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 has been a very challenging task in the field of music information retrieval (MIR) and widely used for digital music service and internet radio. You will properly define the genre classification problem, and indicate a few references to the literature. explaining the problem, the current and common methods to solve this problem. the way that we approach it, the algorithms that we use and the reason we use these algorithms. a very brief overview of the results. The organization of the paper. : Paria

2 Dimensionality Reduction

For analysis and training of our data we need to initially sample the songs . After the sampling of the given data set ,the dimension of the data set is too large to classify them into different genre. When the dimension is enormously huge the data becomes sparse as the volume increase. This is known as the curse for dimensionality. Hence a Dimensionality reduction on the sampled dataset has to be performed to classify it genre. As the dimensionality is reduced we can use different clasiification methods. There is a certain limit to which dimensionality can be reduced without loosing important data. Johnson Lindestrauss Therom provides us with the limit to which the dimension can be reduced. Johnson Lindestrauss states that considering n points in space of dimension R^n where d is really large. The Dimension of my space can be reduced to

$$k = o(logn)/\epsilon^2$$

The mutual distance between the pair of points is within the factor of $1 \pm \epsilon$. This is the minimum dimension to which the data set can be reduced without major data lost.By using this theorem we use a dxn matrice which maps the poins from R^n space to a lower dimension of dxn . when we apply Johnson Lindestrauss to our current data set of 729 songs sample in space , we get that the minimum dimension to which we can reduce the dimensionality is 79.

2.1 mfcc

The First dimensionality reduction technqiue that we used in MFCC (Mel Frequency Cepstrum Coefficient). In Mel Frequency Ceptrum the frequency bands are equally spaced in mel space which is approximated by the human auditory system clearly,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.

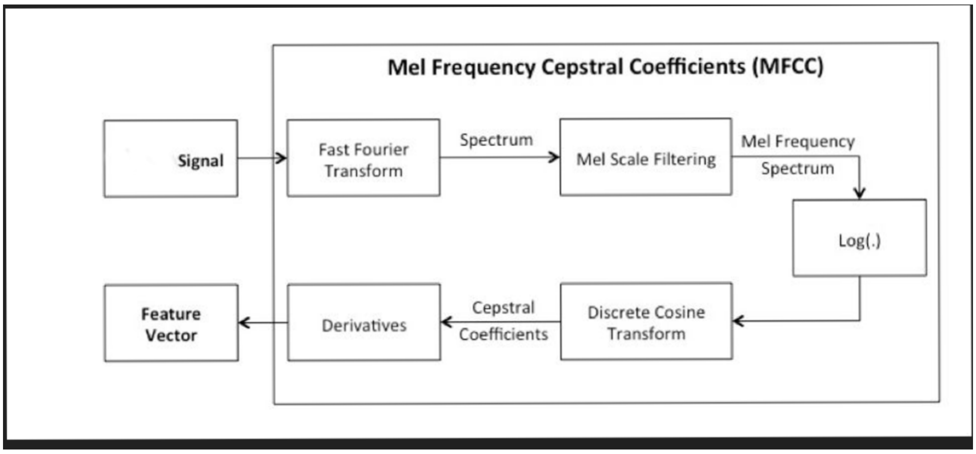


Figure 1: mfcc algorithm

In the above figure as shown after the signal is sampled , first the fourier transformation is performed and the spectrum obtained is passed through the Mel Scale Filter. The output that we obtain is the Mel Frequency spectrum. The log of the result is taken and a discrete Fourier transform is applied to the signal the result of this is the Mel Frequency Coefficient. After performing the MFCC we have the signal saperated into different slots and each slots contain a the feature vectors. As suggested by johnson Lindestrauss we have taken 79 features per slot.The number of slots changes acoording to the length of the song.

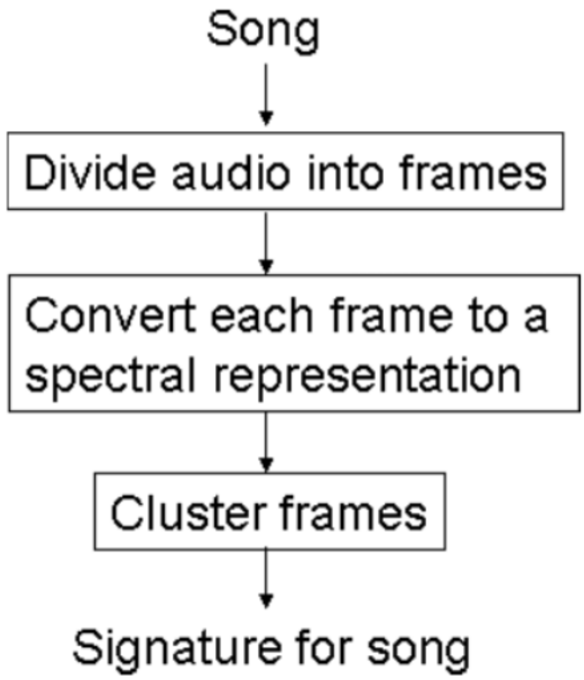
2.2 PCA

Sahana

2.3 Content based similarity

Beth and Ariel(**??**) 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 setup is to divide the audio into frames. Then, each frame is converted into its corresponding spectral representation. In order to generate the spectral representation we make 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.



