# Developing Personalized Classifiers for Retrieving Music by Mood

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**Abstract.** With the increased amount of music that is available to the average user, either online or through their own collection, there is a need to develop new ways to organize and retrieve music. We propose a system by which we develop a set of personalized emotion classifiers, one for each emotion in a set of 16 and a set unique to each user. We train a set of emotion classifiers using feature data extracted from audio which has been tagged with a set of emotions by volunteers. We then develop SVM, kNN, Random Forest, and C4.5 tree based classifiers for each emotion and determine the ideal classification algorithm. Finally, we compare our personalized emotion classifiers to a set of non-personalized classifiers.

**Keywords:** Music information retrieval, classification, SVM, kNN, Random Forest, C4.5

## 1 Introduction

With the average size of a person's digital music collection expanding into the hundreds and thousands, there is a need for creative and efficient ways to search for and index songs. This problem shows up in several sub-areas of music information retrieval such as genre classification, automatic artist identification, and instrument detection. Here we focus on indexing music by emotion, as in how the song makes the listener feel. This way the user could select songs that make him/her happy, sad, excited, depressed, or angry depending on what mood the listener is in (or wishes to be in). However the way a song makes someone feel, or the emotions he associates with the music, varies from person to person for a variety of reasons ranging from personality and taste to upbringing and the music the listener was exposed to growing up. This means that any sort of effective emotion indexing system must be personal and/or adaptive to the user. This is so far a mostly unexplored area of Music Information Retrieval (MIR) research, as many researchers that attempt to personalize their music emotion recognition systems do so from the perspective of finding how likely the song is to be tagged with certain emotions rather than finding a way to create a system that can be personalized.

We present a system through which we can build and train personalized user classifiers, which are unique for individual users. We built these classifiers based on user data accumulated through an online survey and music data collected via a feature extraction toolkit called MIRToolbox [1]. We then use four classification algorithms to determine the ideal algorithm for this data: support vector machines (SVM), k-nearest neighbors (kNN), random forest, and C4.5 trees. We finally take the ideal algorithm and build a broad non-personalized classifier to compare the personalized classifiers to.

## 2 Related Work

There is some discussion as to the possible usefulness of creating a personalized music recommender system. On the one hand [2] demonstrated that emotion in music is not so subjective that it cannot be modeled; on the other hand the results from researchers who attempt to build personalized music emotion recommendation systems are very promising, suggesting personalization is at least a way to improve emotion classification accuracy. Yang et al in [3] was one of the earliest to study the relationship between music emotion recognition and personality. The authors looked at users demographic information, musical experience, and user scores on the Big Five personality test to determine possible relationships and build their system. Classifiers were built based on support vector regression, and test regressors trained on general data and personalized data. The results were that the personalized regressors outperformed the general regressors in terms of improving accuracy, first spotlighting the problem of trying to create personalized recommendation systems for music and mood based on general groups. However, there has been continued work on collaborative filtering, as well as hybridizing personalized and group based preferences. Lu et al in [4] proposed a system that combined emotion-based, content-based, and collaborative-based recommendation and achieved an overall accuracy of 90%. In [5], the author first proposed the idea of using clustering in order to predict emotions for a group of users. The results were good, but some improvement was needed. The users were clustered into only two groups based on their answers to a set of questions, and the prediction was based on MIDI files rather than real audio. In this work, we propose creating personalized classifiers first (trained on real audio data), clustering users, creating representative classifiers for each cluster, and then allowing the classifiers to be altered based on user behavior.

