Assignment 3 CSC 475

Hector Perez V00794415

Part 1. Section A

- Please check the section at the end of part 2 (generation of random songs).
- List of commands used: (Included in each experiment as well)

ZeroR -batch-size-10 (for the Zero R classifier).

NaiveBayes -K (for the Naive Bayes classifier).

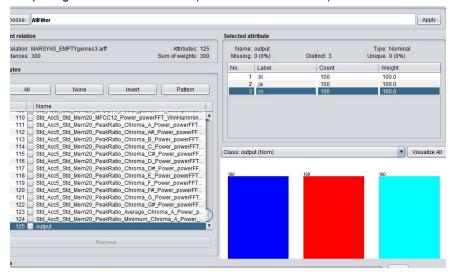
J48 -C 0.25 M 2 (for the J48 Classifier)

J48 -U M5 -A -doNotMakeSplitPointActualValue. (for the J48 Classifier)

SMO -C 1.0 -L 0.001 -P 1.0E-12 -N 0 -V -1 -W 1 -K "weka.classifiers.functions.supportVector.PolyKernel -E 1.0 -C 250007" -calibrator "weka.classifiers.functions.Logistic -R 1.0E-8 -M -1 -num-decimal-places 4" (for the SMO Classifier)

The commands used for SciKit Learn are included in the code portions (greyed out).

This is the result of importing the .arff file into Weka. (Bextract was successful).



The **ZeroR** classifier returned the following confusion matrix and accuracy:

```
ZeroR predicts class value: bl
=== Summary ===
Correctly Classified Instances
                                        100
                                                           33.3333 %
                                        200
Incorrectly Classified Instances
                                                           66.6667 %
Total Number of Instances
=== Confusion Matrix ===
               <-- classified as
       b
           c
   а
100
           0
                 a = b1
100
       0
           0 |
                 b = ja
100
           0 |
                 c = ro
```

Discussion: There is large error because the class predicted for all instances is the same one. The confusion matrix shows this clearly, as there is no correctly identified instances for jazz and rock (these would appear in the diagonal).

Invoking the **NaiveBayes** as is, we get the following classif. accuracy and confusion matrix.

```
=== Stratified cross-validation ===

=== Summary ===

Correctly Classified Instances 224 74.6667 %
Incorrectly Classified Instances 76 25.3333 %

Total Number of Instances 300

=== Confusion Matrix ===

a b c <-- classified as
64 19 17 | a = b1
11 81 8 | b = ja
12 9 79 | c = ro
```

Discussion: The accuracy is good. Blues was the least correctly classified, because only 64/100 were classified correctly. Jazz was the most correctly classified, with 81/100 correct. The NaiveBayes algorithm computes probabilities assuming conditional independence between variables. The class predicted is determined by comparing the probabilities.

Weka allows to choose NaiveBayes -D (Supervised discretization) or NaiveBayes -K (Use Kernel Estimator). From these two, Kernel estimator did better, with 76% accuracy.

Command: NaiveBayes -K

```
=== Summary ===

Correctly Classified Instances 229 76.3333 %
Incorrectly Classified Instances 71 23.6667 %

Total Number of Instances 300

=== Confusion Matrix ===

a b c <-- classified as
69 13 18 | a = bl
13 79 8 | b = ja
10 9 81 | c = ro
```

Discussion: The Kernel estimator did not do such a large difference, but it did increase the accuracy.

Invoking the **J48** classifier as is, which is under 'Tree' classifiers in Weka returns the following. (10-fold and 70% split were the best results, but the 10-fold was better).

Command: J48 -C 0.25 M 2

Names of parameters: C - confidence factor, M - minimum number of objects.

```
=== Summary ===

Correctly Classified Instances 231 77 %
Incorrectly Classified Instances 69 23 %
Total Number of Instances 300

=== Confusion Matrix ===

a b c <-- classified as
77 7 16 | a = bl
8 79 13 | b = ja
19 6 75 | c = ro
```

Discussion: The tree created is very complex, and would be really hard/near impossible to do it by hand. All the classes were classified fairly well, with about 20-25 classified incorrectly.

Other parameters were tried, but none had significant impact on accuracy.

After modifying some of them and trying out which gave better accuracy, the results were: Command used: J48 -U M5 -A -doNotMakeSplitPointActualValue.

```
=== Summary ===

Correctly Classified Instances 223 74.3333 %
Incorrectly Classified Instances 77 25.6667 %

Total Number of Instances 300

=== Confusion Matrix ===

a b c <-- classified as 72 12 16 | a = bl 8 81 11 | b = ja 23 7 70 | c = ro
```

Discussion: The accuracy was lower than the defaults used by Weka. Jazz was the most correctly classified genre.

SMO has many parameters. In weka it is categorized under 'functions'.

SMO stands for sequential minimal optimization, and is related to support vector machines.

As it is, the command to invoke it is:

-P SMO -C 1.0 -L 0.001 1.0E-12 -N 0 -V -1 -W 1 -K -C "weka.classifiers.functions.supportVector.PolyKernel -E 1.0 250007" -calibrator "weka.classifiers.functions.Logistic -R 1.0E-8 -M -1 -num-decimal-places 4"

The results are:

```
=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances 268 89.3333 %
Incorrectly Classified Instances 32 10.6667 %

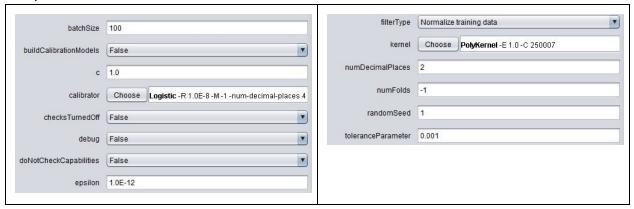
Total Number of Instances 300

=== Confusion Matrix ===

a b c <-- classified as
89 1 10 | a = b1
3 94 3 | b = ja
13 2 85 | c = ro
```

Discussion: This is the highest accuracy achieved with any of the previous methods.

