EE559 HW6

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1 1. Multi-class and Multi-Label Classification Using Support Vector Machines

2 Name:Yuxiang Hou

3 USCID:1126739072

Each instance has three labels: Families, Genus, and Species. Each of the labels has multiple classes. We wish to solve a multi-class and multi-label problem. One of the most important approaches to multi-class classification is to train a classifier for each label. We first try this approach:

i. Research exact match and hamming score/ loss methods for evaluating multi- label classification and use them in evaluating the classifiers in this problem.

1.The hamming scores means that the percent of misclassification.

ii. Train a SVM for each of the labels, using Gaussian kernels and one versus all classifiers. Determine the weight of the SVM penalty and the width of the Gaussian Kernel using 10 fold cross validation.1 You are welcome to try to solve the problem with both normalized and raw attributes and report the results.

```
In [1]: import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
```

```
In [2]: data=pd.read_csv("Frogs_MFCCs.csv")
```

```
In [3]: from sklearn import preprocessing
        from sklearn import svm
```

```
In [4]: def trasfer_data():
            le = preprocessing.LabelEncoder()
            le.fit(data["Family"])
            data["Family"]=le.transform(data["Family"])

            le.fit(data["Genus"])
            data["Genus"]=le.transform(data["Genus"])
```

```
        le.fit(data["Species"])
        data["Species"]=le.transform(data["Species"])
```

In [5]:
```
trasfer_data()
```

In [6]:
```
linear_svc=svm.SVC(kernel='rbf')
```

In [7]:
```
family_data=data.drop(["Genus","Species","RecordID"],axis=1)
genus_data=data.drop(["Family","Species","RecordID"],axis=1)
species_data=data.drop(["Family","Genus","RecordID"],axis=1)
```

In [8]:
```
family_y=list(data["Family"])
family_x=data.drop(["Family","Genus","Species","RecordID"],axis=1)

genus_y=list(data["Genus"])
genus_x=data.drop(["Family","Genus","Species","RecordID"],axis=1)

species_y=list(data["Species"])
species_x=data.drop(["Family","Genus","Species","RecordID"],axis=1)
```

In [9]:
```
from sklearn.metrics import accuracy_score
```

Choose 70% of the data randomly as the training set.

In [10]:
```
from sklearn.model_selection import train_test_split
```

In [11]:
```
family_x_train, family_x_test,family_y_train,family_y_test = train_test_split(family_
genus_x_train, genus_x_test, genus_y_train, genus_y_test = train_test_split(genus_x, g
species_x_train, species_x_test, species_y_train, species_y_test = train_test_split(sp
```

4 Raw SVM Gaussian Kernels

In [50]:
```
from sklearn.model_selection import GridSearchCV
```

In [51]:
```
gamma_range = np.logspace(-3, 1, 5)
```

In [52]:
```
linear_svc=svm.SVC(kernel='rbf') #there are two main parameters, C and degree
parameters = { 'C':[1,2,3,4],'gamma':[x for x in gamma_range]}
clf = GridSearchCV(linear_svc, parameters,cv=10)
clf.fit(family_x_train,family_y_train)
```

Out[52]:
```
GridSearchCV(cv=10, error_score='raise',
       estimator=SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma='auto', kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False),
       fit_params=None, iid=True, n_jobs=1,
       param_grid={'C': [1, 2, 3, 4], 'gamma': [0.001, 0.01, 0.1, 1.0, 10.0]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring=None, verbose=0)
```

```
In [53]: res=clf.predict(family_x_test)

In [54]: accuracy_score(res,family_y_test)

Out[54]: 0.9884205650764243

In [55]: clf.fit(genus_x_train,genus_y_train)
         genus_res=clf.predict(genus_x_train)
         print(accuracy_score(genus_res,genus_y_train))

0.9960285941223193

In [56]: clf.fit(species_x_train,species_y_train)
         species_res=clf.predict(species_x_train)
         print(accuracy_score(species_res,species_y_train))

0.9978157267672756
```

From the above result, we can find that if we use the Raw data without the Normalization, the accuracy score is around 99% percent,and then we will try to utilize the normalized result.

```
In [ ]: from sklearn.preprocessing import MinMaxScaler

In [57]: min_max_scaler = preprocessing.MinMaxScaler()
         family_x_train_normalized=min_max_scaler.fit_transform(family_x_train)
         genus_x_train_normalized=min_max_scaler.fit_transform(genus_x_train)
         species_x_train_normalized=min_max_scaler.fit_transform(species_x_train)

In [58]: clf.fit(family_x_train_normalized,family_y_train)
         family_res=clf.predict(family_x_train_normalized)
         print(accuracy_score(family_res,family_y_train))

1.0
```