Each of the possible classification algorithms has been used commonly in previous music information retrieval research, with varying results. kNN had been evaluated previously in [6] and [7] for genre classification. [6] achieved a 90%-98% classification accuracy by combining kNN and Neural Network classifiers and applying them to MIDI files using a 2-level genre hierarchical system. The authors of [7] on the other hand only achieved a 61% accuracy at the highest using real audio and k of 3. Random Forest was used principally in [8] for instrument classification in noisy audio. Sounds were created with one primary instrument and artificial noise of varying levels added in incrementally. The authors found that the percentage error was overall much lower than previous work done with SVM classifiers on the same sounds up until the noise level in the audio reached 50%. The authors also observed that Random Forest could also indicate the importance of certain attributes in the classification based on the structure of the resulting trees and the attributes used in the splitting. SVM classification is one of the more common algorithms used in music information retrieval for a variety of tasks, such as [9] for mood classification, [10] for artist identification (compared with k-nearest neighbors and Gaussian Mixture Models), and [11] for mood tracking. It has also been evaluated beside other classifiers in [7] for genre identification. These evaluations have shown the SVM classifier to be remarkably accurate, particularly in predicting mood. Regarding C4.5 decision trees, the authors in [12] in a comparison of the J48 implementation of C4.5 to Bayesian network, logical regression, and logically weighted learning classification models for musical instrument classification found that J48 was almost universally the most accurate classifier (regardless of the features used to train the classifier). The classification of musical instrument families (specifically string or woodwind) using J48 ranged in accuracy from 90-92%, and the classification of actual instruments ranged from 60-75% for woodwinds and 60-67% for strings.

## 3 Data Composition and Collection

### 3.1 Music Data

Music data was collected from 100 audio clips 25-30 seconds in length culled from one of the author's personal music collection. These clips were split into 12-15 segments (depending on the length of the original clip) of roughly 0.8 seconds in order to allow for changes in annotation as the clip progresses, resulting in a total of 1440 clips. These clips originated from several film and video game sound tracks in order to achieve a similar effect to the dataset composed in [13] (namely a set composed of songs that are less known and more emotionally evocative). As such the music was mainly instrumental with few if any intelligible vocals. The MIRToolbox[1] collection was then used to extract musical features. MIRToolbox is a set of functions developed for use in MATLAB which uses, among others, MATLAB's Signal Processing toolbox. It reads .wav files at a sample rate of 44100 Hz. The following features were extracted using this toolbox.

- **Rhythmic Features** (fluctuation peak, fluctuation centroid, frame-based tempo estimation, autocorrelation, attack time, attack slope): Rhythmic features refer to the set of audio features that describe a song's rhythm and tempo, or how fast the song is, although features such as attack time and attack slope are better indicators of the rhythmic style of the audio rather than pure tempo estimation. Fluctuation based features are based on calculations to a fluctuation summary (calculated from the estimated spectrum with a Bark-band redistribution), while the rest of the rhythmic features are based on the calculation of an onset detection curve (which shows the rhythmic pulses in the song in the form of amplitude peaks for each frame).

– **Timbral Features** (spectral centroid, spectral spread, coefficient of spectral skewness, kurtosis, spectral flux, spectral flatness, irregularity, Mel-Frequency Cepstral Coefficients (MFCC) features, zero crossings, brightness): Timbral features describe a piece's sound quality, or the sonic texture of a piece of audio. The timbre of a song can change based on instrument composition as well as play style. Most of these features are derived from analysis of the audio spectrum, a decomposition of an audio signal. MFCC features are based on analysis of audio frequencies (based on the Mel scale, which replicates how the human ear processes sound). Brightness and zero crossings are calculated based on the audio signal alone.
– **Tonal Features** (pitch, pitch chromogram peak and centroid, key clarity, mode, HCDF): Tonal features describe the tonal aspects of a song such as key, dissonance, and pitch. These features are based primarily off the formulation of a pitch chromogram, which shows the distribution of energy across pitches based on the calculation of dominant frequencies in the audio.

### 3.2 User Data

We have created a questionnaire so that individuals can go through multiple times and annotate different sets of music based on their moods on a given day. 68 users completed the questionnaire between 1 and 8 times, resulting in almost 400 unique user sessions.

