list()
from sklearn.naive_bayes import GaussianNB
for l in range(20):
    l=l+1
    train_X = createVar['dataset_norm_'+str(l)]
    train_Y = createVar['ym_'+str(l)]
    gnb = GaussianNB()
    scores = model_selection.cross_val_score(gnb , train_X,train_Y.ravel(), cv=4
)
    score_report3.append(np.mean(scores))
```

In [687]:

```
score_report3
```

Out[687]:

```
[0.6086601307189543,
 0.5802521008403362,
 0.5462858220211162,
 0.5652173913043479,
 0.5853047313552526,
 0.5553584764749813,
 0.5630337465564739,
 0.5489130434782608,
 0.5153122415219189,
 0.5200631805350182,
 0.5559245335561125,
 0.5289855072463768,
 0.5227777777777778,
 0.4999142690579884,
 0.526499506150669,
 0.5181159420289855,
 0.4969439994427805,
 0.51202676070947,
 0.5369280040277468,
 0.5130434782608696]
```

In [688]:

```
print("Using Gaussian Naive Bayes to classifiy 6 classes, the best l is: ",score_
report3.index(max(score_report3))+1)
```

Using Gaussian Naive Bayes to classifiy 6 classes, the best l is: 1

In [689]:

```
train_X = createVar['dataset_'+str(score_report3.index(max(score_report3))+1)]
train_Y = createVar['ym_'+str(score_report3.index(max(score_report3))+1)]
gnb = GaussianNB()
y_true3=createVar['tm_'+str(score_report3.index(max(score_report3))+1)]
y_pred3=gnb.fit(train_X ,train_Y.ravel()).predict(createVar['dataset2_'+str(score_report3.index(max(score_report3))+1)])

y_score3=gnb.predict_proba(createVar['dataset2_'+str(score_report3.index(max(score_report3))+1)])

print("The accuracy when use Gaussian Naive Bayes'to classify 6 classes is :",accuracy_score(y_true3, y_pred3))
```

The accuracy when use Gaussian Naive Bayes'to classify 6 classes is :
0.8947368421052632

In [690]:

```
print ("classification_report(left: labels):")
print (confusion_matrix(y_true3,y_pred3))
```

```
classification_report(left: labels):
[[2 0 0 0 0 0 0]
 [0 1 0 1 0 0 0]
 [0 0 3 0 0 0 0]
 [0 0 0 3 0 0 0]
 [0 0 0 0 2 1 0]
 [0 0 0 0 0 3 0]
 [0 0 0 0 0 0 3]]
```

In [691]:

```
from sklearn.preprocessing import label_binarize
y3 = label_binarize(y_true3, classes=[1,2,3,4,5,6,7])
fpr["micro"], tpr["micro"], _ = roc_curve(y3.ravel(), y_score3.ravel())
roc_auc["micro"] = auc(fpr["micro"], tpr["micro"])

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])

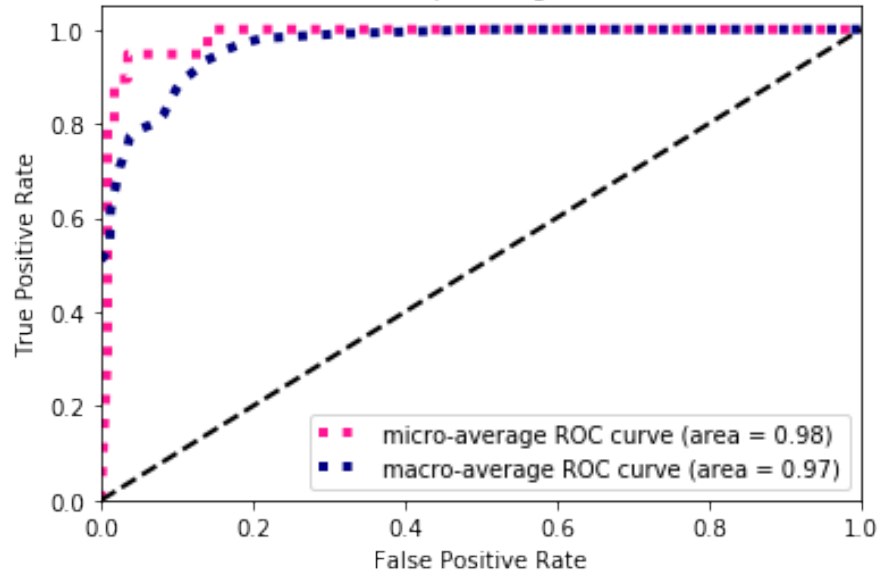
# Finally average it and compute AUC
mean_tpr /= n_classes

