Music Genre Classification

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1 Introduction

Music genre classification is the task of classifying the given audio signal into its corresponding categorical description (a.k.a. genre). It is a very challenging task in the field of music information retrieval (MIR) and widely used for digital music service and Internet radio. For example: music applications such as Shazam identify a song based on its audio content. The goal of this project is to design a classifier that takes audio signal as input and produces its corresponding genre as the output.

The data set we are using for this project is from the website of the 5th International Conference on Music Information Retrieval (ISMIR2004), and it is available in Pulse Coded Modulation (PCM). There are a total of 729 songs. The number of songs in each genre is as follows:

- Classical: 320 songs
- Electronics: 115 songs
- Jazz-blues: 26 songs
- Metal-punk: 45 songs
- Rock-pop: 101 songs
- World: 122 songs

The objective is to train a classifier on this data that can classify any song into these 6 different genres. We have explored and experimented with several approaches to this problem. In order to train and test data, we use 10-fold cross validation (i.e, 90% of the songs are being used for training and 10% of the songs for testing).

Our approach to this problem consists of 3 main components; dimensionality reduction, quantifying the distance between two songs in the reduce spaced and statistical learning. The organization of the paper is as follows: dimensionality reduction techniques are discussed in section 2 followed by section 3 which explores the different distance metrics and section 4 which explains the statistical learning methods we have used to classify the data. In section 5 we represent the results of our approach and finally in section 6 we talk about the results and future work.

2 Dimensionality Reduction

As the first step, we need to sample the songs in order to analyze and train the data. After the sampling of the given data set, we extract features or coefficients from the sampled space. However, the number of features are represented as a point in high dimensional space. When the dimension is enormously huge, the data becomes sparse as the volume increase. This is known as the curse for dimensionality. Hence, in order to classify the data we need to reduce the number of dimensions.Once the dimensionality is reduced, we can use different classification methods.

In order to tackle the curse of dimensionality, we used Johnson-Lindenstrauss lemma to decide the minimum number of dimensions. The idea behind Johnson-Lindenstrauss lemma is that points in high-dimensional space can be projected onto low dimensional space while preserving the distance between the points [8]. For a given dataset, the minimum number of dimension required to preserve the distance between the points is given by the formula

$$n > 8 * ln(m) * \epsilon^2$$

where is a number between 0 and 1. For this project we have

$$n > 77$$

and hence the number of cepstrum coefficients that we have considered is 79.

2.1 MFCC(Mel Frequency cepstrum Coefficient

One of the dimensionality reduction techniques that we were interested in is MFCC (Mel Frequency Cepstrum Coefficient) [6]. In Mel Frequency Cepstrum, the frequency bands are equally spaced in mel space which is approximated by the human auditory system clearly and hence this frequency system allows for better representation of song. The MFCC coefficient follows a sequence of steps through which the coefficients are found. The diagram below shows the sequence of steps in the generation of the MFCC coefficient.

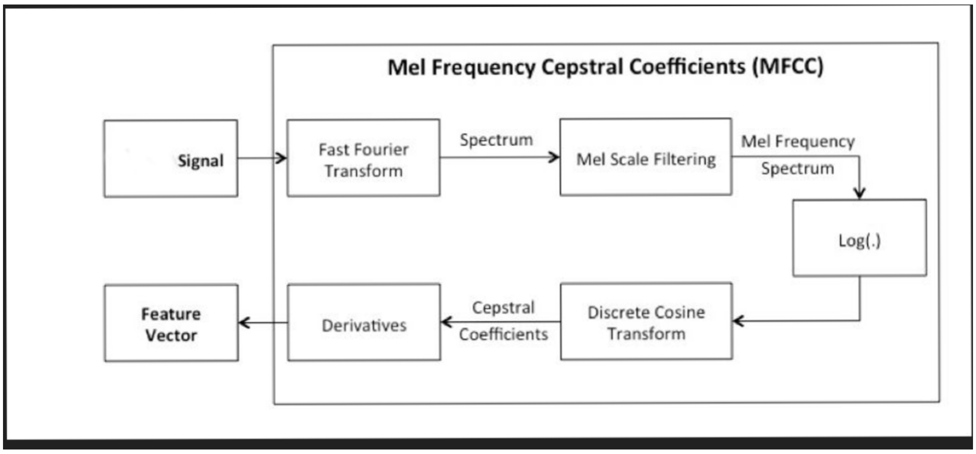


Figure 1: mfcc algorithm

Based on the algorithm, after the signal is sampled , the Fourier transformation is performed and the spectrum obtained is passed through the Mel Scale Filter. The output that we obtain is in the Mel Frequency spectrum. The log of the result is taken and a discrete cosine transform is applied to the signal in order to obtain the Mel Frequency Coefficient. After performing the MFCC we have the signal separated into different frames and each frame contains a set of feature vectors. Based on Johnson Lindenstrauss we have identified 79 coefficients per frame.The number of frames changes based on the length of the song.

2.2 PCA

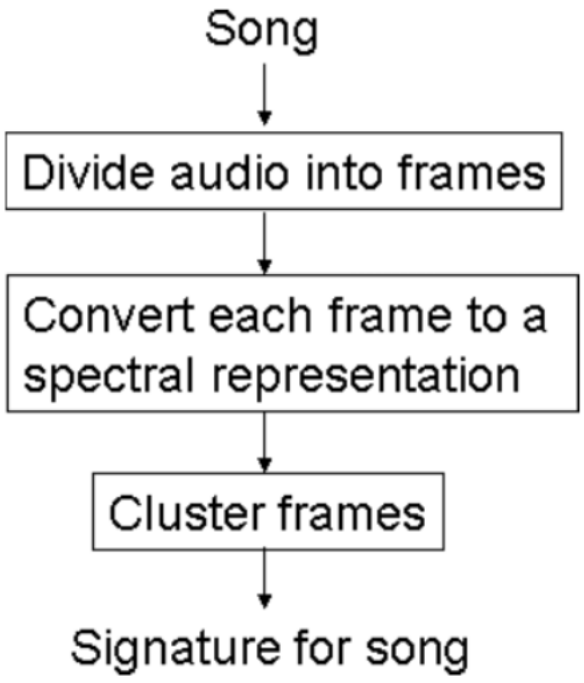
PCA(Principal Component Analysis) is a linear transformation technique which can be used to perform dimensionality reduction. PCA reduces the dimension by projecting the d dimensional data set onto k dimensional subspace where $k < d$ [5]. The data that we obtained from MFCC is taken as the input to PCA. This has been done as an effort to reduce the dimension further.The principal components are identified based on the variance of the data. The first principal component has the maximum variance.The algorithm is as follows:

- The data obtained from MFCC is normalised first
- The mean of the normalised data is put in a matrix and the mean value for all the rows are obtained.
- The variance of the data from MFCC is calculated.
- The Eigen values and Eigen vectors are calculated from the covariance matrix.
- The Eigen vectors are sorted in descending order in order to get the k largest eigen values.A new matrix is formed from the dominant eigen values.
- Then the data set is project on this new subspace and the feature vector are organised.

