MUSIC RECOMMENDATION MODEL BASED ON USER LISTENING BEHAVIOR AND UTILITY BASED PREFERENCE SCORING

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Abstract

Recommending the most appropriate music is one of the most studied fields in the contest of Music Information Retrieval. Music Recommendation modules often take note of the user's music preferences when it comes to recommending music. In this study, approaches such as Music Similarity, have also been applied during the recommendation phase.

The study made use of normalized acoustic features extracted using MIR tools MARSYAS 0.5.0 alpha 1 and jAudio 1.0.4 and utility based preference scoring to find relevant music to be used as recommendations. Using this approach, the study was able to come up with an average True-Positive rating of 54.43% in determining the songs the user will select for the month given previous month's data.

This study made use of a recommendation formula that can be used for future studies. Some examples could be a different set of similarity measures used, more computational functions to use as a basis for recommendation, as well as changing constant values used throughout the computational functions used during the research. Applying suggestions for measuring utility can also be used for further studies who wish to go into dynamic and more active recommendation models.

Keywords: User Behavioral Analysis, Music Recommendation, Music Similarity Recognition, Recommender Systems

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1 Research Description

This section provides an overview of what the research is about and aims to explain to the reader the significance of the study currently in its field.

1.1 Overview of the Current State of Technology

The growth of today's development in technology, the rapid growing contents in multimedia libraries and the digital industries have called for a need of effective information filtering systems, and in particular recommendation systems (Del Castillo, 2007). In the case of the digital music industry, the amount of audio content available is increasing the need to efficiently access, discover, and to present it to the final user. In order to answer this need of delivering relevant information to the user, music recommendation systems are used to ease the retrieval of music (McKay, 2010).

The main purpose of a music recommendation system is to estimate the user's preference and present them with items that may fit their preference (McKay, 2010). This is because users normally do not have the time to search through these collections looking for new items due to the huge amount of music content available. In order to come up with the most suitable recommendation, techniques for classifying, analyzing and retrieving audio content information have to be conducted.

With recent progress in the field of music information retrieval, computers are able to analyze and understand music up to some semantic level. The diversity and the ripe information contained in music required multidisciplinary efforts in identification, ranging from computer science, digital signal processing, mathematics and musicology (Rho et al., 2011). Analyzing the information contained within these music files is a traditional approach in music recommendation called content-based recommendation (Rho et al., 2008).

Researchers have tried to bridge the semantic difference, which is also known as the semantic gap, between the low-level features and high-level concepts (Oscar, 2006). With low-level feature analysis, there may be difficulties in identifying the semantics of musical contents. An example would be an activity that the user would normally do given a certain situation (i.e., Studying, relaxing, reading). A user’s profile, which includes educational background, age, gender, and musical taste, is one possible high-level feature. Due to this semantic gap, Semantic Web technology has been considered as a promising method to bridge them. Recently, with the development of Semantic Web, ontology has been widely used to make easy knowledge sharing and reusing. Also, Emotional Effects of Music work (Klaus and Marcel, 2001) suggested that an emotion experienced by a person listening to some music is determined by a multiplicative function consisting of several factors such as structural, performance, listener, and contextual features.

Although there have been mixed success in the past with regards to these recommendation methods, the approach does not bear much focus on the user’s context (Rho et al., 2008). In recommending music, it is important to take into consideration the user’s context since the user's choice of song could be influenced by their current context (Kaji et al., 2005), such as their activity, schedule, and emotion. It is because of this that researches on context-aware recommendation systems have been gaining popularity (Hu & Ogihara, 2011).

One recently conducted study by (Aquino et al., 2010) recommended music based on the brainwaves denoting the user's affect and their computer activities being conducted. In the study, the activities of the user along with their brainwaves were associated with certain songs. Another study conducted by (Liu et al, 2009) took into consideration timestamps, which denoted the user's daily schedule for recommendation. In this specific study, the schedule of when a user listened to a specific song was noted and recommendation of a similar song took place when a song was due to be listened to.

Recommendations after the study (Liu et al, 2009) emphasized the need to give a more thorough analysis on taking the user's music listening pattern (referred to as "listening behavior" in this paper) rather than merely recommending music based on music similarity. This will allow a recommendation system to provide the most appropriate recommendations during different contexts. Among many contextual dimensions, such as time, location, user, mood, etc., the time dimension is distinguishable in developing a model since timestamp is not just simple continuous or categorical variables. Timestamp is continuous and periodic at the same time. Therefore, preference on some contents or items can also be periodic. (Kahng & Park, 2010)

For example, one can observe that a user likes listening to slow and calming music during the morning and fast songs at the evening during certain days and vice versa during another day. One reason could be due to the user waking up to calm music and working out one day and performing a morning jog and relaxing afterwards during another day. Another example would be the user listening to certain songs during different times of the year (ie. Christmas season) and the recommendations should be suitable for such season (Kahng & Park, 2010). Such analysis should allow a recommendation module that will recognize the user's listening pattern and recommend music that fall within the said pattern.

The concept of a music listening behavior has been conducted by (Kahng & park, 2010) where the listening log of Bugs Music service was investigated upon. Some existing limitations are that the study was a general case study of the listening and not user specific. Also, recommendations indicated that it would be good to observe a specific user and use their listening behavior as a basis for recommending music.

This research aims to find an approach to answer this said limitation existing. By determining the user's listening behavior, the approach should be able to suggest the most appropriate music to the listener that should match the user's observed listening behavior. Aside from taking into consideration the user's listening behavior, the user's preferred songs will also be used as a basis to recommending music. The research also aims to find a connection between the music features and the user's listening behavior.

1.2 Research Objectives

This section describes the main objective that the research wishes to accomplish.

1.2.1 General Objective

The main objective of the research is to create a solution to the question:

> **"What approach can be used to make a user-specific music recommendation model based on their music listening behavior and the attributes of the songs they listen to?"**

This research aims to build a user-specific model that would be able to determine the user's listening pattern based on their activities, schedule of listening to music, and the attributes of the songs they listen to. Given these, the system aims to recommend music that matches their behavior.

1.2.2 Specific Objectives

Specifically, the following sub problems must be answered

1. **WHAT APPROACHES CAN DETERMINE THE USER'S LISTENING PATTERN?**

   A common problem encountered in existing MR systems is the "cold start" problem (Hu & Ogihara, 2011) where the recommendation system has no knowledge as what the user likes listening to and what their listening pattern is. It is because of this that it is important to identify what their listening pattern is to identify the possible types of music to recommend to them. This is due to the change in the user's music listening preference which should also be detected by the module developed in the study.

2. **WHAT MUSIC FEATURES CAN DETERMINE APPROPRIATE SONGS FOR A USER'S LISTENING BEHAVIOR?**

   There are several factors in a music file that deem it as appropriate to the user's music listening pattern. The music file's acoustic and timbre attributes aside from metadata (genre, artist) may be considered to determine if a recommendation is appropriate with regards to the user's listening behavior. It is important to consider several factors as a music recommendation aims to introduce new music or ease the user in determining what to listen to given a certain period.

3. **WHAT APPROACHES CAN BE USED TO MAKE THE MODEL ADAPT TO CHANGES IN THE USER'S LISTENING PATTERN?**

It should be noted that users have the tendency to change their music listening behavior (Liu et al., 2009); therefore a music recommendation system should be able to cope with such changes in listening pattern (McKay, 2010). This is explained as the "concept drift" problem where predictions become less accurate as time passes (Ziliobaite, 2009). How users react to music being played or changes in songs selected is an indication whether their music preference is changing (Pampalk et al., 2005). For example, a user may prefer a certain genre during a few months and switch to another genre for the next months (Kahng & Park, 2010). To keep the recommendation module up to date, it should be able to adjust to such changing music listening behavior.

1.3 Scope and Limitations of the Research

There will be seven test subjects, since the model that this research aims to build is a user-specific model and multiple test subjects enable the validity of the methodology. Furthermore, it does not generalize since the music preference and listening pattern of various people differ from one another (Calvo & D'Mello, 2010). The approximate duration for data gathering will be 7 months, all done during the same instances.

The music files that the module used for the research will be comprised of 427 uncompressed wave files, which consist of Pop Music, Classical Instrumental Music, and Techno music (Zenius, n.d). The attributes of the songs will be extracted using jAudio (McEnnis et al., 2010) (Manalili, 2010). These attributes will not be extracted during real time, but will already be within the system extracted beforehand. This is to speed up the processing and the recommendation process.

The user's input within the system is limited to song skipping, song replaying, and allowing the completion of a song. This is also going to be used as a basis as the user's listening behavior. During the study, whether the user is actively listening to the song or merely using it as a background noise will not be taken into consideration when taking in the user's feedback.

1.4 Significance of the Research

While studies on music recommendation is a field that has been emerging as of late (McKay, 2007), the proposed research aims to conduct a more thorough analysis on modeling the user's music listening behavior and provide new music to the user that will be suited to their listening behavior.

The study should be beneficial to studies that focus on automated music playing. The difficulty of handling a large collection of music files and determining which ones should be played during situations is difficult if users are expected to manually select music. This will cause other songs to be played more often than others, leaving the possibility of other appropriate music forgotten (McKay, 2010).

1.5 Research Methodologies

This chapter enumerates the phases of the study and the specific tasks of each.

1.5.1 Planning and Topic Analysis

This stage involved the formulation and planning of future activities regarding the development of the research. Meetings with the advisor were also included in this phase especially during the analysis of the topic and recommendation of reading materials for the review of related literature.

1.5.2 Documentation

Documentation was done through-out the study. This enabled the researcher to keep track of the development of the research as well as any additional information and findings.

1.5.3 Review of Related Literature and Concept Formulation

The researcher gathered and studied related literature on existing music recommendation systems, relevant attributes used in different music recommendation systems, the description of respective music attributes, and different approaches used in recommendation systems. The studies of the related literature focused on the techniques, algorithms, and equipment used, as well as data gathering and corpus building techniques.

1.5.4 Data Collection and Corpus Building

The researcher selected test subjects who voluntarily listened to music from the corpus. The test subjects were asked to listen to music while being free to do an activity they deem appropriate during the time slot. It was also here where the module provided to them will keep track of all the songs they listened to. Experiments were conducted to determine the user's listening pattern and what music they listen to. It was also during this phase where the proper music corpus used for the research was assembled

1.5.5 Modeling through Data Analysis

This phase covered the modeling of the data which resulted from the data gathered from the users. The resulting output is a model of each user's music listening behavior as well as a model which was used for recommending music that the user would like to listen to.

1.5.6 Testing

This phase was executed iteratively until an accurate model is derived. In order to test the accuracy of the model, the 4 quadrant test (Gunawardana & Shani, 2011) was used for the evaluation of the recommendation systems.

1.5.7 Evaluation of Results

The results from the testing phase were evaluated. Any faults or needs of improvement lead to the remodeling or revising of the model. This phase was be covered from February to March, which was the same with the testing phase since testing and evaluation were done several times in the research. The accuracy was determined based on the ratio of positive feedback to negative feedback with regards to the music recommended by the recommendation module

1.5.8 Calendar of Activities

Table 1.1 is a Gantt chart that presents the activities for this research. Each asterisk represents one week of activity.

Table 1-1 Timetable of Activities (2013)

Activities (2013)	June	July	Aug	Sep	Oct	Nov	Dec
Planning and Topic Analysis	****						
Documentation	****	****	****	****	****	****	****
Review of Related Literature		****	****				
Data Collection			****	****	****	****	****
Modeling and Data Analysis							****
Testing							
Evaluation of Results							

Activities (2014)	Jan	Feb	March
Planning and Topic Analysis			
Documentation	****	****	****
Review of Related Literature			
Data Collection	****		
Modeling and Data Analysis	****		
Testing	***	****	
Evaluation of Results		****	****

2 Review of Related Literature

This chapter discusses about the related literature to the research. They are also summarized accordingly.

2.1 Review on Music and Productivity

Rhythm is the single most influential musical element and tempo is very closely related. Rhythm and tempo have a strong physiological influence on the body. An example is that a certain composition of Domenico Modugnio, which has a fast tempo, raised the heart rate of the subjects in an experiment by 4.7 beats per minute. (Melkinov, 1970).

Many people listen to music, especially rock and its related styles, for the "beat"; in other words, they listen to it for its rhythm and tempo (Wright, 1999). Rhythm and tempo, used harmonically, are sympathetic to the body. The tempo should usually correspond to the normal human heart rate range of approximately sixty to 120 beats per minute, with most music between seventy and eighty beats per minute (Torres & Torres, n.d).

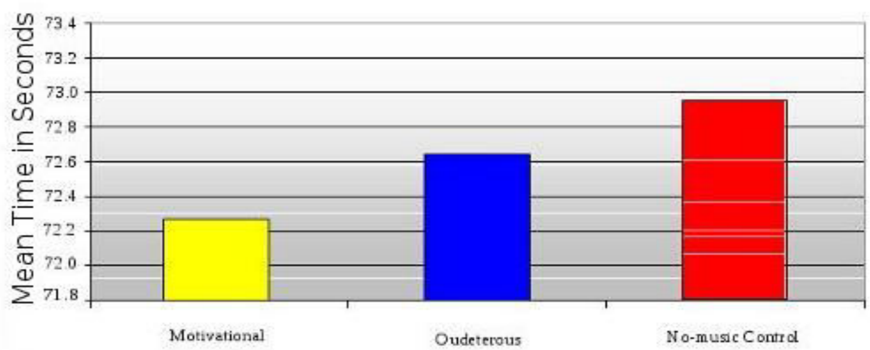


Figure 2-1 Effect of Music in Athlete Runners (Simpsons and Karageorghis, 2006)

For activities, music is often correlated with making the listener more productive or feel more productive. In a competition, where athletes are often very closely matched in ability, music has the potential to elicit a small but significant effect on performance (Karageorghis & Terry, 1997). Research has consistently shown that the synchronization of music with repetitive exercise is associated with increased levels of work output as Figure 2.1 displays. The synchronization effect in running was demonstrated in an experimental setting which found that motivational synchronous music improved running speed by.500 seconds in a 400-m sprint, compared to a no-music control condition (Simpson & Karageorghis, 2006).

2.2 Review on Music Preferences

(Goldberg et al., 2011) introduced a model of musical preferences based on affective reactions to excerpts of music from a variety of musical genres. Their study suggested that a 5-factor structure existed that labeled the subject's music preference which reflected emotional and affective responses.

Their study interpreted these factors as a mellow factor comprising smooth and relaxing styles, unpretentious factor found in country, sophisticated factor which includes classical, operatic, world and jazz, Intense factor found in loud, forceful, and energetic music and a contemporary factor found in percussive music such as rap, funk, and acid jazz. Also, it has been stated that preference for music factors are affected by both social and auditory characteristics (Goldberg et al., 2011).

Another study conducted addressed the classification of music types according to a user's preferences for a hearing aid application (Mo et al., 2008). The classifier in the said study had to operate under limited computational resources and must be capable of adjusting to types of data not represented in the current training set, or changes in the user's preferences. In the study, the user provided occasional feedback which prompted the classifier to change its state. The study also proposed an online learning algorithm capable of incorporating information from unlabeled data by a semi-supervised strategy, and demonstrated that improvement of classification. The study also managed to detect changes in user's preference given limited information provided (Mo et al., 2008).

A study conducted by (Kahng & Park, 2010) explored the concept of temporal context affecting the popularity of items and user preference. Data for their study was gathered from Bugs Music, one of the well-known online music services in Korea and the temporal dynamics in user's music listening behaviors considering periodicity of time dimension and popularity changes were analyzed. The study explained that some genres of music are preferred at specific time of day. Seasonal effect was also prevalent in observed listener's behaviors as well as the popularity of the songs.

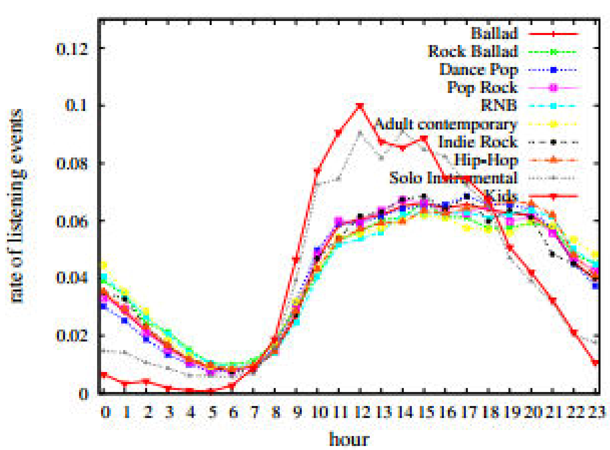


Figure 2-2 Genre popularity according to hour. (Kahng & Park, 2010)

(Lesaffre et al., 2006) revealed that music perception is affected by the context, and this depends on each user. The study explores the dependencies of demographic and musical background for different users in an annotation experiment. Subject dependencies are found for age, music expertise, musicianship, taste and familiarity with the music. The authors proposed a semantic music retrieval system based on fuzzy logic. The system incorporates the annotations of the experiment, and music queries are done using semantic descriptors. The results are returned to the user, based on their profile and preferences. One of the main conclusions of their research is that music search and retrieval systems should distinguish between the different categories of users.

2.3 Review on Music Recommendation

The music recommendation systems that have been developed throughout the years have concentrated on user information such as favorite genre or artists. The contents of the songs were also analyzed (e.g. pitch, lyrics) and correlated with the information supplied by the user.

An example of such system is a Music Recommendation System based on Music and User Grouping (Chen & Chen, 2004). The research presented a music recommendation system, which provides a personalized service of music recommendation. The polyphonic music objects of MIDI format are first analyzed for deriving information for music grouping. For this purpose, the representative track of each polyphonic music object is first determined, and then six features are extracted from this track for proper music grouping. Moreover, the user access histories are analyzed to derive the profiles of user interests and behaviors for user grouping. The content-based, collaborative, and statistics-based recommendation methods are proposed based on the favorite degrees of the users to the music groups, and the user groups they belong to (Chen & Chen, 2004). Figure 2-3 displays the architecture of such system.