The parameters shown are:



I try different kernels as this seems to be an important parameter.

Using NormalizedPolyKernel reduced accuracy to 84%.

Using RBFKernel reduced accuracy to 75%.

Using 'Puk' reduced accuracy to 87%.

Using percentage splits instead of folds, the results were all lower than when using folds.

Discussion: SMO has high accuracy compared to NaiveBayes, J48 tree, and ZeroR.

Part 1. Section B. Trials with **Scikit-learn** in Python.

I converted the .arff file to .libsvm which should work with Scikit learn.

I have Anaconda installed so I checked if it was already included, and it appears to be.

The categories in Weka for the classifiers previously used are:
a)ZeroR - 'Rules' b)NaiveBayes - 'Bayesian' c)J48 - 'Tree' d)SMO - 'Functions.

I couldn't find one-to-one correspondence for ZeroR, J48 and SMO, so I decided to use the following three classifiers, one related to support vector machines, one related to naive bayes, and one related to decision trees:

- 1. sklearn.svm.SVC (As in video tutorial by George Tzanetakis.)
- 2. sklearn.naive bayes.GaussianNB.
- 3. sklearn.tree.DecisionTreeClassifier.
 - 1. Support Vector Classification sklearn.svm.SVC.

```
import sklearn
import matplotlib.pyplot as plt
from sklearn.datasets import load symlight file
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from sklearn import svm
from sklearn.metrics import confusion matrix
#Some parts of this come from George Tzanetakis's implementation
#in the video from mirBook/course site for csc 475.
print "-----Implementation of a classifier with Support Vector Machine-----"
   X, y = load_svmlight_file('a3.libsvm');
    print("Total number of instances: %d" %X.shape[0]);
    X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.4,random_state = 0);
    print("Num Instances of the training set : %d" % X_train.shape[0]);
    print("Num Instances of the testing set : %d" % X_test.shape[0]);
#this is the classifier -> creates a model from the data by calling .fit()
   clf = svm.SVC(kernel = 'linear', C=1).fit(X_train, y_train);
#compute confusion matrix
   y_pred = clf.predict(X_test); #this is a list of 0 = blues, 1 = jazz, and 2 = rock
   y_true = y_test; #ground truth
    c m = confusion_matrix(y_true, y_pred);
   labels = ["blues","jazz","rock"];
    categories = ["a","b","c"];
    print " a b c <-- classified as";</pre>
    for i in range(3):
       print c_m[i],
       print("| %s = %s" % (categories[i],labels[i]));
#running cross validation w 5 folds:
    scores = cross_val_score(clf, X_test, y_test , cv = 5);
    print("Accuracy: %0.2f (+/- %0.2f)" % (scores.mean(), scores.std()*2) );
```

The output of this program was:

```
Total number of instances: 300

Num Instances of the training set: 180

Num Instances of the testing set: 120

a b c <-- classified as

[41 1 3] | a = blues

[ 4 27 4] | b = jazz

[ 8 1 31] | c = rock

Accuracy: 0.72 (+/- 0.16)
```

2. Gaussian Naive Bayes

```
import sklearn
import numpy as np
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import confusion_matrix
from sklearn.datasets import load_svmlight_file
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import train_test_split
print "------Implementation of a classifier with Gaussian Naive Bayes------"
X, y = load_svmlight_file('a3.libsvm');
print("Total number of instances: %d" %X.shape[0]);
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.4, random_state = 0);
print("Num Instances of the training set : %d" % X_train.shape[0]);
print("Num Instances of the testing set : %d" % X_test.shape[0]);
X_train = X_train.toarray();
                                            #X's must be np.array -requested by compiler
                                            #because these are 'dense' scikit matrix
X_test = X_test.toarray();
clf = GaussianNB().fit(X_train, y_train); #however, the y's are np.arrays
y_pred = clf.predict(X_test);
                                            #so there's no need to fix that.
y_true = y_test;
c m = confusion_matrix(y_true, y_pred);
labels = ["blues","jazz","rock"];
categories = ["a","b","c"];
print " a b c <-- classified as";</pre>
for i in range(3):
       print c_m[i],
       print("| %s = %s" % (categories[i],labels[i]));
scores = cross_val_score(clf, X_test, y_test , cv = 5);
print("Accuracy: %0.2f (+/- %0.2f)" % (scores.mean(), scores.std()*2) );
```

The output of this program was:

```
Total number of instances: 300
Num Instances of the training set: 180
Num Instances of the testing set: 120

a b c <-- classified as
[29 4 12] | a = blues
[0 24 11] | b = jazz
[2 1 37] | c = rock

Accuracy: 0.73 (+/- 0.22)
```

3. Decision Tree Classifier

```
import sklearn
from sklearn import tree
from sklearn.metrics import confusion_matrix
from sklearn.datasets import load_svmlight_file
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import train_test_split
X, y = load_svmlight_file('a3.libsvm');
print "------Implementation of a classifier with DecisionTreeClassifier------
print("Total number of instances: %d" %X.shape[0]);
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.4, random_state = 0);
print("Num Instances of the training set : %d" % X_train.shape[0]);
print("Num Instances of the testing set : %d" % X_test.shape[0]);
clf = tree.DecisionTreeClassifier();
clf = clf.fit(X_train, y_train);
y_pred = clf.predict(X_test); #this is a list of 0 = blues, 1 = jazz, and 2 = rock
y_true = y_test; #ground truth
c_m = confusion_matrix(y_true, y_pred);
labels = ["blues","jazz","rock"];
categories = ["a","b","c"];
print " a b c <-- classified as";</pre>
for i in range(3):
       print c_m[i],
       print("| %s = %s" % (categories[i],labels[i]));
scores = cross_val_score(clf, X_test, y_test , cv = 5);
print("Accuracy: %0.2f (+/- %0.2f)" % (scores.mean(), scores.std()*2) );
```

The output of this program was:

```
Total number of instances: 300
Num Instances of the training set: 180
Num Instances of the testing set: 120

a b c <-- classified as
[30 5 10] | a = blues
[5 25 5] | b = jazz
[8 0 32] | c = rock

Accuracy: 0.62 (+/- 0.14)
```

The results were that the Gaussian Naive Bayes classifier achieved the highest accuracy, closely followed by the Support Vector Classifier. The decision tree classifier had some parameters that could be changed, but I wanted to see how it fended off with the default settings. It was the lowest out of the three classifiers.