After normalization, the accuracy improved from 98.8% to 100% percent for family class

```
In [59]: clf.fit(genus_x_train_normalized,genus_y_train)
         genus_res=clf.predict(genus_x_train_normalized)
         print(accuracy_score(genus_res,genus_y_train))

0.9944400317712471
```

After normalization , the accuracy of genus class decreased from 99.6% to 99.4% percent.

```
In [60]: clf.fit(species_x_train_normalized,species_y_train)
         species_res=clf.predict(species_x_train_normalized)
         print(accuracy_score(species_res,species_y_train))

0.9950357426528992
```

Conclusion: From the above experiments, we can find that the normalized result will improve the results from 99.7% percent to 99.5% percent

5 iii. Repeat 1(b)ii with L1-penalized SVMs. Remember to normalize the at- tributes.

```
In [80]: svm_model=svm.LinearSVC(penalty="l1")
```

```
In [88]: # parameters = { 'C':[1,2,3,4,5,6],'tol':[0.0001,0.001,0.01]}
         #then we have to utilize the for loop to get it
         def L1_SVM_Model(x,y):
             best_c=None
             best_tol=None
             res=0
             for i in range(1,11):
                 C=i
                 for j in [0.0001,0.001, 0.01,0.1]:
                     tol=j
                     svm_model=svm.LinearSVC(penalty="l1",C=C,tol=tol,dual=False)
                     scores = cross_val_score(svm_model,x,y,cv=10)
                     avg_scores=np.mean(scores)
                     print("When C = "+str(C)+" And tol= "+str(tol)+" The result is: "+str(avg_

                     if avg_scores>res:
                         res=avg_scores
                         best_c=C
                         best_tol=tol
             return res,best_c,best_tol
```

```
In [89]: print(L1_SVM_Model(family_x_train_normalized,family_y_train))
         print(L1_SVM_Model(genus_x_train_normalized,genus_y_train))
         print(L1_SVM_Model(species_x_train_normalized,species_y_train))
```

```
When C = 1 And tol= 0.0001 The result is: 0.936466680372642
When C = 1 And tol= 0.001 The result is: 0.9378555739481682
When C = 1 And tol= 0.01 The result is: 0.9354730390459987
When C = 1 And tol= 0.1 The result is: 0.928521475627182
When C = 2 And tol= 0.0001 The result is: 0.9368627199766024
When C = 2 And tol= 0.001 The result is: 0.93706152713366
When C = 2 And tol= 0.01 The result is: 0.9356710588479789
When C = 2 And tol= 0.1 The result is: 0.9285242259207338
When C = 3 And tol= 0.0001 The result is: 0.93706152713366
When C = 3 And tol= 0.001 The result is: 0.93706152713366
When C = 3 And tol= 0.01 The result is: 0.9366650946332671
When C = 3 And tol= 0.1 The result is: 0.9277266414575962
When C = 4 And tol= 0.0001 The result is: 0.9374591414477752
When C = 4 And tol= 0.001 The result is: 0.93706152713366
When C = 4 And tol= 0.01 The result is: 0.9362682676742292
When C = 4 And tol= 0.1 The result is: 0.9269329859865703
```

```
When C = 5 And tol= 0.0001 The result is: 0.93706152713366
When C = 5 And tol= 0.001 The result is: 0.9374591414477752
When C = 5 And tol= 0.01 The result is: 0.9366643072781896
When C = 5 And tol= 0.1 The result is: 0.9279266273132134
When C = 6 And tol= 0.0001 The result is: 0.9372603342907176
When C = 6 And tol= 0.001 The result is: 0.9372603342907176
When C = 6 And tol= 0.01 The result is: 0.9360686731620941
When C = 6 And tol= 0.1 The result is: 0.9277286043960705
When C = 7 And tol= 0.0001 The result is: 0.9374591414477752
When C = 7 And tol= 0.001 The result is: 0.9372603342907176
When C = 7 And tol= 0.01 The result is: 0.9364670748312868
When C = 7 And tol= 0.1 The result is: 0.9273325648013723
When C = 8 And tol= 0.0001 The result is: 0.9372611216457951
When C = 8 And tol= 0.001 The result is: 0.9376579486048329
When C = 8 And tol= 0.01 The result is: 0.9364662874762095
When C = 8 And tol= 0.1 The result is: 0.9277266399046461
When C = 9 And tol= 0.0001 The result is: 0.9374591414477752
When C = 9 And tol= 0.001 The result is: 0.9374591414477752
When C = 9 And tol= 0.01 The result is: 0.9362682676742292
When C = 9 And tol= 0.1 The result is: 0.9275286185404532
When C = 10 And tol= 0.0001 The result is: 0.9372611216457951
When C = 10 And tol= 0.001 The result is: 0.9372611216457951
When C = 10 And tol= 0.01 The result is: 0.9364662874762095
When C = 10 And tol= 0.1 The result is: 0.9273306003006855
(0.9378555739481682, 1, 0.001)
When C = 1 And tol= 0.0001 The result is: 0.939441964582055
When C = 1 And tol= 0.001 The result is: 0.9390455227360268
When C = 1 And tol= 0.01 The result is: 0.9384498854674241
When C = 1 And tol= 0.1 The result is: 0.9317128733315044