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

Figure 2: Content based similarity method

2.3.1 Johnson-Lindenstrauss

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. 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.

2.3.2 k-Means

Once each frame is clustered into its corresponding we 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 which makes use of supervised labels during the training phase in order to cluster the points. 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 (2.3.2):

$$\arg\min_{\mathbf{S}} \sum_{i=1}^{k} \sum_{\mathbf{x} \in S_i} \left\| \mathbf{x} - \boldsymbol{\mu}_i \right\|^2$$

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 Modified Gaussian Mixture

Paria

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 (??).

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 4: Minowski distance

3.2 Earth Movers distance

Abhijit

3.3 Euclidean distance

Paria

3.4 Kullback-xLeibler 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 (**??**) 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.

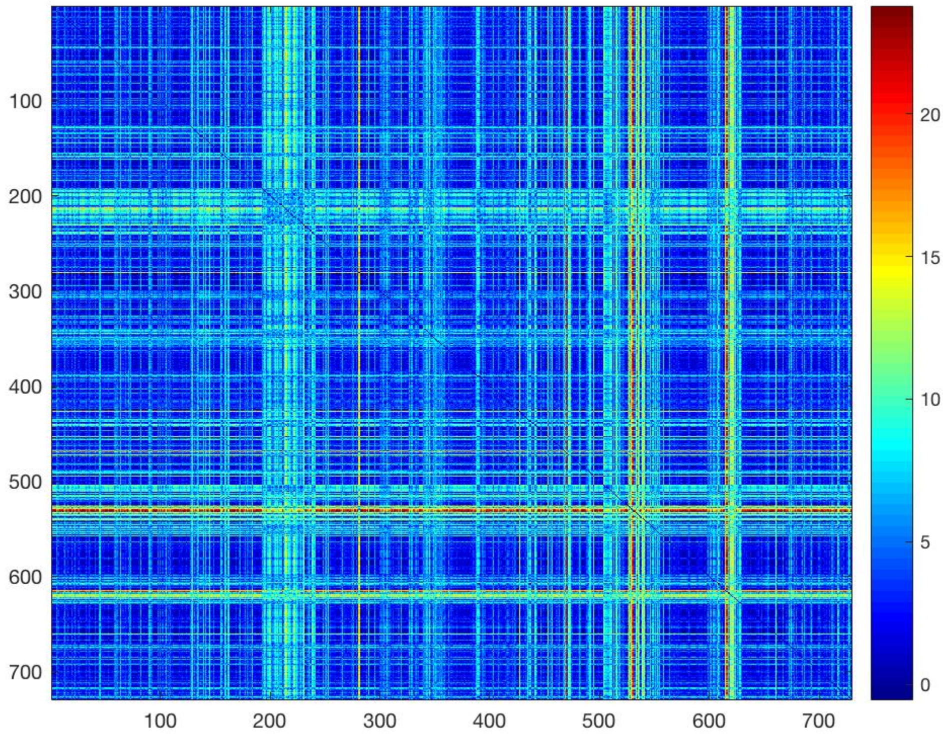


Figure 5: KL distance matrix

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 Statiscal 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). 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.

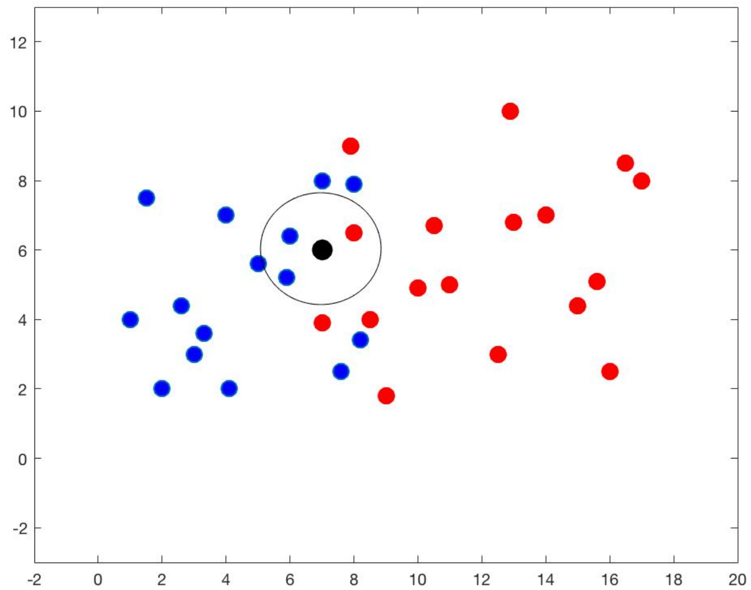


Figure 6: k-nearest neighbors

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

Sahana

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. : Sahana

6 Discussion

Provide a critique of the approach and discuss any potential improvement. Discuss the ability of your approach to classify non-classical into the five remaining genres. Abhijit

References

[1] Logan, B., Salomon, A. (2001). A content-based music similarity function. Cambridge Research Labs-Tech Report.