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This study analyzes five music recommender systems that are also internet radio systems from a user-centric perspective. Ten artists were chosen and ten songs allowed to play for each artist on each of the five systems. Using a 10 point scale on each of five attributes established by the researcher, an overall score for each system was computed and used to rank the systems. Using the rankings, an attempt was made to establish which method (collaborative filtering, content-based analysis, or a hybrid of the two) provides the best music recommendations. Although the results were somewhat inconclusive, collaborative filtering is shown to play an important role in music recommender systems.

Headings:
Music/Internet resources
Information retrieval
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Recommender systems
Collaborative filtering
Content-based analysis

BATTLE OF THE MUSIC RECOMMENDER SYSTEMS: USER-CENTERED EVALUATION OF COLLABORATIVE FILTERING, CONTENT-BASED ANALYSIS AND HYBRID SYSTEMS

by
Alexandra E. Fox

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Approved by:

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Dr. Robert M. Losee

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1 Introduction

1.1 Discovering Music on the Internet

Music has never been quite so accessible as it is now. Music lovers all over the world are connecting with each other through social networking sites built around music and discovering new music through music recommender systems. The term 'information overload' has become a household word and the phrase 'google it' now refers to using any search engine to help find the information. Recommender systems are just another way to sort through all that information. However, while google.com attempts to help you find information you are specifically looking for, recommender systems usually focus on helping to find items the user will like but were not necessarily looking for specifically. They help users discover new information on a particular domain, such as music.

This paper will examine five music recommender systems and rate their performance from a user-centric perspective in order to determine which provides the best recommendations overall. In addition, the functionality of each system will be discussed and analyzed in order to infer which method, collaborative filtering, content-based analysis or a hybrid of the two, provides better music recommendations.

1.2 History of Music on the Internet

Music on the internet is currently a hot topic. Some have referred to it as an "internet music revolution" (Collard, 2006, p. 1). The advent of music on the internet has caused the music industry to scramble to restructure its models for pricing and delivery methods. In this sense, it truly is a revolution. The music industry has spent the past ten years fighting the implications of this technology on the grounds of copyright infringement. Providing a brief overview of the history of music on the internet is a worthwhile endeavor when analyzing recommender systems in order to show how and why music recommender systems were developed.

The MP3 file format, the most common file type for music, was first introduced in 1994. The first MP3 player appeared about a year later. The internet at that time was still fairly new and not widely accessible. While there was almost certainly MP3 file sharing in the early years, it "was a non-trivial task and … remained a niche activity" (Collard, 2006, p. 1). As modem speeds and hard drive space increased and users replaced dial up internet access with broadband access, more and more people began to use digital music files more and CDs less. More MP3 player software emerged and peer-to-peer file sharing networks such as Napster emerged and became immensely popular. The ease and rate of music file sharing alarmed the music industry due to its legal implications on copyright protection.

Lawsuits have been filed against companies and individuals for illegally sharing music files - most notably the suits filed against Napster and the criminal charges filed against some of its individual users by the music industry (artists and record companies). The implications of these lawsuits produced a ripple in pop culture of such magnitude that Pepsi made commercials about preteens being branded as criminals for illegally downloading music. While there are still 'barely legal' file sharing systems being used (e.g. LimeWire, Kazaa), the effects of the music industry's lawsuits against Napster led to the introduction of Digital Rights Management (DRM) technology and internet radio.

DRM technology is controversial because it prevents the owner of the file, even if purchased legally, from making as many copies as she likes. Legally this is referred to in the United States as 'Fair Use' (Arnab, 2003). The DRM technology limits the number of copies and the number and types of devices on which the file can be played. The use of this technology means that if a legally purchased file is then shared illegally, the illegal use can only occur a handful of times since the number of copies is limited by the technology. Unfortunately, this also limits the legal use of the file. Many users feel that although they legally purchased the file, they do not, in fact, truly own it, since its use is limited. One study found that DRM technology "restrict[s] personal use in a manner inconsistent with the norms and expectations governing the purchase and rental of traditional physical CDs" (Mulligan et al., 2000, p. 77). The music industry is trying to limit fair use of its digital products and the consumers want to broaden it – or make it limitless. This perceived ill-will of the record companies against their customers (the lawsuits, the criminal charges and the DRM technology) has led to customers seeking other avenues. These other avenues include internet radio, recommender systems and social networking sites such as MySpace which centralizes its users around music appreciation. Many of these systems concentrate on recommending non-commercial artists in an effort to circumvent the record companies' established protocol and link artists to fans without a record contract or traditional radio airplay.

In addition to providing lesser-known artists an avenue of discovery and a sales outlet, the internet and recommender systems are also allowing well-known artists to break with their record companies and produce their own music. Some artists have been forming their own record labels and relying on their notoriety and the internet for marketing. Internet radio and recommender systems make this all possible. By changing the avenues of discovery from traditional radio airplay to internet radio and recommender systems and allowing listeners to purchase an individual song rather than a whole album on a physical compact disc, music is more available and the role of the record company has been permanently altered.

The record companies have not yet embraced this new technology and have yet to deduce how to make it work for them rather than against them. The file-sharing lawsuits and legislation are still transpiring. Many of the lawsuits have not yet been settled or come to trial. The music industry continues to attempt to adjust to this new environment. Some record labels have recently abandoned the use of DRM technology. Others are still pursuing four year old lawsuits. There is also now legislation championed by the music industry to impose compliance with the payment of royalties and even to raise the rates that internet radio stations must pay for playing songs. Since some internet radio stations attempt to fund their services through advertising alone (i.e. they do not charge a subscription fee to their users) this raise in rates may put them out of business. Those that do charge fees will be forced to raise them and risk losing clientele. The fate of internet radio has not yet been decided.

The fight continues, however. It is clear that music consumers do not appreciate the way the record industry considers them. Recommender systems champion the artists and not the record companies. Given that the record industry has made it more difficult to illegally access music, many users are turning to internet radio and recommender systems as an alternative to purchasing new music. Some users have decided that they don't need to own it if they can hear it on internet radio. Others prefer to discover new music, which they may or may not later purchase, using a recommender system.

1.3 What is a recommender system?

A recommender system is exactly what it sounds like - a system that provides recommendations to a user based on that user's preferences. These systems are designed to perform the same function as a knowledgeable friend who recommends a restaurant or a movie. Recommender systems are somewhat like search engines in that they use algorithms to filter information to provide the user with what it is hopefully only useful information. However, while search engines attempt to find something more or less specific based on the search criteria given by the user, recommender systems are used to find information that is unknown, forgotten or of questionable quality.

1.4 What are recommender systems used for?

Recommender systems can and are used for all sorts of purposes. Some common systems are Netflix.com which recommends movies to its customers, Tivo which recommends TV programs and movies to its customers and Amazon.com which employs a system to recommend items for purchase on its website. Users of Amazon.com will note that a plethora of items are available for purchase which could make recommendations harder to make. It is always easier to compare apples to apples rather than to oranges. For this reason, this study will be conducted on one domain: music.

Although recommendations for sites like Amazon.com can be quite lucrative and are therefore highly important from a marketing perspective, this study focuses on non-commercial systems and the methods employed by them to provide recommendations for a purpose other than exclusively sales and profits. A more exhaustive discussion of recommender systems, their uses and history can be found in Section 2.

2 Literature Review

2.1 History of Recommender Systems

Informal recommender systems have been in use for years. In fact, “even in prehistoric days, our species relied upon informal collaborative filtering” (Riedl & Konstan, 2002, p. 1). When prehistoric man encountered a new berry, not everyone in the tribe ate it right away. Some would wait to see if the others became sick before trying a new food. If no one became sick, then this acted as a recommendation for eating the berry. If people did become sick then it served as a negative recommendation for the berry in question (Riedl & Konstan, 2002). This is a rather simplified view of recommender systems but accurate nonetheless. Positive and negative recommendations help others to avoid things that they don’t like or are bad for them and discover things that they do like.

To continue the prehistoric example, suppose that one tribe came upon another tribe and shared knowledge. As populations grew and spread, so did knowledge. This is the basic tenet behind the collaborative filtering method of recommender systems. As technology has advanced, automated systems have been built and other methods employed to make recommendations.

The first formal recommender system, named Tapestry, was created in 1992 and its developers coined the term “collaborative filtering” (Resnick, 1997, p. 56) Developed by David Goldberg, David Nichols, Brian M. Oki, and Douglas Terry, its function was to filter email from newsgroups using collaborative filtering as opposed to content analysis (Goldberg & Nichols 1992). Goldberg et al were of the opinion that employing a human element would improve the system. They did, indeed, find this to be the case.

Any preliminary research on the subject of recommender systems will yield the names Resnick, Herlocker, Riedl and McNee. Paul Resnick is a self-described pioneer in the field of recommender systems beginning his research in 1994 with his study of collaborative filtering of newsgroups at the University of Minnesota using a system called GroupLens. GroupLens is a system which uses user ratings to recommend news articles to other users. Jonathan Herlocker is also a former student of GroupLens which is now led by John Riedl. The GroupLens group at the University of Minnesota has also now launched MovieLens, which was developed in part by Sean McNee. They have even launched a WikiLens which appears to be attempting to provide recommendations for anything and everything users contribute to the wiki. Since this study focuses on music recommender systems, none of the GroupLens systems will be used. However, there is a vast quantity of Information Science and Computer Science literature surrounding recommender systems, specifically collaborative filtering systems, which bears some relationship to the University of Minnesota and the GroupLens research.

The majority of non-collaborative filtering recommender system research is relatively recent. Collaborative filtering does have some faults and researchers have set out to correct these faults by employing other methods. Each method will be discussed.

2.2 Relevance Feedback

Before discussing the different methods used by recommender systems, it is important to note that relevance feedback is a significant element in many recommender systems regardless of the method employed. Relevance Feedback is a term that comes from the field of Information Retrieval. The term 'relevance feedback' was first coined by John Rocchio in the mid-1960s from his effort to solve the problem of users searching a domain whose terminology may be unfamiliar to the user (Belkin, 2000). If users are not aware of the specific language used in a particular domain it is much more difficult to find the information sought. This is where relevance feedback becomes invaluable. In essence, it asks the user to provide feedback to the retrieval system regarding the relevance of the retrieved information. The system then uses this feedback to tailor results. Measuring relevance is very subjective much like measuring how good a recommendation is (see section 3.4). It is arguable whether it is even possible to measure relevance. However, it is agreed upon that some measure is useful in providing better results to the user. Relevance Feedback is used to 'learn' the individual tastes of the user and mold the retrieved information to those tastes. Nicholas Belkin (2000) found that relevance feedback "worked well in an interactive information retrieval environment" (p. 60).

Relevance Feedback works similarly for recommender systems. Belkin's research (2000) focused on information retrieval in environments where the use was not completely sure of what information she was seeking. Recommender systems are similar in that regard. If the user knew exactly what she was seeking, she wouldn't need a recommendation. Different systems have different methods of incorporating it. The most popular method appears to be a binary function with two basic options: "I Like It" or "I Don't Like It." There is also an implicit third option which is to do nothing and give no feedback. Many music recommender systems also allow the user to skip a song. This information may or may not be included in the algorithm powering the recommendations. It is a very useful function in the music domain because it provides users a method of saying, 'I may like this song but I don't want to hear it now in this context.'

2.3 Types of systems

2.3.1 Collaborative Filtering

As defined by Goldberg & Nichols (1992) "collaborative filtering simply means that people collaborate to help one another perform filtering by recording their reactions to documents they read" (p. 61) This definition is in the context of the aforementioned system Tapestry where information professionals were helping one another save time by recommending, or not recommending, email documents. However, the definition still holds across other domains and with novice users. Analogous to the prehistoric man example, users may not realize they are helping others, but by rating movies on Netflix.com, one user is helping another user receive better movie recommendations.

As previously mentioned, most of the literature surrounding this topic, Resnick et al.(1994), Resnick & Varian (1997), Herlocker et al. (2000), Riedl (2002) and McNee et al. (2006), bears some relation to the GroupLens group from the University of Minnesota. Collaborative Filtering is the most common type of recommender system and is rapidly becoming a quasi household word due to its use in the realm of marketing.

Paul Resnick began the research in 1994 by creating the GroupLens system. GroupLens was designed to filter netnews and recommend news articles to users using collaborative filtering (Resnick, 1994). It is still being used today. Resnick later published a short article comparing five collaborative filtering systems (1997). In it he discusses the implications of using relevance feedback, which is an essential part of collaborative filtering. Without feedback (a.k.a. ratings), there can be no collaborative filtering. Resnick discusses the implications of different scenarios where collaborative filtering can break down due to user ratings (Resnick & Varian, 1997). Specifically, how systems handle ratings given by a handful of users but used to recommend items to a sea of users. Given that relevance feedback is usually voluntary, how well can a system function if the majority of users are not actively participating in the process? They also question the level of trust and security in these user ratings in systems that allow user anonymity. If the user is not accountable in some way for his ratings, how can he be trusted to provide accurate ratings? These are important obstacles to overcome in a collaborative filtering system.

Another similar obstacle to overcome in collaborative filtering is how to treat newly introduced items that have not been rated by anyone. This obstacle has recently been overcome by incorporating content-based filtering which will be discussed in the next section.

Johnathan Herlocker, Joseph Konstan and John Riedl, all students of Resnick, continued collaborative filtering research with their study on automated collaborative filtering (2000). Automated collaborative filtering uses ratings given by humans and automatically connects users with similar ratings which form communities. They state that collaborative filtering has been successful in entertainment domains (such as music and movies) but not in other domains (Herlocker et al, 2000). Once again the concept of trust is examined. User A is more likely to spend $15 on a CD recommended by some User B who is personally unknown to User A, than he is to spend much more on a vacation package recommended by User B (Herlocker et al, 2000). How does User A know he can trust User B's recommendation when he knows nothing else about User B? Herlocker et al (2000) also discusses the issue of sparsity of data previously discussed by Resnick. While collaborative filtering is often very effective, sparsity of data (user ratings) can also occasionally produce spectacularly bad recommendations. With all this is mind, Herlocker, et al (2000) created a new system for the University of Minnesota called MovieLens which recommends movies.

The following year Herlocker again collaborated with the GroupLens Research Group (Konstan, Terveen and Riedl, 2001) to conduct a study on how to evaluate collaborative filtering recommender systems. The paper discusses why it is so difficult to evaluate algorithms and systems since performance may be based on domain or other factors and because researchers themselves often do not agree on which attributes should be measured and what metrics should be used (Herlocker et al., 2001). The group identifies user tasks, datasets and accuracy metrics they believe to be important for evaluating recommender systems while acknowledging that it is a difficult task that has not been widely researched

John Riedl and Joseph Konstan published a book titled *Word of Mouse* on collaborative filtering and its use in marketing (Riedl & Konstan, 2002). The book is written for a general audience and explains how collaborative filtering is used for commercial systems such as Amazon.com. Although it is more of a marketing how-to guide than a scholarly work on collaborative filtering, it makes some excellent points about how best to employ this method in a commercial system and includes an example for Launch.com in the music domain. Unfortunately Launch.com, now Yahoo Radio, is not included in this study for several reasons. Since it is a highly commercial system it is not free and it is also largely genre-based rendering it more of an internet radio system than a recommender system. While it does employ collaborative filtering it does not allow customization and personalization like the other systems in this study.

2.3.2 Content-Based Analysis

While collaborative filtering has been widely used for many domains for some time, only recently has content based analysis been extensively studied. Rooted in the field of information retrieval, it has been principally applied to the domain of text in the past and only recently has the technology been applied to the domains of media (e.g. images, video and audio) (Adomavicius & Tuzhilin, 2005). In the domain of music there are two methods for content analysis: using the metadata from an audio file (e.g. the ID3 tag from an .mp3 file) which is used in normal information retrieval and actually analyzing the content of the file. For music this means the instruments, the tempo, the vocals, etc.

In 2000, Pedro Cano, Markus Koppenberger and Nicholas Wack built a content-based music recommender system which does not use metadata (Cano et al., 2000). Noting the previously mentioned drawbacks in collaborative filtering systems, they developed this system, MusicSurfer, as a content-based recommender to help users sort through obscure or unknown music. As mentioned before, collaborative filtering fails when there are no ratings - which is frequently the case for lesser known artists in music recommender systems.

Miguel Ramírez Jávega wrote his 2005 master's thesis on a prototype content-based music recommender system he developed at the Universitat Pompeu Fabra in Barcelona (Ramírez, 2005). In addition to building a prototype and discussing the algorithm used, his thesis analyzes "the problem of predicting music preferences" (Ramírez, 2005, p. 21). Unlike Cano's system, Ramírez' system does use metadata from ID3 tags (found on mp3 files) as well as content attributes stored in the SIMAC database[1] and the MTG-DB database[2]. He also enumerates the drawbacks of content-based recommender systems. Ramírez calls attention the fact that one of the reasons to employ content-based analysis can also be detrimental to its performance in two different ways. First, the content being analyzed has a limited number of attributes. In the domain of music this may or may not be a factor as there are a large number of potential attributes that can be quantified. The second drawback is that the system might work too well in that it only recommends items that are very similar and thus closes the door to discovering "novel items" (Ramírez, 2005, p. 58).

Lastly, Ramírez notes that for those systems that include an element of relevance feedback, new users will likely not receive as good recommendations as users who have

[1] http://www.semanticaudio.com

[2] university database

been using (and rating) the system for some time. There is normally a level of effort required by the user for content-based systems to be effective.

Hoashi et al. describe a music recommender system which uses an audio retrieval method called TreeQ in conjunction with a relevance feedback element (Hoashi et al., 2003). The TreeQ method used essentially forms a tree of music which is liked by a particular user and a tree of music which is disliked. Vectors are then used to determine which unrated songs that user might like. Hoashi et al., experimented with this system and determined that it worked well but required a lot of input from the user in the form of relevance feedback. In an effort to curb the amount of effort required by the user they examined generating genre profiles but ultimately determined that using the specific ratings data generated better recommendations.