2.3 Content based similarity

Beth and Ariel [1] presents a novel approach to compare songs based on their corresponding audio content. For each song in the dataset, they create a song signature. The song signature is generated based on k-means clustering of spectral features. The algorithm is summarized in figure (2.3) below.

The first step is to divide the audio into multiple frames. Then, each frame is converted into its corresponding spectral representation. In order to generate the spectral representation we made use of MFCC algorithm which is explained in the previous sub section. The number of cepstrum coefficients was calculated based on the Johnson-Lindenstrauss lemma (n=79).



$$P = \{(\mu_{p_1}, \Sigma_{p_1}, w_{p_1}), \ldots, (\mu_{p_m}, \Sigma_{p_m}, w_{p_m})\}$$

Figure 2: Content based similarity method

2.3.1 k-Means

Once each frame is transformed into its corresponding spectral representation, we cluster the frames using unsupervised k-Means clustering algorithm where the value of k is fixed to 10. k-Means is a popular clustering algorithm used in data mining. It is often confused with k-nearest neighbour algorithm. Given a set of n observations in a d dimensional space, k-Means aims to cluster the n dimension into k sets $S = S_1, S_2, ...S_k$ where $k \leq n$. The idea is to find the sum of distance functions of each point in the cluster to the K center. The equation is given by (2.3.1):

$$\underset{\mathbf{S}}{\mathbf{arg\,min}} \sum_{i=1}^{k} \sum_{\mathbf{x} \in S_i} \|\mathbf{x} - \boldsymbol{\mu}_i\|^2$$

Figure 3: k-Means

After identifying the clusters, the mean, covariance and weight is calculated for each cluster. This set of values forms the signature of the song. This signature is used in order to compare two songs.

2.4 Mixture Model

Mixture model is a probabilistic model used in statistics in order to identify the sub-components of a probability distribution. The Gaussian mixture model (GMM) is a special case of mixture model with Gaussian sub-components. The intuition behind the mixture model is that the underlying components represent the set of hidden classes within the system. The following figure is a good representation of the Gaussian mixture model which represents the Gaussian components of a probability distribution.

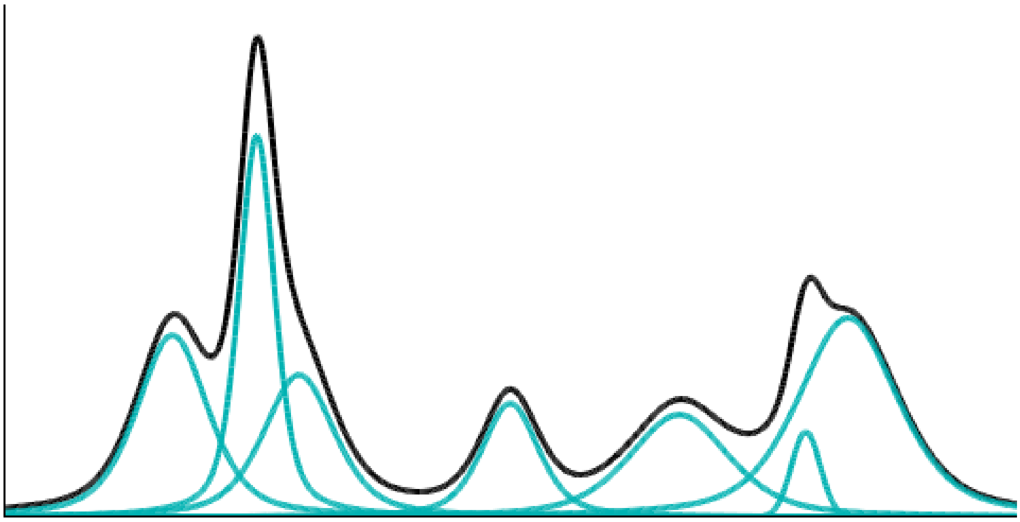


Figure 4: Gaussian mixture model

The computation time for the Gaussian mixture model is more than the other methods that we experimented with. So, we modified the mixture model based on an algorithm suggested in one of the example projects [10]. The following figure outlines the steps of the algorithm.

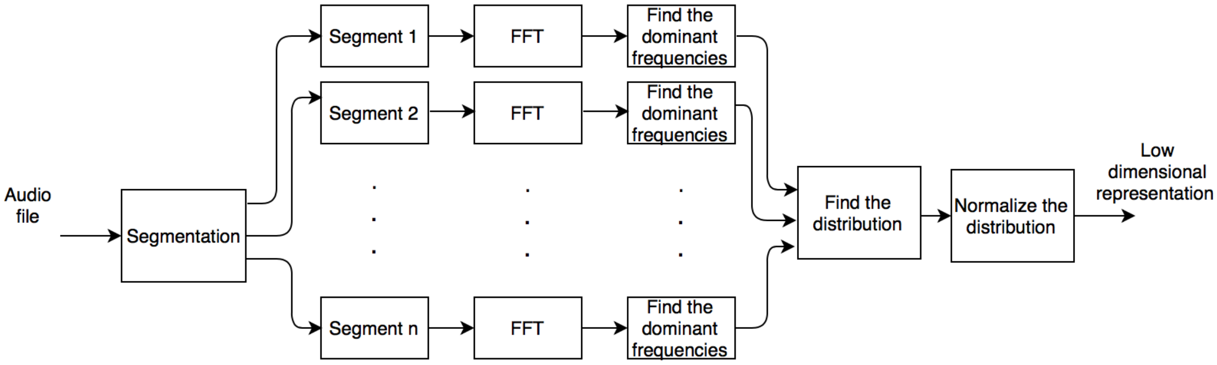

Audio file
Segmentation
Segment 1
Segment 2
Segment n
FFT
FFT
FFT
Find the dominant frequencies
Find the dominant frequencies
Find the dominant frequencies
Find the distribution
Normalize the distribution
Low dimensional representation

Figure 5: Modified mixture model flowchart

Based on the flowchart, we divide each song into smaller windows with the window size of 2000 samples. Then, with moving the signal to the frequency domain, we find the dominant frequency components of the signal. Repeating that for all the segments, we find the histogram of the dominant component frequency through the entire song. Since the songs have different length, we normalize the histogram by the length of each song. This distribution is the low dimension representation of the song. And, the dimension depends on the number of bins in the histogram.

