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A Systematic Review of Machine Learning state of the art in Guitar Playing and Learning

[1]Nipun Sharma, [2]Swati Sharma
[1] Assistant Professor, ECE, Presidency University, Bangalore.
[2] Associate Professor, CSE, Presidency University, Bangalore
[1]Presidency University, Bangalore, India

Abstract: Music Recommendation Systems (MRS) for Guitar Learning have gained traction and popularity during pandemic times and aids in both self-learning and remote learning. The research area gained immense importance because of the changed learning and instructing paradigm during Covid-19 pandemic. Moreover, guitar is one of the toughest instruments to play and growing number of guitar learners, makes system design for guitar learning a very targeted and viable research area. This paper covers development of music recommendation system for guitar learning and guitar playing. The state-of-the-art development shows that many facets of guitar playing and learning are being explored for creating recommender systems and interactive systems. This knowledge makes the guitar playing more flavourful and effortless for users and will aid in developing machine learning based interactive recommender systems for developers.

Keywords: Interactive Systems, Music Recommendation System, Guitar-learning, Machine-learning, Guitar-chords.

Introduction

During the period of Covid-19 Global Pandemic from March 2020 to present day, the paradigm of teaching and learning has shifted drastically. Online and automated teaching methodologies have emerged and evolved in parabolic growth trend. Some of the Teaching or Learning systems employ humans' interactions complimented with advanced teaching aids like 3-D animations and smart boards. However, some self-paced learning systems are completely automated and they work with user's input and then predicting the recommendations in learning. These intelligent recommendation systems cater to wide variety of skills such as imaging, photography, painting, web-designing, soft computing, game developments and music. Machine Learning has played an important role in designing state of the art recommendation systems for learning a skill or rather more precisely to master a skill. With majority of the students acquiring skills from the internet; the online space is thronged with all sorts of teaching applications for users of all age groups and skill sets.
It is said that music is the food for soul so a good and robust Recommendation System for Music has a daunting task at hand. The task of designing a successful Music Recognition and Recommendation system involves a multi layered series of tasks at different stages, that include music notes analysis and synthesizing them for the recommendation system, audio note representation, models used to analyse these recognition tasks and predicting recommendations based on user input [1][2].
Recommender systems have evolved exponentially over the last decade. They are used in multitude of applications. All big enterprises use recommender systems to some extent for increasing their business outreach and customer retention. Spotify, Amazon, Netflix, IMDB use recommender systems for enriching customer experience, whereas applications like Yousion apply these systems for incremental learning. Recommender system design is based on two primary approaches viz:

- Collaborative filtering methods: This method is sub-categorized as model based and memory based. In model-based approach the interaction matrix is used for learning, user and item representations, on the basis of which a model is defined. However, in memory-based approach, no model is defined, rather utilizes similarities between users and/or items.
- Content based methods: This method is based on user and/or item representations. Model is defined for user item interactions.

- Hybrid method takes both the approaches of content based and collaborative filtering into account.

However, with the recent developmental advancements the recommender techniques have incorporated many other approaches which are summarized in the Figure 1

