Classifying Recorded Music

Seth Golub

MSc in Artificial Intelligence
Division of Informatics
University of Edinburgh
2000

Abstract

People are able to make stylistic distinctions between samples of music quickly and easily. Reliably duplicating this ability with computers has proven to be difficult, but a simple system with modest accuracy can still be useful for some music organization applications.

I have created software to extract certain features from recorded music, and trained and tested three classifiers (Generalized Linear Model, Multilayer Perceptron, and k-Nearest Neighbor) each on three tasks of genre classification using a large collection of labelled examples.

There was little variance in performance among the three classifiers. On average the classifiers correctly classified 77% of the test data in a task involving two highly similar genres, 82% in a task with three highly dissimilar genres, and 64% in a task with seven genres of mixed similarity.

Acknowledgements

I'd like to thank my supervisor, Chris Williams, who gave me useful and insightful advice whenever I gave him the opportunity. His feedback and guidance during my project planning and writing were of the highest quality and relevance. The remaining shortcomings of my work reflect only own inadequacy in involving him in my decisions and following his advice.

My appreciation also goes to Noel Welsh, who discussed my work with me during the months of design and implementation and heroically read and commented on a draft of my dissertation despite needing to finish his own.

Ian Flanigan deserves special mention for his valuable feedback on multiple drafts, and for cleverly situating himself in whichever time zone was most convenient for me when I needed him.

A serious error in my feature extractor was discovered only through Nico Kämpchen's interest, acuity, and resistance to hand-waving, so my thanks go to him as well.

I also must thank everyone whose work this builds on, for the inspiration and guidance I drew from their accomplishments. To those whose work this does not sufficiently incorporate, I apologize. I learned a great deal from many people throughout this project, but not always in time to build on it properly.

Finally, I would like to thank my parents for their unwavering lifelong encouragement, which I never fail to notice, appreciate, and benefit from, but which I surely do not acknowledge often enough.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

> "Up until now, you've had to make these record breaking decisions on your own, relying on perplexing intangibilities like taste and intuition." (Negativland, 1987)

1.1 Overview

Artificial Intelligence is sometimes described as the study and practice of tasks that are easy for people and hard for computers (Howe, 1998). Making judgments about music fits that description perfectly. People without formal training can make judgments about musical style quickly and easily, but duplicating these feats computationally has proven to be difficult.

Music is a part of many people's daily lives. We use computers to help us organize information in many domains, but their ability to help us with our music has been fairly limited.

The principal goal of this project was to produce a system that can be used to make better music organization tools. Specifically, this consists of software that extracts features from recorded music and then uses these features to classify the music based on a set of labelled training examples.

I trained and tested three different classifiers (Generalized Linear Model, Multilayer Perceptron, and k-Nearest Neighbor) to classify music into genres in three different tasks. One task involved two highly similar genres, one involved three highly dissimilar genres, and one involved seven genres of mixed similarity.

1.2 Results

On average the three classifiers correctly classified 77% in the 2-class task, 82% in the 3-class task, and 64% in the 7-class task, with little variance among the different types of classifiers. This level of accuracy is not sufficient for all applications, but is still useful for some. A few potential applications are listed in Chapter 4.

1.3 Motivations

My primary motivation on this project is a practical one. I want to be able to organize, search, and browse through music databases more effectively. This includes selecting songs to listen to from my own collection and finding other music I (or others) might like.

Given an accurate measure of music similarity, one could pick a few songs and have a jukebox or music vendor fill out a set autonomously. Finding songs similar to a set of examples is not sufficient to build excellent play lists, but it is necessary and may be sufficient for browsing. For these applications we need a measure of music similarity that can be automatically applied to recordings.

The experiments in this project dealt with music classification, not similarity. This is because human-labelled classification data was much easier to acquire than similarity data. The study of the features and classifiers in genre-labelling tasks should prove useful to further work on similarity metrics.

Judgments of similarity depend on context and task, and no single metric will suffice for all occasions. Minka and Picard (1997) show that several limited similarity metrics can be combined into a more robust query system, and their methods could be applied to music when there are enough metrics to work with.

1.4 Previous Work

1.4.1 Limited Solutions

A great deal of work has been done on classifying or measuring similarity of musical style based on higher level representations of music, such as scores. There are two problems with this approach. One is that some of people's perceptions of music depends on characteristics not captured by the score, such as the sounds of instruments and the way they are played. The other is that we are currently unable to automatically extract a score from most real recordings.

Shuttleworth and Wilson (1995) extracted chords from polyphonic music, Martin (1996) transcribed (extracted notes) from polyphonic music, and Martin and Kim (1998) identified instruments in monophonic samples containing only the instrument to be identified. These are all encouraging signs of progress in auditory music analysis, but they were all developed and tested using only clean audio samples produced in laboratories and would not fare well on the more diverse mix of sounds found on normal recordings.

Dannenberg et al. (1997) classified the performance style of trumpet solos, using an existing tool to convert monophonic audio to MIDI. Scheirer (1995) used signal processing to extract the precise timing and loudness of each note in piano solo recordings, but needed a high-level representation of the original scores as a guide. These both used recordings of real performance, but were limited in one case to monophonic (one note at a time) audio, and in the other to music for which a transcript was already encoded.

1.4.2 General Solutions

Foote (1997) used cepstral coefficients (a spectral measure often used in speech processing) of short audio samples to distinguish between speech and music with excellent accuracy.

Soltau et al. (1998) trained an autoassociative neural network on cepstral coefficients in order to perform nonlinear discriminant analysis. They used the activation strength of the hidden units to determine the most significant component in each audio frame, then trained two classifiers to categorize music into broad genres based on the temporal patterns of component significance. The genres (rock, pop, techno, classical) were similar to ones used in my experiments, and the classification rates achieved were also similar.

Many of the features used in my implementation are (not coincidentally) similar to the ones Wold et al. (1996) use for a query-by-example database of short audio clips. Searches use k-Nearest Neighbor with interactive (user-supplied) feature scaling to find examples similar to a set of exemplars provided by the user.

Hauptmann and Witbrock (1998) describe the use of audio cues in the Informedia project to help segment news broadcasts. The cues included short-term maximum amplitude, signal-to-noise ratio, acoustic environment, channel type, and speaker identification. Spectral characteristics were used to classify the acoustic environment as one of a small set of predefined classes, and to differentiate between different types of channels such as telephones and high quality microphones.

1.4.3 Indirect Solutions

There are ways to measure characteristics of music without measuring the music itself. Since people are so good at reacting to music, we are a rich source of information. The difficulty lies in getting the information reliably and unobtrusively.

Picard (1997) describes methods of directly measuring physiological effects and using them to model and predict human responses to music. Healey et al. (1998) built on this and implemented an "affective DJ". The system is trained by recording arousal changes that occur while each song is played. It later uses this data to select music with arousal effects that fit a high level plan (such as "exciting" or "relaxing").

Retailers (and helpful friends) have long used nearest-neighbor strategies, predicting that if they can find people who share many of your expressed preferences, they can predict your feelings about something by looking at what these other people thought about it. This was automated in a music recommendation system by Shardanand (1994) and similar systems have been used by online music retailers such as Amazon[1] and CDNOW[2]. Retailers use purchases as preference observations, but Shardanand's system used time-consuming surveys. These collaborative solutions require large groups of coordinated participants. They also tend to reinforce existing popularity, never recommending undiscovered music.

1.4.4 Related Work

Beat Tracking

Although not directly related to classification, tracking beats in music is an important music analysis task. A robust beat tracker would be a valuable

[1] `http://www.amazon.com/`

[2] `http://www.cdnow.com/`

component in a music classification system. Working beat trackers have been constructed using peak finding, adjustable oscillators, sets of simple oscillators, and autocorrelation (Allen and Dannenberg, 1990; Dixon, 1999; Gasser and Eck, 1996; Large, 1995; Scheirer, 1997).

Source Separation

It would also be useful to separate audio streams into their component sources (instruments, voices) as humans can. This would allow us to analyze the spectral and temporal behavior of each instrument and voice individually. Human listeners organize auditory input through a process known as auditory scene analysis (Bregman, 1990). The field of computational auditory scene analysis attempts to replicate the human capacity, but has not yet produced robust and powerful systems.

Two recent efforts in computational auditory scene analysis stand out. Ellis (1996) built a probabilistic system that attempts to explain audio streams simultaneously with several competing theories, each one proposing a combination of sounds that might have produced the observed stream. It performs reasonably well considering the primitive sound source models it uses. If combined with more sophisticated models of musical instruments, it could provide us with both instrument identification and source separation, each of which would help music classification immensely.

In addition to a robust beat tracker, Scheirer (2000) built a system that separates sound sources (instruments, voices) using dynamic clustering of frequency comodulation data. His model is strongly grounded in psychoacoustics, and, as far as I know, is the first computational auditory scene analysis system specifically designed for and applied to complex music.

1.5 Overview of Dissertation

The remainder of this dissertation is organized into the following chapters:

- Chapter 2 describes feature extraction: why it is done, what features I have extracted, how they are extracted from the audio source, and how they are processed before classification.

- Chapter 3 describes the classifiers: which ones were used, how they were used, and the results and implications of the tests.

- Chapter 4 reviews the goals and accomplishments of the project, lists some applications the system might be used for at its current level of accuracy, and discusses possible future work.

- The full list of features appears in Appendix A. Appendix B contains source code of the program used for feature extraction. A complete list of the songs used in each data set appears in Appendix C.

Chapter 2

Feature Extraction

2.1 Overview

In this chapter I explain why I've chosen to extract features from the input signal, present some basis for the features I've chosen to extract, and describe the features and how they are computed. I also explain the types of normalization applied to the data and make some observations about the features based on visual inspection.

2.2 Why Extract Features?

Nearly all music in this project was scanned from CDs. CD audio has two channels (left and right) and has been digitally sampled at 44.1kHz. Even after combining the left and right channels (as was done throughout this project), a three minute song is approximately 15MB of data. Although we could attempt to train a classifier using this raw data, this approach has several problems.

2.2.1 Space and Speed

Training and using a classifier with 15 million inputs would be horribly slow, would require large amounts of storage, and would be infeasible on resource-poor platforms.

2.2.2 Constraining the Problem

If we have too many inputs compared to the number of training examples, the problem will be poorly constrained and a classifier will not be able to learn the target function reliably (Bishop, 1995). This is called the "curse of dimensionality". Reducing the input to a set of extracted features is one way to reduce the dimensionality.

2.2.3 Invariances

There are transformations we can apply to our input that would not affect its classification. A classifier would need to learn these invariances and to extrapolate for some new examples. If we can remove some invariances through preprocessing, we can reduce the complexity of the function the classifier needs to learn.

Since our classes depend on how humans process music, we can apply knowledge of psychoacoustics to find invariances and to scale features in helpful ways.

2.3 Biological Motivations

2.3.1 Frequency Decomposition

People's perception of sound is highly dependent on the frequency composition of that sound. This is easily explained by the mechanics of the auditory system.[1] The cochlea, part of the inner ear, performs a spectral decomposition of incident sound waves. This decomposition is one of the most central characteristics of human hearing. Consequently, most of the features used in these experiments are based on the spectral decomposition of sound.

2.3.2 Nonlinear Frequency Scale

Two other important characteristics of human sound perception relate to its nonlinear response and resolution. Frequency plays a large role in sound perception, and our sense of it works on a $\log_2$ scale. When we hear a tone moving at a constant rate from a low note to a high one, its frequency is actually increasing exponentially. In order to more closely match human sound perception, frequency-dependent features use a $\log_2$-frequency scale, rather than a linear one.

2.3.3 Nonlinear Loudness Scale

Loudness perception also works on a logarithmic scale. Our perception of loudness depends to some extent on frequency (because our ears do not have uniform sensitivity over all frequencies), but within any frequency, our perception of loudness is approximately logarithmic. Using a frequency-insensitive log-scale measure of loudness is less accurate, but is a common simplification and is used in this project.

2.3.4 Fourier Transform

The Fourier transform is a mathematical transformation that converts signals in the time domain to the frequency domain, or vice versa. This is most often used to decompose a time-domain signal into its composite frequencies. The

[1] A detailed and fascinating description of the human auditory system can be found in Cook (1999).

true Fourier transform operates on continuous, analog signals, but there is a discrete version, which is what is referred to and used here.

The Fourier transform is a convenient and popular method of spectral decomposition, but in applying it we must overcome two obstacles. One is simply that event frequency occurs over time and doesn't have meaning (and can't be measured) instantaneously. By using longer windows (more samples), we measure frequency more precisely. The best frequency resolution can be attained by transforming the entire sample in a single analysis.

Unfortunately, we also need to worry about time resolution and stationarity. If we transform a whole song in a single analysis, we will have only one frequency snapshot of the entire song, and we will not not learn anything about how frequencies change over time. Doing so would also violate assumptions of the Fourier transform, which would result in significant inaccuracies. The frequencies present in music change over time, but the Fourier transform assumes an infinitely long stationary (unchanging) signal. With a shorter window, the assumption of stationarity and time resolution are more accurate, but the frequency resolution suffers.

The solutions to these problems conflict, and the only option (with the Fourier transform) is to select a window size appropriate to the application. It must be short enough that the signals of interest are nearly stationary and to give us reasonable time resolution for our needs, but must be long enough to provide us with sufficiently precise frequency resolution. Selecting a window size depends on how precise our frequency and time estimations need to be, and over what period frequencies are considered approximately stationary by human listeners.

Wold et al. (1999) suggest that using a window size of 25-40ms is reasonable. An additional practical consideration is that, for most FFT (Fast Fourier Transform) implementations, the number of samples in the window must be a power of two. The library I used (FFTW[2]) doesn't have this restriction, but with the default configuration it does run significantly faster if the sample size is a multiple of small primes. With a 44.1kHz sampling rate, 30ms windows each contain 1470 ($2 \times 3 \times 5 \times 7 \times 7$) samples.

The short window is moved incrementally over the segment and a frequency snapshot is calculated in each position. In some other applications, the window is moved in small increments, and estimates are made using overlapping frames. In this project, the window was applied to adjacent, non-overlapping areas, moving in increments equal to the window size. This reduces the time resolution of the features, but also reduces the amount of computation required. The features used in this project were only used in aggregate, so the additional data would not have been useful enough to warrant the extra computation.

2.4 Features

A total of 46 features are extracted from the audio signal, many of which are closely interrelated. The complete list of features is enumerated in Appendix A.

The features are extracted in three stages at three time scales. First, short term features are extracted from 30ms frames. These form the core of nearly all the final features, but they are first aggregated in two scales. The means and variances of the short term features are measured over 4-second intervals, and the means and variances of those medium term features are calculated over the whole song.

The goal is to measure (albeit roughly) the behavior of the short term features in two different scales. The two-level system gives some measure of the characteristics of the music over the short term (four seconds) and

[2] `http://www.fftw.org/`

long term (whole song). Ideally, this would capture the essential differences between a song in which a short term feature changed rapidly but consistently throughout the song, and one in which there were significant but gradual changes.

2.4.1 Short Term Features

Loudness

The only directly measurable feature of audio is amplitude. It is amplitude data that is sampled at 44.1kHz and recorded onto CDs. "Loudness" refers to what people perceive, and as discussed in Section 2.3, can be approximated as the $\log_2$-amplitude of the signal. Amplitudes in the source data are 16-bit signed integers; the resulting loudness is multiplied by 100 so it can be stored as an integer with reasonable precision. In the formula below, $N = 1470$, the number of samples in the window analyzed.

$$loudness = 100 \log_2 \left(1 + \frac{1}{N} \sum_{t=1}^{N} |a_t| \right) \tag{2.1}$$

An additional complication in measuring loudness is that the signal amplitudes on a recording may not reflect typical listening conditions. Ideally, we would use post-amplification loudness, not the loudness of what's on the recording. While we can't correct for the listening environment without knowing what it would be, we can correct for different recording levels. If, under the same listening conditions, a listener would play two recordings with different amplification, and if we can predict the desired amplification, we should correct for it.

In order to use a song's overall loudness as a single feature and to make the other loudness-related features independent of this level, the loudness-related features are each scaled according to a normalization factor chosen for each song. The loudness scaling factor is discussed in more detail in

Section 2.4.3.

Centroid

The centroid is the energy-weighted mean of the frequencies. It is the weighted mean of the frequencies of sinusoidal components, where each component is weighted by the amount of energy in that frequency (i.e. by the amplitude of the component). To more closely match human frequency perception, a log scale is used for the frequencies. The results are multiplied by 1000 for implementation convenience (so they can be stored as integers with greater precision).

In Equation 2.2, e_f is the energy in frequency bin f. Since each window contains 1470 samples, the FFT yields 735 unique frequency bands. N refers to this number. Because the Fourier transform transforms to a linear frequency scale, $\log_2$ scaling is done here.

$$centroid = \frac{1000}{N} \frac{\sum_{f=1}^{N} e_f \log_2 f}{\sum_{f=1}^{N} e_f} \tag{2.2}$$

Wold et al. (1996) explained the centroid as a measure of brightness, which is especially useful in conjunction with pitch. Polyphonic music doesn't have a single pitch, but the centroid is still a useful coarse measure of frequency distribution.

The centroid and bandwidth are given in units of thousandths of log-frequency-bin. Relating the FFT frequency bin back to Hz depends on the sampling rate of the original source. For 44.1kHz, each bin corresponds to 30Hz.

Bandwidth

Another useful measure of frequency distribution is bandwidth. While centroid is an energy-weighted mean, bandwidth is an energy-weighted standard deviation, and is a measure of the frequency range of the signal. As with the centroid, the bandwidth is multiplied by 1000 for implementation convenience.

$$bandwidth = 1000\sqrt{\frac{\sum_{f=1}^{N}(centroid - \log_2 f)^2 e_f}{\sum_{f=1}^{N} e_f}} \tag{2.3}$$

Uniformity

The final spectral measure used is frequency uniformity, which measures the similarity of the energy levels in the frequency bands. Raw uniformity values are in the range $[0, 1]$, but for implementation convenience are scaled here by 1000 to have a range $[0, 1000]$.

$$uniformity = -1000 \sum_{f=1}^{N} \left(\frac{e_f}{\sum_{f=1}^{N} e_f} \right) \log_N \left(\frac{e_f}{\sum_{f=1}^{N} e_f} \right) \tag{2.4}$$

The formula is identical to that used for information entropy, but it would be inappropriate to call this feature "entropy", since the signal is ordered in ways not captured by it. The limitations of the uniformity measurement are most apparent with highly harmonic sounds. Four voices can lock a chord and and create many strong overtones, resulting in a signal with a high measure of frequency uniformity, though the signal is actually highly organized and sounds very little like noise.

Measuring the tonality or harmonicity of polyphonic music was too difficult to be included in this project. Uniformity is meant to be a rough substitute, measuring one aspect of tonality. The main difference is that uniformity is insensitive to the position of the frequency energies. A pleasant sounding chord would have the same uniformity if the notes were each shifted in frequency, but it would sound quite different (and in most cases, rather unpleasant). Uniformity can, however, distinguish between highly pitched sounds (with most of the energy in relatively few frequencies) and highly unpitched sounds (with the energy distributed across more frequencies). For example, a single sinusoid would have zero uniformity, while white noise would be at the other extreme (Ellis, 1996).

The uniformity measure used here gives equal weight to each frequency band. It might be appropriate in future work to discount higher frequencies on a $\log_2$ scale, as is done with the other spectral measurements.

First Differences

First differences give a rough (though narrow) view of trajectory, and were used by Wold et al. (1996) as a feature for audio database indexing. A first difference is a discrete analog to the derivative.

$$d_t(x) = x_t - x_{t-1} \tag{2.5}$$

First differences are computed for centroid, bandwidth, and uniformity, resulting in an additional three short term features.

2.4.2 Medium Term Features

The medium term features consist entirely of means and standard deviations of the short term features. There are eight short term features: loudness, centroid, bandwidth, uniformity, and the difference of each of those from the previous short frame. The medium frame is four seconds long, so there are 120 samples of each principal short feature and 119 of each first difference.

Wold et al. (1999) use weighted statistics, weighting features of each segment by the segment's loudness, arguing that the characteristics of louder frames are more salient. It sounds plausible, but there was no investigation into whether it actually helped. I used both unweighted and loudness-weighted measurements in order to allow such an investigation, but due to time constraints was unable to follow through.

Means and standard deviations are computed for each of the eight features. Weighted means and deviations are computed for the centroid, bandwidth, and uniformity, resulting in a total of 22 medium term features.

2.4.3 Long Term Features

Length

The first and simplest feature is just the length of the song, measured in seconds. Songs were taken directly from CD tracks, so there's often a short silence at the beginning and end, but usually total less than four seconds (in informal inspections). The average song length across all classes is 245 seconds with a standard deviation of 118 seconds, so the extra few seconds is not significant.

Loudness Scale Factor

Since it's possible that the overall loudness is a useful predictor of musical style, the scale factor is used as a feature. There is no obvious best choice formula for loudness scaling. Some applications linearly scale all amplitudes so that the maximum absolute amplitude in the song equals some predefined constant. This doesn't, however, accurately reflect real listening conditions. A person adjusting a volume control isn't going to play an entire album so quietly they can barely hear it just because there's a loud cymbal crash at one point in one song.

In this project, the loudness scale factor is defined as follows: Each medium (four-second) frame is assigned an overall loudness rating of its mean loudness plus one standard deviation of the loudness in that frame. The maximum of these is chosen as the scale factor.

$$scale\_factor = max(\overline{loudness}_m + \sigma(loudness)_m)$$

Arguments could be made for other methods, such as those based on short term maximums rather than short term averages, or ones that ignored rare loudness peaks.

The scale factor can only be chosen after loudness is measured over the whole song, but the feature extraction software is otherwise a single-pass system that doesn't need to keep a whole song in memory. This is not a problem for the average case (240 seconds $\times$ 44.1kHz $\times$ 16 bits per sample = 20MB), but the longest song in the data set (20 minutes) would require 101MB, and it's not hard to find songs twice as long. Also, if features are added that exploit stereo channels, the system would have to retain them (instead of reducing to a single channel, as is done now) and memory requirements would double. In some applications, the song is available on disk anyway and could be read twice, but it's advantageous to be able to work on audio streams, so a single-pass system is desirable. Therefore, the features that combine loudness with other local measurements use an unscaled loudness measure, since that's all that's available at the time, and the features that depend only on loudness are scaled at the end of the analysis.

Statistics

Just as the medium term features are the means and standard deviations of the short term features, 44 of the 46 long term features are the means and standard deviations of the 22 medium term features.

2.4.4 Normalization

Different features have different means and variances. Some classification methods (neural networks, k-Nearest Neighbor) are sensitive to the scale of the features, especially in relation to each other.

Neural networks function best when the sum of their weighted inputs is near zero so that the sum lies in the most sensitive range of the activation function. Standardizing and scaling the inputs takes care of this (Sarle, 1999).

It is important to transform all data sets in exactly the same way if they are to be used with the same classifiers. The first training set was used to select normalization parameters, and these adjustments were applied to all data sets uniformly.

2.4.5 Revisions

In the first implementation, the loudness measure was based on amplitude instead of log-amplitude. Since the human auditory system perceives loudness as log-amplitude, as described in Section 2.4.1, log-amplitude is more likely to be a useful feature for discriminating among human-labelled classes. The use of raw amplitude was an error, but went unnoticed until discussing the features in detail with a colleague. Having already run classification trials on the amplitude-based features, the usefulness of the two loudness measures could easily be compared, and such comparisons appear in Chapter 3.

2.5 Data

Because audio data takes so much storage space, the songs were stored in compressed form using the MPEG-1 layer 3 (MP3) format. This format uses lossy compression, and encoding the same recordings with a different encoder or the same encoder with different settings might yield slightly different feature vectors. For nearly all the data, `xingmp3enc`[3] was used with variable bitrate and quality setting of 75 (higher than default). For some of the data (encoded earlier), `BladeEnc`[4] was used at 128kbps. In all cases, decoding was

[3] http://www.xingtech.com/mp3/encoder/

[4] http://bladeenc.mp3.no/

done using `mpg123`[5]. Some songs were selected at random for blind listening tests, and in all cases the decompressed audio is nearly indistinguishable from the original CD tracks, and the original could not be identified reliably.

2.5.1 Inspection

Figure 2.1 shows a Hinton diagram of the feature correlation matrix for the 7-class training data. The size of each square corresponds to magnitude of the correlation. White squares represent positive correlations, and black squares represent negative correlations. The features appear in the same order as in Appendix A, with the first feature in the leftmost column and top row.

The Hinton diagram reveals a high degree of correlation between most features. Most pairs of features 8 to 18, 20 to 30, and 36 to 46 are highly positively correlated, and this makes the plot look organized (and a bit like a tartan). These are all the spectral features except mean(mean(centroid)). Features 8 to 18 are the basic aggregated spectral features, features 20 to 30 are the same things with loudness weighting, and features 36 to 46 are their first differences. Each feature has a high positive correlation with its counterpart in the other two blocks. Features which correlate with them also correlate to their counterparts, which causes the large squares in the diagram.

While some of the features may share computational dependencies, some of the correlation is due to musical style common to all classes. For example, mean centroid and uniformity (features 7 & 15) have a 0.54 correlation and mean bandwidth and uniformity (features 11 & 15) have 0.70 correlation. This can be at least partly explained by the typical musical use of different frequency ranges. Pitched instruments are generally pitched in the mid or low range (50Hz-2kHz) and most instruments don't produce significant harmonics three or four octaves above (8-16 times the frequency of)

[5] `http://www.mpg123.de/`

their fundamental tone. The only sources of significant energy in the highest frequencies is from unpitched sources such as percussion or vocal fricatives, which have a fairly uniform energy distribution across all frequencies. The bandwidth and centroid only reach their peak values when there is significant energy in the highest frequencies, which increases their correlation with uniformity.

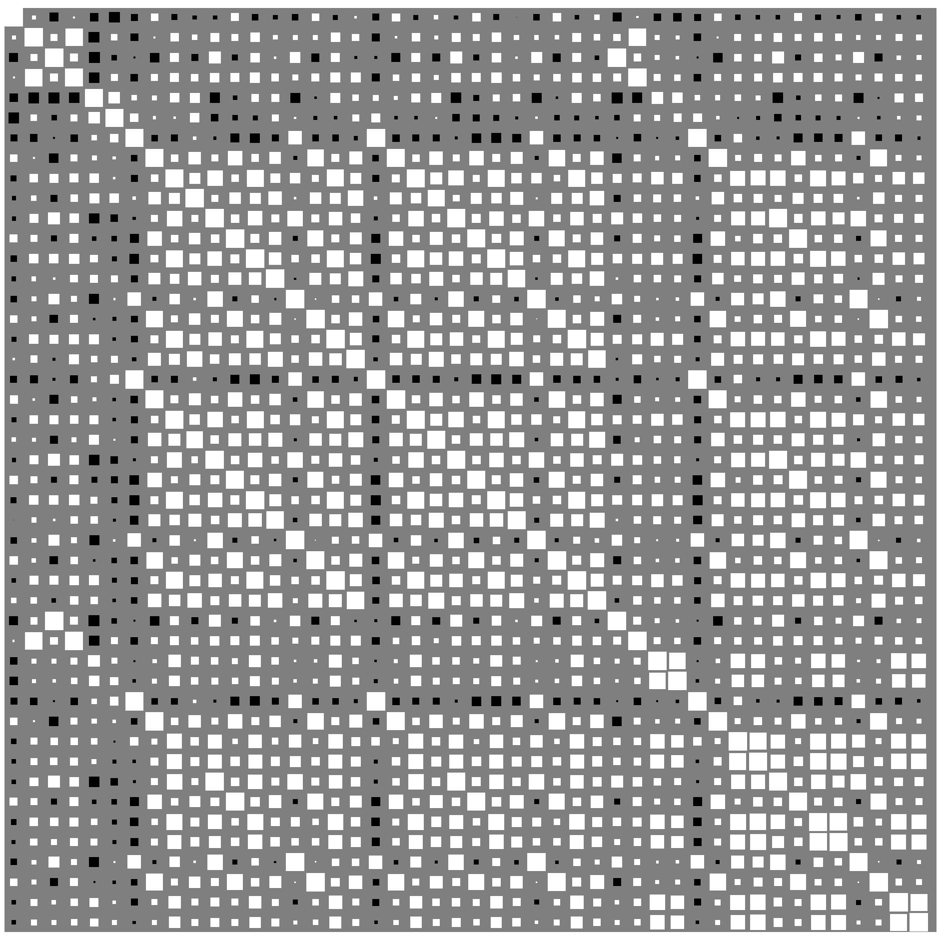

Figure 2.1: Feature correlations

Figure 2.2 shows two features of the 2-class training data: the mean-mean centroid plotted against the mean-std of the centroid. (This is the average frequency against the average deviation of the frequency over four-second segments.) Although there isn't clean separation, even just these two dimensions reveal the different distributions of the two classes.

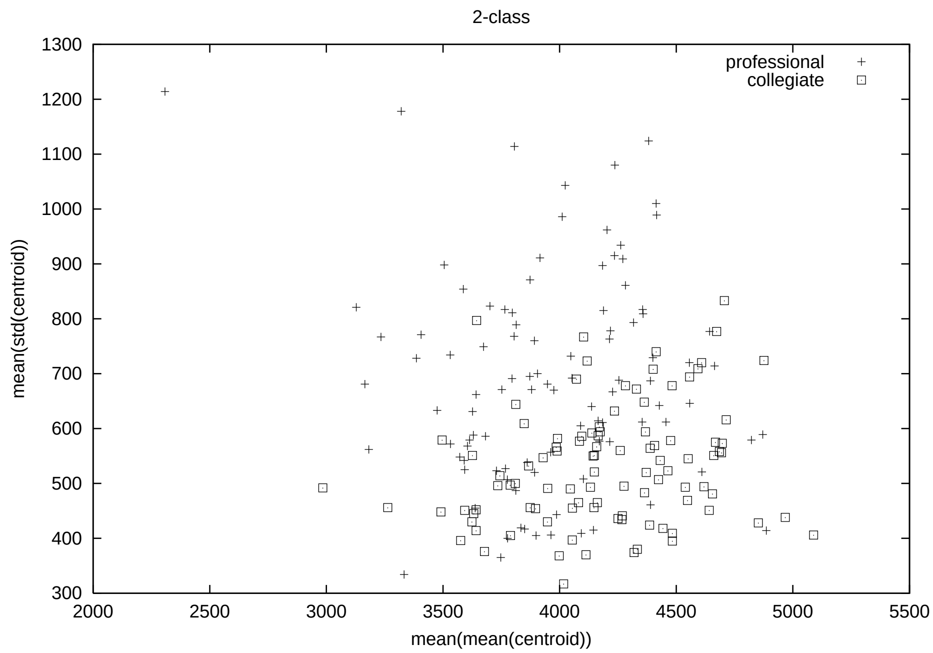

Figure 2.2: mean(mean(centroid)) vs. mean(std(centroid)) with 2-class training data.

Similarly, the distributions of the 3-class data are easily seen in the plot of mean uniformity vs. mean bandwidth, shown in Figure 2.3.

There are no two features that allow us to clearly distinguish all seven classes of the 7-class data, though many pairs of classes are distinguishable (but not separable) with the right pairs of features. Figure 2.4 shows the loudness scale factor, which appears to be useful (though far from sufficient) to distinguish classical music from the other classes.

2.5.2 PCA

Principal Components Analysis (PCA) is a statistical method of unsupervised learning. It discovers an ordered set of orthogonal axes, each one

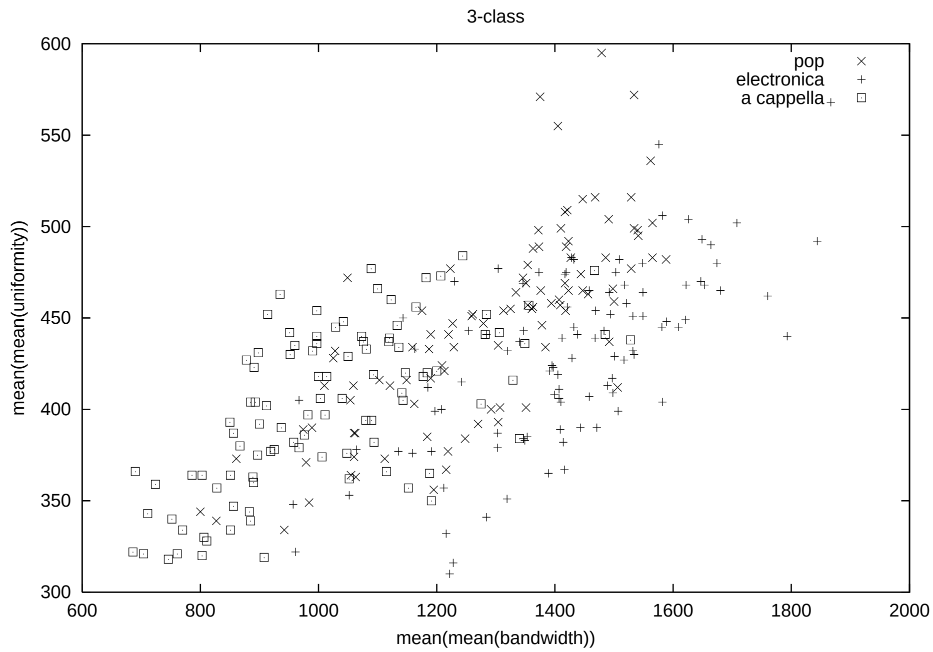

Figure 2.3: mean(mean(uniformity)) vs. mean(mean(bandwidth)) with 3-class training data.

aligned along the maximum variance in the dimensions not described by the higher components. This is done by finding the eigenvectors of the covariance matrix and ordering them by their corresponding eigenvalues. The eigenvalues indicate the relative portion of the data's variance explained by the corresponding eigenvector.

PCA is mainly used for reducing dimensionality by projecting data onto the principal components, then keeping only the k highest components, which describe some desired portion of the total variance. This can be useful if dimensionality reduction is crucial, such as for visualization and computational tractability, or when the problem is underconstrained. Axes of high variance are not necessarily those most useful for classification, so when possible, it's best not to use PCA to discard data.

PCA is useful for visualization because humans find it difficult to view

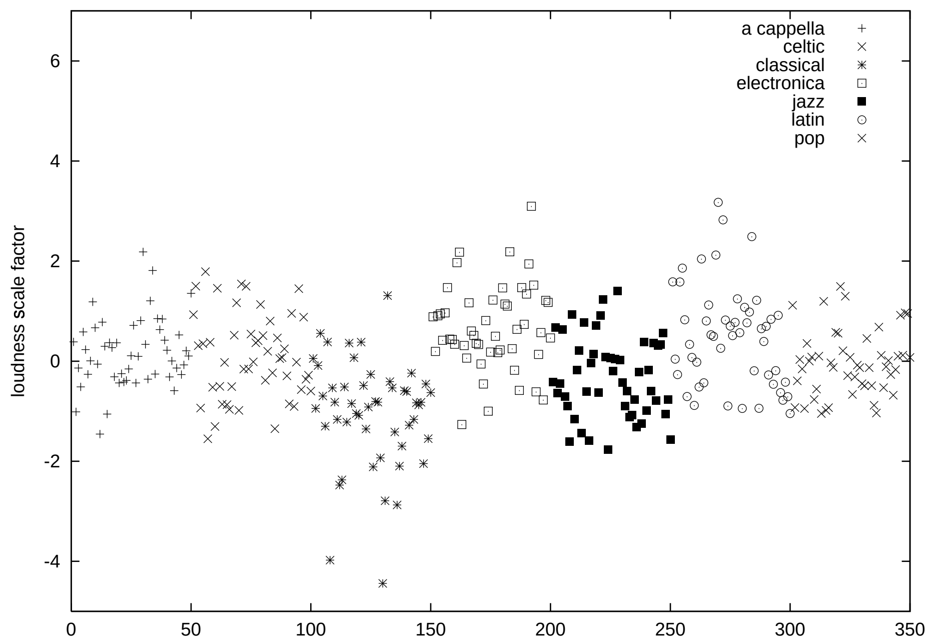

Figure 2.4: Loudness scaling factors in 7-class training data.

data in more than two or three dimensions at a time. Instead of inspecting plots showing the correspondence of two arbitrary raw features, we can see plots of composite features of relatively high variance. Not seeing separation in these pairs doesn't tell us that the data isn't separable, since several dimensions may still be required, but if we do see patterns, they may be helpful in telling us that the data is separable and what sort of shape it takes. Figure 2.5 shows the 3-class data projected onto its first two principal components.