**Questionnaire Structure** The Questionnaire is split into 5 sections

– Demographic Information (where the user is from, age, gender, ethnicity)
– General Interests (favorite books, movies, hobbies)
– Musical Tastes (what music the user generally likes, what he listens to in various moods)
– Mood Information (a list of questions based on the Profile of Mood States)
– Music Annotation (where the user annotates a selection of musical pieces based on mood)

The demographic information section is meant to compose a general picture of the user. The questions included ask for ethnicity (based on the NSF definitions), age, what level of education the user has achieved, what field they work or study in, where the user was born, and where the user currently lives. Also included is whether the user has ever lived in a country other than where he/she was born or where he/she currently lives for more than three years. This question is included because living in another country for that long would expose the user to music from that country (see figure 1).

The general interests section gathers information on the user's interests outside of music. It asks for the user's favorite genre of books, movies, and what kind of hobbies he/she enjoys. It also asks whether the user enjoyed math in school, whether he/she has a pet or would want one, whether he/she believes in an afterlife, and how he/she would handle an aged parent. These questions are all meant to build a more general picture of the user (see figure 2).

The musical tastes section is meant to get a better picture of how the user relates to music. It asks how many years of formal musical training the user has had, as well as his/her level of proficiency in reading or playing music if any. It also asks what genre of music the user listens to when they're happy, sad, angry, and calm (see figure 3).

The mood information section is a shortened version of the Profile of Mood States [14]. The Profile of Mood States asks users to rate how strongly he/she has been feeling a set of emotions over a period of time from the following list of possible responses:

- Not at all
- A little
- Moderately
- Quite a bit
- Extremely

The possible emotions asked about in the mood information session are listed below:

- Tense
- Shaky
- Uneasy
- Sad
- Unworthy
- Discouraged
- Angry
- Grouchy
- Annoyed
- Lively
- Active
- Energetic
- Worn Out
- Fatigued
- Exhausted
- Confused
- Muddled
- Efficient

A sample of these questions can be seen in figure 4. This is the section that is filled out every time the user returns to annotate music, since their mood would affect how they annotate music on a given day. These answers are later converted into a mood vector for each session, which describes the user's mood state at the time of the session.

Finally, the music annotation section is where users go to annotate a selection of clips. 40 clips are selected randomly from the set of 1440 clips mentioned in section 3.1. The user is then asked to check the checkbox for the emotion he/she feels in the music, along with a rating from 1-3 signifying how strongly the user feels that emotion (1 being very little, 3 being very strongly). The user has a choice of 16 possible emotions to pick (to be specific, 12 emotions and 4 generalizations), based on a 2-D hierarchical emotional plane (see figure 6 for the emotion plane and figure 5 for a view of the questionnaire annotation section).

When the user goes through the questionnaire any time after the first time, he only has to fill out the mood profile and the annotations again. Each of these separate sections (along with the rest of the corresponding information) is treated as a separate user, so each individual session has classifiers trained for each emotion, resulting in 16 emotion classifiers for each user session.