Most content-based music recommender systems use content gleaned from metadata and/or musical attributes defined and assigned by humans and then entered in a database. In contrast, Tetsuro Kitahara examines methods for automatically recognizing musical instruments in polyphonic music files and its applications to music information retrieval. If a computer can determine what instruments are present, the pitch and the timber, the technology could be directly applied to music recommender systems and alleviate the human workload. This technology appears to be rather young, however, and is not used in any of the systems in this study.

2.3.3 Hybrid Systems

Robin Burke gives a general overview of recommender systems surveys and introduces a hybrid system for recommending restaurants that uses collaborative filtering and knowledge-based methods. Her study shows that “ratings obtained from the knowledge-based part of the system enhance the effectiveness of collaborative filtering." (Burke, 2000, p. 331)

Although this study concentrates on music recommendations and systems that use a content analysis rather than a knowledge-based method, others have also found that hybrid systems often perform better than single method systems in other domains. Some argue that "secondary content information can often be used to overcome sparsity" in collaborative filtering systems (Popescul, 2001, p. 437). Since each system has its foibles "several researchers are exploring hybrid collaborative and content-based recommenders to smooth out the disadvantages of each" (Popescul, 2001, p. 437). "Pure collaborative systems tend to fail when little is known about a user, or when he or she has uncommon interests. On the other hand, content-based systems cannot account for community endorsements" (Popescul, 2001, p. 437). These are the arguments made by Popescul before describing the probabilistic method developed by his team for unifying collaborative filtering and content-based recommendations.

While Popescul's study focuses on non-specific sparse-data environments, Melville's study looks at "content-boosted collaborative filtering" in movie recommender systems (2002, p. 1). Melville et al., postulate that both content-based and collaborative filtering fail when used individually (Melville et al, 2002). Using the domain of movies, the group built a system and implemented both a pure content-based component and a collaborative filtering component and tested them separately. They then combined the two using an average of the two systems' ratings. They ultimately determined that, for their domain and dataset, a system which employed both methods, but with collaborative filtering given a heavier weighting, functioned best, hence the name "content-boosted collaborative filtering" (Melville et al, 2002, p. 1).

Balbanović and Shoham have similar findings in their work with the Fab system (1997). They begin by providing an overview of content-based and collaborative filtering methods and their shortcomings. They then propose the Fab System, used for recommending digital library items, which uses content-based analysis to create user profiles and collaborative filtering to connect those profiles. The Fab system uses the advantage of other users' experiences in collaborative filtering and content based recommendations for new, unrated items in a digital library setting.

Yoshi's study (2006) examines a hybrid collaborative filtering and content-based probabilistic model for recommending music. This system was built and analyzed for performance. Similar results were found indicating that content-based methodology enhances the performance of a traditional collaborative filtering system. Yoshi agrees that collaborative filtering cannot work if there are no ratings available and "that artist variety… tends to be very poor" (Yoshi, 2006, p. 1).

2.3.4 Other Systems

Although there are more types of recommender systems, as Robin Burkes shows in her 2002 work on hybrid recommender systems, collaborative filtering and content-based systems are the two main types currently relevant to music recommendation. Burke begins by explaining recommender systems and quickly discussing each of the five traditional methods that drive them. She defines these methods as collaborative, content-based, demographic, utility-based and knowledge-based (Burke, 2002). In addition to those systems enumerated by Burke there is also a newly emerging type of system for the music domain: context-based analysis. As the name implies, context-based recommender systems are designed to recommend music for a certain context (e.g. a department store during the Christmas season or a pub on Friday night). However, the scope of this study only includes collaborative filtering, content analysis and hybrids of the two since the other methods are either not usually applied to music recommender systems or context specific. Therefore other types of recommender systems will not be discussed in detail.

2.4 Human-Recommender Interaction

Jonathan Herlocker, formerly of the GroupLens Research Group, investigated the evaluation of collaborative filtering recommender systems and identified six elements that should be included an evaluation. These elements are tasks, datasets, accuracy metrics, comparing metrics on the same system, identifying which metric are effective on which datasets and non-accuracy metrics such as user satisfaction (Herlocker et al., 2001) It is this last class of evaluation metrics that is of interest for this study.

Herlocker identifies the following elements as non-accuracy metrics that should be evaluated: *coverage*, *learning rate*, *novelty and serendipity* and *confidence. Coverage* represents the quantity and variety of items within the dataset with respect to the domain. *Learning Rate* is indicative of how quickly the system learns from the user feedback. *Novelty and serendipity* represent the system's ability to make unexpected good recommendations which lead to discovery of something which is both new and liked.

Confidence in this case is defined as the system's confidence in the strength of recommendation (where strength refers to an accuracy metric).

Sean McNee, a member of the GroupLens Research Group, has co-authored two recent articles on the accuracy and performance of recommender system from a more user-centric perspective. He and his GroupLens colleagues postulate that "most research up to this point has focused on improving the accuracy of recommender systems" and that "this narrow focus has been misguided" and "has even been detrimental to the field" (McNee, Riedl & Konstan, 2006, p. 1097). They argue that "the recommendations that are most accurate according to the metrics are sometimes not the recommendations that are most useful to users" (McNee, Riedl & Konstan, 2006, p. 1097). They further assert that similarity, serendipity and user needs and expectations should play a larger role in evaluating the accuracy of recommender systems.

In a separate work from the same year, the three men further articulate the attributes that should be considered when evaluating a recommender system. They identify eight such attributes: correctness, usefulness, transparency, salience, serendipity, quantity, spread and usability (McNee, Riedl & Konstan, 2006). *Correctness* is judged by the user regarding whether or not the recommendation is good and satisfies his information need. Whether or not the recommendation is *useful* is also user-determined and signifies the probability that the user will employ it or if it is in some way helpful with regard to his information need. *Transparency* indicates whether the user understands why the recommendation was made in the context given. *Salience* indicates that the recommendation is notable in some way or that it "stands out" either negatively or positively. *Serendipity* implies that the recommendation was unexpected but welcome.

Quantity is the number of recommendations received. *Spread* represents the user's opinion of the variety of recommendations or the "percentage of items in the domain considered." Finally, *usability* describes the system interface and its role in manufacturing a pleasant and effortless experience that also satisfies the original information need (McNee, Riedl & Konstan, 2006, p. 1106).

One human element relevant in the study of collaborative filtering recommender systems that has been touched on but not fully discussed yet is trust. In addition to the Resnick study previously discussed, O'Donovan & Smyth discuss how and why the trustworthiness of users should be an important consideration (2005). While this is a valid point, the element of trust should also be examined from a user-system perspective (see section 3.4). Trust is a system encompasses not only the collective trust in the users, but also the trust in the algorithm powering the system.

3 Methodology

In this study, five music recommender systems were evaluated from a user-centric perspective. Ten artists were chosen and ten songs allowed to play for each artist on each of the five systems. Using a 10 point scale on each of five attributes established by the researcher, an overall score for each system was computed and used to rank the systems. System methodologies were also examined and the rankings scrutinized to determine if the rankings indicated which methodology produced the best recommendations for one particular user on one domain. Details of the research and exact methodologies carried out are discussed in this section.

3.1 How Systems Were Chosen

Many systems were evaluated for inclusion in this study. Ultimately five were chosen and each is described in the next section. Systems were chosen based on the following criteria:

1. The system must be capable of playing the recommended music
2. The system must allow a particular artist to be entered
3. The system must employ collaborative filtering, content-based analysis or some hybrid combination of the two
4. The system must be available for use free of charge
5. The system must not be overly genre-based

The use of these criteria eliminated many systems. By limiting the study to systems that double as internet radio systems, the researcher was able to immediately evaluate the recommendations given even if they were unfamiliar. A system which allows customization by entering a particular artist can rightly be considered as a recommender system in that it is supposed to play music similar to the artist entered thus recommending that music. Limiting the systems by method limits the scope of the study to only those methods of interest and allows for the potential to not only compare systems but the methods they employ as well. Using non or less commercial systems aids in weeding out internet radio systems that are less concerned with music discovery and more concerned with profits. Disallowing systems that are genre based further limits the field and further ensures that either collaborative filtering or content-based analysis is at work behind the scenes. While genre is used in many systems, systems that rely on genres for recommendations tend to function poorly in comparison – particularly for users with eclectic cross-genre tastes.

3.2 Systems Chosen

3.2.1 Last.fm (http://www.last.fm)

Owned by CBS with offices headquartered in London and a website registered in the Federated States of Micronesia to attain the top-level domain country code *.fm*, Last.fm is a cross between a social networking site, a music recommender system and internet radio. Not to be confused with other social networking sites like MySpace, Last.fm does not allow customization of user home pages and is much more about the music and connecting users with similar musical tastes. Accounts can be created free of charge with the option of paying to upgrade to a premium user. However, free accounts appear to have most of the functionality as premium accounts. The main difference is that during times of high volume usage, customers with free accounts may have their internet radio cut off in order to preserve service for premium users. In addition, only premium users have the option to play a personalized internet radio station which includes artists they already know and like. Both account levels have the ability to play a radio station of personalized recommendations.

In addition to an internet radio music player which requires a download, users can "scrobble" music played from their computers or other devices. "Scrobbling", a term unique to the AudioScrobbler system which powers Last.fm, also requires the download of a widget that records and then uploads what music has been listened to. Any music played on the player is automatically "scrobbled". Users can add friends and the system compares musical tastes based on the "scrobbled" songs. In keeping with the social networking aspect, the system also displays user information about other users who have similar tastes and allows users to contact each other regardless of whether they have established themselves as friends.

While the player functions as a recommender system itself, the site also occasionally displays recommendations. However, for this study, only the recommendation player, which requires a download, will be used. The player allows the user to pick an artist as a starting point and then plays a personalized radio station based on the original artist chosen. This personalized radio station acts as a recommender station with each song it plays. By incorporating relevance feedback, the player allows the user to further customize his radio station. The user has three relevance feedback options: a heart, a double arrow and a universal No sign. Clicking on a heart indicates that he loves the song or that it is a favorite. The double arrow indicates he does not wish to give it a rating one way or another but merely wants to skip the song. This allows the user to essentially say that he either has a neutral opinion of this song in general or that he simply doesn't feel like hearing it at the moment. The universal No sign indicates dislike and tells the system not to play it again – ever. It is banned.

Last.fm uses the collaborative filtering method of recommendation. It uses the songs you have "scrobbled" to learn what songs you like. The obvious theory here is that if a user played it, she probably owns it and likes it, particularly if it has been played more than once. The system then compares this information with other users. For example, user A has scrobbled many songs by The Rolling Stones. User B has also scrobbled many songs by The Rolling Stones as well as The Who. Last.fm might then recommend The Who to User A based on user B's tastes. With only two users and one band this is somewhat of a risky recommendation. However, Last.fm has data on millions of users listening to thousands of bands which eliminates much of the risk. Given its system of 'scrobbling' it has more user data than other systems because it is able to use data generated from sources other than its player. With over 15 million active users acquired without the use of marketing and only word of mouth, Last.fm has capabilities that many collaborative filtering systems can only wish for (Lake, 2006).

3.2.2 Pandora (http://www.pandora.com)

In contrast to Last.fm, Pandora is a recommender system that is largely content-based. Founded by Tim Westergreen, the idea behind Pandora was simply to classify music. In the beginning there was no thought as to what use they put this classification. This project was coined the Music Genome Project and only later did it evolve into a music recommender system and popular internet radio system.

It is technically a hybrid system since it does incorporate an element of collaborative filtering. But it is not a 50-50 blend. It is impossible to tell how much of any recommendation is made using content information and how much is collaborative filtering. However, given that its content analysis is based on the Music Genome Project and its founder has given many talks around the country about how Pandora generally works, it seems safe to assume that this system is at least 75% content analysis. Pandora is a sort of a 'collaborative-boosted' content based recommender system.

The Music Genome Project has identified hundreds of musical attributes: "everything from melody, harmony and rhythm, to instrumentation, orchestration, arrangement, lyrics, and of course the rich world of singing and vocal harmony" (Pandora, 2007). Every song is classified according to its "genes." This classification is all done by people, most of whom have a background in music.

Pandora does not require a download – merely an Adobe Flash plug-in installed in the internet browser is needed. Accounts are free of charge but not required. It is possible to listen to Pandora internet radio recommendations without an account although without an account, relevance feedback cannot be recorded and recommendations probably won't be as good. Much like Last.fm, relevance feedback in Pandora consists of three elements: a thumbs up, a thumbs down and a skip option.

Although Westergreen declines to answer the question of how many users Pandora has, it can be inferred that it has fewer than Last.fm's 15 million. However, since Pandora is driven more my content-based analysis this may not affect its performance.

Operating as internet radio means that Pandora must pay royalties for the songs it plays. It also must pay all the people it employs to classify each and every song in the Music Genome Project. How then can it provide this service free of charge? Pandora uses advertising and provides inconspicuous links to both Amazon.com and iTunes.com to purchase the music playing. Pandora receives a percentage of each sale made on Amazon which originates from their site. This means that if a user clicks on the link to buy the music from Amazon and then also adds more items to his purchase, Pandora will receive a percentage of the total purchase.

3.2.3 GhanniMusic (http://www.ghannimusic.com)

GhanniMusic, a French company whose system is currently in beta, is unique in two ways. Firstly, it is the only entirely content-based music recommender system included in this study. Secondly, it has a significant constituency of French-language music in its dataset.

As discussed earlier, content-based analysis can be performed on the content of the file or on the metadata associated with the file. In this case it would seem that "in addition to their content-based features related to timbre, pitch and tempo, they are including features that are typically found in a song's metadata. This includes the year of release and the genre of the song" (Lamere, 2007). However, GhanniMuisc itself has this to say about it:

> Ghanni's technology analyses the music content to extract information about rhythm, tempo, timbre, instruments, vocals, and musical surface of a

> song. This information is grouped into Ghanni's fingerprint metadata. Ghanni's fingerprints are independent from the actually used metadata such as genre. Ghanni's fingerprints are extremely compact (as low as 2KB per song), intuitive, easy to obtain, and easy to use. By leveraging them, cost-effective and attractive personalized services can be launched, both for online and offline modes and whatever the support is (Internet, MP3 Player and Mobile phone). (GhanniMusic, 2007)

Perhaps what is actually happening is that while the metadata is not being directly accessed, it is included in the 'fingerprint.'

GhanniMusic requires no special software or downloads (although it does not seem to function properly in Firefox). It is free and does not use accounts. Since there are no accounts, there can be no collaborative filtering. This also means there can be no relevance feedback which may prove detrimental. The user simply enters an artist name and the system plays a song by that artist. The player continues to play music relevant to the artist entered until it is stopped or paused. There is no relevance feedback incorporated in the system so it cannot 'learn' the user's tastes. It can only provide recommendations determined by its algorithm to be valid for the content of the artist entered.

3.2.4 Jango (http://www.jango.com)

Jango is a social networking music recommender system whose tagline is "personal radio that learns from your taste and connects you to others who like what you like" (Jango, 2006). Jango was founded in 2006 in New York and is currently in beta. An invitation is required for use at this time although invitations are not difficult to receive. All that is required is to click on the "Request An Invite" link and fill out the information. An invitation was received within one day of submission. Using a university email address may or may not help in acquiring an invitation.

Due to its social networking component, Jango is obviously employing collaborative filtering behind the scenes. On the surface it appears to be similar to Last.fm. However, being a rather new system, there is a dearth of information regarding Jango. For whatever reason they have managed to stay off the blog radar - until recently. They plan to launch in mid-November of 2007 and claim to have 300,000 beta users (Kirkpatrick, 2007).

3.2.5 MeeMix (http://www.meemix.com)

Headquartered in Tel Aviv, Israel, MeeMix is yet another internet radio music recommender system that incorporates social networking. The system is currently in beta and requires an invitation to use the system. Invitations are not hard to come by at this time, however. All that is required is to go to the website and click on the large blue link that says, “Click Here To Get An Invitation” and approximately 24 hours later an invitation is extended. It may or may not have made a difference that a university email account was used for the request.

Like Pandora, MeeMix employs humans, known as MeeMix musicologists, to classify the music. This indicates the use of content-based analysis in the MeeMix algorithm. Unlike Pandora, however, separate stations created on MeeMix are linked. Unlike most other systems, MeeMix uses a rating scale from -6 to 6 instead of a binary feedback system. There is no option to skip a song and only a rating of -6 will cause a song to stop playing and skip to the next. In addition to the rating scale, there are three other controls to help guide the music played by the system. MeeMix's 'Mood Control' gives the user the option to adjust a 'Surprise Me' level from 0-6, a 'Pulse' level from 0-6 and a Volume control (0-100).

Like Last.fm and Jango, MeeMix is also a social networking site and encourages users to contact one another and share their personalized radio stations. Due to the social nature of the site and system, it can also be assumed that collaborative filtering is also at work behind the scenes making this a hybrid recommender system. The number of current beta users is unknown rendering it impossible to predict its collaborative performance (although it only recently launched in beta).

To elaborate further on how MeeMix works here is a quote from an interview with the MeeMix CEO:

> When a channel is created by a member we consider 3 worlds; behavior, member profile and songs parameters. In a Mee Station there are no play lists, every song you hear was picked up at that same moment in relation to a world of parameters and considerations preformed by our taste engine. Just like the butterfly effect, the members' actions, demographics, rates, immediate relations and many additional aspects affect the next song you will get. That is the beauty of nature, just like the nature of our preferences. (Stern, 2007)

3.3 Artists

3.3.1 How Artists Were Chosen

A list of artists was generated to use on each system. There are 10 artists on the list representing various music genres and eras. The artists were picked using the following criteria:

- Notoriety – each artist is well known

- Consistency of sound – artists whose sound changed significantly (e.g. the Beatles) were not included (with one exception)
- Genre variety – a variety of genres were chosen
- Era variety – artists from different eras were chosen
- Exceptions – Although the goal of genre and era variety was met, there is also some overlap. In addition, one artist included did not have overwhelming consistency of sound. These decisions were partially due to the tastes of the researcher, but also designed as a test of system performance.
- Familiarity - artists/genres which are unfamiliar to the researcher were not included
- Likeability – artists/genres not liked by the researcher were not included

3.3.2 Artists chosen

Ludwig van Beethoven
Aretha Franklin
John Lee Hooker
The Rolling Stones
Led Zeppelin
The Clash
Metallica
Nirvana
Snoop Dogg
Bob Marley & the Wailers

3.4 What Is A Good Recommendation?

Before gathering the data, a system for evaluating that data on the fly must be established. In essence the goal of this study is to determine if any one system is better than another. One way to judge that is to score its recommendations where higher scores indicate a good recommendation and lower scores indicate a bad recommendation. How can a user determine if a recommendation is *good* using something other than a gut feeling?