Even if no dimensionality reduction is necessary and all principal components are used, projecting the data onto their principal components is still useful because the principal components will be completely uncorrelated. Correlated inputs don't pose any problems to most classification systems, but can make feature relevance analysis difficult (Sarle, 2000). Analyzing the relevance of uncorrelated features is simpler, but then there's the prob-

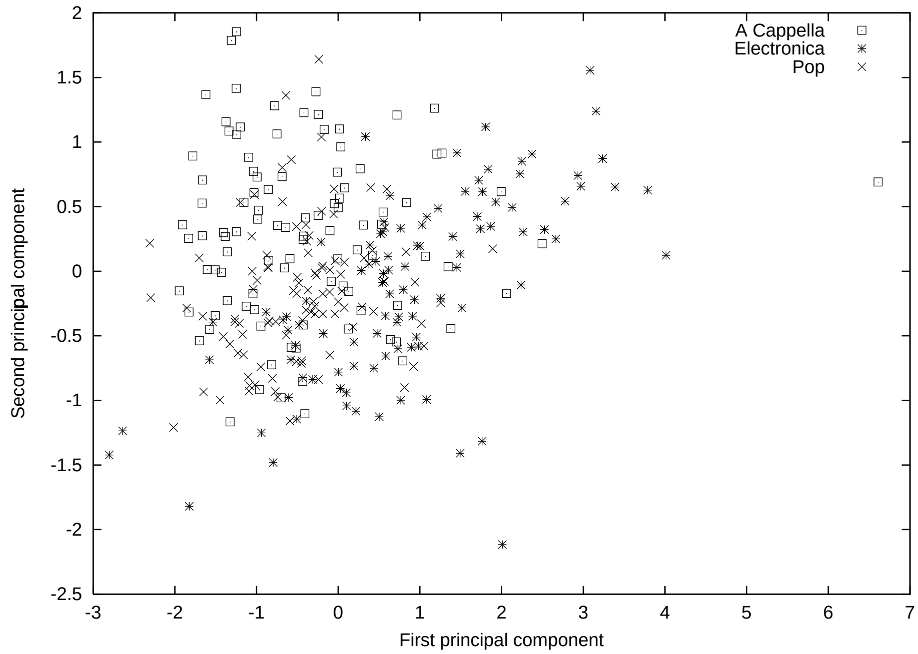

Figure 2.5: 3-class data projected onto first two principal components

lem of the features being hard to understand because they're composites of several possibly unrelated measurements.

Nearest neighbor classifiers also have problems with correlated inputs, but they have problems with features of unspecified relevance in general.

As with normalization, when using one network with two data sets (training and testing, for example), it's crucial to project all sets of data onto the same axes. Each data set was projected on the principal components of the first training set.

Figure 2.6 shows how much variance the first k principal components explain for each data set. In all three tasks, the first 15 principal components explain 95% of the variance. Figures 2.7, 2.8, and 2.9 show the principal components of the 2-class, 3-class, and 7-class data sets respectively.

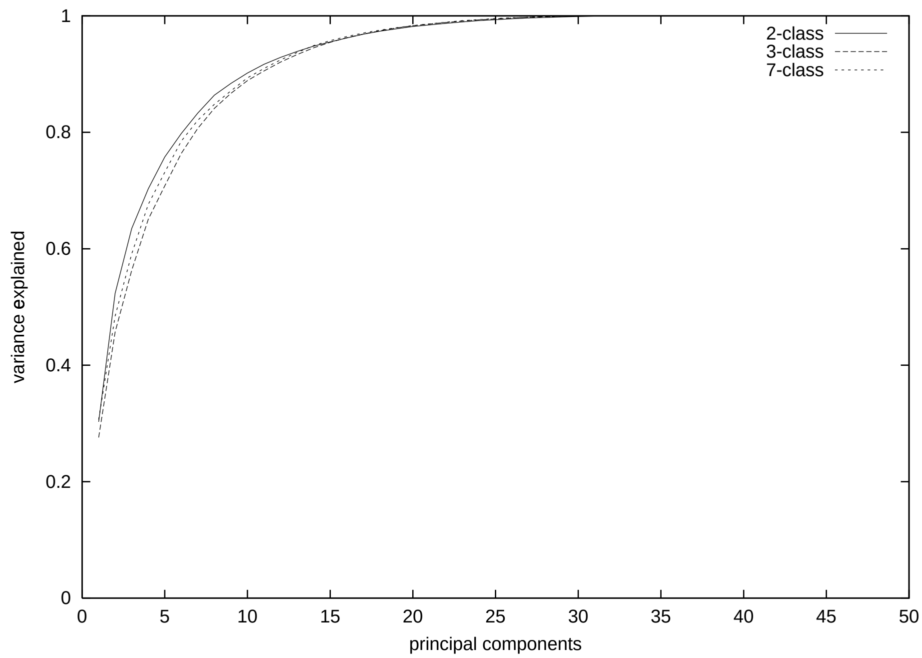

Figure 2.6: Variance explained by first k principal components

2.6 Chapter Summary

In this chapter, I explained why feature extraction is important, described the features I extracted from audio samples, described the normalization applied to the data, and commented on the distribution of the features of the sample data.

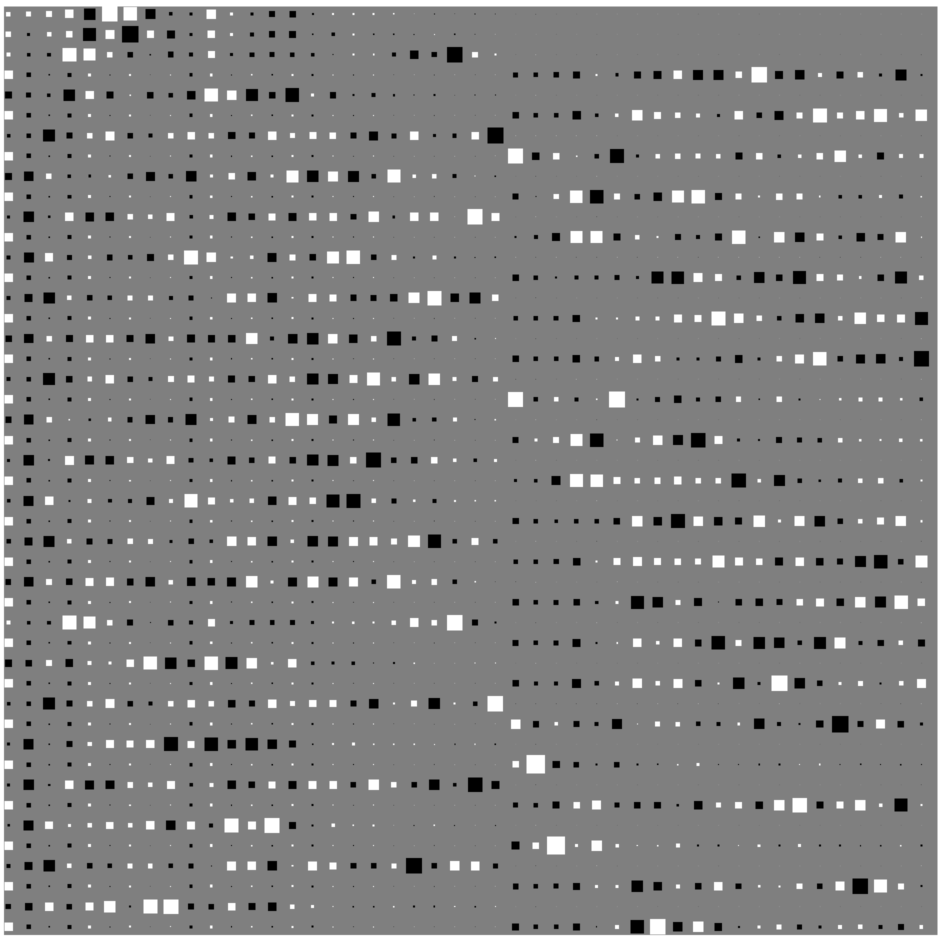

Figure 2.7: Principal Components of 2-class data

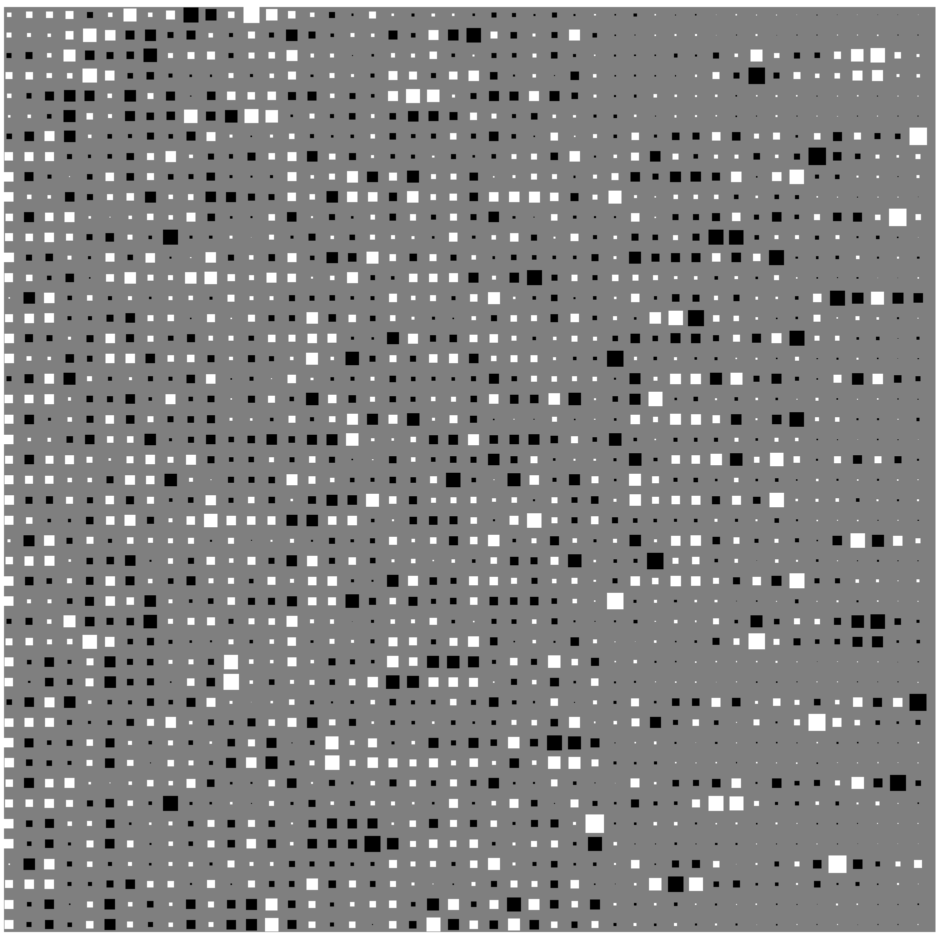

Figure 2.8: Principal Components of 3-class data

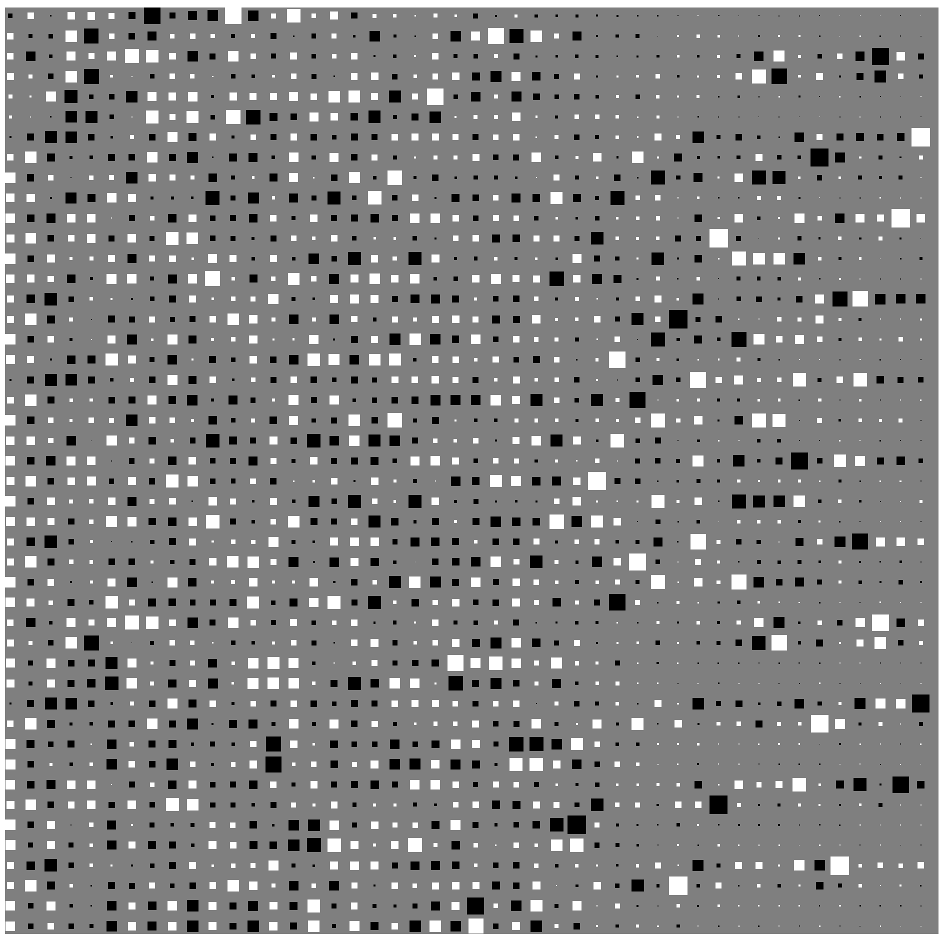

Figure 2.9: Principal Components of 7-class data

Chapter 3

Classification

3.1 Overview

This chapter describes the classification tasks (§3.2) and how the data was partitioned (§3.3) for optimization and training.

Each classification task was done with each of three classifiers: Generalized Linear Model (GLM), Multilayer Perceptron (MLP), and k-Nearest Neighbor (k-NN). A basic knowledge of these classifiers is assumed. Some of the relative advantages of each are mentioned, but for a more thorough understanding of how each classifier works, see Bishop (1995) and Mitchell (1997). Each classifier is presented in its own section (§3.4,§3.5,§3.6) where the classifier is described briefly, the optimization procedures are described, and the test results are presented.

In Section 3.7 I discuss feature relevance, how I had hoped to compute it, the problems encountered, and possible solutions for future endeavors.

At the end of the chapter is a review of the chapter and my observations and conclusions regarding the classifiers, their usefulness at the observed level of accuracy, and the relative merits of each classifier in the context of their performance.

3.2 Classification Tasks

Each classifier is trained on a set of labelled examples, then tested on other cases whose true classification is known to us but not given to the classifier. Experiments were done for three different classification tasks. The three tasks were:

2-class task

1. Collegiate A Cappella
2. Professional A Cappella

3-class task

1. A Cappella
2. Electronica (Techno & House)
3. Pop/Rock

7-class task

1. A Cappella
2. Celtic
3. Classical
4. Electronica
5. Jazz
6. Latin
7. Pop/Rock

The 2-class task used highly similar genres. All songs in both classes contain only vocal music, though the styles vary considerably. College a cappella groups tend to be large (12-20 people) and sing mostly rock and pop covers. Most professional a cappella groups have between four and eight singers, and the styles are a bit more diverse. Most songs in the data sets are rock/pop, but there are also examples of barbershop and classical chorale. A few professional groups also use extensive distortion effects in some songs.

The 3-class task used three highly dissimilar genres. The 7-class task used a broad range of genres, some of which are highly dissimilar (Electronica, Classical), and some of which are fairly similar (Latin, Jazz).

3.3 Data Partitioning

3.3.1 Avoiding Bias

To avoid bias, it is important to use each data example only once in a single analysis. For example, if the same data was used to train and test a classifier, the test would not give a good indication of how we might expect the classifier to perform on new data. Given the amount of time and effort invested in acquiring, labelling, and processing data, it can be tempting to reuse data for seemingly separate parts of a long analysis, such as network model order selection and final testing. But any such reuse is likely to cause overestimation of the accuracy of the classifier and taints the usefulness of the experiment. Also, the same test data was used for all classifiers[1] so that they may be compared fairly.

Each classifier is optimized using a different procedure and requires data to be partitioned in different ways. The GLM is simply trained and tested, but we need to choose the number of hidden units of the MLP and the number of neighbors used in k-NN. These model selection optimizations were done using a separate data set. This will be explained in detail in the sections on each classifier.

Although it would have been simpler to combine model selection and training into a single optimization step, I wanted to compare the three classifiers fairly, using the same training data for each. In hindsight, the distinction between the optimization steps of model selection and training may be arbitrary and perhaps not as useful as I originally envisioned. The optimization steps themselves are important, but performing them serially introduced complication that could have been avoided.

For each task, the training and test sets had the same class distribu-

[1]Except the one in Section 3.4.2 that used data from an older version of the feature extractor.

Task	Model Selection	Training	Testing
2-class	100	100	100
3-class	100	100	50
7-class	50	50	50

Table 3.1: Data set sizes

tion. Table 3.1 shows the number of examples per class for model selection, training, and testing in each task.

Appendix C lists all the songs used in each data set for each task. No data appeared in more than one set within a single task. In many cases there was significant overlap among analogous sets in different tasks. Since tasks are independent, this introduces no bias. The same three data sets were used with each classifier. The exact use of each data set is specific to the classification method and is described in Sections 3.4.1, 3.5.1, and 3.6.1.

3.3.2 Consistency

In many of the experiments, the data is normalized and/or projected onto its principal components. Data remains internally consistent after these transformations, but can no longer be directly compared with other data that has not been transformed identically. Classifiers trained with data transformed to one set of axes would not perform well trying to classify data transformed differently. It is absolutely crucial that all data used by a single classifier be projected on the same axes and scaled identically.[2]

One way to ensure consistency would be to calculate the principal components and normalization parameters of all the data together, and to apply the transformations based on those calculations uniformly on all data. This

[2] I speak with the frustrated voice of experience, despite having known better.

would be inappropriate because the classifiers would then be constructed and trained using data that contained knowledge gleaned from the test sets. This would introduce bias and would cause us to overestimate the reliability of the classifiers. Instead, the data sets must be transformed using only knowledge about themselves and data sets used in earlier processing.

The model selection data set was used as the reference set for all PCA and normalization throughout these experiments. Normalizing raw features vectors usually entails subtracting the mean and dividing by the standard deviation. For the training and test sets, it instead entailed subtracting the mean and dividing by the deviation of the model selection set. Similarly, instead of projecting each data set onto its own principal components, they were each projected onto the principal components of the model selection set.

3.4 GLM

A Generalized Linear Model (GLM) is a neural network consisting of two layers, inputs and outputs, and using linear activation functions. It is a simple network, capable of learning only simple decision boundaries, but it can be trained quickly. Figure 3.1 shows an example GLM network with five inputs and two outputs.

The networks were trained with target values of 0.9 for the output unit corresponding to the correct class, and 0.1 for all other outputs.

The GLM networks had 46 inputs, one for each element of the feature vector, and had one output per class.

3.4.1 Method

For each classification task, two GLM networks were trained and tested. One used the 46 features, normalized; the other used the 46 features projected

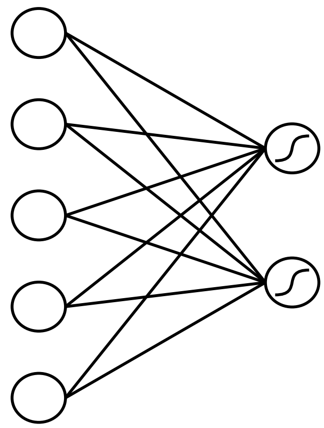

Figure 3.1: GLM network with five inputs and two outputs. (Biases not shown.)

onto the their principal components and then normalized. Reprojecting the data should have no effect on the accuracy of the network, but does affect the interpretability of its internal state. Training a GLM is straightforward, so the use of the data sets was also quite simple. The training data set was used for training, and the test data set was used for testing. The model selection set was not used.

The error function of a GLM is convex and has only one minimum. Consequently, training a GLM is fast, deterministic, and insensitive to the initial weights. The weights are adjusted with an iterative reweighted least squares algorithm until a convergence criteria is satisfied.

3.4.2 Results

Table 3.2 shows the classification rates on the three tasks.

Accuracy of Results

We are interested in the true error rate of the classifiers, but we can only measure them with a limited set of test data. Using larger test sets helps;

Task	Classification rate (%)
2-class	77
3-class	82
7-class	67

Table 3.2: GLM classification rates

the smaller a sample is, the less likely it is to represent the population accurately. The classification rates measured over the test data are estimates of each classifier's true accuracy. The only way to be completely certain that the measured error is an accurate estimate is to test with the entire population, which is usually impractical and often impossible. What we can do is compute the variance of observed estimates and the interval in which the true error of the classifier is likely to be with a specified degree of confidence (Mitchell, 1997).

Equation 3.1 shows the variance, given our estimated error rate $\hat{e}$ and the sample size n.

$$\sigma^2 = \frac{\hat{e}(1-\hat{e})}{n} \tag{3.1}$$

With a sufficiently large sample size (at least 30), it is reasonable to approximate the binomial distribution of our sampling with a Gaussian distribution. In a Gaussian distribution, 95% of data lies within 1.96 standard deviations of the mean. We can therefore say with 95% confidence that true mean lies within 1.96 deviations of our observation.

$$e \text{ in } \hat{e} \pm 1.96\sigma \tag{3.2}$$

Applying this formula to the classification rates in the tests yields the 95% confidence intervals shown in Table 3.3.

Task	Classification rate (%)
2-class	$69 \ldots 85$
3-class	$71 \ldots 93$
7-class	$53 \ldots 80$

Table 3.3: GLM classification rates: 95% confidence intervals.

Confusion

Table 3.4 shows the confusion matrix of the GLM on the 3-class task. Each row in the matrix corresponds to the true class of the data, and each column corresponds to the class predicted by the classifier. The number appearing in cell C_{rc} is the number of test cases of class r which were classified as class c. The same data appears in a Hinton diagram beneath the table in order to make trends easier to see.

Class	AC.	Elec.	Pop	Correct (%)
A Cappella	41	1	8	82
Electronica	2	44	4	88
Pop	7	5	38	76

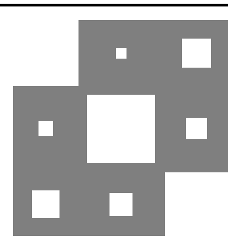

Table 3.4: Confusion matrix of GLM on 3-class task.

The network performs fairly uniformly over all three classes. The errors are roughly symmetric. For example, only two cases of Electronica are labelled as A Cappella, and only one case of A Cappella is labelled as Electronica. This symmetry could indicate simple distributions of each class (possibly convex and contiguous), but to verify this visually would require reducing the data from 46 dimensions to three, without losing information valuable in classification. This is explored in more depth in Section 3.7.

Table 3.5 shows the confusion matrix of the GLM on the 7-class task. The GLM classified Classical and Latin well, but performed poorly on Jazz and Pop.

Class	AC.	Celtic	Class.	Elec.	Jazz	Latin	Pop	Correct (%)
A Cappella	30	3	4	2	5	3	3	60
Celtic	3	35	1	1	1	3	6	70
Classical	0	3	45	0	0	0	2	90
Electronica	1	0	1	38	0	6	4	76
Jazz	4	3	5	3	22	5	8	44
Latin	0	1	1	0	6	41	1	82
Pop	3	0	1	8	9	4	25	50

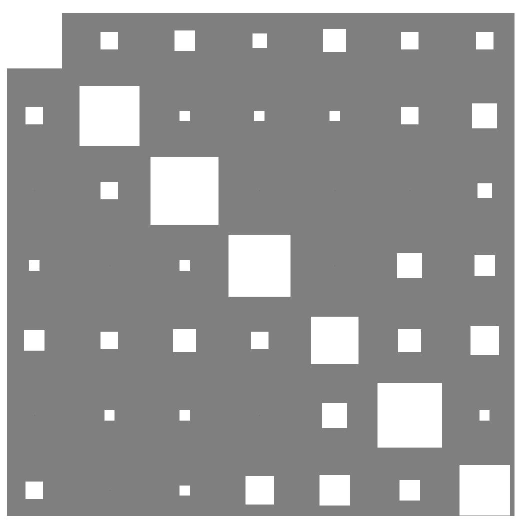

Table 3.5: Confusion matrix of GLM on 7-class task.

Revised Features

On the 2-class task, the GLM achieved a 77% accuracy rate, with a near-equal number of misclassifications of each class. On the same task using the original feature set, with amplitude as loudness instead of log-amplitude, only 61% was achieved, again with a near-equal number of misclassifications of each class.

An important question to address is whether this difference is significant. We expect to see some variance due to sampling error. The classification rates yielded by the tests are estimates of the true accuracy the classifiers would achieve on the entire population from which the test data was drawn.

Sampling theory provides statistical methods of estimating the likelihood that the greater accuracy shown here truly indicates a better classifier (Mitchell, 1997). The estimated difference, $\hat{d}$, is simply the difference between the estimated error rates.

$$\hat{d} = \hat{e_1} - \hat{e_2} \tag{3.3}$$

The true difference between the error rates of the two classifiers is the difference between their true error rates. Just as we can find an interval in which the error lies with a given confidence (see Equation 3.2), we can also find a confidence interval for the true difference between the error rates. The variance of the estimated difference is approximately equal to the sum of the variances of each estimate.

$$\sigma_{\hat{d}}^2 \approx \frac{\hat{e_1}(1-\hat{e_1})}{n_1} + \frac{\hat{e_2}(1-\hat{e_2})}{n_2} \tag{3.4}$$

The likelihood that the classifier using the original feature set is actually as good as the new one is equal to the likelihood that $d \geq 0$, meaning that $\hat{d}$ has overestimated the difference by its mean $\mu_{\hat{d}}$. With Equation 3.4 we find that $\sigma_{\hat{d}} = 0.064$, so our observed difference of 0.16 corresponds to 2.48

standard deviations. A quick table lookup shows that the probability of an observation falling above the mean to this extent is less than 1%. Therefore, we can say with 99% confidence that the classifier trained on the new feature set is indeed better than the original.

Log-loudness is clearly a better choice based on psychoacoustics, and it's reassuring that it results in improved classification accuracy. It's less reassuring though that removing all loudness features increases the accuracy just as much. In Chapter 2, Figure 2.2 showed the mean(mean(centroid)) plotted against the mean(std(centroid)) of the 2-class training data. A GLM trained on only the two features mentioned above achieves 79% accuracy, marginally (but not significantly) better than one trained on all features.

It is not surprising that many of the features are not helpful for this particular task of distinguishing between highly similar styles. It is worth noting, however, that these two features were present in the original feature set. Neither one depends on the loudness measure that was revised. The addition of unhelpful features can reduce the accuracy of a classifier by increasing the degrees of freedom of the solution without increasing the constraints (Bishop, 1995), and this may account for the difference in performance.

3.5 MLP

A multilayer perceptron (MLP) is a feedforward neural network. The ones used here have 46 input units each of which is connected to all the hidden units. The number of hidden units varies and is described below. There is one output unit per class, and all hidden units connect to each one. All hidden and output units in these networks use the logistic activation function. Figure 3.2 shows a multilayer perceptron with a similar architecture to those used, though with a different number of units.

As with the GLM, the target value for the output unit corresponding to

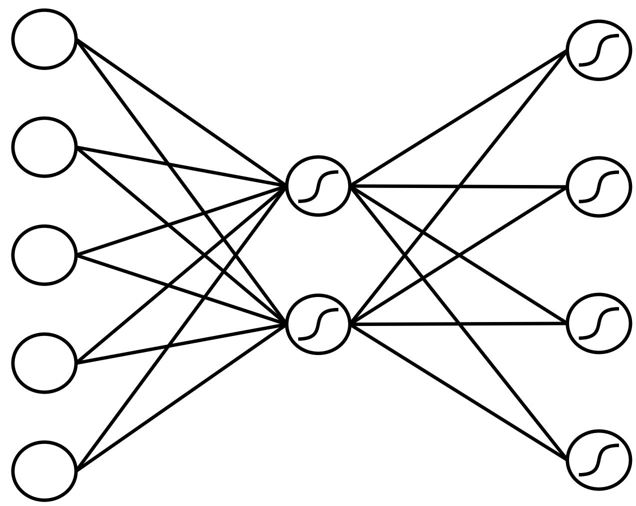

Figure 3.2: MLP network with five inputs, two hidden units, and four outputs. (Biases not shown.)

the correct class was 0.9, and 0.1 for all other outputs.

The procedure for training and testing MLP networks is more complex than that for the GLM networks. The added complexity comes from three complications: the number of hidden units must be chosen; MLPs are sensitive to initial conditions and can get stuck in local minima; MLPs can find class boundaries of complex shape and can easily be overfit to the training data.

Each MLP network was trained with backpropagation using scaled conjugate gradient optimization until the network weights converged. Convergence was defined as a change in training error less than 0.01% in 50 iterations.

3.5.1 Method

Model Order Selection

One way to reduce overfitting is to reduce the network's ability to represent complex functions by limiting the number of hidden units (Bishop, 1995).

This is model order selection and was the only precaution taken here against overfitting. To avoid bias, the data used for model order selection was not used for anything else.

For each classification task, networks with up to seven hidden units were trained and tested. Because MLP networks find locally optimal solutions, but not necessarily globally optimal ones, each order of network was trained and tested 20 times. Each time, the data was randomly repartitioned into training and validation sets and the networks weights were assigned different random initial weights.

It's not clear how to judge the best number of hidden units; it depends on what we'll eventually do with our networks. Best case, worst case, and average case are all valid measures, each useful in different situations. Here I used average case; the overall score for each network order was the mean of the validation rates of each of the 20 trials. The best overall network order was defined as the one with the highest mean validation rate. This is illustrated in pseudocode in Figure 3.3.

```
For each task
·  For h = 1...max_hidden
·  ·  For t = 1...num_restarts
·  ·  ·  Randomly partition data into training and validation sets
·  ·  ·  Train network with h hidden units to convergence
·  ·  ·  Record validation rate r_{h,t}
·  ·  end
·  ·  Record mean validation rate \overline{r_h}
·  end
·  Select best architecture h = argmin(r_h)
end
```

Figure 3.3: MLP model order selection algorithm.

Training and Testing

For each task, a single MLP network is trained. The network has the number of hidden units that perform best in model order selection. The training data is randomly partitioned into training and validation sets, using one seventh of the data for validation. The training data is used to train the network to convergence, then the network is tested with the validation data. If it does not perform as well as the mean performance of the same order network in model order selection, the network is discarded, the data is randomly repartitioned, and the training and validation are repeated. Once a network is accepted, the test data set is run through it to determine its unbiased performance rate.

3.5.2 Results

Table 3.6 shows the mean validation rates for each model order and task. The best model order is for each task is shown in bold. Figure 3.4 shows the same data as a graph, in which it is clear that additional hidden units are not helping.

	% Correct for N hidden units						
Task	1	2	3	4	5	6	7
2-class	**71**	70	68	66	66	65	64
3-class	55	**82**	81	80	78	77	78
7-class	24	36	48	56	**58**	57	57

Table 3.6: Classification rates of MLP network with 1 to 7 hidden units.

The three tasks needed between one and four tries before acceptable networks were trained. Table 3.7 shows the classification rates on the test sets

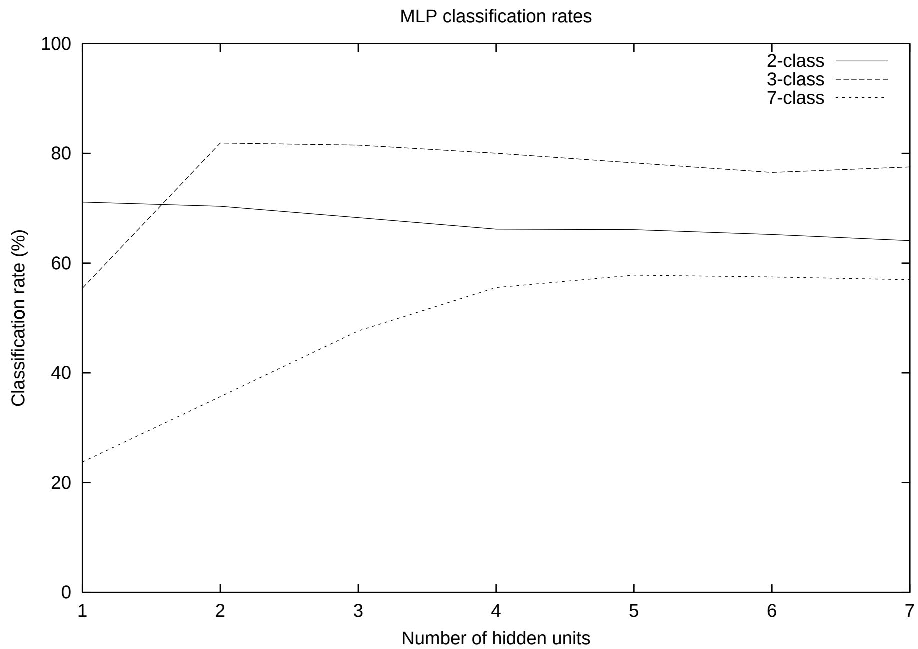

Figure 3.4: Classification rates of MLP network with 1 to 7 hidden units.

for each task. The rates are similar to those achieved by the GLM. Tables 3.8, 3.9, and 3.10 show the confusion matrices for each test set. The distribution of misclassifications is also very similar to those made by the GLM. This suggests that the optimal class boundaries are fairly simple, since the addition of a hidden layer offers no significant improvement.

Task	Classification rate (%)
2-class	79
3-class	83
7-class	62

Table 3.7: MLP classification rates

Class	Col.	Pro.	Correct (%)
College	73	27	73
Professional	16	84	84

Table 3.8: Confusion matrix of MLP on 2-class task.

Class	AC.	Elec.	Pop	Correct (%)
A Cappella	41	3	6	82
Electronica	0	48	2	96
Pop	7	7	36	72

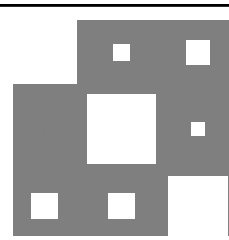

Table 3.9: Confusion matrix of MLP on 3-class task.

Class	AC.	Celtic	Class.	Elec.	Jazz	Latin	Pop	Rate (%)
A Cappella	23	4	3	4	3	5	8	46
Celtic	4	39	2	1	0	2	2	78
Classical	2	6	39	0	3	0	0	78
Electronica	1	1	0	31	12	0	5	62
Jazz	8	0	1	5	26	5	5	52
Latin	2	1	0	0	4	36	7	72
Pop	4	2	0	5	10	7	22	44

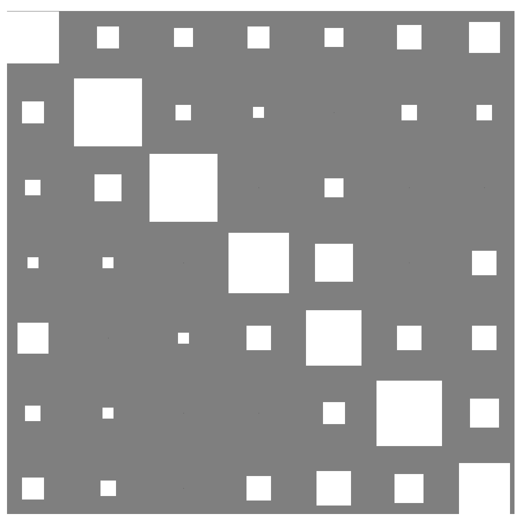

Table 3.10: Confusion matrix of MLP on 7-class task.

3.6 k-NN

Another common classification method is k-Nearest Neighbor (k-NN). This is a lazy-learning, local classification algorithm. While neural networks require training, and build a hypothesis that covers the entire feature space, k-NN requires no training and forms no global hypothesis. When classifying each new data point, it forms a hypothesis covering only that point in the feature space, and discards the hypothesis immediately after classification.

The basic algorithm is simple. For each new data point to be classified, the k nearest training examples are located. The predicted class of the new point is whichever class has the most members in the set of the k nearest points. In this case, "nearest" was defined to mean the smallest Euclidean distance in the feature space. In the case of a tie, the tie was broken randomly. Note that the k-NN algorithm used here does not distance-weight the votes of neighboring points, as is sometimes done.

The chief drawbacks to k-NN are:

1. Large storage requirements; k-NN requires the entire feature vectors of all training data when it classifies new data.

2. Slow classification; k-NN can be slow at classification time compared to neural networks.

3. High sensitivity to feature scaling, redundancy, and interaction.

But k-NN also has important advantages:

1. Requires no training; this is especially helpful when new training data is introduced, since it can be added to the training without any up-front cost.

2. Can learn complex functions; because k-NN uses only local hypotheses, it can learn complex functions without needing to represent them explicitly.

The impact of the storage requirements and postponed computation can only be evaluated in the context of a specific application. There are applications of music classification for which the advantages of k-NN are important and ones where they are not, and the same is true of the disadvantages listed.

What can be evaluated here is the relative accuracy of k-NN for our classification tasks, and here it performs comparably.

3.6.1 Method

There are three important ways to adjust the performance of the k-NN classifier:

1. change the distance function,
2. rescale the features,
3. change k, the number of neighbors consulted in each classification.

The relative scale of each feature determines their relative importance in k-NN's classifications. This can be a crucial optimization, and finding good relative feature scaling can be difficult. Wettschereck et al. (1997) discuss this at length and compare several lazy learning algorithms that attempt to fix this problem, but since the initial performance of the classifier was reasonable, this optimization was not attempted.

k was optimized using the model selection data set. For each value of $k = 1 \ldots 40$, this data set, reprojected and normalized, was randomly partitioned into training and validation sets ($\frac{6}{7}$ training, $\frac{1}{7}$ validation). The classes of each point in the validation set were predicted using this training set. A value of k was chosen by visually inspecting the graph of classification rates and selecting the smallest number that worked reasonably well.