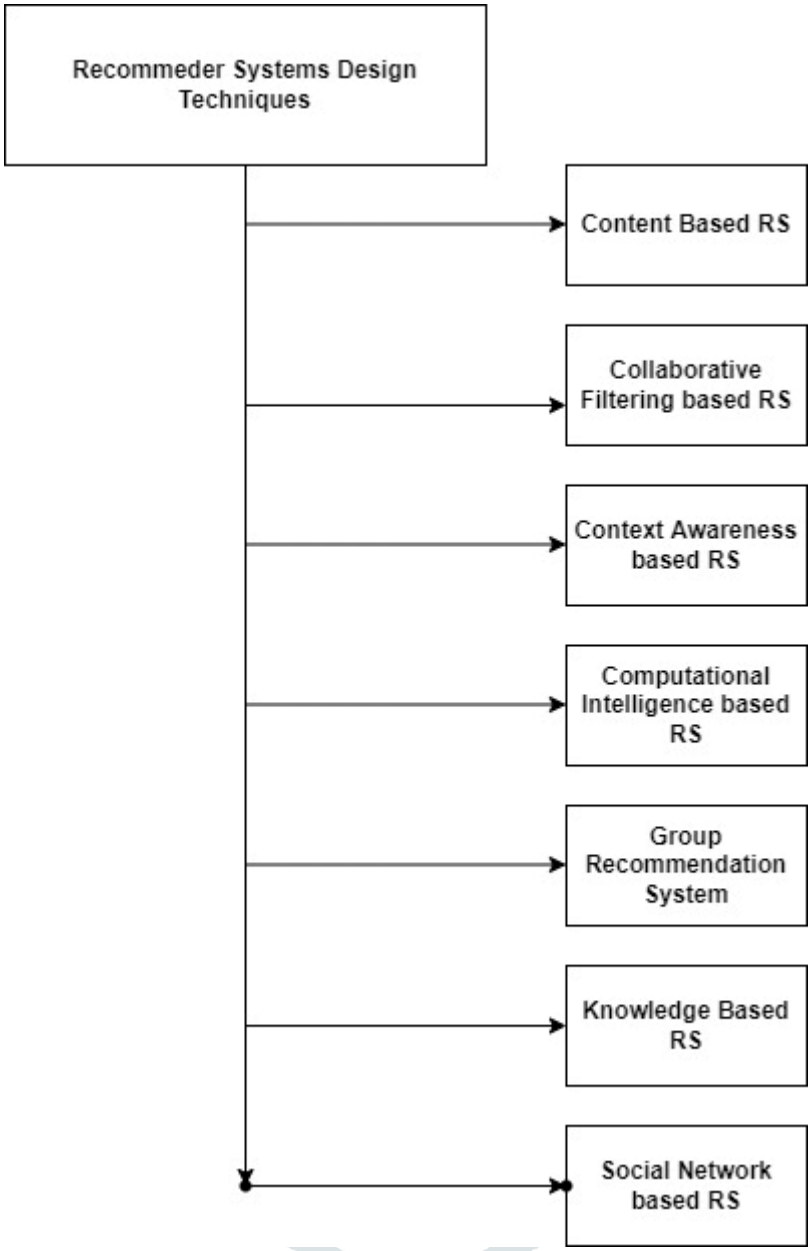

Figure 1 Summary of types of recommender system techniques [3]

A basic recommendation system is a subclass of information filtering system that predicts the choice or preference a user would give to an item. With networks aiming at becoming more and more efficient in becoming heterogeneous in nature to handle multimedia data [4] and aiming at becoming more efficient in throughput [5]; music, videos and movies find their way into mainstream recommendation system design. Streaming heavy content will no longer be a constraint considering phenomenal developments in efficient energy harvesting of energy [6]. Also, a recommendation system may also provide the best option out of all the possible outcomes based on a set of features fed to a machine learning algorithm. The purpose is to suggest the most relevant item to the user. Music recommendation system in particular might suggest instrument specific arrangement to the user in case of learning, song selection belonging to a particular to a particular genre in case of listening to music and infinite number of possible recommendations depending on feature set and the objective of the system designed. A general block diagram of Recommendation system and most popular tools used during each stage is shown in Figure 2

