

# Music Genre Identification

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## Abstract

For this project, we are focusing on using machine learning techniques to classify different music bands/-genres. There are generally two techniques to be used in this project - Naive Bayes, and Decision Trees.

use the data set from [Marsyas](#).

Marsyas has approximately 1.2GB of different genres of music. This data set was used for the well known paper in genre classification "Musical genre classification of audio signals" by G. Tzanetakis and P. Cook in IEEE Transactions on Audio and Speech Processing 2002. And it consists of 1000 audio tracks each 30 seconds long. It contains 10 genres, each represented by 100 tracks. The tracks are all 22050Hz Mono 16-bit audio files in .wav format. I will choose three genres out of the given 10 genres (rock, jazz, classical).

## 1 Introduction and Overview

### 1.1 Introudction

Humans classify audio signals all the time without paying attentions. Classifying who is speaking in a group, or realizing the person on the other side of the phone call, or classifying whether the music that is playing on the radio is rock or jazz. But the problem comes that how could we tell machine to know that, who is speaking (cocktail party problem), or what genre does the playing music belong to.

### 1.2 Overview

The project has three tests to be completed.

- Band Classification
- The Case for Seattle
- Genre Classification

I will pick 6 songs for each of Michael Jackson, Soundgarden, and Beethoven for the Band Classification Test. For the Seattle Case Test, I will pick Soundgarden, Alice in Chains, and Pearl Jam to classify 5-second sound clips with also 6 songs for each artists. And for the general Genre Classification, I will

## 2 Theoretical Background

The machine learning skills I will use for the classification are the most-known classifiers. Naive Bayes classifiers are a family of simple probabilistic classifiers based on applying Bayes' theorem with naive independence assumptions between the features. Naive Bayes classifiers are highly scalable, requiring a number of parameters linear in the number of variables (features/predictors) in a learning problem. Maximum-likelihood training can be done by evaluating a closed-form expression, which takes linear time, rather than by expensive iterative approximation as used for many other types of classifiers.

Decision tree learning uses a decision tree (as a predictive model) to go from observations about an item (represented in the branches) to conclusions about the item's target value (represented in the leaves). It is one of the predictive modelling approaches used in statistics, data mining and machine learning. Tree models where the target variable can take a discrete set of values are called classification trees; in these tree

structures, leaves represent class labels and branches represent conjunctions of features that lead to those class labels. Decision trees where the target variable can take continuous values (typically real numbers) are called regression trees.

### 3 Algorithm Implementation and Development

#### 3.1 General Procedure

- Load the music files. For every band or genre of music, reshape the five-second-audio-clip vector to a data matrix that each column contains a five-second clip. And to keep the data sizes manageable, it is necessary to resample the data matrix.
- Label the clips to keep tracking of which column belongs to who/what genre.
- Collect representative features for each artist/-genre such that we could distinguish one from others. The representative features includes
  - How many times the signal goes across zero
  - The maximum, and minimum absolute value of the signal
  - The mean value, variance, first norm value of the signal
  - The largest frequencies that appears in the signal.
- After collecting the data, construct a matrix contains all features information and divide the matrix into training set and testing set. The way I choose my training/testing sets is that randomly pick 70% of the data to be training data and the other 30% to be testing data.
- Then perform SVD on the data matrix. Pick the modes with more than 10% energy such that it will have a better performance on prediction.
- Train the data set using different classifiers (in this case, decision tree algorithm and naive Bayes classifier).
- Test the prediction and collect the accuracy data.

In order to have a reasonable result, I will train the data and get the accuracy result for 5 times and take the average value.