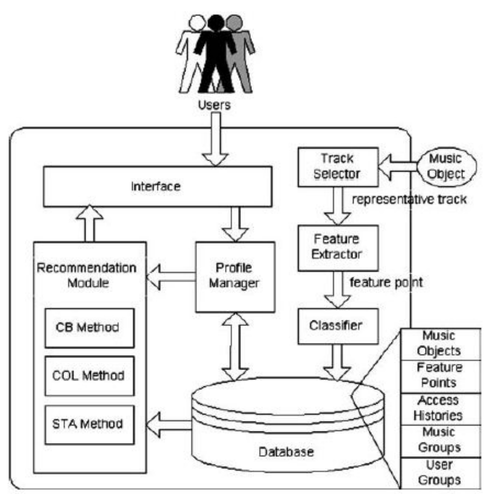


Figure 2-3 System Architecture of Chen & Chen's (2004) Music Recommendation System

Another recommendation system developed by recommended music using annotations based on listeners' preferences and situations (Kaji et al., 2005). The system displayed an initial playlist based on the information, such as the preferred type of music, which the user provided before using the system. Through this information, the user's similarity with other users is calculated by the cosine coefficient from triple feature spaces. Such features include lyrics, scenes that tune expresses, musical scene, and listening situation. The user then selects undesirable songs from the initial playlist, which the system removes to produce a new playlist through transcoding. The system then determines which new songs to recommend by finding the similarity between the users based on the user's preference and listening situation. (Kaji et al., 2005).

The Smart playlist recommendation is a music recommendation system which is able to recommend playlists based on music content and the user's daily behavior (Liu & Hsieh, 2009). The playlist recommendation generator made use of Artificial neural networks (ANN) and the C4.5 decision tree. In the system, the user is allowed to state their music playing preference through the provided music player interface. The preferences are recorded with a time stamp to keep track of when music was played. The user's model is trained and built by features of music that the user has listened to and the associated time parameter through the personal playlist recommendation training model. After the personal recommendation kernel is built, the user is provided with a personalized playlist depending on the time parameter and the user's preference of music. The system's architecture is illustrated in Figure 2-4.

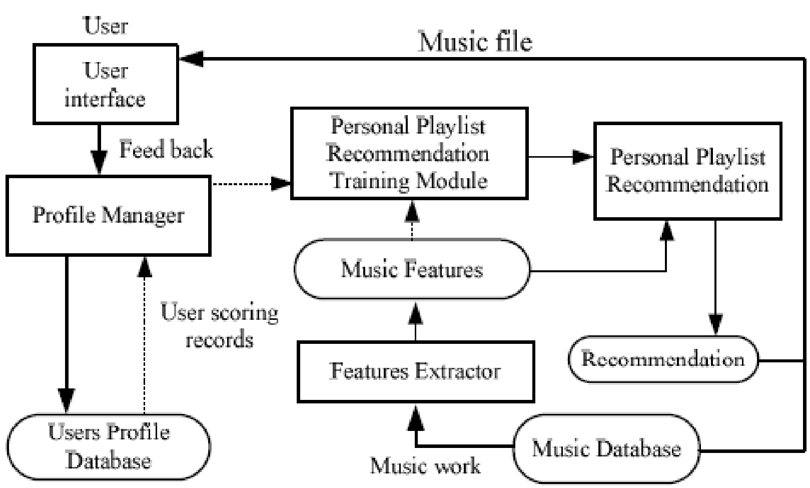


Figure 2-4 The Smart Playlist Recommendation System

Another system was developed by (Liu et al, 2009) provided an algorithm that generates a decision tree, combined with time scheduling, to represent the user's preference after a certain time division as well as content base filtering that extracted the contents of the music. In this system, information and feedback from the user are gathered in order to identify his/her interest. From this information, an exclusive music intelligent scheduling agent learns the preferred music of the user, through the use of decision trees, and uses the content base filtering technique to analyze the songs in the music corpus in order to find other songs of the same type to recommend. In the event of a new user, it would be able to recommend a music playlist based on the information from previous users. In forming the decision tree to classify the music to be added in the playlist, time was used as the continuous attribute in order for an easier establishment of a decision tree.

NextOne player developed by (Hu & Ogihara, 2011) recommended music based on the user's listening pattern and music preference which measured the amount of times the user would play a certain song. The system required the genre and year of the song, users rating, freshness, and time pattern. The corpus used by the study came from AllMusic.com, where relation of each genre is also considered (i.e. a genre being a child or a parent of another genre). Autoregressive Integrated Moving Average is the time series analysis technique which analyzed the similarities and generated the prediction. The user's interaction with the system is also considered, such that the longer the music is played, the more it is considered favorable to the user. The study made use of Gaussian Mixture Model which employed Expectation Maximization to infer the probability of playing a song at a time.

System	Technique	Description	Input Required	Music attributes considered?	User Context Considered?
(Chen & Chen, 2004)	Content – Based and Collaborative Based filtering	User grouping was considered and users with similar preferences and similar music was required	User grouping, MIDI files liked	Yes. Six features from MIDI files	Only User group, and other users with similar preferences
(Kaji et al., 2005)	Collaborative filtering and Automatic Playlist Generation	The system asks for the user's profile which the user will provide the system with. Afterwards, an initial playlist is generated and the user removes songs they do not like.	User feedback with the songs the system initially generates and initial user profile	No. Just similarity between songs considered by users similar in profile	User profile which the system receives as input
(Liu et al., 2009)	Context based recommendation and Articial Neural Networks. Automatic Playlist Generation using C4.5	The user is provided with a playlist that is a result of their interactions with the system regarding their music preference and the time stamp	User feedback, user interaction, and time when the user listened to the music. User profile is also considered to generate an initial playlist	Yes. MIDI extracted files	Time stamping for the user's schedule
(Aquino et al., 2009)	Fast-Fourier Transform (FFT), Music preference tracking for Context based recommendation	Brain signals is analyzed using FFT and Music preference tracking whilst doing activities is used to determine the appropriate music to recommend	Brain wave signals, activity, music being played	Yes. Features extracted using jAudio and MediaMiner were used	User's brainwave signals and activity log

System	Technique	Description	Input Required	Music attributes considered?	User Context Considered?
(Hu & Ogihara, 2011)	Context based recommendation using Autoregressive Integrated Moving Average and Gaussian Mixture Model	The user's listening pattern and behavior is considered in recommending music. The user's interaction with the system is also considered in determining the user's listening behavior.	Time schedule, and the user's interaction with the music player within the interface.	No. Only the Genre and the song's popularity	Time stamping for the user's schedule

Table 2-1 Summary of Music Recommendation Systems

3 Theoretical Framework

3.1 Music Recommendation Theory

3.1.1 Content-Based Recommendation

Information-based prediction techniques base their results in the analysis of all the items plus the preferences of the user. They only consider the actual user and do not take into account the information related to other users. Furthermore, these techniques are considered domain specific since they have to analyze the information stored in the item or the metadata associated with them. (Setten, 2005).

The main assumption under case-based reasoning or content-based techniques is that a user has similar preferences over similar items. The more similar the items the more equal the preferences of the user on those items. In information filtering the system is in charge of ordering huge amounts of items and delivering to the user only the items that are relevant for him. Finally, attribute-based techniques estimate their results on the base of the attributes of an item. Each attribute of an item has an importance weight and the overall prediction is calculated taking into account the value of each attribute.

According to (Schyndel & Uitdenbogerd, 2002) these approaches attempt to retrieve useful information from items of the collection. This extracted information should be a good indicator of how much the items are relevant for the user

.

3.1.2 Music Similarity Recognition

(Del Castillo, 2007) stated that some theories and principles behind music recommendation based on music similarity, have a motivation in theories on music perception. For instance, (Setten, 2005) stated that the enjoyment of music listening can be due to principles of expectation-confirmation and expectation-denial. These principles suggest that similarity in the musical content can be a viable approach to provide users with previously unknown music that can be enjoyed. All these principles and theories made an attempt to understand how humans consider two musical pieces similar.

In order to estimate the similarity or dissimilarity between two musical items it is necessary to compare sets of features which represent the items in a meaningful way. The choice of which features to compare and how to extract them depends mainly in two important aspects: the dimensions of music a user considers important, and on how musical items are represented (i.e., Symbolic or MIDI, audio, or through sheet music). (Del Castillo, 2007)

3.1.3 Music Feature Mapping

(Peeters, 2004) documents a large set of audio features for Music Information Retrieval (MIR). Table 3-1, taken from (Hu, et al., 2010) lists the audio features mapped, which are taken as representative of the current repertoire of features in the MIR literature. The Timbral, Loudness, and Complex-Domain Onset Detection Function (CDF) features are computed over frames of approximately 23 ms. The Harmonic features are computed over frames of approximately 0.75 s. Beat Histogram (BH) and Onset Rate (OR) are computed for the entire clip from the values of CDF.

Table 3-1 Mapping of Music Features Extracted taken from (Hu et al., 2010)

Feature Name	Description
Timbral	
MFCC (20)	20 Mel Frequency Cepstral Coeffs.
HFC	High Frequency Content
SC, SS	Spectral Centroid, Spectral Spread
ZCR	Zero Crossing Rate
Loudness	
Sones (24)	Perceptual loudness in 24 bands
OL, RMS	Overall Loudness, Root Mean Square
Harmonic	
Chroma (12)	Pitch Class Profiles
TS (6)	Mapping onto 6-d Tonal Space (Harte, Sandler, & Gasser, 2006)
CDTS	Cosine Distance between consecutive feature vectors in Tonal Space
TriadSeq	Estimated major/minor Triad Sequence (Bello & Pickens, 2005)
TriadInt	Distance between consecutive triads as unitary steps in the perimeter of the circle of fifths
Rhythmic	
CDF	Complex-Domain Onset Detection Function (Bello, Duxbury, Davies, & Sandler, 2004)
BH (15)	Beat Histogram (15 BPM ranges) (Tzanetakis & Cook, 2002)
OR	Onset Rate

3.1.4 Music Low Level Features

Music files are mainly audio files which come from raw data in the form of wav or mp3 files. For music signal analysis, raw data is transformed into a new space of variables that simplify analysis. This new space of variables represents measurable properties containing information relevant for pattern recognition (Klapuri & Davy, 2006).

3.1.4.1 Zero-Crossings

The Zero-Crossing is defined as the number of waveform changes in a window (McKay, 2005). The Zero-Crossing Rate or ZCR is defined as the number of time-domain zero-crossings within a defined signal range divided by the number of samples within the range (Gouyon, Pachet, & Delerue, 2000). It measures the occurrence of the sound signal crossing between positive and negative values (Jorj et al., 2010). This makes the ZCR to be very useful in characterizing audio signals, thus this is an audio feature used in many speech or music classification algorithms (Lu, Jiang, & Zhang, 2001).

The formula for computing ZCR is as follows: (Liu & Wan, 2001)

$$ZCR = 0.5 * (N-1) * \sum_{m=1}^{N-1} |sgn[x(m+1)] - sgn[x(m)]| \qquad (1)$$

Where $sgn[]$ is a sign function, $x(m)$ is a discrete audio signal from $m = 1$ to frame length N, and 0.5 is the frame overlapping factor (50%).

3.1.4.2 Root-Mean-Square

The Root mean squared (RMS), also known as quadratic mean, is a statistical measurement of the magnitude of a varying set of data (Evans, 2009). RMS is very useful in interpreting analogue waveform data since it allows the generation of the average of positive and negative values. A sine wave for example has equal positive and negative values, calculating its mean sample will only make them cancel each other out. This is enabled through RMS since this allows all samples that have been squared thereby turning negative values into positive ones, making it effective in signal processing (Evans, 2009).

The formula for computing the RMS is as follows:

$$RMS_{amplitude} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \qquad (2)$$

Where x_i are the sample values and N is the total number of sampled values. (Evans, 2009)

3.1.4.3 Beat Histogram

Beat Histograms show the distribution and strength of various beat periodicities in an audio signal which is calculated using the diagram displayed in Figure 3.1. They are generally used for semantic calculation. These histograms are used for pattern recognition in differentiating audio files. A scenario occurs where two audio files can be easily differentiated using beat histogram feature. The spread between each peak can be an indication of tempo variability. (Tzenatakis, 2002)

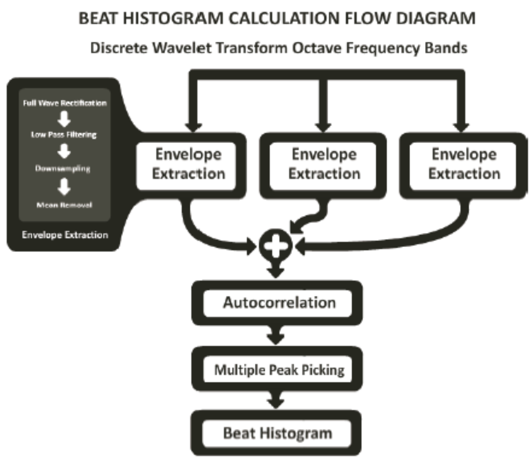


Figure 3-1 Calculating Beat Histogram (Tzenatakis, 2002)

3.1.5 Music High Level Features

Since content-based recommendation methods are based on detecting the similarity between two items by comparing representative sets of features, it is reasonable to present some of the theory behind feature extraction in audio content. Features extraction from audio representation is the major trend for computing music similarity and it is based on the use of technique from the field of signal processing such as Direct Fourier Transform (DFT) or Mel Frequency Cepstral Coefficients (MFCCs).

(Colthart, 2003) attempted to provide definitions for aspects that are truly relevant for music. It was stated that our auditory system works as a set of interconnected modules that can represent clearly rhythm and meter (temporal organization) as well as tonality and melodic contours (pitch organization). (Stephen, 2003) defines some important facets of music such as pitch facet, temporal facet, harmonic facet, and timbral facet.

3.1.5.1 Pitch

The pitch facet is related with the perceived quality of the sound, and it is mainly a function of the fundamental frequency. This facet might range from low or deep to high or acute. Some example of features related with pitch dimension is pitch histograms.

The idea of pitch histograms was introduced by (Tzanetakis, 2002). The main idea was to calculate pitch histograms and then use pattern recognition classifiers to recognize these patterns in songs.

3.1.5.2 Rhythm

(Del Castillo, 2007) stated that the temporal facet of music is concerned with the duration of musical events. It conveys information such as tempo indicators, meter, pitch duration, and harmonic duration. Since temporal aspect is determined by complex combinations of tempo, pitch, harmonic durations, etc, it is quite difficult to represent it for retrieving purposes; percussive sounds are good identifiers of temporal facet.

(Lidy, 2006) explained that rhythm patterns from audio content can be extracted using spectral data and different algorithms such as the short time Fast Fourier Transform and others.

3.1.5.3 Harmony

The harmonic facet is related with the phenomenon that is produced when two or more pitches are produced at the same time; it represents the organization of simultaneous sounds along the axis time (Stephen, 2003). Harmony in an audio content is normally represented by a sequence of chord and the key of the music.

Some works like the ones presented (Gomez, 2006) and (Gomez & Herrera, 2004) attempted to estimate the tonality of songs based on the Harmonic Pitch Class profile (HPCP) The HPCP is a vector of low-level features that allow the estimation of other high-level features such as chords and key of the audio (Del Castillo, 2007).

3.1.5.4 Timbre

The timbral facet is related with the characteristics of sound that allow people to perceive different two sounds with similar pitch and intensity. In order to extract features relates with timbre most the actual systems currently use Mel-frequency cepstrum coefficients (MFCCs) (Logan et al, 2003). Normally MFCC are used in speech recognition since they provide a concise representation of spectral characteristics.

From all the dimensions, timbre is the one that it is used most (Del Castillo, 2007). The reason for this is that it is believed that users are particularly sensible to timbre and less sensible to other dimension of music. (Pampalk, 2006) states that MFCCs can roughly model some important characteristic of the human auditory system. These characteristics are: the non-linear frequency resolution, the non-linear perception of loudness and, to some extent, the spectral masking effects.

3.2 Machine Learning Algorithms

3.2.1 K-Nearest Neighbor

k-Nearest Neighbor or kNN is the machine learning algorithm that classifies the instances based on the output of the closest instances within the feature space (Mitchell, 1997) using the Euclidean distance (As illustrated on Figure 3.1). Classification is done by determining the majority of the k-neighbors an instance is closest to. Figure 3.1 shows the model of the kNN.

$$D(t_l, t_j) = \sqrt{\sum_{i=1}^{a} d(v_{i,l}, v_{i,j})^2}$$

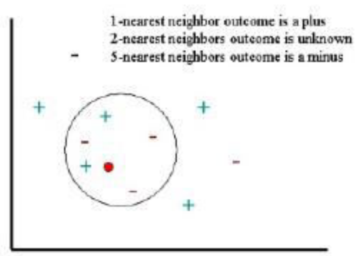


Figure 3.2 k – Nearest Neighbor

3.2.2 Decision Tree

The decision tree uses if-then rules to classify discrete-valued targets. Application of the decision tree includes ID3 (Quinlan, 1986) and C4.5 (Quinlan, 1993). Decision trees consist of three types of nodes, internal nodes for given attributes, edges for subsets of attribute values and terminal nodes for class labels as shown in figure 3.2 using C4.5.

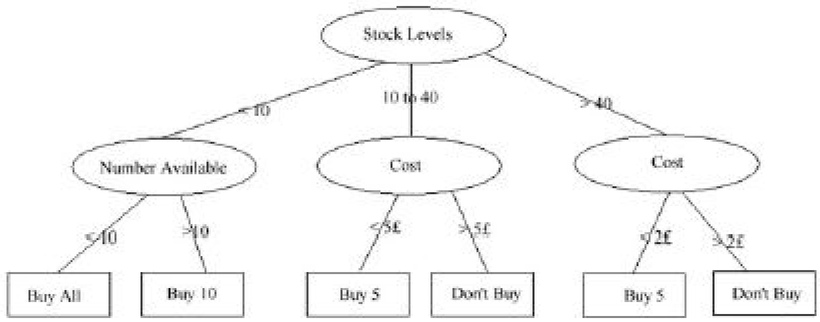


Figure 3.3 Decision Tree

3.2.3 Support Vector Machine

A support vector machine constructs a hyper-plane or set of hyper-planes in a high or infinite dimensional space, which can be used for classification, regression or other tasks. Intuitively, a good separation is achieved by the hyper-plane that has the largest distance to the nearest training data points of any class (so-called functional margin), since in general the larger the margin the lower the generalization error of the classifier.