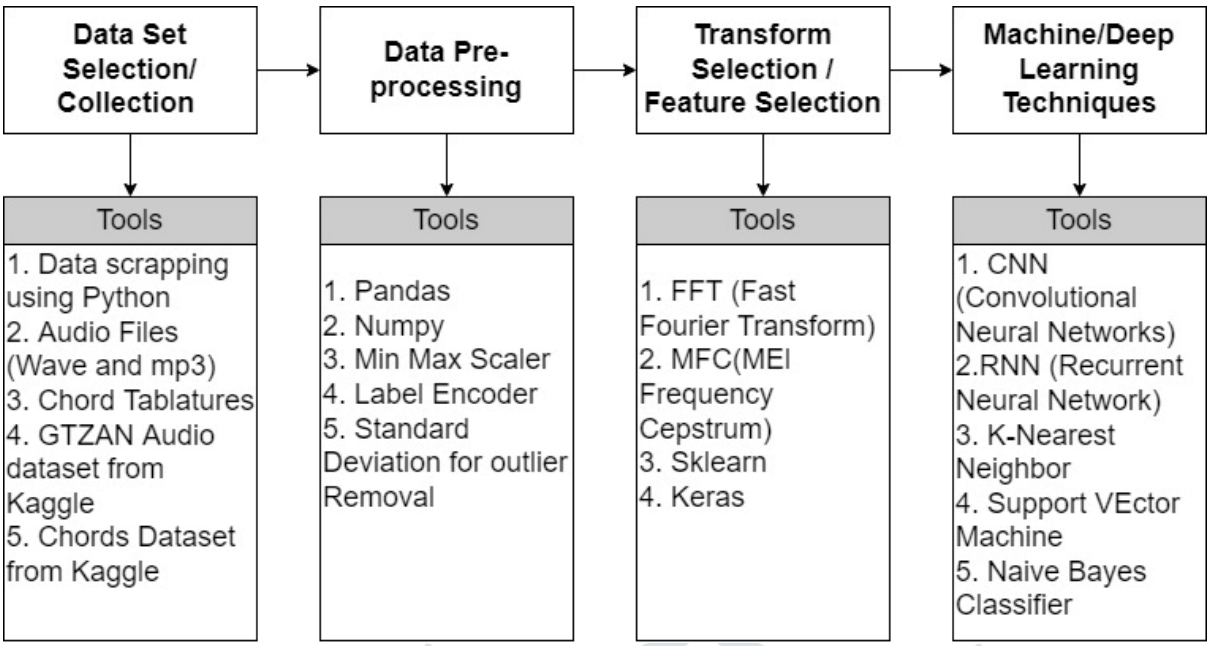

Figure 2 General Block diagram of Recommendation Systems and Tools involved

Systematic Survey of State of the Art

Learning a new musical instrument is a challenging task. Music is a universal phenomenon not bounded by geographies; music learning facilitates people around the globe. Guitar is a string instrument with varying number of strings and is considered one of the toughest [7-8] instruments to play, involving numerous techniques like chords playing, fingerstyle and riffs. Breakthrough systems to assist Indian classical singers [9], system assisting Drum players [10], system assisting music theory learning by understanding music document layout [11], developing datasheets for tablatures of acoustic guitar [12] are utilizing machine learning at their design core. Although music recommendation systems also cater to variety of other applications such as development of software and applications to motivate people for exercising based upon their music preferences [13]. However, guitar being a string instrument features in the list of tough instruments to learn and play. Learning guitar is a multi-faceted activity. The popularity of guitar among musical instruments is paramount. It is however a very difficult instrument for beginners and that is the reason why most beginner guitar learners quit within the first month of learning. The need for learning tools become more important in such cases. Music Recommendation Systems (MRS) developed over the last decade [14], [15], especially focusing on learning guitar have made significant progress. The MRS designed to assist guitar learning span wide aspects of guitar playing. A knowledge repository of MRS devoted to guitar learning suggests that a huge potential of guitar playing aspects can be worked upon. Recommendation systems in the field of audio and music have come a long way and has spanned a much wider variety of applications than anticipated. In this paper, available MRS for aiding Guitar Learning are discussed. All these systems cater to a specific outcome of learning viz, guitar chords, guitar playing techniques, guitar rendition, chord progression etc.

Research in this specific domain can be tracked from earlier system using Augmented Reality (AR) display [16]. The system is helpful in assisting the guitar player by tracking the pose and position of holding the guitar and then presenting a visual guide that may support corrections. The design of support system is an efficient example of using Marker and edge-based tracking in AR for teaching guitars to beginners. Once the guitar player is familiar with holding guitar perfectly, the next stage is to assist the guitar player in chord recognition with greater clarity and decreased level of abstraction. The system in [17] incorporated deep networks consisting of several convolutional layers with Affine layer, 6D-Softmax Layer and Radial Basis Function (RBF) Layer to produce guitar tablature, where the input is music audio and output is human readable chord representation notation that can be widely and easily comprehended by the masses.

Guitar Strumming Teaching system developed in [18], known as strummer is an interactive guitar chord practice system for training musical chords using the data driven approach. The system determines the difficulty of transition from one chord to the other. As there are 180 different types of chords so manually assigning difficulty level for each permutation and combination of transition is not possible. So, linear

regression model is applied to find the difficulty of transition which is mapped to difficulty level on 5 – Likert scale (1: easiest and 5: difficult). The work in [19] proposes a novel representation which collaborates VAE (Variational Auto Encoder) with GP (Gaussian Process) subsequently denoted as GP-VAE. Database is classified into seven playing techniques named as: normal, muting, vibrato, pull off, hammer-on, sliding and bending. Each technique has 1000 epochs. Proposed GP-VAE is claimed to be beneficial for a class relevant discriminative task.