Each genre by itself was well classified by the following classifiers:

Classifier	Blues	Jazz	Rock
Good at classifying genre	SVC	SVC	Naive Bayes
Bad at classifying genre	Naive Bayes	Naive Bayes	SVC

I did notice something that happened with the train_test_split, which is that although the number of instances is indeed the correct split size (e.g. 0.4 of 300 is 120) the number of instances per class were not equal. In Weka they were always the same amount per each class.

Part 2

A) Write code to calc. Probabilities for each dictionary word given the genre.

Probabilities found:

de : 0.08700 de : niggaz : 0.18500 niggaz : niggaz : ya : 0.43900 ya : 0.43900 ya :	ities For Rock Pop 0.03700 0.00600 0.04500 0.03100 0.00600 0.02600 0.08700	Probabilities For Country de: 0.00600 niggaz: 0.00300 ya: 0.05100 und: 0.00000 yall: 0.01900
niggaz : 0.18500 niggaz : ya : 0.43900 ya : und : 0.06200 und : yall : 0.28200 yall : ich : 0.05700 ich : fuck : 0.41200 fuck : shit : 0.50800 shit : yo : 0.41100 yo : bitch : 0.31200 bitch : end : 0.17900 end : wait : 0.11600 wait : again : 0.17100 again : light : 0.19600 light : eye : 0.23200 eye : noth : 0.12000 noth : lie : 0.11100 fall : fall : 0.14100 our : away : 0.16200 away : gone : 0.17300 gone : good : 0.26900 night : blue : 0.09500 blue : home : 0.18900 home : long : 0.18300 long :	0.00600 0.04500 0.03100 0.00600 0.02600	niggaz : 0.00300 ya : 0.05100 und : 0.00000 yall : 0.01900
ya : 0.43900 ya : und : 0.06200 und : yall : 0.28200 yall : ich : 0.05700 ich : fuck : 0.41200 fuck : shit : 0.50800 shit : yo : 0.41100 yo : bitch : 0.31200 bitch : end : 0.17900 end : wait : 0.11600 wait : again : 0.17100 again : light : 0.19600 light : eye : 0.23200 eye : noth : 0.12000 noth : lie : 0.11100 fall : fall : 0.14100 our : away : 0.16200 away : gone : 0.17300 gone : good : 0.26900 night : blue : 0.09500 blue : home : 0.18900 home : long : 0.18300 long :	0.04500 0.03100 0.00600 0.02600	ya : 0.05100 und : 0.00000 yall : 0.01900
und : 0.06200 und : yall : 0.28200 yall : ich : 0.05700 ich : fuck : 0.41200 fuck : shit : 0.50800 shit : yo : 0.41100 yo : bitch : 0.31200 bitch : end : 0.17900 end : wait : 0.11600 wait : again : 0.17100 again : light : 0.19600 light : eye : 0.23200 eye : noth : 0.12000 noth : lie : 0.11100 lie : fall : 0.14100 our : away : 0.16200 away : gone : 0.17300 gone : good : 0.26900 night : blue : 0.09500 blue : home : 0.18900 home : long : 0.18300 long :	0.03100 0.00600 0.02600	und : 0.00000 yall : 0.01900
yall: 0.28200 yall: ich: 0.05700 ich: fuck: 0.41200 fuck: shit: 0.50800 shit: yo: 0.41100 yo: bitch: 0.31200 bitch: end: 0.17900 end: wait: 0.11600 wait: again: 0.17100 again: light: 0.19600 light: eye: 0.23200 eye: noth: 0.12000 noth: lie: 0.11100 fall: fall: 0.14100 our: away: 0.16200 away: gone: 0.17300 gone: good: 0.17300 gone: good: 0.22400 night: blue: 0.09500 blue: home: 0.18900 home: long: 0.18300 long:	0.00600 0.02600	yall : 0.01900
ich: 0.05700 ich: fuck: 0.41200 fuck: 0.50800 shit: yo: 0.41100 yo: bitch: 0.31200 bitch: end: 0.17900 end: again: 0.17100 again: light: 0.19600 light: 0.12000 noth: 0.12000 noth: 0.12000 lie: 0.11100 fall: 0.14100 our: 0.21400 away: 0.16200 good: 0.17300 gone: 0.17300 good: 0.26900 night: 0.22400 home: 0.18900 long: 0.18300 long:	0.02600	-
fuck : 0.41200 fuck : shit : 0.50800 shit : yo : 0.41100 yo : bitch : 0.31200 bitch : end : 0.17900 end : wait : 0.11600 wait : again : 0.17100 again : light : 0.19600 light : eye : 0.23200 eye : noth : 0.12000 noth : lie : 0.11100 lie : fall : 0.14100 fall : our : 0.21400 our : away : 0.16200 gone : good : 0.17300 gone : good : 0.26900 night : blue : 0.09500 blue : home : 0.18900 home : long : 0.18300 long :		