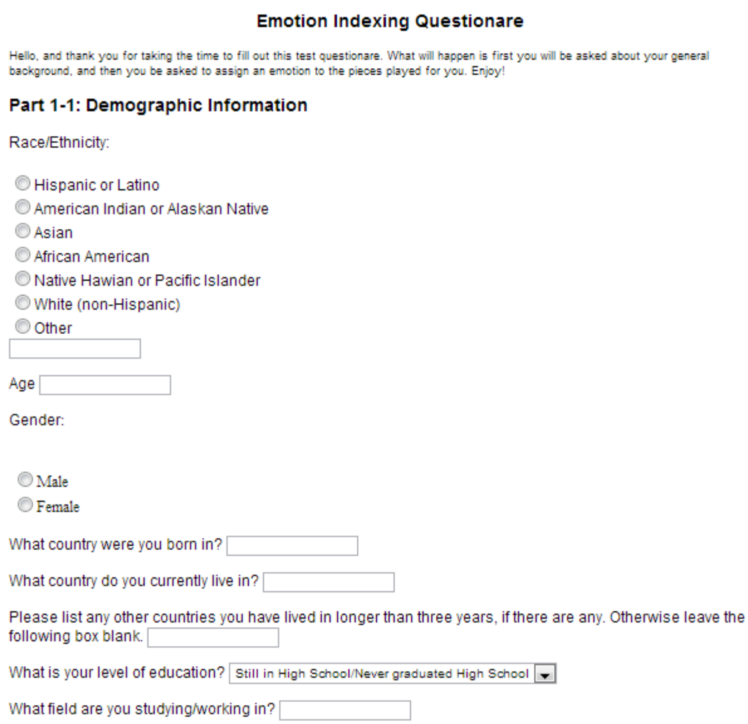
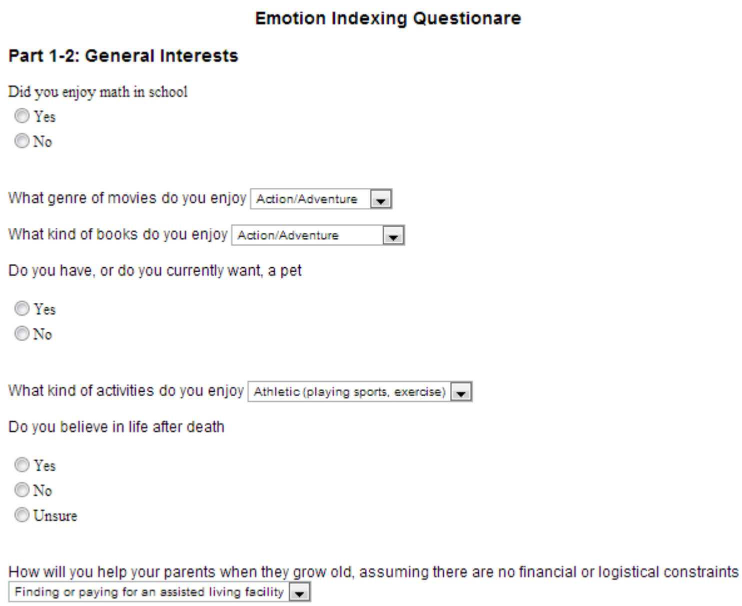



**Fig. 1.** The demographic information section of the questionnaire

**Emotion Model** This model was first presented in [5], and implements a hierarchy on the 2-dimensional emotion model, while also implementing discrete elements. The 12 possible emotions are derived from various areas of the 2-dimensional arousal-valence plane (based on Thayer's 2 dimensional model of arousal and valence [15]). However there are also generalizations for each area of



**Emotion Indexing Questionare**

**Part 1-2: General Interests**

Did you enjoy math in school

- Yes
- No

What genre of movies do you enjoy Action/Adventure

What kind of books do you enjoy Action/Adventure

Do you have, or do you currently want, a pet

- Yes
- No

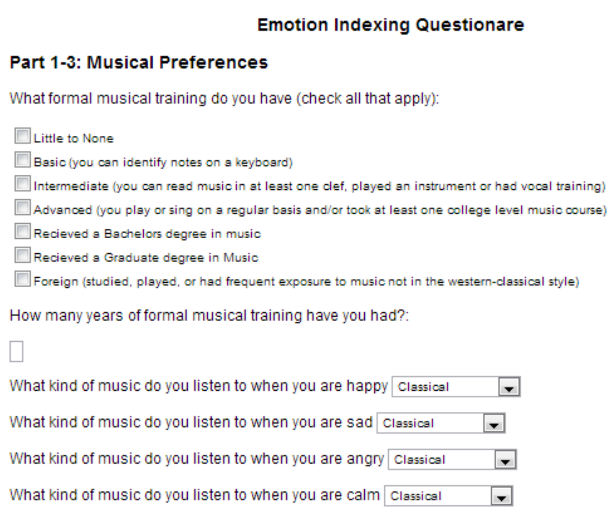
What kind of activities do you enjoy Athletic (playing sports, exercise)