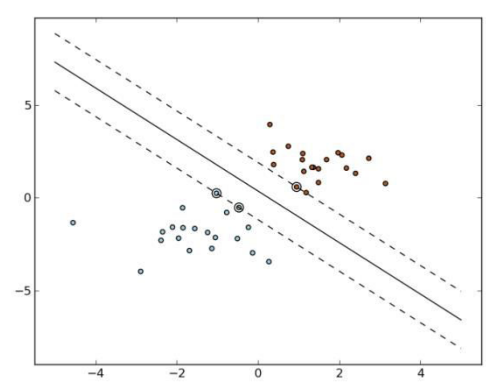


Figure 3.4 Support Vector Machine

3.3 Models for Recommendation Systems

A Recommendation system should be intuitive and consumer driven. It should be able to provide good results to gain users' trust (Mehta, 2012). The soul of the collaborative recommender system is in the users past history, i.e., user preferences and the history of like-minded users. The latter helps us to predict the unknown preferences of the new users.

3.3.1 Utility Matrix

In a recommendation-system application there are two classes of entities: users and items. Users have preferences for certain items, and these preferences must be teased out of the data. The data itself is represented as a utility matrix, giving for each user-item pair, a value that represents what is known about the degree of preference of that user for that item. Values come from an ordered set, e.g., integers 1–5 representing the number of stars that the user gave as a rating for that item.

It is assumed that the matrix is sparse, meaning that most entries are "unknown." An unknown rating implies that no explicit information about the user's preference for the item exists for the time being. The aim of a recommender system is to provide a possible rating that the user might give to these unknown fields.

	HP1	HP2	HP3	TW	SW1	SW2	SW3
A	4			5	1		
B	5	5	4				
C				2	4	5	
D		3					3

Figure 3-5 Example of a Utility Matrix

3.4 Users and Music

Music is an important vehicle for telling other people something relevant about our personality. Musical taste and music preferences are affected by several factors, including demographic and personality traits. It seems reasonable to think that combining music preferences and personal aspects —such as: age, gender, origin, occupation, musical education, and the user's contexts can improve music recommendation (Uitdenbogerd & Van Schnydel, 2002). As certain factors change through time, it is possible for music preferences to change along with them (Herada, 2008).

User modelling has been studied for many years. Yet, extending a user profile with music related information has not been largely investigated. This is an interesting way to communicate with other people, and to express music preferences (Herada, 2008).

Types of users or listeners can be classified according to four groups (Jennings, 2007). The classification included the following categories:

- **Savants** - Everything in life seems to be tied up with music. Their musical knowledge is very extensive.
- **Enthusiasts** - Music is a key part of life for these users but is also balanced by other interests.
- **Casuals** - Music plays a welcome role, but other things are far more important for these users.
- **Indifferents** – Music is not very important for these users and they would not lose sleep if it did not exist

Different types of recommendations should be made for each user type (Jennings, 2007). Savants do not really need popular recommendations, but risky and clever ones. They are the most difficult listeners to provide recommendations. Enthusiasts appreciate a balance between interesting, unknown, recommendations and familiar ones. Casuals and indifferents do not need any complicated recommendations. Probably, popular, mainstream music that they can easily identify would fit their musical needs. Thus, a recommender system should be able to detect the type of user and act accordingly (Herada, 2008).

4 Research Framework

Figure 4.1 shows the architecture of the research, with each module explained by a subsection.

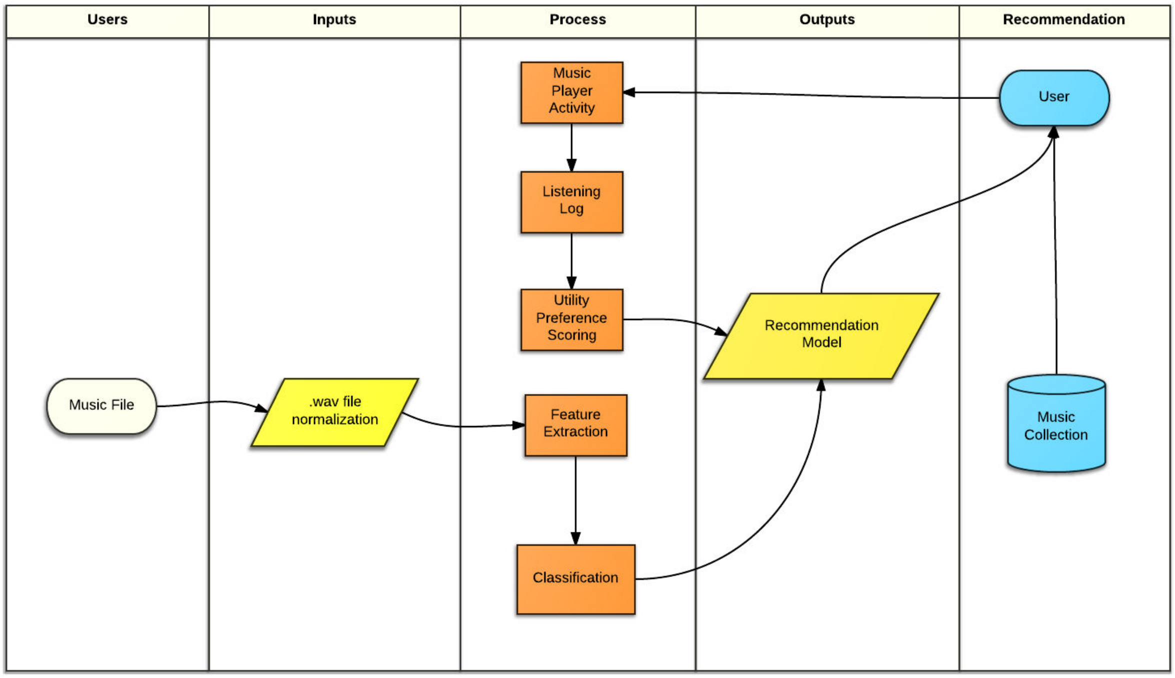


Figure 4-1 Research Framework

4.1 Music Collection

As there are different types of users (Jennings, 2007) (Rho et al., 2008), it is recommended that the users will be provided with a wide selection of different music that could possibly cater to different music needs (Uitdenbogerd & Van Schnydel, 2002), thus such collection of music was selected for this research. Appendix B displays the distribution of the said music collection

4.1.1 WAV File Music Normalization

The music library consisted of 437 .wav files consisting of Classical, Instrumental, Disco, Techno, and Pop music. Originally, each music files were different formats, from mp3 files and wma files. The music files were uncompressed using Audacity 2.0.3 (Audacity Team, 2008) into 1411 kbps .wav files using the “Apply Chain” option.

The options for converting into wav files were the following settings:

1.) Normalize
   1.a) ApplyGain = yes
   1.b) RemoveDcOffset = yes

1.c) Level = -1.000
1.d) StereoIndependent = no
2.) ExportWav

Uncompressing audio files and having them with uniform qualities is needed to ensure that there is consistency with their values in attributes that will be extracted using the selected MIR tool (Manalili, 2010; Mckay, 2007).

4.1.2 Music Acoustic Feature Extraction

The next phase of the research required the music files to undergo feature extraction. All normalized audio files had their features extracted using jAudio-1.0.4 (Mckay, 2007). To ensure that all audio files were valid and supported audio files, the “Validate Recordings” option was checked. Features selected are shown in Table 4-1 while the description of each feature can be found in Appendix F.

Table 4-1 Features selected in jAudio-1.0.4 (Mckay, 2007 ; Aquino et al, 2010).

Attribute	Dimensions
Spectral Centroid	1
Spectral Rolloff Point	1
Spectral Flux	1
Compactness	1
Spectral Variability	1
Root Mean Square	1
Fraction of Low Energy Windows	1
Zero Crossings	1
Strongest Beat	1
Beat Sum	1
Strength of Strongest Beat	1
Strongest Frequency Via Zero Crossings	1
Strongest Frequency Via Spectral Centroid	1
Strongest Frequency Via FFT Maximum	1
MFCC	13
LPC	10
Method of Moments	5
Partial Based Spectral Centroid	1
Partial Based Spectral Flux	1
Peak Based Spectral Smoothness	1
Relative Difference Function	1
Area Method of Moments	10
Area Method of Moments of MFCCs	10
Area Method of Moments of Log of ConstantQ transform	10
Area Method of Moments of ConstantQ-based MFCCs	10

All audio files were added successfully to the program indicating that they were valid formats that were fully supported by jAudio-1.0.4.

4.1.3 Music Classification by Genre

One of the basis for recommending music similarity is through the genre. Each music file is labelled with a particular genre and this is used as a basis for classifying the validity of the acoustic features extracted from the previous phase. The genre are as follows: Classical, Instrumental, Disco, Techno, and Pop music. A separate set of labels were also considered where Instrumental music were considered as Classical as well and Disco were considered as Techno to further balance the music data set.

The experiment was performed using WEKA and the classification models J48 and SVM were experimented with as well as the CFS feature selection algorithm.

4.1.4 Music BPM estimation

BPM or Beats Per Minute is the value which represents music's tempo or speed. The higher the BPM indicates faster music. As jAudio-1.0.4 cannot extract an audio file's BPM, another MIR tool was used. To extract the estimated BPM of an audio file, MARSYAS 0.5.0 alpha1 was used (Tzenatakis & Cook, 1999).

MARSYAS 0.5.0 alpha 1 made use of a method called STEM (Simple Tempo Estimation) as a method of estimating an audio file's tempo and produced the output under the label "Estimated tempo". While it is understood that some audio files may have multiple tempo present, the average tempo is used as a basis in determining how fast a music file is.

4.2 Music Listening

The next part of the research required the users to undergo a music listening phase. This requires the user to make use of a module that will allow the user to select music from the library, music that is either provided to them or provided by them. The user will listen to music and the system will take note of the user's listening activity (Pampalk et al., 2005).The activities that will be considered are listening to the song up to the very end, how much of the song was listened to, the number of times the song is repeated, and how the song was selected.

A music player was developed with the purpose of allowing listeners to listen to music from the collection. The system was developed in Java and made use of JavaZoom, an open source music player as a basis. Figure 4-5 illustrates the music player's interface.

Figure 4-2 Music Player developed in Java used for data gathering

The developed module simulated available operations available in a common music player. Users are able to perform the following tasks in the music player:

1.) Make a New Playlist – Initially add a set of music files to the playlist or load a playlist

2.) Add Music to Playlist – Add a music file or an entire directory of music files to the playlist

3.) Remove Music from Playlist – Remove a music file from the playlist

4.) Play Music – Users may play music, pause music, stop playing, or skip music

5.) Set to Repeat – Repeat a music file after it finishes playing. If unselected, the entire playlist starts from the beginning after it ends

4.3 User Information

When the user listens to music, a timestamp will be recorded of their time of listening as well as a log of their listening activity will be tracked by the module. This will be given to the module that will be used determine the user's listening behavior.

4.3.1 Music Listening Activity Tracking

Attached to the Music Player developed was a module used for tracking the user's listening activity. The module ran in the background as the music application was active which produced the user's listening behavior and interaction with the system. This is displayed in Figure 4-6.

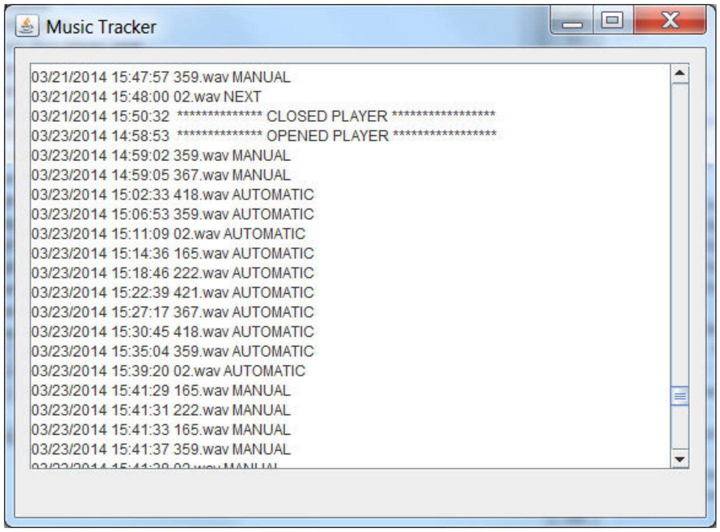


Figure 4-3 Music Activity Tracking Module

The activity tracker identified the date and time when a user listened to music as well as an indication whether the player has been opened or closed. Following the date and time, an indication of the music file played as well as an indication on how it ended up being selected.

The activities considered as “listening activity” and were tracked were limited into the following:

1.) “MANUAL” – Manually selecting a song (Clicking on it or selecting it manually)

2.) “AUTOMATIC” – Allowing a song to play automatically

3.) “REPEAT” – Allowing a song to repeat due to the repeat option being selected

4.) “NEXT” – Skipping a song

5.) “NEWPLAYLIST” – Loading a song via a new playlist

6.) “ADDED” – Adding to the playlist

7.) “DELETE” – Removing from the playlist

4.3.2 Activity data pre-processing

The produced output from the activity tracker is then pre-processed using a separate module. The log is pre-processed into the following syntax:

<Month> <Day> <Activity>

<Activity> can have the following syntaxes:

1.) “CLOSED PLAYER” indicates the player was closed

2.) “OPENED PLAYER” indicates the player was opened

3.) <*Listening Activity*> indicates that the user listened to music. This is given the following syntax:

3.1) <*Audio File*> <*PlaylistActivity*> which indicates whether a user interacted with the playlist such as added a music file, deleted a music file, or loaded through the playlist

3.2) <*Audio File*> <*PlayActivity*> <*Duration*> which indicates whether a user listened to a music file by manually selecting it, repeating it, or automatically proceeding to it as well as skipping the music file. <*Duration*> indicates how long the music file was listened to in seconds

An example of the pre-processed log is displayed in Figure 4-7.

```
2 24 394.wav AUTO 261
2 24 348.wav AUTO 232
2 24 CLOSED PLAYER
2 25 OPENED PLAYER
2 25 426.wav MANUAL 243
2 25 427.wav AUTO 220
2 25 374.wav AUTO 233
2 25 410.wav AUTO 205
2 25 349.wav AUTO 173
2 25 380.wav AUTO 303
2 25 394.wav AUTO 261
2 25 348.wav AUTO 232
2 25 426.wav MANUAL 243
2 25 427.wav AUTO 220
```

Figure 4-4 Pre-processed User Listening Log

The produced pre-processed user listening log is used as an input for the next phase of the research, which is modelling a user’s preference through utility based scoring.

4.4 User Preference Utility Based Scoring

Songs that received a positive response from the user will be analyzed by a feature extraction tool within the research module which will be used for analysis. In order to determine whether a song receives a positive reaction, the output from the previous phase will be needed.

The information produced by the user will be analyzed by a suitable model made by the research to determine the listening behavior of the user. The timestamp will indicate the user’s context which is their interaction with the module provided to them during the said time when they were listening to a certain file of music. (Herada, 2008; Kahng & Park, 2010).

Each user is provided with a *3xn* matrix which represents a user's utility matrix for the song files, where:

n = (no. of songs in the music library) - 1

Table 4-2 Utility Preference Matrix

	0	1	2	...	n
0	w[0,0]	w[0,1]	w[0,2]	...	w[0,n]
1	w[1,0]	w[1,1]	w[1,2]	...	w[1,n]
2	w[2,0]	w[2,1]	w[2,2]	...	w[2,n]

Where:

$w[0,i]$ = Utility value for $(i-1)$ wav file

$w[1,i]$ = A binary value $(0 \text{ or } 1)$ which indicates that $(i-1)$ wav has been played.

$w[2,i]$ = A binary value $(0 \text{ or } 1)$ which indicates that $(i-1)$ wav has been played for the day.

The Utility matrix updates accordingly:

$$w[0,i] = w[0,i] + x$$

Where $x = E$ for manually selected, repeated, first music played upon opening player

$= E / 2$ for automatically selected music

$= -(E / 2)$ for Skipped music or songs unplayed for the day (but played before)

$= |w[0,i]| + \beta$ for Added or Loaded into playlists

$= -w[0,i] + (0 - w[0,i])$ for Deleted music from the playlist if $w[0,i] > 0$

$= 0$ for deleted music from the playlist if $w[0,i] < 0$

$$w[1,i] = a$$

Where $a = 1$ for playing a song in any way or when $w[0,n]$ is updated with a value

$= 0$ otherwise as long as $w[0,n] = 0$

$$w[2,i] = z$$

Where $z = 1$ for playing a song in any way or when $w[0,n]$ is updated with a value for the day

$=$ Refreshed value to 0 *at the start of each day*

Whereas the final utility value U is considered as:

$$U = w[0,i] * w[1,i]$$

Where U > 0 is considered a favorable rating
< 0 is not considered a favorable rating
= 0 is considered as an unplayed music file

The value of E is used to determine whether a particular interaction is considered positive or negative. As stated by (Pampalk, 2005), positive interactions determine a positive value, thus manually selecting a song file to be played, repeating it, and choosing it first are given the full values. A song that is automatically played (not selected by the user but goes automatically to the next item in the playlist) is also considered positive but not given a full value as the aforementioned actions. Songs that are skipped or not listened to within a period (in this case, within a time the player is opened) are considered as negative interactions. Removing a song from the playlist is also considered a negative action (Pampalk, 2005). For the research, the value of E used was 0.5.

β is used as a threshold to ensure that a song will not be considered as unplayed or not recognized by the user because the model considers songs with a utility value of 0 as songs the user has not yet explored. The absolute value is added since adding a song into the playlist is considered a positive reaction, thus a song previously liked by the user that has been removed will obtain its previously positive utility value (Pampalk, 2005). For the research, the value of β used was 0.01.