shit : 0.50800 shit : yo : 0.41100 yo : bitch : 0.31200 bitch : end : 0.17900 end : wait : 0.11600 wait : again : 0.17100 again : light : 0.19600 light : eye : 0.23200 eye : noth : 0.12000 noth : lie : 0.11100 lie : fall : 0.14100 our : away : 0.16200 away : gone : 0.17300 gone : good : 0.26900 night : blue : 0.09500 blue : home : 0.18900 home : long : 0.18300 long :	0.08700	ich : 0.00000
yo : 0.41100	0.00,00	fuck : 0.00800
bitch: 0.31200 bitch: end: 0.17900 end: 0.17900 wait: 0.11600 again: 0.17100 light: 0.19600 eye: 0.23200 eye: noth: 0.12000 noth: 0.12000 lie: 0.11100 fall: 0.14100 fall: 0.0000 away: 0.16200 gone: 0.17300 gone: 0.17300 gone: 0.17300 gone: 0.17300 gone: 0.17300 gone: 0.17300 home: 0.18900 home: 0.18900 long: 0.18300 long:	0.04000	shit : 0.01100
bitch: 0.31200 bitch: end: 0.17900 end: 0.17900 wait: 0.11600 again: 0.17100 light: 0.19600 eye: 0.23200 eye: noth: 0.12000 noth: 0.12000 lie: 0.11100 fall: 0.14100 fall: 0.0000 away: 0.16200 gone: 0.17300 gone: 0.17300 gone: 0.17300 gone: 0.17300 gone: 0.17300 gone: 0.17300 home: 0.18900 home: 0.18900 long: 0.18300 long:	0.02200	yo : 0.01200
wait: 0.11600 wait: again: 0.17100 again: light: 0.19600 light: eye: 0.23200 eye: noth: 0.12000 noth: lie: 0.11100 lie: fall: 0.14100 fall: our: 0.21400 our: away: 0.16200 away: gone: 0.17300 gone: good: 0.26900 night: blue: 0.09500 blue: home: 0.18900 home: long: 0.18300 long:	0.01800	bitch : 0.00500
again: 0.17100 again: light: 0.19600 light: eye: 0.23200 eye: noth: 0.12000 noth: lie: 0.11100 lie: fall: 0.14100 fall: our: 0.21400 our: away: 0.16200 gone: 0.17300 gone: good: 0.26900 night: 0.22400 blue: 0.09500 home: 0.18900 long: 0.18300 long:	0.19900	end : 0.14300
light: 0.19600	0.18900	wait : 0.13900
light: 0.19600	0.22000	again : 0.20900
eye : 0.23200 eye : noth : 0.12000 noth : 0.12000 lie : 0.11100 lie : fall : 0.14100 our : 0.21400 away : 0.16200 gone : 0.17300 gone : good : 0.26900 good : night : 0.22400 home : 0.18900 home : 0.18300 long :	0.19900	light : 0.18900
noth: 0.12000 noth: lie: 0.11100 lie: fall: 0.14100 fall: our: 0.21400 our: away: 0.16200 away: gone: 0.17300 gone: good: 0.26900 good: night: 0.22400 night: blue: 0.09500 blue: home: 0.18900 home: long: 0.18300 long:	0.30800	eye : 0.26100
lie : 0.11100	0.19100	noth : 0.12400
our : 0.21400 our : away : 0.16200 away : gone : 0.17300 gone : good : 0.26900 good : night : 0.22400 night : blue : 0.09500 blue : home : 0.18900 home : long : 0.18300 long :	0.18500	lie : 0.09500
away : 0.16200 away : gone : 0.17300 gone : good : good : good : night : 0.22400 night : blue : 0.09500 blue : home : 0.18900 home : long : 0.18300 long :	0.22300	fall : 0.17000
gone : 0.17300 gone : good : 0.26900 good : night : 0.22400 night : blue : 0.09500 blue : home : 0.18900 home : long : 0.18300 long :	0.23700	our : 0.20600
gone : 0.17300 gone : good : 0.26900 good : night : 0.22400 night : blue : 0.09500 blue : home : 0.18900 home : long : 0.18300 long :	0.32000	away : 0.26900
good : 0.26900 good : night : 0.22400 night : 0.09500 blue : home : 0.18900 home : long : 0.18300 long :	0.15300	gone : 0.20300
night : 0.22400 night : blue : 0.09500 blue : home : 0.18900 home : long : 0.18300 long :	0.15700	good : 0.27300
blue : 0.09500 blue : home : 0.18900 home : long : 0.18300 long :	0.26400	night : 0.37300
home : 0.18900 home : long : 0.18300 long :	0.06300	blue : 0.16000
	0.16000	home : 0.25600
	0.17800	long : 0.31400
littl : 0.24100 littl :	0.14700	littl : 0.31100
	0.19600	well : 0.32000
heart : 0.16400 heart :	0.26000	heart : 0.37100
old: 0.14100 old:		old: 0.29500