Do you believe in life after death

- Yes
- No
- Unsure

How will you help your parents when they grow old, assuming there are no financial or logistical constraints
Finding or paying for an assisted living facility

**Fig. 2.** The general interests section of the questionnaire



**Emotion Indexing Questionare**

**Part 1-3: Musical Preferences**

What formal musical training do you have (check all that apply):

- Little to None
- Basic (you can identify notes on a keyboard)
- Intermediate (you can read music in at least one clef, played an instrument or had vocal training)
- Advanced (you play or sing on a regular basis and/or took at least one college level music course)
- Recieved a Bachelors degree in music
- Recieved a Graduate degree in Music
- Foreign (studied, played, or had frequent exposure to music not in the western-classical style)

How many years of formal musical training have you had?:

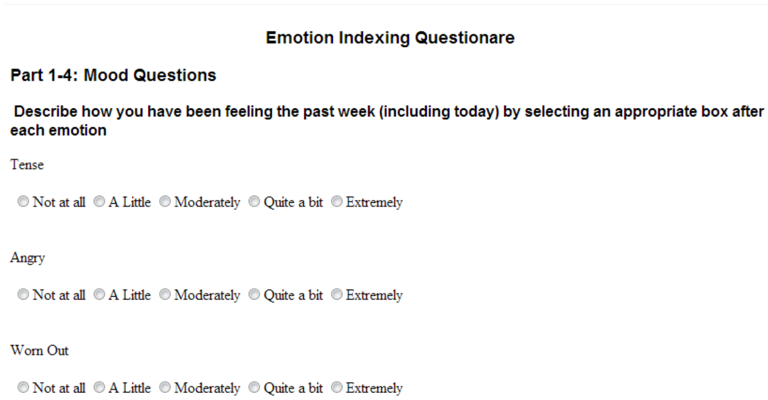
What kind of music do you listen to when you are happy Classical

What kind of music do you listen to when you are sad Classical

What kind of music do you listen to when you are angry Classical

What kind of music do you listen to when you are calm Classical

**Fig. 3.** The musical taste/background information section of the questionnaire


Emotion Indexing Questionare

Part 1-4: Mood Questions

Describe how you have been feeling the past week (including today) by selecting an appropriate box after each emotion

Tense

Not at all / A Little / Moderately / Quite a bit / Extremely

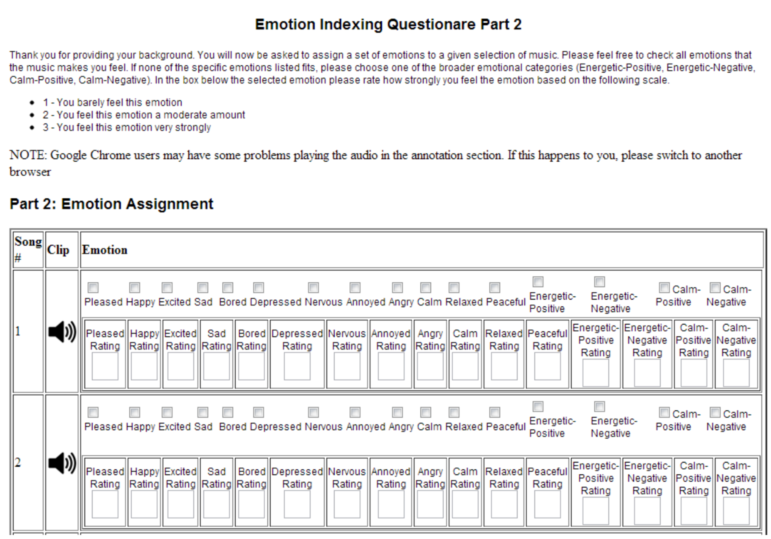
Angry

Not at all / A Little / Moderately / Quite a bit / Extremely

Worn Out

Not at all / A Little / Moderately / Quite a bit / Extremely

**Fig. 4.** Part of the mood state information section of the questionnaire. This section is filled out every time the user reenters the questionnaire (the user starts on this page once he/she has filled out the rest of the questionnaire once)


Emotion Indexing Questionare Part 2

Thank you for providing your background. You will now be asked to assign a set of emotions to a given selection of music. Please feel free to check all emotions that the music makes you feel. If none of the specific emotions listed fits, please choose one of the broader emotional categories (Energetic-Positive, Energetic-Negative, Calm-Positive, Calm-Negative). In the box below the selected emotion please rate how strongly you feel the emotion based on the following scale.