Table 1: Accuracy for Test 1

	Naive Bayes	Decision Tree
<b>Trail 1</b>	66.5823	75.9494
<b>Trail 2</b>	69.1139	79.7468
<b>Trail 3</b>	70.3797	78.2278
<b>Trail 4</b>	66.8354	80.2532
<b>Trail 5</b>	71.3924	78.9873
<b>Average</b>	$68.8608 \pm 4.5185$	$78.6329 \pm 2.8393$

Table 2: Accuracy for Test 2

	Naive Bayes	Decision Tree
<b>Trail 1</b>	56.6092	67.2414
<b>Trail 2</b>	55.1724	72.7011
<b>Trail 3</b>	56.8966	72.4138
<b>Trail 4</b>	53.1609	73.8506
<b>Trail 5</b>	56.3218	74.7126
<b>Average</b>	$55.6322 \pm 2.3368$	$72.1839 \pm 8.4803$

### 4 Computational Results

#### 4.1 Test 1

From Table 1, we can see that the overall result is pretty impressive.  $68.86 \pm 4.5\%$  for naive Bayes classifier and  $78.63 \pm 3.8\%$  for decision tree algorithm. And the point is that this result is only from 6 sample songs. It is reasonable to predict that with more training data, these two algorithms might give a even better performance.

#### 4.2 Test 2

From Table 2, obviously that the overall accuracy has dropped for a little but still acceptable. Using decision tree would have approximately 72.18% accuracy during the testing. And test 2 generally results in a lower accuracy is also reasonable since the three bands (Alice in Chains, Soundgarden and Pearl Jam) are in the same genre. Their music styles are close which might even affect human's decision.

Table 3: Accuracy for Test 2

	Naive Bayes	Decision Tree
<b>Trail 1</b>	50.7407	55.3704
<b>Trail 2</b>	52.7778	50.9259
<b>Trail 3</b>	52.4074	54.4444
<b>Trail 4</b>	55.3704	51.2963
<b>Trail 5</b>	50.9259	55.3704
<b>Average</b>	52.4444± 3.4705	53.4815± 4.8422

since that we could consider how iTunes Store divides all the artists into categories. And we will use decision tree processes to look for the certain artist.

And for the 3-rd test - genre classification, decision tree algorithm and naive Bayes classifier have kind of the same performance, which is also understandable since when we distinguish one genre from another, we will use not only categories but also some "true-false" to classify genre.

### 4.3 Test 3

According to Table 3, the accuracy in test 3 is not as ideal as the previous ones. Some problem to the classifiers might be

- The genre itself has be developing over time.  $\Rightarrow$  For instance, the rock music in 70s should be quite different from rock music recently.
- The decision tree does not have enough branches to have ideal performance.  $\Rightarrow$  This happens due to the limitation of my personal laptop. If I choose to have a larger number of branches for the decision tree, the run time will be extremely costly.