Testing was then done using only the selected value of k. k-NN requires no training; the test set was classified using the training set as the reference.

The input vectors given to the k-NN classifier were the 46 features, projected on their principal components and normalized to have uniform mean and standard deviation[3].

3.6.2 Results

The classification rate for each k appears in Figure 3.5. The rates in each task are fairly flat after a peak around $k = 5$, so that value of k was used for testing in all tasks.

Table 3.11 shows the classification rates of the test set for each task. These are similar to the results of the GLM and MLP networks. In Chapter 2, Figure 2.5 showed the 3-class data projected onto its first two principal components. If the class distributions in this plot are representative, as is hypothesized in Section 3.5.2, it should not be surprising that k-NN performed as it did.

Task	Classification rate (%)
2-class	75
3-class	82
7-class	62

Table 3.11: k-NN classification rates

The classes have simple, partially overlapping distributions. In regions where one class dominates, the neighbors are likely to be of the same class and k-NN will perform well. In regions where the classes are mixed, the mixing is complete enough that k-NN is unlikely to perform well. Thus, k-NN will perform well to the extent that the classes are well separated.

[3]Actually, onto the principal components of the model selection set, as described in Section 3.3.2

The same is true of the GLM and MLP, and their classification rates and confusion matrices are nearly identical to those of k-NN.

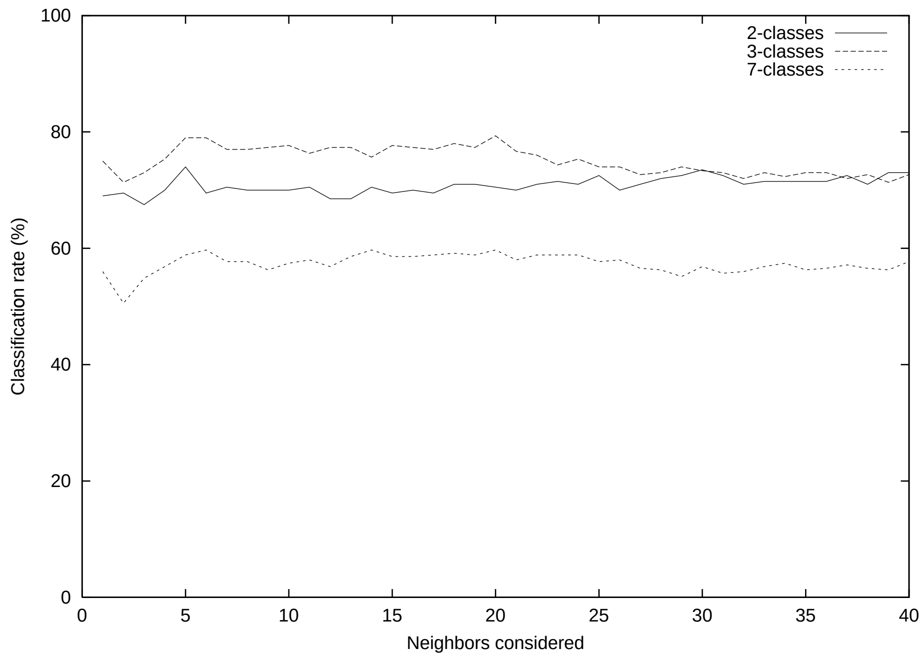

Figure 3.5: k-NN classification rates using k neighbors.

3.7 Feature Relevance

I had originally hoped to inspect a trained GLM network and determine the relevance of the inputs to the classification task. This would allow us in future projects to discard some features or to avoid computing them in the first place, to avoid storing them (in the case of k-NN), and to speed training and classifying. The reduced dimensionality might also increase classification accuracy.

3.7.1 Method

Each input unit corresponds to one feature and each output unit to one class membership (or a likelihood, if scaled appropriately). Ideally, the magnitude of the weights from each input to each output would reflect the importance of that feature to that class distinction within the context of the task for which the network was trained.

3.7.2 Pitfalls of Correlation

One problem with this type of analysis is that there are different types of relevance. John et al. (1994) distinguish between "strong relevance" and "weak relevance". Strong relevance denotes indispensable features whose removal would cause a drop in the classification rate. Weak relevance denotes features which are not strongly relevant and which are part of a set of features such that removing the entire set would cause a drop in performance.

Many of the features used here are weakly relevant at best, due to the high degree of correlation among them. This would complicate experimental feature selection and also causes problems with network weight analysis. A relevant characteristic of the training examples would be partially represented by several correlated features. A network could give this characteristic a strong weight by having smaller weights spread among the features that partially capture it.

Additionally, a network could assign large weights of opposite sign to unimportant but highly correlated inputs. Because the inputs are normalized and strongly correlated, they will usually have nearly the same value. The inputs would appear at first to be relevant due to the large magnitude of the weights, but because they contribute to the output in opposite ways, they would not actually affect the classifications significantly.

This effect was observed in the GLM network trained for the 2-class task.

Features 4 and 32 have the highest magnitude weights of opposite sign (-74 and 76, the next largest is -24) and have correlation of 0.99999. With a correlation that strong, the inputs will usually have nearly the same value and will cancel out due to inverse weights of similar magnitude.

Since the principal components are orthogonal, the features projected onto them are also orthogonal and therefore are completely uncorrelated. Examining the weights of a network trained on projected data would be more fruitful, but the results would hard to interpret because each principal component is an amalgam of features.

It might be useful to perform such an analysis, then reproject the relevant components back into the original feature space for interpretation. Done one component at a time, the projected weights would show the relevance of each feature, though much of the relevance would be as weak as the feature was redundant. This analysis was not done due to time constraints, but would be worth pursuing in future efforts.

3.7.3 Feature Selection

Bishop (1995) and John et al. (1994) discuss feature selection and make it clear that the best way to evaluate the utility of a feature set is to train and test a classifier with it. Unfortunately, the search space is large (2^n - 1), so an exhaustive search is not feasible. There are many heuristics for guided feature selection (forward selection, backward elimination, genetic algorithm), and testing with any of these methods would be a good direction for future work.

A simpler method was done here using a simple forward selection of principal components where choice was based not on classification utility, but on the variance explained by each component. This is done by training and testing a GLM using only the first principal component, then using the first two, etc. Figure 3.6 shows the classification rates for each task using the first N principal components, along with the amount of variance they explain.

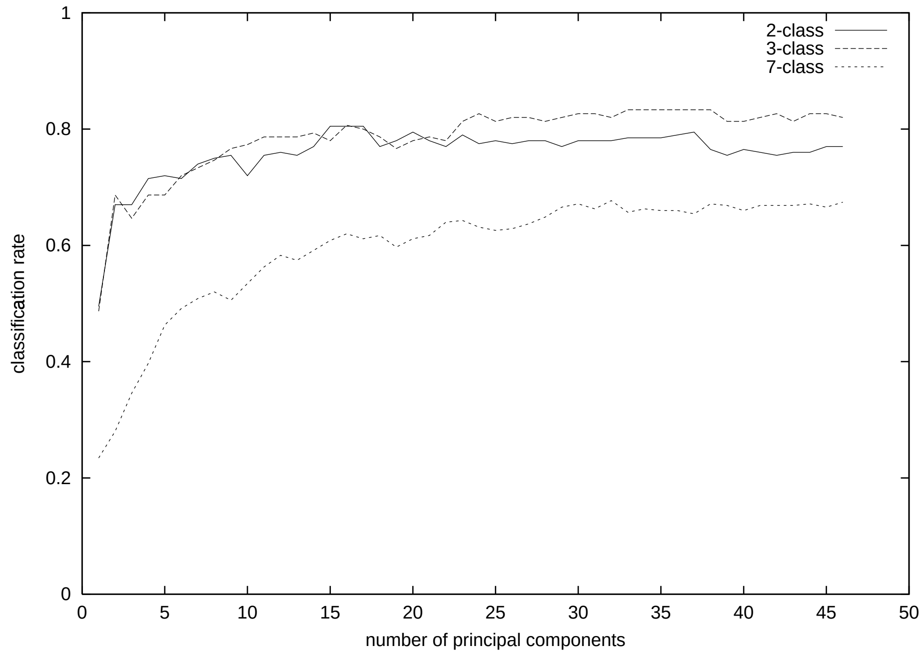

Figure 3.6: GLM classification rates using first N principal components.

3.8 Conclusions

3.8.1 Feature Inadequacy

One of the most significant aspects of the results reported here is the similarity in performance of the different classifiers. MLP networks and k-NN are able to represent more complex functions than GLM networks, but were unable to perform any better. This suggests that the optimal decision boundary between classes in this feature space is both simple and insufficient.

For the 2-class task, this is somewhat supported by Figure 2.2. In it, we can clearly see the overlapping class distributions. Plots of single pairs of features are not strong evidence that all the features together are not sufficient for good discrimination. It could be that although the classes are not separable using any two features, several features together would suffice. For the 2-class task, however, a GLM trained using only these two features performed as well as one trained on all features. The other features did not help classification, so the class separation shown with just the two features was the best available to the classifier. Since this was only tested with a GLM network, we only know that the other features did not add to the *linear* separability. It may be that other classes would have helped separate the data in ways the GLM could not take advantage of. However, if that were true, the MLP should have been able to exploit this advantage and outperform the GLM. We must conclude that the features don't provide enough information to make more accurate predictions.

3.8.2 Choosing a Classifier

All three classifiers performed with similar accuracy. Which classifier is best depends on the advantages inherent in each classifier and which ones were most appropriate for the application. The MLP, however, has only one advantage over the GLM, and that is in its potential for higher accuracy on complex problems. This turned out not to be necessary, and since an MLP takes longer to train than a GLM, it should not be used. This is, of course, based on the experiments here. If different features or classes were used, an MLP might be able to outperform a GLM. The question of GLM versus k-NN remains, and the tradeoffs here are not as simple.

If the accuracy is the same, k-NN has the following important advantages over either neural network:

1. It is easy to add new classes with k-NN.
2. It is easy to ignore classes with k-NN.
3. New training examples can be incorporated at any time with no immediate computational cost.
4. k-NN can easily report similar examples.

To ignore a class in k-NN, we would simply ignore examples of that class and select the k nearest neighbors of classes we wanted to consider. k-NN would have an advantage for applications where the classification task might change. It would also have the advantages a lazy-learning algorithm always exhibits. It allows new classes to be added without requiring expensive retraining, and can exploit labelled examples added later. All of these advantages could be important for music database applications.

k-NN's disadvantages compared to neural networks:

1. k-NN needs more storage.

2. k-NN is slower at classification time.

The speed and storage limitations of k-NN are unlikely to be a significant obstacle for desktop or server based applications, but could be more serious for embedded systems. Storing 46 features for each song, approximately 64000 examples would use the same amount of storage as a three minute song (at 128kbps). If we only needed features of the music on the device to use for song selection tasks, the storage requirements would be insignificant. If, however, we wanted to be able to classify new songs using a vast training database, the storage requirements of k-NN could be a problem.

3.8.3 Performance

The level of accuracy attained is enough to be useful for some applications, but not for all. It is much better than random, but is much worse than a person would fare. For applications directly involving human listeners, this level of accuracy would not be sufficient. If you ask your jukebox to play only music of a certain genre, only few and minor errors would be tolerable. There are, however, applications where any improvement over the prior probabilities of each class is helpful. Some examples are given in Chapter 4.

3.9 Chapter Summary

In this chapter I presented the results of optimizing three classifiers on three different tasks. The tasks were a 2-class task of highly similar genres, a 3-class task of highly dissimilar genres, and a 7-class task with a broad range of genres. I described my procedure for optimizing and testing Generalized Linear Models, Multilayer Perceptrons, and k-Nearest Neighbor classifiers, and presented the results of those procedures.

The results were similar for each classifier. On average the three classifiers correctly classified 77% in the 2-class task, 82% in the 3-class task, and 64% in the 7-class task. Their similarity implies that the classes can not be separated well using this set of features, but allows developers to choose among classifiers based on their other features.

In the next and final chapter, I review the project and discuss its applications and possible future directions.

Chapter 4

Conclusions

4.1 Chapter Overview

In this chapter I summarize the project, list some potential applications appropriate to the performance achieved by the classifiers, and discuss possible future work.

4.2 Summary

The goal of this project was to create a system that could be used for automatic music organization. I extracted features from musical audio signals and used these to train and test three different classifiers (Generalized Linear Model, Multilayer Perceptron, and k-Nearest Neighbor) to classify music into genres. With each classifier, three different experiments were run with different sets of genres.

On average the three classifiers correctly classified 77% in the 2-class task, 82% in the 3-class task, and 64% in the 7-class task, with little variance among classifiers. This level of accuracy is not sufficient for all applications. For example, I would not want to set my jukebox for classical and have a

Scottish jig come up once every twenty songs. It is, however, good enough to be useful for a number of applications, some of which are described in Section 4.3.

4.3 Applications

4.3.1 Providing Good Defaults

Beat Tracking

The beat tracking system developed by Scheirer (1997) has several adjustable parameters that affect its performance. Optimal values for these parameters depend on the rhythmic behavior of music being analyzed, and reasonable values can be chosen based on the genre. The accuracy of the beat tracker would be improved if its parameters were adjusted for each song based on the genre predicted from other features.

Labelling

Many people listen to CDs on their computers using software that retrieves genre and song titles from a central database.[1] If someone plays a CD that is not in the database, they can enter the data themselves and submit it to the database. All submissions must have a genre selected, but not everyone is diligent in setting it properly and it is often left on their software's default setting. If the genre could be predicted with even modest accuracy, the prediction could be used as a default. Users would not need to change the setting as often and the database would contain fewer errors. As an added bonus, some people would be entertained by the predictions, especially when they were wrong.

[1] `http://www.freedb.org/`

4.3.2 Finding Similar Music

The features I've used for classification could work for similarity measures, using any of a variety of unsupervised techniques. For example, we could find songs with the smallest Euclidean distance to the example song in the space defined by the features projected onto their principal components. The success of the k-NN classifier (§3.6.2) indicates that a majority of these songs truly are similar, if our genre labels can be trusted as a measure of similarity.

4.3.3 Enhancing Indirect Methods

In Chapter 1, Section 1.4.3, I described indirect methods of measuring music similarity that measure the similarity of things related to the music, such as purchasing patterns, explicit ratings, or physiological effects correlated to music listening. These methods avoid having to analyze the music, but as a result they are unable to generalize to new cases. When confronted with a new piece of music, they are unable to make any judgments about it at all.

By using the similarity metric described in Section 4.3.2, indirect methods could be extrapolated onto new cases. Predictions could be made for new cases by using the predictions of the most similar case, having a few of the most similar cases vote, or by combining the predictions for the most similar cases if there is reasonable way to do so. This would be especially valuable in applications where data collection was expensive or inconvenient.

4.4 Future Work

4.4.1 Feature Selection

Some of the features used in this project are redundant and could be discarded without diminishing classification accuracy. If we knew which ones, we could discard them. As discussed in Chapter 3, Section 3.7, this would save time and memory during feature extraction, training, and classification, and would reduce storage requirements for lazy algorithms such as k-NN. The reduced dimensionality might also increase classification accuracy.

4.4.2 Sample Size

Parameterizing entire songs was appropriate for the task of classifying entire songs, but other approaches also could prove fruitful for this or other applications. People can classify music using shorter samples, and most other work in computational music analysis has taken a similar approach. It is more justifiable from a psychoacoustic perspective, and is important if the analysis is to be applied in realtime.

4.4.3 Temporal Patterns

My system described the temporal behavior of the features in fairly primitive and coarse ways. First differences captured the magnitude and direction of changes between 30ms frames, but no larger patterns of movement were extracted from this data.

The arbitrary distinction imposed by the 4-second frames was intended to let us differentiate between short term and long term dynamics of each feature, but there are more sophisticated way to accomplish this. Possibilities include hidden Markov models, Kalman filters, and frequency decomposition of the temporal pattern of each feature in a sliding window. Each would describe the behavior in more detail than the methods used here.

4.4.4 Sensitivity to Noise

It would be useful to measure how features are affected by different kinds of data degradation. Examples include loss of high frequencies, the addition of common types of noise, pre-echo, low sampling rate, merging stereophonic to monophonic, and other effects of common audio compression methods.

4.4.5 Multiresolution Spectral Decomposition

Frequency decomposition requires trading frequency resolution for time resolution. The Fourier transform requires us to choose a single balance between the two for all frequencies. There are other methods, such as discrete wavelet transform, that can perform a mulitresolution analysis, using higher frequency resolution at lower frequencies and higher time resolution at higher frequencies (Polikar, 1999). This more closely matches human hearing, which has a higher frequency resolution at lower frequencies.

4.4.6 Other Features

Cepstral Coefficients

Cepstral coefficients have been used successfully in many speech analysis applications. They were used by Soltau et al. (1998) to classify music and by Foote (1997) to distinguish speech from music. There may be redundancies between those features and the ones used here, but perhaps some benefit could be gained by using both.

Stereo Channel Differences

Some artists use stereo panning of instruments to a greater degree and more often than others do. Informal observations[2] indicate that it is correlated to genre and recording date. This feature is more salient to a listener wearing headphones, though it is usually not practical to know when this is the case.

[2]For the past eight months I've been watching realtime stereo spectrograms of the music I listen to, plotted using a program I wrote, available at `http://www.aigeek.com/waterfall/`.

Fully separating sound sources is difficult, but even simple methods appear to be sufficient for this measurement. Preliminary tests indicate that summing the difference in channels in each frequency bin might work well.

$$s = \sum_{f=1}^{N} \left(\frac{|e_f(left) - e_f(right)|}{e_f} \log_2 f \right) \tag{4.1}$$

Band Separation

The crucial advance of the beat tracking system developed by Scheirer (1997) was to separate the audio signal into several frequency bands and analyze each one independently. Other features may also be more useful when measured over separate frequency bands.

Spectral Histogram

It would be easy to accumulate a histogram of log-energy in each frequency band reported by the spectral decomposer. The shape of the histogram might be useful in predicting some aspects of musical style.

If band separation is being done, the mean loudness of each band provides the same type of information, but possibly at a lower resolution than is desired. Also, the histogram is easy to implement and cheap to compute. It may be more appropriate for resource-poor platforms or when development time is scarce.

Distribution Analysis

Many short term features of music depend on whether a particular sound source is active at that moment. In music where some sources are not continuously active, features affected by those sources have multimodal distributions. Mean and variance are not capable of distinguishing between, for example, an instrument with fluctuating loudness and one that is always loud when present, but is not always present.

Rhythm

A beat tracker could provide several good features for music classification. The most obvious is tempo, but also useful would be the tracker's certainly of its estimation and the extent to which the music centers around the beat.

Wold et al. (1999) use a rhythm signature as a feature in their music database. Copying this would be worthwhile. Gasser and Eck (1996) describe another way of extracting rhythm patterns using networks of oscillators. Their system also works, but is probably more difficult to implement.

4.5 Final Remarks

The system I implemented is fairly simple, but works well enough to be used in a supporting role or when an educated guess is better than none. It is not accurate enough to be used in important applications that control music selection.

More accurate and robust systems will come from principled approaches more firmly rooted in psychoacoustics and auditory scene analysis, but until such systems are developed, simpler systems such as this one can be of practical value.

The level of performance of this system can serve as a baseline for future work, and the software is available to researchers and developers who wish to perform further tests or build on it.

Bibliography

Allen, P. E. and Dannenberg, R. B. (1990). Tracking musical beats in real time. Technical report, School of Computer Science, Carnegie Mellon University. http://www.cs.cmu.edu/~rbd/papers/beattrack.ps.Z.

Bishop, C. M. (1995). *Neural Networks for Pattern Recognition*. Oxford University Press. http://www.ncrg.aston.ac.uk/NNPR/.

Bregman, A. S. (1990). *Auditory Scene Analysis: The Perceptual Organization of sound*. MIT Press.

Cook, P. R., editor (1999). *Music, Cognition, and Computerized Sound*. MIT Press.

Dannenberg, R. B. (1993). A brief survey of music representation issues, techniques, and systems. *Computer Music Journal*, 17(3):20–30. http://www.cs.cmu.edu/~rbd/papers/issues.ps.Z.

Dannenberg, R. B., Thom, B., and Watson, D. (1997). A machine learning approach to musical style recognition. In *1997 International Computer Music Conference*, pages 344–347. School of Computer Science, Carnegie Mellon University. http://www.cs.cmu.edu/~rbd/bib-styleclass.html.

Desain, P. and de Vos, S. (1990). Autocorrelation and the study of musical expression. In *1990 International Computer Music Conference*, pages

357–360. Computer Music Association. `http://www.nici.kun.nl/mmm/abstracts/dv-90-a.html`.

Desain, P. and Honing, H. (1999). Computational models of beat induction: The rule-based approach. *Journal of New Music Research, ISSN: 0929-8215*.

Dixon, S. (1999). A beat tracking system for audio signals. Technical report, Austrian Research Institute for Articial Intelligence, simon@ai.univie.ac.at. `http://www.ai.univie.ac.at/~simon/pub/diderot99.ps.gz`.

Ellis, D. P. W. (1996). *Prediction-Driven Computational Auditory Scene Analysis for Dense Sound Mixtures*. PhD thesis, MIT. `http://citeseer.nj.nec.com/52907.html`.

Foote, J. (1997). A similarity measure for automatic audio classification. Technical report, Institute of Systems Science, National University of Singapore. `http://citeseer.nj.nec.com/foote97similarity.html`.

Gasser, M. and Eck, D. (1996). Representing rhythmic patterns in a network of oscillators. In *ICMPC 96*, pages 361–366. 4th international conference on music perception and cognition. `ftp://ftp.cs.indiana.edu/pub/gasser/icmpc.ps.Z`.

Hauptmann, A. and Witbrock, M. (1998). Story segmentation and detection of commercials in broadcast news video. In *Submitted to ADL-98 Advances in Digital Libraries Conference*. `http://www.informedia.cs.cmu.edu/documents/adl98.pdf`.

Healey, J., Picard, R., and Dabek, F. (1998). A new affect-perceiving interface and its application to personalized music selection. Technical Report 478, Massachusetts Institute of Technology, Media Laboratory Perceptual

Computing Section. http://www-white.media.mit.edu/tech-reports/TR-478/TR-478.html.

Howe, D. (1998). Free on-line dictionary of computing. http://www.foldoc.org/.

John, G. H., Kohavi, R., and Pfleger, K. (1994). Irrelevant features and the subset selection problem. In Hirsh, W. W. C. . H., editor, *Machine Learning: Proceedings of the Eleventh International Conference*, pages 121–129. Morgan Kaufmann Publishers, San Francisco, CA. http://citeseer.nj.nec.com/john94irrelevant.html.

Large, E. W. (1995). Beat tracking with a nonlinear oscilator. In *Working Notes of the IJCAI Workshop on AI and Music*, pages 24–31. ftp://ftp.cis.upenn.edu/pub/large/papers/beattracking.ps.Z.

Large, E. W. and Kolen, J. F. (1994). Resonance and the perception of musical meter. *Connection Science*, 6(1):177–208. ftp://archive.cis.ohio-state.edu/pub/neuroprose/large.resonance.ps.Z.

Martin, K. D. (1996). Automatic transcription of simple polyphonic music: Robust front end processing. Technical Report 399, MIT Media Laboratory Perceptual Computing Section. http://citeseer.nj.nec.com/166263.html.

Martin, K. D. and Kim, Y. E. (1998). Musical instrument identification: A pattern-recognition approach. Technical report, MIT Media Laboratory Machine Listening Group. ftp://sound.media.mit.edu/pub/Papers/kdm-asa98.pdf.

Minka, T. P. and Picard, R. W. (1997). Interactive learning using a "society of models". Technical Report 349, MIT Media Laboratory Perceptual Computing Section. http://www-white.media.mit.edu/vismod/publications/techdir/TR-349.ps.Z.

Mitchell, T. M. (1997). *Machine Learning*. McGraw-Hill.

Negativland (1987). Announcement. In *Escape From Noise*. http://www.negativland.com/negdisco_detail.html\#noise.

Picard, R. (1997). *Affective Computing*. MIT Press.

Polikar, R. (1999). The wavelet tutorial. http://www.public.iastate.edu/~rpolikar/WAVELETS/WTtutorial.html.

Sarle, W. S. (1999). Ill-conditioning in neural networks. ftp://ftp.sas.com/pub/neural/illcond/illcond.html.

Sarle, W. S. (2000). How to measure importance of inputs? ftp://ftp.sas.com/pub/neural/importance.html.

Scheirer, E. D. (1995). Extracting expressive performance information from recorded music. Master's thesis, Massachusetts Institute of Technology. http://sound.media.mit.edu/~eds/thesis.pdf.

Scheirer, E. D. (1997). Tempo and beat analysis of acoustic musical signals. *Acoustical Society of America*, 103(1):588–601. http://sound.media.mit.edu/~eds/beat.pdf.

Scheirer, E. D. (2000). *Music-Listening Systems*. PhD thesis, Massachusetts Institute of Technology. http://sound.media.mit.edu/~eds/thesis/.

Shardanand, U. (1994). Social information filtering for music recommendation. Master's thesis, Massachusetts Institute of Technology, Media Laboratory.

Shuttleworth, T. and Wilson, R. (1995). The recognition of musical structures using neural networks. In *IJCAI-95*.

Smith, S. W. (1997). *The Scientist and Engineer's Guide to Digital Signal Processing*. California Technical Publishing. http://www.dspguide.com/.

Soltau, H., Schultz, T., Westphal, M., and Waibel, A. (1998). Recognition of music types. In *Proceedings of ICASSP 98*. http://www.is.cs.cmu.edu/ISL.publications.html\#1998.

Wettschereck, D., Aha, D. W., and Mohri, T. (1997). A review and empirical evaluation of feature weighting methods for a class of lazy learning algorithms. *Artificial Intelligence Review*, 11:273–314.

Wold, E., Blum, T., Keislar, D., and Wheaton, J. (1996). Content-based classification, search, and retrieval of audio. *IEEE Multimedia*, 3(3):27–36. http://www.musclefish.com/ieeemm96/.

Wold, E., Blum, T., Keislar, D., and Wheaton, J. (1999). Classification, search, and retrieval of audio. Technical report, Muscle Fish LLC. http://www.musclefish.com/crc/.

Appendix A

Features

Forty-six features were extracted from each song. The features are enumerated on the next page. Abbreviations are used in each, according to the following key:

Abbreviation	Meaning
std	standard deviation
wmean	loudness-weighted mean
wstd	loudness-weighted standard deviation
diff	first difference

1. length
2. loudness scale factor
3. mean(mean(loudness))
4. std(mean(loudness))
5. mean(std(loudness))
6. std(std(loudness))
7. mean(mean(centroid))
8. std(mean(centroid))
9. mean(std(centroid))
10. std(std(centroid))
11. mean(mean(bandwidth))
12. std(mean(bandwidth))
13. mean(std(bandwidth))
14. std(std(bandwidth))
15. mean(mean(uniformity))
16. std(mean(uniformity))
17. mean(std(uniformity))
18. std(std(uniformity))
19. mean(wmean(centroid))
20. std(wmean(centroid))
21. mean(wstd(centroid))
22. std(wstd(centroid))
23. mean(wmean(bandwidth))
24. std(wmean(bandwidth))
25. mean(wstd(bandwidth))
26. std(wstd(bandwidth))
27. mean(wmean(uniformity))
28. std(wmean(uniformity))
29. mean(wstd(uniformity))
30. std(wstd(uniformity))
31. mean(mean(loudness diff))
32. std(mean(loudness diff))
33. mean(std(loudness diff))
34. std(std(loudness diff))
35. mean(mean(centroid diff))
36. std(mean(centroid diff))
37. mean(std(centroid diff))
38. std(std(centroid diff))
39. mean(mean(bandwidth diff))
40. std(mean(bandwidth diff))
41. mean(std(bandwidth diff))
42. std(std(bandwidth diff))
43. mean(mean(uniformity diff))
44. std(mean(uniformity diff))
45. mean(std(uniformity diff))
46. std(std(uniformity diff))

Appendix B

Feature Extraction Code

This appendix contains the C code to extract features from audio files. It depends on `libsoundfile`[1] to read audio files and `FFTW`[2] to perform Fourier transforms, both of which are free software. The feature extraction code presented here is released under the GNU Public License[3]. You may redistribute this code and derivative works according to the terms of that license. Copies of this code may be found online at http://www.aigeek.com/aimsc/.

B.1 main.c

```
/*
  main.c
  Copyright 2000, Seth Golub <seth@aigeek.com>

  This program is free software; you can redistribute it and/or modify
  it under the terms of the GNU General Public License as published by
  the Free Software Foundation; either version 2 of the License, or
  (at your option) any later version.

  This program is distributed in the hope that it will be useful, but
  WITHOUT ANY WARRANTY; without even the implied warranty of
  MERCHANTABILITY or FITNESS FOR A PARTICULAR PURPOSE.  See the GNU
  General Public License for more details.

  You should have received a copy of the GNU General Public License
  along with this program; if not, write to the Free Software
  Foundation, Inc., 59 Temple Place, Suite 330, Boston, MA 02111-1307,
  USA.
*/

#include <stdio.h>
#include <stdlib.h>
#include <sndfile.h>
#include <rfftw.h>
#include <unistd.h>
```

[1]http://www.zip.com.au/ erikd/libsndfile/

[2]http://www.fftw.org/

[3]http://www.gnu.org/copyleft/gpl.html

```
#include "workspace.h"
#include "long.h"
#include "error.h"

void usage( char *argv0 )
{
  fprintf( stderr, "\nUsage: %s [options] file
  Options:
    -h        Display this help
    -v        Verbose\n\n", argv0 );
  exit( ERR_USAGE );
}

int main( int argc, char *argv[] )
{
  SNDFILE *inputFile;
  SF_INFO sfinfo;
  workspace w;
  l_stats lstats;
  int optret;
  int verbose = 0;

  while ( (optret = getopt( argc, argv, "hv" )) != -1 )
    {
      switch ( optret )
        {
          case ':': /* missing parameter */
          case '?': /* unknown option char */
          case 'h': /* help */
            usage( argv[0] );
          case 'v': /* verbose */
            verbose = 1;
            break;
        }
    }


  if ( (argc - optind) < 1 )
    {
      fprintf( stderr, "No input file specified.\n" );
      usage( argv[0] );
    }

  inputFile = sf_open_read( argv[optind], &sfinfo );
  if ( inputFile == NULL )
    {
      fprintf( stderr, "%s: Can't open file: %s.\n", argv[0], argv[optind] );
      exit( ERR_OPEN );
    }

  if ( sfinfo.channels != 1 && sfinfo.channels != 2 )
    {
      fprintf( stderr, "%s: Strange number of channels: %d.\n",
               argv[0], sfinfo.channels );
      exit( ERR_CHANNELS );
    }

  init_workspace( &w, inputFile, &sfinfo );

  find_long_stats( &w, &lstats );

  if ( verbose )
    print_long_stats_verbose( &lstats );
  else
    print_long_stats( &lstats );

  free_workspace( &w );
  sf_close( inputFile );
  return 0;
}
```

B.2 short.h

```
/* short.h */
#ifndef SHORT_H
#define SHORT_H

#include <sndfile.h>
#include "workspace.h"

/************************************
 * SWPS == Short Windows Per Second
 *
 * SWPS should be in the range [25,40] (as a perceptually reasonable
 * compromise between time and frequency resolution; see Wold '96)
 *
 * and (samplerate / SWPS) should yield a product of small primes
 * (2,3,5,7) because that makes the FFT faster.  Obviously, this
 * depends on samplerate, but most samples use 44100Hz.  30 is a fine
 * value for 22050Hz also, and is terrible for 11025 (25 and 35 are
 * better for that).
*/
#define SWPS 30


void init_s_workspace( s_workspace *sw, SF_INFO *sfinfo );
void free_s_workspace( s_workspace *sw );
int find_short_stats( workspace *w, int *loudnessp, int *centroidp,
                      int *bandwidthp, int *uniformityp );

#endif
```

B.3 short.c

```
/*
  short.c
  Copyright 2000, Seth Golub <seth@aigeek.com>

  This program is free software; you can redistribute it and/or modify
  it under the terms of the GNU General Public License as published by
  the Free Software Foundation; either version 2 of the License, or
  (at your option) any later version.

  This program is distributed in the hope that it will be useful, but
  WITHOUT ANY WARRANTY; without even the implied warranty of
  MERCHANTABILITY or FITNESS FOR A PARTICULAR PURPOSE.  See the GNU
  General Public License for more details.

  You should have received a copy of the GNU General Public License
  along with this program; if not, write to the Free Software
  Foundation, Inc., 59 Temple Place, Suite 330, Boston, MA 02111-1307,
  USA.
*/

#include <stdio.h>
#include <stdlib.h>
#include <sndfile.h>
#include <rfftw.h>
#include <math.h>
#include "short.h"
#include "array.h"
#include "error.h"

void init_s_workspace( s_workspace *sw, SF_INFO *sfinfo )
{
  int i;
  float log2 = log( 2 );

  sw->N = sfinfo->samplerate / SWPS;

  sw->signal_int    = new_int_array( sw->N * sfinfo->channels );
  sw->signal_real   = new_real_array( sw->N );
  sw->freq          = new_real_array( sw->N );
  sw->power         = new_real_array( (sw->N/2 + 1) );
  sw->logscale      = new_real_array( (sw->N/2 + 1) );

  sw->uniformity_scale = log( sw->power->size );
  sw->logscale_sum = 0.0;
  sw->inverse_logscale_sum = 0.0;
  for ( i=0; i < sw->logscale->size; i++ )
    {
      sw->logscale->data[i] = log(i+2) / log2;
      sw->logscale_sum += sw->logscale->data[i];
      sw->inverse_logscale_sum += 1.0 / sw->logscale->data[i];
    }

  sw->plan = rfftw_create_plan( sw->N, FFTW_REAL_TO_COMPLEX, FFTW_ESTIMATE );

  if ( !sw->plan )
    {
      fprintf( stderr, "Out of memory.\n" );
      exit( ERR_MEM );
    }
}

void free_s_workspace( s_workspace *sw )
{
  free_int_array( sw->signal_int );
  free_real_array( sw->signal_real );
  free_real_array( sw->freq );
  free_real_array( sw->power );
  free_real_array( sw->logscale );
  rfftw_destroy_plan( sw->plan );
}


/*
 * Copies a 1-channel signal from an int array to a real array,
 * or mixes a 2-channel stereo signal from int to real.
 * signal_int contains <samples> * <channels> items
 * signal_real must be at least <samples> items long.
 *
 * Assumes channels is 1 or 2.  (This must be ensured elsewhere.)
 */
void mix_to_real( int_array signal_int, real_array signal_real,
                  int channels )
```

```
{
  int i;
  if ( channels == 1 )
    for ( i=0; i < signal_int->size; i++ )
      signal_real->data[i] = signal_int->data[i];
  else
    for ( i=0; i < signal_real->size; i++ )
      signal_real->data[i] = (signal_int->data[i*2]
                              + signal_int->data[i*2+1]) / 2;
}


/* power spectrum code snippet from FFTW docs */
void find_power_spectrum( real_array freq, real_array power )
{
  int i, N;
  N = freq->size;
  power->data[0] = freq->data[0]*freq->data[0];  /* DC component */
  for (i = 1; i < (N+1)/2; ++i)
    power->data[i] =(freq->data[i]*freq->data[i] + freq->data[N-i]*freq->data[N-i]);
  if (N % 2 == 0)
    power->data[N/2] = freq->data[N/2]*freq->data[N/2];
}

/*
  centroid:  power-weighted mean, expressed in the logscale * 1000.
  bandwidth: power-weighted std deviation, also on the logscale * 1000.
  uniformity:  negative entropy of frequency, not on the logscale.  range 0-1000.
*/
void find_freq_stats( s_workspace *sw, int *centroidp, int *bandwidthp, int *uniformityp )
{
  int i;
  double centroid;
  double sum = 0.0, weighted_sum = 0.0;
  double uniformity;
  for ( i=0; i < sw->power->size; i++ )
    {
      sum                    += sw->power->data[i];
      weighted_sum           += sw->power->data[i] * sw->logscale->data[i];
    }

  centroid = weighted_sum / sum;

  weighted_sum = 0.0;
  uniformity = 0.0;
  for ( i=0; i < sw->power->size; i++ )
    {
      if ( sw->power->data[i] > 0 )
        uniformity += (sw->power->data[i] / sum) * log(sw->power->data[i] / sum);
      weighted_sum += ( (centroid - sw->logscale->data[i])
                       * (centroid - sw->logscale->data[i])
                       * sw->power->data[i] );
    }
  *centroidp  = (int) (1000.0 * centroid);
  *bandwidthp = (int) (1000.0 * sqrt(weighted_sum / sum));
  *uniformityp  = (int) (-1000.0 * uniformity / sw->uniformity_scale);
}


/* Reads data from input file and calculates short window statistics.
 * Returns nonzero iff a full window could be read.  */
int find_short_stats( workspace *w, int *loudnessp, int *centroidp,
                      int *bandwidthp, int *uniformityp )
{
  if ( sf_readf_int( w->inputFile, w->sw.signal_int->data, w->sw.N ) < w->sw.N )
    return 0;

  *loudnessp = mean_log2_abs( w->sw.signal_int );
  if ( *loudnessp == 0 )
    {
      *centroidp = 0; /* These won't matter, but we need to record something. */
      *bandwidthp = 0;
      *uniformityp = 0;
    }
  else
    {
      mix_to_real( w->sw.signal_int, w->sw.signal_real, w->sfinfo->channels );
      rfftw_one( w->sw.plan, w->sw.signal_real->data, w->sw.freq->data );
      find_power_spectrum( w->sw.freq, w->sw.power );
      find_freq_stats( &(w->sw), centroidp, bandwidthp, uniformityp );
    }
  return 1;
}
```