Whether or not a recommendation is *good* is largely based on the user's opinion and therefore highly subjective. A recommendation is ultimately deemed *good* if the user likes the item being recommended and *bad* if he doesn't. Of course, it is much easier to make a judgment after the fact - he either liked the song or he didn't. The recommendation proved to be either *good* or *bad* (or perhaps neutral) only after examination. So, by extension, a good recommender system would be a system that consistently provides good recommendations.

Although seeking recommendations is an act not generally considered high-risk, in order to find out whether a recommendation is good there is an element risk involved. The user must risk a bad recommendation in order to potentially discover a good one. Common sense dictates that the perceived gain must be perceived as greater than the potential loss or harm in order for the risk to be taken. Given that the risk of suffering a bad music recommendation is neither life-threatening nor terribly time consuming, the risk is likely to be taken. After taking such risks with a recommender system, the user often discerns a pattern. If the recommendations prove to be frequently *good*, then over time the perceived risk lessens as the user begins to trust the system. Conversely, if the recommendations are frequently bad, the user will likely discontinue taking the risk of using that particular system.

There are many factors that can be used to predict whether a recommendation will prove to be *good*. As just described above, one of these factors is trust in the source of the recommendation. In this case, it applies to recommender systems but the general concept of trusting a system is not that different from trusting a person. Although there is some argument among scholars on this point, they do agree that a loose definition of trust can apply to both humans and systems (Friedman, 2000). For the purposes of this study, relying on a general concept of the idea of trust is sufficient and can be applied to both humans and recommender systems. The general concept of trust used here will be made clear shortly.

Morton Deutsch, one of the pioneers in the subject of trust in the realm of psychology states that "one element common to many usages of [the word] 'trust' is the notion of expectation or predictability" (Deutsch, 1958, p. 265). As mentioned earlier, a user may come to trust a system over time which then allows him to better predict the value of any recommendation from a given trusted system. Consider this scenario: Bob, who you have known for years and who has consistently provided you with good recommendations, makes a new recommendation to you. In contrast, Jill, who you met only a month ago and has never made a recommendation to you, also makes a recommendation to you. Which recommendation would be considered better? Most likely Bob's recommendation. Why? Because you trust the source of the recommendation. Why do you trust Bob? Because you have a history of receiving *good* recommendations from Bob which therefore allows for a high degree of predictability.

The same is true of systems. People are likely to trust a recommender system only after having used it for some time and it consistently providing recommendations subjectively deemed as *good*. The inverse of this is also true. Have you ever had a friend that you knew fairly well and even trusted with your life but who consistently made *bad* recommendations? You may still like and trust this person but history has proven to you that her recommendations are *bad* for you (although someone else may find them *good*). You *trust* that her recommendations are *bad*. Trust is still playing a very crucial role in determining the value of the recommendation itself. From this trust, predictability and expectation are derived.

Trustworthiness is closely linked with credibility. Credibility, particularly when interacting with other people, is often associated with appearance (Fogg, 2003). For example, a person attempting to sell insurance neatly groomed and wearing a suit may be found more trustworthy or credible than an unkempt man wearing torn jeans and a dirty T-shirt. This is also true on the internet. Site design, user interface and company name all play an important role in establishing the credibility of a website or a recommender system. Company names that are well known, such as Microsoft or Google, will have a higher perceived credibility than those that are not so recognizable (Fogg, 2003). While all of these elements play a role in determining credibility and trustworthiness, these elements are outside the scope of this paper. The intention here is to analyze the system itself, as well as its output (i.e. the recommendation), and not its packaging. Therefore, the front end design of the system will be mostly ignored.

The question of what makes a recommendation *good* is still unanswered, however. Suppose a system has been used for some time and is now trusted because it has consistently recommended liked items. But why were those items liked in the first place? What made them *good* recommendations? McNee, et al. argue that "salient recommendations" are "recommendations that strike an emotional response from a user" (2006, p. 1106). Richins states that many studies "have found emotions to be an important component of consumer response" (1997, p. 127). Although the systems in this study are less commercial than others, such as Amazon.com, they are still providing a consumer product. Unfortunately, an emotional response or a 'gut reaction' is difficult to quantify for a study. What then makes up an emotional response? "An emotion is a valenced affective reaction to perceptions of situations" (Richins, 1997, p. 127). This indicates that the situation, or context, is an important element of the emotional response. The context may be determined by the intended use of the system, the user's expectation at any given moment, or a combination of both.

Consciously or unconsciously the user must have set some expectation which was then met by the recommendation. In music recommender systems, expectations are usually set by first choosing an artist or a song that the user likes and allowing the system to choose another song for her based on the knowledge that she likes first song. Just like a friend, the system knows something about her likes, and perhaps her dislikes as well, and therefore recommends another song that is either similar in sound/content or liked by other users who have similar tastes. Regardless of the method used by the system, which is transparent to most users, there is still an expectation being set by the user and potentially being met by the system using some sort of similarity measure.

Similarity may be judged by the system in different ways. Content-based similarity in music recommendations may include elements such as genre, rhythm, vocal qualities, instruments used, melody, harmony, etc. The user may not even be aware of all these individual qualities but has a general idea of an overall sound which represents the complex relationship between all the audio elements. Even this general idea is often difficult for the user to define (Hoashi, 2003). In contrast, collaborative filtering similarity is based on a comparison of one user's tastes to another's. If one user has similar tastes to 10 others and those 10 all indicate a preference for an artist that the first user has not, then that artist is said to be similar to the first user's over all tastes.

There may, however, be more to her music recommender expectations than similarity. A good recommendation should be useful as well. To be useful, the user's expectation must be met within the context of the intended use. If her expectation is simply to hear a song that she enjoys then it would also be deemed useful if she enjoyed it. However, if she set her expectations slightly higher, and hopes to hear something new, then the recommendation is only useful if the system plays a song with which she is unfamiliar. Context, or rather the reason she is seeking the recommendation, plays a crucial role.

As just established, there are many different reasons to use a music recommender system. Since this paper focuses on music recommender systems that are also music players the user expectation could be to discover new music in order to simply listen to it. Or to listen to it in order to make an informed decision about whether or not to buy it. Or the user may simply want to hear a radio station tailored to his tastes, or perhaps even use the system to produce a playlist which is used to set the mood for a party. In all these cases, a recommendation would be deemed *good* if it meets the user's expectation – whatever that expectation may be. What if the expectation is not clearly defined? What if, as Belkin states, the user is in an "anomalous state of knowledge" (ASK) and is not clear on what his information needs are (1980, p. 133)? He knows he wants to hear music that he likes and he knows what he likes. Beyond that, he may not have any specific purpose or expectation. If the user is in the ASK state then he is not going to be able to fully define his expectation until after it has been met. Therefore, while it is possible to make a prediction about the quality of the recommendation by measuring the level of trust in the system, the user will not be able to determine the *goodness* of any recommendation until after it has been examined.

Having now identified five factors that can affect the user's opinion of whether a recommendation is *good*, perhaps a scale can be built in order to quantify the subjective opinions and emotions of the user in regard to each recommendation. The five factors are: Trust, Expectation, Similarity, Usefulness and Context. These factors incorporate many of the eight attributes identified by McNee et al. referenced earlier (McNee, Riedl & Konstan, 2006). In this case **Expectation** will capture McNee's *correctness*, *transparency* and *salience* attributes. **Similarity** is a concept not accounted for amongst McNee's attributes although he mentions its importance as an accuracy metric. **Context** will include McNee's *spread* and *serendipity* attributes. **Usefulness** incorporates the gut reaction of liking the song with McNee's *usability* attribute. **Trust** will capture the user's level of trust in the system based on all recommendations made before the current song.

3.5 Quantifying the Recommendations as Good or Bad

Using the five factors just established, a formula was generated to quantify the emotional responses for the purposes of this study. A ten point scale for each of the five elements listed above was used. The scale spans from -5 to 5 with a zero value reflecting a neutral opinion. For the first artist test on each system, the value for trust was set to zero. The level of trust was then expected to rise or fall as the tests continued in order to reflect the level of trust in the system as more recommendations were made. The other four elements were similarly evaluated after examining the recommendation, resulting in an overall score ranging from -25 to 25 for each song. These values were then averaged for each artist and those averages further averaged for an overall system score. Scores of 10 or higher were deemed *good* and scores of -10 or lower *bad*. Any scores between -10 and 10 were considered neutral or anomalous.

3.6 System Testing

3.6.1 Computer Set up

Now that a scale has been established to use for rating each site, the methodology of the system testing can now be described. Since all of these systems are web-based and most likely use cookies, and at least one of these systems attempts to access local Windows Media Player and iTunes music playing histories, a clean computer was used for testing. The School of Information & Library Science (SILS) computer lab houses 'frozen' computers which return to their original state after each restart. By using these frozen machines for testing, there was no danger of previous session cookies or application data skewing results. The PCs in the SILS computer lab run Windows Vista and Internet Explorer 7.

3.6.2 Testing

3.6.2.1 Creation of Test Accounts

New accounts were created for each system that uses accounts just before the testing began. This ensured that no previous data collected during the research phase was used to generate recommendations during the testing. A university email address was used to create all accounts. For the two systems that required invitations, the invitations had been issued approximately one week before testing began. However, they were not redeemed until the day of the day of testing.

3.6.2.2 Determining System Order

System testing order was determined to have little effect on the overall study and therefore the order in which the systems were tested was somewhat arbitrary. Considering this, the systems were loosely ordered by user experience. Systems with which the researcher had the most familiarity were tested last.

System Order:

1. Jango
2. MeeMix
3. GhanniMusic
4. Last.fm
5. Pandora

3.6.2.3 Determining Artist Order

Ten artist names were printed on a piece of paper and cut into strips of equal size. During the testing of the first system, fellow students in the SILS computer lab were asked to pick a strip from a hat to determine a random order for testing the artists. The same artist order was then used for all subsequent system testing. The artist order is as follows:

1. The Rolling Stones
2. Aretha Franklin
3. Nirvana
4. Led Zeppelin
5. Snoop Dogg
6. The Clash
7. Metallica
8. John Lee Hooker
9. Bob Marley & the Wailers
10. Ludwig van Beethoven

3.6.2.4 The Test

Testing was conducting over a period of 7 days in the SILS computer lab and cumulated approximately 30 hours. All systems were tested using Internet Explorer 7 running on Windows Vista. For each system, an account was created where necessary and each artist was entered in the order previously given. Ten songs were allowed to play for each artist. Before each song played a trust rating was assigned (-5 to 5). The first trust rating for each system was always a neutral score of zero. The songs were then evaluated using the same -5 to 5 scale for the following factors: Expectation, Similarity, Context and Usefulness. Each song, therefore, could potentially score from -25 to 25. An Excel spreadsheet was used to record song title and artist name for all songs played. The spreadsheet was also used to record all scores and average scores for each artist and system were automatically computed during the testing.

Although each system began with a trust rating of zero, trust ratings were carried over from artist to artist throughout the system test. This allowed the level of trust in the system to grow or deteriorate over time and usage. It also allowed one artist's score to be influenced by the previous artist. This effect can be counterbalanced by observing the change in the trust score from Song 1 to Song 10 for any particular artist.

3.7 Data Analysis

The simplest way to analyze the data is to simply rank the five systems by their overall scores. In addition to ranking the systems, which may overlook subtle nuances that could be important, other analyses were also performed. The methodology for each analysis is discussed in the sections that follow. An analysis of the actual data can be found in section 4.

3.7.1 Ranking

Rankings were generated by using the previously described overall average scores. These scores were generated automatically during the testing by averaging the average artist scores. The score closest to 25 is deemed the best system and given the number one rank.

3.7.2 Artist Performance

Performance by artist was examined to determine if any one or more artist(s) skewed the data. The standard deviation was computed for all average artist scores across all five systems. Due to the behavior of one particular system, the standard deviation was again computed across only four of the systems.

3.7.3 Learning Ability

To determine how well the system learned over the course of ten songs, the scores of the last songs for each artist on each system were averaged and compared across systems. Higher scores may indicate that learning took place. In addition, the difference between the ratings for the last songs and the overall system average score were also compared. Last song scores should be higher than the average score if learning has occurred.

3.7.4 Trust Fluctuation

To determine how the user's level of trust fluctuated throughout the test, the standard deviation of trust scores for each artist on each system was computed and then those numbers were averaged. An average standard deviation closest to zero indicates a lower fluctuation in trust and therefore a more stable and trustworthy system.

4 Results

4.1 The Rankings

Using the overall system scores, the systems are ranked in order of highest to lowest score (see figure 1). Not surprisingly, the two most well known systems, Pandora and Last.fm, are ranked in first and second place respectively. All but one system achieved a score of 10 or higher indicating that it provides *good* recommendations.

Figure 1: Original Rankings

Rank	System	Method	Overall Score
1	Pandora	Hybrid	15.87
2	Last.fm	Collaborative	14.33
3	GhanniMusic	Content	13.41
4	Jango	Collaborative	11.20
5	MeeMix	Hybrid	-0.46

*Please see Appendix for more specific data

4.2 Analysis of the Rankings

The rankings in this study do not directly indicate that one recommender system method is necessarily better than another since the two hybrid systems ranked first and last and collaborative filtering systems are not ranked next to one another. However, there may be underlying factors affecting the outcome that are not immediately apparent (see section 4.3).

The winner here is Pandora which is a hybrid system that heavily employs content-based analysis in its algorithm. Rather surprisingly, GhanniMusic, a wholly content-based system is ranked in the number 3 slot. This is surprising for two reasons: (1) much of the literature indicates that stand-alone content based systems do not perform as well as stand-alone collaborative filtering systems; and (2) the GhanniMusic system has no relevance feedback element. While it is true that Last.fm, a collaborative filtering system, is ranked above GhanniMusic, Jango, another collaborative filtering system, is ranked just below it. When viewed in context with the performance of Pandora, the performance of the GhanniMusic system may indicate that content-based analysis should not be dismissed so quickly. As most researchers have noted, this is still a young field and further research is needed.

The collaborative filtering results may be influenced more by the number of users as opposed to the method itself. With 15 million users on Last.fm, many of the weaknesses discussed in collaborative filtering may be absent for that system. Given that the Jango system is still in beta and that Last.fm has more users than any other system in this study, it may be the case that stand-alone collaborative filtering systems are only more effective than content-based systems when there are *x* number of users active on the system. Although the number of users on the Jango system is unknown, it is almost certainly not in the millions but more likely in the thousands. It would be interesting to study exactly how many users it takes to make an effective recommender system on the music domain.

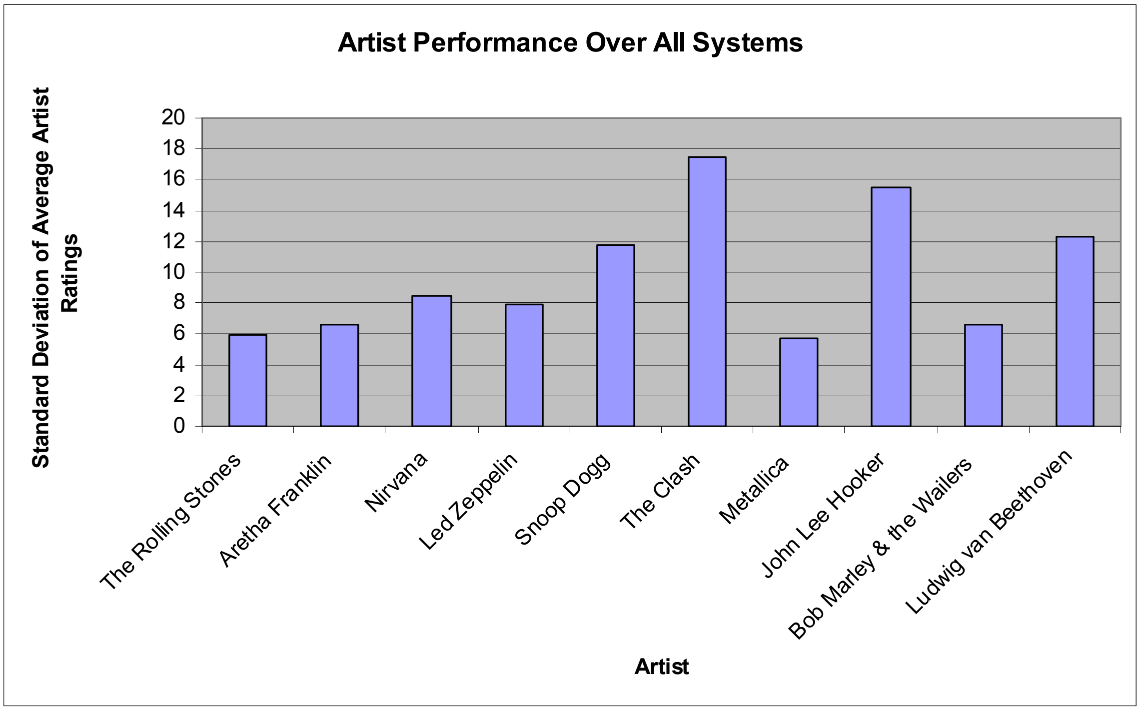
Lastly, as previously mentioned, the hybrid systems did not rank closely at all. They are in the first and last slots. Given that MeeMix did not perform well in this study, perhaps its ranking should be ignored. One of the most likely causes of MeeMix's poor performance is the portion of its algorithm that mixes individual stations in order to produce one overall sound for its users. This may function well for users with limited musical tastes confined to one or two related genres. However, for users with more eclectic tastes, it actually serves to prevent the appropriate music from playing.