## 5 Summary and Conclusions

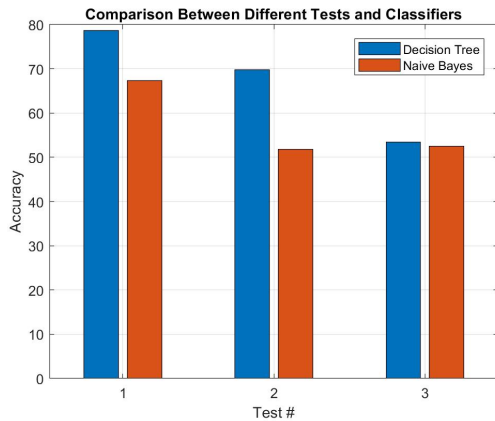


Figure 1: Accuracy Comparison

From the graph Figure 1, we can see that generally, decision tree algorithm has a better overall result comparing to naive Bayes classifier. This is reasonable

```

1  %% TEST 1
2  clc; clear all; close all;
3  %% Import MP3 Files
4  % Choice: Michael Jackson, Soundgarden, Beethoven
5  % myDir = 'C:\Users\Johnnia\Desktop\46\UW\SchoolWorks\2018Winter\AMATH482\HW3\MP3';
6  % [mj, Rmj] = importData([myDir '\MichaelJackson']);
7  % [sg, Rsg] = importData([myDir '\SoundGarden']);
8  % [bee, Rbee] = importData([myDir '\Beethoven']);
9  %
10 % % Resample the data
11 % mj = resample(mj, 1, 2);
12 % sg = resample(sg, 1, 2);
13 % bee = resample(bee, 1, 2);
14 %
15 % % Save for further use
16 % save('mj.mat', 'mj');
17 % save('sg.mat', 'sg');
18 % save('bee.mat', 'bee');
19
20 % Load if possible
21 load('mj.mat');
22 load('sg.mat');
23 load('bee.mat');
24
25 % Make into one data matrix
26 X = [mj, sg, bee];
27
28 %% Label
29
30 for i = 1:size(mj, 2)
31     labs{i} = 'MichaelJackson';
32 end
33
34 for i = 1:size(sg, 2)
35     labs{i+size(mj, 2)} = 'SoundGarden';
36 end
37
38 for i = 1:size(bee, 2)
39     labs{i+size(mj, 2)+size(sg, 2)} = 'Beethoven';
40 end
41
42 %% Get Distinguishable Features
43
44 zcd = dsp.ZeroCrossingDetector;
45 for i = 1:size(X, 2)
46
47     % Count the number of times the signal crosses zero.
48     cross0(i, :) = double(zcd(X(:, i)));
49
50     % Get the max, min, mean, variance and norm of the signal
51     maxV(i, :) = max(abs(X(:, i)));
52     minV(i, :) = min(abs(X(:, i)));
53     meanV(i, :) = mean(X(:, i));
54     varV(i, :) = var(X(:, i));
55     normV(i, :) = norm(X(:, i));
56
57     % Get the first 2 highest frequencies from the FFT.
58     fs = abs(fft(X(:, i)));
59     fs = fs(1:floor(end/2));
60     [~, f1(i, :)] = max(fs);
61     fs(f1(i)) = 0;
62     [~, f2(i, :)] = max(fs);
63 end
64
65 % Create the feature matrix

```

```

66 featureData = [cross0, maxV, minV, meanV, varV, normV, f1, f2];
67
68 %% Train the classifier and get the test result for 5 loops
69 acc_dt = zeros(5, 1);
70 acc_nb = zeros(5, 1);
71 for i = 1:5
72     acc_dt(i) = Classifier(featureData, labs, 'DecisionTree');
73     acc_nb(i) = Classifier(featureData, labs, 'NaiveBayes');
74 end
75
76 %% TEST 2
77 clc; clear all; close all;
78 %% Import MP3 Files
79 % % Choice: Alice In Chains, Soundgarden, Pearl Jam
80 % myDir = 'C:\Users\Johnnia\Desktop\46\UW\SchoolWorks\2018Winter\AMATH482\HW3\MP3';
81 % [aic, Raic] = importData([myDir '\AliceInChains']);
82 % [sg, Rsg] = importData([myDir '\SoundGarden']);
83 % [pj, Rpj] = importData([myDir '\PearlJam']);
84 %
85 % % Resample the data
86 % aic = resample(aic, 1, 2);
87 % sg = resample(sg, 1, 2);
88 % pj = resample(pj, 1, 2);
89 %
90 % % Save for further use
91 % save('aic.mat', 'aic');
92 % save('sg.mat', 'sg');
93 % save('pj.mat', 'pj');
94
95 % Load if possible
96 load('aic.mat');
97 load('sg.mat');
98 load('pj.mat');
99
100 % Make into one data matrix
101 X = [aic, sg, pj];
102
103 %% Label
104
105 for i = 1:size(aic, 2)
106     labs{i} = 'AliceInChains';
107 end
108
109 for i = 1:size(sg, 2)
110     labs{i+size(aic, 2)} = 'SoundGarden';
111 end
112
113 for i = 1:size(pj, 2)
114     labs{i+size(aic, 2)+size(sg, 2)} = 'PearlJam';
115 end
116
117 %% Get Distinguishable Features
118
119 zcd = dsp.ZeroCrossingDetector;
120 for i = 1:size(X, 2)
121
122     % Count the number of times the signal crosses zero.
123     cross0(i, :) = double(zcd(X(:, i)));
124
125     % Get the max, min, mean, variance and norm of the signal
126     maxV(i, :) = max(abs(X(:, i)));
127     minV(i, :) = min(abs(X(:, i)));
128     meanV(i, :) = mean(X(:, i));
129     varV(i, :) = var(X(:, i));
130     normV(i, :) = norm(X(:, i));