B.4 workspace.h

```
#ifndef WORKSPACE_H
#define WORKSPACE_H
#include <sndfile.h>
#include "array.h"

/* The s_workspace is to hold arrays for the short window analysis.
 * This way we can put the short window routines in a separate
 * function without having to allocate new space each time and without
 * depending on the sample size not changing.  The sample size is
 * constant for a given sample rate (e.g. 44100Hz), but it would be
 * nice to be able to run this program on multiple files.
*/
typedef struct
{
  int N;
  int_array signal_int;
  real_array signal_real;
  real_array freq;
  real_array power;
  real_array logscale;
  double logscale_sum, inverse_logscale_sum;
  double uniformity_scale;  /* == log( power->size ), cached here */
  rfftw_plan plan;
} s_workspace;

/* medium window workspace */
typedef struct
{
  int_array loudness;
  int_array centroid;
  int_array bandwidth;
  int_array uniformity;
  int_array loudness_diff;
  int_array centroid_diff;
  int_array bandwidth_diff;
  int_array uniformity_diff;
} m_workspace;

/* long window (entire file) workspace */
typedef struct
{
  float_array loudness_mean;
  float_array loudness_std;

  float_array centroid_mean;
  float_array centroid_std;
  float_array bandwidth_mean;
  float_array bandwidth_std;
  float_array uniformity_mean;
  float_array uniformity_std;

  float_array centroid_wmean;
  float_array centroid_wstd;
  float_array bandwidth_wmean;
  float_array bandwidth_wstd;
  float_array uniformity_wmean;
  float_array uniformity_wstd;

  float_array loudness_diff_mean;
  float_array loudness_diff_std;
  float_array centroid_diff_mean;
  float_array centroid_diff_std;
  float_array bandwidth_diff_mean;
  float_array bandwidth_diff_std;
  float_array uniformity_diff_mean;
  float_array uniformity_diff_std;
} l_workspace;

typedef struct
{
  SF_INFO *sfinfo;
  SNDFILE *inputFile;
  s_workspace sw;
  m_workspace mw;
  l_workspace lw;
} workspace;

void init_workspace( workspace *w, SNDFILE *inputFile, SF_INFO *sfinfo );
void free_workspace( workspace *w );

#endif
```

B.5 workspace.c

```
/*
  workspace.c
  Copyright 2000, Seth Golub <seth@aigeek.com>

  This program is free software; you can redistribute it and/or modify
  it under the terms of the GNU General Public License as published by
  the Free Software Foundation; either version 2 of the License, or
  (at your option) any later version.

  This program is distributed in the hope that it will be useful, but
  WITHOUT ANY WARRANTY; without even the implied warranty of
  MERCHANTABILITY or FITNESS FOR A PARTICULAR PURPOSE.  See the GNU
  General Public License for more details.

  You should have received a copy of the GNU General Public License
  along with this program; if not, write to the Free Software
  Foundation, Inc., 59 Temple Place, Suite 330, Boston, MA 02111-1307,
  USA.
*/

#include <sndfile.h>
#include "array.h"
#include "short.h"
#include "medium.h"
#include "long.h"

void init_workspace( workspace *w, SNDFILE *inputFile, SF_INFO *sfinfo )
{
  w->inputFile = inputFile;
  w->sfinfo = sfinfo;
  init_s_workspace( &(w->sw), sfinfo );
  init_m_workspace( &(w->mw) );
  init_l_workspace( &(w->lw), sfinfo );
}

void free_workspace( workspace *w )
{
  free_s_workspace( &(w->sw) );
  free_m_workspace( &(w->mw) );
  free_l_workspace( &(w->lw) );
}
```

B.6 long.h

```
/* long.h */
#ifndef LONG_H
#define LONG_H

#include <sndfile.h>
#include "workspace.h"

typedef struct
{
  int loudness_mean_mean, loudness_mean_std;
  int loudness_std_mean, loudness_std_std;

  int centroid_mean_mean, centroid_mean_std;
  int centroid_std_mean, centroid_std_std;
  int bandwidth_mean_mean, bandwidth_mean_std;
  int bandwidth_std_mean, bandwidth_std_std;
  int uniformity_mean_mean, uniformity_mean_std;
  int uniformity_std_mean, uniformity_std_std;

  int centroid_wmean_mean, centroid_wmean_std;
  int centroid_wstd_mean, centroid_wstd_std;
  int bandwidth_wmean_mean, bandwidth_wmean_std;
  int bandwidth_wstd_mean, bandwidth_wstd_std;
  int uniformity_wmean_mean, uniformity_wmean_std;
  int uniformity_wstd_mean, uniformity_wstd_std;

  int loudness_diff_mean_mean, loudness_diff_mean_std;
  int loudness_diff_std_mean, loudness_diff_std_std;
  int centroid_diff_mean_mean, centroid_diff_mean_std;
  int centroid_diff_std_mean, centroid_diff_std_std;
  int bandwidth_diff_mean_mean, bandwidth_diff_mean_std;
  int bandwidth_diff_std_mean, bandwidth_diff_std_std;
  int uniformity_diff_mean_mean, uniformity_diff_mean_std;
  int uniformity_diff_std_mean, uniformity_diff_std_std;
  float loudness_scale_factor;
  int length;
} l_stats;

void init_l_workspace( l_workspace *lw, SF_INFO *sfinfo );
void free_l_workspace( l_workspace *lw );
void find_long_stats( workspace *w, l_stats *lstat );
void print_long_stats( l_stats *lstat );
void print_long_stats_verbose( l_stats *lstat );

#endif
```

B.7 long.c

```
/*
  long.c
  Copyright 2000, Seth Golub <seth@aigeek.com>

  This program is free software; you can redistribute it and/or modify
  it under the terms of the GNU General Public License as published by
  the Free Software Foundation; either version 2 of the License, or
  (at your option) any later version.

  This program is distributed in the hope that it will be useful, but
  WITHOUT ANY WARRANTY; without even the implied warranty of
  MERCHANTABILITY or FITNESS FOR A PARTICULAR PURPOSE.  See the GNU
  General Public License for more details.

  You should have received a copy of the GNU General Public License
  along with this program; if not, write to the Free Software
  Foundation, Inc., 59 Temple Place, Suite 330, Boston, MA 02111-1307,
  USA.
*/

#include <math.h>
#include "short.h"
#include "medium.h"
#include "long.h"

void collect_medium_stats( workspace *w )
{
  int i;
  m_stats mstats;

  for ( i=0; find_medium_stats( w, &mstats ); i++ )
    {
      w->lw.loudness_mean->data[i] = mstats.loudness_mean;
      w->lw.loudness_std->data[i] = mstats.loudness_std;

      w->lw.centroid_mean->data[i] = mstats.centroid_mean;
      w->lw.centroid_std->data[i] = mstats.centroid_std;
      w->lw.bandwidth_mean->data[i] = mstats.bandwidth_mean;
      w->lw.bandwidth_std->data[i] = mstats.bandwidth_std;
      w->lw.uniformity_mean->data[i] = mstats.uniformity_mean;
      w->lw.uniformity_std->data[i] = mstats.uniformity_std;

      w->lw.centroid_wmean->data[i] = mstats.centroid_wmean;
      w->lw.centroid_wstd->data[i] = mstats.centroid_wstd;
      w->lw.bandwidth_wmean->data[i] = mstats.bandwidth_wmean;
      w->lw.bandwidth_wstd->data[i] = mstats.bandwidth_wstd;
      w->lw.uniformity_wmean->data[i] = mstats.uniformity_wmean;
      w->lw.uniformity_wstd->data[i] = mstats.uniformity_wstd;

      w->lw.loudness_diff_mean->data[i] = mstats.loudness_diff_mean;
      w->lw.loudness_diff_std->data[i] = mstats.loudness_diff_std;
      w->lw.centroid_diff_mean->data[i] = mstats.centroid_diff_mean;
      w->lw.centroid_diff_std->data[i] = mstats.centroid_diff_std;
      w->lw.bandwidth_diff_mean->data[i] = mstats.bandwidth_diff_mean;
      w->lw.bandwidth_diff_std->data[i] = mstats.bandwidth_diff_std;
      w->lw.uniformity_diff_mean->data[i] = mstats.uniformity_diff_mean;
      w->lw.uniformity_diff_std->data[i] = mstats.uniformity_diff_std;
    }
}

float loudness_scale_factor( workspace *w )
{
  float max=0.0;
  int i;
  float frame_max;
  for ( i=0; i < w->lw.loudness_mean->size; i++ )
    {
      frame_max = w->lw.loudness_mean->data[i] + w->lw.loudness_std->data[i];
      if ( frame_max > max )
        max = frame_max;
    }
  return max / 1000.0;
}


void find_long_stats( workspace *w, l_stats *lstat )
{
  collect_medium_stats( w );

  lstat->length = (w->sfinfo->samples / w->sfinfo->samplerate);
  lstat->loudness_scale_factor = loudness_scale_factor( w );
```

```
  if ( lstat->loudness_scale_factor < 0.001 ) /* Silent sample? */
    {
      /* This introduces a discontinuity in the scaled features, but
         they're all garbage at this loudness level anyway. */
      lstat->loudness_scale_factor = 1.0;  /* We don't want errors, nor do we
                                            want to scale up tiny noise. */
    }

  lstat->loudness_mean_mean = meanf( w->lw.loudness_mean ) / lstat->loudness_scale_factor;
  lstat->loudness_mean_std = stdf( w->lw.loudness_mean, lstat->loudness_mean_mean ) / lstat->loudness_scale_factor;
  lstat->loudness_std_mean = meanf( w->lw.loudness_std ) / lstat->loudness_scale_factor;
  lstat->loudness_std_std = stdf( w->lw.loudness_std, lstat->loudness_std_mean ) / lstat->loudness_scale_factor;

  lstat->centroid_mean_mean = meanf( w->lw.centroid_mean );
  lstat->centroid_mean_std = stdf( w->lw.centroid_mean, lstat->centroid_mean_mean );
  lstat->centroid_std_mean = meanf( w->lw.centroid_std );
  lstat->centroid_std_std = stdf( w->lw.centroid_std, lstat->centroid_std_mean );

  lstat->bandwidth_mean_mean = meanf( w->lw.bandwidth_mean );
  lstat->bandwidth_mean_std = stdf( w->lw.bandwidth_mean, lstat->bandwidth_mean_mean );
  lstat->bandwidth_std_mean = meanf( w->lw.bandwidth_std );
  lstat->bandwidth_std_std = stdf( w->lw.bandwidth_std, lstat->bandwidth_std_mean );

  lstat->uniformity_mean_mean = meanf( w->lw.uniformity_mean );
  lstat->uniformity_mean_std = stdf( w->lw.uniformity_mean, lstat->uniformity_mean_mean );
  lstat->uniformity_std_mean = meanf( w->lw.uniformity_std );
  lstat->uniformity_std_std = stdf( w->lw.uniformity_std, lstat->uniformity_std_mean );

  lstat->centroid_wmean_mean = meanf( w->lw.centroid_wmean );
  lstat->centroid_wmean_std = stdf( w->lw.centroid_wmean, lstat->centroid_wmean_mean );
  lstat->centroid_wstd_mean = meanf( w->lw.centroid_wstd );
  lstat->centroid_wstd_std = stdf( w->lw.centroid_wstd, lstat->centroid_wstd_mean );

  lstat->bandwidth_wmean_mean = meanf( w->lw.bandwidth_wmean );
  lstat->bandwidth_wmean_std = stdf( w->lw.bandwidth_wmean, lstat->bandwidth_wmean_mean );
  lstat->bandwidth_wstd_mean = meanf( w->lw.bandwidth_wstd );
  lstat->bandwidth_wstd_std = stdf( w->lw.bandwidth_wstd, lstat->bandwidth_wstd_mean );

  lstat->uniformity_wmean_mean = meanf( w->lw.uniformity_wmean );
  lstat->uniformity_wmean_std = stdf( w->lw.uniformity_wmean, lstat->uniformity_wmean_mean );
  lstat->uniformity_wstd_mean = meanf( w->lw.uniformity_wstd );
  lstat->uniformity_wstd_std = stdf( w->lw.uniformity_wstd, lstat->uniformity_wstd_mean );

  lstat->loudness_diff_mean_mean = meanf( w->lw.loudness_diff_mean )
                                   / lstat->loudness_scale_factor;
  lstat->loudness_diff_mean_std = stdf( w->lw.loudness_diff_mean, lstat->loudness_diff_mean_mean )
                                   / lstat->loudness_scale_factor;
  lstat->loudness_diff_std_mean = meanf( w->lw.loudness_diff_std ) / lstat->loudness_scale_factor;
  lstat->loudness_diff_std_std = stdf( w->lw.loudness_diff_std, lstat->loudness_diff_std_mean )
                                   / lstat->loudness_scale_factor;

  lstat->centroid_diff_mean_mean = meanf( w->lw.centroid_diff_mean );
  lstat->centroid_diff_mean_std = stdf( w->lw.centroid_diff_mean, lstat->centroid_diff_mean_mean );
  lstat->centroid_diff_std_mean = meanf( w->lw.centroid_diff_std );
  lstat->centroid_diff_std_std = stdf( w->lw.centroid_diff_std, lstat->centroid_diff_std_mean );

  lstat->bandwidth_diff_mean_mean = meanf( w->lw.bandwidth_diff_mean );
  lstat->bandwidth_diff_mean_std = stdf( w->lw.bandwidth_diff_mean, lstat->bandwidth_diff_mean_mean );
  lstat->bandwidth_diff_std_mean = meanf( w->lw.bandwidth_diff_std );
  lstat->bandwidth_diff_std_std = stdf( w->lw.bandwidth_diff_std, lstat->bandwidth_diff_std_mean );

  lstat->uniformity_diff_mean_mean = meanf( w->lw.uniformity_diff_mean );
  lstat->uniformity_diff_mean_std = stdf( w->lw.uniformity_diff_mean, lstat->uniformity_diff_mean_mean );
  lstat->uniformity_diff_std_mean = meanf( w->lw.uniformity_diff_std );
  lstat->uniformity_diff_std_std = stdf( w->lw.uniformity_diff_std, lstat->uniformity_diff_std_mean );
}


/*
 * The m_workspace is to hold arrays for the medium window analysis.
 */
void init_l_workspace( l_workspace *lw, SF_INFO *sfinfo )
{
  int N = sfinfo->samples / (sfinfo->samplerate / SWPS) / SWPMW;
  lw->loudness_mean         = new_float_array( N );
  lw->loudness_std          = new_float_array( N );

  lw->centroid_mean       = new_float_array( N );
  lw->centroid_std        = new_float_array( N );
  lw->bandwidth_mean      = new_float_array( N );
  lw->bandwidth_std       = new_float_array( N );
  lw->uniformity_mean       = new_float_array( N );
```

```
  lw->uniformity_std        = new_float_array( N );

  lw->centroid_wmean       = new_float_array( N );
  lw->centroid_wstd        = new_float_array( N );
  lw->bandwidth_wmean      = new_float_array( N );
  lw->bandwidth_wstd       = new_float_array( N );
  lw->uniformity_wmean       = new_float_array( N );
  lw->uniformity_wstd        = new_float_array( N );

  lw->loudness_diff_mean    = new_float_array( N );
  lw->loudness_diff_std     = new_float_array( N );
  lw->centroid_diff_mean  = new_float_array( N );
  lw->centroid_diff_std   = new_float_array( N );
  lw->bandwidth_diff_mean = new_float_array( N );
  lw->bandwidth_diff_std  = new_float_array( N );
  lw->uniformity_diff_mean  = new_float_array( N );
  lw->uniformity_diff_std   = new_float_array( N );
}

void free_l_workspace( l_workspace *lw )
{
  free_float_array( lw->loudness_mean );
  free_float_array( lw->loudness_std );

  free_float_array( lw->centroid_mean );
  free_float_array( lw->centroid_std );
  free_float_array( lw->bandwidth_mean );
  free_float_array( lw->bandwidth_std );
  free_float_array( lw->uniformity_mean );
  free_float_array( lw->uniformity_std );

  free_float_array( lw->centroid_wmean );
  free_float_array( lw->centroid_wstd );
  free_float_array( lw->bandwidth_wmean );
  free_float_array( lw->bandwidth_wstd );
  free_float_array( lw->uniformity_wmean );
  free_float_array( lw->uniformity_wstd );

  free_float_array( lw->loudness_diff_mean );
  free_float_array( lw->loudness_diff_std );
  free_float_array( lw->centroid_diff_mean );
  free_float_array( lw->centroid_diff_std );
  free_float_array( lw->bandwidth_diff_mean );
  free_float_array( lw->bandwidth_diff_std );
  free_float_array( lw->uniformity_diff_mean );
  free_float_array( lw->uniformity_diff_std );
}

/* Need to make shorter lines to print dissertation */
#define CONCAT(a,b) a##b

void print_long_stats( l_stats *lstat )
{
  printf( CONCAT("%d %f %d %d %d %d %d %d %d %d %d %d %d %d %d %d %d %d %d %d %d %d %d",
                 " %d %d %d %d %d %d %d %d %d %d %d %d %d %d %d %d %d %d %d %d %d\n"),
          lstat->length, lstat->loudness_scale_factor,

          lstat->loudness_mean_mean, lstat->loudness_mean_std,
          lstat->loudness_std_mean, lstat->loudness_std_std,

          lstat->centroid_mean_mean, lstat->centroid_mean_std,
          lstat->centroid_std_mean, lstat->centroid_std_std,
          lstat->bandwidth_mean_mean, lstat->bandwidth_mean_std,
          lstat->bandwidth_std_mean, lstat->bandwidth_std_std,
          lstat->uniformity_mean_mean, lstat->uniformity_mean_std,
          lstat->uniformity_std_mean, lstat->uniformity_std_std,

          lstat->centroid_wmean_mean, lstat->centroid_wmean_std,
          lstat->centroid_wstd_mean, lstat->centroid_wstd_std,
          lstat->bandwidth_wmean_mean, lstat->bandwidth_wmean_std,
          lstat->bandwidth_wstd_mean, lstat->bandwidth_wstd_std,
          lstat->uniformity_wmean_mean, lstat->uniformity_wmean_std,
          lstat->uniformity_wstd_mean, lstat->uniformity_wstd_std,

          lstat->loudness_diff_mean_mean, lstat->loudness_diff_mean_std,
          lstat->loudness_diff_std_mean, lstat->loudness_diff_std_std,
          lstat->centroid_diff_mean_mean, lstat->centroid_diff_mean_std,
          lstat->centroid_diff_std_mean, lstat->centroid_diff_std_std,
          lstat->bandwidth_diff_mean_mean, lstat->bandwidth_diff_mean_std,
          lstat->bandwidth_diff_std_mean, lstat->bandwidth_diff_std_std,
          lstat->uniformity_diff_mean_mean, lstat->uniformity_diff_mean_std,
          lstat->uniformity_diff_std_mean, lstat->uniformity_diff_std_std );
}
```

```
void print_long_stats_verbose( l_stats *lstat )
{
  printf( "    length: %d
    loudness_scale_factor: %f
    loudness_mean_mean: %d
    loudness_mean_std: %d
    loudness_std_mean: %d
    loudness_std_std: %d
    centroid_mean_mean: %d
    centroid_mean_std: %d
    centroid_std_mean: %d
    centroid_std_std: %d
    bandwidth_mean_mean: %d
    bandwidth_mean_std: %d
    bandwidth_std_mean: %d
    bandwidth_std_std: %d
    uniformity_mean_mean: %d
    uniformity_mean_std: %d
    uniformity_std_mean: %d
    uniformity_std_std: %d
    centroid_wmean_mean: %d
    centroid_wmean_std: %d
    centroid_wstd_mean: %d
    centroid_wstd_std: %d
    bandwidth_wmean_mean: %d
    bandwidth_wmean_std: %d
    bandwidth_wstd_mean: %d
    bandwidth_wstd_std: %d
    uniformity_wmean_mean: %d
    uniformity_wmean_std: %d
    uniformity_wstd_mean: %d
    uniformity_wstd_std: %d
    loudness_diff_mean_mean: %d
    loudness_diff_mean_std: %d
    loudness_diff_std_mean: %d
    loudness_diff_std_std: %d
    centroid_diff_mean_mean: %d
    centroid_diff_mean_std: %d
    centroid_diff_std_mean: %d
    centroid_diff_std_std: %d
    bandwidth_diff_mean_mean: %d
    bandwidth_diff_mean_std: %d
    bandwidth_diff_std_mean: %d
    bandwidth_diff_std_std: %d
    uniformity_diff_mean_mean: %d
    uniformity_diff_mean_std: %d
    uniformity_diff_std_mean: %d
    uniformity_diff_std_std: %d\n",
          lstat->length, lstat->loudness_scale_factor,

          lstat->loudness_mean_mean, lstat->loudness_mean_std,
          lstat->loudness_std_mean, lstat->loudness_std_std,

          lstat->centroid_mean_mean, lstat->centroid_mean_std,
          lstat->centroid_std_mean, lstat->centroid_std_std,
          lstat->bandwidth_mean_mean, lstat->bandwidth_mean_std,
          lstat->bandwidth_std_mean, lstat->bandwidth_std_std,
          lstat->uniformity_mean_mean, lstat->uniformity_mean_std,
          lstat->uniformity_std_mean, lstat->uniformity_std_std,

          lstat->centroid_wmean_mean, lstat->centroid_wmean_std,
          lstat->centroid_wstd_mean, lstat->centroid_wstd_std,
          lstat->bandwidth_wmean_mean, lstat->bandwidth_wmean_std,
          lstat->bandwidth_wstd_mean, lstat->bandwidth_wstd_std,
          lstat->uniformity_wmean_mean, lstat->uniformity_wmean_std,
          lstat->uniformity_wstd_mean, lstat->uniformity_wstd_std,

          lstat->loudness_diff_mean_mean, lstat->loudness_diff_mean_std,
          lstat->loudness_diff_std_mean, lstat->loudness_diff_std_std,
          lstat->centroid_diff_mean_mean, lstat->centroid_diff_mean_std,
          lstat->centroid_diff_std_mean, lstat->centroid_diff_std_std,
          lstat->bandwidth_diff_mean_mean, lstat->bandwidth_diff_mean_std,
          lstat->bandwidth_diff_std_mean, lstat->bandwidth_diff_std_std,
          lstat->uniformity_diff_mean_mean, lstat->uniformity_diff_mean_std,
          lstat->uniformity_diff_std_mean, lstat->uniformity_diff_std_std );
}
```

B.8 medium.h

```
/* medium.h */
#ifndef MEDIUM_H
#define MEDIUM_H

#include "workspace.h"

/************************************
 * SWPMS == Short Windows Per Medium Window
 *
 * Measurements are analyzed in medium-length window segments,
 * such as 4 seconds (120 short windows).
 */
#define SWPMW 120


typedef struct
{
  float loudness_mean;
  float loudness_std;

  float centroid_mean;
  float centroid_std;
  float bandwidth_mean;
  float bandwidth_std;
  float uniformity_mean;
  float uniformity_std;

  float centroid_wmean;
  float centroid_wstd;
  float bandwidth_wmean;
  float bandwidth_wstd;
  float uniformity_wmean;
  float uniformity_wstd;

  float loudness_diff_mean;
  float loudness_diff_std;
  float centroid_diff_mean;
  float centroid_diff_std;
  float bandwidth_diff_mean;
  float bandwidth_diff_std;
  float uniformity_diff_mean;
  float uniformity_diff_std;
} m_stats;

void init_m_workspace( m_workspace *mw );
void free_m_workspace( m_workspace *mw );
int find_medium_stats( workspace *w, m_stats *mstat );

#endif
```

B.9 medium.c

```
/*
  medium.c
  Copyright 2000, Seth Golub <seth@aigeek.com>

  This program is free software; you can redistribute it and/or modify
  it under the terms of the GNU General Public License as published by
  the Free Software Foundation; either version 2 of the License, or
  (at your option) any later version.

  This program is distributed in the hope that it will be useful, but
  WITHOUT ANY WARRANTY; without even the implied warranty of
  MERCHANTABILITY or FITNESS FOR A PARTICULAR PURPOSE.  See the GNU
  General Public License for more details.

  You should have received a copy of the GNU General Public License
  along with this program; if not, write to the Free Software
  Foundation, Inc., 59 Temple Place, Suite 330, Boston, MA 02111-1307,
  USA.
*/

#include <math.h>
#include "short.h"
#include "medium.h"

/*
 * Reads data from input file and calculates medium window statistics.
 * Returns nonzero iff a full window could be read.
 */
int collect_short_stats( workspace *w )
{
  int i, centroid, bandwidth, loudness, uniformity;

  for ( i=0; (i < SWPMW) && find_short_stats( w, &loudness, &centroid, &bandwidth, &uniformity ); i++ )
    {
      w->mw.loudness->data[i] = loudness;
      w->mw.centroid->data[i] = centroid;
      w->mw.bandwidth->data[i] = bandwidth;
      w->mw.uniformity->data[i] = uniformity;
      if ( i != 0 )
        {
          w->mw.loudness_diff->data[i-1]    = loudness    - w->mw.loudness_diff->data[i-2];
          w->mw.centroid_diff->data[i-1]  = centroid  - w->mw.centroid_diff->data[i-2];
          w->mw.bandwidth_diff->data[i-1] = bandwidth - w->mw.bandwidth_diff->data[i-2];
          w->mw.uniformity_diff->data[i-1]  = uniformity  - w->mw.uniformity_diff->data[i-2];
        }
    }
  return (i == SWPMW);
}

int find_medium_stats( workspace *w, m_stats *mstat )
{
  long weightsum;
  if ( !collect_short_stats( w ) )
    return 0;

  mstat->loudness_mean         = mean( w->mw.loudness );
  mstat->loudness_std          = std( w->mw.loudness, mstat->loudness_mean );
  mstat->centroid_mean       = mean( w->mw.centroid );
  mstat->centroid_std        = std( w->mw.centroid, mstat->centroid_mean );
  mstat->bandwidth_mean      = mean( w->mw.bandwidth );
  mstat->bandwidth_std       = std( w->mw.bandwidth, mstat->bandwidth_mean );
  mstat->uniformity_mean      = mean( w->mw.uniformity );
  mstat->uniformity_std       = std( w->mw.uniformity, mstat->uniformity_mean );
  mstat->loudness_diff_mean    = mean( w->mw.loudness_diff );
  mstat->loudness_diff_std     = std( w->mw.loudness_diff, mstat->loudness_diff_mean );
  mstat->centroid_diff_mean  = mean( w->mw.centroid_diff );
  mstat->centroid_diff_std   = std( w->mw.centroid_diff, mstat->centroid_diff_mean );
  mstat->bandwidth_diff_mean = mean( w->mw.bandwidth_diff );
  mstat->bandwidth_diff_std  = std( w->mw.bandwidth_diff, mstat->bandwidth_diff_mean );
  mstat->uniformity_diff_mean = mean( w->mw.uniformity_diff );
  mstat->uniformity_diff_std  = std( w->mw.uniformity_diff, mstat->uniformity_diff_mean );

  weightsum = sum( w->mw.loudness );
  if ( weightsum == 0 )
    {
      mstat->centroid_wmean  = 0.0;
      mstat->centroid_wstd   = 0.0;
      mstat->bandwidth_wmean = 0.0;
      mstat->bandwidth_wstd  = 0.0;
      mstat->uniformity_wmean  = 0.0;
      mstat->uniformity_wstd   = 0.0;
    }
```

```
  else
    {
      mstat->centroid_wmean  = wmean( w->mw.centroid, w->mw.loudness, weightsum );
      mstat->centroid_wstd   = wstd( w->mw.centroid, mstat->centroid_wmean, w->mw.loudness, weightsum );
      mstat->bandwidth_wmean = wmean( w->mw.bandwidth, w->mw.loudness, weightsum );
      mstat->bandwidth_wstd  = wstd( w->mw.bandwidth, mstat->bandwidth_wmean, w->mw.loudness, weightsum );
      mstat->uniformity_wmean  = wmean( w->mw.uniformity, w->mw.loudness, weightsum );
      mstat->uniformity_wstd   = wstd( w->mw.uniformity, mstat->uniformity_wmean, w->mw.loudness, weightsum );
    }
  return 1;
}


/*
 * The m_workspace is to hold arrays for the medium window analysis.
 */
void init_m_workspace( m_workspace *mw )
{
  mw->loudness         = new_int_array( SWPMW );
  mw->centroid       = new_int_array( SWPMW );
  mw->bandwidth      = new_int_array( SWPMW );
  mw->uniformity       = new_int_array( SWPMW );
  mw->loudness_diff    = new_int_array( SWPMW - 1 );
  mw->centroid_diff  = new_int_array( SWPMW - 1 );
  mw->bandwidth_diff = new_int_array( SWPMW - 1 );
  mw->uniformity_diff  = new_int_array( SWPMW - 1 );
}

void free_m_workspace( m_workspace *mw )
{
  free_int_array( mw->loudness );
  free_int_array( mw->centroid );
  free_int_array( mw->bandwidth );
  free_int_array( mw->uniformity );
  free_int_array( mw->loudness_diff );
  free_int_array( mw->centroid_diff );
  free_int_array( mw->bandwidth_diff );
  free_int_array( mw->uniformity_diff );
}
```

B.10 array.h

```
/* array.h */
#ifndef ARRAY_H
#define ARRAY_H
#include <rfftw.h>

typedef struct real_array_struct
{
  fftw_real *data;
  int size;
} *real_array;

typedef struct int_array_struct
{
  int *data;
  int size;
} *int_array;

typedef struct float_array_struct
{
  float *data;
  int size;
} *float_array;

int_array new_int_array( int size );
real_array new_real_array( int size );
float_array new_float_array( int size );

void free_int_array( int_array arr );
void free_real_array( real_array arr );
void free_float_array( float_array arr );

long sum( int_array array );
int mean_log2_abs( int_array array );
float mean( int_array arr );
float std( int_array arr, float mean );
float wmean( int_array arr, int_array weights, long weightsum );
float wstd( int_array arr, float mean, int_array weights, long weightsum );
float meanf( float_array arr );
float stdf( float_array arr, float mean );
float stdr( real_array arr, fftw_real mean );

#endif
```

B.11 array.c

```
/*
  array.c
  Copyright 2000, Seth Golub <seth@aigeek.com>

  This program is free software; you can redistribute it and/or modify
  it under the terms of the GNU General Public License as published by
  the Free Software Foundation; either version 2 of the License, or
  (at your option) any later version.

  This program is distributed in the hope that it will be useful, but
  WITHOUT ANY WARRANTY; without even the implied warranty of
  MERCHANTABILITY or FITNESS FOR A PARTICULAR PURPOSE.  See the GNU
  General Public License for more details.

  You should have received a copy of the GNU General Public License
  along with this program; if not, write to the Free Software
  Foundation, Inc., 59 Temple Place, Suite 330, Boston, MA 02111-1307,
  USA.
*/

#include <math.h>
#include "array.h"
#include "error.h"

void massert( void *x )
{
  if ( x == NULL )
    {
      fprintf( stderr, "Out of memory.\n" );
      exit( ERR_MEM );
    }
}

int_array new_int_array( int size )
{
  int_array arr = (int_array) malloc( sizeof(struct int_array_struct) );
  massert( arr );
  arr->size = size;
  arr->data = (int *) malloc( sizeof(int) * size );
  massert( arr->data );
  return arr;
}

real_array new_real_array( int size )
{
  real_array arr = (real_array) malloc( sizeof(struct real_array_struct) );
  massert( arr );
  arr->size = size;
  arr->data = (fftw_real *) malloc( sizeof(fftw_real) * size );
  massert( arr->data );
  return arr;
}

float_array new_float_array( int size )
{
  float_array arr = (float_array) malloc( sizeof(struct float_array_struct) );
  massert( arr );
  arr->size = size;
  arr->data = (float *) malloc( sizeof(float) * size );
  massert( arr->data );
  return arr;
}


void free_int_array( int_array arr )
{
  free( arr->data );
  free( arr );
}

void free_real_array( real_array arr )
{
  free( arr->data );
  free( arr );
}

void free_float_array( float_array arr )
{
  free( arr->data );
  free( arr );
}
```

```
/* Finds 100 * mean of log2 of absolute values of array elements
 * Useful for finding the mean loudness of the (rectified) signal
 */
int mean_log2_abs( int_array array )
{
  static double log2 = 0;
  int i, sum = 0;
  if ( log2 == 0 )
    log2 = log(2);  /* Only want to compute this once. */

  for ( i=0; i < array->size; i++ )
    {
      if ( array->data[i] >= 0 )
        sum += array->data[i];
      else
        sum -= array->data[i];
    }
  return 100.0 * log(1 + (double) sum / array->size) / log2;
}

float mean( int_array arr )
{
  int i;
  double sum = 0.0;
  for ( i=0; i < arr->size; i++ )
    {
      sum += arr->data[i];
    }
  return sum / arr->size;
}

float std( int_array arr, float mean )
{
  double sumsq = 0.0;
  int i;
  for ( i=0; i < arr->size; i++ )
    {
      sumsq += (arr->data[i] - mean) * (arr->data[i] - mean);
    }
  return sqrt( sumsq / (arr->size - 1) );
}

long sum( int_array array )
{
  int i;
  long sum = 0L;
  for ( i=0; i < array->size; i++ )
    {
      sum += array->data[i];
    }
  return sum;
}

/* weighted mean */
float wmean( int_array arr, int_array weights, long weightsum )
{
  int i;
  double sum = 0.0;
  for ( i=0; i < arr->size; i++ )
    {
      sum += ((double) arr->data[i]) * weights->data[i];
    }
  return sum / weightsum;
}

/* weighted std */
float wstd( int_array arr, float mean, int_array weights, long weightsum )
{
  double sumsq = 0.0;
  int i;
  for ( i=0; i < arr->size; i++ )
    {
      sumsq += ((double) (arr->data[i] - mean)) * (arr->data[i] - mean)
               * weights->data[i];
    }
  return sqrt( sumsq / weightsum );
}


float meanf( float_array arr )
{
```

```
  int i;
  double sum = 0.0;
  for ( i=0; i < arr->size; i++ )
    {
      sum += arr->data[i];
    }
  return (float) (sum / arr->size);
}

float stdf( float_array arr, float mean )
{
  double sumsq = 0.0;
  int i;
  for ( i=0; i < arr->size; i++ )
    {
      sumsq += (arr->data[i] - mean) * (arr->data[i] - mean);
    }
  return (float) sqrt( sumsq / (arr->size - 1) );
}

float stdr( real_array arr, fftw_real mean )
{
  double sumsq = 0.0;
  int i;
  for ( i=0; i < arr->size; i++ )
    {
      sumsq += (arr->data[i] - mean) * (arr->data[i] - mean);
    }
  return (float) sqrt( sumsq / (arr->size - 1) );
}
```

B.12 error.h

```
/* error.h */
#ifndef ERROR_H
#define ERROR_H

#define ERR_USAGE    1
#define ERR_OPEN     2
#define ERR_CHANNELS 3
#define ERR_MEM      4

#endif
```

Appendix C

Data

Features were extracted from 1714 songs, totalling over 118 hours of music. The songs are listed starting on the next page, along with codes to indicate which data set the song was assigned to for each of the three classification tasks.