3 Distance Metrics

This section provides the different types of distance metrics that we used in our project. Distance metric is used to quantify the distance between two different songs in the song space. However, the distance metric is valid only on a low-dimensional sub space due to curse of dimensionality. For example: Consider a hypersphere. As the number of dimension increases the volume of hypersphere tends to zero. This phenomenon is also called as concentration of measure. In such a concentrated space euclidean or any type of distance is not meaningful. Hence, before calculating the distance we need to use dimension reduction as pre-processing step. The list of techniques that we experiment with for dimension reduction is discussed in the previous section (2).

3.1 Minowski

Minowski distance is considered as the generalization between euclidean distance and Manhattan distance. This distance metric is used along with k-nearest neighbour for classification of points for songs which was reduced by content based similarity method. The reason why we used Minowski distance over other distance metric is based on experimentation. The distance between two n-dimensional point $X = x_1, x_2, ..., x_n$ and $Y = y_1, y_2, ..., y_n$ is calculated as:

$$\left(\sum_{i=1}^{n} |x_i - y_i|^p\right)^{1/p}$$

Figure 6: Minowski distance

3.2 Earth Movers distance

Earth Movers distance is the distance between two different probability distributions over a region D. This is the distance metric used to compare the distance between two songs using the signatures generated by the content similarity method. In the field of mathematics, it is also known as wasserstein metric. Informally, it is defined as the cost of turning one pile of dirt into another. EMD value is given by the formula:

$$EMD(P,Q) = \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} f_{i,j} d_{i,j}}{\sum_{i=1}^{m} \sum_{j=1}^{n} f_{i,j}}$$

Figure 7: EMD

where $f_{i,j}$ is the flow between cluster i and j and is calculated based on weight of the cluster. $d_{i,j}$ is the ground distance between the clusters. In this case euclidean distance is used as the ground distance. The numerator is denoted by the work and is normalized by the flow. The distance matrix generated by EMD is as follows:

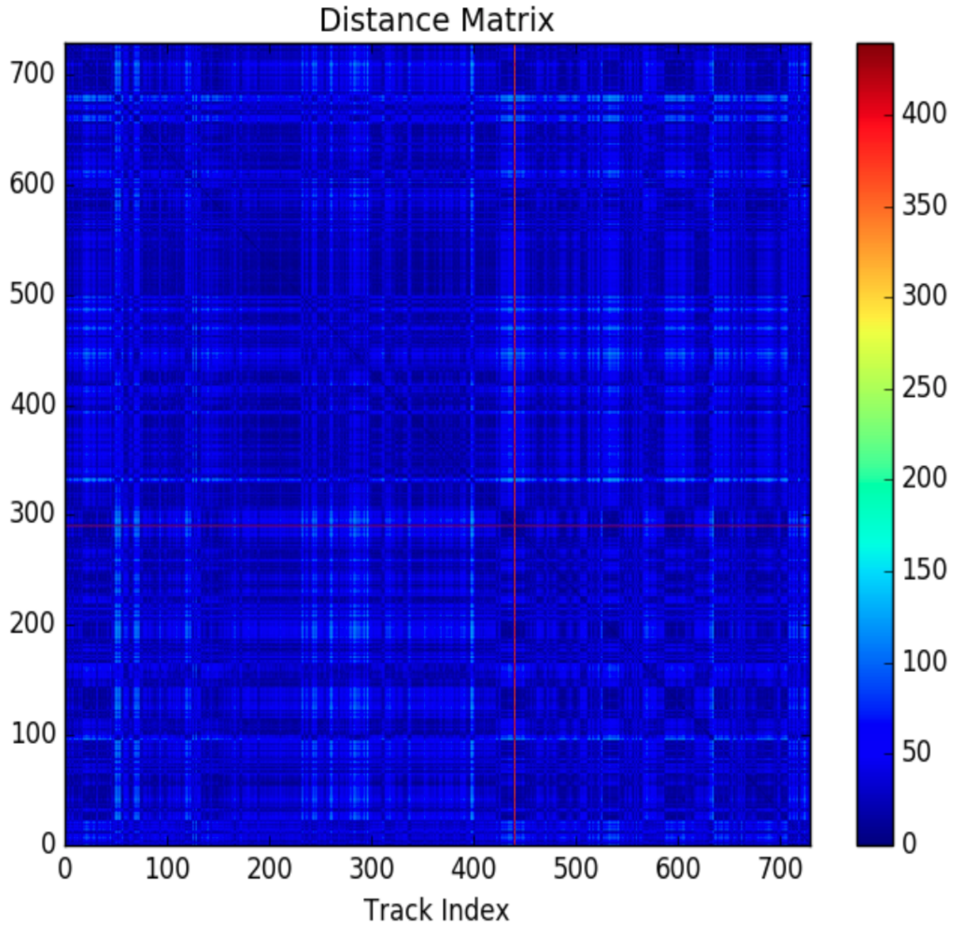


Figure 8: Distance matrix using EMD

In order visualize the distance matrix as scatter plot, we use multidimensional scaling (MDS). MDS is a means of visualizing the level of individual classes of a dataset. In this case, the classes refer to the different genres. Based on the scatter plot we find that there are no linearly separable regions to separate once class from another. The classes seem to be correlated to each other. Hence, linear classification algorithms such as linear regression will not perform as expected.