```

```

131
132     % Get the first 2 highest frequencies from the FFT.
133     fs = abs(fft(X(:,i)));
134     fs = fs(1:floor(end/2));
135     [~,f1(i,:)] = max(fs);
136     fs(f1(i)) = 0;
137     [~,f2(i,:)] = max(fs);
138
139     wavl(i,:) = sum(abs(diff(X(:,i))));
140 end
141
142 % Create the feature matrix
143 featureData = [cross0, maxV, minV, meanV, varV, normV, f1, f2, wavl];
144
145 %% Train the classifier and get the test result for 5 loops
146 acc_dt = zeros(5, 1);
147 acc_nb = zeros(5, 1);
148 for i = 1:5
149     acc_dt(i) = Classifier(featureData, labs, 'DecisionTree');
150     acc_nb(i) = Classifier(featureData, labs, 'NaiveBayes');
151 end
152
153 %% TEST 3
154 clc; clear all; close all;
155 %% Import MP3 Files
156 % Choice: Alice In Chains, Soundgarden, Pearl Jam
157 myDir = 'C:\Users\Johnnia\Desktop\46\UW\SchoolWorks\2018Winter\AMATH482\HW3\genres';
158 [blues, Rb] = importData([myDir '\blues']);
159 [classical, Rclas] = importData([myDir '\classical']);
160 [country, Rcoun] = importData([myDir '\country']);
161 [disco, Rd] = importData([myDir '\disco']);
162 [hiphop, Rhh] = importData([myDir '\hiphop']);
163 [jazz, Rjz] = importData([myDir '\jazz']);
164 [metal, Rm] = importData([myDir '\metal']);
165 [pop, Rp] = importData([myDir '\pop']);
166 [reggae, Rr] = importData([myDir '\reggae']);
167 [rock, Rrc] = importData([myDir '\rock']);
168
169 %% Resample the data
170 blues = resample(blues, 1, 2);
171 classical = resample(classical, 1, 2);
172 country = resample(country, 1, 2);
173 disco = resample(disco, 1, 2);
174 hiphop = resample(hiphop, 1, 2);
175 hiphop = hiphop(:, 1:end-1);
176 jazz = resample(jazz, 1, 2);
177 metal = resample(metal, 1, 2);
178 pop = resample(pop, 1, 2);
179 reggae = resample(reggae, 1, 2);
180 rock = resample(rock, 1, 2);
181
182 % Save for further use
183 save('blues.mat', 'blues');
184 save('classical.mat', 'classical');
185 save('country.mat', 'country');
186 save('disco.mat', 'disco');
187 save('hiphop.mat', 'hiphop');
188 save('jazz.mat', 'jazz');
189 save('metal.mat', 'metal');
190 save('pop.mat', 'pop');
191 save('reggae.mat', 'reggae');
192 save('rock.mat', 'rock');
193
194 %% Load if possible
195 load('blues.mat');