Class	Data Sets 2cl	3cl	7cl	Artist	Album	Song
Ac	ts	tr		Amherst Zumbyes	Beelzebubs Winter Invitational	Copacabana
Ac	ms	tr		Amherst Zumbyes	Beelzebubs Winter Invitational	Love
Ac	tr			Amherst Zumbyes	Beelzebubs Winter Invitational	My Romance
Ac	tr	ms		Amherst Zumbyes	Beelzebubs Winter Invitational	Straight To My Heart
Ac	ms	ms	ms	Amherst Zumbyes	Beelzebubs Winter Invitational	Train
Ac	ts			Amherst Zumbyes	Beelzebubs Winter Invitational	What's Your Name
Ac	ms			Artists in Resonance	We Did It with Our Mouths	Express Yourself
Ac	ts	ts	ts	Artists in Resonance	We Did It with Our Mouths	Future Love Paradise
Ac	tr			Artists in Resonance	We Did It with Our Mouths	Higher Love
Ac	ts			Artists in Resonance	We Did It with Our Mouths	I'll Give My All to You
Ac	ms			Artists in Resonance	We Did It with Our Mouths	Leave It
Ac	ts			Artists in Resonance	We Did It with Our Mouths	One More Minute
Ac	ts			Artists in Resonance	We Did It with Our Mouths	Sweet in the Mornin'
Ac	ts			Beelzebubs	Infinity	All I Want Is You
Ac	tr			Beelzebubs	Infinity	All Night Long
Ac	ms	ts	ts	Beelzebubs	Infinity	Brothers, Sing On!
Ac	ms			Beelzebubs	Infinity	It Ain't Over 'Til It's Over
Ac	ms			Beelzebubs	Infinity	No Diggity
Ac	ts			Beelzebubs	Infinity	She's Always a Woman to Me
Ac	tr			Beelzebubs	Infinity	Signed, Sealed, Delivered
Ac	ts			Beelzebubs	Infinity	Why Should I Cry For You
Ac	ms			Beelzebubs	Infinity	You And Me & The Bottle Makes Three
Ac	ms			Brandeis Voicemale	Malestrom	Brick House
Ac	ts			Brandeis Voicemale	Malestrom	Fell in Love
Ac	ts			Brandeis Voicemale	Malestrom	Freight Train
Ac	ts			Brandeis Voicemale	Malestrom	Heaven on Their Minds
Ac	ts			Brandeis Voicemale	Malestrom	Soul to Squeeze
Ac	tr			Brandeis Voicemale	Malestrom	The Letter ('98)
Ac	tr			Brandeis Voicemale	Malestrom	Typical Situation
Ac	ms			Everyday People	2648 West Grand Blvd.	Hard to Say I'm Sorry
Ac	tr	ms	ms	Everyday People	2648 West Grand Blvd.	I Heard It Through the Grapevine
Ac	tr			Everyday People	2648 West Grand Blvd.	Seasons of Love
Ac	ms			Everyday People	2648 West Grand Blvd.	Tell Me
Ac	tr			Everyday People	2648 West Grand Blvd.	The Love You Save
Ac	ts			Everyday People	2648 West Grand Blvd.	Together Again
Ac	tr			Everyday People	2648 West Grand Blvd.	You Make Me Wanna
Ac	ts	ms		Everyday People	2648 West Grand Blvd.	You're All I Need to Get By
Ac	ts	tr		Everyday People	EP Jones	Doo Wop (That Thing) [EP Remix
Ac	tr			Everyday People	EP Jones	Gonna Love You Right
Ac	ts			Everyday People	EP Jones	I Can't Get Next To You [Freak
Ac	ms			Everyday People	EP Jones	Knocks Me Off My Feet
Ac	ms			Everyday People	EP Jones	Let's Stay Together
Ac	ms			Everyday People	EP Jones	Take Me There
Ac	ms			Mosaic Whispers	Don't Tell My Parents	3 a.m.
Ac	ms			Mosaic Whispers	Don't Tell My Parents	Airbag
Ac	ms			Mosaic Whispers	Don't Tell My Parents	Condemnation
Ac	tr			Mosaic Whispers	Don't Tell My Parents	Drive
Ac	ts	tr	tr	Mosaic Whispers	Don't Tell My Parents	Foolish Games
Ac	ms			Mosaic Whispers	Don't Tell My Parents	She's Every Woman
Ac	ts			Mosaic Whispers	Don't Tell My Parents	Suddenly Seymour
Ac	tr	ts	ts	Mosaic Whispers	Don't Tell My Parents	Sunday Morning

ms≡model selection; tr≡training; ts≡testing

Ac≡College A Cappella; Ap≡Pro A Cappella; A≡A Cappella; E≡Electronica; P≡Pop; Ce≡Celtic; Cl≡Classical; J≡Jazz; L≡Latin

	Data Sets					
Class	2cl	3cl	7cl	Artist	Album	Song
Ac	ts			Mosaic Whispers	Don't Tell My Parents	Walk Like an Egyptian
Ac	ms			Mosaic Whispers	Don't Tell My Parents	We Built This City
Ac	tr			Mosaic Whispers	Don't Tell My Parents	Where's the Love
Ac	tr	ms	ms	Mosaic Whispers	Watercolors	500 Miles
Ac	ms			Mosaic Whispers	Watercolors	I Can't Make You Love Me
Ac	ms	ts	ts	Mosaic Whispers	Watercolors	I Hope That Something Better Comes Along
Ac	tr			Mosaic Whispers	Watercolors	Just For You
Ac	ts	tr	tr	Mosaic Whispers	Watercolors	Kiss the Girl
Ac	tr	ms		Mosaic Whispers	Watercolors	Please Don't Go
Ac	ts			Mosaic Whispers	Watercolors	Somebody to Love
Ac	ts	ts	ts	Mosaic Whispers	Watercolors	Standin' by the Bedside
Ac	tr			Mosaic Whispers	Watercolors	The Logical Song
Ac	ms			Off the Beat	Bombtracks	Boys of Summer
Ac	tr	tr	tr	Off the Beat	Bombtracks	Freedom '90
Ac	ts			Off the Beat	Bombtracks	Gangsta's Paradise
Ac	tr	ms	ms	Off the Beat	Bombtracks	St. Theresa
Ac	ms	ts	ts	Off the Beat	Bombtracks	Still Haven't Found What I'm Looking For
Ac	ts			Off the Beat	Bombtracks	You Oughta Know
Ac	ms			Off the Beat	Flail	Blood and Fire
Ac	ms			Off the Beat	Flail	Candy Everybody Wants
Ac	ts	ms	ms	Off the Beat	Flail	Jeremy
Ac	ms			Off the Beat	Flail	Plush
Ac	ts			Off the Beat	Flail	mmm mmm mmm mmm
Ac	ms	ts	ts	Off the Beat	Patio	Angel
Ac	ms			Off the Beat	Patio	Back on Earth
Ac	ts			Off the Beat	Patio	Brick
Ac	tr			Off the Beat	Patio	Criminal
Ac	ts			Off the Beat	Patio	Don't Stand So Close to Me
Ac	ms			Off the Beat	Patio	Every Little Bit
Ac	ts			Off the Beat	Patio	Foolish Games
Ac	ts			Off the Beat	Patio	If You Could Only See
Ac	ts			Off the Beat	Patio	Landslide
Ac	ts			Off the Beat	Patio	Push
Ac	tr	ts	ts	Off the Beat	Patio	She Talks to Angels
Ac	ts	ms	ms	Off the Beat	Patio	The Mummers' Dance
Ac	tr			Off the Beat	Patio	Virtual Insanity
Ac	tr	ms		Rochester Yellowjackets	Wilson Boulevard	Birdland
Ac	ts			Rochester Yellowjackets	Wilson Boulevard	Footloose
Ac	tr			Rochester Yellowjackets	Wilson Boulevard	Karma Chameleon
Ac	tr			Rochester Yellowjackets	Wilson Boulevard	That Cat Is High
Ac	ts			Rochester Yellowjackets	Wilson Boulevard	Ventura Highway
Ac	ts			Spur of the Moment	Two Flights Up	Blame-December
Ac	ts	ms	ms	Spur of the Moment	Two Flights Up	Charming
Ac	ts			Spur of the Moment	Two Flights Up	She Runs Away
Ac	ms	ts	ts	Spur of the Moment	Two Flights Up	Signed Sealed Delivered
Ac	tr	tr		Spur of the Moment	Two Flights Up	Spirit of Radio
Ac	ts			Spur of the Moment	Two Flights Up	Strut
Ac	ms	tr		Spur of the Moment	Two Flights Up	Wisconsin
Ac	tr			Spur of the Moment	Two Flights Up	Wishing I Was There
Ac	tr	ts	ts	Stanford Fleet Street Singers	50-Minute Fun Break	Dat Dere
Ac	ms			Stanford Fleet Street Singers	50-Minute Fun Break	Hello, My Baby
Ac	ms			Stanford Fleet Street Singers	50-Minute Fun Break	It's a Blue World

ms≡model selection; tr≡training; ts≡testing

Ac≡College A Cappella; Ap≡Pro A Cappella; A≡A Cappella; E≡Electronica; P≡Pop; Ce≡Celtic; Cl≡Classical; J≡Jazz; L≡Latin

	Data Sets					
Class	2cl	3cl	7cl	Artist	Album	Song
Ac	tr	tr		Stanford Fleet Street Singers	50-Minute Fun Break	My Funny Valentine
Ac	tr			Stanford Fleet Street Singers	50-Minute Fun Break	Natural Woman
Ac	tr	tr		Stanford Fleet Street Singers	50-Minute Fun Break	Ruby Baby
Ac	ms			Stanford Fleet Street Singers	50-Minute Fun Break	Since I Fell for You
Ac	tr			Stanford Fleet Street Singers	50-Minute Fun Break	Stanford Girl
Ac	ms			Stanford Fleet Street Singers	50-Minute Fun Break	Their Hearts Were Full of Spring
Ac	tr			Stanford Fleet Street Singers	50-Minute Fun Break	Think
Ac	ms			Stanford Fleet Street Singers	50-Minute Fun Break	When I Fall in Love
Ac	ts	ts	ts	Stanford Fleet Street Singers	50-Minute Fun Break	Wonder Woman
Ac	ts			Stanford Fleet Street Singers	All The Rage	All the Rage
Ac	tr			Stanford Fleet Street Singers	All The Rage	How Deep Is Your Love
Ac	ts	ms		Stanford Fleet Street Singers	All The Rage	Joyful, Joyful
Ac	ts	ms	ms	Stanford Fleet Street Singers	All The Rage	The Time Warp
Ac	ts			Stanford Fleet Street Singers	What You Want	Ave Maria
Ac	tr	ms	ms	Stanford Fleet Street Singers	What You Want	Black Coffee
Ac	ts			Stanford Fleet Street Singers	What You Want	Blizzard of Lies
Ac	ms			Stanford Fleet Street Singers	What You Want	Duran Duran
Ac	ts			Stanford Fleet Street Singers	What You Want	Hail Stanford, Hail
Ac	tr			Stanford Fleet Street Singers	What You Want	House at Pooh Corner
Ac	ts			Stanford Fleet Street Singers	What You Want	Smut
Ac	ms			Stanford Fleet Street Singers	What You Want	Tenderly
Ac	tr			Stanford Fleet Street Singers	What You Want	The Neb Song
Ac	ts			Stanford Fleet Street Singers	What You Want	Too Young for the Blues
Ac	tr			Stanford Harmonics	Insanity Laughs	Criminal
Ac	ms			Stanford Harmonics	Insanity Laughs	Goodbye
Ac	tr			Stanford Harmonics	Insanity Laughs	One
Ac	ms			Stanford Harmonics	Insanity Laughs	Push
Ac	ts			Stanford Harmonics	Insanity Laughs	Push It
Ac	ms			Stanford Harmonics	Insanity Laughs	Ray of Light
Ac	tr	tr		Stanford Harmonics	Insanity Laughs	Stay (Wastin' Time)
Ac	ms			Stanford Harmonics	Insanity Laughs	Under Pressure
Ac	tr			Stanford Harmonics	Insanity Laughs	Uninvited
Ac	ms			Stanford Mendicants	Besides What You See	At the Hop
Ac	ms	tr	tr	Stanford Mendicants	Besides What You See	Dream Lover
Ac	ms			Stanford Mendicants	Besides What You See	I Won't Stand in Your Way
Ac	ts			Stanford Mendicants	Besides What You See	Killed by a Flower
Ac	ms			Straight No Chaser	Last Call	A Song For Mama
Ac	ts	ms	ms	Straight No Chaser	Last Call	Back Home Again In Indiana
Ac	ms			Straight No Chaser	Last Call	Ghost Train
Ac	tr	tr	tr	Straight No Chaser	Last Call	Hi-De-Ho
Ac	tr			Straight No Chaser	Last Call	Superstition
Ac	tr	ms		Straight No Chaser	Last Call	This Boy
Ac	ts			Straight No Chaser	Last Call	This Is How We Do It
Ac	ts			The Brown Derbies	Down Time	Alive
Ac	ms			The Brown Derbies	Down Time	Down on the Corner
Ac	tr	tr		The Brown Derbies	Down Time	In Your Eyes – Live
Ac	ms			The Brown Derbies	Down Time	Mensaje de Telefono
Ac	tr			The Brown Derbies	Down Time	Superstition Take 1
Ac	ts			The Brown Derbies	Down Time	Tarzan Boy
Ac	tr	ms		The Brown Derbies	Down Time	Telephone Message
Ac	ts			The Brown Derbies	Down Time	The Derby Show – Live
Ac	ms			The Brown Derbies	Down Time	Veronica – Live

ms≡model selection; tr≡training; ts≡testing

Ac≡College A Cappella; Ap≡Pro A Cappella; A≡A Cappella; E≡Electronica; P≡Pop; Ce≡Celtic; Cl≡Classical; J≡Jazz; L≡Latin

Class	Data Sets 2cl	3cl	7cl	Artist	Album	Song
Ac	ts			The Brown Derbies	Down Time	When I'm Sixty-Four
Ac	tr	ts	ts	The Brown Derbies	Hat Trick	A Little Respect
Ac	ts			The Brown Derbies	Hat Trick	Black Or White
Ac	ms	ms	ms	The Brown Derbies	Hat Trick	Can't You Hear Me Knockin'
Ac	ts			The Brown Derbies	Hat Trick	Changes
Ac	ts	ms	ms	The Brown Derbies	Hat Trick	Love The One You're With
Ac	ms			The Buffalo Chips	Remember The Songs	Fee
Ac	ms			The Buffalo Chips	Remember The Songs	Fozz Rap
Ac	ts	ms		The Chattertocks	Aire	Always Be My Baby
Ac	tr	ts	ts	The Chattertocks	Aire	As Cool As I Am
Ac	ts			The Chattertocks	Aire	Breakout
Ac	tr	ts	ts	The Chattertocks	Aire	Foolish Games
Ac	tr			The Chattertocks	Aire	Frozen
Ac	ts			The Chattertocks	Aire	In the Gloaming
Ac	ts			The Chattertocks	Aire	Kiss the Rain
Ac	ts			The Chattertocks	Aire	Say Goodbye
Ac	tr			The Chattertocks	Aire	Show Me Love
Ac	ms			The Chattertocks	Aire	Spice Up Your Life
Ac	tr	ts	ts	The Chattertocks	Aire	Sunday Morning Yellow Sky
Ac	ms	tr	tr	The Chattertocks	Aire	The Ladder
Ac	ms			The Jabberwocks	Liz's Slingback Boots	Black Dog
Ac	ms			The Jabberwocks	Liz's Slingback Boots	Don't Stop Believin'
Ac	tr			The Jabberwocks	Liz's Slingback Boots	Farewell Song
Ac	ms			The Jabberwocks	Liz's Slingback Boots	I Will Survive
Ac	ms			The Jabberwocks	Liz's Slingback Boots	Just the Two of Us
Ac	ts			The Jabberwocks	Liz's Slingback Boots	Me and The Boys
Ac	ts			The Jabberwocks	Liz's Slingback Boots	Never Tear Us Apart
Ac	tr			The Jabberwocks	Liz's Slingback Boots	Walking On The Moon
Ac	tr			The Jabberwocks	Sermons and Soda Water	All Night Long
Ac	ms			The Jabberwocks	Sermons and Soda Water	Farewell Song
Ac	ts			The Jabberwocks	Sermons and Soda Water	It's Still Rock and Roll to Me
Ac	ms			The Jabberwocks	Sermons and Soda Water	Me and the Boys
Ac	ms	ts	ts	The Jabberwocks	Sermons and Soda Water	Volare
Ac	tr			Tufts Beelzebubs	Beelzebubs Winter Invitational	Don't Get Around Much Anymore
Ac	ts			Tufts Beelzebubs	Beelzebubs Winter Invitational	Empty Garden
Ac	tr			Tufts Beelzebubs	Beelzebubs Winter Invitational	Hard To Handle
Ac	tr			Tufts Beelzebubs	Beelzebubs Winter Invitational	Wicked Game
Ac	ms	ms	ms	Tufts Beelzebubs	Foster Street	Always Something There to Remind Me
Ac	tr			Tufts Beelzebubs	Foster Street	Beyond the Sea
Ac	tr	ms		Tufts Beelzebubs	Foster Street	Big Shot
Ac	ms			Tufts Beelzebubs	Foster Street	Comfortably Numb
Ac	tr	ms		Tufts Beelzebubs	Foster Street	I Can't Tell You Why
Ac	ts			Tufts Beelzebubs	Foster Street	Let's Go Crazy
Ac	ts			Tufts Beelzebubs	Foster Street	Pinball Wizard
Ac	tr	tr		Tufts Beelzebubs	Foster Street	She's Leaving Home
Ac	ts	tr	tr	Tufts Beelzebubs	Foster Street	You Can't Touch This
Ac	ts			Tufts Beelzebubs	Foster Street	Your Smilin' Face
Ac	tr			Tufts Beelzebubs	Foster Street	Your Song
Ac	tr			Tufts Beelzebubs	Gilding	Ants Marching
Ac	ts	ms	ms	Tufts Beelzebubs	Gilding	Blood of Eden
Ac	tr			Tufts Beelzebubs	Gilding	Bridge Over Troubled Water
Ac	tr			Tufts Beelzebubs	Gilding	Crosstown Traffic

ms≡model selection; tr≡training; ts≡testing

Ac≡College A Cappella; Ap≡Pro A Cappella; A≡A Cappella; E≡Electronica; P≡Pop; Ce≡Celtic; Cl≡Classical; J≡Jazz; L≡Latin

Class	Data Sets 2cl	3cl	7cl	Artist	Album	Song
Ac	ms			Tufts Beelzebubs	Gilding	Family Snapshot
Ac	ts			Tufts Beelzebubs	Gilding	Janie's Got a Gun
Ac	ts	tr		Tufts Beelzebubs	Gilding	Prayer For The Dying
Ac	ms			Tufts Beelzebubs	Gilding	The Surrey with the Fringe on
Ac	ms			Tufts Beelzebubs	Gilding	Wicked Game
Ac	tr	ms		Tufts Beelzebubs	Vince	Father Figure
Ac	ts			Tufts Beelzebubs	Vince	Red Rain
Ac	ms			UPenn Counterparts	High Dive	Alone
Ac	tr	tr	tr	UPenn Counterparts	High Dive	Bewitched, Bothered, and Bewildered
Ac	tr	ms		UPenn Counterparts	High Dive	Hang On To Your Love
Ac	tr	tr	tr	UPenn Counterparts	High Dive	I Can't Make You Love Me
Ac	ts			UPenn Counterparts	High Dive	Karma Police
Ac	ms			UPenn Counterparts	High Dive	Love Is Blindness
Ac	ms			UPenn Counterparts	High Dive	Love, Thy Will Be Done
Ac	ms			UPenn Counterparts	High Dive	That's The Way Love Goes
Ac	ts			UPenn Counterparts	Housekeeping	All Of Me
Ac	tr			UPenn Counterparts	Housekeeping	Housekeeping
Ac	ts			UPenn Counterparts	Housekeeping	I Remember Clifford
Ac	ms	tr		UPenn Counterparts	Housekeeping	If It makes You Happy
Ac	ts			UPenn Counterparts	Housekeeping	My Lovin' (You're Never Gonna
Ac	ms			UPenn Counterparts	Housekeeping	Stay
Ac	ms	ms		Vassar Measure 4 Measure	Beelzebubs Winter Invitational	Long Train Running
Ac	ts			Vassar Measure 4 Measure	Beelzebubs Winter Invitational	Remember That
Ac	tr			Vassar Measure 4 Measure	Beelzebubs Winter Invitational	Somebody To Love
Ac	ms			Vassar Measure 4 Measure	Beelzebubs Winter Invitational	Temps Jam
Ac	tr			Vassar Measure 4 Measure	Beelzebubs Winter Invitational	Waterfall
Ac	ms			Washington University Pikers	4th and Ten	Blister In The Sun
Ac	ms			Washington University Pikers	4th and Ten	Dust in the Wind
Ac	tr	tr		Washington University Pikers	4th and Ten	Ev'ry Breath You Take
Ac	tr			Washington University Pikers	4th and Ten	I Still Haven't Found What I'm Looking For
Ac	ts	ts	ts	Washington University Pikers	4th and Ten	Prologne de Piseis
Ac	ms	ms	ms	Washington University Pikers	4th and Ten	R.E.M.edley
Ac	tr			Washington University Pikers	4th and Ten	Something
Ac	ms			Washington University Pikers	4th and Ten	Thriller
Ac	tr			Washington University Pikers	4th and Ten	True Companion
Ac	ms			Washington University Pikers	4th and Ten	Waiting Faithfully
Ac	ts			Washington University Pikers	Feed Our Starving Egos	Anna Begins
Ac	ts	ms		Washington University Pikers	Feed Our Starving Egos	Down Under
Ac	ts	ms		Washington University Pikers	Feed Our Starving Egos	Early in the Mornin' (live)
Ac	ms	tr		Washington University Pikers	Feed Our Starving Egos	Flashdance... What a Feeling!
Ac	tr			Washington University Pikers	Feed Our Starving Egos	If I Had A Million Dollars
Ac	tr	ms		Washington University Pikers	Feed Our Starving Egos	Julius
Ac	ts			Washington University Pikers	Feed Our Starving Egos	Starfish and Coffee
Ac	ms			Washington University Pikers	Feed Our Starving Egos	The Safety Dance
Ac	tr			Washington University Pikers	Feed Our Starving Egos	What R.O.C.K.S. About You
Ac	ts			Washington University Pikers	On the Rocks	Birthday
Ac	ms			Washington University Pikers	On the Rocks	Cold as Ice
Ac	ts			Washington University Pikers	On the Rocks	Gimme Some Lovin'
Ac	tr	tr	tr	Washington University Pikers	On the Rocks	I'm a Believer
Ac	tr			Washington University Pikers	On the Rocks	Just Like You
Ac	tr			Washington University Pikers	On the Rocks	Late in the Evening
Ac	ts			Washington University Pikers	On the Rocks	Lean on Me

ms≡model selection; tr≡training; ts≡testing
Ac≡College A Cappella; Ap≡Pro A Cappella; A≡A Cappella; E≡Electronica; P≡Pop; Ce≡Celtic; Cl≡Classical; J≡Jazz; L≡Latin

Class	Data Sets 2cl	3cl	7cl	Artist	Album	Song
Ac	ms	ts	ts	Washington University Pikers	On the Rocks	Steam
Ac	tr			Washington University Pikers	On the Rocks	Take Me Home
Ac	tr			Washington University Pikers	On the Rocks	The Daze of Christmas
Ac	ts			Washington University Pikers	On the Rocks	Wonderful Tonight
Ac	tr			Washington University Pikers	On the Rocks	You Can Call Me Al
Ac	ts			Washington University Pikers	World Detour	Blue Moon
Ac	ms			Washington University Pikers	World Detour	Crazy Little Thing Called Love
Ac	ms			Washington University Pikers	World Detour	Hazy Shade of Winter
Ac	tr			Washington University Pikers	World Detour	Heavenly
Ac	ts	tr	tr	Washington University Pikers	World Detour	Istanbul (Not Constantinople)
Ac	ms			Washington University Pikers	World Detour	Kiss Him Goodbye
Ac	ts			Washington University Pikers	World Detour	My Girl / You Really Got Me
Ac	ms			Washington University Pikers	World Detour	You've Lost That Lovin' Feeling
Ac	ts			Williams Ephlats	Live from the Spa City Diner	Back in the USSR
Ac	tr			Williams Ephlats	Live from the Spa City Diner	Helplessly Hoping
Ac	tr			Williams Ephlats	Live from the Spa City Diner	I Want You Back
Ac	ms			Williams Ephlats	Live from the Spa City Diner	Jezebel
Ac	tr			Williams Ephlats	Live from the Spa City Diner	Steven's Last Night in Town
Ac	ts			Williams Ephlats	Live from the Spa City Diner	Still Haven't Found What I'm Looking For
Ac	tr	ms		Williams Ephlats	Live from the Spa City Diner	What I Got
Ac	ms			Xtension Chords	Aftershock	Jesse's Girl
Ac	tr			Xtension Chords	Aftershock	Just a Gigolo
Ac	ms	tr	tr	Xtension Chords	Aftershock	Kiss from a Rose
Ac	ts			Xtension Chords	Aftershock	One More Minute
Ac	ms	tr		Xtension Chords	Aftershock	Ordinary World
Ac	ms			Xtension Chords	Aftershock	Something About You
Ac	ms	tr		Xtension Chords	Shock Value	'39
Ac	ms			Xtension Chords	Shock Value	Africa
Ac	tr			Xtension Chords	Shock Value	Freeze Frame
Ac	tr			Xtension Chords	Shock Value	Good Vibrations
Ac	ms			Xtension Chords	Shock Value	Hushabye
Ac	ts			Xtension Chords	Shock Value	Island Girl
Ac	ts			Xtension Chords	Shock Value	On the Turning Away
Ac	ms	tr	tr	Xtension Chords	Shock Value	Picture Perfect
Ac	tr	ts	ts	Xtension Chords	Shock Value	Saturday in the Park
Ac	tr	ts	ts	Xtension Chords	Shock Value	The Look
Ac	ts			Xtension Chords	Shock Value	You Took The Words Right Out Of My Mouth
Ap	ts			6 Day Week	Hot Lips: Vocal Band Sampler	Presto Change-o
Ap	tr			AC Rock	Acappellago	409
Ap	ms			AC Rock	Acappellago	Because
Ap	ms			AC Rock	Acappellago	Bus Stop
Ap	ts	ms	ms	AC Rock	Acappellago	Coconut
Ap	ms			AC Rock	Acappellago	Come Go With Me
Ap	ts	ms	ms	AC Rock	Acappellago	I Want You To Want Me
Ap	tr	tr	tr	AC Rock	Acappellago	Istanbul
Ap	ms			AC Rock	Acappellago	It's For You
Ap	ms	tr	tr	AC Rock	Acappellago	Kiss From a Rose
Ap	tr	tr		AC Rock	Acappellago	Need You Tonight
Ap	tr			AC Rock	Acappellago	Vehicle
Ap	ms	tr	tr	AC Rock	Acappellago	Witch Doctor
Ap	tr			AC Rock	UR What UR	Bohemian Rhapsody
Ap	ms			AC Rock	UR What UR	Break My Stride

ms≡model selection; tr≡training; ts≡testing

Ac≡College A Cappella; Ap≡Pro A Cappella; A≡A Cappella; E≡Electronica; P≡Pop; Ce≡Celtic; Cl≡Classical; J≡Jazz; L≡Latin

Class	Data Sets 2cl	3cl	7cl	Artist	Album	Song
Ap	ts			AC Rock	UR What UR	Carry on Wayward Son
Ap	ts			AC Rock	UR What UR	Get Off Of My Cloud
Ap	ts			AC Rock	UR What UR	Like a Rolling Stone
Ap	tr			AC Rock	UR What UR	More Than Words
Ap	ms			AC Rock	UR What UR	Silhouettes
Ap	tr			AC Rock	UR What UR	Things We Said Today
Ap	ms			Artisan	A Cappella All-Stars The 1997	Lest We Forget
Ap	tr			Ball In The House	Hot Lips: Vocal Band Sampler	Burned
Ap	ts			Ball in the House	Ball in the House	Ask
Ap	ts			Ball in the House	Ball in the House	Burned
Ap	ts			Ball in the House	Ball in the House	Don't Say You're Sorry
Ap	ms	ts	ts	Ball in the House	Ball in the House	Fantasyland
Ap	ms	tr		Ball in the House	Ball in the House	Get It On
Ap	ms			Ball in the House	Ball in the House	Giving You Me
Ap	tr	tr	tr	Ball in the House	Ball in the House	Gravity Buster
Ap	tr	ms	ms	Ball in the House	Ball in the House	Helen
Ap	tr			Ball in the House	Ball in the House	I Couldn't Run
Ap	ts	ms		Ball in the House	Ball in the House	Should I
Ap	ts			Ball in the House	Ball in the House	The More That I Say
Ap	ts	tr		Blind Man's Bluff	Hot Lips: Vocal Band Sampler	Wake Up Call
Ap	tr			Bobby McFerrin	Simple Pleasures	All I Want
Ap	ts			Bobby McFerrin	Simple Pleasures	Come To Me
Ap	ms	tr	tr	Bobby McFerrin	Simple Pleasures	Don't Worry, Be Happy
Ap	ts	ms		Bobby McFerrin	Simple Pleasures	Drive
Ap	ts			Bobby McFerrin	Simple Pleasures	Drive My Car
Ap	ts	tr	tr	Bobby McFerrin	Simple Pleasures	Simple Pleasures
Ap	tr			Bobby McFerrin	Simple Pleasures	Them Changes
Ap	tr			Bobby McFerrin	Spontaneous Inventions	Another Night in Tunisia
Ap	tr			Bobby McFerrin	Spontaneous Inventions	Beverly Hills Blues
Ap	tr			Bobby McFerrin	Spontaneous Inventions	Cara Mia
Ap	ms	ts	ts	Bobby McFerrin	Spontaneous Inventions	From Me to You
Ap	ts			Bobby McFerrin	Spontaneous Inventions	I Hear Music
Ap	ts			Bobby McFerrin	Spontaneous Inventions	Manana Iguana
Ap	ms			Bobby McFerrin	Spontaneous Inventions	There Ya Go
Ap	tr			Bobby McFerrin	Spontaneous Inventions	Thinkin' About Your Body
Ap	ts	ms	ms	Bobby McFerrin	Spontaneous Inventions	Turtle Shoes
Ap	ts			Bobby McFerrin	Spontaneous Inventions	Walkin'
Ap	tr	tr	tr	Boyz Nite Out	A Cappella All-Stars The 1997	Crazy
Ap	ts			Boyz Nite Out	Hot Lips: Vocal Band Sampler	My Heart
Ap	tr	tr		DaVinci's Notebook	Bendy's Law	(Sittin' on) The Dock of the Bay
Ap	ms			DaVinci's Notebook	Bendy's Law	Call Me
Ap	ms	ms		DaVinci's Notebook	Bendy's Law	Fish Sticks
Ap	ts			DaVinci's Notebook	Bendy's Law	I Dream of Jeannie
Ap	ms	tr		DaVinci's Notebook	Bendy's Law	Liposuction
Ap	tr			DaVinci's Notebook	Bendy's Law	Metal Shop
Ap	ts			DaVinci's Notebook	Bendy's Law	Shoehorn with Teeth
Ap	ms			DaVinci's Notebook	Bendy's Law	Stuck in the Middle With You
Ap	ts			DaVinci's Notebook	Bendy's Law	Traffic Jam
Ap	ms			DaVinci's Notebook	Bendy's Law	Window-Washing Cowboy
Ap	ts			En Vogue	Modern A Cappella	The Star Spangled Banner
Ap	ts	tr	tr	Extempo	A Cappella All-Stars The 1997	Bionic
Ap	ms	ms		Extempo	Channel 32	Autum Leaves

ms≡model selection; tr≡training; ts≡testing

Ac≡College A Cappella; Ap≡Pro A Cappella; A≡A Cappella; E≡Electronica; P≡Pop; Ce≡Celtic; Cl≡Classical; J≡Jazz; L≡Latin

Class	Data Sets 2cl	3cl	7cl	Artist	Album	Song
Ap	ts			Extempo	Channel 32	Blessed Are...
Ap	ts			Extempo	Channel 32	Every Man
Ap	ms			Extempo	Channel 32	How Long
Ap	ts			Extempo	Channel 32	Killing Me Softly
Ap	ms			Extempo	Channel 32	Magalenha
Ap	ms			Extempo	Channel 32	Magic Carpet Ride
Ap	ms			Extempo	Channel 32	Mary Mary
Ap	ts			Extempo	Channel 32	Sound Check
Ap	tr	ts	ts	Extempo	Channel 32	Summertime
Ap	tr	tr	tr	Extempo	Channel 32	bluegreen
Ap	ms			Five Live	Quintessence	Everything Must Change
Ap	ms			Five Live	Quintessence	Homeless
Ap	ts			Five Live	Quintessence	I Like To Move It
Ap	ms	ms		Five Live	Quintessence	Love Your Smile
Ap	ts	ts	ts	Five Live	Quintessence	Serious
Ap	ts			Five Live	Quintessence	Sometimes Something
Ap	ms	ms		Five Live	Quintessence	Tu Was Du Willst
Ap	tr	tr	tr	Five Live	Quintessence	Two Different Views
Ap	tr			Five Live	Quintessence	Walking On The Right Side
Ap	ms			Five Live	Quintessence	Without Love
Ap	tr			Five O'Clock Shadow	Hot Lips: Vocal Band Sampler	What's It All About
Ap	tr			Five O'Clock Shadow	So There	Get Down Tonight-That's The Way
Ap	ts			Five O'Clock Shadow	So There	If You Could Only See
Ap	tr			Five O'Clock Shadow	So There	Move On
Ap	tr	tr		Five O'Clock Shadow	So There	Stop And Say Hello
Ap	tr			Five O'Clock Shadow	So There	Tribute
Ap	ms			Ladysmith Black Mambazo With T	Spike & Co. Do It A Cappella	The Lion Sleeps Tonight
Ap	ts			M-Pact	2	2
Ap	ms			M-Pact	2	A Mile in My Shoes
Ap	ts			M-Pact	2	Fantasy
Ap	ts			M-Pact	2	First Steps
Ap	ts			M-Pact	2	Hold On To My Heart
Ap	ts			M-Pact	2	If We Try
Ap	ms			M-Pact	2	My Way
Ap	ms			M-Pact	2	Rain
Ap	ms			M-Pact	2	Under the Sun
Ap	tr			M-Pact	2	Without Your Love
Ap	ms			M-Pact	It's All About Harmony	29 Ways
Ap	ms			M-Pact	It's All About Harmony	Change in My Life
Ap	ms	tr	tr	M-Pact	It's All About Harmony	Higher and Higher
Ap	ms	ms		M-Pact	It's All About Harmony	If I Lost You
Ap	ms			M-Pact	It's All About Harmony	Love the One You're With
Ap	ts			M-Pact	It's All About Harmony	She Won't Believe In Me
Ap	tr			Mary Schmary	Smarty Pants	Already Gone
Ap	ts	ts	ts	Mary Schmary	Smarty Pants	Human Bean
Ap	tr			Mary Schmary	Smarty Pants	I Put You There
Ap	tr			Mary Schmary	Smarty Pants	Inmigrantes
Ap	ts			Mary Schmary	Smarty Pants	Little Fish
Ap	ms			Mary Schmary	Smarty Pants	More Than Human
Ap	ms	ms		Mary Schmary	Smarty Pants	Never Will
Ap	tr			Mary Schmary	Smarty Pants	Peace
Ap	ms			Mary Schmary	Smarty Pants	Shadows

ms≡model selection; tr≡training; ts≡testing

Ac≡College A Cappella; Ap≡Pro A Cappella; A≡A Cappella; E≡Electronica; P≡Pop; Ce≡Celtic; Cl≡Classical; J≡Jazz; L≡Latin