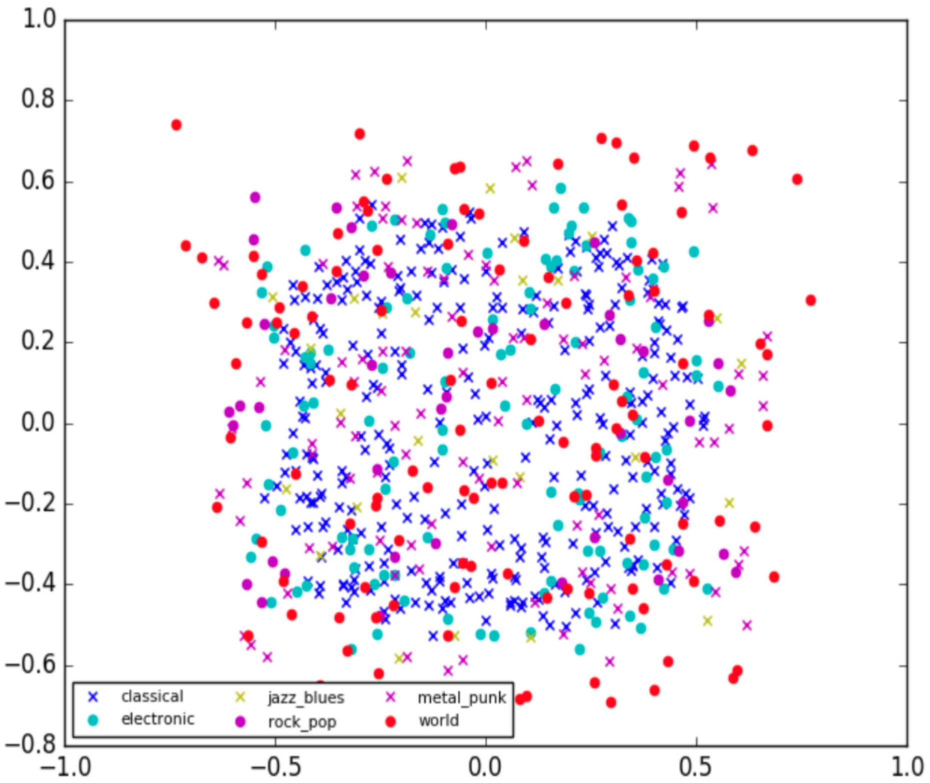


Figure 9: Scatter Plot

3.3 Euclidean distance

Euclidean distance also known as l^2-norm is a common measure of distance between two points in n-dimension space. Euclidean norm is simply the magnitude of the vector. This norm is very simple to calculate. Therefore, in our experiments we start with the Euclidean norm and if the result did not provide a good performance, then we test other distance metrics relevant to the data. In addition to be simple to calculate, Euclidean distance has a good performance in a broad range of settings. The following picture represents the distance matrix using modified Gaussian mixture model and Euclidean distance.

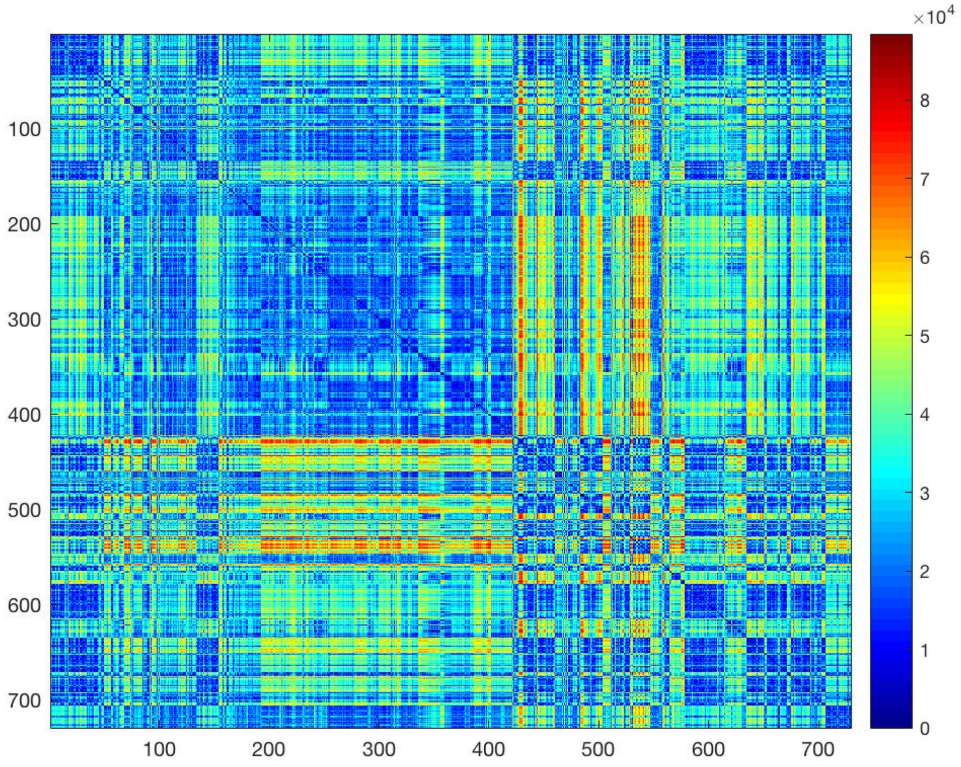


Figure 10: Euclidean distance matrix for modified Gaussian mixture model

We had also calculated the distance matrix using the Euclidean Distance using MFFC & PCA as well, the corresponding distance matrix is show below

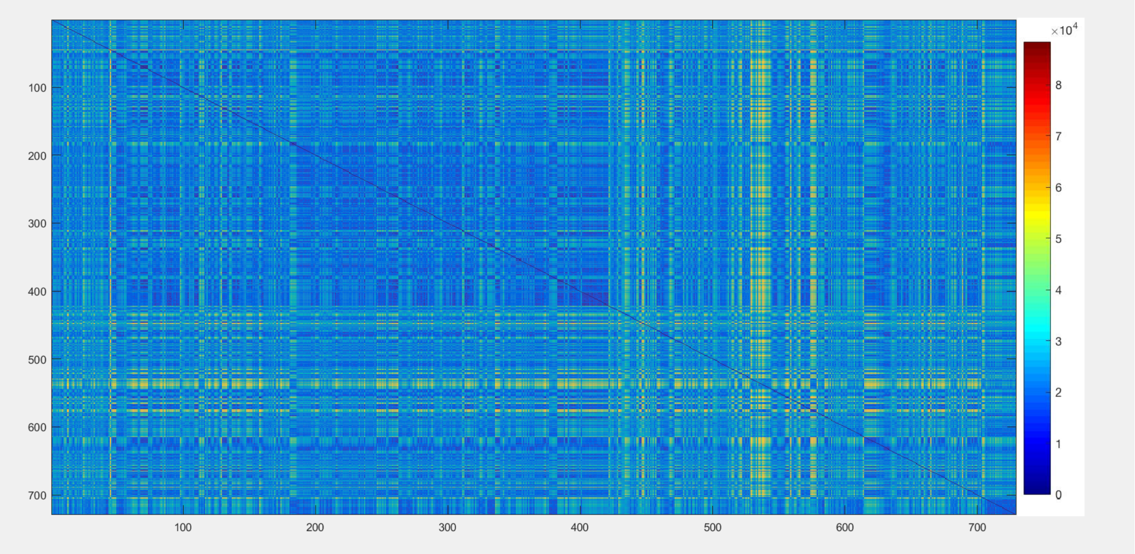


Figure 11: Euclidean distance matrix for modified Gaussian mixture model

3.4 Kullback-Leibler Divergence

Kullback-Leibler divergence (KL) distance is a measure of distance between two given probability distributions. If P and Q are two probability distributions, then the KL-divergence can be written as:

$$D_{KL}(P||Q) = H(P,Q) - H(P) \tag{1}$$

In this equation, $H(P,Q)$ is the cross entropy of the two probability distributions, and $H(P)$ is the entropy of P.
For discrete probability distributions, the KL-divergence is given as the following equation:

$$D_{KL}(P||Q) = \sum_i P(i) log \frac{P(i)}{Q(i)} \tag{2}$$

Therefore, the KL distance is a measure of the information loss in estimating probability distribution P with probability distribution Q. As you can see from equation (2) this distance is not a symmetric distance. The following figure shows the distance matrix for our data set using modified Gaussian mixture model and KL-divergence as distance metric.

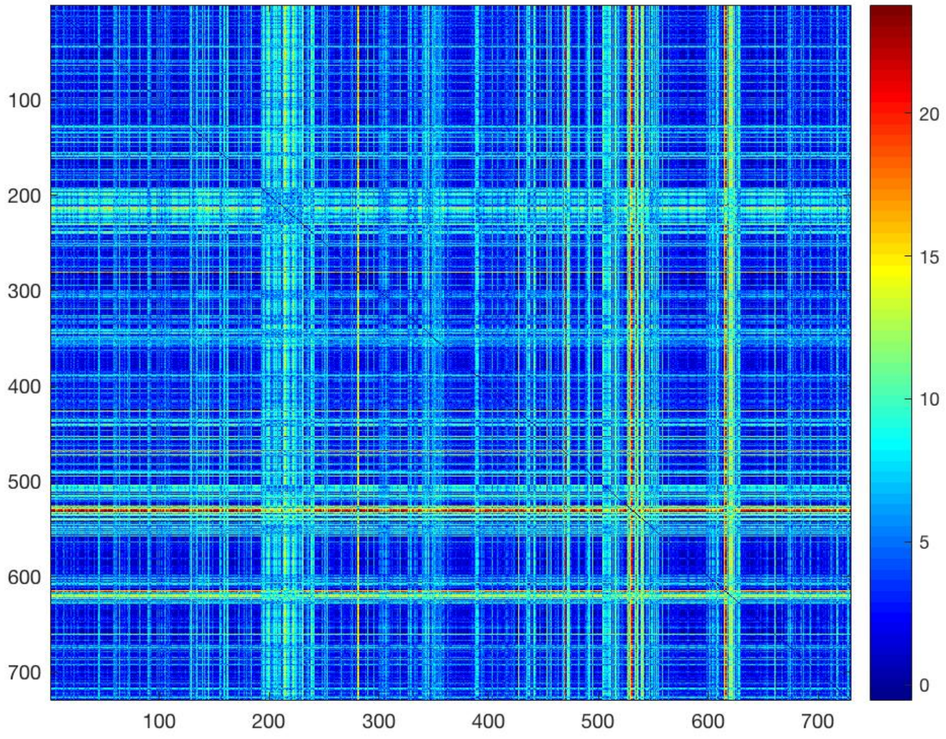


Figure 12: KL distance matrix

In this distance matrix, we can see the genre classes that we have as squares around the main diagonal of the matrix. But, there is also small distance across multiple genres. For example, we can see small distance between the songs in the classical genre and the songs in the world genre.

4 Statistical learning

In previous sections we discussed the projection of audio files into lower dimensional space. And we introduced the measure of distances we use to represent the distance between the new representations of the audio files. The next step is to build the classifier to these information for genre classification. We have implemented three classifiers that we explain here.

4.1 k-Nearest Neighbors

One of the common algorithms for classifying multi-class data is k-nearest neighbors (kNN) [7]. This algorithm simply finds the k closest data points to the testing point and determines which class owns the majority of points among these points. Therefore, the label for the testing data point would be the label of the majority of k closest data points. The following figure represents the kNN algorithm for $k = 3$. There are 2 classes in this example represented with blue and red color. The testing point is the black circle and because 2 out of 3 closest neighbors are in blue, the classifier will assign it to the blue class.

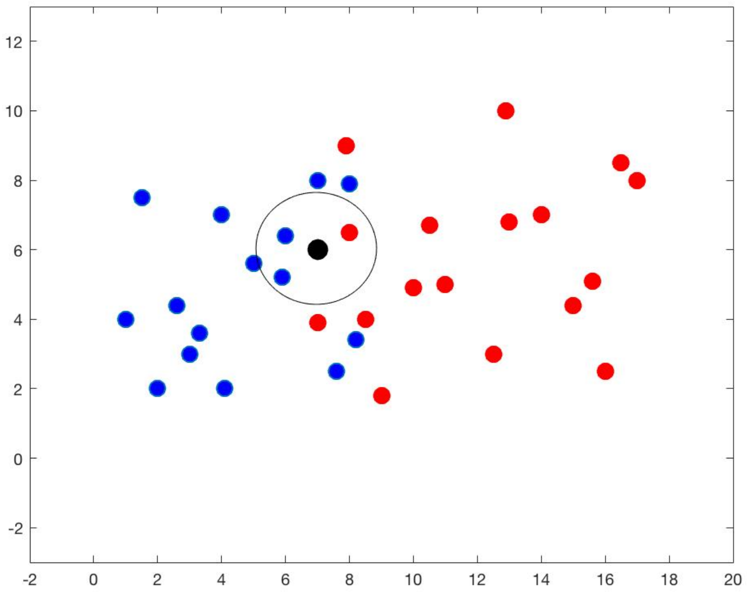


Figure 13: k-nearest neighbors

The kNN algorithm do not provide a good performance if the training data points are not distributed uniformly among the classes. In this project we are using 729 songs, which contains 320 classical, 115 electronics, 26 jazz-blues, 45 metal-punk, 101 rock-pop and 122 world genre. Therefore, 43% of all songs are classical and so, in any neighborhood it is more probable to have more data points from classical genre than any other genre. On the other hand, there are 26 jazz-blues songs which is less than 4%. Thus, the probability of classifying a song as a jazz-blues song using kNN classifier is very low. Therefore, the kNN does not provide a good performance for the data set that we are using. The major error using kNN is classifying non-classical songs as classical songs. It also has a 100% error for jazz-blues genre. In order to overcome this problem we have modified the kNN algorithm to take into account the frequency of each genre.