Code: (I eliminated some print statements).

```
probabilityForGenre = 1000/3000.0;
probabilitiesForWords = np.zeros(len(wordsArray));
probabilitiesForWordsRap = np.zeros(len(wordsArray));
probabilitiesForWordsRockPop = np.zeros(len(wordsArray));
probabilitiesForWordsCountry = np.zeros(len(wordsArray));
tracksArray = np.load('csc475_asn3_data/tracks.pck');
previousGenre = '';
for i in range(len(dataArray)):
       currentGenre = labelsArray[i];
       if(currentGenre != previousGenre):
              print("Currently analysing: %s" % genres[currentGenre]);
              print;
       for j in range (len(wordsArray)):
              if dataArray[i][j] > 0:
                      if currentGenre == 12:
                             countForWordsRap[j] += 1;
                      elif currentGenre == 1:
                             countForWordsRockPop[j] += 1;
                      else:
                             countForWordsCountry[j] +=1;
       previousGenre = currentGenre;
#here there were some print statements
#compute the probabilites
#a. get overall probability P(word) = is N_inst_with_Word / 3000;
for i in range (len(wordsArray)):
       #probs for individual word in the whole dataset
       probabilitiesForWords[i] =
(countForWordsRap[i]+countForWordsRockPop[i]+countForWordsCountry[i])/3000.0;
       #conditional probs. --- Using general multiplication rule.
       # Since P(A \text{ and } B) = P(A) * P(B|A)
    \# P(B|A) = P(A and B) / P(A)
    # P(word|genre) = P(word and genre) / P(genre);
       # P(word and genre) = #instances with the word that are that genre / total number
of instances.
       # P(genre) = 1/3.
       probabilitiesForWordsRap[i] = (countForWordsRap[i]/3000.0)/probabilityForGenre;
       probabilitiesForWordsRockPop[i] =
(countForWordsRockPop[i]/3000.0)/probabilityForGenre;
       probabilitiesForWordsCountry[i] =
(countForWordsCountry[i]/3000.0)/probabilityForGenre;
```

B) Explain how these probability estimates can be combined to form a Naive Bayes classifier. Calculate the classification accuracy and confusion matrix that you would obtain using the whole data set for both training and testing partitions. (1pt, 0.5pt)

Using the probabilities, we can find P(Genre | X = feature vector) for all three genres. The Bayes' rule and assumption of conditional independence, allows us to compute this by multiplication of conditional probabilities. The genre with highest probability will be the class that a new instance is labeled as.

P(Genre|
$$X_{features}$$
) = P(Genre) * $\prod_{i=1}^{n} P(X_i|Genre)$

Results: (Confusion matrix and accuracy).

```
a b c

751 154 95 | a = Rap

64 629 307 | b = Rock Pop

28 263 709 | c = Country

Accuracy: 69.63 %
```

Code: findProbabilities.py and genreclf b.py (with some prints eliminated)

```
import numpy as np
def trainModel(dataArray, labelsArray, genres, wordsArray,
probabilitiesForWords,probabilitiesForWordsRap,probabilitiesForWordsRockPop,probabilitiesFor
WordsCountry):
       probabilityForGenre = 1000/3000.0;
       countForWordsRap = np.zeros(len(wordsArray));
       countForWordsRockPop = np.zeros(len(wordsArray));
       countForWordsCountry = np.zeros(len(wordsArray));
       previousGenre = '';
       for i in range(len(dataArray)):
              currentGenre = labelsArray[i];
              if(currentGenre != previousGenre):
                      print("Currently analysing: %s" % genres[currentGenre]);
                      print;
              for j in range (len(wordsArray)):
                      if dataArray[i][j] > 0:
                             if currentGenre == 12:
                                     countForWordsRap[j] += 1;
                             elif currentGenre == 1:
                                     countForWordsRockPop[j] += 1;
                             else:
                                     countForWordsCountry[j] +=1;
              previousGenre = currentGenre;
       for i in range (len(wordsArray)):
              probabilitiesForWords[i] =
(countForWordsRap[i]+countForWordsRockPop[i]+countForWordsCountry[i])/3000.0;
              probabilitiesForWordsRap[i] =
(countForWordsRap[i]/3000.0)/probabilityForGenre;
              probabilitiesForWordsRockPop[i] =
(countForWordsRockPop[i]/3000.0)/probabilityForGenre;
              probabilitiesForWordsCountry[i] =
(countForWordsCountry[i]/3000.0)/probabilityForGenre;
```

```
def testModel(dataArray, labelsArray, genres, wordsArray,
probabilitiesForWords,probabilitiesForWordsRap,probabilitiesForWordsRockPop,probabilitiesFor
WordsCountry):
       probabilityForGenre = 1000/3000.0;
       classification = np.zeros(len(dataArray));
       for i in range (len(dataArray)):
              probabilityRap = probabilityForGenre;
              probabilityRockPop = probabilityForGenre;
              probabilityCountry = probabilityForGenre;
              for j in range (len(wordsArray)):
                      if dataArray[i][j]<=0:</pre>
                             probabilityRap *= (1-probabilitiesForWordsRap[j]);
                             probabilityRockPop *= (1-probabilitiesForWordsRockPop[j]);
                             probabilityCountry *= (1-probabilitiesForWordsCountry[j]);
                      if dataArray[i][j]>0:
                             probabilityRap *= probabilitiesForWordsRap[j];
                             probabilityRockPop *= probabilitiesForWordsRockPop[j];
                             probabilityCountry *= probabilitiesForWordsCountry[j]
              MAX_A_POST = np.argmax([probabilityRap, probabilityRockPop,
probabilityCountry]);
              if(MAX_A_POST == 0):classification[i] = 12;
              elif(MAX A POST == 1):classification[i] = 1;
              elif(MAX_A_POST == 2):classification[i] = 3;
       return classification;
def accuracyAndConfusionMatrix(classification,labelsArray):
       correctCounter = 0;
       matrix = [[0,0,0],[0,0,0],[0,0,0]];
       for i in range (len(labelsArray)):
              if(classification[i] == labelsArray[i]):
                      correctCounter += 1;
                 if labelsArray[i] == 12 and classification[i] == 12: matrix[0][0] += 1;
                 elif labelsArray[i] == 1 and classification[i] == 1: matrix[1][1] += 1;
                 elif labelsArray[i] == 3 and classification[i] == 3: matrix[2][2] += 1;
              else:
                      #rap classified as rock pop
                 if labelsArray[i] == 12 and classification[i] == 1: matrix[0][1] += 1;
                      #rap classified as country
                 elif labelsArray[i] == 12 and classification[i] == 3: matrix[0][2] += 1;
                      #rock pop classified as rap
                 elif labelsArray[i] == 1 and classification[i] == 12: matrix[1][0] += 1;
                      #rock pop classified as country
                 elif labelsArray[i] == 1 and classification[i] == 3: matrix[1][2] += 1;
                      #country classified as rap
                 elif labelsArray[i] == 3 and classification[i] == 12: matrix[2][0] += 1;
                      #country classf as rock pop
                 elif labelsArray[i] == 3 and classification[i] == 1: matrix[2][1] += 1;
       totalInst = 3000.0;
       accuracy = correctCounter/totalInst;
       accuracyPercentage = accuracy*100.0;
       labels = ["Rap", "Rock Pop", "Country"];
       categories = ["a","b","c"];
       print( "%8s %8s %8s" % (categories[0], categories[1], categories[2]));
       for i in range(3):
              print("%8d %8d %8d" %(matrix[i][0], matrix[i][1], matrix[i][2])),
              print("| %s = %s" % (categories[i],labels[i]));
       print;
       print("Accuracy: %0.2f %% " % accuracyPercentage );
```

```
import numpy as np
import findProbabilities
class genreclf b():
       def main():
              data = np.load('csc475 asn3 data/data.npz');
              dataArray = data['arr_0'];
              labels = np.load('csc475_asn3_data/labels.npz');
              labelsArray = labels['arr_0'];
              genres = dict([(12, 'Rap'), (1, 'Rock Pop'), (3, 'Country')]);
              words = np.load('csc475_asn3_data/words.npz');
              dictionary = np.load('csc475_asn3_data/dictionary.pck');
              wordsArray = [];
              for i in words['arr_0']:
                      wordsArray.append(dictionary[i]);
              probabilitiesForWords = np.zeros(len(wordsArray));
              probabilitiesForWordsRap = np.zeros(len(wordsArray));
              probabilitiesForWordsRockPop = np.zeros(len(wordsArray));
              probabilitiesForWordsCountry = np.zeros(len(wordsArray));
              tracksArray = np.load('csc475_asn3_data/tracks.pck');
              findProbabilities.trainModel(dataArray, labelsArray, genres, wordsArray,
probabilitiesForWords,probabilitiesForWordsRap,probabilitiesForWordsRockPop,probabilitiesFor
WordsCountry);
              classification = findProbabilities.testModel(dataArray, labelsArray, genres,
wordsArray,probabilitiesForWords,probabilitiesForWordsRap,probabilitiesForWordsRockPop,proba
bilitiesForWordsCountry);
              findProbabilities.accuracyAndConfusionMatrix(classification, labelsArray);
              return 0;
       if __name__ == "__main__": main()
```

