Abstract — The shuffle mode, where songs are played in a randomized order that is decided upon for all tracks at once, is widely found and known to exist in music player systems. There are only few music enthusiasts who use this mode since it either is too random to suit their mood or it keeps on repeating the same list every time. In this paper, we propose to build a convolutional deep belief network (CDBN) that is trained to perform genre recognition based on audio features retrieved from the records of the Million Song Dataset. The learnt parameters shall be used to initialize a multi-layer perceptron which takes extracted features of user’s playlist as input alongside the metadata to classify to various categories. These categories will be shuffled retrospectively based on the metadata to autonomously provide with a list that is efficacious in playing songs that are desired by humans in normal conditions.

Keywords—convolutional deep belief network (CDBN); million song dataset (msd);

I. INTRODUCTION

With rapid advancement in music technology and Music Information Retrieval [1, 2, 3], it has been found that people follow a pattern, unique to them in a certain way which develops their taste for certain type of music and that this pattern might vary with the environment or the time of the day for a person. Yet there has not been any rule or formula to understand this pattern. Also, the availability of user preferences is limited (e.g. for new, unknown artists or type of song) with respect to the surrounding environment. Many users may be very picky, who like listening to their well-organized playlist. They might spend hours altogether to organize their playlist. Few might not be so fussy. A simple playlist, filled with randomly chosen songs can be satisfactory for them. The shuffle mode where songs are played in a randomized order that is decided upon for all tracks at once, is widely found and known to exist in music player applications, but used by only such few. The reason many listeners don’t use it, either because this randomized playlist doesn’t suit their mood or it is prone to repeat the same list every day.

Inspired by the observations described herein, a deep learning based model to produce a shuffled playlist from previously experienced patterns such that it suits the listeners needs and yet produces a seemingly random list, is proposed in this paper.

The main aim of the model is to understand the music preferences of the user based on the metadata (Time, Music tags) and the information retrieved from the played audio files and correspondingly assign tags that group them based on their properties. These groups then will be used depending on the current environment to autonomously shuffle songs within and give the user a good listening experience.

The paper follows the following pattern: Section II is the Literature Review, Section III provides the overall workflow of the proposed system. It gives a brief description of the approach that shall be used. Section IV provides conclusion and future scope of the paper. Discussion is provided in Section V. Section VI includes all the references that were studied to write this paper.

II. LITERATURE REVIEW

A. Fisher-Yates Shuffle Algorithm

The original Fisher-Yate’s algorithm for randomness was presented in the book “Statistical tables for biological, agricultural and medical research” [6]. Later the algorithm found its popularity in many fields including the music shuffle that has been established and appears as a functionality in many music applications till date. In order to maintain the randomness of the songs with an approach to list them based on user preferences, we shall be using the algorithm in a restricted domain.
B. Million Song Dataset

Million Song Dataset (MSD) [7] is a compilation of all the information that is available through The Echo Nest API for one million popular songs. Metadata available includes artist and album information and the year of the performance. Musical information extracted directly from the audio signal includes the key, the duration and the time segments. Apart from that some other derived features like “Loudness”, “Tempo”, “Beats Confidence” and user assigned tags are also provided.

The dataset shall provide us with the necessary features for a spectrogram representation of the audio data. Since it has about a million popular songs, it will suffice the training of the Deep Belief Network.

C. Random Forest Selection

Feature Selection is an important step before doing the classification because an audio file contains many features and all the features are not necessary to do the classification. So, selecting the most relevant features which would contribute the most to the classification task is our first step. Here, we propose to use Random forest algorithm for selecting the features because it creates a lot of decision trees each for a distinct random combination of features. For each combination of features, a misclassification rate is calculated. The set of features which gives the least rate is selected by Random Forest algorithm [8] as most relevant. By using the most relevant features we can get almost the same accuracy as with all the features.

The steps involved in Random forest algorithm is as follows:

- Bagging (Bootstrap Aggregating): Select 2/3 dataset for training sample.
- Attribute Bagging: Randomly select “n” features from total “m” features, where n << m (n = \sqrt{m})
- Decision tree formation:
  a) Information gain
  b) Gain ratio
  c) Gini index
- Confusion Matrix: Figure 1 is a schematic representation of the matrix that gets generated.

\[ \frac{(FP + FN)}{Total} \]

(FP + FN)/Total

representation of the matrix that gets generated.

- Misclassification Rate is calculated as
- Repeat steps 2 to 5 for “k” iterations.
- The set of features which gives least misclassification rate are selected as most relevant.

D. Deep Belief Networks

Neural Networks are used to learn more abstract data, to form a pattern, layer by layer. These learnt layers of data are used later in supervised tasks such as classification and regression of data. Unfortunately, it is really complex to train these networks using gradient descent. It is highly probable that during backpropagation, these neural networks lead to “Local Minima”. The deep belief networks (DBNs) overcome this problem by going through a greedy layer-wise training phase [9, 10]. This phase leads to an error rate which is mostly optimal. Using back propagation, the error rate is slowly reduced later.