	Data Sets					
Class	2cl	3cl	7cl	Artist	Album	Song
Ap	ms			Mary Schmary	Smarty Pants	Uterus
Ap	ts			Mary Schmary	Smarty Pants	Who Are You
Ap	tr			Monkey Puzzle	Hot Lips: Vocal Band Sampler	If It Wasn't
Ap	ms			Moxy Früvous	Bargainville	Gulf War Song
Ap	tr	tr		Moxy Früvous	You Will Go To The Moon	You Will Go To The Moon
Ap	ts			No Place For Jennifer	A Cappella All-Stars The 1997	Tell My Feet
Ap	ms			Rockapella And True Image	Spike & Co. Do It A Cappella	Under The Boardwalk
Ap	ms			Rockapella & The Persuasions	Where in The World Is Carmen S	My Home
Ap	ts			Rockapella	Primer	Come My Way
Ap	ts			Rockapella	Primer	For The Love
Ap	ts	tr	tr	Rockapella	Primer	Kingdom Of Shy
Ap	ms			Rockapella	Primer	Last Night
Ap	ts			Rockapella	Primer	Long Cool Woman In A Black Dre
Ap	ts			Rockapella	Primer	My Home
Ap	ts			Rockapella	Primer	Nowhere
Ap	ts			Rockapella	Primer	Pretty Woman
Ap	tr			Rockapella	Primer	Shambala
Ap	ms			Rockapella	Primer	Sixty Minute Man
Ap	ms	ms	ms	Rockapella	Primer	Where In The World Is Carmen Sandiego
Ap	ms			Rockapella	Primer	Zombie Jamboree
Ap	ts			Rockapella	Spike & Co. Do It A Cappella	Zombie Jamboree
Ap	tr			Rockapella	Where in The World Is Carmen S	Capital
Ap	ms	ms	ms	Rockapella	Where in The World Is Carmen S	Everything to Me
Ap	ms			Rockapella	Where in The World Is Carmen S	Where in The World Is Carmen Sandiego
Ap	ts	ts	ts	STREETNiX	Hot Lips: Vocal Band Sampler	Make Me Want You
Ap	ms			Schrödingers Cat	Big Beat A Cappella	Day-O
Ap	tr	tr		Schrödingers Cat	Big Beat A Cappella	In Your Eyes
Ap	ms			Schrödingers Cat	Big Beat A Cappella	Jump In Line
Ap	tr			Schrödingers Cat	Big Beat A Cappella	No Diggity
Ap	ms			Schrödingers Cat	Big Beat A Cappella	Sexual Healing
Ap	ms	ms	ms	Schrödingers Cat	Big Beat A Cappella	That Lonesome Road
Ap	ts			Schrödingers Cat	Big Beat A Cappella	The Secret Track - Go Cats!
Ap	ms			Schrödingers Cat	Big Beat A Cappella	Through The Wall
Ap	ms			Schrödingers Cat	Big Beat A Cappella	When Doves Cry
Ap	tr	tr	tr	Schrödingers Cat	Big Beat A Cappella	Yes, You
Ap	ms			Schrödingers Cat	Big Beat A Cappella	You Can Leave Your Hat On
Ap	ts			Schrodinger's Cat	Hot Lips: Vocal Band Sampler	When Doves Cry
Ap	tr			SoVoSó	SoVoSó	Dirt
Ap	ts			SoVoSó	SoVoSó	Down By The Riverside
Ap	tr			SoVoSó	SoVoSó	First Words
Ap	ts			SoVoSó	SoVoSó	Fop
Ap	ms			SoVoSó	SoVoSó	Home
Ap	tr			SoVoSó	SoVoSó	People Get Ready
Ap	ms			SoVoSó	SoVoSó	Say
Ap	ms			SoVoSó	SoVoSó	Say A Prayer
Ap	tr			SoVoSó	SoVoSó	Show Them Dance
Ap	ts			SoVoSó	SoVoSó	Thank You
Ap	ms	ts	ts	SoVoSó	SoVoSó	That Day
Ap	ts			SoVoSó	SoVoSó	Tu Para Mi
Ap	ms			SoVoSó	SoVoSó	U
Ap	tr	ms	ms	SoVoSó	SoVoSó	Wa Wa Wa
Ap	ts	tr	tr	SoVoSó	Truth & Other Stories	Afro Blue

ms≡model selection; tr≡training; ts≡testing

Ac≡College A Cappella; Ap≡Pro A Cappella; A≡A Cappella; E≡Electronica; P≡Pop; Ce≡Celtic; Cl≡Classical; J≡Jazz; L≡Latin

Class	Data Sets 2cl	3cl	7cl	Artist	Album	Song
Ap	tr	ts	ts	SoVoSó	Truth & Other Stories	Be Of Love
Ap	ts	tr		SoVoSó	Truth & Other Stories	Clear Winter Skies
Ap	tr	ts	ts	SoVoSó	Truth & Other Stories	For The Forest
Ap	ts			SoVoSó	Truth & Other Stories	Gift of Music
Ap	ts			SoVoSó	Truth & Other Stories	In My Prime
Ap	tr			SoVoSó	Truth & Other Stories	Thank You For The Dream
Ap	tr			Street Sounds	Street Sounds	Blues Medley – You Got Me Running, C.C. Rider
Ap	ts			Street Sounds	Street Sounds	Change
Ap	tr			Street Sounds	Street Sounds	Down By the Riverside / This L
Ap	tr			Street Sounds	Street Sounds	Dream Variations
Ap	ms			Street Sounds	Street Sounds	Home Africa
Ap	ms			Street Sounds	Street Sounds	Jesus Hits Like an Atom Bomb
Ap	ms			Street Sounds	Street Sounds	Let Us Break Bread Together
Ap	ts			Street Sounds	Street Sounds	Miss Me From the Back of the Bus, Sister Rosa
Ap	ts	ms		Street Sounds	Street Sounds	No More Auction Block For Me
Ap	ms			Street Sounds	Street Sounds	On Children
Ap	ts	tr	tr	Sweet Deliverance	A Cappella All-Stars The 1997	Poor Wayfaring Stranger
Ap	ts			Take 6	Modern A Cappella	Spread Love
Ap	ts	ts	ts	The Bangles	Modern A Cappella	Walk Like an Egyptian
Ap	ts			The Edlos	A Cappella Country	Big Bad John
Ap	ts			The Edlos	A Cappella Country	Born to Yodel
Ap	tr	ms	ms	The Edlos	A Cappella Country	Castin' My Lasso
Ap	ts	ms		The Edlos	A Cappella Country	Faded Love
Ap	ts			The Edlos	A Cappella Country	For Ever and Ever, Amen
Ap	ms	ms		The Edlos	A Cappella Country	I Think It's Gonna Rain Today
Ap	ms			The Edlos	A Cappella Country	The Cattle Call
Ap	tr			The Edlos	A Cappella Country	Tupelo Honey
Ap	tr	ms		The Edlos	A Cappella Country	Your Cheatin' Heart
Ap	ms			The Flirtations	A Cappella All-Stars The 1997	Do Not Turn Away
Ap	tr	ts	ts	The Flying Pickets	Modern A Cappella	Only You
Ap	tr			The Gas House Gang	A Cappella All-Stars The 1997	Strike Up The Band Medley
Ap	ts			The House Jacks	Funkwich	All Of My Life
Ap	tr	ms	ms	The House Jacks	Funkwich	Completely
Ap	ts	tr	tr	The House Jacks	Funkwich	Crazy Maze
Ap	tr			The House Jacks	Funkwich	Dirt
Ap	tr			The House Jacks	Funkwich	Don't Turn Away
Ap	ts			The House Jacks	Funkwich	Express Yourself
Ap	tr			The House Jacks	Funkwich	Kashmir
Ap	ms			The House Jacks	Funkwich	Let's Get To It
Ap	ts			The House Jacks	Funkwich	Saturnalia Smile
Ap	ts			The House Jacks	Funkwich	Slide
Ap	ms	tr		The House Jacks	Funkwich	The Star-Spangled Banner
Ap	ts			The House Jacks	Funkwich	The Way It Makes Me Feel
Ap	ms			The House Jacks	Naked Noise	Another Chance
Ap	ms	tr		The House Jacks	Naked Noise	Attitude
Ap	ts			The House Jacks	Naked Noise	Erotica Bazaar
Ap	ts			The House Jacks	Naked Noise	Gone
Ap	tr			The House Jacks	Naked Noise	Jack It Up
Ap	ts	ts	ts	The House Jacks	Naked Noise	Palm Sunday
Ap	ms	ts	ts	The House Jacks	Naked Noise	Superhero
Ap	ms			The House Jacks	Naked Noise	Tear Down The Walls
Ap	ts			The House Jacks	Naked Noise	The Last To Know

ms≡model selection; tr≡training; ts≡testing

Ac≡College A Cappella; Ap≡Pro A Cappella; A≡A Cappella; E≡Electronica; P≡Pop; Ce≡Celtic; Cl≡Classical; J≡Jazz; L≡Latin

	Data Sets					
Class	2cl	3cl	7cl	Artist	Album	Song
Ap	ms			The House Jacks	Naked Noise	The Way It Makes Me Feel
Ap	tr	tr	tr	The Mint Julips	Spike & Co. Do It A Cappella	Don't Let Your Heart
Ap	tr			The Mint Julips	Spike & Co. Do It A Cappella	Higher And Higher
Ap	tr			The Persuasions	Spike & Co. Do It A Cappella	Looking For An Echo
Ap	tr			The Persuasions	Spike & Co. Do It A Cappella	Pass On The Love
Ap	ts	tr	tr	The Persuasions	Spike & Co. Do It A Cappella	Up On The Roof
Ap	ms			The Real Group	A Cappella All-Stars The 1997	Waltz For Debbie
Ap	ms			The Roches	Modern A Cappella	The Hallelujah Chorus
Ap	ms			The Trenchcoats	It Turns Me On	A Tribute to Vanilla Ice
Ap	ms			The Trenchcoats	It Turns Me On	Come Together
Ap	ts			The Trenchcoats	It Turns Me On	Elvira
Ap	tr			The Trenchcoats	It Turns Me On	Is That the Way You Look
Ap	ms			The Trenchcoats	It Turns Me On	It Turns Me on
Ap	tr			The Trenchcoats	It Turns Me On	Joy to the World
Ap	tr			The Trenchcoats	It Turns Me On	Mama Told Me (Not to Come)
Ap	tr			The Trenchcoats	It Turns Me On	Some Kind of Wonderful
Ap	tr			The Trenchcoats	It Turns Me On	The Lion Sleeps Tonight
Ap	ts			The Trenchcoats	It Turns Me On	Track13
Ap	ts			The Trenchcoats	It Turns Me On	We'll Make History
Ap	ts			The Trenchcoats	Your Joy	All You Can Eat Buffet
Ap	tr			The Trenchcoats	Your Joy	Crack That Whip - Working In A Coal Mine
Ap	ms			The Trenchcoats	Your Joy	Everyday People
Ap	ms			The Trenchcoats	Your Joy	I Can See Clearly Now
Ap	tr			The Trenchcoats	Your Joy	Jet Airliner
Ap	ms			The Trenchcoats	Your Joy	Route 66
Ap	tr			The Trenchcoats	Your Joy	Spinning Wheel
Ap	ms	ms	ms	The Trenchcoats	Your Joy	Stray Cat Strut
Ap	tr			The Trenchcoats	Your Joy	The A Cappello Blues
Ap	tr			The Trenchcoats	Your Joy	These Boots Were Made For Walking
Ap	tr			The Trenchcoats	Your Joy	Your Joy
Ap	ms			Throat Culture	Acappella Head	50 Ways to Leave Your Lover
Ap	ms			Throat Culture	Acappella Head	Also Too
Ap	tr			Throat Culture	Acappella Head	Crasstown Traffic
Ap	tr			Throat Culture	Acappella Head	Easter Island Head
Ap	ms			Throat Culture	Acappella Head	Fly Like an Eagle
Ap	tr			Throat Culture	Acappella Head	Fonemate
Ap	tr	ms	ms	Throat Culture	Acappella Head	Jack Bates (bail bonds)
Ap	ts			Throat Culture	Acappella Head	Life
Ap	ms			Throat Culture	Acappella Head	Mr. America
Ap	ms	tr	tr	Throat Culture	Acappella Head	Only the Lonely
Ap	ts			Throat Culture	Acappella Head	Sittin' On the Groom's Side
Ap	ms			Throat Culture	Acappella Head	St. James Infirmary
Ap	tr			Throat Culture	Acappella Head	The Israelites
Ap	tr	ms	ms	Toxic Audio	Hot Lips: Vocal Band Sampler	You Can't Win
Ap	ms			True Image	Spike & Co. Do It A Cappella	I Need You
Ap	ts	ts	ts	Vocal Sampling	Una Forma Mas	Canto al Beny More
Ap	ts			Vocal Sampling	Una Forma Mas	Canto al Chango
Ap	tr	tr	tr	Vocal Sampling	Una Forma Mas	Congo Yambumba
Ap	ms	ms	ms	Vocal Sampling	Una Forma Mas	Del Caribe Vengo
Ap	tr			Vocal Sampling	Una Forma Mas	Exclusiva
Ap	ts			Vocal Sampling	Una Forma Mas	La Negra Tomasa
Ap	ts			Vocal Sampling	Una Forma Mas	Montuno Sampling

ms≡model selection; tr≡training; ts≡testing

Ac≡College A Cappella; Ap≡Pro A Cappella; A≡A Cappella; E≡Electronica; P≡Pop; Ce≡Celtic; Cl≡Classical; J≡Jazz; L≡Latin

Class	Data Sets 2cl	3cl	7cl	Artist	Album	Song
Ap	tr	tr	tr	Vocal Sampling	Una Forma Mas	Ojos Malignos
Ap	tr			Vocal Sampling	Una Forma Mas	Que Bueno Baila Usted (Castellano)
Ap	tr			Vocal Sampling	Una Forma Mas	Radio Reloj
Ap	tr	tr		Vocal Sampling	Una Forma Mas	Soy Del Monte
Ap	tr			Vocal Sampling	Una Forma Mas	Una Forma Mas
Ap	tr	tr		Vox One	Out There	Gone By
Ap	ts	ms	ms	Vox One	Out There	Morning
Ap	tr			Vox One	Out There	Out There
Ap	tr			Vox One	Out There	Say You'll Always Be
Ap	ts	ts	ts	Vox One	Out There	Searching For You
Ap	tr	tr		Vox One	Out There	That Which You Love
Ap	ms			Vox One	Out There	The Eyes Of A Jungle
Ap	tr			Vox One	Out There	The Sky Is Crying
Ap	tr			Vox One	Out There	Whisper When I Speak
Ap	ts			spiralmouth	Hot Lips: Vocal Band Sampler	Live Alive
Ap	tr			spiralmouth	spiralmouth	Closer
Ap	tr	ms		spiralmouth	spiralmouth	Come Together
Ap	ts	tr		spiralmouth	spiralmouth	Flood
Ap	ts			spiralmouth	spiralmouth	Live Alive
Ap	ms			spiralmouth	spiralmouth	Love is a Good Thing
Ap	tr			spiralmouth	spiralmouth	Nothing is Written
Ap	ts			spiralmouth	spiralmouth	Sated
Ap	ms			spiralmouth	spiralmouth	Spend Another Minute
Ap	tr			spiralmouth	spiralmouth	Spoonman
Ap	ms			spiralmouth	spiralmouth	Wanna Be Startin' Somethin'
A		tr	tr	Ball in the House	Ball in the House	Try
A		ms	ms	Beelzebubs	Infinity	Loungin'
A		ms	ms	Bobby McFerrin	Simple Pleasures	Sunshine Of Your Love
A		tr		Brandeis Voicemale	Malestrom	Hooch
A		ts	ts	Brandeis Voicemale	Malestrom	I Walk With You
A		tr	tr	Brandeis Voicemale	Malestrom	Spine of a Dog
A		ms		Brandeis Voicemale	Malestrom	Superstition
A		tr		Everyday People	2648 West Grand Blvd.	Blues in the Night
A		tr	tr	Everyday People	2648 West Grand Blvd.	Fantasy
A		tr	tr	Everyday People	2648 West Grand Blvd.	Grandma's Hands
A		ms	ms	Everyday People	2648 West Grand Blvd.	Hopeless
A		ms	ms	Everyday People	2648 West Grand Blvd.	Thank You
A		tr	tr	Everyday People	EP Jones	Nobody's Supposed To Be Here
A		tr		Everyday People	EP Jones	Weak
A		ts	ts	Five Live	Quintessence	I'll Be There
A		tr		Five O'Clock Shadow	So There	What's It All About
A		ts	ts	Grafitti Tribe	Hot Lips: Vocal Band Sampler	Make Up Your Mind
A		ms		Ladysmith Black Mambazo	Spike & Co. Do It A Cappella	Phansi Em Godini Down In The Mines
A		tr	tr	Mary Schmary	Smarty Pants	Kicking Stones
A		ts	ts	Mosaic Whispers	Don't Tell My Parents	Goldeneye
A		tr	tr	Mosaic Whispers	Don't Tell My Parents	Not the Doctor
A		ms	ms	Mosaic Whispers	Don't Tell My Parents	Whistling in the Dark
A		ts	ts	Mosaic Whispers	Watercolors	December 63
A		tr		Mosaic Whispers	Watercolors	Hope of Deliverance
A		ms	ms	Mosaic Whispers	Watercolors	The Rose
A		ms		Off the Beat	Flail	No Rain
A		tr	tr	Off the Beat	Flail	Nothing Else Matters

ms≡model selection; tr≡training; ts≡testing

Ac≡College A Cappella; Ap≡Pro A Cappella; A≡A Cappella; E≡Electronica; P≡Pop; Ce≡Celtic; Cl≡Classical; J≡Jazz; L≡Latin

	Data Sets					
Class	2cl	3cl	7cl	Artist	Album	Song
A		tr	tr	Off the Beat	Flail	Soul To Squeeze
A		tr		Off the Beat	Patio	Surrounded
A		ts	ts	Off the Beat	Patio	The Impression That I Get
A		ms		Rochester Yellowjackets	Wilson Boulevard	Dust in the Wind
A		tr		Rockapella	Primer	Bed Of Nails
A		ms		SoVoSó	Truth & Other Stories	Life & Love
A		ms		SoVoSó	Truth & Other Stories	With You
A		ms	ms	Spur of the Moment	Two Flights Up	Criminal
A		ts	ts	Spur of the Moment	Two Flights Up	Ghost Train
A		tr		Spur of the Moment	Two Flights Up	Nynex Suite
A		ts	ts	Stanford Fleet Street Singers	What You Want	Baby Driver
A		tr	tr	Stanford Fleet Street Singers	What You Want	On the Street Where You Live
A		ts	ts	Stanford Fleet Street Singers	What You Want	What's Opera Doc?
A		ms		Stanford Harmonics	Insanity Laughs	32 Flavors
A		ms	ms	Stanford Harmonics	Insanity Laughs	Snow on the Sahara
A		ms	ms	Stanford Mendicants	Besides What You See	A Quiet Place
A		ts	ts	Stanford Mendicants	Besides What You See	Just a Gigolo-I Ain't Got Nobody
A		ts	ts	Straight No Chaser	Last Call	Moondance
A		ms		Street Sounds	Street Sounds	The Duke of Dubuque
A		tr		Street Sounds	Street Sounds	Tschot Sho Losa / Sada Go Demo
A		ms	ms	The Brown Derbies	Down Time	Rocket Man
A		tr	tr	The Brown Derbies	Hat Trick	Brown Eyed Girl
A		tr		The Brown Derbies	Hat Trick	Brown Sheep
A		ms	ms	The Brown Derbies	Hat Trick	Hungry Like The Wolf
A		tr	tr	The Brown Derbies	Hat Trick	Love Potion 9
A		tr		The Brown Derbies	Hat Trick	No Reply
A		ms		The Brown Derbies	Hat Trick	Wonderful Tonight
A		ms	ms	The Buffalo Chips	Remember The Songs	King Of Spain
A		ms		The Buffalo Chips	Remember The Songs	Love The One You're With
A		ms		The Buffalo Chips	Remember The Songs	Semi-Charmed Life
A		ts	ts	The Chattertocks	Aire	Mysterious Ways
A		ms	ms	The Jabberwocks	Liz's Slingback Boots	7
A		tr		The Jabberwocks	Liz's Slingback Boots	Why Should I Cry For You
A		ms	ms	The Jabberwocks	Sermons and Soda Water	Change the World
A		ts	ts	The Jabberwocks	Sermons and Soda Water	Ebony & Ivory
A		ms		The Jabberwocks	Sermons and Soda Water	Send Me On My Way
A		ms		The King's Singers	A Cappella All-Stars The 1997	Totus Tuus
A		ms		The Knudsen Bros.	Hot Lips: Vocal Band Sampler	Shower The People
A		ms		The Mint Julips	Spike & Co. Do It A Cappella	I Want To Live Easy
A		ms	ms	The Nylons	A Cappella All-Stars The 1997	Human Family
A		ms		The Trenchcoats	It Turns Me On	X-mas Rapping
A		tr		Tufts Beelzebubs	Beelzebubs Winter Invitational	Sympathy For The Devil
A		tr		Tufts Beelzebubs	Foster Street	And So It Goes
A		ms	ms	Tufts Beelzebubs	Foster Street	Rio
A		ms	ms	Tufts Beelzebubs	Foster Street	Rock This Town
A		tr	tr	Tufts Beelzebubs	Gilding	Windmills
A		tr		UPenn Counterparts	High Dive	Baby
A		ms		UPenn Counterparts	High Dive	Mysterious Ways
A		ms		UPenn Counterparts	Housekeeping	Shadowboxer
A		tr		Vassar Measure 4 Measure	Beelzebubs Winter Invitational	The Tide Is High
A		ms	ms	Vox One	Out There	Save Me
A		ts	ts	Washington University Pikers	4th and Ten	No One Is to Blame

ms≡model selection; tr≡training; ts≡testing

Ac≡College A Cappella; Ap≡Pro A Cappella; A≡A Cappella; E≡Electronica; P≡Pop; Ce≡Celtic; Cl≡Classical; J≡Jazz; L≡Latin

	Data Sets					
Class	2cl	3cl	7cl	Artist	Album	Song
A		tr	tr	Washington University Pikers	Feed Our Starving Egos	Why Don't We Do It In The Road
A		tr	tr	Washington University Pikers	On the Rocks	Momma, Look Sharp
A		tr	tr	Washington University Pikers	On the Rocks	Supermedley
A		ts	ts	Washington University Pikers	World Detour	Johnny's Room
A		ms	ms	Washington University Pikers	World Detour	That Lonesome Road
A		tr		Williams Ephlats	Live from the Spa City Diner	All Through the Night
A		tr		Williams Ephlats	Live from the Spa City Diner	Tupelo Honey
A		tr		Xtension Chords	Aftershock	Also Sprach Zarathustra
A		ms	ms	Xtension Chords	Aftershock	Pride (in the Name of Love)
A		ms		Xtension Chords	Shock Value	Critical Mass
E		tr		3 Phase feat. Dr. Motte	Reactivate Classics	Der Klang der Familie
E		tr	tr	403		Cruel
E		tr		403		Cruel (DJ Olis Remix)
E		ts	ts	403	Solstice	Come On
E		tr		403	Solstice	Dance To This Beat (DJ Spaz Mi
E		tr		403	Unreleased	Get Your Hands Up (On Stage Ra
E		ms	ms	403	Unreleased	The Official DJ Spaz Mastermix
E		tr		808 State	Ninety	808080808
E		ts	ts	808 State	Ninety	Ancodia
E		ms		808 State	Ninety	Cobra Bora
E		tr	tr	808 State	Ninety	Donkey Doctor
E		ms	ms	808 State	Ninety	Magical Dream
E		tr	tr	808 State	Ninety	Pacific 202
E		tr	tr	808 State	Ninety	Sunrise
E		ms		808 State	Ninety	The Fat Shadow (pointy head mix)
E		tr	tr	A Covenant Of Thorns		Purgatory
E		tr		A Kay & BJ	The Very Best of Steppin' Out	Sleeping in My Car
E		tr		Albion	GlobalUnderground - Departures	Air
E		ms		Alison Limerick	Mix Heaven 97	Put Your Faith in Me
E		ms		Allure	Mix Heaven 97	Head Over Heels (Main Clue Mix)
E		ms	ms	Anjo	GlobalUnderground - Departures	Sunrise
E		ts	ts	Apollo 440	Mix Heaven 97	Ain't Talkin' 'bout Dub
E		ts	ts	Atmosfear	Mix Heaven 97	Dancing in Outer Space
E		tr		B-Sides	Reactivate Classics	Magic Orchestra
E		ms		BT	Mix Heaven 97	Flaming June (BT and PVD Edit)
E		tr		Babyface	Mix Heaven 97	Rock Bottom (CJ Deep Club Mix)
E		tr	tr	Bandido	The Very Best of Steppin' Out	I Drove All Night
E		ts	ts	Bath	n-graver	Sentinel
E		tr	tr	Bath	n-graver	The Wading Pool
E		ts	ts	Bee Buzz	The Very Best of Steppin' Out	Ohh Ahh La La La
E		ts	ts	Bellini	Mix Heaven 97	Samba de Janeiro (Radio Edit)
E		tr	tr	Blueboy	Mix Heaven 97	Sandman (Phunk Phlava Radio Mix)
E		ms		Bobby D'Ambrosio	Mix Heaven 97	Moment of My Life (Classic Club Remix)
E		tr	tr	Bombers	The Very Best of Steppin' Out	Independent Love Song
E		ms		Bounce	The Very Best of Steppin' Out	Popcorn
E		tr	tr	Brenda	The Very Best of Steppin' Out	All the Things I Like
E		ms		Brownstone	Mix Heaven 97	5 Miles to Empty (R H Factor 215th Place Mix)
E		ts	ts	CJ Bolland	Reactivate Classics	Horsepower
E		tr	tr	CLS	Reactivate Classics	Can You Feel It?
E		tr	tr	Capella	Mix Heaven 97	Be My Baby (Bismark Mix)
E		ms	ms	Carl Cox	Psychotrance 2000	Phuture 2000 (Deepsky Remix)
E		ms		Celine Dion	Mix Heaven 97	It's All Coming Back to Me Now

ms≡model selection; tr≡training; ts≡testing

Ac≡College A Cappella; Ap≡Pro A Cappella; A≡A Cappella; E≡Electronica; P≡Pop; Ce≡Celtic; Cl≡Classical; J≡Jazz; L≡Latin

	Data Sets					
Class	2cl	3cl	7cl	Artist	Album	Song
E		ms		Chakra	Mix Heaven 97	Home (The Space Brothers Remix)
E		ts	ts	Chemical Brothers	Dig Your Own Hole	Block Rockin' Beats
E		ts	ts	Chemical Brothers	Dig Your Own Hole	Dig Your Own Hole
E		ms	ms	Chemical Brothers	Dig Your Own Hole	Don't Stop The Rock
E		ms		Chemical Brothers	Dig Your Own Hole	Elektro Bank
E		tr	tr	Chemical Brothers	Dig Your Own Hole	Get Up On It Like This
E		ts	ts	Chemical Brothers	Dig Your Own Hole	It Doesn't Matter
E		tr		Chemical Brothers	Dig Your Own Hole	Lost In The K Hole
E		ms	ms	Chemical Brothers	Dig Your Own Hole	Piku
E		tr	tr	Chemical Brothers	Dig Your Own Hole	Setting Sun
E		tr	tr	Chemical Brothers	Dig Your Own Hole	The Private Psychedelic Reel
E		tr		Chemical Brothers	Dig Your Own Hole	Where Do I Begin?
E		ms	ms	Chemical Brothers	Exit Planet Dust	Alive Alone
E		tr	tr	Chemical Brothers	Exit Planet Dust	Chemical Beats
E		ts	ts	Chemical Brothers	Exit Planet Dust	Chico's Groove
E		ms	ms	Chemical Brothers	Exit Planet Dust	Fuck Up Beats
E		ms		Chemical Brothers	Exit Planet Dust	In Dust We Trust
E		ms		Chemical Brothers	Exit Planet Dust	Leave Home
E		ms	ms	Chemical Brothers	Exit Planet Dust	Life Is Sweet
E		ms		Chemical Brothers	Exit Planet Dust	One Too Many Mornings
E		ms	ms	Chemical Brothers	Exit Planet Dust	Playground For A Wedgeless Firm
E		tr	tr	Chemical Brothers	Exit Planet Dust	Song To The Siren
E		ms	ms	Chemical Brothers	Exit Planet Dust	Three Little Birdies Down Beats
E		tr	tr	Chemical Brothers	Surrender	Asleep From Day
E		tr		Chemical Brothers	Surrender	Dream on
E		ts	ts	Chemical Brothers	Surrender	Got Glint
E		ms	ms	Chemical Brothers	Surrender	Hey Boy Hey Girl
E		ms		Chemical Brothers	Surrender	Let Forever Be
E		tr	tr	Chemical Brothers	Surrender	Music Response
E		ms	ms	Chemical Brothers	Surrender	Orange Wedge
E		ts	ts	Chemical Brothers	Surrender	Out Of Control
E		tr	tr	Chemical Brothers	Surrender	Racing the tide
E		ts	ts	Chemical Brothers	Surrender	The Sunshine Underground
E		tr		Chemical Brothers	Surrender	Under the Influence
E		tr		Chicane	Mix Heaven 97	Sunstroke (DJ Quicksilver Remix)
E		tr	tr	Chris Jackson	Subtle Frequencies	Check Our Beats
E		ts	ts	Chupito	The Very Best of Steppin' Out	Kick Your Leg in the Air
E		tr		Cupito	The Very Best of Steppin' Out	American Pie
E		tr		Cybersonik	Reactivate Classics	Technarchy
E		ts	ts	D-Note	Mix Heaven 97	Waiting Hopefully (Deep Dish Burning Cold Remix)
E		ms		D-Shake	Reactivate Classics	Techno Trance (Paradise Is Now)
E		ms	ms	DHS	Reactivate Classics	House of God
E		tr	tr	DJ Cartoons	The Very Best of Steppin' Out	Popeye
E		ms	ms	DJ Dado	The Very Best of Steppin' Out	Face It
E		ms	ms	DJ Dado	The Very Best of Steppin' Out	The Same
E		tr		DJ M.B.		Feeling free
E		ms	ms	DJ M.B.		Just because you make me happy
E		tr		DJ M.B.		Make the dancefloor burn!
E		ts	ts	DJ M.B.		Saturday Night
E		tr	tr	DJ M.B.		The feeling stays
E		ts	ts	DJ M.B.		The legend of techno (mp3.com
E		ms		DJ M.B.		There's no way out

ms≡model selection; tr≡training; ts≡testing
Ac≡College A Cappella; Ap≡Pro A Cappella; A≡A Cappella; E≡Electronica; P≡Pop; Ce≡Celtic; Cl≡Classical; J≡Jazz; L≡Latin

Class	Data Sets 2cl	3cl	7cl	Artist	Album	Song
E		ms	ms	DJ Scott	The Very Best of Steppin' Out	Do You Wanna Party
E		ms	ms	DJ Scott	The Very Best of Steppin' Out	Let's Make it Happen
E		ms		DJ Scott	The Very Best of Steppin' Out	Sweet Dreams
E		tr	tr	Datura	The Very Best of Steppin' Out	7th Hallucination
E		ts	ts	Datura	The Very Best of Steppin' Out	El Sueno
E		tr		Dave Randall	GlobalUnderground - Departures	Bombay
E		ms	ms	Deftones	The Matrix	My Own Summer (Shove It)
E		tr	tr	Delta Lady	Reactivate Classics	Anything You Want '93
E		ms	ms	Desert	GlobalUnderground - Departures	Lose It
E		tr	tr	EJ Doubell	GlobalUnderground - Departures	Axiatonal
E		tr	tr	ETA	Mix Heaven 97	Casual Sub (45 or 33 Mix)
E		tr		Echo Bass	The Very Best of Steppin' Out	Give It Up
E		ts	ts	Elevator	Reactivate Classics	Shinny
E		ms	ms	F8		Funk Your Bassbins
E		ms		F8		Jiggered
E		ts	ts	F8	To Be Announced	You Are My Fantasy - featuring
E		tr	tr	Fierce Ruling Diva	Reactivate Classics	Rubb It In
E		tr	tr	Forth	GlobalUnderground - Departures	Reality Detached
E		tr		Freak & Mac Zimms	GlobalUnderground - Departures	Submissions
E		tr		Full Intention	Mix Heaven 97	Shake Your Body (Down to the Ground)
E		tr		GTO	Reactivate Classics	Pure (Energy)
E		ts	ts	Ginuwine	Mix Heaven 97	Pony (Ride It Mix)
E		tr	tr	Gloria Estefan	Mix Heaven 97	You'll Be Mine (Party Time)
E		tr	tr	Grace	Mix Heaven 97	Down to Earth (Ascension Radio Edit)
E		ms	ms	Greece 2000	GlobalUnderground - Departures	3 Drives On Vinyl
E		ts	ts	Hardfloor	Reactivate Classics	Acperience
E		ms	ms	Hive	The Matrix	Ultrasonic Sound
E		ms		Hong Kong Trash	GlobalUnderground - Departures	Down The River
E		ms		Howie B	Mix Heaven 97	Angels Go Bald (Original Mix Edit)
E		ms		II Examples	The Very Best of Steppin' Out	Let it Come Into Your Heart
E		ms	ms	Isha D	Mix Heaven 97	Stay (Shiva Vocal Edit)
E		ms		Jam & Spoon	Mix Heaven 97	Right in the Night (Flamenc-O-Matic Radio Mix)
E		ms	ms	Jamiroquai	Mix Heaven 97	Cosmic Girl (Classic Mix)
E		ms	ms	Joe Paradiso	The Very Best of Steppin' Out	Tribal Lyrics
E		ts	ts	Liquid Language	GlobalUnderground - Departures	Blu Savannah
E		ts	ts	LoopSonic		Bubba Scratch
E		ms		LoopSonic		Non-Verbal
E		tr	tr	LoopSonic		Shadow Trax
E		tr		Lords of Acid	Lust	Hey Ho!
E		tr		Lords of Acid	Lust	I Must Increase My Bust
E		tr	tr	Lords of Acid	Lust	I Sit On Acid (Original)
E		ms	ms	Lords of Acid	Lust	I Sit On Acid (Remix)
E		tr	tr	Lords of Acid	Lust	Lessons In Love
E		tr		Lords of Acid	Lust	Let's Get High
E		tr		Lords of Acid	Lust	Mixed Emotions
E		ts	ts	Lords of Acid	Lust	Rough Sex
E		ms		Lords of Acid	Lust	Spacy Bitch
E		ms	ms	Lords of Acid	Lust	Take Control
E		tr	tr	Lords of Acid	Lust	The Most Wonderful Girl
E		ms		Lords of Acid	Our Little Secret	(Concerto For) Me And Myself
E		tr		Lords of Acid	Our Little Secret	Cybersex (Scherzo)
E		ts	ts	Lords of Acid	Our Little Secret	Deep Sexy Space (Chorale)

ms≡model selection; tr≡training; ts≡testing

Ac≡College A Cappella; Ap≡Pro A Cappella; A≡A Cappella; E≡Electronica; P≡Pop; Ce≡Celtic; Cl≡Classical; J≡Jazz; L≡Latin

Class	Data Sets 2cl	3cl	7cl	Artist	Album	Song
E		tr	tr	Lords of Acid	Our Little Secret	Doggie Tom (Overture)
E		ts	ts	Lords of Acid	Our Little Secret	Fingerlickin' Good
E		tr		Lords of Acid	Our Little Secret	LSD = Truth (Solo)
E		tr	tr	Lords of Acid	Our Little Secret	Lover (Cantata)
E		tr	tr	Lords of Acid	Our Little Secret	Man's Best Friend
E		ms	ms	Lords of Acid	Our Little Secret	Pussy (Round)
E		ms	ms	Lords of Acid	Our Little Secret	Rubber Doll (Opus)
E		ts	ts	Lords of Acid	Our Little Secret	Spank My Booty (Reprise)
E		ts	ts	Lords of Acid	Our Little Secret	The Power Is Mine (Coda)
E		ts	ts	Lords of Acid	Our Little Secret	You Belong To Me (Theme)
E		tr		Love4Sale	The Very Best of Steppin' Out	Do You Feel So Right
E		ms		Lunatic Calm	The Matrix	Leave You Far Behind
E		tr	tr	Luxor	The Very Best of Steppin' Out	The Big Bang
E		ts	ts	MK	Mix Heaven 97	Always (Visnadi's Pauls Cut)
E		ms		Marilyn Manson	The Matrix	Rock is Dead
E		tr	tr	Marmion	Reactivate Classics	Schoneberg
E		ts	ts	Meat Beat Manifesto	The Matrix	Prime Audio Soup
E		tr		Meng Syndicate	Reactivate Classics	Sonar System
E		ms	ms	Michael Jackson	Mix Heaven 97	Money (Rife Island Radio Edit)
E		tr		Millenium	The Very Best of Steppin' Out	Take Me Higher
E		ms	ms	Mind Reflection		Another Time
E		ts	ts	Mind Reflection	This World	In Search Of The Paradise
E		ts	ts	Mind Reflection	This World	Waiting For The Future
E		ts	ts	Ministry	The Matrix	Bad Blood
E		ts	ts	Moby	Everything is Wrong	All That I Need
E		ms		Moby	Everything is Wrong	Anthem
E		tr		Moby	Everything is Wrong	Bring back My Happiness
E		ms		Moby	Everything is Wrong	Everything Is Wrong
E		ms	ms	Moby	Everything is Wrong	Everytime You Touch Me
E		ms		Moby	Everything is Wrong	Feeling So Real
E		tr	tr	Moby	Everything is Wrong	First Cool Hive
E		ms		Moby	Everything is Wrong	God Moving Over The Face Of The Waters
E		tr		Moby	Everything is Wrong	Hymn
E		tr	tr	Moby	Everything is Wrong	Into The Blue
E		ts	ts	Moby	Everything is Wrong	What Love
E		ts	ts	Moby	Everything is Wrong	When It's Cold I'd Like To Die
E		tr	tr	Monster Magnet	The Matrix	Look to Your Orb for the Warning
E		ms		Ni-Do	The Very Best of Steppin' Out	A.S.I.L.O.
E		tr		Nuyorican Soul	Mix Heaven 97	It's alright, I Feel It! (MAW
E		ms	ms	Outer Rhythm	The Very Best of Steppin' Out	Energy
E		ts	ts	Outer Rhythm	The Very Best of Steppin' Out	Plano Madness
E		ms		PPK		21 Century (radio mix)
E		tr		PPK		21 century (extended club mix)
E		ms	ms	PPK		Dance With Me
E		ms		PPK		Feel! (dj zoomer mix)
E		ts	ts	PPK		Gold Sunrise
E		ms		PPK		Hey DJ!!!
E		ms	ms	PPK		Resurection
E		ms	ms	PPK		SUN (feat.Sveta)
E		ts	ts	PPK		We'll See (feat. SVETA)
E		tr	tr	Paradise Fall	The Very Best of Steppin' Out	7 Seconds
E		tr	tr	Pink Bomb	GlobalUnderground - Departures	Indica

ms≡model selection; tr≡training; ts≡testing

Ac≡College A Cappella; Ap≡Pro A Cappella; A≡A Cappella; E≡Electronica; P≡Pop; Ce≡Celtic; Cl≡Classical; J≡Jazz; L≡Latin