- 1 - You barely feel this emotion
- 2 - You feel this emotion a moderate amount
- 3 - You feel this emotion very strongly

NOTE: Google Chrome users may have some problems playing the audio in the annotation section. If this happens to you, please switch to another browser

Part 2: Emotion Assignment

| Song # | Clip | Emotion |
|---|---|---|
| 1 | | Pleased Happy Excited Sad Bored Depressed Nervous Annoyed Angry Calm Relaxed Peaceful Energetic-Positive Energetic-Negative Calm-Positive Calm-Negative<br>Pleased Rating, Happy Rating, Excited Rating, Sad Rating, Bored Rating, Depressed Rating, Nervous Rating, Annoyed Rating, Angry Rating, Calm Rating, Relaxed Rating, Peaceful Rating, Energetic-Positive Rating, Energetic-Negative Rating, Calm-Positive Rating, Calm-Negative Rating |
| 2 | | Pleased Happy Excited Sad Bored Depressed Nervous Annoyed Angry Calm Relaxed Peaceful Energetic-Positive Energetic-Negative Calm-Positive Calm-Negative<br>Pleased Rating, Happy Rating, Excited Rating, Sad Rating, Bored Rating, Depressed Rating, Nervous Rating, Annoyed Rating, Angry Rating, Calm Rating, Relaxed Rating, Peaceful Rating, Energetic-Positive Rating, Energetic-Negative Rating, Calm-Positive Rating, Calm-Negative Rating |

**Fig. 5.** The music emotion annotation section, also filled out every time the user goes through the questionnaire. The user clicks on a speaker to hear a music clip, then checks an emotion and supplies a rating 1 to 3

the plane (excited-positive, excited-negative, calm-positive, and calm-negative) that the users can select as well. This compensates for songs that might be more ambiguous to the user; if a user generally knows that a song is high-energy and positive feeling but the words excited, happy, or pleased don't adequately describe it, they can select the generalization of energetic-positive.

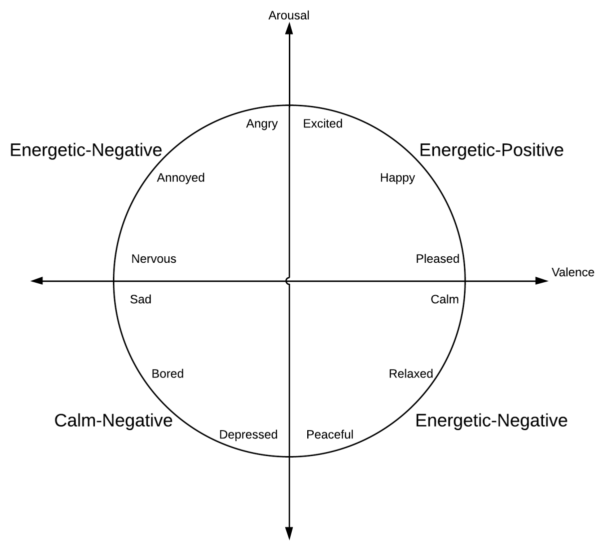



**Fig. 6.** A diagram of the emotional model to be used for classifier clustering

### 3.3 Classifier Development

Personalized classifiers were trained and tested using the classification algorithms listed previously (C4.5, SVM, Random Forest, kNN). The user annotation data was first converted so that each annotation for each song was represented as a vector of 16 numbers with each number representing the emotion labeling. The numbers ranged from 0 to 3, with 0 representing an emotion that was not selected by the user and the remaining numbers being the strength the user entered with the annotation. These vectors for all the users were then linked with the feature data extracted from the corresponding music clips. From this resulting table all the annotations and music data linked with individual user IDs were separated and used to train and test personalized classifiers for each emotion. This resulted in each user having at most 16 personalized classifiers (depending on whether the user used a given emotion during the course of annotating), where for each classifier the class attribute was one of the 16 possible emotions.