Deep Belief Networks can be considered to be a bunch of Restricted Boltzmann Machines aligned one above the other. A RBM can be represented as a visible layer or input layer of neurons, each connected fully to neurons of a hidden layer. A visual representation of a DBN is shown in Figure 2. They are useful for tasks requiring dimensionality reduction followed by classification or regression. We stack these RBMs on top of each other such that the hidden layer of one RBM is followed by the perceptible layer of the next RBM. We use DBNs here mainly because of its ability to learn the representations of abstract data with optimal and minimal errors and to use them later in a supervised model for classification.
Using Deep learning methods for generation of a personalized list of shuffled songs

E. Related Works

- Honglak Lee (2009) gave a good analysis of various results for music artist classification which showed CDBN bases trained on the audio files gave a better result compared to other methods [10].
- Later Philippe Hamel and Douglas Eck (2010) presented a system that could automatically extract relevant features from the audio for a given task. No research on User based automation was performed [11].
- A predictive shuffling algorithm was proposed [12]. The algorithm took temperature like genre, artist, play duration and release date into consideration to predict the next shuffle song. It required all the metadata to work successfully.
- There have been quite some online music recommendation systems which are primarily based on collaborative filtering [13]. To resolve the cold start problem issue, Spotify has started analyzing raw audio models which also takes into consideration new songs. They use audio features like key, mode, tempo, time signature and loudness which helps in understanding fundamental similarities through which user can enjoy songs based on his own history.
- A music streaming and recommendation service, Pandora fundamentally relies on the inherent qualities of the music. Instead of recommending based on social factors it finds similar music in terms of melody, harmony, lyrics, vocal characters etc. This quality of Pandora makes it immune to the cold-start problem [14].

III. PROPOSED APPROACH

A systematic workflow of the proposed system that we shall be executing is shown in Figure 3. We will be using the Theano2 python library to build and train the models.

- **Acquiring Subset of Million Song Dataset**
  The MSD will be used to create a subset of dataset which will contain data of songs with all the features extracted from it. This dataset will be used as an input in the next step, i.e. for selecting the most relevant features using Random Forest Algorithm.

- **Feature Selection**
  The million song dataset consists of a lot of features directly extracted from a lot of segments of the same audio file. Since all the features might not be relevant for generating a spectrogram for the audio file, it is necessary that the most useful features are segregated and used for the generation.
  In order to do that, Random Forest selection shall be performed. Based on the analysis done by Philippe Hamel and Douglas Eck [11], we can ensure the subsets formed after selection shall be optimal for further use.

- **Pre-classification using Convolutional Deep Belief Networks**
  Convolutional deep belief networks will be applied to unlabeled auditory information(music) and later we will assess the learned feature representations on several tasks like audio classification. For the task of genre classification, the initial and second-layer CDBN representations will be trained on an unlabeled collection of music data.
  The initial step here will be training the layers of CDBN on unlabeled list of records obtained from the MSD. In order to do that, spectrogram representations for each song shall be generated from the features selected using the above random forest algorithm followed by PCA- whitening before feeding it to the CDBN.[4, 5] The training will consist of segregating the records into groups. Following the training, the obtained parameters will be used in the MLP.
  For evaluation of the CDBN model, a subset2 will be generated from the labeled dataset extracted from the MSD.
  - The subset in total will consist of 10 common genres that are included in the MSD namely Folk, Metal, Jazz, World, Rock and Pop, Rap, Soul, classical, techno and classical. For each genre approximately 1000 tracks each will be chosen.

- **Feature Extraction from Audio for Personalised Training**
  For feature extraction from audio we will be using an open-source library named pyAudioAnalysis. It provides a us with various sound analysis methods, one of which is feature extraction. The source code for pyAudioAnalysis is available on GitHub and licensed under Apache License.
  Once we get the list of relevant features from the Random Forest Algorithm, we can extract those features from the user’s music directory using the pyAudioAnalysis library of Python.

Figure 3: Workflow

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1. [http://deeplearning.net/software/theano/](http://deeplearning.net/software/theano/)
2. The subset will have a conventional three-fold distribution of 80%, 10%, 10% for training, evaluation and testing respectively.
E. Classification of user specific audio

As mentioned earlier, we will use the weights of the connections and biases of the hidden layers of the CDBN to initialize the Multi-Layer Perceptron. The properties that are relevant for certain genres are expected to be in the form of these biases at this step.

After adding a logistic regression layer the MLP shall be trained with backpropagation method for the further classification task [13].

Classification shall take place with the input being the features extracted in the previous step along with the metadata (like Time and music tags) of the user.

F. Shuffling of songs

The most important part of the process is to make the song list to appear random to the user. To achieve this, we shall be considering the time of the day as the surrounding environment feature and correspondingly choosing the group with similar metadata. This cluster shall be shuffled using the Fisher-Yates algorithm [6] to generate a playlist for the user at that time of the day.

IV. RESULTS AND CONCLUSION

A predictive shuffling algorithm based on Deep Belief Networks has been proposed for an individual’s music library. The algorithm tends to shuffle the user’s collection based on the metadata collected and the featured groups so that it suits the listening preferences of the user. This is established by extracting the relevant features from the user’s music playlist and the time of the day the user prefers the songs to be played. Further it uses these features to classify into groups based on the similarity of metadata and user’s preferences.

The effectiveness of the algorithm shall be obtained by analyzing individual user’s music collection and their feedback on how does the algorithm help them organize it based on their preferences. Statistical approach, the comparison of proportions where the improvements are needed.

V. FUTURE WORK AND DISCUSSION

The proposed algorithm once developed to its full potential shall revolutionize the music information retrieval industry for the simple fact that it will allow the software models to perform recommendation or predictions offline on a pretrained model thus reducing the computation power needed on the cloud servers. Also, it will help users use their time productively instead of spending time organizing a playlist according to their preferences. One significant factor that would affect the execution of the algorithm shall be the availability of the audio segments from the MSD to perform certain statistical corrections if needed. An open access to the audio file segments in the future may encourage further research in this field of music automation.

We also plan on approaching this problem of shuffling using different methods involving overall spectrogram analysis and user assigned tags only without any feature selection.

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