```

```

196 load('classical.mat');
197 load('country.mat');
198 load('disco.mat');
199 load('hiphop.mat');
200 load('jazz.mat');
201 load('metal.mat');
202 load('pop.mat');
203 load('reggae.mat');
204 load('rock.mat');
205
206 % Make into one data matrix
207 X = [blues, classical, country, disco, hiphop, jazz, metal, pop, reggae, rock];
208
209 %% Label
210
211 for i = 1:size(blues, 2)
212     labs{i} = 'blues';
213 end
214
215 for i = 1:size(classical, 2)
216     labs{i+size(blues, 2)} = 'classical';
217 end
218
219 for i = 1:size(country,2)
220     labs{i+size(blues, 2)+size(classical, 2)} = 'country';
221 end
222
223 for i = 1:size(disco,2)
224     labs{i+size(blues, 2)+size(classical, 2)+size(country, 2)} = 'disco';
225 end
226
227 for i = 1:size(hiphop,2)
228     labs{i+size(blues, 2)+size(classical, 2)+size(country, 2)...
229         +size(disco, 2)} = 'hiphop';
230 end
231
232 for i = 1:size(jazz,2)
233     labs{i+size(blues, 2)+size(classical, 2)+size(country, 2)...
234         +size(disco, 2)+size(hiphop, 2)} = 'jazz';
235 end
236
237 for i = 1:size(metal,2)
238     labs{i+size(blues, 2)+size(classical, 2)+size(country, 2)...
239         +size(disco, 2)+size(hiphop, 2)+size(jazz, 2)} = 'metal';
240 end
241
242 for i = 1:size(pop,2)
243     labs{i+size(blues, 2)+size(classical, 2)+size(country, 2)...
244         +size(disco, 2)+size(hiphop, 2)+size(jazz, 2)...
245         +size(metal, 2)} = 'pop';
246 end
247
248 for i = 1:size(reggae,2)
249     labs{i+size(blues, 2)+size(classical, 2)+size(country, 2)...
250         +size(disco, 2)+size(hiphop, 2)+size(jazz, 2)...
251         +size(metal, 2)+size(pop, 2)} = 'reggae';
252 end
253
254 for i = 1:size(rock,2)
255     labs{i+size(blues, 2)+size(classical, 2)+size(country, 2)...
256         +size(disco, 2)+size(hiphop, 2)+size(jazz, 2)...
257         +size(metal, 2)+size(pop, 2)+size(reggae, 2)} = 'rock';
258 end
259
260 %% Label2

```

```

261 for i = 1:size(rock, 2)
262     labs{i} = 'rock';
263 end
264
265 for i = 1:size(jazz, 2)
266     labs{i+size(rock, 2)} = 'jazz';
267 end
268
269 for i = 1:size(classical,2)
270     labs{i+size(rock, 2)+size(jazz, 2)} = 'classical';
271 end
272 %% Get Distinguishable Features
273
274 zcd = dsp.ZeroCrossingDetector;
275 for i = 1:size(X,2)
276
277     % Count the number of times the signal crosses zero.
278     cross0(i,:) = double(zcd(X(:,i)));
279
280     % Get the max, min, mean, variance and norm of the signal
281     maxV(i,:) = max(abs(X(:,i)));
282     minV(i,:) = min(abs(X(:,i)));
283     meanV(i,:) = mean(X(:,i));
284     varV(i,:) = var(X(:,i));
285     normV(i,:) = norm(X(:,i));
286
287     % Get the first 2 highest frequencies from the FFT.
288     fs = abs(fft(X(:,i)));
289     fs = fs(1:floor(end/2));
290     [~,f1(i,:)] = max(fs);
291     fs(f1(i)) = 0;
292     [~,f2(i,:)] = max(fs);
293
294     wavl(i,:) = sum(abs(diff(X(:,i))));
295 end
296
297 % Create the feature matrix
298 featureData = [cross0, maxV, minV, meanV, varV, normV, f1, f2, wavl];
299
300 %% Train the classifier and get the test result for 5 Loops
301 acc_dt = zeros(5, 1);
302 acc_nb = zeros(5, 1);
303 for i = 1:5
304     acc_dt(i) = Classifier(featureData, labs, 'DecisionTree');
305     acc_nb(i) = Classifier(featureData, labs, 'NaiveBayes');
306 end
307
308
309 %%
310 clc; clear all; close all;
311 %% Comparison
312 load('dt_1.mat'); load('nb_1.mat');
313 dt1 = acc_dt; nb1 = acc_nb;
314 load('dt_2.mat'); load('nb_2.mat');
315 dt2 = acc_dt; nb2 = acc_nb;
316 load('dt_3.mat'); load('nb_3.mat');
317 dt3 = acc_dt; nb3 = acc_nb;
318
319 dt1_mean = mean(dt1); dt1_var = var(dt1);
320 nb1_mean = mean(nb1); nb1_var = var(nb1);
321 dt2_mean = mean(dt2); dt2_var = var(dt2);
322 nb2_mean = mean(nb2); nb2_var = var(nb2);
323 dt3_mean = mean(dt3); dt3_var = var(dt3);
324 nb3_mean = mean(nb3); nb3_var = var(nb3);
325