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)
plt.plot([0, 1], [0, 1], 'k--', lw=lw)
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()
```

Some extension of Receiver operating characteristic to multi-class



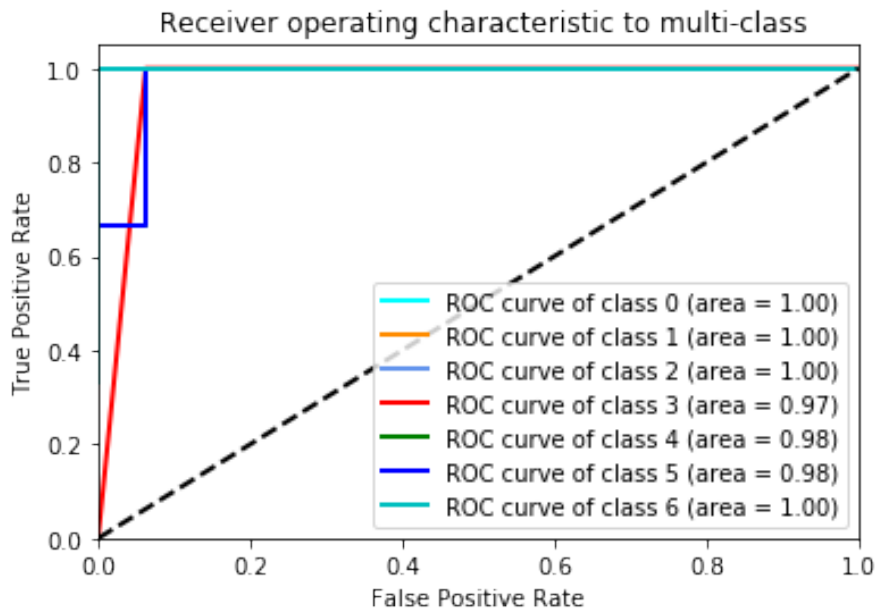
In [692]:

```
from sklearn.preprocessing import label_binarize
y3 = label_binarize(y_true3, classes=[1,2,3,4,5,6,7])

from sklearn.metrics import roc_curve, auc
from itertools import cycle
import matplotlib.pyplot as plt
fpr = dict()
tpr = dict()
roc_auc = dict()
for i in range(7):
    fpr[i], tpr[i], _ = roc_curve(y3[:, i], y_score3[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

lw=2
colors = cycle(['aqua', 'darkorange', 'cornflowerblue', 'r', 'g', 'b', 'c'])
for i, color in zip(range(7), 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--', lw=lw)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title(' Receiver operating characteristic to multi-class')
plt.legend(loc="lower right")
plt.show()
```



In [693]:

```
from sklearn.naive_bayes import MultinomialNB
score_report4 = list()
for l in range(20):
    l=l+1
    train_X = createVar['dataset_'+str(l)]
    train_Y = createVar['ym_'+str(l)]
    mnb = MultinomialNB()
    #y_pred = gnb.fit(createVar['dataset_norm_'+str(l)], createVar['ym_'+str(i)])
    ).predict(createVar['dataset_norm_'+str(l)])
    scores = model_selection.cross_val_score(mnb , train_X,train_Y.ravel(), cv=5
)
    score_report4.append(np.mean(scores))
```

In [694]:

```
score_report4
```

Out[694]:

```
[0.4639928698752228,
 0.47431998286571,
 0.46007423117709445,
 0.47277444273814506,
 0.4608695652173913,
 0.4592728969279357,
 0.47116329274874447,
 0.4569510824237589,
 0.46276147299769355,
 0.4666666666666667,
 0.4691318467200693,
 0.45013696322090535,
 0.46306967820464884,
 0.4556291828472279,
 0.44734299516908216,
 0.4576096892822731,
 0.45584753602282885,
 0.45605043255261013,
 0.46481895887556257,
 0.455072463768116]
```

In [695]:

```
print("Using multinomial Naive Bayes to classifiy 6 classes, the best l is: ",s
core_report4.index(max(score_report4))+1)
```

Using multinomial Naive Bayes to classifiy 6 classes, the best l is
: 2

In [696]:

```
train_X = createVar['dataset_'+str(score_report4.index(max(score_report4))+1)]
train_Y = createVar['ym_'+str(score_report4.index(max(score_report4))+1)]
mnb = MultinomialNB()
y_true4=createVar['tm_'+str(score_report4.index(max(score_report4))+1)]
y_pred4=mnb.fit(train_X ,train_Y.ravel()).predict(createVar['dataset2_'+str(score_report4.index(max(score_report4))+1)])
y_score4=gnb.predict_proba(createVar['dataset2_'+str(score_report4.index(max(score_report4))+1)]))

print("The accuracy when use Gaussian Naive Bayes multinomial to classify 6 classes is :",accuracy_score(y_true4, y_pred4))
```

The accuracy when use Gaussian Naive Bayes multinomial to classify 6 classes is : 0.7105263157894737

In [697]:

```
print ("classification_report(left: labels):")
print (confusion_matrix(y_true4,y_pred4))
```

```
classification_report(left: labels):
[[4 0 0 0 0 0 0]
 [2 1 1 0 0 0 0]
 [0 0 5 0 0 0 1]
 [0 0 0 2 1 3 0]
 [0 0 0 1 4 1 0]
 [0 0 0 1 0 5 0]
 [0 0 0 0 0 0 6]]
```

In [698]:

```
from sklearn.preprocessing import label_binarize
y4= label_binarize(y_true4, classes=[1,2,3,4,5,6,7])
fpr["micro"], tpr["micro"], _ = roc_curve(y4.ravel(), y_score4.ravel())
roc_auc["micro"] = auc(fpr["micro"], tpr["micro"])

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])

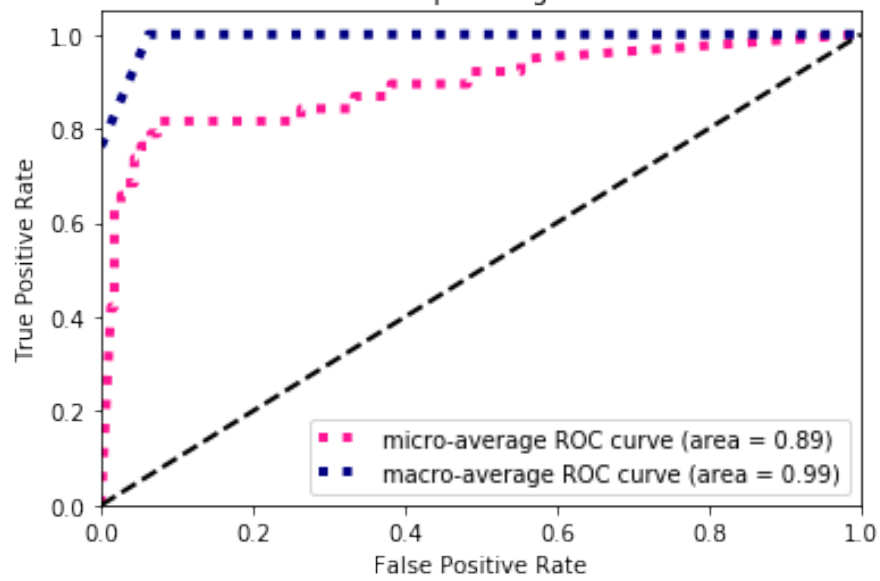
# Finally average it and compute AUC
mean_tpr /= n_classes

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)
plt.plot([0, 1], [0, 1], 'k--', lw=lw)
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()
```

Some extension of Receiver operating characteristic to multi-class



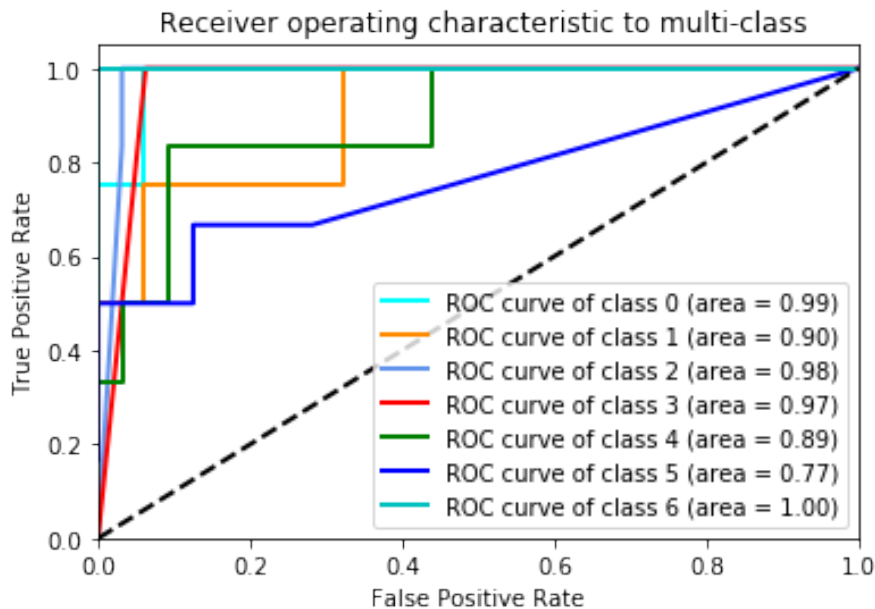
In [699]:

```
from sklearn.preprocessing import label_binarize
y4 = label_binarize(y_true4, classes=[1,2,3,4,5,6,7])

from sklearn.metrics import roc_curve, auc
from itertools import cycle
import matplotlib.pyplot as plt
fpr = dict()
tpr = dict()
roc_auc = dict()
for i in range(7):
    fpr[i], tpr[i], _ = roc_curve(y4[:, i], y_score4[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

lw=2
colors = cycle(['aqua', 'darkorange', 'cornflowerblue', 'r', 'g', 'b', 'c'])
for i, color in zip(range(7), 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--', lw=lw)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title(' Receiver operating characteristic to multi-class')
plt.legend(loc="lower right")
plt.show()
```



In [704]:

```
print("Based on the data, using Gaussian Naive Bayes is the best way in this prob  
lem.")  
print("because the test accuracy is the highest and also computational friendly"  
)
```

Based on the data, using Gaussian Naive Bayes is the best way in this
problem.

because the test accuracy is the highest and also computational frie
ndly