However, this is not the only reason MeeMix performed badly. Considering the performance of the first artist, before there was a chance to combine stations, there must be other reasons MeeMix performed badly. Not knowing its specific algorithm or its precise, or even estimated, mix of content-based and collaborative filtering, it is impossible to intimate the exact reason for its low ranking. However, given that the other hybrid system ranked so highly, the low score of MeeMix should not necessarily indicate that hybrid systems do not perform well.

4.3 Artist Performance Across Systems

While the overall rankings are a useful measure in determining system performance, the do not capture any subtleties that may affect system performance. Because the artist list was not scientifically generated, the artists should be examined to establish whether any one or more artist(s) performance skewed the overall data. Figure 2 shows that there were four artists whose performance was spotty (having a standard deviation higher than 10): The Clash, John Lee Hooker, Ludwig van Beethoven and Snoop Dogg.

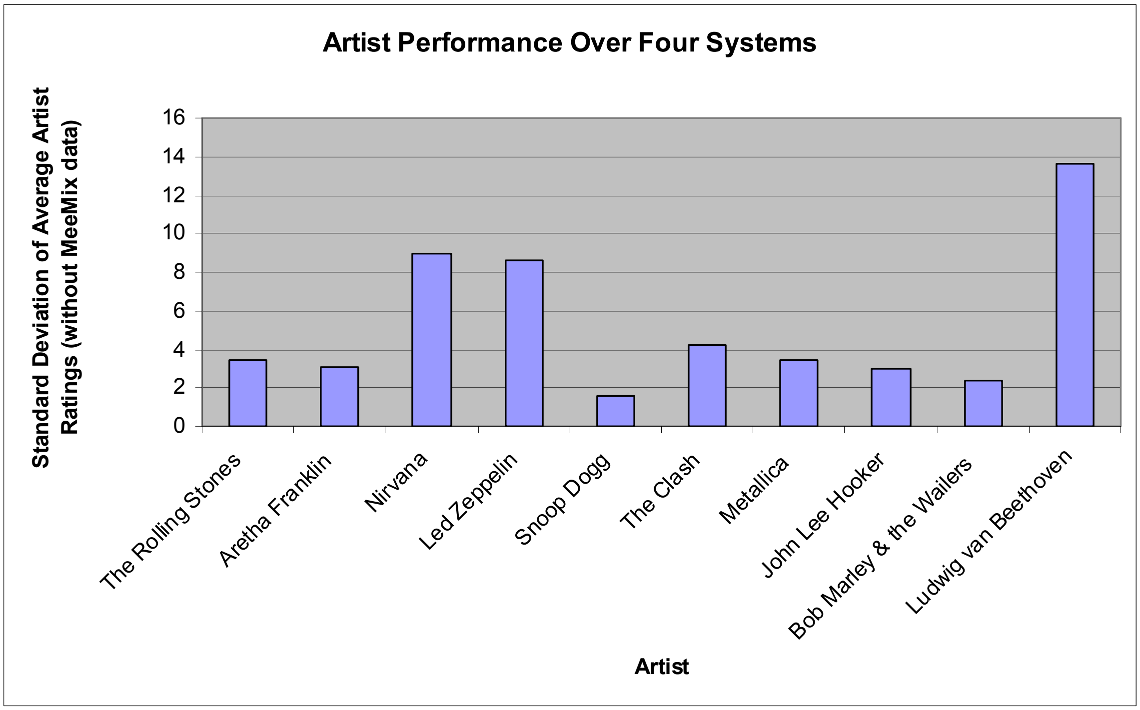
Figure 2: Artist Performance



Although there are obvious reasons for two of these artists to have questionable scores, it is not immediately apparent for the other two. As mentioned previously, there was one artist included whose sound changed: The Clash. The Clash began as a Punk band in the 1970s, but always retained a strong Reggae influence which was more prominent in their later songs. While most systems concentrate on the Punk sound for which they are better known, it could be a confusing factor. The other artist with known issues is Ludwig van Beethoven. Many of the systems simply did not have any classical music in their datasets or had only a very limited amount.

This still does not explain the other two artists' erratic performances. However, when viewing the raw data, the majority of these disparate scores come from one system: MeeMix. Therefore, the data was analyzed and recalculated using only the other four systems the results of which are reflected in Figure 3.

Figure 3: Recalculated Artist Performance



These new results indicate that only Ludwig van Beethoven was a significant discordant factor in determining the scores of the systems. The rankings were then recomputed without using the data from Ludwig van Beethoven.

Figure 4: Revised Rankings

Rank	System	Method	Score
1	Pandora	Hybrid	21.10
2	Last.fm	Collaborative	17.27
3	Jango	Collaborative	15.68
4	GhanniMusic	Content	15.39
5	MeeMix	Hybrid	-0.60

*Please see Appendix for more specific data

The rankings are indeed slightly different. GhanniMusic has moved down a slot and is now in fourth place. This change may indicate that stand-alone collaborative filtering does indeed outperform stand-alone content-based analysis. Or it may simply indicate that GhanniMusic had a more comprehensive dataset that included Beethoven. The scores are so (within .3) that their slots could still be interchangeable.

4.4 Trust Fluctuation

It is important to analyze the level of trust the user has in the system since this is one of the crucial elements in determining whether or not a recommender system is *good*. A trusted system, just like a trusted friend, that provides recommendations should not behave erratically. In this study this is measured by analyzing the standard deviation of the trust scores for each artist and averaging them for an overall score for each system.

Figure 5: Trust Fluctuation

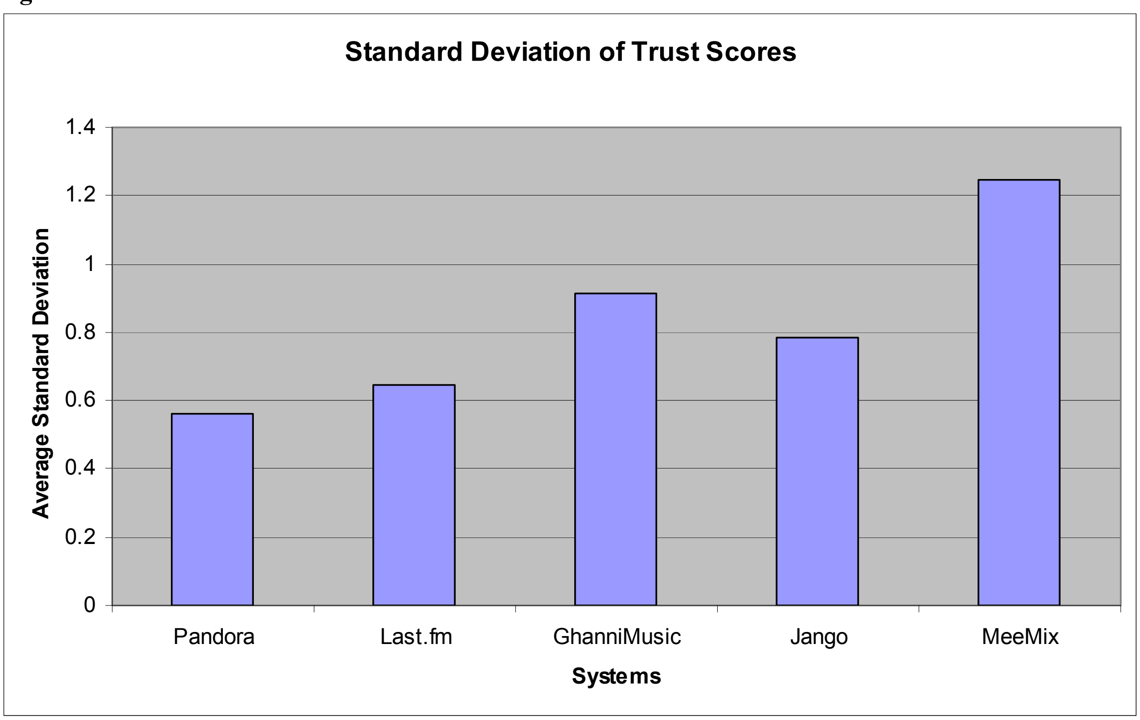


Figure 5 shows that the average standard deviations for trust scores follow the revised rankings. The most trusted system has the lowest standard deviation and holds the number one rank when comparing average scores and the least trusted system has the highest standard deviation and holds the lowest rank. This indicates that perhaps the revised rankings are indeed correct and also demonstrates the importance of trust in evaluating recommender systems. The agreement of these two measures further indicates that collaborative filtering may, in fact, function better on the music domain than content-based analysis.

4.5 System Ability to Learn

The ability of the system to use relevance feedback to 'learn' the users' tastes is reflected only in part by the level of trust the user has in the system. The user will not trust the system if it does not appear to be learning from the feedback given. Its ability to learn can also be measured by comparing the scores given for song number 10, the last song, for each artist.

Figure 6: System Learning Ability

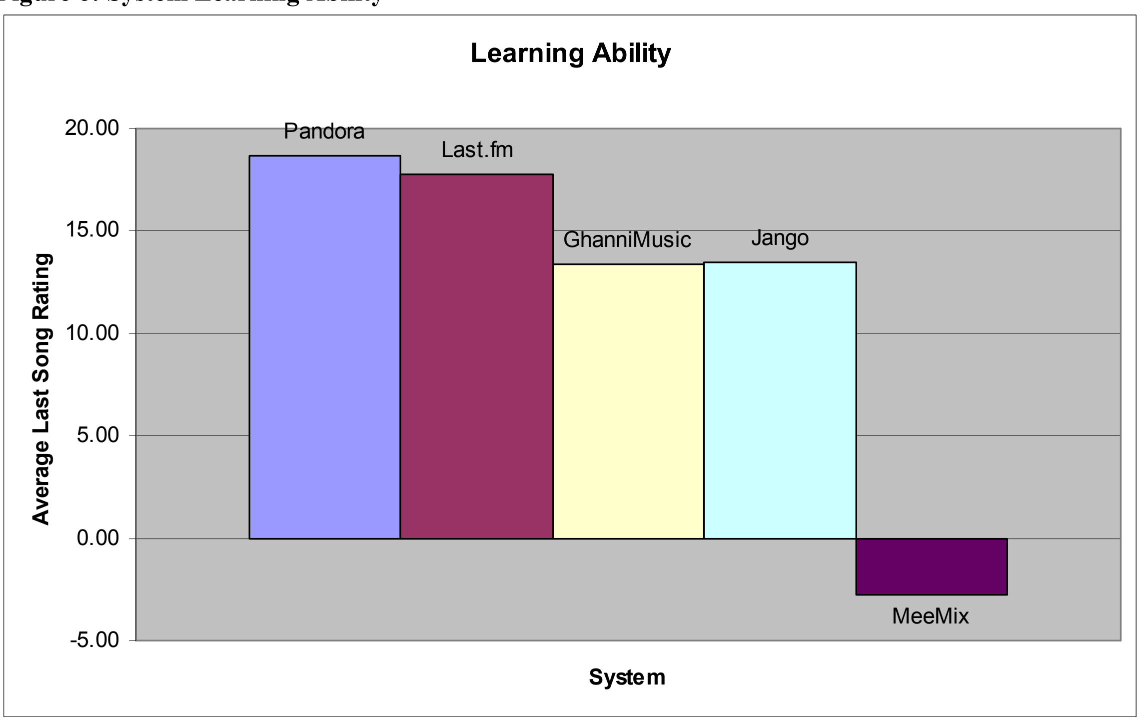
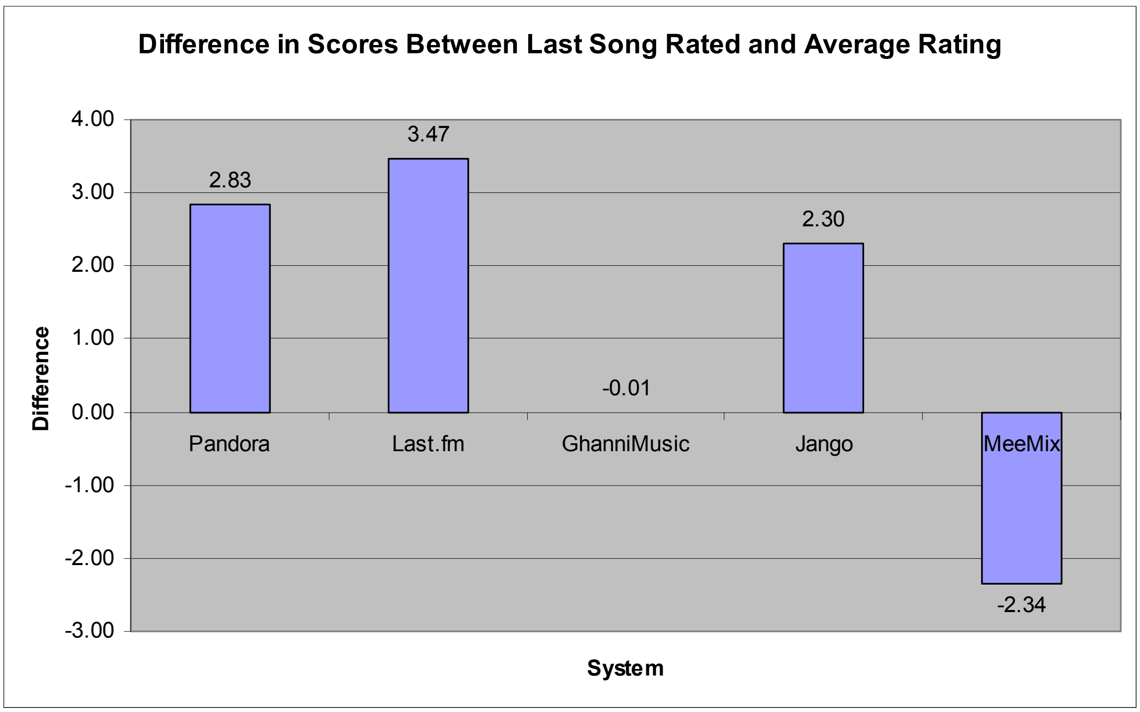


Figure 6 shows that the average ratings for the last songs for each artist also adhere to the revised ranking of the systems. It is notable that GhanniMusic, the one system that had no relevance feedback element did not place last. Although it cannot be said that the system 'learned' anything, at least it did not behave erratically. To further analyze this relationship, the difference between the average of the scores for the last song for each artist and the average overall score was also compared.

Figure 7: Alternate System Learning Ability



Using this alternate comparison (see Figure 7) yields a slightly different ranking order. This methodology places Last.fm before Pandora indicating that Last.fm 'learned' more or better. While this can be interpreted as better system performance in the implementation of relevance feedback, there is an alternate explanation: that Last.fm had more to learn because it started farther behind. In either case, Figure 7 better shows that

GhanniMusic did not learn and that MeeMix seemingly ignored the relevance feedback or processed it in reverse.

Figure 7 may also indicate that less relevance feedback is better. The top two systems, Pandora and Last.fm both use binary relevance feedback systems: Like It/Love It or Don't Like It/Ban It. Jango's relevance feedback has three options: Don't Like It, Like It and Love It. GhanniMusic scores almost at a zero with no relevance feedback. MeeMix, however, uses a scale of -6 to 6 which means that the user effectively has 13 options. This was clearly not effective. The system obviously did not learn from negative ratings. Perhaps fewer options are easier to account for in an algorithm. Or perhaps the MeeMix algorithm is simply faulty. In any case, it seems clear that for relevance feedback, less may be more.

4.6 Other Opinions

Due to the fact that this is a subjective study carried out by only one user it is important to note how the results compare to other people's opinions. Many blogs and online articles were read in order to get a feel for how others rate these systems.

Given that MeeMix, Jango and GhanniMusic are still all in beta, there are fewer opinions out there on these systems. However, some opinions do exist. Beginning with MeeMix, a TechCrunch reviewer based in Israel states that "In my personal tests, MeeMix's music selection was near perfect" (Carthy, 2007). Unfortunately there's not much else to say about MeeMix since it is "another brand new entrant and has yet to really get beyond Alpha phase. They're behind in the pack at this point" (Savelson, 2007). Despite the poor results of MeeMix in this study, or perhaps because of them, it seems the jury is still out on the evaluation of MeeMix.

Jango was also reviewed by TechCrunch by a user who had this to say: “Now this isn’t to say that Jango is perfect. It’s pretty damn close and it’s only in Beta so you can see what is possible for the future” (Ha, 2007). Another reviewer had this to say “The social music market is a crowded one, but it looks like Jango has learned from its quicker competitors and has launched a very nice service” (Kirkpatrick, 2007)

Other reviewers were not so kind. The title of one review on The Hippodrome, a media blog, was “Custom Radio Network Jango, a Poor Realization of a Good Idea“ (Bernstein, 2007). One of the reasons given for the poor realization is “the fact that no unsigned artist has any chance of getting their own work on the site” (Bernstein, 2007). It seems that the overall opinion on Jango is that it may not be a bad recommender, but rather “a roundabout way to the same old, same old” (Savelson, 2007).

GhanniMusic however is rather “curious” (Lamere, 2007). “The curious thing about Ghanni is that their recommendations seemed more like social recommendations than content-based recommendations” (Lamere, 2007). Paul Lamere, a music researcher in Sun Labs, goes on to say this:

> Ghanni seems to have some smart people on their team, so we can expect them to improve their recommendations. But for right now, the recommendations don't seem to be any better than what you could get from the many other music recommenders that are out there. (2007)

In contrast, a casual user has this to say: “A nice discovery, an original idea and innovative Ghanni Music allows you to use the principle of search engine to find music

...” (Caillean, 2006). It would seem that, like MeeMix, perhaps GhanniMusic still has some kinks to work out and may prove to perform better in the future.