4.2 Modified-kNN

As we mentioned in the previous section, in order to make kNN classifier more powerful we introduced the modified kNN algorithm. In the modified-kNN classifier, we normalize the number of neighbors in each genre by the frequency of that genre (the number of training points in that genre divided by the total number of training points) in the training data. This classifier can be considered a special case of weighted-kNN, where the weights are the frequency of that genre. This algorithm improves are results for genres other than classical genre, but degrades the performance for the classical genre. And, the overall accuracy of the classifier increases.

4.3 Neural Network

Neural Network is a machine learning algorithm that is inspired by the method the brain functions when a problem is given. The large number of neurons have so many connections that it computes many combinations and gives us the most accurate answer. As in the human brain as the signal goes back and forth , similarly in the neural network used of classification we have used the feedforward-back propagation. The neural network basically consist of three different layers

- Input Layer
- Hidden Layer
- Output Layer

Below Diagram shows a basic diagram showing the layers of a Neural Network

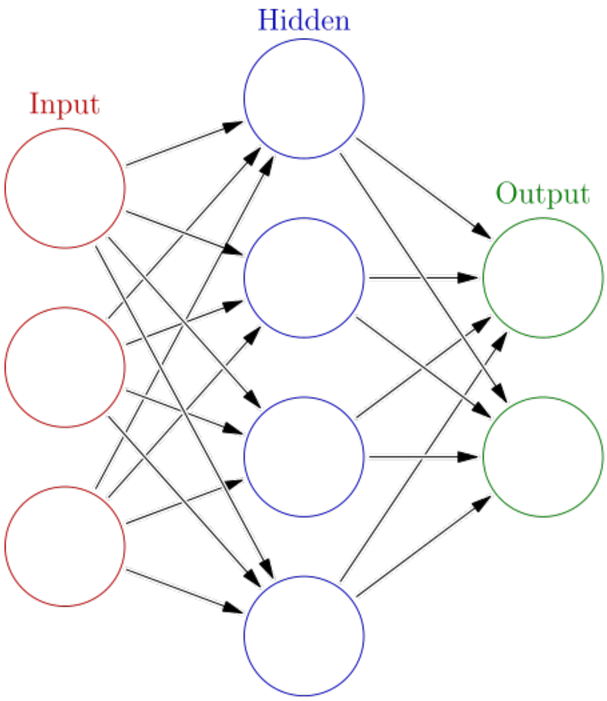


Figure 14: Sample Neural Network

The connections between the input Layer and the hidden layer have weights that are multiplied to each connection. The weights are selected as per Gaussian values i.e they are between 0 and 1. The Hidden Layer also have an active function which could be any mathematical function. For our classification we have used Levenberg-Marquardt

The neural network has three contributing factor that changes the efficiency of the output.

- Weights given to the connections
- Active Function of the hidden layer
- The Learning algorithm

The Back propagation method is the learning algorithm used, in this algorithm we calculate the error when the synoptic weights are chosen randomly and calculate back the weights. By this method the error is reduced by calculating back the synoptic weights.
The neural network used in this project is shown below

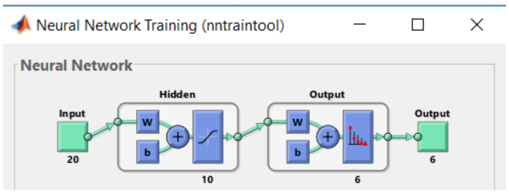
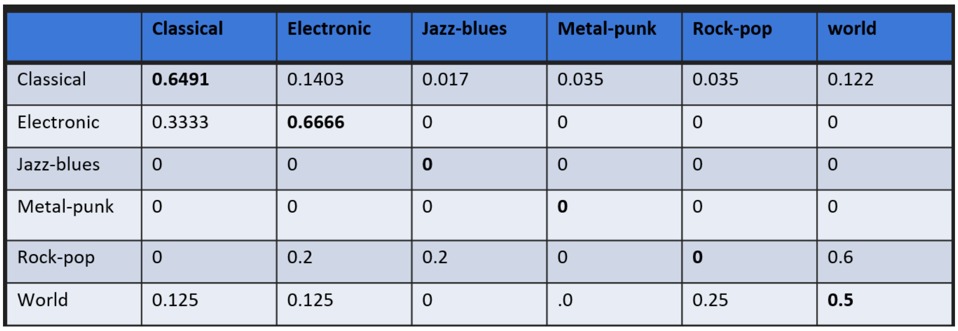


Figure 15: Neural network model

The input given is 20 features for each song and this is passed to hidden layer that contains 10 neurons and finally classifies the input to 6 genres.

5 Experiments

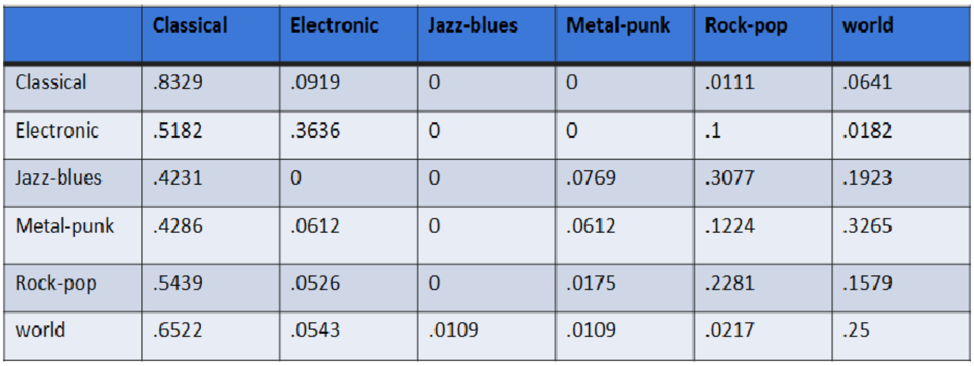
Describe the experiments, and include the confusion matrix. Discuss the influence of the various parameters, and describe how the optimal parameters were chosen. Include the computation time for your method. The general idea for genre classification is first Dimensionality Reduction, finding the distance matrix and then classifying the genres. Hence in this project we used various dimensionality reductions such as MFCC,PCA,Modified Gaussian Mixture Model and Content based similarity. Decreasing the dimension is a crucial in genre classification as it avoids dimensionality curse. In this project we tried a different set of combinations of the dimensionality reduction,distance calculation and classification methods. The distance matrix is calculated for all the methods.
The confusion matrix for all the methods are shown below. First is the result of the Signature method (content based similarity) Dimensionality reduction for which the distance is calculated through Earth mover distance method and classified into genre using KNN Classification.