The procedure of updating the utility matrix is summarized using the pseudocode indicated below.

```
At month start
      n = number_of_songs
      for i = 0 to n do
            w[0,i] = 0
            w[1,i] = 0
            w[2,i] = 0
      end for

      while day is active
            i = song number - 1 interacted with
            Update w[0,i] with value accordingly
            w[1,i] = 1
            w[2,i] = 1
      end while
      At the end of day
      n = number_of_songs
      for i = 0 to n do
            if w[1,i] is 1 but w[2,i] is 0
                  Update w[0,i] with value accordingly
            end if
            w[2,i] = 0
      end for
```

The resulting utility matrix is going to be used as basis for recommending music and is used to model a user's listening behavior and music preferences.

4.5 Music Recommendation

The model produced will recommend the appropriate type of music given the model of the user's listening behavior. The recommendation should be able to produce appropriate music that will follow suit to the user's listening behavior (Mehta, 2012).

Performances of the model will be evaluated using the following metric obtained from (Gunawardana & Shani, 2011) as illustrated in table 4-3

Table 4-3 Recommendation System Metrics by (Gunawardana & Shani, 2011)

	Recommended	Not Recommended
Used	True-Positive (TP)	False-Negative (FN)
Not Used	False-Positive (FP)	True-Negative (TN)

The percentage of TP obtained by each model will be used as a distinguishing factor with regards to the recommendation model's effectiveness (Herada, 2008)(Gunawardana & Shani, 2011).

The music recommendation model produces a list of music that consists of a maximum of 20 music files. Five songs from the playlist will be considered as basis songs, or music files that obtained the top 5 highest utility values.

Each basis song is used as a basis for computing a maximum of 3 recommendation songs given the following equation:

$$RV = \sum_{i=1}^{n} w_i f_i \tag{3}$$

Where n = number of functions, w_i = weight of f_i and f_i = computational function.

For this research, all values of w_i were equal with each other and there were a total of 3 computational functions. f_0 was used to compute for the absolute difference among the acoustic values extracted using jAudio (Process was explained in section 4.1.2).

$$f_0 = \sum_{i=1}^{n} (|X_r - Y_i| * 1/n) \tag{4}$$

$$X_r = \left| bs_i \ldots bs_5 \right|$$

X_r is one of the basis songs where n is the number of acoustic attributes. The lower the value of f_0, the more similar the songs are based on their acoustic attributes. A value of 0.00 indicates that two audio files are exactly the same.

$$f_1 = |X_r - Y_i| \tag{5}$$

f_1 is the function used to calculate for the difference between genres. If two songs are of the same genre, the result will always be 0. X_r and Y_i will have values that range from 0 to 2. The value 0 is assigned for classical music, 1 for pop music, and 2 for techno music.

$$f_2 = floor(X_r - Y_i/\alpha)/\theta \tag{6}$$

f_2 is the function used to calculate for the difference between BPM. The α indicates an allowance amongst songs to be recommended, therefore if α = 20, then a song that is 130 BPM will consider songs from 110 BPM to 150 BPM as similar songs. θ is the value determining (in %) distinguishing how much difference a song with different BPMs will be considered, therefore if θ = 10, then a song's BPM difference of α*2 will be considered to have an added value of *.10*. The lower value, the more important a difference between BPM is considered as a similarity measure. For the study, the value of α used was 20.

The lower the total RV, the more similar the song is according to the research's selected similarity measures. For each basis song, the songs with the 3 lowest RV values are added to the recommendation playlist. If the song already exists in the recommendation playlist, it is no longer added. This means that a smaller recommendation playlist generated indicates that songs used as basis are more similar amongst one another while a larger recommendation playlist generated indicates that songs used as basis are more distinct from each other.

5 Results and Analysis of Research

This chapter discusses about the results and analysis of the research. During the course of the research, the following experiments were performed:

1.) An experiment that determines how valid the genre labels provided to the music files were in accordance with the extracted acoustic values

2.) An experiment to model a user's listening behavior to determine the songs that will be used for recommendation

3.) Evaluation of the computational model's performance in determining the similarity between the songs that users would select

5.1 Grouping Music Selection

For determining the validity of the corpus amongst genre types, Table 5-1 shows the results of the models with the highest performance for categorizing the music dataset according to type.

Table 5-1 Analysis between models

Model	Accuracy	Kappa Statistic	Mean Absolute Error
SVM & CFS	82.4	0.77	0.070
SVM & CFS & Merged	91.3	0.87	0.058
J48 & CFS & Merged	90.6	0.86	0.068

Amongst the models, it was the model with SVM, CFS, and Merged genre types that performed the best amongst genre classification, thus it was used as a basis for selecting the similarity measures amongst the music and attributes that will be used by the model. Table 5-2 and 5-3 represent the model's summary as well as the confusion matrix produced respectively.

Table 5-2 Summary of SVM & CFS & Merged

TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
0.93	0.02	0.94	0.93	0.94	0.96	Classical
0.80	0.03	0.93	0.80	0.86	0.89	Pop
0.99	0.09	0.89	0.99	0.94	0.95	Techno
0.91	**0.05**	**0.92**	**0.91**	**0.91**	**0.93**	**Average**

Table 5-3 Confusion Matrix of SVM & CFS & Merged

	Classical	Pop	Techno
Classical	112	6	2
Pop	7	106	20
Techno	0	2	172

Songs tagged as “Classical” are song types that are mainly instrumental music with no lyrics present. They may consist of single instruments to multiple instruments. The reason why some songs were classified as Pop or Techno were due to the fact that some instrumental songs had enough energy to match those of a pop song or a techno song. The classifier on the other hand had slight trouble with Pop types but still managed to classify majority of them correctly. This is because while majority of pop songs carry a common sound consisting of multiple instruments, some pop songs were slow and consisted of only acoustic instruments which made the classifier mistaken them as Classical songs while others were labeled as Techno due to the sounds these songs emitted. While the classifier performed excellently for Techno songs, there were still some that got classified as Pop, although none of them were classified as Classical types due to the very distinct sound between them.

Table 5-4 illustrates the distinct attributes and values per Genre Label.

Table 5-4 Distinct Values per Genre Label

Classical	
Area Method of Moments Overall Standard Deviation	<= 1.197
Pop	
LPC Overall Standard Deviation 6	> 0.1004
Area Method of Moments Overall Standard Deviation 2	> 5691.000
Techno	
Method of Moments Overall Average 3	> 2876.000
Area Method of Moments Overall Standard Deviation 2	< 5691.000
LPC Overall Average 8	< 0.0350
Compactness Overall Average	<= 1593.000
Area Method of Moments of MFCCs Overall Average 1	<= -834.300

5.2 User Evaluation of Music Player Module

The users were each provided with a module (as described in section 4.2) used to listen to music for the duration of the study. To check if the module was effective in gathering their data, the users were asked for their feedback at the end of the data gathering session.

Users reported that the module simulated a normal music player but it needed some time to get used to the interface. Some users also reported that the space needed for the music was large. Some users also stated that the window which lists their listening activity was distracting at times. There was also some feedback from users that wished that the music files were grouped more accordingly and named more specifically (i.e. Title.wav instead of number.wav) instead of being randomly scattered across the directory.

In validating their behavior, the users were asked questions whether the first music they play upon opening the player is their favorite song or a song they really like and whether they skip a song they do not like. On a scale of 1 to 5, with 5 being “Strongly Agree” and 1 being “Strongly Disagree”, the average rating of all users was **4.57** where 4 users answered with 5 and 3 users answered with 4. In terms of skipping music if they do not like it, the average rating of all users was **4.86** where 6 users answered with 5 and only 1 user answered with 4.

Users have reported that they would add music to the playlist under two conditions. The first condition is if they like listening to it and the other condition is if they want to try listening to it. However, they all answered similarly in terms of removing music from the playlist, where they all gave the feedback that they remove it if they do not want to listen to it because it does not sound nice or it does not suit their preference.

The complete feedback of all the users can be found in Appendix G.

5.3 Analysis of User Models

For each user, their listening preference was analyzed as well as the songs with the highest utility value. Users were evaluated on a per monthly basis as well as the performance of the recommendation module in determining the song to be used as a basis for recommendation. The recommendation playlist consisted of the following:

- 5 songs as a basis (Selected as the top 5 songs with the highest positive utility values)
- A maximum of 15 additional songs, where 3 songs are derived from each song in the basis list using the formula mentioned.

A larger recommendation playlist produced indicated that there is a big difference between the top music selected by the user, while smaller recommendation playlists produced indicated that there is a smaller difference amongst the music listened and preferred by the listener.

Each user's recommendation summary will be evaluated during a per-monthly basis and will contain the following values:

Y = no. of basis songs (constantly 5)
X = no. of recommendation songs (Maximum value of 15)
β = no. of basis songs selected
α = no. of recommendation songs selected
Ω = no. of basis songs selected with a negative utility end value
π = no. of recommendation songs selected with a negative utility end value.

No. of Recommendations	$Y + X$
No. selected from Basis	β
No. selected from Recommendations	α
Ratio selected from basis	β / Y
Ratio selected from basis with negative Utility	Ω / Y
Ratio selected from recommendations	α / X
Ratio selected from recommendations with negative utility	π / X
Overall Performance	$(\beta + \alpha) / (Y + X)$

5.3.1 User 1

User 1 listened predominantly to pop music as indicated in Table 5-4.

Table 5-5 User 1's Highest Scoring Music per Month

Month	August	September	October	November	December	January	February
Dominant	367.wav	418.wav	418.wav	418.wav	418.wav	418.wav	427.wav
Utility	71.51	60.51	26.05	25.50	20.75	25.50	21.76

The dominant song for August was used as one of 4 songs as basis for recommendation for the month of September, September for October, and so on. Table 5-5 shows the recommender's performance for User 1's listening preference for the duration of September to February.

Table 5-6 Recommendation Summary for User 1

Month	September	October	November	December	January	February
No. of Recommendations	20	20	20	20	12	12
No. selected from Basis	5	5	5	5	5	5
No. selected from Recommendations	0	0	2	6	2	3
Ratio selected from basis	1.00	1.00	1.00	1.00	1.00	1.00
Ratio selected from basis with negative Utility	25.00	0.00	0.00	25.00	0.00	0.00
Ratio selected from recommendations	0.00	0.00	0.13	0.40	.28	0.43
Ratio selected from recommendations with negative utility	0.00	0.00	0.00	0.00	0.00	0.00
Overall Performance	0.250	0.250	0.350	0.550	0.583	0.667

As indicated in Table 5-4, User 1's listening preference, whilst majority was pop songs, were very distinct types between September to November, but started to become more consistent during December to February. This is consistent as it appeared that the recommender performed better for these months as described in Table 5-5.

5.3.2 User 2

User 2 listened predominantly to classical instrumental and classical solo instrumental music as indicated in Table 5-6.

Table 5-7 User 2's Highest Scoring Music per Month

Month	August	September	October	November	December	January	February
Dominant	53.wav	53.wav	47.wav	200.wav	200.wav	53.wav	425.wav
Utility	24.26	56.75	54.00	64.05	78.06	35.76	33.76

The dominant song for August was used as one of 4 songs as a basis for recommendation for the month of September, September for October, and so on. Table 5-7 shows the recommender's performance for User 2's listening preference for the duration of September to February.

Table 5-8 Recommendation Summary for User 2

Month	September	October	November	December	January	February
No. of Recommendations	18	13	13	15	9	15
No. selected from Basis	5	5	5	3	4	4
No. selected from Recommendations	3	1	3	2	0	0
Ratio selected from basis	1.00	1.00	1.00	0.60	0.80	0.80
Ratio selected from basis with negative Utility	0.00	0.00	0.25	0.00	1.00	0.40
Ratio selected from recommendations	0.231	0.125	0.00	0.20	0.00	0.00
Ratio selected from recommendations with negative utility	0.077	0.00	0.00	0.00	0.00	0.00
Overall Performance	0.444	0.462	0.385	0.333	0.4444	0.3333

While User 2 had the tendency to listen to classical instrumental music, user 2's listening preference changed very frequently and sometimes several times a month. As the model only learned during a per monthly basis, it was unable to take into consideration user 2's changes that occur during the middle of the month, thus the low performance. This is evident when User 2 had a consistent listening period during December which made the recommender produce only 9 recommendations, but their preference changed immediately again which caused a low performance. This is indicated in Table 5-7.

5.3.3 User 3

User 3 listened predominantly to techno music which is displayed in Table 5-8.

Table 5-9: User 3's Highest Scoring Music per Month

Month	August	September	October	November	December	January	February
Dominant	279.wav	279.wav	279.wav	279.wav	135.wav	135.wav	166.wav
Utility	54.01	48.76	38.75	35.76	60.07	38.26	29.25

The dominant song for August was used as one of 4 songs as basis for recommendation for the month of September, September for October, and so on. Table 5-9 shows the recommender's performance for User 3's listening preference for the duration of September to February.

Table 5-10 Recommendation Summary of User 3

Month	September	October	November	December	January	February
No. of Recommendations	18	17	17	14	14	10
No. selected from Basis	5	5	5	5	5	5
No. selected from Recommendations	1	2	1	1	1	0
Ratio selected from basis	1.00	1.00	1.00	1.00	1.00	1.00
Ratio selected from basis with negative Utility	0.00	0.40	0.40	0.20	0.40	1.00
Ratio selected from recommendations	0.077	0.167	0.083	0.111	0.111	0.00
Ratio selected from recommendations with negative utility	0.00	0.00	0.00	0.00	0.00	0.00
Overall Performance	0.333	0.412	0.353	0.429	0.429	0.500

User 3's listening remained consistent which were songs that were quite different from each other as Table 5-8 displays. The user's listening preference also changed very often (Less than within the span of a month) which is shown when songs that acted as a basis for the recommendation playlist actually ended up having negative utility values for the next month as indicated in Table 5-9. This means that User 3 frequently changes and removes songs from their respective playlist within weeks to days.

5.3.4 User 4

User 4 listened predominantly to classical solo instrumental music as indicated in Table 5-10.

Table 5-11 User 4's Highest Scoring Music per Month

Month	August	September	October	November	December	January	February
Dominant	4.wav	4.wav	15.wav	15.wav	15.wav	47.wav	47.wav
Utility	26.75	15.01	16.09	59.750	37.25	44.75	37.51

The dominant song for August was used as one of 4 songs as basis for recommendation for the month of September, September for October, and so on. Table 5-11 shows the recommender's performance for User 4's listening preference for the duration of September to February.

Table 5-12 Recommendation Summary of User 4

Month	September	October	November	December	January	February
No. of Recommendations	12	15	15	14	12	12
No. selected from Basis	5	4	5	5	5	5
No. selected from Recommendations	5	8	10	5	7	0
Ratio selected from basis	1.00	0.80	1.00	1.00	1.00	1.00
Ratio selected from basis with negative Utility	0.00	00.00	00.00	00.00	00.00	00.00
Ratio selected from recommendations	0.714	0.800	1.000	0.889	1.000	0.429
Ratio selected from recommendations with negative utility	0.00	0.00	0.000	0.00	0.00	0.00
Overall Performance	0.833	0.800	1.000	0.929	1.000	0.667

User 4 had a very consistent listening behavior and song preference. Their respective listening preference did not change dramatically and the similarity of the songs listened to were very close to each other, thus the performance of the recommendation was good for majority of the study's duration. However, by the month of January, there was a shift in the songs listened to by the user which caused a decrease in the performance for February, which indicated that the user's preference also changed during February.

5.3.5 User 5

User 5 listened predominantly to instrumental music as indicated in Table 5-12.

Table 5-13 User 5's Highest Scoring Music per Month

Month	August	September	October	November	December	January	February
Dominant	91.wav	95.wav	95.wav	166.wav	249.wav	239.wav	274.wav
Utility	23.259	32.270	25.75	29.2734	37.25	19.27	17.75

The dominant song for August was used as one of 4 songs as basis for recommendation for the month of September, September for October, and so on. Table 5-13 shows the recommender's performance for User 5's listening preference for the duration of September to February.

Table 5-14 Recommendation Summary of User 5

Month	September	October	November	December	January	February
No. of Recommendations	19	16	11	14	13	14
No. selected from Basis	5	5	5	5	1	5
No. selected from Recommendations	5	3	0	5	1	5
Ratio selected from basis	1.00	1.00	1.00	1.00	0.20	1.00
Ratio selected from basis with negative Utility	0.25	00.00	00.00	0.20	00.00	00.00
Ratio selected from recommendations	0.143	0.231	0.000	0.556	0.125	0.333
Ratio selected from recommendations with negative utility	0.00	0.00	0.000	0.111	0.00	0.00
Overall Performance	0.368	0.500	0.454	0.714	0.154	0.571

User 5's listening behavior and music preference changed very frequently, sometimes very distinctly. There were also instances when songs used as a basis ended up having a negative utility which indicated that songs that the user used to like from the previous month was no longer a favorable song for them. Their frequent preference change was also observed between the months of December and January when almost none of the songs selected as a basis were selected. This means that User 5's music preference changed within weeks and the new songs selected by User 5 had a very large difference.

5.3.6 User 6

User 6 listened predominantly to pop music as indicated in Table 5-14.

Table 5-15 User 6's Highest Scoring Music per Month

Month	August	September	October	November	December	January	February
Dominant	349.wav	349.wav	410.wav	356.wav	426.wav	426.wav	427.wav
Utility	86.509	53.51	55.51	43.01	49.01	46.76	24.76

The dominant song for August was used as one of 4 songs as basis for recommendation for the month of September, September for October, and so on. Table 5-15 shows the recommender's performance for User 6's listening preference for the duration of September to February.

Table 5-16 Recommendation Summary of User 6

Month	September	October	November	December	January	February
No. of Recommendations	16	17	17	17	20	17
No. selected from Basis	5	5	5	5	5	5
No. selected from Recommendations	2	3	2	2	2	0
Ratio selected from basis	1.00	1.00	1.00	1.00	1.00	1.00
Ratio selected from basis with negative Utility	0.00	0.00	0.00	0.00	0.00	0.40
Ratio selected from recommendations	0.181	0.250	0.167	0.167	0.133	0.00
Ratio selected from recommendations with negative utility	0.00	0.00	0.000	0.000	0.067	0.00
Overall Performance	0.438	0.471	0.412	0.412	0.35	0.294

User 6 mainly listened to pop music, and the songs were very distinct from each other. However, despite the distinction, the changes were not very abrupt thus the model managed to consistently identify the songs used as a basis every month. However, the recommendation module recommended several songs which indicated that the user had very different liked songs at the same time according to the similarity measures used as a basis for finding similarities between songs.