There is an overwhelming amount of information on Last.fm and Pandora since they are both well established. One blogger even refers to them as “dinosaurs” (Savelson, 2007). Casual users are in constant debate on blogs about which is the better system. The divide is often based on age group for these two systems. The social networking aspect of Last.fm draws younger users and the lack of social networking in Pandora draws older users who are not interesting in connecting with strangers or sharing music online with existing friends. This study found that both performed well but that Pandora was better. Paul Lamere disagrees however. Here is what he has to say about Last.fm:

> There are some other advantages to the last.fm model. Since it relies on an instrumented player to automatically send info back to the server, last.fm has been able to amass a very large database of music profiles. For any kind of recommendation system, the more data the better. Last.fm gives very good music recommendations (the best I've seen) with very good coverage (it is extremely rare to encounter a band that last.fm doesn't know about). (2007)

Lamere’s assertion that more data is better is a critical observation when comparing these two systems. The Last.fm system accumulates data from users in an almost effortless manner. In contrast, Pandora employs humans to analyze content by hand. Pandora can’t possibly accumulate as much data as quickly as Last.fm. However, although Lamere states that Last.fm gives “the best” recommendations, he also states that “the Pandora radio gives consistent high quality music that is similar to music that you already know and like” (Lamere, 2007). He elaborates by saying that “one of the advantages of a content-based recommender like Pandora has over the more traditional collaborative filtering models used in systems like last.fm is that they are immune to the popularity bias that is found in the collaborative filtering systems" (Lamere, 2007). Given these statements, perhaps the answer is that both systems provide consistently *good* recommendations. And perhaps both methods, collaborative filtering and content-centric hybrid systems, are viable methods for recommending music. Perhaps the answer is not scientifically quantifiable but that the best system is whichever works best for you.

5 Conclusion

This study offers a subjective and user-centric evaluation of music recommender systems as opposed to evaluating the accuracy of recommendations produced by various algorithms. By evaluating five systems which employ three different methods from this perspective, the systems were ranked not only to determine which system performed best and offered the most *good* recommendations, but also to attempt to identify which system method produces the best recommendations consistently. In this study, Pandora occupies the number one slot using a hybrid of collaborative filtering and content-based analysis. Last.fm occupies the second slot using only collaborative filtering. There are other users in cyberspace who will also argue that Pandora is best as well as users that vehemently defend Last.fm and collaborative filtering.

Last.fm, a standalone collaborative filtering music recommender system is arguably the best system even though it does not occupy the number one slot in this study. Pandora, which does occupy the number one slot, incorporates a small element of collaborative filtering in its hybrid music recommender system. Given that both systems use collaborative filtering, and based on this study as well as popular and expert opinion, it appears that a truly effective music recommender system must at least incorporate collaborative filtering.

However, content-based analysis and hybrid systems cannot be completely dismissed since they are used in the number one system: Pandora. As previously mentioned, Pandora's hybrid system relies heavily on content-based analysis. Achieving the number one rank indicates that content-based analysis cannot be dismissed as an effective method of recommending music.

Although the second hybrid system, MeeMix, did not perform well in this study, Pandora's performance shows that hybrid systems can be effective. It may be a matter of the exact mix within the algorithm. Or it may be due to the exhaustivity of the Music Genome Project. Little is known about MeeMix musicologists and exactly how they classify music.

Despite the fact that it cannot be conclusively stated that hybrid systems provide the best music recommendations, this study was not fruitless. Many valuable lessons were learned as well as points identified for further research.

5.1 Lessons Learned

As previously mentioned collaborative filtering is a crucial element in music recommender systems. However, to achieve a truly effective system there must be a large quantity of users when stand-alone collaborative filtering is employed. Last.fm would likely not be as effective with significantly fewer users.

The sheer volume of users on Last.fm and the exhaustivity of the Music Genome Project used for Pandora show that recommendations still need to have a human element and will likely always perform better than a completely automated system should the technology allow such a system to exist. It also shows that Lamere is absolutely correct when he states that "the more data the better" (2007). Not only does this apply to the number of users in Last.fm but also the number of 'genes' classified by the Music Genome Project used for Pandora.

Another lesson learned is that relevance feedback is paramount to system performance. Although this lesson was roughly established prior to this study, it has now been reinforced and further indicates that too many options can negatively impact relevance feedback in a recommender system.

In addition to having too many options in the relevance feedback element of a system, a system can also attempt to incorporate too many conflicting factors in its algorithm. Although the exact algorithm is not known, the description of the MeeMix system given by its CEO coupled with its poor performance indicates that there may be too much going on behind the scenes for anything useful to occur for a wide range of users.

5.2 Further Research

All of the lessons learned could benefit from further research. While there has been considerable research on collaborative filtering, and rightly so, more research on content-based analysis and hybrid systems would help round out the field and further establish whether one is better than another.

More research in the area of user-centric metrics for evaluation of recommender systems is also warranted. There are comparatively few studies from this perspective as opposed to evaluation by accuracy metrics. This study was one attempt in this area but more are needed. Perhaps a study could be conducted which combines the two.

And finally, relevance feedback in music recommender systems or on any single item domain requires further study. It would be interesting to attempt to find the threshold at which relevance feedback ceases to be useful and begins to be detrimental. Additionally, it is interesting to note that most music recommender systems incorporate vastly different relevance feedback than other entertainment media recommender systems, such as movies or books. Those systems generally use a rating system of 1-5 stars. Has this been tried and rejected on the music domain?

5.3 Future of Recommender Systems

Recommender systems are most certainly here to stay. Their marketing power alone dictates that. In that respect, large store websites will likely always employ some sort of recommender system in an effort to boost sales. But recommender systems are also carving a niche for themselves on several domains in order to help people weed through the overwhelming amount of information on the Internet and help them discover new items. Discovery is the future of recommender systems.

There may be different motivations for wanting to discover and/or play music, however. Most current systems do not account for context. These systems are two dimensional in that they only consider the user and the dataset. These two dimensional systems do not account for a third dimension of context (Adomavicius & Tuzhilin, 2005). The MeeMix system appears to be attempting to do this but does not quite reach its goal. Recommender systems will almost surely try to incorporate more information in the future but it may take some time to work out the kinks.

5.4 Final Thoughts

Music recommender systems are invaluable for helping people discover music they like but have not heard before. Many systems also include a social aspect that allows users to discover new music by viewing what their ‘nearest neighbors’ are listening to. Although the social networking aspect is generally not attractive to older users, it is still very much a part of the discovery process and should not be viewed as frivolous. Music recommender systems allow music lovers to easily find music they like and listen to it. Traditional radio was never that adept at this process. Music recommender systems are simply another information tool, somewhat akin to a search engine, for the general public to use to wade through all the music available in cyberspace.

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7 Appendix

7.1 Jango Data

7.1.1 Songs Played

Jango		
Artist 1	**The Rolling Stones**	
	Song Title	**Artist**
Song 1	Wild Horses	The Rolling Stones
Song 2	Lyla	Oasis
Song 3	Tired of Waiting for You	The Kinks
Song 4	Substitute	The Who
Song 5	Running On Faith	Eric Clapton
Song 6	Keep Your Hands to Yourself	Georgia Satellites
Song 7	Brown Sugar	The Rolling Stones
Song 8	The Black Angel's Death	The Velvet Underground
Song 9	Gimme Shelter	The Rolling Stones
Song 10	Black Tambourine	Beck

Jango		
Artist 2	**Aretha Frankin**	
	Song Title	**Artist**
Song 1	Chain of Fools	Aretha Franklin
Song 2	I Can't Stand Up For Falling Down	Sam & Dave
Song 3	Drown In My Own Tears	Ray Charles
Song 4	How Sweet It Is (To Be Loved By You)	Marvin Gaye
Song 5	Get Up Offa That Thing	James Brown
Song 6	You Ought To Be With Me	Al Green
Song 7	Do What You Gotta Do	Nina Simone
Song 8	Spanish Harlem	Aretha Franklin
Song 9	Respect	Otis Redding
Song 10	Move Over	Janis Joplin

Jango		
Artist 3	**Nirvana**	
	Song Title	**Artist**
Song 1	Polly	Nirvana
Song 2	Wonderwall	Oasis
Song 3	Gotta Get Away	The Offspring
Song 4	End of a Centruy	Blur
Song 5	Evenflow	Pearl Jam
Song 6	The Fox	Sleater-Kinney
Song 7	Time Is Running Out	Muse
Song 8	Kickstand	Soundgarden
Song 9	Mosquito Song	Queens of the Stone Age
Song 10	World Wide Suicide	Pearl Jam

Jango		
Artist 4	**Led Zeppelin**	
	Song Title	**Artist**
Song 1	Black Dog	Led Zeppelin
Song 2	Crosstown Traffic	Jimi Hendrix
Song 3	Smoke On the Water (live version)	Deep Purple
Song 4	Black Hole Sun	Soundgarden
Song 5	Patience	Guns N' Roses
Song 6	We're Going Wrong	Cream
Song 7	What Is and What Should Never Be	Led Zeppelin
Song 8	Under My Wheels	Alice Cooper (feat Axl Rose, Slash and Izzy)
Song 9	Walk This Way	Aerosmith
Song 10	Daughter	Pearl Jam

Jango		
Artist 5	**Snoop Dogg**	
	Song Title	**Artist**
Song 1	Vato	Snoop Dogg
Song 2	Everybody	Tha Dogg Pound
Song 3	Change Clothes	Jay-Z (feat Pharrell Williams)
Song 4	Got Beef	Tha Eastsidaz (feat Jayo Felony and Sylk E. Fine)
Song 5	I Do	Chingy
Song 6	Number One Spot	Ludacris
Song 7	Who Ride Wit Us	Kurupt
Song 8	If Dead Men Could Talk	G-Unit
Song 9	Bring Em Out	T.I.
Song 10	Air Force Ones	Nelly

Jango		
Artist 6	**The Clash**	
	Song Title	**Artist**
Song 1	Spanish Bombs	The Clash
Song 2	Help	The Beatles
Song 3	Supersonic	Oasis
Song 4	From the Ritz to the Rubble	The Arctic Monkeys
Song 5	Lost In the Supermarket	The Clash
Song 6	Approaching Pavonis Mons	The Flaming Lips
Song 7	Heroin	The Doors
Song 8	How To Disappear Completely	Radiohead
Song 9	Rock the Casbah	The Clash
Song 10	Like Eating Glass	Bloc Party

Jango		
Artist 7	**Metallica**	
	Song Title	**Artist**
Song 1	Master of Puppets	Metallica
Song 2	Mouth for War	Pantera
Song 3	Black Lodge	Anthrax
Song 4	Symptom of the Universe	Sepultura
Song 5	Duality	Slipknot
Song 6	Original Prankster	The Offspring
Song 7	Stairway to Heaven	Led Zeppelin
Song 8	Them Bones	Alice In Chains
Song 9	Belly of the Beast	Anthrax
Song 10	Iron Man	Ozzy Osbourne (feat Therapy)

Jango		
Artist 8	**John Lee Hooker**	
	Song Title	**Artist**
Song 1	Dimples	John Lee Hooker
Song 2	(Night Time Is) The Right Time	Ray Charles
Song 3	Key to the Highway	Big Bill Broonzy
Song 4	House of the Rising Sun	The Animals
Song 5	Hallelujah I Love Her So	Ray Charles
Song 6	Something To Talk About	Bonnie Raitt
Song 7	Maybellene	Chuck Berry
Song 8	Third Stone From the Sun	Jimi Hendrix
Song 9	Work Song	Nina Simone
Song 10	The Death of J.B. Lenoir	John Mayall & The Bluesbreakers

Jango		
Artist 9	**Bob Marley & The Wailers**	
	Song Title	**Artist**
Song 1	Trenchtown Rock	Bob Marley and Peter Tosh
Song 2	Hail King Selassie I	Capleton
Song 3	Stir It Up	Bob Marley & The Wailers
Song 4	Gal Pon De Side	Frisco Kid
Song 5	Guns of Navarone	The Skatalites
Song 6	Do Your Work	Horace Andy
Song 7	Viva Tirado	Augustus Pablo
Song 8	Pickney Gal	Desmond Dekker
Song 9	Weh Dem Woulda Do	Mr. Vegas
Song 10	Steppin' Out	Steel Pulse

Jango		
Artist 10	**Ludwig van Beethoven (Wolfgang Amadeus Mozart was substituted for this system)**	
	Song Title	**Artist**
Song 1	Figaro's Wedding	Wolfgang Amadeus Mozart
Song 2	Battlestar Gallactica	Boston Pops
Song 3	Eleanor Rigby	Chick Corea
Song 4	Don't Worry Be Happy	Bobby McFarrin
Song 5	Spain	Chick Corea
Song 6	Stamping Ground	Moondog
Song 7	500 Hundred Miles High	Chick Corea & Return to Forever
Song 8	Lament I, Bird's Lament	Moondog
Song 9	Don't Worry Be Happy	Bobby McFarrin
Song 10	Don't Worry Be Happy	Bobby McFarrin

7.1.2 Ratings Given

Jango							
Artist 1	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	0	-	-	-	-	-	-
Song 1	1	-2	4	5	2	Like It	9
Song 2	2	3	3	5	4	Like It	16
Song 3	2	0	3	5	3	Like It	13
Song 4	3	3	4	4	3	no rating	16
Song 5	2	-2	2	2	0	Don't Like It/skipped	5
Song 6	3	3	3	4	3	Like It	15
Song 7	4	4	5	3	2	Love It	17
Song 8	3	-3	3	4	3	Don't Like it/skipped	11
Song 9	3	3	5	3	2	Like It	16
Song 10	-	4	4	4	5	Like It	20
Average Score *(out of 25 possible points)*							**13.80**
Notes:							

Jango							
Artist 2	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	2	-	-	-	-	-	-
Song 1	3	3	5	5	4	Love It	19
Song 2	2	-1	3	1	-2	no rating	4
Song 3	3	4	4	4	3	Like It	17
Song 4	3	3	3	3	2	no rating	14
Song 5	4	2	2	4	4	Like It	15
Song 6	3	3	2	1	-2	Don't Like It/skipped	8
Song 7	3	2	2	2	4	no rating	13
Song 8	3	3	5	2	0	Like It	13
Song 9	4	4	4	4	3	Love It	18
Song 10	-	5	4	5	5	Love It	23
Average Score *(out of 25 possible points)*							**14.40**
Notes:							

Jango							
Artist 3	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	3	-	-	-	-	-	-
Song 1	3	3	4	4	3	Like It	17
Song 2	3	3	2	3	2	no rating	13
Song 3	4	4	4	4	3	Like It	18
Song 4	4	3	3	5	4	no rating	19
Song 5	3	4	3	4	-4	Don't Like/skipped	11
Song 6	3	2	2	2	-2	no rating	7
Song 7	3	2	-1	-2	-3	Don't Like It/skipped	-1
Song 8	3	3	2	3	3	no rating	14
Song 9	2	-1	0	1	-2	Don't Like It/skipped	1
Song 10	-	3	2	3	-3	no rating	7
Average Score *(out of 25 possible points)*							**10.60**
Notes:							

Jango							
Artist 4	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	3	-	-	-	-	-	-
Song 1	4	5	5	5	5	Love It	23
Song 2	4	4	4	4	4	Like It	20
Song 3	4	2	4	5	4	Like It	19
Song 4	4	4	3	5	4	Like It	20
Song 5	3	3	2	3	2	no rating	14
Song 6	3	3	2	2	1	Don't Like It/skipped	11
Song 7	4	4	5	4	4	Like It	20
Song 8	4	4	2	4	5	Like It	19
Song 9	4	4	3	4	2	Like It	17
Song 10	-	-2	2	3	-4	Don't Like It	3
Average Score *(out of 25 possible points)*							**16.60**
Notes:							

Jango							
Artist 5	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	3	-	-	-	-	-	-
Song 1	4	4	5	4	5	Like It	21
Song 2	4	4	4	5	5	Like It	22
Song 3	4	4	2	2	0	no rating	12
Song 4	3	2	2	2	-2	Don't Like/skipped	8
Song 5	4	4	4	4	4	Like It	19
Song 6	4	3	3	5	4	Like It	19
Song 7	4	4	4	5	5	Like It	22
Song 8	4	3	3	4	2	no rating	16
Song 9	4	4	4	5	4	Like It	21
Song 10	-	3	3	4	3	no rating	17
Average Score *(out of 25 possible points)*							**17.70**
Notes:							

Jango							
Artist 6	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	4	-	-	-	-	-	-
Song 1	4	3	4	3	3	no rating	17
Song 2	3	-3	-1	-4	-5	Don't Like/skipped	-9
Song 3	3	2	2	3	3	Like It	13
Song 4	4	5	4	5	5	Love It	22
Song 5	4	4	5	3	2	Like It	18
Song 6	3	2	2	3	-2	Don't Like It /skipped	9
Song 7	3	2	3	4	1	Don't Like/skipped	13
Song 8	3	3	2	4	1	Don't Like/skipped	13
Song 9	3	4	5	4	3	Like It	19
Song 10	-	4	4	5	4	Like It	20
						Average Score *(out of 25 possible points)*	**13.50**
Notes:							

Jango							
Artist 7	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	4	-	-	-	-	-	-
Song 1	4	4	5	4	4	Like It	21
Song 2	4	4	4	3	3	no rating	18
Song 3	4	3	4	4	4	Like It	19
Song 4	3	2	2	3	3	Don't Like/skipped	14
Song 5	4	5	4	5	5	Love It	22
Song 6	4	2	2	4	3	no rating	15
Song 7	3	-2	1	-3	-3	Don't Like/skipped	-3
Song 8	4	5	4	5	5	Love It	22
Song 9	4	4	4	5	4	Like It	21
Song 10	-	5	4	5	5	Love It	23
						Average Score *(out of 25 possible points)*	**17.20**
Notes:							

Jango							
Artist 8	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	4	-	-	-	-	-	-
Song 1	5	5	5	5	5	Love It	24
Song 2	5	4	4	5	3	Like It	21
Song 3	5	5	4	5	5	Like It	24
Song 4	4	1	2	3	-2	Don't Like It/skipped	9
Song 5	3	3	2	3	2	no rating	14
Song 6	4	4	3	5	3	Like It	18
Song 7	4	5	3	5	2	Like It	19
Song 8	3	-2	-2	-4	-5	Don't Like It/skipped	-9
Song 9	3	3	2	4	2	no rating	14
Song 10	-	5	3	5	5	Like It	21
						Average Score *(out of 25 possible points)*	**15.50**
Notes:							