	Classical	Electronic	Jazz-blues	Metal-punk	Rock-pop	world
Classical	**0.6491**	0.1403	0.017	0.035	0.035	0.122
Electronic	0.3333	**0.6666**	0	0	0	0
Jazz-blues	0	0	**0**	0	0	0
Metal-punk	0	0	0	**0**	0	0
Rock-pop	0	0.2	0.2	0	**0**	0.6
World	0.125	0.125	0	.0	0.25	**0.5**

Figure 16: Confusion Matrix for Content based similarity approach

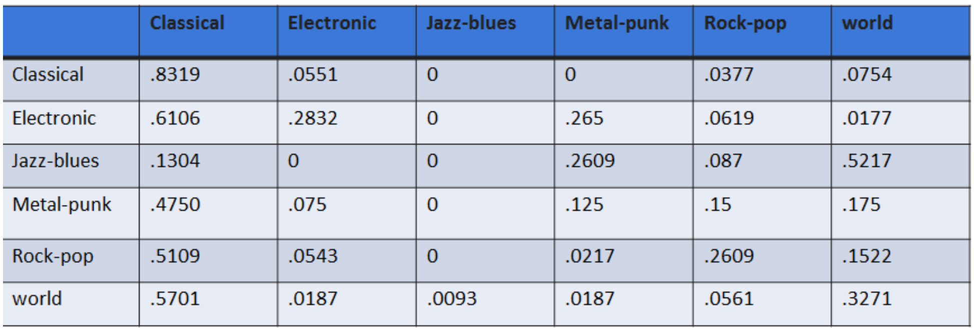
The average accuracy for this method was 54.
The second method that was performed was using Modified Gaussian mixture with euclidean distance and KNN classification.The efficiency obtained for this method is 52.



	Classical	Electronic	Jazz-blues	Metal-punk	Rock-pop	world
Classical	.8329	.0919	0	0	.0111	.0641
Electronic	.5182	.3636	0	0	.1	.0182
Jazz-blues	.4231	0	0	.0769	.3077	.1923
Metal-punk	.4286	.0612	0	.0612	.1224	.3265
Rock-pop	.5439	.0526	0	.0175	.2281	.1579
world	.6522	.0543	.0109	.0109	.0217	.25

Figure 17: Confusion Matrix for Gaussian mixture and KNN d=20

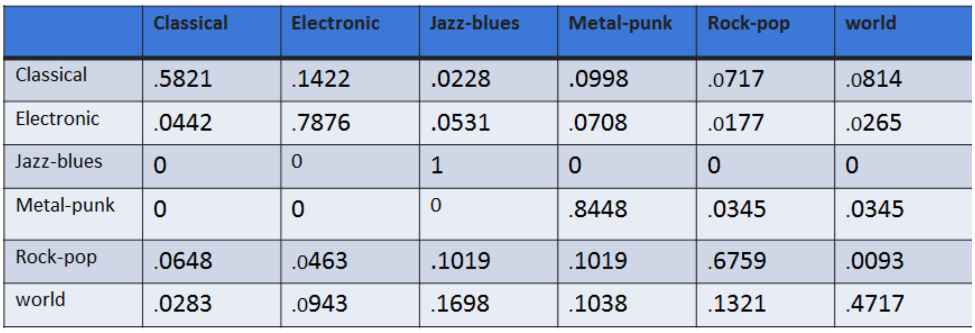
We tried increasing the dimension and performed the same methods as above we can say that the efficiency increases as the dimensions are increased. Below is the confusion matrix when d=50.



	Classical	Electronic	Jazz-blues	Metal-punk	Rock-pop	world
Classical	.8319	.0551	0	0	.0377	.0754
Electronic	.6106	.2832	0	.265	.0619	.0177
Jazz-blues	.1304	0	0	.2609	.087	.5217
Metal-punk	.4750	.075	0	.125	.15	.175
Rock-pop	.5109	.0543	0	.0217	.2609	.1522
world	.5701	.0187	.0093	.0187	.0561	.3271

Figure 18: Confusion Matrix for Gaussian mixture and KNN d=50

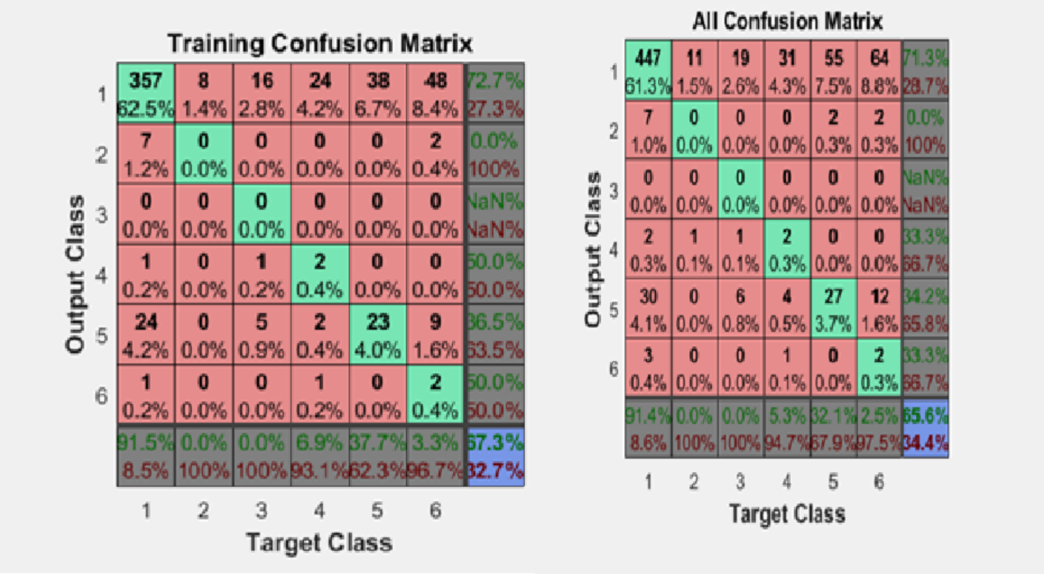
Next we changed the method by which the classification to obtain better classification of genre.Modified KNN method was used which gave better results as shown in the confusion matrix below.