When C = 2 And tol= 0.0001 The result is: 0.942616990354242
When C = 2 And tol= 0.001 The result is: 0.9420201681288202
When C = 2 And tol= 0.01 The result is: 0.9412217837383643
When C = 2 And tol= 0.1 The result is: 0.9328974558803198
When C = 3 And tol= 0.0001 The result is: 0.9447995612444234
When C = 3 And tol= 0.001 The result is: 0.9444023335404728
When C = 3 And tol= 0.01 The result is: 0.9426177761283606
When C = 3 And tol= 0.1 The result is: 0.9344910564940039
When C = 4 And tol= 0.0001 The result is: 0.9447987707555854
When C = 4 And tol= 0.001 The result is: 0.9451971771300874
When C = 4 And tol= 0.01 The result is: 0.9432106661443276
When C = 4 And tol= 0.1 The result is: 0.933696241034435
When C = 5 And tol= 0.0001 The result is: 0.9455932229459221
When C = 5 And tol= 0.001 The result is: 0.9449971865877588
When C = 5 And tol= 0.01 The result is: 0.9436098552429915
When C = 5 And tol= 0.1 The result is: 0.9360744555641087
When C = 6 And tol= 0.0001 The result is: 0.9459924104823736
When C = 6 And tol= 0.001 The result is: 0.9461900373879214
When C = 6 And tol= 0.01 The result is: 0.9449948244668793
```

```
When C = 6 And tol= 0.1 The result is: 0.9350914258252814
When C = 7 And tol= 0.0001 The result is: 0.9463896381863245
When C = 7 And tol= 0.001 The result is: 0.9467856730755653
When C = 7 And tol= 0.01 The result is: 0.9445995800664768
When C = 7 And tol= 0.1 The result is: 0.9372688764153537
When C = 8 And tol= 0.0001 The result is: 0.9471844770612193
When C = 8 And tol= 0.001 The result is: 0.9467880445608264
When C = 8 And tol= 0.01 The result is: 0.9453932449017362
When C = 8 And tol= 0.1 The result is: 0.934283617844524
When C = 9 And tol= 0.0001 The result is: 0.9457955819141448
When C = 9 And tol= 0.001 The result is: 0.9465896318624137
When C = 9 And tol= 0.01 The result is: 0.9451932512256469
When C = 9 And tol= 0.1 The result is: 0.934688695897694
When C = 10 And tol= 0.0001 The result is: 0.9459939868291347
When C = 10 And tol= 0.001 The result is: 0.946986854851645
When C = 10 And tol= 0.01 The result is: 0.9453948258981593
When C = 10 And tol= 0.1 The result is: 0.9352855087681448
(0.9471844770612193, 8, 0.0001)
When C = 1 And tol= 0.0001 The result is: 0.9501431651468467
When C = 1 And tol= 0.001 The result is: 0.9503419551555095
When C = 1 And tol= 0.01 The result is: 0.9483542340860097
When C = 1 And tol= 0.1 The result is: 0.9404285464331421
When C = 2 And tol= 0.0001 The result is: 0.9533284958623487
When C = 2 And tol= 0.001 The result is: 0.9537225708544715
When C = 2 And tol= 0.01 The result is: 0.9509388024529437
When C = 2 And tol= 0.1 The result is: 0.9443906170222032
When C = 3 And tol= 0.0001 The result is: 0.9547209882113634
When C = 3 And tol= 0.001 The result is: 0.9545158334101689
When C = 3 And tol= 0.01 The result is: 0.9527249642965824
When C = 3 And tol= 0.1 The result is: 0.94478905008569
When C = 4 And tol= 0.0001 The result is: 0.9567122611676098
When C = 4 And tol= 0.001 The result is: 0.9561138469069848
When C = 4 And tol= 0.01 The result is: 0.9537229574550018
When C = 4 And tol= 0.1 The result is: 0.9463779420990039
When C = 5 And tol= 0.0001 The result is: 0.956112284602273
When C = 5 And tol= 0.001 The result is: 0.9567055674963665
When C = 5 And tol= 0.01 The result is: 0.9533249487011378
When C = 5 And tol= 0.1 The result is: 0.944993381385299
When C = 6 And tol= 0.0001 The result is: 0.9565095044577431
When C = 6 And tol= 0.001 The result is: 0.9569075476943864
When C = 6 And tol= 0.01 The result is: 0.9527257579379279
When C = 6 And tol= 0.1 The result is: 0.9471727824437071
When C = 7 And tol= 0.0001 The result is: 0.9561099286373193
When C = 7 And tol= 0.001 The result is: 0.956512284602273
When C = 7 And tol= 0.01 The result is: 0.9539182502869427
When C = 7 And tol= 0.1 The result is: 0.9461854245574903
When C = 8 And tol= 0.0001 The result is: 0.9565122830400604
When C = 8 And tol= 0.001 The result is: 0.9569055611912024
```

```
When C = 8 And tol= 0.01 The result is: 0.9543178510853458
When C = 8 And tol= 0.1 The result is: 0.9453834882344185
When C = 9 And tol= 0.0001 The result is: 0.9569087171026658
When C = 9 And tol= 0.001 The result is: 0.9567099286373193
When C = 9 And tol= 0.01 The result is: 0.9537230027713776
When C = 9 And tol= 0.1 The result is: 0.9463771577290423
When C = 10 And tol= 0.0001 The result is: 0.9569095357408866
When C = 10 And tol= 0.001 The result is: 0.9573071484927898
When C = 10 And tol= 0.01 The result is: 0.9543186510318558
When C = 10 And tol= 0.1 The result is: 0.9477680456562334
(0.9573071484927898, 10, 0.001)
```