The classifiers were all evaluated via Weka[16] using 10-fold cross validation. For the C4.5 classifier we used the J48 implementation in Weka and for kNN we used Weka's IBk implementation. Analysis of these results indicates which classifier algorithm is most effective for personalized classification and, therefore, the most effective cluster-driven classifier.

## 4 Results

All four classifiers achieved a relatively high average accuracy, all above 80%. SVM achieved the lowest accuracy, 82.35%, while J48 trees achieved the highest accuracy, 86.62%. However, SVM as well as Random Forest achieved the highest average F-score (a combined measure of precision and recall), implying a higher precision and recall for those classifiers. IBk on the other hand had the lowest F-score of 0.92. SVM was expected to have a higher accuracy since it works so well with music data, but our previous success with J48 means the high accuracies and F-scores are not surprising.

Looking at the average Kappa statistic reveals further insights into the effectiveness of each classifier. The Kappa statistic measures the agreement between a true class and the prediction, and the closer to 1 the statistic is the more agreement (1 represents complete agreement). None of the classifiers reaches higher than 0.1, although again IBk has the highest average Kappa (J48, again, the lowest). This all suggests that while J48 is overall very accurate it is more inconsistent in terms of this particular set of data, while SVM is moderately accurate and very consistent.

**Table 1.** Table of classifier accuracies and F-scores

| Classifier | Average Accuracy | Average F-Score | Average Kappa |
|---|---|---|---|
| SVM | 82.35% | 0.90 | 0.137658 |
| IBk | 85.7% | 0.87 | 0.153468 |
| J48 | 86.62% | 0.89 | 0.076869 |
| Random Forest | 84.25% | 0.90 | 0.133027 |

### 4.1 Comparison with Non-Personalized Classifiers

As it proved to be the most accurate classifier, we have chosen J48 as the algorithm to use to build the non-personalized classifiers for comparison. We again built 16 emotion classifiers, this time using all the user annotations to train and test rather than individual user annotations. The results compared to the personalized J48 classifiers are shown in Table 2.

The average accuracy doesn't change too much between personalized and non-personalized classifiers (only 0.7%), however this was mainly due to the fact that several of the emotions were not used to the same extent as others

**Table 2.** Comparison of classifier accuracies and F-scores between personalized and non-personalized classifiers

| Classifier | Average Accuracy | Average F-Score | Average Kappa |
|---|---|---|---|
| Personalized J48 | 86.62% | 0.89 | 0.076869 |
| Non-personalized J48 | 87.29% | 0.82 | 0.00015 |

when tagging (for example, the generalized emotions), and in that case all the classifier did was predict '0' (for emotions that were not selected). This raised the accuracy for those classifiers, but it's not nearly as indicative as to the quality of the classifier as the F-Score and Kappa, which showed a great deal of improvement in the personalized classifier. The average F-score for the non-personalized classifiers is 0.08 less than the average F-score for personalized classifiers, and the average Kappa for the non-personalized classifiers is far less than the personalized classifiers. These both signify a significant loss in classifier consistency once the classifiers are no longer personalized.

## 5 Conclusion

We have presented a system through which we build personalized music emotion classifiers based on user data accumulated through an online survey. Using this data, we have been able to build classifiers that are about as accurate as standard, non-personalized classifiers but far more consistent. In a real world situation, this would mean that music that accurately reflects the user's mood (or desired mood) would be recommended far more often than not. Future work would involve using these classifiers in a full music player, and improving classifiers even further by clustering users.

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