An interesting system development illustrated in [20] estimates the guitar string, fret and plucking position. It uses parametric pitch estimation to extract the location where the hands are interacting with the fretboard of guitar and string. The system uses feature set of three parameters and these parameters are estimated with Non-linear Least Squares (NLS) pitch estimators. String model is developed by modelling string displacement, activated by plucking. String is modelled with an initial deflection excited at plucking position by the plucking hand with an edge sharp pick at a fraction of the length. Electrical transducer has been employed to measure displacement. The observed signal is modelled in vector matrix notation. Least square method is used to estimate the amplitudes and the estimated amplitude vector is used to further estimate the plucking position. The proposed method starts with detecting the onset event followed by extraction of one segment. As for plucking position estimation, log spectral (LS) distance is minimized between observation and the model. It uses recorded data at 44.1 KHz which consists of electric and acoustic guitar recordings specific to their string and fret combination. Further classifier is trained on 9360 recordings. Through the obtained confusion matrices, very low error rate is obtained for acoustic guitar while electric guitar shows average error rate of 3% which lies in the range of 1 to 3 percent. Finally plucking position estimation is done on two 12 second recordings of electric guitar.

The chord recognition system proposed in [21] uses a transform domain approach using Discrete Sine Transform (DST). Its aim is to investigate the influence of sampling frequencies which do not follow Shannon sampling theorem. This system proposes the input as an isolated wave format of recorded chord signal. The said chord signals are recorded employing sampling frequencies from 2500 Hz to 78Hz. Normalization of input signal data has been done to correct variation on its maximum absolute value. After normalisation, silence area and transition removal has been done on the left side of the signal data. Various operations such as frame blocking and windowing are performed. Quasi Harmonic Product Spectrum (QHPS) is used for eliminating unwanted harmonic signals. Significant local peak's appearance is increased by logarithmic scaling. Further ten feature extractions are obtained through a total of ten samples per chord, which are then averaged to obtained a reference feature extraction for each chord. All seven chords are recorded ten times to obtain 70 test chords. It is observed that no influence on recognition rates for values above 95 percent is observed for a sampling frequency range of 2500Hz to 156 Hz. However, lowest sampling frequency of 156 Hz and shortest feature extraction length of 16 points are obtained. Also, it is noticed that sampling frequency below 625Hz do not follow Shannon sampling theorem where Least frame blocking length of 128 points and feature extraction length of 16 points are used.

The Guitar Ontology system in [22], a goal-oriented form of description is employed with a focus on classical guitar. Usage of OWL (Ontology Web Language) has significantly enhanced machine readability and machine processability. It describes an annotation method that integrated data between the ontology and score information. Guitar rendition ontology for teaching and learning support of classical has been developed, action processes are focussed upon to explain the concept which are classified according to purposes related to sound such as timber, articulation, percussion etc. Further properties such as primary action and conditional action have been explored to define the action processes on the basis of which the concepts are explained. Finally, a method is presented that annotates the ontology knowledge onto musical structures. It aims to bridge the gap between humans understanding of rendition knowledge and computer processing in order to build and develop an interactive and knowledge intensive system.

The system in [23] determines a correct chord label by observing 'altered' notes. The allocated notes are often reduced, increased and changed to other notes in real musical concerts and compositions. As a result of omitting, inversions and tension voicing, the allocation of notes is not the same as the definition of chords. The system aims to provide solution to such discrepancies by constructing and applying a searching tree for chord labels and chord progressions database. Though the estimation accuracy changes with played guitar, which is addressed by investigating the difference in electric guitars. Chroma vectors representing the power of all pitch classes are generated from the sounds of an electric guitar. Further, the chord label is estimated by calculating a logical AND operation between results from the search tree and the chord progression database. Finally, the average chord label estimation accuracy is obtained on each guitar from guitar number 1 to guitar number 4. It suggests the effectiveness of cutting high frequency components in order to reduce the influence of difference in electric guitars. The systems' average accuracy is around 40%.

Guitar Playing Technique (GPT) classification is yet another interesting area of research that involves various GPTs like normal, muting, vibrato, sliding, hammer-on, pull offs and bending. The system in [24] endeavours to automatically segregate GPTs. Spectral Temporal Receptive Field (STRF) based scale and rate descriptor constructed system identifies GPTs which results in very high recognition rates. It shows improvement as high as 11.47 and 13.32 percent in average F-scores in the baseline and Deep Belief Network (DBN) baseline respectively. GPT classification system results in an average F-score of 80.23 percent with the split signal and 96.82 percent with the complete signal.