Jango							
Artist 9	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	4	-	-	-	-	-	-
Song 1	4	3	5	4	3	Like It	19
Song 2	4	4	4	5	5	Like It	22
Song 3	4	5	5	5	5	Love It	24
Song 4	4	5	3	5	5	Like It	22
Song 5	5	5	3	5	5	Like It	22
Song 6	4	3	3	5	2	no rating	18
Song 7	5	5	4	5	5	Like It	23
Song 8	4	5	3	5	5	no rating	23
Song 9	4	5	3	5	5	Like It	22
Song 10	-	5	4	5	5	Love It	23
						Average Score *(out of 25 possible points)*	**21.80**
Notes:							

Jango							
Artist 10	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	5	-	-	-	-	-	-
Song 1	5	5	5	5	5	Love It	25
Song 2	4	0	2	0	0	no rating	7
Song 3	3	-4	-1	-5	-5	Don't Like It/skipped	-11
Song 4	2	-5	-3	-5	-5	Don't Like It/skipped	-15
Song 5	1	-5	-1	-4	-5	Don't Like It/skipped	-13
Song 6	0	-3	-1	-3	-3	Don’t Like It/skipped	-9
Song 7	-1	-5	-3	-5	-5	Don't Like It/skipped	-18
Song 8	0	2	2	2	2	Like It	7
Song 9	-1	-5	-5	-5	-5	Don’t Like It/skipped	-20
Song 10	-	-5	-5	-5	-5	Don’t Like It/skipped	-21
						Average Score *(out of 25 possible points)*	**-6.70**
Notes:							

7.2 MeeMix Data

7.1.1 Songs Played

MeeMix		
Artist 1	**The Rolling Stones**	
	Song Title	**Artist**
Song 1	Brown Sugar	The Rolling Stones
Song 2	Rock and Roll Never Forgets	Bob Seger & the Silver Bullet Band
Song 3	You're The One That I Want	Frankie Valli from the Grease Soundtrack
Song 4	Heading for the Light	The Travelling Wilburys
Song 5	Travelin' Band	Creedence Clearwater Revival
Song 6	Have You Seen Your Mother	The Rolling Stones
Song 7	Sometimes A Fantasy	Billy Joel
Song 8	Ladies Choice	from the Hairspray Soundtrack
Song 9	Love For Sale	Bon Jovi
Song 10	Miracle	Bon Jovi

MeeMix		
Artist 2	**Aretha Frankin**	
	Song Title	**Artist**
Song 1	Respect	Aretha Franklin
Song 2	If I Love You	The Stylistics
Song 3	Let's Get It On	Marvin Gaye
Song 4	Love Like Honey	Little Ricky
Song 5	Blunt Time - RBX	Dr. Dre
Song 6	Alter Ego	Tyrese
Song 7	The Blues	Naughty By Nature
Song 8	Jealous Guy	Mase
Song 9	All Night Long	Robin Thicke
Song 10	Here My Dear	Marvin Gaye

MeeMix		
Artist 3	**Nirvana**	
	Song Title	**Artist**
Song 1	Heart Shaped Box	Nirvana
Song 2	Fell On Black Days	Soundgarden
Song 3	World Wide Suicide	Pearl Jam
Song 4	Dry the Rain	The Beta Band
Song 5	Time Is Coming	Bongwater
Song 6	Nice Cuffs	Citay
Song 7	(Reprise)	The Verve
Song 8	Good Girl	Panda Bear
Song 9	The Room Got Heavy	Yo La Tengo
Song 10	About A Girl	Nirvana

MeeMix		
Artist 4	**Led Zeppelin**	
	Song Title	**Artist**
Song 1	All My Love	Led Zeppelin
Song 2	Beast of Burden	The Rolling Stones
Song 3	Night Moves	Bob Seger & the Silver Bullet Band
Song 4	The Song Is Over	The Who
Song 5	The Long Run	The Eagles
Song 6	Heading For the Light	The Traveling Wilburys
Song 7	Sometimes A Fantasy	Billy Joel
Song 8	Open All Night	Bruce Springsteen
Song 9	Mama Told Me Not To Come	Randy Newman
Song 10	Come Down Easy	Carole King

MeeMix		
Artist 5	**Snoop Dogg**	
	Song Title	**Artist**
Song 1	I Wanna Fuck You	Snoop Dogg
Song 2	6 Minutes of Pleasure	LL Cool J
Song 3	Sadie	R. Kelly
Song 4	That's the Way of the World	Earth Wind & Fire
Song 5	You Met Your Match	Mark Broussard
Song 6	Disrespectful	Chaka Khan (feat Mary J Blige)
Song 7	It's Love	Jill Scott
Song 8	Respect	Aretha Franklin
Song 9	Satisfied	Prince
Song 10	Hold On	Wild Cherry

MeeMix		
Artist 6	**The Clash**	
	Song Title	**Artist**
Song 1	The Guns of Brixton	The Clash
Song 2	Instant Hit	The Slits
Song 3	Summer Bunnies	R. Kelly
Song 4	To the Floor	Mariah Carey
Song 5	Hip Hop Star	Beyonce
Song 6	Soldier	Destiny's Child
Song 7	The Word	Prince
Song 8	Mona Lisa	Wycliff
Song 9	My Boyfriend's Back	Paris Bennett
Song 10	My Phone	Jodeci

MeeMix		
Artist 7	**Metallica**	
	Song Title	**Artist**
Song 1	Nothing Else Matters	Metallica
Song 2	Someone Else	Queensrÿche
Song 3	Never Say Goodbye	Bon Jovi
Song 4	What It Takes	Aerosmith
Song 5	Another Time	Edguy
Song 6	Love Bites	Def Leppard
Song 7	Poor Twisted Me	Metallica
Song 8	It's Not Over	Daughtry
Song 9	She's Too Tough	Foreigner
Song 10	Kill the King	Rainbow

MeeMix		
Artist 8	**John Lee Hooker**	
	Song Title	**Artist**
Song 1	Set You Free This Time	The Byrds
Song 2	Comin' Back To Me	Jefferson Airplane
Song 3	Andmoreagain	Love
Song 4	Turn! Turn! Turn!	The Byrds
Song 5	Our Prayer/Gee	Brian Wilson
Song 6	No Love To Give	The United States of America
Song 7	Ship of Fools	The Doors
Song 8	Misty Mountains	Silver Apples
Song 9	Onie	The Electric Prunes
Song 10	You Send Me	The Steve Miller Band

MeeMix		
Artist 9	**Bob Marley & The Wailers**	
	Song Title	**Artist**
Song 1	Could You Be Loved	Bob Marley & The Wailers
Song 2	Bad Card	Bob Marley & The Wailers
Song 3	Guelah Papyrus	Phish
Song 4	Until Kingdom Comes	Bad Brains
Song 5	Lovely Lady	Masta Killa
Song 6	Many Rivers to Cross	UB40
Song 7	Mama Africa	Akon
Song 8	Natural Mystic	Bob Marley & The Wailers
Song 9	Less Is More	Jess Stone
Song 10	911	Wycleff Jean

MeeMix		
Artist 10	**Ludwig van Beethoven**	
	Song Title	**Artist**
Song 1	NO SONGS PLAYED	
Song 2		
Song 3		
Song 4		
Song 5		
Song 6		
Song 7		
Song 8		
Song 9		
Song 10		

7.1.2 Ratings Given

MeeMix							
Artist 1	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	0	-	-	-	-	-	-
Song 1	1	2	5	4	-3	+3	8
Song 2	2	4	4	4	3	+4	15
Song 3	0	-4	-3	-4	-5	-6/skipped	-14
Song 4	1	2	3	4	2	+2	11
Song 5	2	3	3	4	3	0	14
Song 6	2	3	5	4	3	+4	17
Song 7	1	-2	2	0	-1	-1	1
Song 8	-1	-4	-3	-5	-5	-6/skipped	-16
Song 9	0	3	3	4	4	+4	13
Song 10	-	2	1	-2	-3	-2	-2
						Average Score *(out of 25 possible points)*	**4.80**
Notes: Song 1 did not play properly, the vocals sounded like chipmunks making it difficult to rate Song 5 was given a feedback score of 0 due to player malfunction							

MeeMix							
Artist 2	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	0	-	-	-	-	-	-
Song 1	-1	0	0	0	-5	-6/skipped	-5
Song 2	0	3	3	4	4	+3	13
Song 3	1	4	4	5	5	+6	18
Song 4	0	1	1	3	-2	-3	4
Song 5	-1	-2	-2	-3	-4	-6/skipped	-11
Song 6	0	0	-1	-2	-3	-5	-7
Song 7	0	1	1	2	3	+1	7
Song 8	0	2	2	2	2	-6/skipped	8
Song 9	-1	0	0	0	0	-6/skipped	0
Song 10	-	3	3	5	5	+3	15
						Average Score *(out of 25 possible points)*	**4.20**
Notes: Song 1 did not play properly; the title/artist info displayed and recorded here did not match the song that actually played Song 8 made some sense as a recommendation but I just really didn't like it							

MeeMix							
Artist 3	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	-1	-	-	-	-	-	-
Song 1	0	5	5	5	5	+6	19
Song 2	1	4	4	5	4	+5	17
Song 3	2	5	4	5	-5	-6/skipped	10
Song 4	1	0	2	1	3	-2	2
Song 5	0	-1	1	-1	-5	-6/skipped	-5
Song 6	0	1	2	3	2	+2	8
Song 7	0	1	2	2	0	-2	5
Song 8	-1	-2	-2	-4	-5	-6	-13
Song 9	-2	-2	-1	-2	-3	-4	-9
Song 10	-	5	5	5	5	+6	18
Average Score *(out of 25 possible points)*							**5.20**
Notes: Song 3 made perfect sense as a recommendation, I just HATE Pearl Jam							

MeeMix							
Artist 4	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	-1	-	-	-	-	-	-
Song 1	0	5	5	5	5	+6	19
Song 2	1	3	3	4	4	+4	14
Song 3	2	3	2	3	2	+2	11
Song 4	3	3	3	3	4	+4	15
Song 5	4	3	3	5	4	+5	18
Song 6	4	3	3	4	4	+3	18
Song 7	3	-2	0	-2	-4	-4/artist blocked	-4
Song 8	2	-2	-3	-3	-4	-4	-9
Song 9	2	2	2	3	3	+2	12
Song 10	-	0	-2	-4	-3	-4	-7
Average Score *(out of 25 possible points)*							**8.70**
Notes:							

MeeMix							
Artist 5	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	1	-	-	-	-	-	-
Song 1	1	4	5	4	4	+4	18
Song 2	1	3	3	3	3	+3	13
Song 3	0	-2	2	-3	-5	-6/skipped	-7
Song 4	-1	-3	1	-4	-5	-6/skipped	-11
Song 5	-2	-3	1	-3	-5	-6	-11
Song 6	-2	-2	2	-1	-3	-4	-6
Song 7	-3	-3	1	-5	-5	-6/skipped	-14
Song 8	-3	-3	2	-4	-4	-6/skipped	-12
Song 9	-4	-4	0	-5	-5	-6/skipped	-17
Song 10	-	-5	0	-5	-5	-6/skipped	-19
Average Score *(out of 25 possible points)*							**-6.60**
Notes:							

MeeMix							
Artist 6	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	-4	-	-	-	-	-	-
Song 1	-3	5	5	5	5	5	16
Song 2	-3	-3	2	-2	-1	-3	-7
Song 3	-4	-5	-5	-5	-5	-6/skipped	-23
Song 4	-5	-5	-5	-5	-5	-6/skipped	-24
Song 5	-5	-5	-5	-5	-5	-6/skipped	-25
Song 6	-5	-5	-5	-5	-5	-6/skipped	-25
Song 7	-5	-5	-5	-5	-5	-6/skipped	-25
Song 8	-5	-5	-5	-5	-5	-6/skipped	-25
Song 9	-5	-5	-5	-5	-5	-6/skipped	-25
Song 10	-	-5	-5	-5	-5	-6/skipped	-25
Average Score *(out of 25 possible points)*							**-18.80**
Notes:							

MeeMix							
Artist 7	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	-5	-	-	-	-	-	-
Song 1	-4	5	5	5	5	+6	15
Song 2	-3	4	3	2	2	+4	7
Song 3	-3	3	3	2	2	+4	7
Song 4	-2	2	2	0	1	+1	2
Song 5	-3	-3	0	-4	-5	-6/skipped	-14
Song 6	-2	-2	2	-4	-3	-6/skipped	-10
Song 7	-1	3	5	5	5	+6	16
Song 8	0	4	4	5	5	+4	17
Song 9	0	-1	-2	2	1	+1	-2
Song 10	-	3	4	5	5	+4	16
Average Score *(out of 25 possible points)*							**5.80**
Notes:							

MeeMix							
Artist 8	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	0	-	-	-	-	-	-
Song 1	-1	-3	-2	-3	-4	-6/skipped	-12
Song 2	-2	-3	-1	-3	-4	-6/skipped	-12
Song 3	-2	-3	-1	-3	-4	-6/skipped	-13
Song 4	-3	-2	-2	-4	-5	-6/artist blocked	-15
Song 5	-3	-2	-2	-4	-5	-6/skipped	-16
Song 6	-4	-3	-3	-5	-5	-6/skipped	-19
Song 7	-4	0	0	-2	-4	-3	-10
Song 8	-5	-3	-2	-5	-5	-6/skipped	-19
Song 9	-5	-5	-5	-5	-5	-6/skipped	-25
Song 10	-	-1	-1	-3	-4	-4	-14
Average Score *(out of 25 possible points)*							**-15.50**
Notes:							

MeeMix							
Artist 9	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	-5	-	-	-	-	-	-
Song 1	-4	5	5	5	5	+6	15
Song 2	-4	3	5	3	3	+4	10
Song 3	-4	-2	1	0	-2	-3	-7
Song 4	-4	0	2	0	1	+2	-1
Song 5	-3	3	3	5	5	+4	12
Song 6	-2	4	4	5	3	+4	13
Song 7	-1	3	3	3	3	+3	10
Song 8	0	5	5	5	5	+5	19
Song 9	0	0	1	2	-2	-1	1
Song 10	-	0	0	-2	-2	-2	-4
Average Score *(out of 25 possible points)*							**6.80**
Notes: Song 9 did not play correctly (vocals off)							

MeeMix							
Artist 10	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	-1	-	-	-	-	-	-
Song 1	0	0	0	0	0	0	0
Song 2	0	0	0	0	0	0	0
Song 3	0	0	0	0	0	0	0
Song 4	0	0	0	0	0	0	0
Song 5	0	0	0	0	0	0	0
Song 6	0	0	0	0	0	0	0
Song 7	0	0	0	0	0	0	0
Song 8	0	0	0	0	0	0	0
Song 9	0	0	0	0	0	0	0
Song 10	-	0	0	0	0	0	0
Average Score *(out of 25 possible points)*							**-0.10**
Notes: No songs were played for this artist							

7.3 GhanniMusic Data

7.3.1 Songs Played

GhanniMusic		
Artist 1	**The Rolling Stones**	
	Song Title	**Artist**
Song 1	Miss Amanda Jones	The Rolling Stones
Song 2	Barstool Blues	Neil Young & Crazy Horse
Song 3	Fixing A Hole	The Beatles
Song 4	Don't Stop Me Now	Queen
Song 5	In My Defence	Freddie Mercury
Song 6	Free Fallin'	Tom Petty
Song 7	Who Are you	The Who
Song 8	So Lonely	The Police
Song 9	Mystify	INXS
Song 10	Tom And Frayed	The Rolling Stones

GhanniMusic		
Artist 2	**Aretha Frankin**	
	Song Title	**Artist**
Song 1	Chain of Fools	Aretha Franklin
Song 2	It's a Man's, Man's, Man's World	James Brown
Song 3	How Sweet It Is (To Be Loved By You)	Marvin Gaye
Song 4	In the Midnight Hour	Wilson Pickett
Song 5	Everybogy Needs Somebody To Love	Solomon Burke
Song 6	You're The First, The Last, My Everything	Barry White
Song 7	High Upon This Love	Dionne Warwick
Song 8	Spanish Harlem	Ben E. King
Song 9	Mr. Pitiful	Otis Redding
Song 10	Nowhere To Run To	Martha Reeves & the Vandellas

GhanniMusic		
Artist 3	**Nirvana**	
	Song Title	**Artist**
Song 1	Rain When I Die	Alice In Chains
Song 2	Jesus Doesn't Want Me For A Sun	Nirvana
Song 3	Rain When I Die	Alice In Chains
Song 4	Jesus Doesn't Want Me For A Sun	Nirvana
Song 5	Rain When I Die	Alice In Chains
Song 6	Jesus Doesn't Want Me For A Sun	Nirvana
Song 7	Rain When I Die	Alice In Chains
Song 8	Jesus Doesn't Want Me For A Sun	Nirvana
Song 9	Rain When I Die	Alice In Chains
Song 10	Jesus Doesn't Want Me For A Sun	by Nirvana

GhanniMusic		
Artist 4	**Led Zeppelin**	
	Song Title	**Artist**
Song 1	Fosaken	Queen of the Damned
Song 2	Wasted Time	The Eagles
Song 3	Misty Mountain Hop	Led Zeppelin
Song 4	Love Street	The Doors
Song 5	Raving and Drooling	Pink Floyd
Song 6	Love In Vain	The Rolling Stones
Song 7	Isn't It A Pity	George Harrison
Song 8	Novus	Carlos Santana
Song 9	Burnin' Alive	AC/DC
Song 10	Love Reign O'er Me	The Who

GhanniMusic		
Artist 5	**Snoop Dogg**	
	Song Title	**Artist**
Song 1	Woof!	Snoop Dogg
Song 2	Sweet Dreams Without Me	Eminem
Song 3	Live It Up	2Pac
Song 4	I Know What You Want	Busta Rhymes
Song 5	Dirt Off Your Shoulder	Jay-Z
Song 6	Say What You Say	Eminem & Dr. Dre
Song 7	Panther Power	Tupac Shakur
Song 8	D12 World	D12
Song 9	Nasty Girl	The Notorious BIG
Song 10	I Need A Girl	P. Diddy