5.3.7 User 7

User 7 listened predominantly to classical solo instrumental music as indicated in Table 5-16.

Table 5-17 User 7's Highest Scoring Music per Month

Month	August	September	October	November	December	January	February
Dominant	27.wav	27.wav	27.wav	29.wav	29.wav	29.wav	29.wav
Utility	45.76	45.51	39.76	44.02	37.02	31.05	27.5

The dominant song for August was used as one of 4 songs as basis for recommendation for the month of September, September for October, and so on. Table 5-17 shows the recommender's performance for User 7's listening preference for the duration of September to February.

Table 5-18 Recommendation Summary of User 7

Month	September	October	November	December	January	February
No. of Recommendations	19	13	15	13	13	13
No. selected from Basis	5	5	5	5	5	5
No. selected from Recommendations	5	7	9	4	7	8
Ratio selected from basis	1.00	1.00	1.00	1.00	1.00	1.00
Ratio selected from basis with negative Utility	0.00	0.00	0.00	0.00	0.00	0.00
Ratio selected from recommendations	0.357	0.875	0.900	0.500	0.875	1.00
Ratio selected from recommendations with negative utility	0.00	0.00	0.00	0.00	0.00	0.00
Overall Performance	0.526	0.923	0.933	0.692	0.923	1.000

User 7 had a very uniform music preference, although the songs listened to at the start of the study's duration were quite distinct. However, User 7 started listening to more music, majority of them being the same type thus the recommender's behavior started to improve. While a slight change occurred between the months of November and December (which caused a slight decline in the performance), User 7's overall music preference remained the same which enabled the model to perform consistently. The high ratings were due to User 7's listening activity where the songs that were selected (Classical solo instrumental music) and received a favorable utility value were deemed to be similar according to the similarity measures used by the model.

5.3.8 Summary of all users

The summary of the recommendation model's performance per user is given in Table 5-18.

Table 5-19 Overall Recommendation Performance

	Sept	Oct	Nov	Dec	Jan	Feb	Ave	Genre
User 1	0.250	0.250	0.350	0.550	0.583	0.667	0.442	Pop
User 2	0.444	0.462	0.385	0.333	0.444	0.333	0.399	Classical Instrumental
User 3	0.333	0.412	0.353	0.429	0.429	0.500	0.409	Techno
User 4	0.833	0.800	1.000	0.929	1.000	0.667	0.872	Classical Solo Instrument
User 5	0.368	0.500	0.454	0.714	0.154	0.571	0.460	Classical Instrumental
User 6	0.438	0.471	0.412	0.412	0.350	0.294	0.396	Pop and Techno
User 7	0.526	0.923	0.933	0.692	0.923	1.000	0.833	Classical Solo Instrument

As shown in Table 5-18, the recommendation model performed better for Users 4 and 7 respectively because of their music preference being Classical Solo Instrument music as well as their preference not changing during a very significant period. As mentioned in Tables 5-10 and 5-16, their music preference would change sparingly during the month, which is enough time to correctly adjust the utility values to be used as a basis for next month's recommendation. In contrast to User 2 and User 5, while they listened to music considered in the Classical category, they mainly listened to Multiple Instrumental music which gave the model a hard time in distinguishing similarity and due to their changing preference very frequently that occurred within the month. When it comes to Pop and Techno, the model has a harder time because there are several pop songs or techno songs that sound similar to each other but may contain different factors why the user may not like them. Some reasons could be because the user did not go through the playlist due to the large number or because of a different metric that exists in those songs that are not obtainable through their acoustic values such as lyrics, artist, or mood / scale type.

Analyzing User 4 and User 7 further, it was taken into consideration that they listened to similar music types. Table 5-20 displays the minimum RV computed for both users (Refer to section 4.5 for the formula) while Table 5-21 and 5-22 display the Standard Deviations and Averages respectively

Table 5-20 Recommendation Values of Users 4 and 7

	Value (RV1)	Value (RV2)	Value (RV3)
MIN (RV)	0.336	0.56	0.732

Table 5-21 Recommendation Values of User 4

	VALUE (RV1)	VALUE (RV2)	VALUE (RV3)
STDEV (RV)	0.143926	0.119635	0.108006
AVE	0.704154	0.780229	0.854274

Table 5-22 Recommendation Values of User 7

	VALUE (RV1)	VALUE (RV2)	VALUE (RV3)
STDEV (RV)	0.150315	0.095662	0.074866
AVE	0.6128	0.743457	0.825571

This indicates that along with consistency amongst the songs they would listen to, similarity measures used by the computational function was consistent in distinguishing the types of music users would like listening to. This is evident in the RV values where the values are close to each other and none produced a value that is too large indicating that the differences of the reference songs are small enough to be liked by the user.

The average performance of the recommendation model is displayed in Table 5-19. The performance is the TP (True Positive) rating obtained from songs selected, or from Quadrant I of the “4 Quadrant” test (Recommended and Used) (Gunawardana & Shani, 2011).

Table 5-23 Average TP Rate for all users

Month	Average
September	0.455
October	0.545
November	0.555
December	**0.580**
January	0.555
February	0.576
Average	**0.544**

The average recommendation performance peaked during December at **0.57987** while the average performance rating was at **0.544381.** This indicated that given the user’s listening behavior and utility scores towards their songs, the model was able to determine the type of songs the user would listen to with a **54.43%** success rate on average during the next month. The values were quite around that range except for September, but this could be attributed to the users were still unsure as to what they really liked to listen to as well as familiarizing themselves with the interface they were provided with.

5.4 Addressing Concept Drift Problem

In dealing with the concept drift problem, it was indeed observed that users changed their preferences through time. However, despite the change in preference, it was observed that the recommendation performance did not decrease, staying almost the same and even increasing at some points. An example was that user 5's favorite song changed from 95.wav to 166.wav from October to November, but this did not hinder the performance of the model which saw its performance rise from **.454** to **.714** during November to December. Another instance was user 4's favorite song changing from 4.wav to 15.wav from September to October which saw the recommender's performance rise from **.800** to **1.000** during the time of October to September. Another instance showed user 6's favorite song changing from 410.wav to 356.wav but the performance remained at **.412** during the period. While this was because their music preference changed, it changed during a time when the utility matrix was able to properly detect the change (which is within a month's time).

However, there were instances when the performance was worse. An example can be seen in user 7's performance where their song favor changed from 27.wav to 29.wav from October to November which saw the performance fall from **.933** to **.692**. Despite falling, the performance started to improve again, going up to **0.923** during the next month. The reason about the model performing worse under these circumstances is because the music preferences of the users changed within a span that the utility matrix could not clearly distinguish it (i.e. a week or towards the end of the month). However, once the change has been detected and settled, the model managed to determine the updated favorite song of the user and perform well again.

5.5 Addressing Cold Start Problem

In dealing with the cold start problem, an additional experiment was performed where recommendations were based off of a random playlist. The results were compared with the actual model used for recommending music. For each user, a module which produced a random playlist was executed 10 times and the average TP rate was calculated for each user. The combined average of all their TP rates was used as the value for the particular month. The results are shown in Table 5-24 where it is clearly shown that using the model is more effective than generating a random playlist.

Table 5-24 Comparison between the Model and Random Playlists

Month	Using Model	Random Playlist
September	0.455	0.112
October	**0.545**	0.092
November	0.555	0.011
December	0.580	0.114
January	0.555	**0.137**
February	0.576	0.012
Average	**0.544**	**0.080**

Despite achieving the lowest score during the month of September, the model still outperformed the random playlist generator module in terms of recommending music and determining what types of music the user would like. This indicates that the model will perform better at recommending music using the approach proposed over randomly selecting music for the user, which is often the case during the cold start problem phenomenon.

6 Conclusions and Recommendations

The user's listening behavior and preference can be modeled based on the types of songs they listen to. This can be used as a basis for recommending songs where each song is provided with a utility value which changes depending on their interaction with a particular song. The more interactions a user has with a particular song, the higher the utility is while the less interactions they have with it, the less lower its utility value is.

The study can make a conclusion that the similarity measures used for music can be its acoustic values along with a specific genre tag and the BPM of the music.

By modeling the user's listening behavior through the utility values obtained in a per monthly basis, the performance of the recommendation performed an average of 54.43% given the data of 7 users and a span of 7 months. While the performance yielded that rating, it can be considered that it performed better than recommending music from a random playlist generated which had no information about the user's music preference, which is one of the issues in music recommendation, called the cold start phenomenon. However, more data will be needed to explore the concept drift problem due to the study's limitation of recommending music in a per monthly basis. This is because there is a possibility for users to change preference within a period that the model cannot distinguish due to the said limitation.

Therefore, one of the recommendations for future studies could be to have a module that could learn how long it takes for users to change their preference. While some users were observed to change listening preferences very often, others changed music preferences less frequently which made the model perform differently. This could probably help in determining how long it takes for the module to come up with recommendations per user, hopefully addressing the concept drift issue more accurately with the approach.

Also the study limited its music types to Classical Music, Pop Music, and Techno Music. Future studies could further expand types of Music particularly Classical, separating them between Piano Solo to Multi-Instrumental music, expanding the genre of Pop Music and differentiate clusters of Techno Music as well as have different similarity measures for each genre. Since the study made use of similar similarity measures for all genre, it provided different results for users who preferred certain music types over others.

The study also limited its scope to the User's Listening Behavior as a basis for recommendation. Future studies can cover more information about the User's Context, such as their mood and/or emotion, and their temporal context (i.e., some prefer to listen to different songs at night, others at particular days of the week) as a basis for recommendation. Also, exploring how active a user is with regards to listening to a song could be used as a basis for adding weights to a song's utility (i.e., Actively listening vs. Passively listening) as the study's scope did not focus on that.

Being able to recommend music real-time and having a dynamic model for the user at a more active basis instead of a per-monthly basis can also be explored. Allowing this can have several similarity measures with varying weights that will change depending on the recommender's performance with 4 quadrants in measuring Recommendation performance (Gunawardana & Shani, 2011) to come up with possibly better models for recommending music. Also, receiving immediate feedback from the user about the recommendations could be used as a basis in adjusting weights for different similarity measures used.

This study made use of a recommendation formula that can be used for future studies. Some examples could be a different set of similarity measures used, more computational functions to use as a basis for recommendation, as well as changing constant values used throughout the computational functions used during the research. Applying suggestions for measuring utility can also be used for further studies who wish to go into dynamic and more active recommendation models.

Appendix A: Preliminary Experiments

Music Preference Experiment (2012)

Preliminary experiments were conducted during the course of the research. The first preliminary experiment involved users who would listen to music using Genre as a metric in determining recommendation. Genre was selected as the measurement due to the availability of the measurement as obtained from (Manalili, 2010)

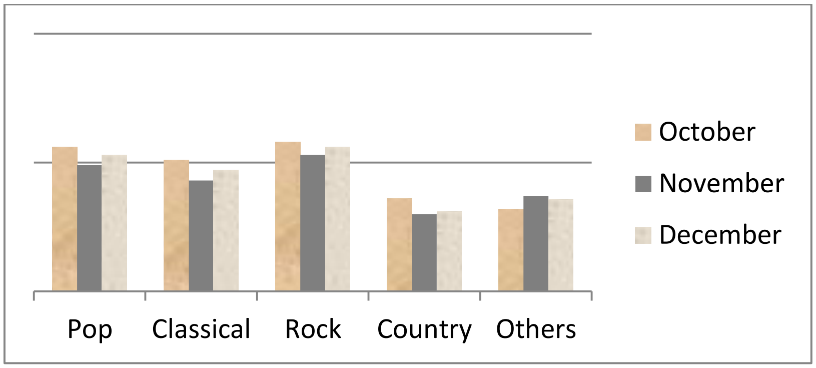


Figure A.1 User1's listening log

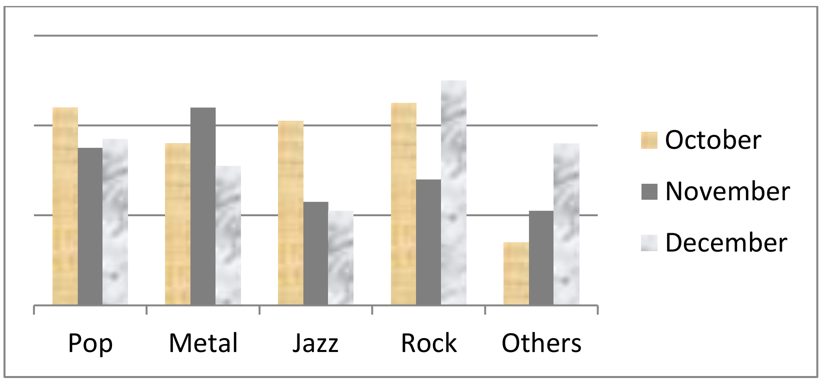


Figure A.2 User2's listening log

The obtained data indicated that the User1 showed consistency with their music preference. However, User2 had a tendency to have a more ambiguous preference. When asked, this was because User2 indicated that he had been preparing for an upcoming board exam, and the urgency of his upcoming exam made him prefer a specific genre over the other during a specific time.

Music Listening Behavior Experiment (2013)

Another experiment was conducted which required users to listen to a set of songs. The aim of the experiment was to determine whether a particular user's favor towards a song selection will decline over time or according to the context. In this experiment, the play counts of a particular song made by users were recorded. The songs of interest are as follows:

1.) Song 1 is the user's favorite song (This varied from user to user)
2.) Song 2 was a classical / instrumentally soothing musical piece to keep them calm (Was the same for all users)
3.) Song 3 was a song that was popular during that time (Was the same for all users)
4.) Song 4 was a Christmas song (Same for all users)

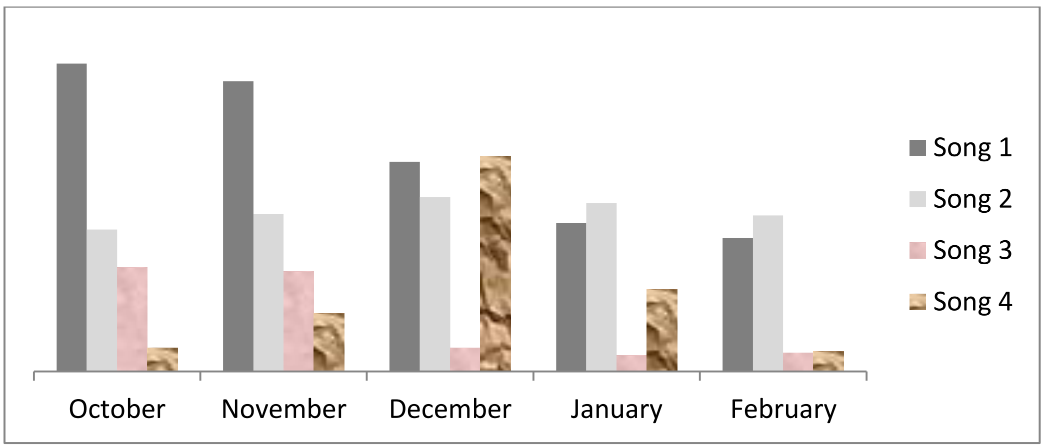


Figure A.3 Summary of Users and their play count with regards to these songs

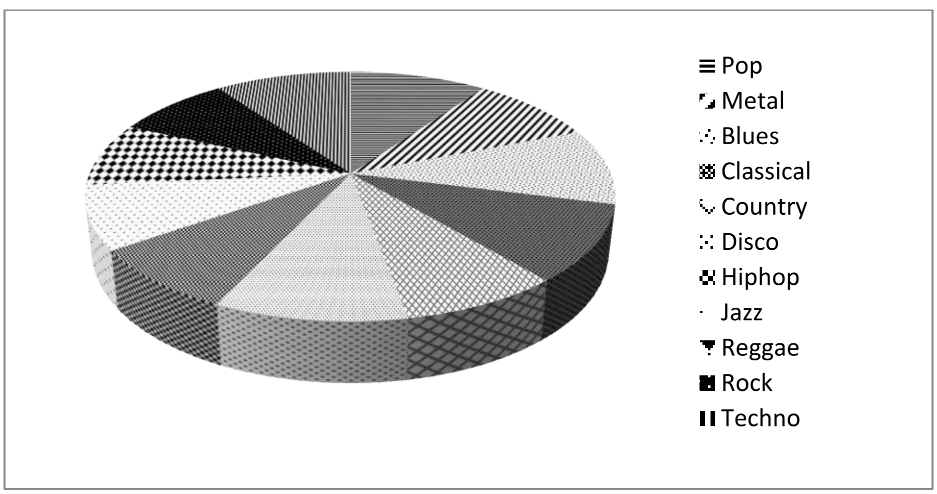
While Song 1 varied for all users, there was a consistency with regards to their play count decreasing over time, indicating that users eventually reach a saturation point for their favorite songs. Song 2 however remained consistent with regards to the number of times it is played, mainly because it is a song that is used depending on the situation that arose. Song 3's play count was affected by its popularity. Song 4 received a sharp increase in its play count due to the month, specifically December, as Song 4 was a Christmas Song and Christmas season fell on the month of December.

This experiment shows that it is plausible that a user's song selection would change through time and that their music preference changes.

Appendix B: Distribution of Music Used In Preliminary Experiments (By Genre) (Manalili, 2010) (Zenius, n.d)

Preliminary experiments made use of a music corpus that consists of 10 genre coming from a Self Organizing Map made by (Manalili, 2010). An additional genre was added which came from (Zenius, n.d) which consisted of Techno music. Additional music was also added for Pop, Classical, and Disco genre respectively.