C) Read the Wikipedia page about cross-validation in statistics Calculate the classification accuracy and confusion matrix using the k-fold cross-validation, where k = 10. Note that you would use both the training and testing data and generate your own splits. (2pt, 1pt)

Results: I iterated several times and achieved a similar accuracy to not doing cross validation. Two iterations show this accuracy and confusion matrices.

```
а
                b
                         C
                                                     а
                                                               b
                                                                        C
     784
              134
                        82 | a = Rap
                                                     753
                                                              139
                                                                        108 | a = Rap
      91
              579
                       330 | b = Rock Pop
                                                      81
                                                               599
                                                                        320 | b = Rock Pop
                       689 | c = Country
      30
              281
                                                      19
                                                                        711 | c = Country
Accuracy: 68.40 %
                                                Accuracy: 68.77 %
```

```
import numpy as np
import findProbabilities2
class genreclf_b():
       def main():
               k = 10;
              data = np.load('csc475 asn3 data/data.npz');
              dataArray = data['arr 0'];
              indexes = np.arange(3000);
               np.random.shuffle(indexes);
              labels = np.load('csc475_asn3_data/labels.npz');
              labelsArray = labels['arr_0'];
              newData = [[]*30]*3000;
              newLabels = np.zeros(3000);
              for i in range (3000):
                      newData[i] = dataArray[indexes[i]];
                      newLabels[i] = labelsArray[indexes[i]];
              words = np.load('csc475_asn3_data/words.npz');
              dictionary = np.load('csc475_asn3_data/dictionary.pck');
              wordsArray = [];
              for i in words['arr 0']:
                      wordsArray.append(dictionary[i]);
               probabilitiesForWords = np.zeros(len(wordsArray));
              probabilitiesForWordsRap = np.zeros(len(wordsArray));
              probabilitiesForWordsRockPop = np.zeros(len(wordsArray));
              probabilitiesForWordsCountry = np.zeros(len(wordsArray));
              main_matrix = [[0,0,0],[0,0,0],[0,0,0]];
              main_accuracy = 0;
              accuracySum = 0;
              for i in range (k):
                      testingData = newData[i*300:(i+1)*300];
                      labelsData = newLabels[i*300:(i+1)*300];
                      findProbabilities2.trainModel(k,i, newData, newLabels, wordsArray,
probabilitiesForWords,probabilitiesForWordsRap,probabilitiesForWordsRockPop,probabilitiesFor
WordsCountry);
                      classification = findProbabilities2.testModel(testingData, wordsArray,
probabilitiesForWords,probabilitiesForWordsRap,probabilitiesForWordsRockPop,probabilitiesFor
WordsCountry);
                      accuracy =
findProbabilities2.calculateAccuracy(classification,labelsData);
                      accuracySum = accuracySum+accuracy;
                      iterationConfusionMatrix =
findProbabilities2.calculateConfusionMatrix(classification,labelsData);
                      main_matrix = np.add(main_matrix, iterationConfusionMatrix );
              main accuracy = accuracySum/k;
              main accuracy = main accuracy*100.0;
              labels = ["Rap", "Rock Pop", "Country"];
               categories = ["a","b","c"];
              print( "%8s %8s %8s" % (categories[0], categories[1], categories[2]));
              for i in range(3):
                      print("%8d %8d %8d" %(main matrix[i][0], main matrix[i][1],
main_matrix[i][2])),
                      print("| %s = %s" % (categories[i],labels[i]));
              print("Accuracy: %0.2f %% " % main_accuracy );
               return 0;
       if __name__ == "__main__": main()
```

```
import numpy as np
def trainModel(k,index, newData, newLabels , wordsArray,
probabilitiesForWords,probabilitiesForWordsRap,probabilitiesForWordsRockPop,probabilitiesFor
WordsCountry):
       probabilityForGenre = 1000.0/3000.0;
       countForWordsRap = np.zeros(len(wordsArray));
       countForWordsRockPop = np.zeros(len(wordsArray));
       countForWordsCountry = np.zeros(len(wordsArray));
       number = 0;
       for i in range(k):
              if i != index:
                      currentSubset = newData[i*300:(i+1)*300];
                      countWords(number, currentSubset,newData,newLabels, wordsArray,
countForWordsRap,countForWordsRockPop,countForWordsCountry);
       for i in range (len(wordsArray)):
              probabilitiesForWords[i] =
(countForWordsRap[i]+countForWordsRockPop[i]+countForWordsCountry[i])/2700.0;
              probabilitiesForWordsRap[i] =
(countForWordsRap[i]/2700.0)/probabilityForGenre;