Class	Data Sets 2cl	3cl	7cl	Artist	Album	Song
E		tr	tr	Pizzaman	Mix Heaven 97	Gottaman (Pizzaman Remix)
E		tr		Prodigy	The Matrix	Mindfields
E		tr	tr	Propellerheads	The Matrix	Spybreak! (Short One)
E		ms	ms	Propellorheads	Decksandrumsandrockandroll	On Her Majesty's Secret Service
E		ms	ms	Quadrophonia	Reactivate Classics	Quadrophonia
E		ms		Rage Against the Machine	The Matrix	Wake Up
E		ts	ts	Ramirez	Reactivate Classics	La Musika Tremenda
E		ms		Rammstein	The Matrix	Du Hast
E		ms	ms	Reservoir Gods	The Very Best of Steppin' Out	Stuck in the Middle With You
E		tr		Rob D	The Matrix	Clubbed to Death (Kurayamino Mix)
E		ms		Rob Zombie	The Matrix	Dragula (Hot Rod Herman Remix)
E		tr		Robert Armani	Reactivate Classics	Circus Bells
E		ms		Rosie Gaines	Mix Heaven 97	Closer Than Close (Mentor Original Mix)
E		ts	ts	Rozalla	Mix Heaven 97	Coming Home (Casino Main Mix)
E		ms		Scanning		2002
E		tr		Scanning		Higher
E		ms	ms	Scanning		Movin
E		ts	ts	Scanning		Orange vocal mix
E		ts	ts	Second Phase	Reactivate Classics	Mentasm
E		tr	tr	Shena	Mix Heaven 97	Let the Beat Him 'Em (Original Mix)
E		ms		Slacker	Mix Heaven 97	Your Face
E		ms	ms	Sour Mash	Reactivate Classics	Pilgrimage To Paradise (Barrel Beat Mix)
E		ts	ts	Strike	Mix Heaven 97	I Have Peace (Uno Clio Mix)
E		ms	ms	Taste Experience	GlobalUnderground - Departures	Summersault
E		tr		Technocat	The Very Best of Steppin' Out	Technocat
E		tr		Tekara	GlobalUnderground - Departures	Breathe In Me
E		ms		The Age of Love	Reactivate Classics	The Age of Love
E		ts	ts	The Course	Mix Heaven 97	Ain't Nobody
E		tr		The Crystal Method	Vegas	Bad Stone
E		tr		The Crystal Method	Vegas	Busy Child
E		ms		The Crystal Method	Vegas	Cherry Twist
E		tr		The Crystal Method	Vegas	Comin' Back
E		ms		The Crystal Method	Vegas	High Roller
E		ms	ms	The Crystal Method	Vegas	Jaded
E		ms		The Crystal Method	Vegas	Keep Hope Alive
E		tr	tr	The Crystal Method	Vegas	She's My Pusher
E		tr		The Crystal Method	Vegas	Trip Like I Do
E		tr		The Crystal Method	Vegas	Vapor Trail
E		ms		The Priest	The Very Best of Steppin' Out	Gimme Your Love
E		tr		The RaVe MeThOd		Analog Beats
E		ms	ms	The RaVe MeThOd		Blizzard
E		ms		The RaVe MeThOd		Deep Space (Industrial Mix)
E		tr		The Source	Mix Heaven 97	Clouds (Now Voyager Radio Edit)
E		ms	ms	Toucher	GlobalUnderground - Departures	Waters
E		ms	ms	Trancenden	NicotineStains&AnalogueBeats	Scenes from New York
E		ms	ms	Ultra Nate	Mix Heaven 97	Free
E		ts	ts	United Colours	The Very Best of Steppin' Out	Missing You
E		ms		VFR	GlobalUnderground - Departures	Tranceilliusion
E		ms		Yo Yo Honey featuring Anita Ja	Mix Heaven 97	Groove On (M&S Epic Klub)
E		tr	tr	t r a n c e [] c o n t r o l	N/A	Atomic Dance Explosion [Radio
E		tr		t r a n c e [] c o n t r o l	b e y o n d . 2 0 0 0	Beyond 303 [TC Edit]
E		ms	ms	unknown	The Very Best of Steppin' Out	track 11

ms≡model selection; tr≡training; ts≡testing

Ac≡College A Cappella; Ap≡Pro A Cappella; A≡A Cappella; E≡Electronica; P≡Pop; Ce≡Celtic; Cl≡Classical; J≡Jazz; L≡Latin

Class	Data Sets 2cl	3cl	7cl	Artist	Album	Song
P		ms		Alanis Morissette	Jagged Little Pill	All I Really Want
P		ms	ms	Alanis Morissette	Jagged Little Pill	Head Over Feet
P		ms		Alanis Morissette	Jagged Little Pill	Perfect
P		ms	ms	Alanis Morissette	Jagged Little Pill	Wake Up
P		tr		Alanis Morissette	Jagged Little Pill	You Learn
P		ts	ts	Aretha Franklin	30 Greatest Hits	Baby I Love You
P		ms		Aretha Franklin	30 Greatest Hits	Don't Play That Song
P		ts	ts	Aretha Franklin	30 Greatest Hits	Eleanor Rigby
P		ms		Aretha Franklin	30 Greatest Hits	Oh Me Oh My (I'm a Fool For You Baby)
P		ts	ts	Aretha Franklin	30 Greatest Hits	Respect
P		ms		Aretha Franklin	30 Greatest Hits	See Saw
P		tr	tr	Aretha Franklin	30 Greatest Hits	The House That Jack Built
P		ms	ms	Aretha Franklin	30 Greatest Hits	Until You Come Back To Me
P		tr	tr	Aretha Franklin	30 Greatest Hits	You're All I Need To Get By
P		tr	tr	Barenakedladies	Stunt	In The Car
P		tr	tr	Barenakedladies	Stunt	Never is Enough
P		tr	tr	Barenakedladies	Stunt	Told You so
P		tr		Barenakedladies	Stunt	When You Dream
P		tr	tr	Billy Joel	Greatest Hits Volume I 1973-19	Just The Way You Are
P		ms	ms	Billy Joel	Greatest Hits Volume I 1973-19	New York State Of Mind
P		tr		Billy Joel	Greatest Hits Volume I 1973-19	Only The Good Die Young
P		ms	ms	Billy Joel	Greatest Hits Volume I 1973-19	Say Goodbye To Hollywood
P		ts	ts	Billy Joel	Greatest Hits Volume I 1973-19	Scenes From An Italian Restaurant
P		ms	ms	Billy Joel	Greatest Hits Volume II 1978-1	Don't Ask Me Why
P		tr	tr	Billy Joel	Greatest Hits Volume II 1978-1	Pressure
P		tr		Billy Joel	Greatest Hits Volume II 1978-1	She's Got A Way
P		ms		Billy Joel	Greatest Hits Volume II 1978-1	Tell Her About It
P		ms		Billy Joel	Greatest Hits Volume II 1978-1	You May Be Right
P		tr	tr	Blondie	The Best of Blondie	Dreaming
P		ms	ms	Christy Moore	Christy Moore	Biko Drum
P		tr	tr	Christy Moore	Christy Moore	Delirium Tremens
P		ms		Christy Moore	Christy Moore	Sweet Music Roll On
P		ms	ms	Dan Phillips	2.98	Cold in Chicago
P		tr		Dan Phillips	2.98	Fitting In
P		ts	ts	Dan Phillips	2.98	House of Rain
P		tr	tr	Dan Phillips	2.98	See You Here
P		tr		Devo	Hot Potatoes: The Best Of Devo	Beautiful World
P		tr	tr	Devo	Hot Potatoes: The Best Of Devo	Come Back Jonee
P		tr		Devo	Hot Potatoes: The Best Of Devo	Freedom Of Choice
P		tr	tr	Devo	Hot Potatoes: The Best Of Devo	Girl U Want
P		ms	ms	Devo	Hot Potatoes: The Best Of Devo	Mongoloid
P		ms		Devo	Hot Potatoes: The Best Of Devo	Satisfaction (I Can't Get Me No)
P		ms	ms	Devo	Hot Potatoes: The Best Of Devo	Through Being Cool
P		tr		Devo	Hot Potatoes: The Best Of Devo	Whip It
P		ms	ms	Duran Duran	Decade	A View to a Kill
P		ms		Duran Duran	Decade	All She Wants Is
P		tr	tr	Duran Duran	Decade	Hungry Like the Wolf
P		ms		Duran Duran	Decade	Notorious
P		tr		Duran Duran	Decade	Skin Trade
P		tr		Duran Duran	Decade	The Reflex
P		ts	ts	Duran Duran	Decade	Union of the Snake
P		ms	ms	Elvis Costello	Imperial Bedroom	Boy With A Problem

ms≡model selection; tr≡training; ts≡testing

Ac≡College A Cappella; Ap≡Pro A Cappella; A≡A Cappella; E≡Electronica; P≡Pop; Ce≡Celtic; Cl≡Classical; J≡Jazz; L≡Latin

Class	Data Sets 2cl	3cl	7cl	Artist	Album	Song
P		ts	ts	Elvis Costello	Imperial Bedroom	Little Savage
P		ts	ts	Elvis Costello	Imperial Bedroom	Shabby Doll
P		ms		Elvis Costello	Imperial Bedroom	The Long Honeymoon
P		tr		Elvis Costello	Imperial Bedroom	The Loved Ones
P		ms		Elvis Costello	Imperial Bedroom	The Stamping Ground
P		ts	ts	Elvis Costello	Imperial Bedroom	You Little Fool
P		tr		Elvis Costello	My Aim Is True	Blame It On Cain
P		ms	ms	Elvis Costello	My Aim Is True	No Dancing
P		ms	ms	Elvis Costello	My Aim Is True	Pay It Back
P		ms	ms	Elvis Costello	My Aim Is True	Waiting For The End Of The World
P		tr	tr	Elvis Costello	Spike	Chewing Gum
P		ms		Elvis Costello	Spike	Deep Dark Truthful Mirror
P		ms		Elvis Costello	Spike	Last Boat Leaving
P		ms		Elvis Costello	Spike	Let Him Dangle
P		tr		Elvis Costello	Spike	Pads, Paws and Claws
P		ms	ms	Elvis Costello	Spike	Stalin Malone
P		ms		Elvis Costello	Spike	Tramp The Dirt Down
P		ms	ms	Elvis Costello	This Year's Model	Hand In Hand
P		ms	ms	Elvis Costello	This Year's Model	Little Triggers
P		tr	tr	Elvis Costello	This Year's Model	Living In Paradise
P		ts	ts	Elvis Costello	This Year's Model	Pump It Up
P		ms		Elvis Costello	This Year's Model	The Beat
P		ts	ts	Elvis Costello	This Year's Model	This Year's Girl
P		tr	tr	Eurythmics	Greatest Hits	Here Comes The Rain Again
P		ms		Eurythmics	Greatest Hits	I Need A Man
P		ms		Eurythmics	Greatest Hits	Sweet Dreams (Are Made Of This)
P		tr		Eurythmics	Greatest Hits	The King & Queen Of America
P		tr	tr	Eurythmics	Greatest Hits	There Must Be An Angel (Playing With My Heart)
P		tr	tr	Eurythmics	Greatest Hits	When Tomorrow Comes
P		ts	ts	Eurythmics	Greatest Hits	Would I Lie To You?
P		ms		Everything But The Girl	Amplified Heart	I Don't Understand Anything
P		ts	ts	Everything But The Girl	Amplified Heart	RollerCoaster
P		ts	ts	Everything But The Girl	Amplified Heart	Troubled Mind
P		ms	ms	Everything But The Girl	Home Videos	Another Bridge
P		ts	ts	Everything But The Girl	Home Videos	Come On Home
P		ms	ms	Everything But The Girl	Home Videos	Driving
P		tr		Everything But The Girl	Home Videos	Fascination
P		ts	ts	Everything But The Girl	Home Videos	Imagining America
P		tr		Everything But The Girl	Home Videos	Love Is Strange
P		ts	ts	Everything But The Girl	Home Videos	Twin Cities
P		tr	tr	Fiona Apple	Tidal	Never Is a Promise
P		ms		Fiona Apple	Tidal	Sleep to Dream
P		tr	tr	Heart	Heart	If Looks Could Kill
P		ts	ts	Heart	Heart	What About Love
P		tr		Indigo Girls	Nomads - Indians - Saints	1 2 3
P		tr		Indigo Girls	Nomads - Indians - Saints	Keeper Of My Heart
P		tr	tr	Indigo Girls	Nomads - Indians - Saints	The Girl With The Weight Of The World. . .
P		ms		Indigo Girls	Nomads - Indians - Saints	World Falls
P		ms	ms	Indigo Girls	Rites of Passage	Airplane
P		ms		Indigo Girls	Rites of Passage	Cedar Tree
P		ms		Indigo Girls	Rites of Passage	Chickenman
P		ms	ms	Indigo Girls	Rites of Passage	Joking

ms≡model selection; tr≡training; ts≡testing

Ac≡College A Cappella; Ap≡Pro A Cappella; A≡A Cappella; E≡Electronica; P≡Pop; Ce≡Celtic; Cl≡Classical; J≡Jazz; L≡Latin

Class	Data Sets 2cl	3cl	7cl	Artist	Album	Song
P		ms	ms	Indigo Girls	Rites of Passage	Love Will Come to Me
P		ms	ms	Indigo Girls	Rites of Passage	Nashville
P		tr		Indigo Girls	Rites of Passage	Three Hits
P		tr		Indigo Girls	Rites of Passage	Virginia Wolf
P		ms	ms	Jethro Tull	Aqualung	Aqualung
P		ms		Jethro Tull	Aqualung	Cross-Eyed Mary
P		tr		Jethro Tull	Aqualung	Hymn 43
P		tr	tr	Jethro Tull	Aqualung	Wind-Up
P		ms		Jethro Tull	Aqualung	Wond'ring Aloud
P		tr		Joe Jackson	Big World	(It's A) Big World
P		tr	tr	Joe Jackson	Big World	Man In The Street
P		tr	tr	Joe Jackson	Big World	Precious Time
P		ts	ts	Joe Jackson	Big World	Right And Wrong
P		ts	ts	Joe Jackson	Big World	Tango Atlantico
P		ts	ts	Joe Jackson	Big World	Tonight And Forever
P		tr		Joe Jackson	Big World	We Can't Live Together
P		ms		Joe Jackson	Look Sharp!	Happy Loving Couples
P		ms	ms	Joe Jackson	Look Sharp!	Pretty Girls
P		tr		Joe Jackson	Look Sharp!	Sunday Papers
P		tr	tr	Madonna	The Immaculate Collection	Crazy For You
P		ts	ts	Madonna	The Immaculate Collection	Express Yourself
P		ts	ts	Madonna	The Immaculate Collection	Into the Groove
P		tr	tr	Madonna	The Immaculate Collection	Papa Don't Preach
P		tr		Marc Cohn	The Rainy Season	Medicine Man
P		tr		Marc Cohn	The Rainy Season	She's Becoming Gold
P		tr		Marc Cohn	The Rainy Season	The Rainy Season
P		ms		Marc Cohn	The Rainy Season	The Things We've Handed Down
P		tr		Moxy Früvous	Bargainville	Drinking Song
P		ms		Moxy Früvous	Bargainville	Fell in Love
P		tr	tr	Moxy Früvous	Bargainville	Laika
P		tr	tr	Moxy Früvous	Bargainville	My Baby Loves A Bunch of Authors
P		ts	ts	Moxy Früvous	Bargainville	The Lazy Boy
P		tr	tr	Moxy Früvous	Wood	Down From Above
P		tr		Moxy Früvous	Wood	Misplaced
P		tr		Moxy Früvous	Wood	Poor Mary Lane
P		tr	tr	Moxy Früvous	Wood	The Present Tense Tureen
P		ms		Moxy Früvous	You Will Go To The Moon	I've Gotta Get A Message To You
P		ms		Moxy Früvous	You Will Go To The Moon	Kick In The Ass
P		ms		Moxy Früvous	You Will Go To The Moon	Lazlo's Career
P		tr		Moxy Früvous	You Will Go To The Moon	Love Set Fire
P		ms	ms	Moxy Früvous	You Will Go To The Moon	No No Raja
P		ts	ts	Moxy Früvous	You Will Go To The Moon	Sahara
P		ts	ts	Moxy Früvous	You Will Go To The Moon	The Incredible Medicine Show
P		ts	ts	Pat Benatar	Best Shots	All Fired Up
P		ms	ms	Pat Benatar	Best Shots	Fire And Ice
P		ms		Pat Benatar	Best Shots	Heartbreaker
P		ms	ms	Pat Benatar	Best Shots	One Love
P		ms	ms	Pat Benatar	Best Shots	Suffer The Little Children-Hell Is For Children
P		tr		Pat Benatar	Best Shots	We Belong
P		tr	tr	Paul Simon	Graceland	Crazy Love, Vol. II
P		tr	tr	Paul Simon	Graceland	The Boy in the Bubble
P		tr		Paul Simon	Graceland	You Can Call Me Al

ms≡model selection; tr≡training; ts≡testing

Ac≡College A Cappella; Ap≡Pro A Cappella; A≡A Cappella; E≡Electronica; P≡Pop; Ce≡Celtic; Cl≡Classical; J≡Jazz; L≡Latin

Class	Data Sets 2cl	3cl	7cl	Artist	Album	Song
P		tr	tr	Queen	Greatest Hits I	Another One Bites The Dust
P		tr		Queen	Greatest Hits I	Crazy Little Thing Called Love
P		tr		Queen	Greatest Hits I	Don't Stop Me Now
P		tr		Queen	Greatest Hits I	Flash
P		ms	ms	Queen	Greatest Hits I	Good Old-fashioned Lover Boy
P		tr	tr	Queen	Greatest Hits I	Play The Game
P		tr	tr	Queen	Greatest Hits I	Seven Seas Of Rhye
P		ms		Queen	Greatest Hits I	We Are The Champions
P		tr	tr	R.E.M.	Document	Disturbance At The Heron House
P		ms	ms	R.E.M.	Document	King Of Birds
P		tr	tr	R.E.M.	Document	Lightnin' Hopkins
P		ts	ts	R.E.M.	Document	The One I Love
P		ms		R.E.M.	Fables Of The Reconstruction	Auctioneer (Another Engine)
P		tr		R.E.M.	Fables Of The Reconstruction	Can't Get There From Here
P		ms		R.E.M.	Fables Of The Reconstruction	Driver 8
P		tr	tr	R.E.M.	Fables Of The Reconstruction	Feeling Gravity's Pull
P		ms	ms	R.E.M.	Green	I Remember California
P		ts	ts	R.E.M.	Green	Orange Crush
P		ms	ms	R.E.M.	Green	Turn You Inside-out
P		ms	ms	R.E.M.	Green	World Leader Pretend
P		tr	tr	R.E.M.	Murmur	Moral Kiosk
P		ms		R.E.M.	Murmur	Radio Free Europe
P		ts	ts	R.E.M.	Murmur	Talk About The Passion
P		ts	ts	R.E.M.	Murmur	We Walk
P		tr		R.E.M.	Out Of Time	Half A World Away
P		ts	ts	R.E.M.	Out Of Time	Losing My Religion
P		ms	ms	R.E.M.	Out Of Time	Shiny Happy People
P		ms	ms	R.E.M.	Out Of Time	Texarkana
P		tr		R.E.M.	reckoning	(don't Go back To) ROCKVILLE
P		ts	ts	R.E.M.	reckoning	HarborcOat
P		tr		R.E.M.	reckoning	letter Never seNt
P		ms		R.E.M.	reckoning	so. Central Rain
P		tr	tr	Sarah McLachlan	Fumbling Towards Ecstasy	Circle
P		tr	tr	Sarah McLachlan	Fumbling Towards Ecstasy	Mary
P		tr		Squeeze	Singles 45 and Under	Cool for Cats
P		tr	tr	Squeeze	Singles 45 and Under	If I Didn't Love You
P		ms	ms	Squeeze	Singles 45 and Under	Pulling Mussels (From the Shell)
P		ms		Squeeze	Singles 45 and Under	Up the Junction
P		ts	ts	Sting	Bring On The Night	We Work The Black Seam
P		ts	ts	Sting	Bring on the Night	Another Day
P		tr		Sting	The Dream Of The Blue Turtles	If You Love Somebody Set Them
P		ms		Sting	The Dream Of The Blue Turtles	Shadows In The Rain
P		ts	ts	Sting	The Soul Cages	The Soul Cages
P		ts	ts	Sting	The Soul Cages	When the Angels Fall
P		tr		Styx	Crystal Ball	This Old Man
P		ms		Styx	Paradise Theatre	A.D. 1958
P		ts	ts	Tears For Fears	Elemental	Brian Wilson Said
P		ms		Tears For Fears	Elemental	Mr. Pessimist
P		ms	ms	The Blues Brothers	Soundtrack	Gimme Some Lovin'
P		ms	ms	The Blues Brothers	Soundtrack	Jailhouse Rock
P		ts	ts	The Blues Brothers	Soundtrack	The Old Landmark
P		ms	ms	The Commitments	The Commitments	Bye Bye Baby

ms≡model selection; tr≡training; ts≡testing

Ac≡College A Cappella; Ap≡Pro A Cappella; A≡A Cappella; E≡Electronica; P≡Pop; Ce≡Celtic; Cl≡Classical; J≡Jazz; L≡Latin

Class	Data Sets 2cl	3cl	7cl	Artist	Album	Song
P		tr	tr	The Commitments	The Commitments	Do Right Woman Do Right Man
P		ms		The Commitments	The Commitments	Mr. Pitiful
P		ms	ms	The Commitments	The Commitments	Mustang Sally
P		tr		The Commitments	The Commitments	Slip Away
P		ts	ts	The Commitments	The Commitments	Treat Her Right
P		ms	ms	The Commitments	The Commitments	Try a Little Tenderness
P		ts	ts	The Other Side	The Other Side	Falling
P		ms	ms	The Other Side	The Other Side	Got to get out
P		tr		The Other Side	The Other Side	I can't seem to find me
P		ts	ts	The Other Side	The Other Side	Pursue the darkness
P		tr	tr	The Other Side	The Other Side	Sister
P		ms		They Might Be Giants	John Henry	A Self Called Nowhere
P		ts	ts	They Might Be Giants	John Henry	Extra Savoir-Faire
P		ms		They Might Be Giants	John Henry	Snail Shell
P		tr	tr	They Might Be Giants	John Henry	Stomp Box
P		ms		They Might Be Giants	John Henry	Thermostat
P		tr	tr	They Might Be Giants	Lincoln	Ana Ng
P		ms	ms	They Might Be Giants	Lincoln	Cowtown
P		tr	tr	They Might Be Giants	Lincoln	I've Got a Match
P		ms	ms	They Might Be Giants	Lincoln	Pencil Rain
P		tr	tr	They Might Be Giants	Lincoln	Shoehorn with Teeth
P		ms		They Might Be Giants	Lincoln	The World's Address
P		tr		They Might Be Giants	Lincoln	Where Your Eyes Don't Go
P		ms		Toad The Wet Sprocket	Dulcinea	Nanci
P		ms	ms	Toad The Wet Sprocket	Dulcinea	Something's Always Wrong
P		tr		Toad The Wet Sprocket	Dulcinea	Windmills
P		tr		Toad The Wet Sprocket	Fear	Before You Were Born
P		ts	ts	Toad The Wet Sprocket	Fear	Stories I Tell
P		tr	tr	Toad The Wet Sprocket	Fear	Walk On The Ocean
P		ms	ms	Tori Amos	Boys for Pele	Blood Roses
P		ts	ts	Tori Amos	Boys for Pele	Doughnut Song
P		ts	ts	Tori Amos	Boys for Pele	Father Lucifer
P		ms	ms	Tori Amos	Boys for Pele	Hey Jupiter
P		tr		Tori Amos	Boys for Pele	Horses
P		ts	ts	Tori Amos	Boys for Pele	Muhammad My Friend
P		ts	ts	Tori Amos	Boys for Pele	Putting the Damage On
P		ms	ms	Tori Amos	Boys for Pele	Talula
P		ts	ts	Tori Amos	Little Earthquakes	Crucify
P		tr	tr	Tori Amos	Little Earthquakes	Silent All These Years
P		ts	ts	Tori Amos	Little Earthquakes	Tear In Your Hand
P		ms		Traffic	John Barleycorn Must Die	Freedom Rider
P		tr		Traffic	John Barleycorn Must Die	John Barleycorn
Ce			ts	Alasdair Fraser	The Rough Guide To The Music O	Wooden Whale/Leaps & Bounds
Ce			ms	Alasdair MacCuish and The Blac	Alasdair MacCuish and The Blac	Canadian Barn Dance
Ce			ts	Alasdair MacCuish and The Blac	Alasdair MacCuish and The Blac	Continental Waltz
Ce			ts	Alasdair MacCuish and The Blac	Alasdair MacCuish and The Blac	Medley
Ce			tr	Alasdair MacCuish and The Blac	Alasdair MacCuish and The Blac	Waltz
Ce			ms	Alison Kinnaird	The Rough Guide To The Music O	The Crags Of Ailsa/Staffa's Sh
Ce			ms	Anam	Anam	Cën Treo Anois-
Ce			tr	Anam	Anam	Down the Hill
Ce			tr	Anam	Anam	Hó Ró m'Inion Donn Bhóidheach
Ce			ts	Anam	Anam	Mickey Dan's Jig

ms≡model selection; tr≡training; ts≡testing

Ac≡College A Cappella; Ap≡Pro A Cappella; A≡A Cappella; E≡Electronica; P≡Pop; Ce≡Celtic; Cl≡Classical; J≡Jazz; L≡Latin

	Data Sets					
Class	2cl	3cl	7cl	Artist	Album	Song
Ce			tr	Battlefield Band	At The Front	Ge Do Theid Mi Do M'Leabiadh
Ce			ms	Battlefield Band	At The Front	Lady Carmichael/South of the G
Ce			ms	Battlefield Band	At The Front	Lang Jonnie Moir
Ce			ts	Battlefield Band	At The Front	Tae the Beggin'
Ce			ts	Battlefield Band	At The Front	The Blackbird and the Thrush/T
Ce			tr	Battlefield Band	At The Front	The Tamosher
Ce			ms	Battlefield Band	Opening Moves	Jenny Nettles/The Grays of Ton
Ce			tr	Battlefield Band	Opening Moves	Miss Drummond of Perth/Fiddler
Ce			ts	Battlefield Band	Opening Moves	Silver Spear/Humours of Tulla
Ce			ms	Battlefield Band	Opening Moves	The Battle of Falkirk Muir
Ce			ts	Battlefield Band	Opening Moves	The Blackbird and the Thrush/T
Ce			ts	Battlefield Band	Opening Moves	The Lady Leroy
Ce			ms	Battlefield Band	The Rough Guide To The Music O	Clan Coco/The Road To Benderlo
Ce			tr	Boys of the Lough	The West Of Ireland	Dark is the Colour
Ce			ms	Boys of the Lough	The West Of Ireland	Glin Cottage Polka No1, No2, Julias Polka
Ce			ts	Boys of the Lough	The West Of Ireland	Sharon Eubank's Waltz
Ce			tr	Boys of the Lough	The West Of Ireland	Small Coals and Little Money
Ce			ms	Boys of the Lough	The West Of Ireland	Stella's Trip to Kamloops Farw
Ce			ts	Boys of the Lough	The West Of Ireland	The Steamboat
Ce			ms	Capercaillie	Root, Reels, & Rhythms: A Scot	Inexile
Ce			tr	Charlie McKerron	The White Heather Show	Jigs
Ce			tr	Charlie McKerron	The White Heather Show	Reels
Ce			ms	Christine Primrose	The Rough Guide To The Music O	Tha M'eudail Is M'aighear
Ce			ms	Clannad	2	By Chance It Was
Ce			ts	Clannad	2	Fairly Shot of Her
Ce			tr	Clannad	2	Rince Briotãnach
Ce			ts	Clannad	2	Rince Philib a'Cheoil
Ce			ms	Clannad	Dulaman	Mo Mhaire
Ce			ms	Clannad	Dulaman	dTigeas A Damhsa
Ce			ts	Deaf Shepherd	Synergy	Jean Carignan
Ce			ts	Deaf Shepherd	Synergy	Keys, Money, Fags
Ce			ts	Deaf Shepherd	Synergy	Pawkie Paiterson
Ce			tr	Deaf Shepherd	Synergy	Strathspeys
Ce			ms	Deaf Shepherd	Synergy	The Coarncraik
Ce			tr	Deaf Shepherd	Synergy	Weepers I Shall Wear
Ce			tr	Deaf Shepherd	Synergy	Winter O Life
Ce			ms	Dean Park	The White Heather Show	Uist Tramping Song
Ce			tr	Dordan	Jigs to the Moon	Gottlieb Muffat
Ce			ts	Dordan	Jigs to the Moon	Lady Dillon (air and jig)
Ce			ts	Dordan	Jigs to the Moon	Mr O' Connor (air and jig)
Ce			ms	Dordan	Jigs to the Moon	Sonatina (Beethoven), The Lass O'Corrie Mil, ...
Ce			ms	Dordan	Jigs to the Moon	Sonitina
Ce			ts	Dordan	Jigs to the Moon	The Green Fields of Rossbeigh, ... (reels)
Ce			tr	Dordan	Jigs to the Moon	The Newcastle, ... (polkas)
Ce			tr	Dysart & Dundonald	The Pipes and Drums	Burns Medley
Ce			ts	Eilidh Shaw, Kathryn Nicoll, R	Ceilidh House Sessions from Th	The Full Rigged Ship, ...
Ce			ms	Four Men and a Dog	Shifting Gravel	Another Irish Rover
Ce			ts	Four Men and a Dog	Shifting Gravel	Bertha's Goat
Ce			ts	Four Men and a Dog	Shifting Gravel	I'm Walkin'
Ce			tr	Four Men and a Dog	Shifting Gravel	Joh
Ce			ts	Four Men and a Dog	Shifting Gravel	Newmarket Polkas
Ce			tr	Four Men and a Dog	Shifting Gravel	Struggle On

ms≡model selection; tr≡training; ts≡testing

Ac≡College A Cappella; Ap≡Pro A Cappella; A≡A Cappella; E≡Electronica; P≡Pop; Ce≡Celtic; Cl≡Classical; J≡Jazz; L≡Latin

Class	Data Sets 2cl	3cl	7cl	Artist	Album	Song
Ce			ts	George Duff & Adam Jack	Ceilidh House Sessions from Th	Maggie Lauder
Ce			tr	George Duff, Adam Jack	Ceilidh House Sessions from Th	Mountains of Mourne
Ce			ts	Graham Macleod, Sharon Colvn	The White Heather Show	Leezie Lindsay
Ce			ms	Graham Macleod	The White Heather Show	Glencoe
Ce			ts	Graham Macleod	The White Heather Show	Maggie
Ce			tr	Hamish Moore	Stepping on the Bridge	Blue Bonnets / Larach Alasdair
Ce			ts	Hamish Moore	Stepping on the Bridge	Cameron's Strathspey; The Crippled Boy, ...
Ce			tr	Hamish Moore	Stepping on the Bridge	Father John MacMillan of Barra, ...
Ce			tr	Hamish Moore	Stepping on the Bridge	Helen Black of Inveran,*ldots*
Ce			ts	Hamish Moore	Stepping on the Bridge	King Georve IV Strathspey / Th
Ce			tr	Hamish Moore	Stepping on the Bridge	Molly Rankin's, ...
Ce			tr	Hamish Moore	Stepping on the Bridge	O' A' the Airts the Wind Can Blaw
Ce			ts	Ian Carmichael & Michael Gill	Ceilidh House Sessions from Th	Silent Running
Ce			tr	Ian Carmichael	Ceilidh House Sessions from Th	Shady Grove
Ce			ms	Jennifer Forrest and her Scott	The Skye Connection	6/8 Marches led by David Hume
Ce			ts	Jennifer Forrest and her Scott	The Skye Connection	A Tribute to Alex McArthur - 24 Pipe March
Ce			ms	Jennifer Forrest and her Scott	The Skye Connection	Continental Waltz
Ce			tr	Jennifer Forrest and her Scott	The Skye Connection	Highland Scottishe - Scottishes
Ce			ts	Jennifer Forrest and her Scott	The Skye Connection	Selection of Reels - 5/32 Reel
Ce			ts	Jennifer Forrest and her Scott	The Skye Connection	Strip the Willow - Pipe Jigs
Ce			ms	Jennifer Forrest and her Scott	The Skye Connection	The Gay Gordons - 4/4 Marches
Ce			tr	Jennifer Forrest and her Scott	The Skye Connection	The Isle of Skye - Reels
Ce			ts	Jennifer Forrest and her Scott	The Skye Connection	The Linton Ploughman - Jigs 4x32
Ce			ts	Jennifer & Hazel Wrigley	The Watch Stone	Jim & Sylvia Barnes / The Gree
Ce			ms	Jennifer & Hazel Wrigley	The Watch Stone	Skeldaquoy Point / Birsay Beac
Ce			ts	Jennifer & Hazel Wrigley	The Watch Stone	The Corn Holm / Harris Stevens
Ce			ts	Jennifer & Hazel Wrigley	The Watch Stone	The Heroes of Longhope
Ce			ms	Jennifer & Hazel Wrigley	The Watch Stone	Wild Fiddler's Rag
Ce			ms	John Renbourn	The Lady And The Unicorn	Bransle Gay/Bransle de Bourgog
Ce			ms	John Renbourn	The Lady And The Unicorn	Trotto/Saltarello
Ce			tr	John Renbourn	The Lady And The Unicorn	Veri Floris/Triple Ballade
Ce			ts	Joseph Cormier	Old Time Wedding Reels And Oth	Annie is My Darling Medley
Ce			ts	Joseph Cormier	Old Time Wedding Reels And Oth	Ashokan Farewell
Ce			ts	Joseph Cormier	Old Time Wedding Reels And Oth	Culloden House
Ce			tr	Joseph Cormier	Old Time Wedding Reels And Oth	Flee as a Bird Clog
Ce			ms	Joseph Cormier	Old Time Wedding Reels And Oth	Forth Bridge
Ce			tr	Joseph Cormier	Old Time Wedding Reels And Oth	Miss Hutton
Ce			tr	Joseph Cormier	Old Time Wedding Reels And Oth	Niel Gow's Lament ...
Ce			ts	Joseph Cormier	Old Time Wedding Reels And Oth	Old Time Wedding Reels
Ce			tr	Karen Tweed	The Silver Spire	Ailbe Grace's / Art O'Keefe's
Ce			ms	Karen Tweed	The Silver Spire	Brïd Harper's / Dennis Langtou
Ce			ts	Karen Tweed	The Silver Spire	Connie O'Connell's / The flowe
Ce			ms	Karen Tweed	The Silver Spire	Merrily kiss the Quaker's wife, ... (slides)
Ce			tr	Karen Tweed	The Silver Spire	Seämus Meehan's / Return to Mi
Ce			tr	Karen Tweed	The Silver Spire	Spellan the fiddler / Smith's
Ce			ts	Karen Tweed	The Silver Spire	The broken pledge / Paddy Lynn
Ce			ms	Karen Tweed	The Silver Spire	The bush on the hill / Conway'
Ce			ts	Karen Tweed	The Silver Spire	The watchmaker / The milliner'
Ce			tr	Liz Doherty	Last Orders	Feed the Ducks (jigs)
Ce			ms	Liz Doherty	Last Orders	Jimmy's (highlands-reel)
Ce			ts	Liz Doherty	Last Orders	Last Orders (reels)
Ce			ms	Liz Doherty	Last Orders	Maid in Taiwan (reels)

ms≡model selection; tr≡training; ts≡testing

Ac≡College A Cappella; Ap≡Pro A Cappella; A≡A Cappella; E≡Electronica; P≡Pop; Ce≡Celtic; Cl≡Classical; J≡Jazz; L≡Latin