So the result above for family class, the best classification rate is 93.7%. For Genus class, the classification rate is 94.7%, and for Species, the rate is 95.7%.

6 Repeat 1(b)iii by using SMOTE or any other method you know to remedy class imbalance. Report your conclusions about the classifiers you trained.

```
In [11]: from imblearn.over_sampling import SMOTE
```

```
In [26]: def getPerecentInList(alist):
             adict={}
             for number in alist:
                 if number not in adict:
                     adict[number]=1
                 else:
                     adict[number]+=1

             for key in adict:
                 adict[key]=(adict[key])/len(alist)

             return adict

         print(getPerecentInList(family_y))
```

```
{3: 0.6143154968728284, 1: 0.07533009034051424, 2: 0.30090340514246006, 0: 0.00945100764419736
```

```
In [37]: #from the smote algorithm
         #family, genus,species
         #smote algroithm will increase the imbalance data by
         sm = SMOTE(random_state=12)

         family_train_x_sm,family_train_y_sm=sm.fit_sample(family_x_train,family_y_train)
         genus_train_x_sm,genus_train_y_sm=sm.fit_sample(genus_x_train,genus_y_train)
         species_train_x_sm,species_train_y_sm=sm.fit_sample(species_x_train,species_y_train)
```

```
In [36]: #baseline is 92%

         svm_model=svm.LinearSVC()
         svm_model.fit(family_x_train,family_y_train)
         family_test_pre_y=svm_model.predict(family_x_test)
         print("Accuracy Score is: "+str(accuracy_score(family_test_pre_y,family_y_test)))
```

```
Accuracy Score is: 0.9277443260768874
```

```
In [38]: svm_model=svm.LinearSVC()
         svm_model.fit(family_train_x_sm,family_train_y_sm)
         family_test_pre_y=svm_model.predict(family_x_test)
         print("Accuracy Score is: "+str(accuracy_score(family_test_pre_y,family_y_test)))
```

```
Accuracy Score is: 0.8985641500694767
```

```
In [39]: svm_model=svm.LinearSVC()
         svm_model.fit(genus_train_x_sm,genus_train_y_sm)
         score=svm_model.score(genus_x_test,genus_y_test)
         print(score)
```

```
0.9018063918480778
```

```
In [40]: svm_model=svm.LinearSVC()
         svm_model.fit(species_train_x_sm,species_train_y_sm)
         score=svm_model.score(species_x_test,species_y_test)
         print(score)
```

```
0.9620194534506716
```

From the above experiments, for some classification situation, SMOTE algoritgm improves the accuracy. But some classes like family, it did not behave very well.