              probabilitiesForWordsRockPop[i] =
(countForWordsRockPop[i]/2700.0)/probabilityForGenre;
              probabilitiesForWordsCountry[i] =
(countForWordsCountry[i]/2700.0)/probabilityForGenre;
def countWords(number, currentSubset, newData, newLabels, wordsArray, countForWordsRap,
countForWordsRockPop, countForWordsCountry):
       for j in range(len(currentSubset)):
              genre = newLabels[j] ;
              for m in range(len(wordsArray)):
                      if newData[j][m] > 0:
                             if genre == 12:countForWordsRap[m] += 1;
                             elif genre == 1:countForWordsRockPop[m] += 1;
                             else: countForWordsCountry[m] +=1;
def testModel(testingData, wordsArray,
probabilitiesForWords,probabilitiesForWordsRap,probabilitiesForWordsRockPop,probabilitiesFor
WordsCountry):
       probabilityForGenre = 1000/3000.0;
       classification = np.zeros(len(testingData));
       for i in range (len(testingData)):
              probabilityRap = probabilityForGenre;
              probabilityRockPop = probabilityForGenre;
              probabilityCountry = probabilityForGenre;
              for j in range (len(wordsArray)):
                      if testingData[i][j]<=0:</pre>
                             probabilityRap *= (1-probabilitiesForWordsRap[j]);
                             probabilityRockPop *= (1-probabilitiesForWordsRockPop[j]);
                             probabilityCountry *= (1-probabilitiesForWordsCountry[j]);
                      if testingData[i][j]>0:
                             probabilityRap *= probabilitiesForWordsRap[j];
                             probabilityRockPop *= probabilitiesForWordsRockPop[j];
                             probabilityCountry *= probabilitiesForWordsCountry[j]
       MAX_A_POST = np.argmax([probabilityRap, probabilityRockPop, probabilityCountry]);
              if(MAX_A_POST == 0):classification[i] = 12;
              elif(MAX_A_POST == 1):classification[i] = 1;
              elif(MAX_A_POST == 2):classification[i] = 3;
       return classification;
```

```
def calculateAccuracy(classification, labelsArray):
       correctCounter = 0;
       for i in range (len(labelsArray)):
              if(classification[i] == labelsArray[i]):
                      correctCounter += 1;
       totalInst = 300.0;
       accuracy = correctCounter/totalInst;
       return accuracy;
def calculateConfusionMatrix(classification,labelsArray):
       matrix = [[0,0,0],[0,0,0],[0,0,0]];
       for i in range (len(labelsArray)):
              if(classification[i] == labelsArray[i]):
              if labelsArray[i] == 12 and classification[i] == 12: matrix[0][0] += 1;
              elif labelsArray[i] == 1 and classification[i] == 1: matrix[1][1] += 1;
              elif labelsArray[i] == 3 and classification[i] == 3: matrix[2][2] += 1;
              else:
                      #rap classified as rock pop
                      if labelsArray[i] == 12 and classification[i] == 1: matrix[0][1] += 1;
                      #rap classified as country
              elif labelsArray[i] == 12 and classification[i] == 3: matrix[0][2] += 1;
                      #rock pop classified as rap
              elif labelsArray[i] == 1 and classification[i] == 12: matrix[1][0] += 1;
                      #rock pop classified as country
              elif labelsArray[i] == 1 and classification[i] == 3: matrix[1][2] += 1;
                      #country classified as rap
              elif labelsArray[i] == 3 and classification[i] == 12: matrix[2][0] += 1;
                      #country classf as rock pop
              elif labelsArray[i] == 3 and classification[i] == 1: matrix[2][1] += 1;
       return matrix:
```

Part 2.4 Generation of random songs from the model created.(And output) Code: generateSongs.py

```
Must import findProbabilities, import auxForGenerateSongs, import numpy as np
class generateSongs():
       def main():
              data = np.load('csc475 asn3 data/data.npz');
              dataArray = data['arr 0'];
              words = np.load('csc475 asn3 data/words.npz');
              dictionary = np.load('csc475 asn3 data/dictionary.pck');
              wordsArray = [];
              for i in words['arr 0']: wordsArray.append(dictionary[i]);
              probabilitiesForWords = np.zeros(len(wordsArray));
              probabilitiesForWordsRap = np.zeros(len(wordsArray));
              probabilitiesForWordsRockPop = np.zeros(len(wordsArray));
              probabilitiesForWordsCountry = np.zeros(len(wordsArray));
              findProbabilities.trainModel(dataArray, labelsArray, genres, wordsArray,
probabilitiesForWords,probabilitiesForWordsRap,probabilitiesForWordsRockPop,probabilitiesFor
WordsCountry);
              print 'Generating 5 Rap Songs'
              auxForGenerateSongs.generate5Songs(probabilitiesForWordsRap, wordsArray);
              print 'Generating 5 Rock Pop Songs'
              auxForGenerateSongs.generate5Songs(probabilitiesForWordsRockPop, wordsArray);
              print 'Generating 5 Country Songs'
              auxForGenerateSongs.generate5Songs(probabilitiesForWordsCountry, wordsArray);
              return 0;
                        _main__": main()
       if __name__ == "_
```