In the system presented in [25], the generation of chord progression from symbolic representation as a prediction problem is formulated. Neural attention mechanism has been incorporated to investigate the overall performance of the system. In order to generate candidate chords from chord progression sequences, a Long Short-Term Memory (LSTM) based neural network is employed, along with a multi modal interface deploying a Kinect device. A total of 560 unique chords are present in the data set presented in Mc-Gill Billboard datasets containing chord sequences of all weekly number 1 billboard hits between 1958-1992. Three different architectures are deployed viz the baseline, the baseline utilizing a switch mechanism and the attention utilizing architecture in the interactive environment using *tensorflow* framework. The results obtained with the use of LSTM based architecture exploiting attention modules are found to be relatively satisfying only with regard to short term prediction ability. It is also observed that the use of neural attention mechanism in the chord generator significantly increased the variety of chords offered.

An interesting work is observed in the paper [26] that illustrates the dynamic generation of fingerings on the basis of user configurable parameters, thus can accommodate novel chords, unusual number of strings and frets besides disability or medical condition of the user. *Combino-chord* app is divided into two packages namely domain and User Interface (UI). Domain package has core chord fingering functionality whereas UI package further has seven fragments namely home, guitar, tuning, hand, chord, advance and about. The tests were run on a hex core processor AMD X-86-64 processor at 2.8 GHz. Averages and standard deviation are computed over major and minor chords in all scales. For guitars with extended fretboards, only first 12-14 frets are considered to speed up the search time. The summary of all the key points of the above discussed papers is presented below in Table 1 for a clearer comprehension.

Table 1 Overview of Discussed research articles

Reference	Year	Knowledge Acquisition Process/Dataset	Framework/Platform	Task Performed/Expected Output
[16]	**2006**	USB camera and a display connected to a PC	**Augmented Reality, Vision Marker model-based tracking**	Guitar Playing (Holding Frets and strings)
[17]	**2014**	475 Music recordings consisting of 181 songs from Christopher Harte's Beatles dataset* 100 songs from the RWC pop dataset 194 songs from the US pop dataset 200 tracks from Mc-Gill Billboard Data set with 560 unique chords. [27]	**Deep Networks with convolutional layers, AFFINE layers, 6D softmax layer, RBF layer**	Guitar Chord Recognition (Representation Learning)
[18]	**2017**	Mc-Gill Billboard Data set with 560 unique chords.[27] using context-free transition representation. [28]	**Akaike Information Criterion (AIC) Model Optimization**	Guitar Strumming
[19]	**2018**	Sound Clips in GPT Database (GPT Dataset from the work of Su-et-al[29]	**Gaussian Process Variational Auto Encoder (GP-VAE)**	Guitar Playing Techniques (GPT)
[20]	**2019**	Guitar Recordings of electric and acoustic guitar, electric LesPaul Firebrand with Elixir Nanoweb (0.10-0.54) strings and an acoustic Martin DR with SP(0.12-0.52) strings.	**Non-Linear Least Square (NLS) Inharmonic Pitch Estimation**	Guitar string, fret and plucking position.
[21]	**2019**	Chords Signals recorded from Yamaha CPX-500-II in wave format	**DST based Segment Averaging**	Guitar Chord Recognition
[22]	**2019**	Declarative and Procedural Knowledge using Protégé	**Web Ontology Language (OWL)**	Guitar Renditions

[23]	**2019**	Chord Progression Database /Search Trees using Pitch Class Profiles (PCPs) or Chroma Vectors	**Chord Label Estimation Method Using Comb Filter**	Guitar Chord Labels
[24]	**2020**	Sound Clips in GPT Database (GPT Dataset from the work of Su-et-al [29][30]	**Hierarchical Cascaded Deep Belief Network/Spectral Temporal Receptive Fields (STRF)**	Guitar Playing Techniques (GPT)
[25]	**2020**	Mc-Gill Billboard Dataset with 560 unique chords. [27]	**LSTM based Neural Network**	Guitar Chord Progression
[26]	**2021**	Chord, Tuning and Hand-Geometry Parameters	**State-space search, Multithreading, Heuristic Function**	List of viable fingerings of chord.

Conclusion

The key takeaway of the MRS is to make a beginner guitar player more confident about using the entire fretboard for playing and making the learning fun. The major advantage of designing such an MRS system is that it is extensible. The MRS system can be used to extend the design to make interactive learning systems for scales like pentatonic, major scales etc. The MRS for guitar teaching and learning have come a long way and yet there is tremendous scope of development for systems that can aid various aspects of the guitar playing. The systematic survey in this paper will help in design of chord specific designs. This system has a lot of scope of scalability and future improvisations. Further research and enhancements can be made in system developments that uses seventh chords and power chords and triad chords. There is vast scope of system development and implementation in the area of cadence suggestions and recommendations.

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