7 v. Extra Practice: Study the Classifier Chain method and apply it to the above problem.

```
In [32]: from sklearn.multioutput import ClassifierChain
         from sklearn.model_selection import train_test_split
         from sklearn.multiclass import OneVsRestClassifier
         from sklearn.metrics import jaccard_similarity_score
         from sklearn.linear_model import LogisticRegression
         from sklearn.datasets import fetch_mldata
```

```
In [33]: #for the family situation
         ovr = OneVsRestClassifier(LogisticRegression())
         ovr.fit(family_x_train,family_y_train)
```

```
Out[33]: OneVsRestClassifier(estimator=LogisticRegression(C=1.0, class_weight=None, dual=False
                   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),
                   n_jobs=1)
```

```
In [34]: Y_pred_ovr = ovr.predict(family_x_test)
         ovr_jaccard_score = jaccard_similarity_score(family_y_test, Y_pred_ovr)
```

```
In [35]: chains = [ClassifierChain(LogisticRegression(), order='random', random_state=i,cv=5)
                   for i in range(10)]
```

```
In [38]: Y = label_binarize(Y, classes=[0, 1, 2,3])
```

```
In [43]: X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=.3)
```

```
In [44]: chains = [ClassifierChain(LogisticRegression(), order='random', random_state=i)
                   for i in range(10)]
         for chain in chains:
             chain.fit(X_train, Y_train)

         Y_pred_chains = np.array([chain.predict(X_test) for chain in
                                   chains])
         chain_jaccard_scores = [jaccard_similarity_score(Y_test, Y_pred_chain >= .5)
                                 for Y_pred_chain in Y_pred_chains]

         Y_pred_ensemble = Y_pred_chains.mean(axis=0)
         ensemble_jaccard_score = jaccard_similarity_score(Y_test,
                                                           Y_pred_ensemble >= .5)

         model_scores = [ovr_jaccard_score] + chain_jaccard_scores
         model_scores.append(ensemble_jaccard_score)
```

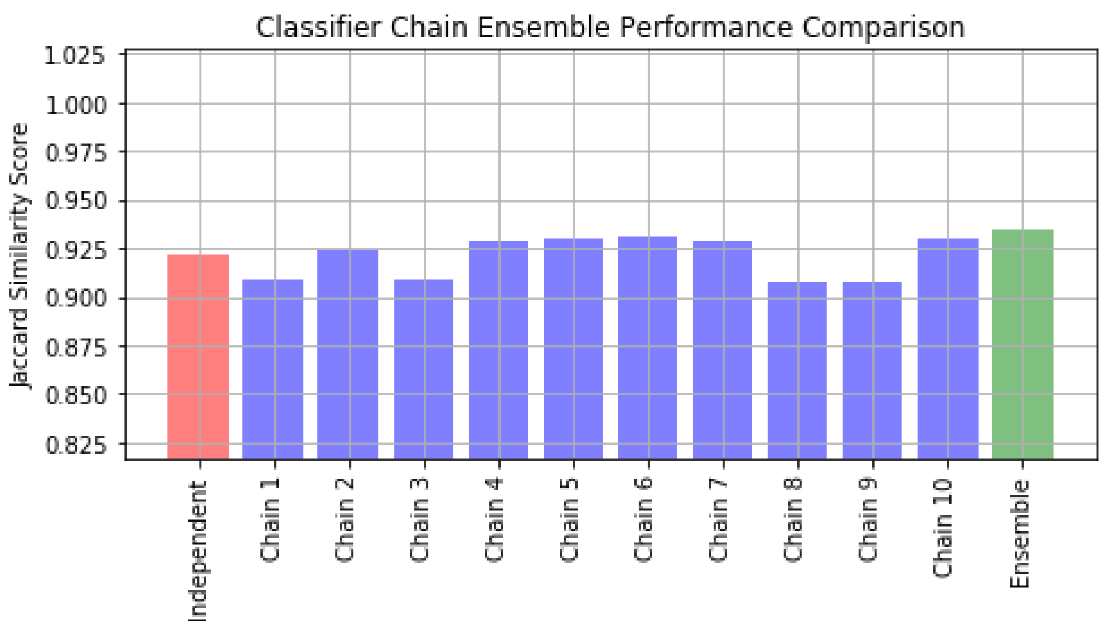
```
In [45]: model_names = ('Independent',
                        'Chain 1',
                        'Chain 2',
                        'Chain 3',
                        'Chain 4',
                        'Chain 5',
                        'Chain 6',
                        'Chain 7',
                        'Chain 8',
                        'Chain 9',
                        'Chain 10',
                        'Ensemble')

         x_pos = np.arange(len(model_names))

         # Plot the Jaccard similarity scores for the independent model, each of the
```

```
# chains, and the ensemble (note that the vertical axis on this plot does
# not begin at 0).

fig, ax = plt.subplots(figsize=(7, 4))
ax.grid(True)
ax.set_title('Classifier Chain Ensemble Performance Comparison')
ax.set_xticks(x_pos)
ax.set_xticklabels(model_names, rotation='vertical')
ax.set_ylabel('Jaccard Similarity Score')
ax.set_ylim([min(model_scores) * .9, max(model_scores) * 1.1])
colors = ['r'] + ['b'] * len(chain_jaccard_scores) + ['g']
ax.bar(x_pos, model_scores, alpha=0.5, color=colors)
plt.tight_layout()
plt.show()
```