Code: auxForGenerateSongs.py

```
import numpy as np
def generate5Songs(probabilitiesArray, wordsArray):
    numSongs = 5;
    limit = 30;
    wordsInSong = [];
    for n in range(numSongs):
        for m in range(limit):
            randomProbability = np.random.random();
            randomIndex = np.random.randint(0,limit);
            if(randomProbability > probabilitiesArray[randomIndex]):
                  wordsInSong = np.append(wordsInSong,wordsArray[randomIndex]);
            print wordsInSong;
            wordsInSong = [];
```

Output

```
Generating 5 Rap Songs
['away' 'night' 'niggaz' 'de' 'long' 'away' 'again' 'away' 'lie' 'niggaz' 'heart' 'old' 'yo'
'yall' 'niggaz' 'end' 'heart' 'our' 'de' 'eye' 'und' 'again' 'de' 'bitch' 'und']
['blue' 'lie' 'noth' 'yo' 'ya' 'wait' 'light' 'end' 'wait' 'away' 'long' 'long' 'blue' 'our'
shit' 'end' 'yo' 'light' 'night' 'heart' 'bitch' 'well' 'our' 'old' 'ya']
['de' 'end' 'gone' 'good' 'eye' 'lie' 'gone' 'niggaz' 'again' 'gone' 'gone' 'fall' 'lie'
'old' 'away' 'end' 'light' 'good' 'noth' 'wait']
['lie' 'blue' 'und' 'old' 'littl' 'shit' 'light' 'blue' 'well' 'wait' 'away' 'littl' 'long'
und' 'away' 'yall' 'noth' 'eye' 'away' 'niggaz' 'gone' 'again' 'blue' 'blue' 'our' 'good']
['fall' 'long' 'heart' 'old' 'heart' 'yo' 'yall' 'niggaz' 'ya' 'de' 'wait' 'yall' 'old'
'blue' 'wait' 'noth' 'good' 'yo' 'our' 'blue' 'old' 'niggaz' 'well' 'littl' 'fall']
Generating 5 Rock Pop Songs
['fuck' 'old' 'ich' 'eye' 'ich' 'und' 'fuck' 'bitch' 'away' 'fuck' 'bitch' 'niggaz' 'littl'
'night' 'home' 'und' 'our' 'again' 'ya' 'yo' 'niggaz' 'und' 'old' 'gone' 'ya' 'our' 'home']
['fall' 'heart' 'littl' 'shit' 'fall' 'lie' 'lie' 'away' 'shit' 'away' 'fuck' 'yall' 'noth'
de' 'away' 'night' 'shit' 'und' 'light' 'fall' 'und' 'lie' 'niggaz' 'littl' 'lie' 'well']
['noth' 'old' 'shit' 'littl' 'home' 'light' 'our' 'und' 'away' 'well' 'well' 'lie' 'niggaz'
'niggaz' 'night' 'fuck' 'eye' 'home' 'good' 'yo' 'fall' 'niggaz' 'de' 'fuck' 'shit']
['gone' 'yall' 'light' 'fall' 'home' 'yo' 'wait' 'ya' 'blue' 'heart' 'wait' 'noth' 'fuck'
'de' 'well' 'littl' 'shit' 'de' 'und' 'yo' 'shit' 'gone' 'niggaz' 'ya']
['night' 'yall' 'old' 'ya' 'shit' 'bitch' 'long' 'light' 'well' 'yall' 'fuck' 'littl' 'end'
'fuck' 'again' 'wait' 'gone' 'de' 'long' 'bitch' 'good' 'und' 'lie' 'blue']
Generating 5 Country Songs
['noth' 'wait' 'niggaz' 'fuck' 'home' 'ich' 'blue' 'shit' 'littl' 'well' 'shit' 'well'
'night' 'noth' 'home' 'light' 'wait' 'littl' 'wait' 'und' 'gone' 'bitch' 'yall']
['ich' 'night' 'bitch' 'home' 'de' 'heart' 'shit' 'littl' 'lie' 'light' 'fuck' 'shit'
```

```
'littl' 'noth' 'gone' 'shit' 'yo' 'fuck' 'yall' 'eye' 'fall' 'fuck' 'our' 'littl' 'long']

['heart' 'our' 'de' 'yall' 'yo' 'noth' 'littl' 'noth' 'yall' 'away' 'littl' 'home' 'und'
'light' 'shit' 'away' 'ya' 'end' 'long' 'long' 'niggaz' 'yo' 'ich' 'yo' 'away' 'long''blue']

['end' 'old' 'yo' 'ich' 'fuck' 'niggaz' 'fuck' 'littl' 'fuck' 'yall' 'blue' 'yall' 'fall'
'old' 'old' 'end' 'gone' 'lie' 'niggaz' 'heart' 'wait' 'night' 'littl' 'und']

['home' 'und' 'blue' 'ya' 'end' 'night' 'heart' 'blue' 'yo' 'home' 'und' 'away' 'well'
'gone' 'de' 'de' 'yall' 'fall' 'niggaz' 'noth' 'yo' 'de']
```