```



```

326 dtmeans = [dt1_mean, dt2_mean, dt3_mean];
327 nbmeans = [nb1_mean, nb2_mean, nb3_mean];
328 dtvars = [dt1_var, dt2_var, dt3_var];
329 nbvars = [nb1_var, nb2_var, nb3_var];
330
331 figure
332 hb = bar([1, 2, 3], [dtmeans, nbmeans]);
333 set(hb(1), 'FaceColor','r')
334 set(hb(2), 'FaceColor','b')
335 set(hb(3), 'FaceColor','g')
336
337 %%
338 data = [[dt1_mean, nb1_mean]; [dt2_mean, nb2_mean]; [dt3_mean, nb3_mean]];
339 figure(1)
340 b = bar(data);
341 err = [[dt1_var, nb1_var]; [dt2_var, nb2_var]; [dt3_var, nb3_var]];
342 hold on;
343 title('Comparison Between Different Tests and Classifiers')
344 xlabel('Test #');
345 ylabel('Accuracy');
346 legend('Decision Tree', 'Naive Bayes');
347 grid on;
348
349 function accuracy = Classifier(dat, labs, classifier)
350 n = size(dat,1);
351 trainSize = floor(n*0.7);
352 testSize = floor(n*0.3);
353
354 %% Divide data to be training set and testing set
355 randIndex = randperm(n);
356 randData = dat(randIndex,:);
357 randlabs = labs(randIndex);
358
359 % First 70% to be training data
360 train = randData(1:trainSize,:);
361 trainlabs = randlabs(1:trainSize);
362
363 % The other 30% to be testing data
364 test = randData(trainSize+1:end,:);
365 testlabs = randlabs(trainSize+1:end);
366
367 %% Perform SVD
368
369 [u,s,v] = svd(train','econ');
370
371 % Compute energy
372 energy = diag(s)/sum(diag(s));
373
374 % Find modes with less than 10% energy
375 i = find(energy < 0.1);
376
377 % If the above all modes are within 10%
378 if isempty(i)
379     endInd = size(v,2);
380 else
381     endInd = i(1)-1;
382 end
383
384 % Get the data with only modes with more than 10% energy
385 train = v(:,1:endInd);
386 test = s\ u'*test';
387 test = test(1:endInd,:);
388
389 %% Train
390 if (strcmp(classifier, 'DecisionTree'))

```

```

391     model = TreeBagger(30, train, trainlabs);
392 elseif (strcmp(classifier, 'NaiveBayes'))
393     model = fitcnb(train, trainlabs);
394 end
395 %% Test
396
397 predictions{testSize,1} = [];
398 correctness = zeros(testSize, 1);
399
400 for i = 1:testSize
401     predictions{i,:} = predict(model, test(i,:));
402     correctness(i) = strcmp(predictions{i,:), testlabs{i});
403 end
404
405 accuracy = 100*sum(correctness)/length(correctness);
406
407 end
408
409 function [dat, Fs] = importData(myDir)
410
411 musics = dir(fullfile(myDir));
412 musics = musics(3:end, :);
413 n = length(musics);
414
415 dat = [];
416
417 for i = 1:n
418     [song, Fs] = audioread(fullfile(myDir, musics(i).name));
419     vectorSong = song(:,1);
420     dat = [dat; vectorSong];
421 end
422
423 % Get the number of frames in 5 seconds
424 nIn5 = Fs*5;
425
426 % Get the number of 5-second clips
427 nClips = floor(length(dat)/nIn5);
428
429 % Trim the data matrix
430 dat = dat(1:nIn5*nClips);
431
432 % Reshape the data matrix
433 dat = reshape(dat,[nIn5, nClips]);
434
435 end

```