From the above result we can find that the ensemble model has almost 92.5% accuracy

8 vi. Extra Practice: Research how confusion matrices, precision, recall, ROC, and AUC are defined for multi-label classification and compute them for the classifiers you trained in above.

Precision-recall curves are typically used in binary classification to study the output of a classifier. In order to extend the precision-recall curve and average precision to multi-class or multi-label classification, it is necessary to binarize the output. So we will calculate the average precision and recall, result

9 For family

In [25]:
```
X=np.array(family_data.drop("Family",axis=1))
Y=family_data["Family"]
```

In [26]:
```
from sklearn.preprocessing import label_binarize
Y = label_binarize(Y, classes=[0, 1, 2,3])
n_classes = Y.shape[1]
```

In [27]:
```
Y
```

Out[27]:
```
array([[0, 0, 0, 1],
       [0, 0, 0, 1],
       [0, 0, 0, 1],
       ...,
       [0, 0, 1, 0],
       [0, 0, 1, 0],
       [0, 0, 1, 0]])
```

In [28]:
```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=.3)


# We use OneVsRestClassifier for multi-label prediction
from sklearn.multiclass import OneVsRestClassifier

# Run classifier
classifier = OneVsRestClassifier(svm.LinearSVC(random_state=42))
classifier.fit(X_train, Y_train)
y_score = classifier.decision_function(X_test)
```

In [29]:
```
from sklearn.metrics import precision_recall_curve
from sklearn.metrics import average_precision_score

# For each class
precision = dict()
recall = dict()
average_precision = dict()
for i in range(n_classes):
    precision[i], recall[i], _ = precision_recall_curve(Y_test[:, i],
                                                        y_score[:, i])
    average_precision[i] = average_precision_score(Y_test[:, i], y_score[:, i])

# A "micro-average": quantifying score on all classes jointly
precision["micro"], recall["micro"], _ = precision_recall_curve(Y_test.ravel(),
    y_score.ravel())
average_precision["micro"] = average_precision_score(Y_test, y_score,
                                                     average="micro")
print('Average precision score, micro-averaged over all classes: {0:0.2f}'
      .format(average_precision["micro"]))
```

```
Average precision score, micro-averaged over all classes: 0.96
```

```
In [30]: #then make the confusion matrix, it is same as the binary situation
         X=family_data.drop("Family",axis=1)
         Y=family_data["Family"]
         svm_linear=svm.LinearSVC(random_state=41)
         X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=.3)
         svm_linear.fit(X_train,Y_train)
         Y_test_pre=svm_linear.predict(X_test)
```

```
In [31]: from sklearn.metrics import confusion_matrix
         print(confusion_matrix(Y_test_pre,Y_test))
```

```
[[   0    0    0    0]
 [   0  154   14   12]
 [  13   12  597   23]
 [   0    3   57 1274]]
```

10 Make ROC and AUC curve

```
In [18]: #then make the ROC and AUC Curve for the family class.
         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 = family_data.drop("Family",axis=1)
         y = list(family_data["Family"])

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

```
In [19]: # 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, 2 * n_features)]
```

```
In [20]: # 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)
```

In [21]:
```
# 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 [22]:
```
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 [23]:
```
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"])
```

```python
# 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()
```