	Classical	Electronic	Jazz-blues	Metal-punk	Rock-pop	world
Classical	.5821	.1422	.0228	.0998	.0717	.0814
Electronic	.0442	.7876	.0531	.0708	.0177	.0265
Jazz-blues	0	0	1	0	0	0
Metal-punk	0	0	0	.8448	.0345	.0345
Rock-pop	.0648	.0463	.1019	.1019	.6759	.0093
world	.0283	.0943	.1698	.1038	.1321	.4717

Figure 19: Confusion Matrix for Gaussian mixture and Modified KNN d=50

Finally the basic method of dimensionality reduction was implemented a(MFCC and PCA),euclidean distance and neural network method of classification was performed.



Training Confusion Matrix

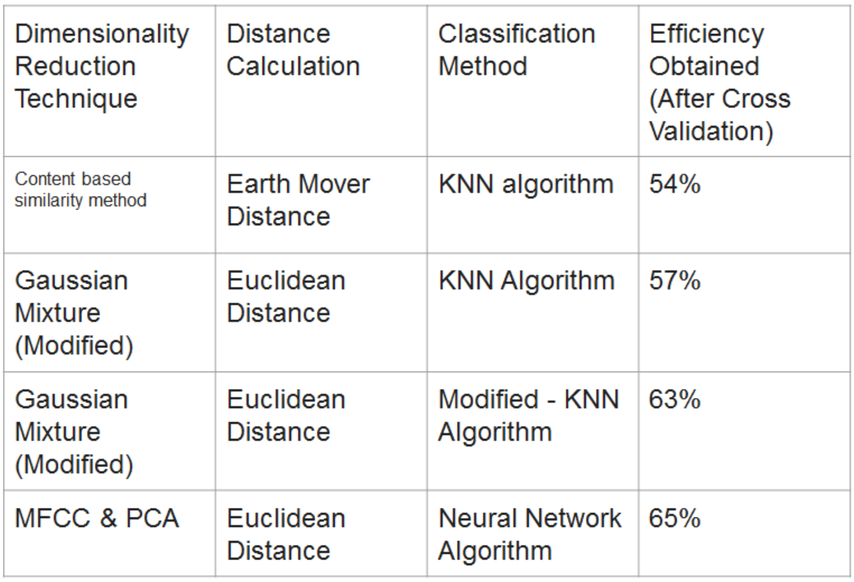
	1	2	3	4	5	6	
1	357 62.5%	8 1.4%	16 2.8%	24 4.2%	38 6.7%	48 8.4%	72.7% 27.3%
2	7 1.2%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	2 0.4%	0.0% 100%
3	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	NaN% NaN%
4	1 0.2%	0 0.0%	1 0.2%	2 0.4%	0 0.0%	0 0.0%	50.0% 50.0%
5	24 4.2%	0 0.0%	5 0.9%	2 0.4%	23 4.0%	9 1.6%	36.5% 63.5%
6	1 0.2%	0 0.0%	0 0.0%	1 0.2%	0 0.0%	2 0.4%	50.0% 50.0%
	91.5% 8.5%	0.0% 100%	0.0% 100%	6.9% 93.1%	37.7% 62.3%	3.3% 96.7%	67.3% 32.7%

All Confusion Matrix

	1	2	3	4	5	6	
1	447 61.3%	11 1.5%	19 2.6%	31 4.3%	55 7.5%	64 8.8%	71.3% 28.7%
2	7 1.0%	0 0.0%	0 0.0%	0 0.0%	2 0.3%	2 0.3%	0.0% 100%
3	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	NaN% NaN%
4	2 0.3%	1 0.1%	1 0.1%	2 0.3%	0 0.0%	0 0.0%	33.3% 66.7%
5	30 4.1%	0 0.0%	6 0.8%	4 0.5%	27 3.7%	12 1.6%	34.2% 65.8%
6	3 0.4%	0 0.0%	0 0.0%	1 0.1%	0 0.0%	2 0.3%	33.3% 66.7%
	91.4% 8.6%	0.0% 100%	0.0% 100%	5.3% 94.7%	32.1% 67.9%	2.5% 97.5%	65.6% 34.4%

Figure 20: Confusion Matrix for Neural network

The input given Below is the table that shows the combination of methods we tried and their result.



Dimensionality Reduction Technique	Distance Calculation	Classification Method	Efficiency Obtained (After Cross Validation)
Content based similarity method	Earth Mover Distance	KNN algorithm	54%
Gaussian Mixture (Modified)	Euclidean Distance	KNN Algorithm	57%
Gaussian Mixture (Modified)	Euclidean Distance	Modified - KNN Algorithm	63%
MFCC & PCA	Euclidean Distance	Neural Network Algorithm	65%

Figure 21: Summary

We could say that our algorithms for genre classification worked fairly. If we had randomly classified our input data into classical and non-classical we would have got 50% accuracy. All our algorithm gave us more than 50% efficiency with 6 genre classification. The computation time for running all,these programs were long as we had to sample and reduce dimension for 729 songs.Though Gaussian mixture model gave us the fastest results among all three.

6 Discussion

Music genre classification is a hard task. Our approach is three fold: Apply dimension reduction, calculate distance matrix and classify the data into its corresponding genres. For each stage, we experimented with different algorithms in an effort to achieve better accuracy across individual genres as well as overall accuracy.One of the important challenge that we encountered was the distribution of the data. The dataset has proportionately more classical songs than the other genres such as jazz or rock pop. This bias led to higher accuracy in classical and bad performance across another genres. As a solution we tried implementing modified k-nearest neighbours. Although, the accuracy improved from 57% to 63%, the accuracy across classical dropped while the accuracy increased across other genres.

As the next steps, we would like to try extracting features such as rhythm, modulation, amplification and other parameters instead of just the raw signal [4] [3]. In addition, we are interested in studying the performance of the algorithm across different possible distance metrics. For example: In content based similarity dimensionality reduction, we use k-Means along with euclidean distance to cluster. How would it differ if we used Kullback Leibler instead of euclidean?. With respect of neural networks we would like to try different learning algorithms such as particle swarm optimization in order to find the synaptic weights of the network [9]. Overall, the next steps would focus on improving the accuracy across genres as well as the overall accuracy.

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