GhanniMusic		
Artist 6	**The Clash**	
	Song Title	**Artist**
Song 1	Portrait of Authority	by Bad Religion
Song 2	Mr. Jones	by NOFX
Song 3	Complete Control	by The Clash
Song 4	Problems	by The Sex Pistols
Song 5	Going Away To College	by blink-182
Song 6	Original Prankster	by The Offspring
Song 7	Rebel Yell	by Billy Idol
Song 8	Anarchie En Chiraquie	by Parabellum
Song 9	Move Your Car	by Millencolin
Song 10	Shoes	by Burning Heads

GhanniMusic		
Artist 7	**Metallica**	
	Song Title	**Artist**
Song 1	All Within My Hands	Metallica
Song 2	Trippin'	Kittie
Song 3	Running Free	Iron Maiden
Song 4	Sean Olsen	KoRn
Song 5	Heretic Song	Slipknot
Song 6	Crush	Anthrax
Song 7	Ma Rivale	Dis
Song 8	TNT	AC/DC
Song 9	Burnt Offerings	testament
Song 10	All Within My Hands	Metallica

GhanniMusic		
Artist 8	**John Lee Hooker**	
	Song Title	**Artist**
Song 1	Blue Eyes Blue	Eric Clapton
Song 2	Boom Boom	john Lee Hooker
Song 3	Hallelujah I Love Her So	Ray Charles
Song 4	It Keeps Rainin'	Fats Domino
Song 5	I'm A King Bee	Muddy Waters
Song 6	Worried Life Blues	James Cotton
Song 7	Black, Brown And White	Big Bill Broonzy
Song 8	My Eyes Keep Me In Trouble	R.L. Burnside
Song 9	Every Day I Have the Blues	B.B. King
Song 10	Personne Ne Saurait	Carole Fredericks

GhanniMusic		
Artist 9	**Bob Marley & The Wailers**	
	Song Title	**Artist**
Song 1	Lively Up Yourself	Bob Marley
Song 2	Bionic Skank	Jacob Miller
Song 3	I can See Clearly Now	Jimmy Cliff
Song 4	Melt Away	Max Romeo
Song 5	Weeping Pirates	Groundation
Song 6	Extra	Cidade Negra
Song 7	Fire	Capelton
Song 8	Auction Block Jah House	Cocoa Tea
Song 9	Pressure Drop	Toots And The Maytals
Song 10	Qu'Elle Est Bleue	Massilia Sound System

GhanniMusic		
Artist 10	**Ludwig van Beethoven**	
	Song Title	**Artist**
Song 1	Symphony No 5	Ludwig van Beethoven
Song 2	O Mensch, Bewein Dein Sunde Gross	Johann Sebastian Bach
Song 3	5th Symphony Movement 1	Ludwig van Beethoven
Song 4	Symphony No 28 Abado	Wolfgang Amadeus Mozart
Song 5	Requiem	Wolfgang Amadeus Mozart
Song 6	Gloria in D major	Antonio Vivaldi
Song 7	Ballad Nr 1 in G	Frédéric Chopin
Song 8	PSM 54	Johann Sebastian Bach
Song 9	Carmina Burana	Carmina Burana
Song 10	Vivaldi	Antonio Vivaldi

7.3.2 *Ratings Given*

GhanniMusic							
Artist 1	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	0	-	-	-	-	-	-
Song 1	1	5	5	5	5	N/A	20
Song 2	1	3	3	4	3	N/A	14
Song 3	1	3	2	4	2	N/A	12
Song 4	2	4	3	5	4	N/A	17
Song 5	1	2	2	2	2	skipped	10
Song 6	2	3	3	3	3	N/A	13
Song 7	3	5	4	5	4	N/A	20
Song 8	2	-2	-2	-2	-2	N/A	-5
Song 9	3	5	4	5	5	N/A	21
Song 10	-	4	5	4	3	N/A	19
						Average Score *(out of 25 possible points)*	**14.10**
Notes: Song 8 Did not play the song indicated							

GhanniMusic							
Artist 2	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	3	-	-	-	-	-	-
Song 1	4	5	5	5	5	N/A	23
Song 2	5	4	4	4	4	N/A	20
Song 3	5	4	3	4	3	N/A	19
Song 4	5	5	4	2	2	N/A	18
Song 5	5	5	4	5	5	N/A	24
Song 6	5	4	3	4	4	N/A	20
Song 7	4	4	3	3	-2	skipped	13
Song 8	3	3	2	4	1	N/A	14
Song 9	4	5	4	5	5	N/A	22
Song 10	-	5	4	4	4	N/A	21
						Average Score *(out of 25 possible points)*	**19.40**
Notes: Song 7 was an adequate recommendation but I just didn't like it							

GhanniMusic							
Artist 3	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	5	-	-	-	-	-	-
Song 1	4	5	3	4	3	N/A	20
Song 2	5	4	5	5	5	N/A	23
Song 3	4	2	2	3	2	N/A	14
Song 4	3	1	5	-2	-5	skipped	3
Song 5	2	-2	3	-3	-5	skipped	-4
Song 6	1	-1	3	-4	-5	skipped	-5
Song 7	0	-2	3	-5	-5	skipped	-8
Song 8	-1	-3	3	-5	-5	skipped	-10
Song 9	-2	-4	3	-5	-5	skipped	-12
Song 10	-	-5	3	-5	-5	N/A	-14
						Average Score *(out of 25 possible points)*	**0.70**
Notes:							

GhanniMusic							
Artist 4	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	-3	-	-	-	-	-	-
Song 1	-4	-2	1	-3	-4	N/A	-11
Song 2	-4	-3	-1	-4	-5	N/A	-17
Song 3	-3	5	5	5	5	N/A	16
Song 4	-2	3	3	3	3	N/A	9
Song 5	-2	1	0	1	1	skipped	1
Song 6	-1	2	2	2	2	N/A	6
Song 7	-1	0	1	-1	-2	skipped	-3
Song 8	-2	-2	1	-3	-4	skipped	-9
Song 9	-1	4	4	5	5	N/A	16
Song 10	-	5	4	5	5	N/A	18
						Average Score *(out of 25 possible points)*	**2.60**
Notes: Song 1 was not performed by the artist indicated Song 2 was also mislabeled							

GhanniMusic							
Artist 5	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	0	-	-	-	-	-	-
Song 1	1	5	5	5	5	N/A	20
Song 2	2	4	3	5	5	N/A	18
Song 3	3	5	4	5	5	N/A	21
Song 4	4	5	4	5	5	N/A	22
Song 5	5	5	4	5	5	N/A	23
Song 6	5	5	4	5	4	N/A	23
Song 7	5	5	4	5	4	N/A	23
Song 8	5	5	4	5	5	N/A	24
Song 9	5	5	3	5	3	N/A	21
Song 10	-	4	3	4	2	N/A	18
						Average Score *(out of 25 possible points)*	**21.30**
Notes:							

GhanniMusic							
Artist 6	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	5	-	-	-	-	-	-
Song 1	5	5	4	5	5	N/A	24
Song 2	5	5	3	5	5	N/A	23
Song 3	5	5	5	5	5	N/A	25
Song 4	5	5	4	5	5	N/A	24
Song 5	5	5	4	5	5	N/A	24
Song 6	5	5	4	5	5	N/A	24
Song 7	4	3	3	5	4	N/A	20
Song 8	5	5	4	5	5	N/A	23
Song 9	5	5	3	5	5	N/A	23
Song 10	-	5	4	5	5	N/A	24
						Average Score *(out of 25 possible points)*	**23.40**
Notes:							

GhanniMusic							
Artist 7	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	5	-	-	-	-	-	-
Song 1	5	5	5	5	5	N/A	25
Song 2	5	5	4	5	5	N/A	24
Song 3	5	5	4	5	5	N/A	24
Song 4	5	5	4	5	-5	skipped	14
Song 5	5	3	3	4	-4	skipped	11
Song 6	5	5	4	5	4	N/A	23
Song 7	3	-2	-3	-5	-5	skipped	-10
Song 8	4	5	3	5	5	N/A	21
Song 9	5	5	4	5	5	N/A	23
Song 10	-	-2	5	0	-3	N/A	5
						Average Score *(out of 25 possible points)*	**16.00**
Notes:							

GhanniMusic							
Artist 8	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	5	-	-	-	-	-	-
Song 1	4	1	1	2	-2	skipped	7
Song 2	5	5	5	5	5	N/A	24
Song 3	4	4	3	3	3	N/A	18
Song 4	4	3	3	4	3	N/A	17
Song 5	5	5	4	5	5	N/A	23
Song 6	5	5	4	5	5	N/A	24
Song 7	5	5	4	5	5	N/A	24
Song 8	5	4	3	5	4	N/A	21
Song 9	5	4	3	5	4	N/A	21
Song 10	-	-2	1	1	-2	N/A	3
						Average Score *(out of 25 possible points)*	**18.20**
Notes:							

GhanniMusic							
Artist 9	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	4	-	-	-	-	-	-
Song 1	5	5	5	5	5	N/A	24
Song 2	5	5	4	5	5	N/A	24
Song 3	5	4	3	4	5	N/A	21
Song 4	5	4	4	5	4	N/A	22
Song 5	5	5	4	5	5	N/A	24
Song 6	5	5	4	5	4	N/A	23
Song 7	5	5	4	5	5	N/A	24
Song 8	5	5	4	5	4	N/A	23
Song 9	5	5	4	5	5	N/A	24
Song 10	-	4	3	4	3	N/A	19
						Average Score *(out of 25 possible points)*	**22.80**
Notes:							

GhanniMusic							
Artist 10	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	5	-	-	-	-	-	-
Song 1	5	5	5	5	5	N/A	25
Song 2	5	5	4	4	4	N/A	22
Song 3	5	4	5	3	3	N/A	20
Song 4	5	5	4	5	5	N/A	24
Song 5	5	5	3	4	3	N/A	20
Song 6	5	5	3	4	4	N/A	21
Song 7	5	5	4	5	5	N/A	24
Song 8	5	5	4	4	4	N/A	22
Song 9	5	5	4	4	4	N/A	22
Song 10	-	5	4	5	5	N/A	24
						Average Score *(out of 25 possible points)*	**22.40**
Notes:							

7.4 Last.fm Data

7.4.1 Songs Played

Last.fm		
Artist 1	**The Rolling Stones**	
	Song Title	**Artist**
Song 1	Let It Rock	The Rolling Stones
Song 2	Everything I Do	The Knack
Song 3	White Summer/Black Mountain	Led Zeppelin
Song 4	We Believe	Red Hot Chili Peppers
Song 5	Circles	Ten Years After
Song 6	Hustler	Journey
Song 7	Rockstar	Everclear
Song 8	Margaritaville	Jimmy Buffet
Song 9	Love Stinks	The J. Geils Band
Song 10	Restless	George Thorogood

Last.fm		
Artist 2	**Aretha Frankin**	
	Song Title	**Artist**
Song 1	Skylark	Aretha Franklin
Song 2	Huey Smith Medley	Dr. John
Song 3	Girl	Destiny's Child
Song 4	Newborn Friend	Seal
Song 5	Move On Drifter	Carla Davis
Song 6	Give Me Time	Minnie Ripperton
Song 7	Summertime	Ohio Players
Song 8	Strawberry Letter 23	Brothers Johnson
Song 9	Gonna Give Her All the Love I've Got	Jimmy Ruffin
Song 10	Needle In A Haystack	The Velvelettes

Last.fm		
Artist 3	**Nirvana**	
	Song Title	**Artist**
Song 1	All Apologies (home demo)	Nirvana
Song 2	Put Your Money Where Your Mouth Is	Jet
Song 3	Mouthful of Cavities	Blind Melon
Song 4	Can't Let You Go	Matchbox Twenty
Song 5	Do You Feel Loved	U2
Song 6	Unterwegs	Sportfreunde Stiller
Song 7	Bones & Joints	Finger Eleven
Song 8	Ark if the Envious	The Verve Pipe
Song 9	Swing Swing	The All American Rejects
Song 10	Walrus	Unwritten Law

Last.fm		
Artist 4	**Led Zeppelin**	
	Song Title	**Artist**
Song 1	Hats Off to Roy (Harper)	Led Zeppelin
Song 2	The Farm	Aerosmith
Song 3	Mary Queen of Arkansas	Bruce Springsteen
Song 4	Let Me Live	Queen
Song 5	Wait and See	Canned Heat
Song 6	Gonna Send You Back to Walker	The Animals
Song 7	Everybody Want To Be Someone	Sweet
Song 8	Love Lives Here	Faces
Song 9	Flesh And Bone	Alien Ant Farm
Song 10	Painful	Staind

Last.fm		
Artist 5	**Snoop Dogg**	
	Song Title	**Artist**
Song 1	Tru Tank Doggs	Snoop Dogg
Song 2	Can You Dance 2 This	Baby Bash
Song 3	Shorty Be Mine	Pretty Ricky
Song 4	Swass	Sir Mix A Lot
Song 5	Wylin Out	Mos Def
Song 6	Live Intro	N.W.A.
Song 7	Radio (edited)	Eazy-E
Song 8	Love In War	Andre 3000
Song 9	Cashmoney	Baby
Song 10	Is This Life	Gang Starr (feat Snoop Dogg)

Last.fm		
Artist 6	**The Clash**	
	Song Title	**Artist**
Song 1	Groovy Times	The Clash
Song 2	Buckle Up	Heideroosjes
Song 3	True	Propagandhi
Song 4	Speak Of the Devil	Misfits
Song 5	Handsome Man	The 5.6.7.8's
Song 6	Infested: Lindance Conspiracy Pt 1	Choking Victim
Song 7	4th of July	X
Song 8	I Am Forever	Rancid
Song 9	One Chord Wonders	The Adverts
Song 10	Airplanes	28 Days

Last.fm		
Artist 7	**Metallica**	
	Song Title	**Artist**
Song 1	The Call of Ktulu	Metallica
Song 2	Inner Combustion	Vivod
Song 3	Shadows of Mine	Crematory
Song 4	Rockin' Again	Saxon
Song 5	Era of the Merciless	Kataklysm
Song 6	Rejoicing the Utter Black Bitterness	Apocrypha
Song 7	The Arrival of Satan's Empire	Dark Funeral
Song 8	Erase the Doubt	Mushroomhead
Song 9	Vazka	Turbo
Song 10	Here Of the Elements Enslaved	Enslaved

Last.fm		
Artist 8	**John Lee Hooker**	
	Song Title	**Artist**
Song 1	You Ain't Too Old To Shift Them Gears	John Lee Hooker
Song 2	Helping Hand	Dr. John
Song 3	Caterpillar Crawl	Canned Heat
Song 4	Shiny Things	Tom Waits
Song 5	Sun Gonna Shine In My Door	Washboard Sam
Song 6	Tu Peux Cogner Mais Tu Peux Pas Rentrer	Clifton Chenier
Song 7	I Got A Bad Mind	Big Joe Williams
Song 8	Gemini Blues	Sonny Landreth
Song 9	Well Alright	Blind Faith
Song 10	You'll Be Mine	Stevie Ray Vaughan and Double Trouble

Last.fm		
Artist 9	**Bob Marley & The Wailers**	
	Song Title	**Artist**
Song 1	All In One	Bob Marley & The Wailers
Song 2	O nous a vole notre futr	Brain Damage
Song 3	Spying Glass	Horace Andy
Song 4	Jingle Lion	Lee "Scratch" Perry & The Upsetters
Song 5	Adapter Changer	Scientist
Song 6	Jersusalem	Matisyahu
Song 7	Historiens Slut	Svenska Akademien
Song 8	007	Desmond Dekker & The Aces
Song 9	Skinhead Moonstomp	Symarip
Song 10	Dodar o sorterar dom sen	Helt Off

Last.fm		
Artist 10	**Ludwig van Beethoven**	
	Song Title	**Artist**
Song 1	Clarinets, horms, bassoons and flutes	Ludwig van Beethoven
Song 2	The Bartered Bride: Overature	Bedrich Smetana
Song 3	Lachian Dance III Dymak	Leos Janacek
Song 4	Dance of the Cygnets (from Swan Lake)	London Symphony Orchestra / Pyotr Ilyich Tchaikovsky
Song 5	Le fromveur	Yann Tiersen
Song 6	Instead of a Tango	Gidon Kremer
Song 7	Ciacona in D minor	Johann Pachelbel
Song 8	Also Sprach Zarathustra	Johann Strauss II
Song 9	Wie schoen leuchtet der Morgenstern: Opening Chorus	Johann Sebastian Bach
Song 10	VI Epilogue: Adagio	Dmitri Shostakovich

7.4.2 Ratings Given

Last.fm							
Artist 1	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	0	-	-	-	-	-	-
Song 1	1	5	5	5	5	Love	20
Song 2	1	3	3	4	2	skipped	13
Song 3	1	3	4	4	2	skipped	14
Song 4	2	3	2	4	3	none	13
Song 5	2	4	3	5	4	none	18
Song 6	2	3	3	3	2	skipped	13
Song 7	3	5	3	5	4	Love	19
Song 8	2	2	2	0	-2	skipped	5
Song 9	3	5	3	4	5	none	19
Song 10	-	5	4	5	5	Love	22
						Average Score *(out of 25 possible points)*	**15.60**
Notes:							

Last.fm							
Artist 2	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	3	-	-	-	-	-	-
Song 1	2	2	5	2	2	skipped	14
Song 2	2	4	3	4	3	none	16
Song 3	2	1	2	0	-2	Banned	3
Song 4	2	1	2	1	0	Skipped	6
Song 5	3	5	4	5	5	none	21
Song 6	3	4	3	4	2	none	16
Song 7	4	4	3	5	4	none	19
Song 8	4	3	2	4	3	none	16
Song 9	5	5	4	5	5	Love	23
Song 10	-	5	4	5	5	Love	24
						Average Score *(out of 25 possible points)*	**15.80**
Notes:							