Genre	Pop	Metal	Blues	Classical	Country	Disco	Hiphop	Jazz	Reggae	Rock	Techno
Count	120	110	120	120	100	120	100	100	100	100	120
%	9.92	9.1	9.92	9.92	8.30	9.93	8.30	8.30	8.30	8.30	9.92



Appendix C: Features selected and extracted from jAudio (McEnnis et al., 2007)

featureNo	Feature Name
1	Spectral Centroid Overall Standard Deviation
2	Spectral Rolloff Point Overall Standard Deviation
3	Spectral Flux Overall Standard Deviation
4	Compactness Overall Standard Deviation
5	Spectral Variability Overall Standard Deviation
6	Root Mean Square Overall Standard Deviation
7	Fraction Of Low Energy Windows Overall Standard Deviation
8	Zero Crossings Overall Standard Deviation
9	Strongest Beat Overall Standard Deviation
10	Beat Sum Overall Standard Deviation
11	Strength Of Strongest Beat Overall Standard Deviation
12	Strongest Frequency Via Zero Crossings Overall Standard Deviation
13	Strongest Frequency Via Spectral Centroid Overall Standard Deviation
14	Strongest Frequency Via FFT Maximum Overall Standard Deviation
15	MFCC Overall Standard Deviation 1
16	MFCC Overall Standard Deviation 2
17	MFCC Overall Standard Deviation 3
18	MFCC Overall Standard Deviation 4
19	MFCC Overall Standard Deviation 5
20	MFCC Overall Standard Deviation 6
21	MFCC Overall Standard Deviation 7
22	MFCC Overall Standard Deviation 8
23	MFCC Overall Standard Deviation 9
24	MFCC Overall Standard Deviation 10
25	MFCC Overall Standard Deviation 11
26	MFCC Overall Standard Deviation 12
27	MFCC Overall Standard Deviation 13
28	LPC Overall Standard Deviation 1
29	LPC Overall Standard Deviation 2
30	LPC Overall Standard Deviation 3
31	LPC Overall Standard Deviation 4
32	LPC Overall Standard Deviation 5
33	LPC Overall Standard Deviation 6
34	LPC Overall Standard Deviation 7

35	LPC Overall Standard Deviation 8
36	LPC Overall Standard Deviation 9
37	Method of Moments Overall Standard Deviation 1
38	Method of Moments Overall Standard Deviation 2
39	Method of Moments Overall Standard Deviation 3
40	Method of Moments Overall Standard Deviation 4
41	Method of Moments Overall Standard Deviation 5
42	Peak Based Spectral Smoothness Overall Standard Deviation
43	Relative Difference Function Overall Standard Deviation
44	Area Method of Moments Overall Standard Deviation 1
45	Area Method of Moments Overall Standard Deviation 2
46	Area Method of Moments Overall Standard Deviation 3
47	Area Method of Moments Overall Standard Deviation 4
48	Area Method of Moments Overall Standard Deviation 5
49	Area Method of Moments Overall Standard Deviation 6
50	Area Method of Moments Overall Standard Deviation 7
51	Area Method of Moments Overall Standard Deviation 8
52	Area Method of Moments Overall Standard Deviation 9
53	Area Method of Moments Overall Standard Deviation 10
54	Area Method of Moments of MFCCs Overall Standard Deviation 1
55	Area Method of Moments of MFCCs Overall Standard Deviation 2
56	Area Method of Moments of MFCCs Overall Standard Deviation 3
57	Area Method of Moments of MFCCs Overall Standard Deviation 4
58	Area Method of Moments of MFCCs Overall Standard Deviation 5
59	Area Method of Moments of MFCCs Overall Standard Deviation 6
60	Area Method of Moments of MFCCs Overall Standard Deviation 7
61	Area Method of Moments of MFCCs Overall Standard Deviation 8
62	Area Method of Moments of MFCCs Overall Standard Deviation 9
63	Area Method of Moments of MFCCs Overall Standard Deviation 10
64	Spectral Centroid Overall Average
65	Spectral Rolloff Point Overall Average
66	Spectral Flux Overall Average
67	Compactness Overall Average
68	Spectral Variability Overall Average

69	Root Mean Square Overall Average
70	Fraction Of Low Energy Windows Overall Average
71	Zero Crossings Overall Average
72	Strongest Beat Overall Average
73	Beat Sum Overall Average
74	Strength Of Strongest Beat Overall Average
75	Strongest Frequency Via Zero Crossings Overall Average
76	Strongest Frequency Via Spectral Centroid Overall Average
77	Strongest Frequency Via FFT Maximum Overall Average
78	MFCC Overall Average 1
79	MFCC Overall Average 2
80	MFCC Overall Average 3
81	MFCC Overall Average 4
82	MFCC Overall Average 5
83	MFCC Overall Average 6
84	MFCC Overall Average 7
85	MFCC Overall Average 8
86	MFCC Overall Average 9
87	MFCC Overall Average 10
88	MFCC Overall Average 11
89	MFCC Overall Average 12
90	MFCC Overall Average 13
91	LPC Overall Average 1
92	LPC Overall Average 2
93	LPC Overall Average 3
94	LPC Overall Average 4
95	LPC Overall Average 5
96	LPC Overall Average 6
97	LPC Overall Average 7
98	LPC Overall Average 8
99	LPC Overall Average 9
100	Method of Moments Overall Average 1
101	Method of Moments Overall Average 2
102	Method of Moments Overall Average 3
103	Method of Moments Overall Average 4
104	Method of Moments Overall Average 5
105	Peak Based Spectral Smoothness Overall Average
106	Relative Difference Function Overall Average
107	Area Method of Moments Overall Average 1
108	Area Method of Moments Overall Average 2
109	Area Method of Moments Overall Average 3
110	Area Method of Moments Overall Average 4

111	Area Method of Moments Overall Average 5
112	Area Method of Moments Overall Average 6
113	Area Method of Moments Overall Average 7
114	Area Method of Moments of MFCCs Overall Average 1
115	Area Method of Moments of MFCCs Overall Average 2
116	Area Method of Moments of MFCCs Overall Average 3
117	Area Method of Moments of MFCCs Overall Average 4
118	Area Method of Moments of MFCCs Overall Average 5
119	Area Method of Moments of MFCCs Overall Average 6

Appendix D: List of Music files used, genre labels, and estimated BPM.

.wav file	Genre	Adjusted Genre	Estimated BPM
1	Classical	Classical	124
2	Pop	Pop	66
3	Pop	Pop	95
4	Classical	Classical	53
5	Classical	Classical	111
6	Classical	Classical	108
7	Classical	Classical	77
8	Classical	Classical	118
9	Pop	Pop	88
10	Classical	Classical	98
11	Classical	Classical	72
12	Classical	Classical	87
13	Classical	Classical	80
14	Pop	Pop	96
15	Classical	Classical	163
16	Classical	Classical	69
17	Classical	Classical	139
18	Classical	Classical	82
19	Classical	Classical	112
20	Classical	Classical	102
21	Classical	Classical	45
22	Classical	Classical	80
23	Classical	Classical	128
24	Classical	Classical	74
25	Classical	Classical	116
26	Classical	Classical	111
27	Classical	Classical	124
28	Classical	Classical	103
29	Classical	Classical	129
30	Classical	Classical	73
31	Classical	Classical	101
32	Classical	Classical	134
33	Classical	Classical	93
34	Classical	Classical	96
35	Classical	Classical	107
36	Classical	Classical	135
37	Classical	Classical	120

38	Classical	Classical	92
39	Classical	Classical	80
40	Classical	Classical	87
41	Pop	Pop	78
42	Classical	Classical	107
43	Pop	Pop	78
44	Classical	Classical	85
45	Classical	Classical	137
46	Pop	Pop	102
47	Classical	Classical	122
48	Classical	Classical	83
49	Classical	Classical	92
50	Classical	Classical	121
51	Classical	Classical	93
52	Classical	Classical	95
53	Classical	Classical	134
54	Pop	Pop	75
55	Pop	Pop	90
56	Classical	Classical	109
57	Pop	Pop	70
58	Classical	Classical	94
59	Pop	Pop	88
60	Disco	Techno	140
61	Classical	Classical	102
62	Pop	Pop	88
63	Classical	Classical	118
64	Pop	Pop	75
65	Pop	Pop	80
66	Classical	Classical	133
67	Classical	Classical	100
68	Classical	Classical	67
69	Classical	Classical	114
70	Pop	Pop	120
71	Classical	Classical	107
72	Pop	Pop	100
73	Pop	Pop	88
74	Pop	Pop	116
75	Pop	Pop	80
76	Pop	Pop	83
77	Pop	Pop	63
78	Instrumental	Classical	102
79	Instrumental	Classical	98
80	Instrumental	Classical	63

81	Instrumental	Classical	110
82	Pop	Pop	66
83	Instrumental	Classical	68
84	Pop	Pop	125
85	Instrumental	Classical	74
86	Instrumental	Classical	106
87	Instrumental	Classical	120
88	Instrumental	Classical	85
89	Instrumental	Classical	79
90	Instrumental	Classical	120
91	Instrumental	Classical	65
92	Instrumental	Classical	134
93	Instrumental	Classical	120
94	Instrumental	Classical	73
95	Instrumental	Classical	125
96	Instrumental	Classical	92
97	Techno	Techno	111
98	Techno	Techno	93
99	Techno	Techno	77
100	Classical	Classical	139
101	Techno	Techno	71
102	Techno	Techno	100
103	Techno	Techno	98
104	Techno	Techno	100
105	Techno	Techno	79
106	Techno	Techno	130
107	Techno	Techno	83
108	Techno	Techno	100
109	Techno	Techno	113
110	Classical	Classical	119
111	Techno	Techno	65
112	Techno	Techno	95
113	Techno	Techno	83
114	Techno	Techno	85
115	Techno	Techno	136
116	Pop	Pop	95
117	Techno	Techno	150
118	Techno	Techno	150
119	Techno	Techno	83
120	Techno	Techno	85
121	Techno	Techno	136
122	Disco	Techno	85
123	Pop	Pop	62

124	Disco	Techno	85
125	Techno	Techno	80
126	Disco	Techno	85
127	Pop	Pop	82
128	Techno	Techno	100
129	Techno	Techno	85
130	Techno	Techno	88
131	Disco	Techno	89
132	Classical	Classical	63
133	Pop	Pop	86
134	Disco	Techno	142
135	Instrumental	Classical	79
136	Disco	Techno	160
137	Disco	Techno	150
138	Techno	Techno	95
139	Techno	Techno	74
140	Techno	Techno	112
141	Disco	Techno	142
142	Techno	Techno	130
143	Disco	Techno	76
144	Disco	Techno	136
145	Disco	Techno	75
146	Techno	Techno	106
147	Disco	Techno	86
148	Pop	Pop	103
149	Classical	Classical	100
150	Instrumental	Classical	98
151	Instrumental	Classical	113
152	Instrumental	Classical	60
153	Instrumental	Classical	55
154	Instrumental	Classical	90
155	Instrumental	Classical	100
156	Instrumental	Classical	70
157	Instrumental	Classical	55
158	Instrumental	Classical	100
159	Pop	Pop	90
160	Disco	Techno	71
161	Techno	Techno	95
162	Instrumental	Classical	170
163	Techno	Techno	100
164	Techno	Techno	100
165	Pop	Pop	83
166	Instrumental	Classical	76

167	Techno	Techno	150
168	Pop	Pop	104
169	Disco	Techno	84
170	Techno	Techno	87
171	Techno	Techno	73
172	Techno	Techno	75
173	Techno	Techno	80
174	Disco	Techno	124
175	Disco	Techno	132
176	Techno	Techno	90
177	Classical	Classical	157
178	Disco	Techno	81
179	Disco	Techno	73
180	Techno	Techno	80
181	Techno	Techno	80
182	Techno	Techno	78
183	Techno	Techno	98
184	Techno	Techno	98
185	Techno	Techno	90
186	Pop	Pop	110
187	Disco	Techno	138
188	Techno	Techno	83
189	Techno	Techno	136
190	Disco	Techno	126
191	Instrumental	Classical	70
192	Disco	Techno	116
193	Pop	Pop	75
194	Disco	Techno	91
195	Disco	Techno	136
196	Disco	Techno	70
197	Instrumental	Classical	52
198	Disco	Techno	90
199	Disco	Techno	90
200	Instrumental	Classical	83
201	Instrumental	Classical	83
202	Techno	Techno	74
203	Techno	Techno	100
204	Disco	Techno	95
205	Instrumental	Classical	70
206	Pop	Pop	81
207	Disco	Techno	91
208	Disco	Techno	91
209	Techno	Techno	75

210	Techno	Techno	78
211	Techno	Techno	85
212	Disco	Techno	95
213	Disco	Techno	77
214	Disco	Techno	77
215	Disco	Techno	124
216	Disco	Techno	118
217	Disco	Techno	119
218	Techno	Techno	90
219	Techno	Techno	75
220	Techno	Techno	150
221	Disco	Techno	90
222	Pop	Pop	94
223	Techno	Techno	75
224	Techno	Techno	75
225	Techno	Techno	100
226	Pop	Pop	72
227	Techno	Techno	80
228	Instrumental	Classical	111
229	Instrumental	Classical	115
230	Instrumental	Classical	100
231	Instrumental	Classical	77
232	Disco	Techno	130
233	Techno	Techno	85
234	Techno	Techno	110
235	Pop	Pop	65
236	Techno	Techno	100
237	Techno	Techno	95
238	Techno	Techno	69
239	Instrumental	Classical	85
240	Instrumental	Classical	48
241	Techno	Techno	70
242	Instrumental	Classical	141
243	Instrumental	Classical	60
244	Instrumental	Classical	128
245	Instrumental	Classical	120
246	Instrumental	Classical	90
247	Instrumental	Classical	164
248	Instrumental	Classical	57
249	Classical	Classical	92
250	Techno	Techno	75
251	Techno	Techno	100
252	Techno	Techno	105

253	Techno	Techno	50
254	Techno	Techno	86
255	Techno	Techno	75
256	Techno	Techno	100
257	Techno	Techno	100
258	Techno	Techno	90
259	Techno	Techno	95
260	Techno	Techno	95
261	Techno	Techno	75
262	Techno	Techno	90
263	Techno	Techno	146
264	Techno	Techno	136
265	Techno	Techno	91
266	Disco	Techno	85
267	Instrumental	Classical	71
268	Techno	Techno	100
269	Techno	Techno	110
270	Techno	Techno	100
271	Techno	Techno	76
272	Techno	Techno	75
273	Techno	Techno	93
274	Instrumental	Classical	116
275	Instrumental	Classical	67
276	Techno	Techno	87
277	Techno	Techno	85
278	Disco	Techno	75
279	Techno	Techno	85
280	Pop	Pop	96
281	Techno	Techno	79
282	Techno	Techno	111
283	Techno	Techno	91
284	Techno	Techno	75
285	Pop	Pop	88
286	Pop	Pop	88
287	Techno	Techno	90
288	Pop	Pop	85
289	Techno	Techno	100
290	Pop	Pop	125
291	Disco	Techno	96
292	Disco	Techno	80
293	Disco	Techno	75
294	Disco	Techno	89
295	Techno	Techno	74

296	Techno	Techno	140
297	Techno	Techno	160
298	Disco	Techno	134
299	Pop	Pop	90
300	Disco	Techno	93
301	Pop	Pop	100
302	Pop	Pop	85
303	Disco	Techno	108
304	Instrumental	Classical	76
305	Techno	Techno	83
306	Disco	Techno	144
307	Pop	Pop	90
308	Classical	Classical	87
309	Techno	Techno	80
310	Techno	Techno	74
311	Techno	Techno	85
312	Techno	Techno	140
313	Instrumental	Classical	112
314	Techno	Techno	100
315	Techno	Techno	85
316	Techno	Techno	90
317	Techno	Techno	96
318	Techno	Techno	160
319	Techno	Techno	85
320	Techno	Techno	80
321	Techno	Techno	80
322	Techno	Techno	96
323	Techno	Techno	83
324	Pop	Pop	104
325	Pop	Pop	128
326	Disco	Techno	138
327	Techno	Techno	85
328	Classical	Classical	59
329	Disco	Techno	88
330	Pop	Pop	90
331	Techno	Techno	93
332	Techno	Techno	93
333	Instrumental	Classical	70
334	Techno	Techno	120
335	Techno	Techno	140
336	Classical	Classical	127
337	Techno	Techno	85
338	Classical	Classical	138

339	Disco	Techno	88
340	Disco	Techno	150
341	Techno	Techno	79
342	Pop	Pop	85
343	Pop	Pop	90
344	Pop	Pop	110
345	Pop	Pop	128
346	Pop	Pop	73
347	Pop	Pop	126
348	Pop	Pop	72
349	Pop	Pop	122
350	Pop	Pop	73
351	Pop	Pop	128
352	Pop	Pop	90
353	Pop	Pop	71
354	Pop	Pop	128
355	Pop	Pop	85
356	Pop	Pop	69
357	Pop	Pop	113
358	Pop	Pop	107
359	Pop	Pop	72
360	Pop	Pop	124
361	Pop	Pop	103
362	Pop	Pop	56
363	Pop	Pop	59
364	Pop	Pop	72
365	Pop	Pop	134
366	Pop	Pop	75
367	Pop	Pop	78
368	Pop	Pop	112
369	Pop	Pop	74
370	Pop	Pop	116
371	Pop	Pop	81
372	Pop	Pop	82
373	Pop	Pop	126
374	Pop	Pop	148
375	Pop	Pop	68
376	Pop	Pop	132
377	Pop	Pop	100
378	Pop	Pop	64
379	Pop	Pop	77
380	Pop	Pop	68
381	Pop	Pop	73

382	Pop	Pop	110
383	Pop	Pop	104
384	Pop	Pop	84
385	Pop	Pop	101
386	Pop	Pop	66
387	Pop	Pop	65
388	Pop	Pop	77
389	Pop	Pop	118
390	Pop	Pop	120
391	Pop	Pop	120
392	Pop	Pop	95
393	Pop	Pop	91
394	Pop	Pop	80
395	Pop	Pop	78
396	Pop	Pop	126
397	Pop	Pop	122
398	Pop	Pop	120
399	Pop	Pop	108
400	Pop	Pop	104
401	Pop	Pop	75
402	Pop	Pop	80
403	Pop	Pop	111
404	Pop	Pop	60
405	Pop	Pop	83
406	Pop	Pop	110
407	Pop	Pop	80
408	Pop	Pop	112
409	Pop	Pop	67
410	Pop	Pop	79
411	Pop	Pop	74
412	Pop	Pop	81
413	Pop	Pop	69
414	Pop	Pop	122
415	Pop	Pop	80
416	Pop	Pop	86
417	Pop	Pop	66
418	Pop	Pop	146
419	Pop	Pop	94
420	Pop	Pop	107
421	Pop	Pop	78
422	Pop	Pop	120
423	Pop	Pop	130
424	Instrumental	Classical	66