Class	Data Sets 2cl	3cl	7cl	Artist	Album	Song
Ce			ts	Liz Doherty	Last Orders	Mutt's Favourite (strathspey-reels)
Ce			ms	Liz Doherty	Last Orders	New Hands (jigs)
Ce			tr	Liz Doherty	Last Orders	The Swan (hornpipes)
Ce			tr	Mac Talla	The Rough Guide To The Music O	Griogal Cridhe
Ce			ms	Ossian	The Rough Guide To The Music O	S Gann Gunn Dirich Mi Chaoidh
Ce			tr	Palaver	Ceilidh House Sessions from Th	Laddie Lie Near Me
Ce			ms	Peatbog Faeries	Root, Reels, & Rhythms: A Scot	Macedonian Woman's Rant
Ce			tr	Seannachie	Ceilidh House Sessions from Th	Trowie Burn, . . .
Ce			ms	Sharon Colvin, Graham Macleod	The White Heather Show	Crookit Bawbee
Ce			ms	Sharon Colvin	The White Heather Show	Come In Come In
Ce			tr	Sharon Colvin	The White Heather Show	Dancing in Kyle
Ce			ms	Sharon Colvin	The White Heather Show	How Are Things in Glocca Morra?
Ce			ts	Shooglenifty	Root, Reels, & Rhythms: A Scot	Venus in Tweeds
Ce			ts	Shotts & Dykehead Caledonia	The Pipes and Drums	Medley
Ce			ts	Skyedance	Way Out To Hope Street	Bannockburn
Ce			ms	Skyedance	Way Out To Hope Street	Dark Jewel
Ce			ms	Skyedance	Way Out To Hope Street	Dizzy
Ce			tr	Skyedance	Way Out To Hope Street	Midnight on Raasay, The Braemar Cappuccino
Ce			ms	Skyedance	Way Out To Hope Street	Reel De Flores
Ce			tr	Skyedance	Way Out To Hope Street	Skerray
Ce			ms	Skyedance	Way Out To Hope Street	Stoney Run
Ce			ms	Skyedance	Way Out To Hope Street	The Lupine
Ce			tr	Skyedance	Way Out To Hope Street	Walking The Plank
Ce			ms	Talitha MacKenzie	Root, Reels, & Rhythms: A Scot	Funky Bird Medley
Ce			ms	Tannahill Weavers, The	The Rough Guide To The Music O	Good Drying Set
Ce			tr	The Royal Scots Dragoon Guards	The Pipes and Drums	Medley
Ce			tr	The Royal Scots Dragoon Guards	The Pipes and Drums	Medley (2)
Ce			tr	The Royal Ulster Constabulary	The Pipes and Drums	34 Marches
Ce			ms	The Tron Session Band	Ceilidh House Sessions from Th	John Steven of Chance Inn, . . .
Ce			ts	Tom Anderson & Aly Bain	The Rough Guide To The Music O	Jack Broke Da Prison Door/Dona
Ce			tr	William Haines & Martainn Beag	Ceilidh House Sessions from Th	Christmas Evening in the Morning, . . .
Ce			tr	Wolfstone	The Rough Guide To The Music O	Heart And Soul
Ce			ts	various artists	The Dance Music of Ireland	Johnny Doherty's, . . . - reels
Ce			ms	various artists	The Dance Music of Ireland	The Congress Reel, . . . (reels)
Ce			ms	various artists	The Dance Music of Ireland	The Green Fields of Woodford, . . . (jigs)
Ce			tr	various artists	The Dance Music of Ireland	The Stone in the Field, . . .
Cl			tr	Aaron Copland	Appalachian Spring	Allegro
Cl			tr	Aaron Copland	Appalachian Spring	Allegro - Solo Dance of the Bride
Cl			tr	Aaron Copland	Appalachian Spring	Doppio Movimento - Variations
Cl			ts	Aaron Copland	Appalachian Spring	Meno Mosso
Cl			ts	Aaron Copland	Appalachian Spring	Moderato - Coda
Cl			ts	Aaron Copland	Appalachian Spring	Moderato - The Bride and Her Intended
Cl			ms	Aaron Copland	Appalachian Spring	Very Slowly
Cl			ts	Aaron Copland	Billy the Kid	Billy's Death
Cl			ms	Aaron Copland	Billy the Kid	Celebration
Cl			tr	Aaron Copland	Billy the Kid	Introduction
Cl			ts	Aaron Copland	Billy the Kid	Prairie Night
Cl			ts	Aaron Copland	Billy the Kid	The Open Prairie Again
Cl			ts	Aaron Copland	Billy the Kid	Waltz
Cl			ms	Aaron Copland	Misc	El Salon Mexico
Cl			tr	Carl Orff	Carmina Burana	Ave formosissima
Cl			tr	Carl Orff	Carmina Burana	Chramer, gip die varwe mit

ms≡model selection; tr≡training; ts≡testing

Ac≡College A Cappella; Ap≡Pro A Cappella; A≡A Cappella; E≡Electronica; P≡Pop; Ce≡Celtic; Cl≡Classical; J≡Jazz; L≡Latin

Class	Data Sets 2cl	3cl	7cl	Artist	Album	Song
Cl			ms	Carl Orff	Carmina Burana	Dies, nox et omnia
Cl			ms	Carl Orff	Carmina Burana	Dulcissime
Cl			ms	Carl Orff	Carmina Burana	Ecce gratum
Cl			ts	Carl Orff	Carmina Burana	Ego sum abbas
Cl			ms	Carl Orff	Carmina Burana	Floret silva
Cl			ts	Carl Orff	Carmina Burana	Fortune plango vulnera
Cl			tr	Carl Orff	Carmina Burana	O Fortuna (2)
Cl			ms	Carl Orff	Carmina Burana	Olim lacus colueram
Cl			ms	Carl Orff	Carmina Burana	Omnia Sol temperat
Cl			tr	Carl Orff	Carmina Burana	Reie/Swaz hie gat umbe/Chume,
Cl			ts	Carl Orff	Carmina Burana	Si puer cum peullula
Cl			ms	Carl Orff	Carmina Burana	Stetit puella
Cl			ts	Carl Orff	Carmina Burana	Veni, veni, venias
Cl			ts	Carl Orff	Carmina Burana	Veris leta facies
Cl			ts	Carl Orff	Carmina Burana	Were diu werlt alle min
Cl			ts	Edward Elgar	Violin Concerto in B min, Op61	Allegro
Cl			ms	Edward Elgar	Violin Concerto in B min, Op61	Andante
Cl			ms	Gabriel Faure	Requiem	Cantique de Jean Racine Op. 11
Cl			ts	Gabriel Faure	Requiem	Messe Basse - Agnus Dei
Cl			ts	Gabriel Faure	Requiem	Messe Basse - Benedictus
Cl			ms	Gabriel Faure	Requiem	Messe Basse - Kyrie
Cl			ts	Gabriel Faure	Requiem	Messe Basse - Sanctus
Cl			ms	Gabriel Faure	Requiem	Requiem Op. 48 - Agnus Dei
Cl			tr	Gabriel Faure	Requiem	Requiem Op. 48 - Introit et Kyrie
Cl			ts	Gabriel Faure	Requiem	Requiem Op. 48 - Sanctus
Cl			ts	Holst	The Planets	Mars, the Bringer of War
Cl			tr	Holst	The Planets	Mercury, the Winged Messenger
Cl			ms	Holst	The Planets	Saturn, the Bringer of Old Age
Cl			ts	Holst	The Planets	Uranus, the Magician
Cl			ts	Holst	The Planets	Venus, the Bringer of Peace
Cl			ms	Johann Sebastian Bach	Toccata & Fugue (Bach Organ Mu	Chorale Preludes: Wachet auf,
Cl			tr	Johann Sebastian Bach	Toccata & Fugue (Bach Organ Mu	Fantasia and Fugue in G minor
Cl			ts	Johann Sebastian Bach	Toccata & Fugue (Bach Organ Mu	Prelude & Fugue in E flat major
Cl			ts	Johann Sebastian Bach	Toccata & Fugue (Bach Organ Mu	Toccata and Fugue in D minor
Cl			tr	Johann Sebastian Bach	Toccata & Fugue (Bach Organ Mu	Trio Sonata No. 5 in C major - 1. Allegro
Cl			ms	Johann Sebastian Bach	Toccata & Fugue (Bach Organ Mu	Trio Sonata No. 5 in C major - 2. Largo
Cl			tr	Johann Sebastian Bach	Toccata & Fugue (Bach Organ Mu	Trio Sonata No. 5 in C major - 3. Allegro
Cl			tr	Ludwig Von Beethoven	Beethoven: Missa Solemnis (Gar	Credo
Cl			ms	Ludwig Von Beethoven	Beethoven: Missa Solemnis (Gar	Gloria
Cl			ms	Ludwig Von Beethoven	Beethoven: Missa Solemnis (Gar	Kyrie
Cl			ms	Ludwig Von Beethoven	Casadesus: Piano Sonatas	: Adagio sostenuto
Cl			tr	Ludwig Von Beethoven	Casadesus: Piano Sonatas	: Allegro assai
Cl			ms	Ludwig Von Beethoven	Casadesus: Piano Sonatas	Allegro vivace
Cl			ms	Ludwig Von Beethoven	Casadesus: Piano Sonatas	Allegro, ma non troppo-Presto
Cl			ms	Ludwig Von Beethoven	Casadesus: Piano Sonatas	Sonata n.24 in F sharp, Op.78
Cl			ms	Ludwig Von Beethoven	Casadesus: Piano Sonatas	Sonata n.26 in E flat, Op.81
Cl			ts	Ludwig Von Beethoven	Casadesus: Piano Sonatas	Viviacissimamente (Le Retour)
Cl			tr	Mendelssohn	Symphonien 3 & 4	Overture The Hebrides (Fingal's Cave)
Cl			ms	Mendelssohn	Symphonien 3 & 4	Symp 3 in A min Scottish 1: An
Cl			ts	Mendelssohn	Symphonien 3 & 4	Symp 3 in A min Scottish 2: Vi
Cl			ts	Mendelssohn	Symphonien 3 & 4	Symp 3 in A min Scottish 3: Ad
Cl			ms	Mendelssohn	Symphonien 3 & 4	Symp 4 in A Maj Italian 1: (Al

ms≡model selection; tr≡training; ts≡testing
Ac≡College A Cappella; Ap≡Pro A Cappella; A≡A Cappella; E≡Electronica; P≡Pop; Ce≡Celtic; Cl≡Classical; J≡Jazz; L≡Latin

Class	Data Sets 2cl	3cl	7cl	Artist	Album	Song
Cl			ts	Mendelssohn	Symphonien 3 & 4	Symp 4 in A Maj Italian 2: And
Cl			tr	Mendelssohn	Symphonien 3 & 4	Symp 4 in A Maj Italian 3: Con
Cl			ms	Mendelssohn	Symphonien 3 & 4	Symp 4 in A Maj Italian 4: Sal
Cl			ms	Mousorgsky	Pictures at an Exhibition, Pia	Bydlo
Cl			tr	Mousorgsky	Pictures at an Exhibition, Pia	Cum mortuis in lingua mortua
Cl			ms	Mousorgsky	Pictures at an Exhibition, Pia	Promenade
Cl			ts	Mousorgsky	Pictures at an Exhibition, Pia	Promenade (2)
Cl			ts	Mousorgsky	Pictures at an Exhibition, Pia	Promenade (4)
Cl			ts	Mousorgsky	Pictures at an Exhibition, Pia	Promenade (5)
Cl			ts	Mousorgsky	Pictures at an Exhibition, Pia	Promenade (6)
Cl			tr	Mousorgsky	Pictures at an Exhibition, Pia	Promenade (7)
Cl			tr	Mousorgsky	Pictures at an Exhibition, Pia	Promenade (9)
Cl			ts	Mousorgsky	Pictures at an Exhibition, Pia	Samuel Goldenberg and Schmuyle
Cl			ms	Mousorgsky	Pictures at an Exhibition, Pia	Samuel Goldenberg and Schmuyle (2)
Cl			ts	Mousorgsky	Pictures at an Exhibition, Pia	The Catacombs
Cl			ts	Mousorgsky	Pictures at an Exhibition, Pia	The Catacombs (2)
Cl			ts	Mousorgsky	Pictures at an Exhibition, Pia	The Gnome
Cl			ms	Mousorgsky	Pictures at an Exhibition, Pia	The Gnome (2)
Cl			ts	Mousorgsky	Pictures at an Exhibition, Pia	The Great Gate of Kiev
Cl			ms	Mousorgsky	Pictures at an Exhibition, Pia	The Great Gate of Kiev (2)
Cl			ts	Mousorgsky	Pictures at an Exhibition, Pia	The Hut on Fowl's Legs
Cl			ts	Mousorgsky	Pictures at an Exhibition, Pia	The Market-Place at Limoges
Cl			tr	Mousorgsky	Pictures at an Exhibition, Pia	The Market-Place at Limoges (2)
Cl			ms	Mousorgsky	Pictures at an Exhibition, Pia	Tuileries
Cl			ms	Mousorgsky	Pictures at an Exhibition, Pia	Tuileries (2)
Cl			ms	Mozart	The Amadeus Mozart	Concerto for 2 Pianos in E-flat Major
Cl			ms	Mozart	The Amadeus Mozart	Dies Irae
Cl			ms	Mozart	The Amadeus Mozart	Lacrimosa
Cl			ms	Mozart	The Amadeus Mozart	Piano Concerto No. 20 in D Minor
Cl			tr	Mozart	The Amadeus Mozart	Piano Concerto No. 22 in E-flat Major
Cl			tr	Mozart	The Amadeus Mozart	Rex Tremendae
Cl			tr	Mozart	The Amadeus Mozart	Serenade No. 10 in B-flat Major
Cl			ms	Mozart	The Amadeus Mozart	Symphony No. 25 in G Minor
Cl			ms	Mozart	The Amadeus Mozart	Symphony No. 29 in A Major
Cl			ts	Prokofiev	Lieutenant Kije	Romance
Cl			ts	Prokofiev	Lieutenant Kije	The Birth of Kije
Cl			ts	Prokofiev	Lieutenant Kije	The Burial of Kije
Cl			ts	Prokofiev	Lieutenant Kije	The Wedding of Kije
Cl			ms	Prokofiev	Lieutenant Kije	Troika
Cl			ts	Prokofiev	Symphony No. 1 in D Major	Finale
Cl			tr	Tchaikovsky	Manfred	Allegro con fuoco
Cl			ts	Tchaikovsky	Manfred	Andante con moto
Cl			tr	Tchaikovsky	Manfred	Lento Legubre
Cl			ms	Tchaikovsky	Manfred	Vivace con Spirito
Cl			ms	W.A. Mozart	Requiem	Agnus Dei
Cl			tr	W.A. Mozart	Requiem	Communio
Cl			ts	W.A. Mozart	Requiem	Confutatis
Cl			ms	W.A. Mozart	Requiem	Dies irae
Cl			tr	W.A. Mozart	Requiem	Domae Jesu
Cl			ms	W.A. Mozart	Requiem	Hostias
Cl			ts	W.A. Mozart	Requiem	Recordare
Cl			ms	W.A. Mozart	Requiem	Rex tremendae

ms≡model selection; tr≡training; ts≡testing

Ac≡College A Cappella; Ap≡Pro A Cappella; A≡A Cappella; E≡Electronica; P≡Pop; Ce≡Celtic; Cl≡Classical; J≡Jazz; L≡Latin

	Data Sets					
Class	2cl	3cl	7cl	Artist	Album	Song
Cl			ms	W.A. Mozart	Requiem	Sanctus
Cl			ts	W.A. Mozart	The Piano Concertos, Disc 10	PC #22 in Eb Maj, KV 482: Alle
Cl			ts	W.A. Mozart	The Piano Concertos, Disc 10	PC #23 in A Maj, KV 488: Adagi
Cl			ts	W.A. Mozart	The Piano Concertos, Disc 10	PC #23 in A Maj, KV 488: Alleg
Cl			tr	W.A. Mozart	The Piano Concertos, Disc 9	PC #20 in D min, KV 466: Alleg
Cl			ms	W.A. Mozart	The Piano Concertos, Disc 9	PC #21 in C Maj, KV 467: (Alle
Cl			ms	W.A. Mozart	The Piano Concertos, Disc 9	PC #21 in C Maj, KV 467: Alleg
Cl			ms	W.A. Mozart	The Piano Concertos, Disc 9	PC #21 in C Maj, KV 467: Andan
J			ms	After Hours Jazz		Aguirre 1.0
J			ts	After Hours Jazz		Sunsurfer
J			ms	After Hours Jazz	title	Solar Wind
J			ts	B.B. King	Deuces Wild	Ain't Nobody Home with D'Angelo
J			ms	B.B. King	Deuces Wild	Baby I Love You with Bonnie Raitt
J			ts	B.B. King	Deuces Wild	Confessin' The Blues with Marty Stuart
J			ms	B.B. King	Deuces Wild	Cryin' Won't Help You Babe
J			tr	B.B. King	Deuces Wild	Dangerous Mood with Joe Cocker
J			tr	B.B. King	Deuces Wild	If You Love Me with Van Morrison
J			tr	B.B. King	Deuces Wild	Keep It Coming with Heavy D
J			tr	B.B. King	Deuces Wild	Night Life with Willie Nelson
J			tr	B.B. King	Deuces Wild	Paying The Cost To Be The Boss
J			ts	B.B. King	Deuces Wild	Please Send Me Someone To Love
J			tr	B.B. King	Deuces Wild	Rock Me Baby with Eric Clapton
J			ms	B.B. King	Deuces Wild	The Thrill Is Gone with Tracy
J			ms	B.B. King	Deuces Wild	There Must Be A Better World Somewhere
J			ms	B.B. King	The Fabulous B.B. King	Three O'Clock Blues
J			tr	B.B. King	The Fabulous B.B. King	You Know I Love You
J			ts	Buddy Guy	My Time After Awhile	24 Hours of the Day
J			tr	Buddy Guy	My Time After Awhile	A Man and the Blues
J			tr	Buddy Guy	My Time After Awhile	Checking On My Baby
J			ms	Buddy Guy	My Time After Awhile	Five Long Years
J			ms	Buddy Guy	My Time After Awhile	Hello San Francisco
J			ts	Buddy Guy	My Time After Awhile	I'm Ready
J			ts	Buddy Guy	My Time After Awhile	It Hurts Me Too (When Things Go Wrong)
J			tr	Buddy Guy	My Time After Awhile	My Time After Awhile
J			ts	Buddy Guy	My Time After Awhile	One Room Country Shack
J			tr	Buddy Guy	My Time After Awhile	So Sad This Morning
J			ts	Buddy Guy	My Time After Awhile	Stormy Monday Blues
J			ms	Buddy Guy	My Time After Awhile	Sweet Little Angel
J			ts	Buddy Guy	My Time After Awhile	The things I Used to Do
J			tr	Buddy Guy	My Time After Awhile	You Give Me Fever
J			ts	Cannonball Adderley	Cannonball Adderley And The Ri	Batida Diferentes
J			tr	Cannonball Adderley	Cannonball Adderley And The Ri	Clouds
J			ms	Cannonball Adderley	Cannonball Adderley And The Ri	Clouds (2)
J			ms	Cannonball Adderley	Cannonball Adderley And The Ri	Corcovado
J			ms	Cannonball Adderley	Cannonball Adderley And The Ri	Corcovado (2)
J			ts	Cannonball Adderley	Cannonball Adderley And The Ri	Groovy Sambas
J			tr	Cannonball Adderley	Cannonball Adderley And The Ri	Joyce's Sambas
J			ts	Cannonball Adderley	Cannonball Adderley And The Ri	Minha Saudades
J			ms	Cannonball Adderley	Cannonball Adderley And The Ri	O Amor Em Paz (Once I Loved)
J			tr	Cannonball Adderley	Cannonball Adderley And The Ri	Sambops
J			tr	Charles Mingus	Mingus Ah Um	Better Git It In Your Soul
J			ts	Charles Mingus	Mingus Ah Um	Bird Calls

ms≡model selection; tr≡training; ts≡testing
Ac≡College A Cappella; Ap≡Pro A Cappella; A≡A Cappella; E≡Electronica; P≡Pop; Ce≡Celtic; Cl≡Classical; J≡Jazz; L≡Latin

Class	Data Sets 2cl	3cl	7cl	Artist	Album	Song
J			ts	Charles Mingus	Mingus Ah Um	Boogie Stop Shuffle
J			tr	Charles Mingus	Mingus Ah Um	Fables Of Faubus
J			ms	Charles Mingus	Mingus Ah Um	Goodbye Pork Pie Hat
J			ms	Charles Mingus	Mingus Ah Um	Jelly Roll
J			ts	Charles Mingus	Mingus Ah Um	Open Letter To Duke
J			tr	Charles Mingus	Mingus Ah Um	Pussy Cat Dues
J			ms	Charles Mingus	Mingus Ah Um	Self-portrait In Three Colors
J			ms	Charles Mingus	Shoes of the Fisherman's Wife	Far Wells, Mill Valley
J			ms	Charles Mingus	Shoes of the Fisherman's Wife	Gunslinging Bird
J			ms	Charles Mingus	Shoes of the Fisherman's Wife	Mood Indigo
J			ts	Charles Mingus	Shoes of the Fisherman's Wife	Slop
J			tr	Charles Mingus	Shoes of the Fisherman's Wife	Song With Orange
J			ts	Charles Mingus	Shoes of the Fisherman's Wife	The Shoes Of The Fisherman's Wife . . .
J			ts	Charles Mingus	Shoes of the Fisherman's Wife	Things Ain't What They Used To Be
J			tr	Gil Scott-Heron	The Revolution Will Not Be Tel	A Sign of the Ages
J			tr	Gil Scott-Heron	The Revolution Will Not Be Tel	Brother
J			ms	Gil Scott-Heron	The Revolution Will Not Be Tel	Did You Hear What They Said?
J			ms	Gil Scott-Heron	The Revolution Will Not Be Tel	Home Is Where the Hatred Is
J			ts	Gil Scott-Heron	The Revolution Will Not Be Tel	I Think I'll Call It Morning
J			ts	Gil Scott-Heron	The Revolution Will Not Be Tel	Lady Day and John Coltrane
J			ms	Gil Scott-Heron	The Revolution Will Not Be Tel	No Knock
J			ts	Gil Scott-Heron	The Revolution Will Not Be Tel	Or Down You Fall
J			tr	Gil Scott-Heron	The Revolution Will Not Be Tel	Pieces of a Man
J			ms	Gil Scott-Heron	The Revolution Will Not Be Tel	Save the Children
J			ts	Gil Scott-Heron	The Revolution Will Not Be Tel	Sex Education - Ghetto Style
J			ms	Gil Scott-Heron	The Revolution Will Not Be Tel	The Get Out of the Ghetto Blues
J			ms	Gil Scott-Heron	The Revolution Will Not Be Tel	The Needle's Eye
J			ts	Gil Scott-Heron	The Revolution Will Not Be Tel	The Prisoner
J			tr	Gil Scott-Heron	The Revolution Will Not Be Tel	The Revolution Will Not Be Televised
J			tr	Gil Scott-Heron	The Revolution Will Not Be Tel	When You Are Who You Are
J			ts	Gil Scott-Heron	The Revolution Will Not Be Tel	Whitey On the Moon
J			tr	Holly Cole Trio	Blame It On My Youth	Calling You
J			ms	Holly Cole Trio	Blame It On My Youth	God Will
J			ts	Holly Cole Trio	Blame It On My Youth	Honeysuckle Rose
J			ts	Holly Cole Trio	Blame It On My Youth	I'll Be Seeing You
J			tr	Holly Cole Trio	Blame It On My Youth	I'm Gonna Laugh You Right Out
J			tr	Holly Cole Trio	Blame It On My Youth	If I Were a Bell
J			ts	Holly Cole Trio	Blame It On My Youth	On the Street Where You Live
J			ms	Holly Cole Trio	Blame It On My Youth	Purple Avenue
J			tr	Holly Cole Trio	Blame It On My Youth	Smile
J			ms	Holly Cole Trio	Blame It On My Youth	Trust In Me
J			ts	John Coltrane	Blue Train	Blue Train
J			tr	John Coltrane	Blue Train	I'm Old Fashioned
J			tr	John Coltrane	Blue Train	Lazy Bird
J			tr	John Coltrane	Blue Train	Locomotion
J			ts	John Coltrane	Blue Train	Moment's Notice
J			tr	John Coltrane	Giant Steps	Countdown
J			tr	John Coltrane	Giant Steps	Cousin Mary
J			tr	John Coltrane	Giant Steps	Cousin Mary (2)
J			tr	John Coltrane	Giant Steps	Giant Steps
J			ts	John Coltrane	Giant Steps	Giant Steps (2)
J			ts	John Coltrane	Giant Steps	Mr. P.C

ms≡model selection; tr≡training; ts≡testing

Ac≡College A Cappella; Ap≡Pro A Cappella; A≡A Cappella; E≡Electronica; P≡Pop; Ce≡Celtic; Cl≡Classical; J≡Jazz; L≡Latin

Class	Data Sets 2cl	3cl	7cl	Artist	Album	Song
J			ts	John Coltrane	Giant Steps	Naima
J			tr	John Coltrane	Giant Steps	Naima (2)
J			tr	John Coltrane	Giant Steps	Spiral
J			ms	John Coltrane	Giant Steps	Syeeda's Song Flute
J			ms	Louis Armstrong		SnakeRag
J			ms	Medeski Martin & Wood	Notes From the Underground	Caravan
J			tr	Medeski Martin & Wood	Notes From the Underground	Hermeto's Daydream
J			ts	Medeski Martin & Wood	Notes From the Underground	La Garonne
J			ts	Medeski Martin & Wood	Notes From the Underground	Orbits
J			ms	Medeski Martin & Wood	Notes From the Underground	Otis
J			ms	Medeski Martin & Wood	Notes From the Underground	Querencia
J			ms	Medeski Martin & Wood	Notes From the Underground	Rebirth
J			ts	Medeski Martin & Wood	Notes From the Underground	The Saint
J			ts	Medeski Martin & Wood	Notes From the Underground	Uncle Chubb
J			ts	Medeski Martin & Wood	Notes From the Underground	United
J			tr	Miles Davis	Bitches Brew	Bitches Brew
J			ts	Miles Davis	Bitches Brew	John McLaughlin
J			tr	Miles Davis	Bitches Brew	Miles Runs The Voodoo Down
J			tr	Miles Davis	Bitches Brew	Pharaoh's Dance
J			ms	Miles Davis	Bitches Brew	Sanctuary
J			ts	Miles Davis	Bitches Brew	Spanish Key
J			tr	Miles Davis	Kind of Blue	All Blues
J			tr	Miles Davis	Kind of Blue	Blue in Green
J			tr	Miles Davis	Kind of Blue	Flamenco Sketches
J			ts	Miles Davis	Kind of Blue	Freddie Freeloader
J			ms	Miles Davis	Kind of Blue	So What
J			ms	Miles Davis	doo-bop	Blow
J			ms	Miles Davis	doo-bop	Chocolate Chip
J			ts	Miles Davis	doo-bop	Duke Booty
J			ms	Miles Davis	doo-bop	Fantasy
J			ms	Miles Davis	doo-bop	High Speed Chase
J			ms	Miles Davis	doo-bop	Mystery
J			ms	Miles Davis	doo-bop	Mystery (Reprise)
J			ms	Miles Davis	doo-bop	Sonya
J			tr	Miles Davis	doo-bop	The Doo Bop Song
J			ms	Reminiscence Quartet	Psychodelico	Injury Time
J			ts	Reminiscence Quartet	Psychodelico	Inspiration
J			tr	Reminiscence Quartet	Psychodelico	Onde Anda O Meu Amor
J			ts	Reminiscence Quartet	Psychodelico	Peace of Mind
J			ts	Reminiscence Quartet	Psychodelico	Psycoledico
J			ms	Reminiscence Quartet	Psychodelico	Roda Mundo
J			ms	Reminiscence Quartet	Psychodelico	Saudade
J			ms	Reminiscence Quartet	Psychodelico	Un Premier Jour Sans Toi
J			ts	Turtle Island String Quartet	Who Do We Think We Are?	Blues on the Corner
J			ts	Turtle Island String Quartet	Who Do We Think We Are?	Dromedary
J			ts	Turtle Island String Quartet	Who Do We Think We Are?	Ecotopia
J			ts	Turtle Island String Quartet	Who Do We Think We Are?	Gypsy Eyes
J			ms	Turtle Island String Quartet	Who Do We Think We Are?	Josey
J			tr	Turtle Island String Quartet	Who Do We Think We Are?	Moose the Mooche
J			tr	Turtle Island String Quartet	Who Do We Think We Are?	Ruby My Dear
J			ts	Turtle Island String Quartet	Who Do We Think We Are?	Seven Steps to Heaven
J			ms	Turtle Island String Quartet	Who Do We Think We Are?	Who Do You Think You Are

ms≡model selection; tr≡training; ts≡testing

Ac≡College A Cappella; Ap≡Pro A Cappella; A≡A Cappella; E≡Electronica; P≡Pop; Ce≡Celtic; Cl≡Classical; J≡Jazz; L≡Latin

Class	Data Sets 2cl	3cl	7cl	Artist	Album	Song
J			tr	Turtle Island String Quartet	Who Do We Think We Are?	You've Changed
J			tr	Uncensored Jazz		Eyes Wide Open
L			ts	Alex Torres	Entre Amigos	Para Poncho
L			ts	Alex Torres	Entre Amigos	Senorita Swing
L			ms	Alex Torres	Entre Amigos	Tus Mentiras
L			ms	Alex Torres	Entre Amigos	Yo No Puedo Vivir Sin Tu Carino
L			ms	B. Marïn	El Rey del Timbal	Para Los Rumberos
L			ms	B. Marïn	El Rey del Timbal	TP Treat
L			ms	Bobby Valentin	Ritmo Caliente	Huracan
L			ms	Bobby Vince Paunetto	Nu Yorica!	Little Rico, Little Rico's The
L			ms	Cortijo Y Su Maquina Del Tiemp	Nu Yorica!	Carnaval
L			ts	Cortijo y Su Maquina del Tiemp	Nu Yorica!	Gumbo
L			ms	Cuarteto Patria & Manu Difango	CubAfrica	Carnaval
L			ts	Cuarteto Patria & Manu Difango	CubAfrica	Cerisiers roses
L			ts	Cuarteto Patria & Manu Difango	CubAfrica	Cielito lindo
L			ms	Cuarteto Patria & Manu Difango	CubAfrica	Cosita linda
L			ms	Cuarteto Patria & Manu Difango	CubAfrica	Promesa
L			ms	Cuarteto Patria & Manu Difango	CubAfrica	Quizas quizas
L			ts	Cuarteto Patria & Manu Difango	CubAfrica	Son de la loma
L			ms	Cuarteto Patria & Manu Difango	CubAfrica	Terberito
L			ts	Duduca	Encontro Com A Velha Guarda	Clara de Ovo
L			ts	Eddie Palmieri	Ritmo Caliente	Muneca
L			ts	Estrella de la Charanga	Sones y Danzones	Almendra
L			ms	Estrella de la Charanga	Sones y Danzones	Angoa
L			ms	Estrella de la Charanga	Sones y Danzones	El Niche
L			ts	Estrella de la Charanga	Sones y Danzones	Ella
L			ts	Estrella de la Charanga	Sones y Danzones	Fefita
L			ts	Estrella de la Charanga	Sones y Danzones	La Melcocha
L			ts	Estrella de la Charanga	Sones y Danzones	La Negra Tomasa
L			ms	Estrella de la Charanga	Sones y Danzones	Los Tamalitos de Olga
L			ms	Estrella de la Charanga	Sones y Danzones	Olvido
L			ts	Estrella de la Charanga	Sones y Danzones	Pare Cochero
L			ms	Estrella de la Charanga	Sones y Danzones	Si Me Comprendieras
L			ts	Estrella de la Charanga	Sones y Danzones	Yo Si Como Candela
L			tr	Grupo Folklorico y Experimenta	Nu Yorica!	Anabacoa
L			ts	Guillermo Portabales	Aqui Estä Portabales	A Borinquen
L			ms	Guillermo Portabales	Aqui Estä Portabales	Alborada
L			ts	Guillermo Portabales	Aqui Estä Portabales	Amorosa Guajira
L			ts	Guillermo Portabales	Aqui Estä Portabales	El Buen Borincano
L			ts	Guillermo Portabales	Aqui Estä Portabales	El Sitierito
L			ts	Guillermo Portabales	Aqui Estä Portabales	Mi Fiel Enamorado
L			ts	Guillermo Portabales	Aqui Estä Portabales	My Querer
L			ms	Guillermo Portabales	Aqui Estä Portabales	Soy Hijo de Siboney
L			ts	Guillermo Portabales	Aqui Estä Portabales	Ven
L			ms	Harlem River Drive	Nu Yorica!	Harlem River Drive Theme
L			ts	Harlem River Drive	Nu Yorica!	Idle Hands
L			ms	Iracy Serra	Encontro Com A Velha Guarda	Eu Vou Sorrir
L			ms	Ismael Silva	Encontro Com A Velha Guarda	Ingratidao
L			ms	Jóvenes Cläsicos del Son	Fruta Bomba	Esa mujer El traguito
L			ms	Jóvenes Cläsicos del Son	Fruta Bomba	La flor y la hoja seca
L			ms	Jóvenes Cläsicos del Son	Fruta Bomba	Para siempre tenerte
L			ms	Jóvenes Cläsicos del Son	Fruta Bomba	Rezo

ms≡model selection; tr≡training; ts≡testing

Ac≡College A Cappella; Ap≡Pro A Cappella; A≡A Cappella; E≡Electronica; P≡Pop; Ce≡Celtic; Cl≡Classical; J≡Jazz; L≡Latin

Class	Data Sets 2cl	3cl	7cl	Artist	Album	Song
L			ms	Jóvenes Cläsicos del Son	Fruta Bomba	Ya se durmió la guitarra
L			ms	Jimmy Bosch	Salsa Dura	Amor Por Tï
L			ms	Jimmy Bosch	Salsa Dura	Impacto Tendremos
L			ts	Jimmy Bosch	Salsa Dura	La Noticia
L			ms	Jimmy Bosch	Salsa Dura	Pa' Manterner Tradición
L			ms	Jimmy Bosch	Salsa Dura	Sigo Cambiando
L			ts	Jimmy Bosch	Salsa Dura	Speak No Evil
L			ts	Jimmy Bosch	Salsa Dura	Un Poquito Mäs
L			ts	Jimmy Bosch	Salsa Dura	Vengo De Amor
L			ms	Jimmy Bosch	Soneando Trombon	Cha Cha Gabriel
L			ts	Jimmy Bosch	Soneando Trombon	Crisis De Identidad
L			ms	Jimmy Bosch	Soneando Trombon	Descargarana
L			ms	Jimmy Bosch	Soneando Trombon	Erben On The Phone
L			ms	Jimmy Bosch	Soneando Trombon	Gaviota
L			ms	Jimmy Bosch	Soneando Trombon	Jimmy's Bop
L			ts	Jimmy Bosch	Soneando Trombon	La Soledad
L			ts	Jimmy Bosch	Soneando Trombon	Muy Joven Para Mi
L			ts	Jimmy Bosch	Soneando Trombon	Padre Soy
L			ts	Joe Bataan	Nu Yorica!	Aftershower Funk
L			ts	Larry Harlow	Ritmo Caliente	Arsenio
L			ts	Machito Orchestra	Nu Yorica!	Macho
L			ts	Mamba percussions	Jean-Claude KERINEC	Ambiance / Vendetta Conga
L			ms	Mamba percussions	Jean-Claude KERINEC	Cristal
L			ms	Mamba percussions	Jean-Claude KERINEC	Kericongaia
L			ts	Mano Cedio da Viola	Encontro Com A Velha Guarda	Saudade Do Passado
L			ms	Nelson Cavaquinho	Encontro Com A Velha Guarda	Juizo Final
L			ts	O. Estivill	El Rey del Timbal	A Gozar Timbero
L			ts	Ocho	Nu Yorica!	Coco May May
L			ts	Orchestra Harlow	Ritmo Caliente	El Malecon
L			ms	Pelado da Mangueira	Encontro Com A Velha Guarda	Reliquias da Bahia
L			ts	Pete Rodriquez	Ritmo Caliente	Mi Negra Mariana
L			ts	R. Ortïz	El Rey del Timbal	El Plato Roto
L			ms	Ray Barretto	Ritmo Caliente	Quitate Le Mascara
L			ts	Ricardo Ray	Ritmo Caliente	Aguzate
L			ts	Roberto Roena	Ritmo Caliente	Tu Loco Locoy Yo Tranquillo
L			ms	Ry Cooder	Buena Vista Social Club	¿Y Tü Quë Has Hecho?
L			ts	Ry Cooder	Buena Vista Social Club	Chan Chan
L			ms	Ry Cooder	Buena Vista Social Club	De Camino a La Verda
L			ms	Ry Cooder	Buena Vista Social Club	Dos Gardenias
L			ts	Ry Cooder	Buena Vista Social Club	El Carretero
L			ms	Ry Cooder	Buena Vista Social Club	El Cuarto deTula
L			ts	Ry Cooder	Buena Vista Social Club	Murmullo
L			ms	Ry Cooder	Buena Vista Social Club	Orgullecida
L			ms	Ry Cooder	Buena Vista Social Club	Veinte A os
L			ts	S. Mëndez	El Rey del Timbal	Guaguancó Margarito
L			ts	S. Mëndez	El Rey del Timbal	Juventud del Presente
L			ms	Stone Alliance	Nu Yorica!	Amigos
L			ms	Tito Puente	El Rey del Timbal	El Rey del Timbal
L			ts	Tito Puente	El Rey del Timbal	Mambo a la Tito
L			ms	Tito Puente	Ritmo Caliente	Oye Comova
L			ts	Willie Colon	Ritmo Caliente	Che Che Cole

ms≡model selection; tr≡training; ts≡testing

Ac≡College A Cappella; Ap≡Pro A Cappella; A≡A Cappella; E≡Electronica; P≡Pop; Ce≡Celtic; Cl≡Classical; J≡Jazz; L≡Latin