Last.fm							
Artist 3	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	5	-	-	-	-	-	-
Song 1	5	3	5	3	4	none	20
Song 2	5	4	3	4	4	none	20
Song 3	5	4	4	4	3	none	20
Song 4	4	2	2	0	-2	Banned	7
Song 5	3	0	1	-1	-2	Banned	2
Song 6	4	5	3	5	4	none	20
Song 7	5	5	4	5	5	Love	23
Song 8	5	5	4	5	4	none	23
Song 9	5	5	4	5	5	Love	24
Song 10	-	2	2	3	3	none	15
Average Score *(out of 25 possible points)*							**17.40**
Notes:							

Last.fm							
Artist 4	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	5	-	-	-	-	-	-
Song 1	5	3	5	3	2	none	18
Song 2	5	5	4	5	4	Love	23
Song 3	4	5	4	5	5	none	24
Song 4	5	4	3	2	3	none	16
Song 5	5	5	3	5	5	Love	23
Song 6	5	3	2	4	3	none	17
Song 7	5	5	3	4	3	none	20
Song 8	5	4	3	3	3	none	18
Song 9	5	5	3	4	4	none	21
Song 10	-	1	1	0	-2	Banned	5
Average Score *(out of 25 possible points)*							**18.50**
Notes:							

Last.fm							
Artist 5	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	4	-	-	-	-	-	-
Song 1	4	4	5	4	4	none	21
Song 2	4	4	4	3	3	none	18
Song 3	3	2	3	-2	-2	Banned	5
Song 4	4	5	4	5	5	Love	22
Song 5	5	5	4	5	5	none	23
Song 6	5	4	3	3	3	none	18
Song 7	5	4	5	5	5	Love	24
Song 8	4	3	2	2	-2	Banned	10
Song 9	5	4	4	4	4	none	20
Song 10	-	5	5	5	5	none	25
Average Score *(out of 25 possible points)*							**18.60**
Notes:							

Last.fm							
Artist 6	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	5	-	-	-	-	-	-
Song 1	5	3	5	3	3	none	19
Song 2	5	5	3	4	4	none	21
Song 3	5	5	3	4	4	none	21
Song 4	5	5	4	5	5	Love	24
Song 5	5	5	4	5	5	Love	24
Song 6	5	5	3	4	4	none	21
Song 7	5	3	1	1	0	none	10
Song 8	5	5	4	5	5	Love	24
Song 9	5	5	4	5	4	none	23
Song 10	-	5	4	5	5	Love	24
Average Score *(out of 25 possible points)*							**21.10**
Notes:							

Last.fm							
Artist 7	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	5	-	-	-	-	-	-
Song 1	5	5	5	5	5	none	25
Song 2	5	5	4	5	5	none	24
Song 3	4	3	1	1	-3	Banned	7
Song 4	5	4	3	4	3	none	18
Song 5	4	2	2	1	-2	Banned	8
Song 6	3	0	1	-1	-4	Banned	0
Song 7	2	-1	1	-1	-5	Banned	-3
Song 8	3	2	2	4	4	none	14
Song 9	4	4	3	5	4	Love	19
Song 10	-	3	1	2	2	none	12
Average Score *(out of 25 possible points)*							**12.40**
Notes:							

Last.fm							
Artist 8	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	4	-	-	-	-	-	-
Song 1	5	4	5	5	4	Love	22
Song 2	5	5	3	4	4	none	21
Song 3	4	3	2	3	3	none	16
Song 4	3	2	1	2	2	none	11
Song 5	4	5	4	5	5	Love	22
Song 6	5	5	1	4	5	Love	19
Song 7	5	5	4	5	5	Love	24
Song 8	5	5	3	5	4	none	22
Song 9	5	3	1	2	2	none	13
Song 10	-	3	2	4	3	none	17
Average Score *(out of 25 possible points)*							**18.70**
Notes:							

Last.fm							
Artist 9	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	5	-	-	-	-	-	-
Song 1	5	5	5	5	5	Love	25
Song 2	4	1	-1	0	-2	Banned	3
Song 3	5	4	4	5	3	none	20
Song 4	4	3	2	3	1	none	14
Song 5	5	5	4	5	5	Love	23
Song 6	5	5	4	5	5	Love	24
Song 7	4	2	1	2	-2	Skipped	8
Song 8	4	3	3	3	2	none	15
Song 9	5	5	4	5	5	Love	23
Song 10	-	3	3	4	3	none	18
Average Score *(out of 25 possible points)*							**17.30**
Notes:							

Last.fm							
Artist 10	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	5	-	-	-	-	-	-
Song 1	4	-3	1	-3	1	none)	1
Song 2	4	4	3	4	3	none	18
Song 3	5	5	4	4	4	none	21
Song 4	5	5	4	5	5	Love	24
Song 5	5	5	2	5	5	Love	22
Song 6	5	4	3	3	2	none	17
Song 7	5	5	4	5	4	none	23
Song 8	4	-3	0	-4	-3	none	-5
Song 9	5	4	4	5	4	none	21
Song 10	-	5	4	5	5	Love	24
Average Score *(out of 25 possible points)*							**16.60**
Notes:							

7.5 Pandora Data

7.5.1 Songs Played

Pandora		
Artist 1	**The Rolling Stones**	
	Song Title	**Artist**
Song 1	Moonlight Mile	The Rolling Stones
Song 2	Especially In Michigan	Red Hot Chili Peppers
Song 3	Throw Down A Line	The Jeff Beck Group
Song 4	Now Look	Ron Wood
Song 5	Short And Curlies	The Rolling Stones
Song 6	Watch That Man	David Bowie
Song 7	Running On Empty	Jackson Browne
Song 8	(I Know) I'm Losing You	The Faces
Song 9	I Go Wild	The Rolling Stones
Song 10	Mr. Jones	Counting Crows

Pandora		
Artist 2	**Aretha Frankin**	
	Song Title	**Artist**
Song 1	Giving It	Aretha Franklin
Song 2	You Send Me	Aretha Franklin
Song 3	I Can't Believe You Love Me	Marvin Gaye & Tammi Terrell
Song 4	Bring It On Home To Me	Otis Redding & Carla Thomas
Song 5	Didn't You Know (You'd Have To Cry Sometime)	Gladys Knight And the Pips
Song 6	Busted	Ray Charles
Song 7	Do Right Woman Do Right Man	Aretha Franklin
Song 8	How Can I Put Out the Flame (When You Keep the Fire Burning)	Candy Staton
Song 9	Tell It Like It Is	Aaron Neville
Song 10	Time Is On My Side	Wilson Pickett

Pandora		
Artist 3	**Nirvana**	
	Song Title	**Artist**
Song 1	Stay Away	Nirvana
Song 2	The Middle	Jimmy Eat World
Song 3	Damn That River	Alice In Chains
Song 4	Medication	Queens of the Stone Age
Song 5	Flex Plexico	The Shanners
Song 6	Crackerman	Stone Temple Pilots
Song 7	Walter's Walk	Led Zeppelin
Song 8	First Date	blink-182
Song 9	Slide Away	Oasis
Song 10	Say It	Scatterheart

Pandora		
Artist 4	**Led Zeppelin**	
	Song Title	**Artist**
Song 1	What Is And What Should Never Be	Led Zeppelin
Song 2	Hey Joe	Jimi Hendrix
Song 3	Shoot To Thrill	AC/DC
Song 4	Working Man	Rush
Song 5	Good Times Bad Times	Led Zeppelin
Song 6	Her Strut	Bob Seger
Song 7	Moneytalks	AC/DC
Song 8	Voodoo Child	Jimi Hendrix
Song 9	SWLBR	Cream
Song 10	Night Flight	Led Zeppelin

Pandora		
Artist 5	**Snoop Dogg**	
	Song Title	**Artist**
Song 1	Who Am I (What's My Name)	Snoop Dogg
Song 2	What Would You Do?	Tha Dogg Pound
Song 3	B***** Please II	Eminem
Song 4	Until We Rich	Ice Cube
Song 5	Let's Get High	Dr. Dre
Song 6	Gotta Get Dis Money	Soopafly
Song 7	Snoop D.O. Double G	Snoop Dogg
Song 8	Check Yo Self	Ice Cube
Song 9	21 Jump Street	Snoop Dogg
Song 10	Keepin' It Gangsta	Tha Dogg Pound

Pandora		
Artist 6	**The Clash**	
	Song Title	**Artist**
Song 1	Rock the Casbah	The Clash
Song 2	Aunties and Uncles	The Jam
Song 3	Monkey Gone to Heaven	The Pixies
Song 4	Violent & Funky	Infectious Grooves
Song 5	Pure Joy	The Teardrop Explodes
Song 6	Eton Rifles	The Jam
Song 7	Uptight	Green Day
Song 8	Borstal	Oxymoron
Song 9	I'm So Bored With the U.S.A	The Clash
Song 10	Listed M.I.A.	Rancid

Pandora		
Artist 7	**Metallica**	
	Song Title	**Artist**
Song 1	For Whom The Bell Tolls	Metallica
Song 2	Where Eagles Dare	Iron Maiden
Song 3	You've Got Another Thing Comin'	Jodas Priest
Song 4	Paranoid	Black Sabbath
Song 5	Ace of Spades	Motorhead
Song 6	Everlong	Foo Fighters
Song 7	Master of Puppets	Whitfield Crane, Rocky George, Randy Castillio & Mike Inez (Metallica tribute band)
Song 8	Psycho Holiday	Pantera
Song 9	Sabbra Cadabra	Metallica
Song 10	Sex Type Thing	Stone Temple Pilots

Pandora		
Artist 8	**John Lee Hooker**	
	Song Title	**Artist**
Song 1	That's Alright	John Lee Hooker
Song 2	I Asked the Bossman	Lightnin' Hopkins
Song 3	Just Can't Sleep At Night	Jimmy Reed
Song 4	My Road Lies In Darkness	Charlie Musselwhite
Song 5	Boom Boom	John Lee Hooker
Song 6	Don't Lie to Me	Albert King & Stevie Ray Vaughan
Song 7	I Ain't Superstitious	Willie Dixon
Song 8	Your Stuff Is Ruff	Johnny Jones
Song 9	I'm A King Bee	Slim Harpo
Song 10	This Little Voice	Byther Smith

Pandora		
Artist 9	**Bob Marley & The Wailers**	
	Song Title	**Artist**
Song 1	Sun Is Shining	Bob Marley & The Wailers
Song 2	Cool Rastaman Cool	Steve Boswell & Jah Berry
Song 3	Why Should I	Bob Marley
Song 4	Bandits	The Wailing Souls
Song 5	Who Is Mr. Brown	Bob Marley & The Wailers
Song 6	The Beatitude	Slim Smith
Song 7	Soul Rebel	Bob Marley
Song 8	Love of a Woman	Dillinger
Song 9	Maccabee Version	Max Romeo
Song 10	Let The Power Fall On I	Max Romeo

Pandora		
Artist 10	**Ludwig van Beethoven**	
	Song Title	**Artist**
Song 1	NO SONGS PLAYED	
Song 2		
Song 3		
Song 4		
Song 5		
Song 6		
Song 7		
Song 8		
Song 9		
Song 10		

7.5.2 Ratings Given

Pandora							
Artist 1	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	0	-	-	-	-	-	-
Song 1	0	4	5	4	3	none	16
Song 2	1	5	3	5	4	Thumbs Up	17
Song 3	2	5	4	5	4	Thumbs Up	19
Song 4	3	5	4	5	5	none	21
Song 5	4	5	4	5	5	Thumbs Up	22
Song 6	5	5	4	5	5	Thumbs Up	23
Song 7	5	5	4	5	3	none	22
Song 8	5	5	4	5	5	Thumbs Up	24
Song 9	5	5	4	5	5	Thumbs Up	24
Song 10	-	5	4	5	5	Thumbs Up	24
Average Score *(out of 25 possible points)*							**21.20**
Notes:							

Pandora							
Artist 2	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	5	-	-	-	-	-	-
Song 1	4	2	5	-2	-2	Thumbs Down	8
Song 2	4	4	5	4	3	none	20
Song 3	5	5	4	5	4	none	22
Song 4	5	5	4	5	5	Thumbs Up	24
Song 5	5	5	4	5	4	none	23
Song 6	5	5	4	4	4	none	22
Song 7	5	3	4	4	5	Thumbs Up	21
Song 8	5	5	4	5	5	Thumbs Up	24
Song 9	5	5	4	5	5	Thumbs Up	24
Song 10	-	4	3	4	5	Thumbs Up	21
Average Score *(out of 25 possible points)*							**20.90**
Notes:							

Pandora							
Artist 3	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	5	-	-	-	-	-	-
Song 1	5	5	5	5	5	Thumbs Up	25
Song 2	5	5	4	5	5	Thumbs Up	24
Song 3	5	4	3	4	3	none	19
Song 4	5	5	4	5	5	Thumbs Up	24
Song 5	4	2	2	4	3	none	16
Song 6	5	5	4	5	5	Thumbs Up	23
Song 7	5	4	3	3	3	none	18
Song 8	5	4	3	5	5	Thumbs Up	22
Song 9	5	4	3	4	5	Thumbs Up	21
Song 10	-	4	3	4	4	none	20
Average Score *(out of 25 possible points)*							**21.20**
Notes:							

Pandora							
Artist 4	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	5	-	-	-	-	-	-
Song 1	5	5	5	5	5	Thumbs Up	25
Song 2	5	5	4	5	5	Thumbs Up	24
Song 3	5	4	3	4	5	Thumbs Up	21
Song 4	5	5	4	5	3	none	22
Song 5	5	4	5	4	4	Thumbs Up	22
Song 6	5	4	3	5	5	Thumbs Up	22
Song 7	5	4	3	4	5	Thumbs Up	21
Song 8	5	4	4	4	3	none	20
Song 9	5	5	4	5	3	none	22
Song 10	-	4	5	5	5	none	24
Average Score *(out of 25 possible points)*							**22.30**
Notes:							

Pandora							
Artist 5	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	5	-	-	-	-	-	-
Song 1	5	5	5	5	5	Thumbs Up	25
Song 2	5	4	4	5	3	none	21
Song 3	5	5	4	5	5	Thumbs Up	24
Song 4	5	4	3	3	3	none	18
Song 5	5	5	4	5	4	Thumbs Up	23
Song 6	5	4	3	4	2	none	18
Song 7	5	4	5	5	4	none	23
Song 8	5	4	3	4	3	none	19
Song 9	4	2	5	2	1	none	15
Song 10	-	3	4	3	2	none	16
Average Score *(out of 25 possible points)*							**20.20**
Notes:							

Pandora							
Artist 6	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	4	-	-	-	-	-	-
Song 1	5	5	5	5	5	Thumbs Up	24
Song 2	5	5	4	5	5	Thumbs Up	24
Song 3	4	-2	1	2	-2	Thumbs Down	4
Song 4	5	5	2	5	4	Thumbs Up	20
Song 5	5	4	3	4	2	none	18
Song 6	5	3	3	2	3	none	16
Song 7	5	5	3	5	4	Thumbs Up	22
Song 8	5	5	4	5	5	Thumbs Up	24
Song 9	5	4	5	4	4	Thumbs Up	22
Song 10	-	5	4	5	5	Thumbs Up	24
						Average Score *(out of 25 possible points)*	**19.80**
Notes:							

Pandora							
Artist 7	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	5	-	-	-	-	-	-
Song 1	5	5	5	5	5	Thumbs Up	25
Song 2	5	5	4	5	5	Thumbs Up	24
Song 3	5	5	4	5	5	Thumbs Up	24
Song 4	5	4	4	4	5	Thumbs Up	22
Song 5	5	4	4	4	5	Thumbs Up	22
Song 6	4	2	2	3	2	none	14
Song 7	4	3	5	3	0	none	15
Song 8	5	5	4	5	5	Thumbs Up	23
Song 9	5	3	5	2	4	Thumbs Up	19
Song 10	-	4	3	4	4	Thumbs Up	20
						Average Score *(out of 25 possible points)*	**20.80**
Notes:							

Pandora							
Artist 8	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	5	-	-	-	-	-	-
Song 1	5	5	5	5	5	Thumbs Up	25
Song 2	5	5	4	4	5	Thumbs Up	23
Song 3	5	5	4	5	5	Thumbs Up	24
Song 4	5	5	4	5	4	Thumbs Up	23
Song 5	5	4	5	4	4	Thumbs Up	22
Song 6	5	5	3	5	4	Thumbs Up	22
Song 7	5	5	3	5	4	Thumbs Up	22
Song 8	5	5	4	5	5	Thumbs Up	24
Song 9	5	4	4	5	2	none	20
Song 10	-	5	4	5	3	none	22
						Average Score *(out of 25 possible points)*	**22.70**
Notes:							

Pandora							
Artist 9	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	5	-	-	-	-	-	-
Song 1	5	4	5	4	2	none	20
Song 2	5	4	4	4	3	none	20
Song 3	5	4	5	4	4	Thumbs Up	22
Song 4	5	5	4	5	5	Thumbs Up	24
Song 5	5	4	5	4	3	none	21
Song 6	5	5	4	5	3	none	22
Song 7	5	3	5	3	4	Thumbs Up	20
Song 8	5	5	4	5	4	Thumbs Up	23
Song 9	5	5	4	4	2	Thumbs Down	20
Song 10	-	5	4	2	0	Thumbs Down	16
						Average Score *(out of 25 possible points)*	**20.80**
Notes:							

Pandora							
Artist 10	**Trust**	**Expectation**	**Similarity**	**Context**	**Usefulness**	**Feedback**	**Total**
	5	-	-	-	-	-	-
Song 1	0	0	0	0	0	0	0
Song 2	0	0	0	0	0	0	0
Song 3	0	0	0	0	0	0	0
Song 4	0	0	0	0	0	0	0
Song 5	0	0	0	0	0	0	0
Song 6	0	0	0	0	0	0	0
Song 7	0	0	0	0	0	0	0
Song 8	0	0	0	0	0	0	0
Song 9	0	0	0	0	0	0	0
Song 10	-	0	0	0	0	0	0
						Average Score *(out of 25 possible points)*	**0.50**
Notes:							