425	Instrumental	Classical	73
426	Pop	Pop	59
427	Pop	Pop	69

Appendix E: Reference Songs Utility Values per user

User 1

August	
367.wav	71.51
418.wav	54.01
359.wav	42.26
165.wav	40.26
127.wav	22.76
September	
418.wav	60.51
127.wav	31.01
413.wav	29.51
367.wav	26.51
359.wav	24.01
October	
418.wav	26.05
413.wav	25.01
127.wav	24.26
359.wav	19.01
367.wav	15.01
November	
418.wav	25.50
127.wav	19.75
359.wav	19.75
367.wav	19.75
413.wav	19.75

December	
418.wav	20.75
412.wav	18.02
416.wav	18.02
411.wav	15.27
415.wav	15.27
January	
418.wav	25.5
413.wav	20
127.wav	19.5
359.wav	19.5
367.wav	19.5
February	
427.wav	21.76
367.wav	11.76

418.wav	11.76
359.wav	11.51
127.wav	6.76

User 2

August	
53.wav	24.26
17.wav	15.76
27.wav	15.76
47.wav	15.76
15.wav	14.51
September	
53.wav	56.75
17.wav	33
47.wav	33
48.wav	33
66.wav	33
October	
47.wav	54
26.wav	32
66.wav	32
68.wav	32
50.wav	28.5
November	
200.wav	64.05
201.wav	39.75
47.wav	34.75
249.wav	27.5
50.wav	25
December	
200.wav	78.06
177.wav	55.51
201.wav	55.51
249.wav	55.51
132.wav	46
January	
53.wav	35.76
44.wav	15.75
42.wav	14
51.wav	13.5
52.wav	13
February	

425.wav	33.76
42.wav	19.51
56.wav	15.5
424.wav	13.5
24.wav	11.5

User 3

August	
279.wav	54.01
60.wav	32.01
177.wav	31.76
262.wav	31.76
273.wav	31.26
September	
279.wav	48.76
60.wav	26.76
177.wav	26.51
204.wav	23.51
262.wav	20.51
October	
279.wav	38.75
177.wav	27.26
262.wav	27.26
204.wav	27.01
311.wav	26.01
November	
279.wav	35.76
204.wav	34.76
276.wav	24.76
311.wav	22.76
135.wav	23.5
December	
135.wav	60.07
279.wav	43.26
276.wav	42.26
80.wav	34.5
88.wav	30
January	
135.wav	38.26
80.wav	21.26
88.wav	21.26
89.wav	17.75
94.wav	15.5
February	

166.wav	29.25
95.wav	19.25
81.wav	18.25
91.wav	17.5
427.wav	17.25

User 4

August	
4.wav	26.75
5.wav	10.51
6.wav	7.21
8.wav	6.25
7.wav	5.25
September	
4.wav	15.01
17.wav	7.75
5.wav	6.5
6.wav	5.5
7.wav	5.5
October	
15.wav	16.09
16.wav	8.01
17.wav	8.01
18.wav	7.76
19.wav	7.76
November	
15.wav	59.75
16.wav	33.25
17.wav	33.25
4.wav	33.01
18.wav	32
December	
15.wav	37.25
16.wav	26.5
17.wav	25.5
18.wav	22.5
19.wav	21.5
January	
47.wav	44.75
4.wav	27.75
5.wav	22.75
6.wav	22.5
7.wav	22
February	

47.wav	37.51
4.wav	25.26
5.wav	20.25
6.wav	17.26
15.wav	16.25

User 5

August	
91.wav	23.26
83.wav	16.77
93.wav	16.77
79.wav	16.51
245.wav	14.77
September	
95.wav	32.27
91.wav	18.76
83.wav	16.01
79.wav	15.51
93.wav	15.51
October	
95.wav	25.75
166.wav	16.51
81.wav	13
91.wav	12.75
78.wav	12.5
November	
166.wav	29.27
338.wav	15.02
95.wav	14.53
177.wav	8.76
78.wav	8.52
December	
249.wav	37.25
338.wav	15.01
177.wav	13.76
239.wav	13.26
132.wav	11.27
January	
239.wav	19.27
81.wav	17.02
274.wav	16.51
197.wav	14.78
91.wav	14.77
February	

274.wav	17.75
81.wav	14.75
91.wav	13.75
95.wav	12.05
197.wav	11.75

User 6

August	
349.wav	86.51
351.wav	47.26
356.wav	35.01
358.wav	29.01
363.wav	23.01
September	
349.wav	53.51
351.wav	37.01
356.wav	26.75
358.wav	23.01
363.wav	21.02
October	
410.wav	55.51
349.wav	28.01
351.wav	25.02
356.wav	23.75
406.wav	21.50
November	
356.wav	43.01
410.wav	42.51
349.wav	22.01
351.wav	20
406.wav	19.01
December	
426.wav	49.01
356.wav	29.77
348.wav	26.76
349.wav	23.75
363.wav	22.50
January	
426.wav	46.76
349.wav	27.26
410.wav	25.26
348.wav	25.01
356.wav	25.01
February	

427.wav	47.51
349.wav	23.76
374.wav	23.76
380.wav	20.76
394.wav	19.75

User 7

August	
27.wav	45.76
28.wav	23.51
29.wav	22.51
30.wav	22.51
31.wav	22.51
September	
27.wav	45.51
28.wav	26.51
29.wav	26.51
30.wav	23.51
31.wav	22.50
October	
27.wav	39.76
28.wav	24.01
29.wav	24.01
30.wav	23.76
31.wav	23.76
November	
29.wav	44.02
47.wav	42.26
48.wav	23.25
49.wav	23
50.wav	22.50
December	
29.wav	37.02
47.wav	34.26
27.wav	18.51
28.wav	18.51
30.wav	17.51
January	
29.wav	31.05
47.wav	27.5
15.wav	15.75
16.wav	15.75

17.wav	15.75
February	
29.wav	27.5
47.wav	25
48.wav	14
49.wav	14
15.wav	13.75

Appendix F: Feature Definitions (McEnnis et al., 2007)

Feature	Definition
Spectral Centroid Overall Standard Deviation	The centre of mass of the power spectrum. This is the overall standard deviation over all windows.
Spectral Rolloff Point Overall Standard Deviation	The fraction of bins in the power spectrum at which 85% of the power is at lower frequencies. This is a measure of the right-skewedness of the power spectrum. This is the overall standard deviation over all windows.
Spectral Flux Overall Standard Deviation	A measure of the amount of spectral change in a signal. Found by calculating the change in the magnitude spectrum from frame to frame. This is the overall standard deviation over all windows.
Compactness Overall Standard Deviation	A measure of the noisiness of a signal. Found by comparing the components of a window's magnitude spectrum with the magnitude spectrum of its neighbouring windows. This is the overall standard deviation over all windows.
Spectral Variability Overall Standard Deviation	The standard deviation of the magnitude spectrum. This is a measure of the variance of a signal's magnitude spectrum. This is the overall standard deviation over all windows.
Root Mean Square Overall Standard Deviation	This is defined as a measure of the power of a sound's signal. This is the overall standard deviation over all windows.
Fraction Of Low Energy Windows Overall Standard Deviation	The fraction of the last 100 windows that has an RMS less than the mean RMS in the last 100 windows. This can indicate how much of a signal is quiet relative to the rest of the signal. This is the overall standard deviation over all windows.
Zero Crossings Overall Standard	MFCC calculations based upon Orange Cow code

Deviation	This is the overall standard deviation over all windows.
Strongest Beat Overall Standard Deviation	Linear Prediction Coeffecients calculated using autocorrelation and Levinson-Durbin recursion. This is the overall standard deviation over all windows.
Beat Sum Overall Standard Deviation	Statistical Method of Moments of the Magnitude Spectrum. This is the overall standard deviation over all windows.
Strength Of Strongest Beat Overall Standard Deviation	Spectral Centroid calculated based on the center of mass of partials instead of center of mass of bins. This is the overall standard deviation over all windows.
Strongest Frequency Via Zero Crossings Overall Standard Deviation	Calculate the correlation between adjacent frames based peaks instead of spectral bins. Peak tracking is primitive - where the number of bins changes, the bottom bins are matched sequentially and the extra unmatched bins are ignored. This is the overall standard deviation over all windows.
Strongest Frequency Via Spectral Centroid Overall Standard Deviation	Peak Based Spectral Smoothness is calculated from partials, not frequency bins. It is implemented according to McAdams 99 McAdams, S. 1999. This is the overall standard deviation over all windows.
Strongest Frequency Via FFT Maximum Overall Standard Deviation	log of the derivative of RMS. Used for onset detection. This is the overall standard deviation over all windows.
MFCC Overall Standard Deviation	2D statistical method of moments This is the overall standard deviation over all windows.
LPC Overall Standard Deviation	2D statistical method of moments of MFCCs This is the overall standard deviation over all windows.
Method of Moments Overall Standard Deviation	2D statistical method of moments of the log of the ConstantQ transform This is the overall standard deviation over all windows.

Partial Based Spectral Centroid Overall Standard Deviation	2D statistical method of moments of ConstantQ-based MFCCs This is the overall standard deviation over all windows.
Partial Based Spectral Flux Overall Standard Deviation	The centre of mass of the power spectrum. This is the overall average over all windows.
Peak Based Spectral Smoothness Overall Standard Deviation	The fraction of bins in the power spectrum at which 85% of the power is at lower frequencies. This is a measure of the right-skewedness of the power spectrum. This is the overall average over all windows.
Relative Difference Function Overall Standard Deviation	A measure of the amount of spectral change in a signal. Found by calculating the change in the magnitude spectrum from frame to frame. This is the overall average over all windows.
Area Method of Moments Overall Standard Deviation	A measure of the noisiness of a signal. Found by comparing the components of a window's magnitude spectrum with the magnitude spectrum of its neighbouring windows. This is the overall average over all windows.
Area Method of Moments of MFCCs Overall Standard Deviation	The standard deviation of the magnitude spectrum. This is a measure of the variance of a signal's magnitude spectrum. This is the overall average over all windows.
Area Method of Moments of Log of ConstantQ transform Overall Standard Deviation	This is considered as a measure of the power of a signal. This is the overall average over all windows.
Area Method of Moments of ConstantQ-based MFCCs Overall Standard Deviation	The fraction of the last 100 windows that has an RMS less than the mean RMS in the last 100 windows. This can indicate how much of a signal is quiet relative to the rest of the signal. This is the overall average over all windows.
Spectral Centroid Overall Average	The number of times the waveform changed sign. An indication of frequency as well as noisiness. This is the overall average over all windows.

Spectral Rolloff Point Overall Average	The strongest beat in a signal, in beats per minute, found by finding the strongest bin in the beat histogram. This is the overall average over all windows.
Spectral Flux Overall Average	The sum of all entries in the beat histogram. This is a good measure of the importance of regular beats in a signal. This is the overall average over all windows.
Compactness Overall Average	How strong the strongest beat in the beat histogram is compared to other potential beats. This is the overall average over all windows.
Spectral Variability Overall Average	The strongest frequency component of a signal, in Hz, found via the number of zero-crossings. This is the overall average over all windows.
Root Mean Square Overall Average	The strongest frequency component of a signal, in Hz, found via the spectral centroid. This is the overall average over all windows.
Fraction Of Low Energy Windows Overall Average	The strongest frequency component of a signal, in Hz, found via finding the FFT bin with the highest power. This is the overall average over all windows.
Zero Crossings Overall Average	MFCC calculations based upon Orange Cow code This is the overall average over all windows.
Strongest Beat Overall Average	Linear Prediction Coeffecients calculated using autocorrelation and Levinson-Durbin recursion. This is the overall average over all windows.
Beat Sum Overall Average	Statistical Method of Moments of the Magnitude Spectrum. This is the overall average over all windows.
Strength Of Strongest Beat Overall Average	Spectral Centroid calculated based on the center of mass of partials instead of center of mass of bins. This is the overall average over all windows.

Strongest Frequency Via Zero Crossings Overall Average	Calculate the correlation between adjacent frames based peaks instead of spectral bins. Peak tracking is primitive - where the number of bins changes, the bottom bins are matched sequentially and the extra unmatched bins are ignored. This is the overall average over all windows.
Strongest Frequency Via Spectral Centroid Overall Average	Peak Based Spectral Smoothness is calculated from partials, not frequency bins. It is implemented according to McAdams 99 McAdams, S. 1999. This is the overall average over all windows.
Strongest Frequency Via FFT Maximum Overall Average	log of the derivative of RMS. Used for onset detection. This is the overall average over all windows.
MFCC Overall Average	2D statistical method of moments This is the overall average over all windows.
LPC Overall Average	2D statistical method of moments of MFCCs This is the overall average over all windows.
Method of Moments Overall Average	2D statistical method of moments of the log of the ConstantQ transform This is the overall average over all windows.
Partial Based Spectral Centroid Overall Average	2D statistical method of moments of ConstantQ-based MFCCs This is the overall average over all windows.

Appendix G: User Feedback about experience

At the end of the research, the users were provided with a questionnaire detailing their experience. The questionnaire consists of two sections, the first section describing their music preference and the other their interactions with music using the player module provided to each of them. The questionnaire used the format obtained from *http://www.slideshare.net/lewisharland/music-media-questionnaire* as a basis.

User 1

Age: 21

Gender: M / F

Section A: Music Preference

1.) How often did you listen to music per day?

1 – 2 hrs [ ]

2 – 3 hrs [ ]

3 – 4 hrs [x]

4 – 5 hrs [ ]

5+ hrs [ ]

2.) What is your most preferred genre of music among the following?

Pop [x]

Classical / Instrumental [ ]

Techno / Electronic [ ]

3.) What makes you decide that you like certain music? (Check all that applies)

Genre [x]

Popularity [ ]

Tempo [x]

Lyrics [x]

Others [x] *If I am familiar with the artist or if I can relate with the lyrics*

4.) Under what circumstances do you listen to music? (Explain in at most 50 words)

I usually listen to music while working or while browsing the web

5.) Under what circumstances do you select a particular music over another (i.e. you like Song A and Song B, but you prefer to play Song A at a certain point over Song B and vice versa)

Usually, it depends on my mood or how I feel.

Section B: Using the player

1.) What makes you decide to load a particular song from a playlist?

If I want to check it out or if I want to listen to it

2.) The first music I play whenever I open the player is my favourite song or I song I really like (Answer on a scale of 1 – 5 with 5 being Strongly agree and 1 being Strongly disagree) __*5*__

3.) If I do not like what I am listening to, I skip it (Answer on a scale of 1 – 5 with 5 being Strongly agree and 1 being Strongly disagree) __*5*__

4.) What makes you remove a song from your playlist? (Explain in at most 50 words)

If I don't want to listen to it or if it doesn't sound nice to me

5.) Overall, how would you describe your experience with using the player?

It was a bit confusing to use at first, and the songs needed a lot of space, but it was okay.

User 2

Age: 18

Gender: M / F

Section A: Music Preference

1.) How often did you listen to music per day?

1 – 2 hrs [ ]

2 – 3 hrs [x]

3 – 4 hrs [ ]

4 – 5 hrs [ ]

5+ hrs [ ]

2.) What is your most preferred genre of music among the following?

Pop [ ]

Classical / Instrumental [x]

Techno / Electronic [ ]

3.) What makes you decide that you like certain music? (Check all that applies)

Genre [x]

Popularity [ ]

Tempo [x]

Lyrics [ ]

Others [x] *Scale. I prefer music in the major scale than pieces in the minor scale*

4.) Under what circumstances do you listen to music? (Explain in at most 50 words)

When I'm trying to finish something or when I am trying to come up with ideas

5.) Under what circumstances do you select a particular music over another (i.e. you like Song A and Song B, but you prefer to play Song A at a certain point over Song B and vice versa)

It depends on my mood or what I feel like listening to.

Section B: Using the player

1.) What makes you decide to load a particular song from a playlist?

<u>If I really like listening to it or if it sounds nice</u>

2.) The first music I play whenever I open the player is my favourite song or I song I really like (Answer on a scale of 1 – 5 with 5 being Strongly agree and 1 being Strongly disagree) __*4*__

3.) If I do not like what I am listening to, I skip it (Answer on a scale of 1 – 5 with 5 being Strongly agree and 1 being Strongly disagree) __*5*__

4.) What makes you remove a song from your playlist? (Explain in at most 50 words)

<u>If I find a song that I like more than it and I prefer listening to it now</u>

5.) Overall, how would you describe your experience with using the player?

<u>I eventually got used to playing my music with it instead of using Media Player, but it was a bit hard navigating to the folders with my music whenever I open it at times</u>

User 3

Age: 23

Gender: <u>M</u> / F

Section A: Music Preference

1.) How often did you listen to music per day?

1 – 2 hrs [ ]

2 – 3 hrs [ ]

3 – 4 hrs [x]

4 – 5 hrs [ ]

5+ hrs [ ]

2.) What is your most preferred genre of music among the following?

Pop [ ]

Classical / Instrumental [ ]

Techno / Electronic [x]

3.) What makes you decide that you like certain music? (Check all that applies)

Genre [ ]

Popularity [ ]

Tempo [x]

Lyrics [ ]

Others [x] *Melody. If it sounds catchy.*

4.) Under what circumstances do you listen to music? (Explain in at most 50 words)

During my breaks from work or when I am not doing anything.

5.) Under what circumstances do you select a particular music over another (i.e. you like Song A and Song B, but you prefer to play Song A at a certain point over Song B and vice versa)

If I feel like listening to music. Usually, the songs I want to listen to sound similar so they are really interchangeable.

Section B: Using the player

1.) What makes you decide to load a particular song from a playlist?

If I want to know how it sounds like or if I'm familiar with it and it sounds catchy.

2.) The first music I play whenever I open the player is my favourite song or I song I really like (Answer on a scale of 1 – 5 with 5 being Strongly agree and 1 being Strongly disagree) __*4*__

3.) If I do not like what I am listening to, I skip it (Answer on a scale of 1 – 5 with 5 being Strongly agree and 1 being Strongly disagree) __*5*__

4.) What makes you remove a song from your playlist? (Explain in at most 50 words)

If it does not sound nice or if I find it boring.

5.) Overall, how would you describe your experience with using the player?

It would have been better if the music files were actually provided with filenames that can be distinguishable instead of just numbers since it is sometimes hard to navigate. I wanted to listen *to all of them but there is not enough time. However, using the player was like using any other music player so it is good.*

User 4

Age: 18

Gender: M / F

Section A: Music Preference

1.) How often did you listen to music per day?

1 – 2 hrs [ ]

2 – 3 hrs [ ]

3 – 4 hrs [ ]

4 – 5 hrs [x]

5+ hrs [ ]

2.) What is your most preferred genre of music among the following?

Pop [ ]

Classical / Instrumental [x]

Techno / Electronic [ ]

3.) What makes you decide that you like certain music? (Check all that applies)

Genre [x]

Popularity [ ]

Tempo [x]

Lyrics [ ]

Others [x] *Mood. If it sounds relaxing or if it portrays a mood I want to feel.*

4.) Under what circumstances do you listen to music? (Explain in at most 50 words)

When I'm working on my projects or when I want to relax and just meditate on things.

5.) Under what circumstances do you select a particular music over another (i.e. you like Song A and Song B, but you prefer to play Song A at a certain point over Song B and vice versa)

Depends on how I feel or what I am about to do.

Section B: Using the player

1.) What makes you decide to load a particular song from a playlist?

If it sounds like it will help me and not distract me from what I am doing

2.) The first music I play whenever I open the player is my favourite song or I song I really like (Answer on a scale of 1 – 5 with 5 being Strongly agree and 1 being Strongly disagree) __*5*__

3.) If I do not like what I am listening to, I skip it (Answer on a scale of 1 – 5 with 5 being Strongly agree and 1 being Strongly disagree) __*5*__

4.) What makes you remove a song from your playlist? (Explain in at most 50 words)

If it sounds too distracting or I do not like it

5.) Overall, how would you describe your experience with using the player?

Without the instructions provided, I would not know what that small window was for, but it was like any normal music player. The music selections were also quite a lot and there were a lot of nice ones as well. However, it would have been better if they were grouped more accordingly and not randomly jumbled because it was a bit confusing at first in determining what music I should play and what music I should avoid.

User 5

Age: 22

Gender: M / F

Section A: Music Preference

1.) How often did you listen to music per day?

1 – 2 hrs [ ]

2 – 3 hrs [ ]

3 – 4 hrs [x]

4 – 5 hrs [ ]

5+ hrs [ ]

2.) What is your most preferred genre of music among the following?

Pop [ ]

Classical / Instrumental [x]

Techno / Electronic [ ]

3.) What makes you decide that you like certain music? (Check all that applies)

Genre [x]

Popularity [ ]

Tempo [x]

Lyrics [x]

Others [x] ___*The tone that it portrays or if it is something I'm familiar with*________

4.) Under what circumstances do you listen to music? (Explain in at most 50 words)

I use music so that it keeps me active or I won't feel bored while working

5.) Under what circumstances do you select a particular music over another (i.e. you like Song A and Song B, but you prefer to play Song A at a certain point over Song B and vice versa)

Usually it depends on the time because I like more calm stuff in the evening and more active stuff while I'm working during the day

Section B: Using the player

1.) What makes you decide to load a particular song from a playlist?

If I discover that I like it or if I feel adventurous and check other songs out

2.) The first music I play whenever I open the player is my favourite song or I song I really like (Answer on a scale of 1 – 5 with 5 being Strongly agree and 1 being Strongly disagree) __*4*__

3.) If I do not like what I am listening to, I skip it (Answer on a scale of 1 – 5 with 5 being Strongly agree and 1 being Strongly disagree) __*4*__

4.) What makes you remove a song from your playlist? (Explain in at most 50 words)

Usually if it turns out that I do not like it or if I want to listen to other things

5.) Overall, how would you describe your experience with using the player?

There was a lot of music and they were varying in almost all aspects. It took me some time to get used to using the player as well especially since I was initially bothered with that small window that pops up with it, but I got used to it eventually.

User 6

Age: 25

Gender: M / F

Section A: Music Preference

1.) How often did you listen to music per day?

1 – 2 hrs [ ]

2 – 3 hrs [ ]

3 – 4 hrs [x]

4 – 5 hrs [ ]

5+ hrs [ ]

2.) What is your most preferred genre of music among the following?

Pop [x]

Classical / Instrumental [ ]

Techno / Electronic [ ]

3.) What makes you decide that you like certain music? (Check all that applies)

Genre [x]

Popularity [ ]

Tempo [x]

Lyrics [x]

Others [x] *If I know who the artist is or if it sounds positive*

4.) Under what circumstances do you listen to music? (Explain in at most 50 words)

Work so I don't fall asleep during the night shift

5.) Under what circumstances do you select a particular music over another (i.e. you like Song A and Song B, but you prefer to play Song A at a certain point over Song B and vice versa)

It depends. Usually, I select a song and then I just let the player play the rest of the playlist

Section B: Using the player

1.) What makes you decide to load a particular song from a playlist?

If it sounds nice and I like it

2.) The first music I play whenever I open the player is my favourite song or I song I really like (Answer on a scale of 1 – 5 with 5 being Strongly agree and 1 being Strongly disagree) __*5*__

3.) If I do not like what I am listening to, I skip it (Answer on a scale of 1 – 5 with 5 being Strongly agree and 1 being Strongly disagree) __*5*__

4.) What makes you remove a song from your playlist? (Explain in at most 50 words)

If it doesn't sound nice or I am familiar with the artist and I do not like them (i.e. One Direction)

5.) Overall, how would you describe your experience with using the player?

The music took a lot of space in my system. As for the player, it was okay to use thanks to the instructions provided. I just wish it was easier to minimize the window that pops up with it because it's distracting at times.

User 7

Age: 30

Gender: M / F

Section A: Music Preference

1.) How often did you listen to music per day?

1 – 2 hrs [ ]

2 – 3 hrs [ ]

3 – 4 hrs [ ]

4 – 5 hrs [x]

5+ hrs [ ]

2.) What is your most preferred genre of music among the following?

Pop [ ]

Classical / Instrumental [x]

Techno / Electronic [ ]

3.) What makes you decide that you like certain music? (Check all that applies)

Genre [x]

Popularity [ ]

Tempo [x]

Lyrics [ ]

Others [x] *If it is instrumental and not dissonant*

4.) Under what circumstances do you listen to music? (Explain in at most 50 words)

While I am reading or focusing on something because it makes me focus better

5.) Under what circumstances do you select a particular music over another (i.e. you like Song A and Song B, but you prefer to play Song A at a certain point over Song B and vice versa)

Mood or the task I have at hand. Certain music is better when I am performing certain tasks

Section B: Using the player

1.) What makes you decide to load a particular song from a playlist?

If it is something I think I will like or if I want to explore with the music in the folders

2.) The first music I play whenever I open the player is my favourite song or I song I really like (Answer on a scale of 1 – 5 with 5 being Strongly agree and 1 being Strongly disagree) __*5*__

3.) If I do not like what I am listening to, I skip it (Answer on a scale of 1 – 5 with 5 being Strongly agree and 1 being Strongly disagree) __*5*__

4.) What makes you remove a song from your playlist? (Explain in at most 50 words)

If it is too noisy or if I do not like it because it does not sound nice

5.) Overall, how would you describe your experience with using the player?

It would have been better if the player developed was bigger in size because the buttons were so small. Also, it was hard to navigate to the music files at times but I got used to it.

Appendix H: RESOURCE PERSONS

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References

Adomavicius, G. and Tuzhilin, A., "Towards the next generation of recommender systems: a survey of the state-of-the-art and possible extensions," IEEE Trans. on Data and Knowledge Engineering 17:6, pp. 734–749, 2005.

Aquino, R. J., Battad, J. R., Ngo, C. F., Uy, G., Trogo, R., & Suarez, M. (2011, October). *Towards Empathic Music Provision for Computer Users.* In 2011 third international conference on knowledge and systems engineering. IEEE pp. 245 - 251.

Audacity Team. 2008. *Audacity 2.0.3 [Computer program]*. Retrieved January 5, 2013, from http://audacity.sourceforge.net/

Bustos M., Chua G., Cruz R., Santos J. (2011) *Markerless Gesture Recognition In the Context of Affect Modeling for Intelligent Tutoring Systems.*

Cano, P., Koppenberger M, and Wack, N. *"An industrialstrength content-based music recommendation system,"* in Proc. of 28th ACM SIGIR, pp. 673, 2005.

Coen M. *"The Future of human-computer interaction or how I learned to stop worrying and love my intelligent room*", IEEE Intelligent System,1999,14(2):8-10

Chen Rui, Hou Yi-bin, Huang Zhang-qin, Zhang Yong, Li Hui. (2007). *A Framework for Local Ambient Intelligence Space: The AmI-Space Project*

Coltheart, M. and Peretz, I. *Modularity of music processing*. Nature Neuroscience 6, pp 688 – 691. 25 June 2003.

Cu J., Cabredo R., Cu G., Inventado P., Trogo R., Suarez M. (2010). *The TALA Empathic Space: Integrating Affect and Activity Recognition into a Smart Space*

Del Castillo, H. *Hybrid Content-Based Collaborative-Filtering Music Recommendation.* University of Twente, The Netherland, 2007.

D.N. Sotiropoulos, A.S. Lampropoulos, and G.A. Tsihrintzis. (2007) *Evaluation of Modeling Music Similarity Perception Via Feature Subset Selection.* UM 2007, LNAI 4511, pp. 288–297

Donaldson, J. *"A hybrid social-acoustic recommendation system for popular music,"* in Proc. of the ACM Recommender Systems, pp. 187–190, 2007.

Ekman, P. *An argument for basic emotions*. Cognition & Emotion, 6(3/4):169–200, 1992.

Evans, A. (2009). *To what extent does the root-mean-squared (rms) amplitude value of a music track alter a song and does this contrast between different genres of music?*

(Tech. Rep.). Bournemouth University.

Foerster, F.; Smeja, M.; and Fahrenberg, J. 1999. *Detection of posture and motion by accelerometry: a validation in ambulatory monitoring.* Computers in Human Behavior 571–583.

Garlan D., et al. "*Project Aura:Toward distraction-free pervasive computing"*. IEEE Pervasive Computing,2002,1(2):22-31

Gomez, E. *Tonal description of polyphonic audio for music content processing*. Informs Journal on Computing, Vol. 18, No. 3, pp. 294-304, Summer 2006.

Gomez, E. and Herrera, P. *Estimating the tonality of polyphonic audio files: Cognitive versus machine learning modeling strategies*. ISMIR 2004, 5th International Conference on Music Information Retrieval, Barcelona, Spain, October 10-14, 2004, Proceedings

Grahn, J., & Brett, M. (2007*). Rhythm and Beat Perception in Motor Areas of the Brain.* Journal of Cognitive Neuroscience , 893-906.

Gunawardana A., Shani G. (2011). *Evaluating Recommender Systems*. Recommender Systems Handbook 2011, pp 257-297

Hani Hagras, Victor Callaghan, Martin Colley, et al. *Creating an Ambient-Intelligence Environment Using Embedded Agents".* IEEE INTELLIGENT SYSTEMS, 2004, 11:12-20.

Herrada, O. (2008). *Music Recommendation and Discovery in the Long Tail.* Universitat Pempeu Fabra, Barcelona, Spain.

Hevner, K. (1935). *Expression in music: A discussion of experimental studies and theories,* Psychological Review, Vol. 42, pp. 186–204

Hevner, K. (1935). *The affective character of the major and minor modes in music*, The American Journal of Psychology, Vol. 47, No. 1, pp. 103–118

Hevner, K. (1936). *Experimental studies of the elements of expression in music*, The American Journal of Psychology, Vol. 48, No. 2 pp. 246–268

Hevner, K. (1937). The *affective value of pitch and tempo in music*, The American Journal of Psychology, Vol. 49, No. 4, pp. 621–630

Hung-Chen Chen, Arbee Chen. (2004). *A Music Recommendation System Based on Music and User Grouping*

Huq, A., Bello, J., & and Rowe, R. (2010). *Automated Music Emotion Recognition: A Systematic Evaluation*, Journal of New Music Research, 39: 3, 227 — 244

Jennings, D (2007). Net, *Blogs and Rock 'n' Roll: How Digital Discovery Works and What it Means for Consumers*. Nicholas Brealey Publishing.

Johnson B, et al. *"The interactive workspaces project: Experiences with ubiquitous computing rooms".* IEEE Pervasive Computing, 2002, 1(2): 67-74.

Kaji, K., Hirata, K., & Nagao, K. (2005). *A music recommendation system based on annotations about listeners' preferences and situations.*

Kahng, M. and Park, C.H. *Temporal Dynamics in Music Listening Behavior: A Case Study of Online Music Service.* 9th IEEE/ACIS International conference on Computer and Information Science, 2010

Klapuri, A., Davy, M. (2006). "Signal Processing Methods for Music Transcription" Springer, New York.

Lesaffre, M., Leman, M., and Martens, J.-P. (2006). *A user-oriented approach to music information retrieval*. In Content-Based Retrieval.

Lidy, T. Evaluation *of new Audio Features and their utilization in novel music retrieval application*, Master's Thesis, Vienna University of Technology, December 2006.

Liu N & Hsieh S. (2009). *Intelligent Music Playlist Recommendation Based on User Daily Behavior and Music Content.*

Logan, B., Ellis, D. P. W, and Whitman, B. *A Large-Scale Evaluation of Acoustic and Subjective Music Similarity Measures*. A. Berenzweig, In Proceedings of the 4th International Symposium on Music Information Retrieval (ISMIR'03), Washington, D.C., USA, 2003

Manalili, S. (2010). *i3DMO - Interactive 3D Music Organizer*. (Master's Thesis, De La Salle University). Retrieved from project documentation.

McEnnis, D., C. McKay, I. Fujinaga, and P. Depalle. 2005. *jAudio: A feature extraction library*. Proceedings of the International Conference on Music Information Retrieval. 600–3.

McKay, C. (2010). *Automatic music classification with jMIR*. Ph.D. Thesis. McGill University, Canada.

Mehta, Ruchit V., "Session Based Music Recommendation using Singular Value Decomposition (SVD)" (2012).Master's Projects.Paper 237.

Meyer, L. B. (1956). *Emotion and Meaning in Music*. Chicago: University of Chicago Press.

Meyers, O. C. (2007). *A mood-based music classification and exploration system*. (Master's Thesis, Massachusetts Institute of Technology).

Pampalk, E. *Computational Models of Music Similarity and their Application to Music Information Retrieval*. Doctoral Thesis, Vienna University of Technology, Austria, March 2006

Pampalk, E, Pohle, T. and Widmer, G: *"Dynamic playlist generation based on skipping behavior"* in Proc. of 6th ISMIR pp. 634-637, 2005.

Peeters, G. (2004). A *large set of audio features for sound description (similarity and classification)* in the CUIDADO project (Technical Report). Paris: IRCAM.

Ragno R., Burges C and C. Herley: *"Inferring similarity between music objects with application to playlist generation,"* in Proc. of 7th ACM Multimedia, Workshop on MIR, pp. 73–80, 2005.

Quinlan, J. R. (1986). *Induction of decision tree. Machine Learning*, 1(1), 81–106.

Quinlan, J. R. (1993). *C4.5: Programs for machine learning*. San Mateo, California: Morgan Kaufman.

S. Russell and P. Norvig, *Artificial Intelligence, A Modern Approach*. Prentice Hall, second ed., 2003.

Sotiropoulos, D. N., Lampropoulos, A. S., and Tsihrintzis, G. A. (2007). *Evaluation ofmodeling music similarity perception via feature subset selection*. In User Modeling, volume 4511 of Lecture Notes in Computer Science, pages 288–297. Springer.

Stephen, D. *Music information retrieval (Chapter 7).. In Annual Review of Information Science and Technology 37*, pp 295-340. Medford, New Jersey, USA. 2003

Stephen M. Omohundro. (2007). *The Nature of Self-Improving Artificial Intelligence*

Thayer, R. E. (1989). *The biopsychology of mood and arousal*, Oxford University Press

Tzanetakis, G. *Pitch histograms in audio and symbolic MIR. ISMIR 2002, Proceedings 3rd International Conference on Music Information Retrieval*, pp 31-38 Paris, France, October 13-17, 2002

Tzanetakis, G. and Cook, P. (1999). *MARSYAS: a framework for audio analysis*. Organised Sound archive Volume 4 Issue 3, Pages 169 - 175

Uitdenbogerd A. and Van Schyndel, *A review of factors affecting music recommender success.* G. ISMIR 2002, 3rd International Conference on Music Information Retrieval, Paris, France, October 13-17, 2002

Van Setten, M. *Supporting people in finding information. Hybrid recommender systems and goal-based structuring*. Telematica Instituut Fundamental Research Series, vol. 016. Enschede, the Netherlands: Telematica Instituut, 2005 ISBN 90-75176-89-9

Weisstein, E. (2010). *Covariance [online]*. http://mathworld.wolfram.com/Covariance.html.

Weisstein, E. (2010). *The Standard Deviation [online].* http://mathworld.wolfram.com/StandardDeviation.html

Zenius (n.d.) *Zenius-i-vanisher.com -5th style- Repository of Simfiles*. Retrieved October 2012, from http://zenius-i-vanisher.com/v5.2/simfiles.php

Zliobaite, I. (2009). *Learning under Concept Drift: an Overview*. Technical Report. Faculty of Mathematics and Informatics, Vilnius University: Vilnius, Lithuania.