

# The bias of knowing: Emotional response to computer generated music

Bachelor Thesis Artificial Intelligence, Social Studies, Radboud University Nijmegen

Anne van Peer s4360842

Supervisor

Makiko Sadakata

Artificial Intelligence, Social Studies, Radboud University Nijmegen

14-07-2016

## ABSTRACT

---

This thesis aims to detect effect of composer information when listening to music. In particular, I researched whether a listener has a different emotional response to a melody when informed the melody was generated by a computer, as when informed it was composed by a human. If a bias exists, it may have an effect on the mutual –nonverbal- understanding of emotions between humans and computers, which is key to a natural interaction since our perception of computerised emotions may be different from human emotions. Two groups of participants listened to identical melodies: one group was told that they were going to rate emotion of computer generated music and the other group was told that they were going to rate that of human composed music. Given this information, I expected the ‘human composed’ group would have a stronger emotional response. This result did not show since –possibly- the given prime – human or computer music- was not strong enough to trigger a biased opinion in the participants. Participants agreed that happy songs correlate with a high energy and sad songs with low energy in the melody. It was found that these effects are caused by a combination of pitch change and variability of note length/tempo.

# INDEX

---

Abstract.....	1
Introduction.....	3
Music and Emotion.....	5
Emotional state.....	5
Music elements and emotion.....	6
Music, emotion and culture.....	6
AI Generated Expression.....	8
AI and emotion.....	8
AI and music.....	8
Pilot Study.....	10
Set up.....	10
Results.....	11
Main experiment.....	13
Methods.....	13
Results.....	14
Pre-processing.....	14
Identified valence and identified energy level.....	14
Familiarity.....	15
Response strength differences.....	15
FANTASTIC melody analysis.....	17
Conclusion and Discussion.....	20
References.....	21
Appendix.....	23
I - Pilot Questions.....	23
II - Experiment Questions.....	24
III - FANTASTIC analysis.....	25

## INTRODUCTION

---

A lot of communication between humans is nonverbal. We show and read information and emotions via facial expressions, body-language, and voice intonation. As computers become a larger part of our lives, it becomes more important that human-computer interaction is easy and natural. Incorporating nonverbal communication like expressing and recognising emotions in computer-mediator software is a key point of enhancing the interaction between computers and humans. One way of expressing emotion, is via music. It is a rare day that goes by without hearing a melody, song or jingle. Combining this information, it is not strange that computer generated music is a rising field of interest. For example, professor David Cope of the University of California, created an automatic composer as a result of a “composer’s block” (Cope, 1991). This program mimics the style of a composer, using original music as input. A more recent system is Iamus, a computer cluster made by Melomics, developed at the University of Malaga (“Melomics,” n.d.)<sup>1</sup>. Iamus uses a strategy modelled on biology to learn and evolve ever-better and more complex mechanisms for composing music (Moss, 2015).

*Iamus was alternately hailed as the 21st century's answer to Mozart and the producer of superficial, unmemorable, dry material devoid of soul. For many, though, it was seen as a sign that computers are rapidly catching up to humans in their capacity to write music.* (Moss, 2015, para. 10)

“Now, maybe I’m falling victim to a perceptual bias against a faceless computer program but I just don’t think Hello World! is especially impressive.” Writes Service (2012, para. 2) in The Guardian about a composition written by Iamus. I don’t think he is the only person falling victim to this bias, which is letting your knowledge about the composer (in this case the “faceless computer”) influence how you perceive the music. As described by Mantaras and Arcos (2002) the most researched topic within computer generated music –both generated and performed by the computer- is to incorporate the human expressiveness. However I wonder whether this is reachable given that our perception of computer generated music tends to be biased. In other words, it is possible that computers can never make ‘human-like’ (or at least truly appreciated) music when the listener knows it is made by a computer.

I am very much interested in the effect of this listeners’ bias. Not much is known about the effect of knowing whether the music attended to is made by humans or computers on the response to the music. In particular, the emotional response to the music interests me, given that the a natural interaction between computers and humans relies on mutual emotional

---

<sup>1</sup> Retrieved February 01, 2016, from <http://geb.uma.es/melomics/melomics.html>

understanding. The current thesis investigates this issue, namely, to what extent our emotional response is influenced by the fact that we know the music was generated by a computer. This is important for on-going efforts on incorporating human expressiveness in computer generated music, and mediator software in the future.

To answer this question I will firstly review the known effects of music on emotional state, more specifically which components of music contribute most to this effect and which types of emotions are mostly influenced by music. It is also important to take a look at a person's background, e.g. whether musical education and musical preferences influence the emotional response to music. Secondly I will review the importance of emotional interaction for computer systems. Also, it is important to review how –well- computers can generate music, and then perform this music. Using all the obtained information I set up an experiment to test my hypothesis; when informed the music attended to is generated by a computer, the listener will not have an equally strong emotional response to the music as when informed the music was composed by a human.

Finally, I used the FANTASTIC software toolbox (Müllensiefen, 2009) to identify the musical features which contribute to the emotional perception of music. The FANTASTIC toolbox is able to identify 83 different features in melodies. These include for example pitch change, tonality, note density, and duration entropy. Based on these feature values for each melody, principal components that best describe a set of melodies were analysed.

# MUSIC AND EMOTION

## EMOTIONAL STATE

Music has a big influence on our emotional state. For example, when we listen to pleasant or unpleasant music different brain areas are activated (Koelsch, Fritz, Cramon, Müller, & Friederici, 2006). Also, when primed with a happy song, participants were more likely to categorize a neutral face as happy, and when the prime was sad they were more likely to classify a neutral face as sad (Logeswaran & Bhattacharya, 2009).

Experts disagree on the amount and nature of the basic emotions of humans. Mohn, Argstatter, & Wilker (2010) experimented on how six basic emotions (happiness, anger, disgust, surprise, sadness, and fear), as proposed by Ekman (1992), are identified in music. They found that happiness and sadness were easiest to identify among these. As described in *Music, Thought, and Feeling* (Thompson, 2009), there exist only four basic emotions namely; happiness, sadness, anger and fear. Thompson describes that there also exist secondary emotions, and that emotions are typically considered basic is they contribute to survival, are found in all cultures, and have distinct facial expressions.

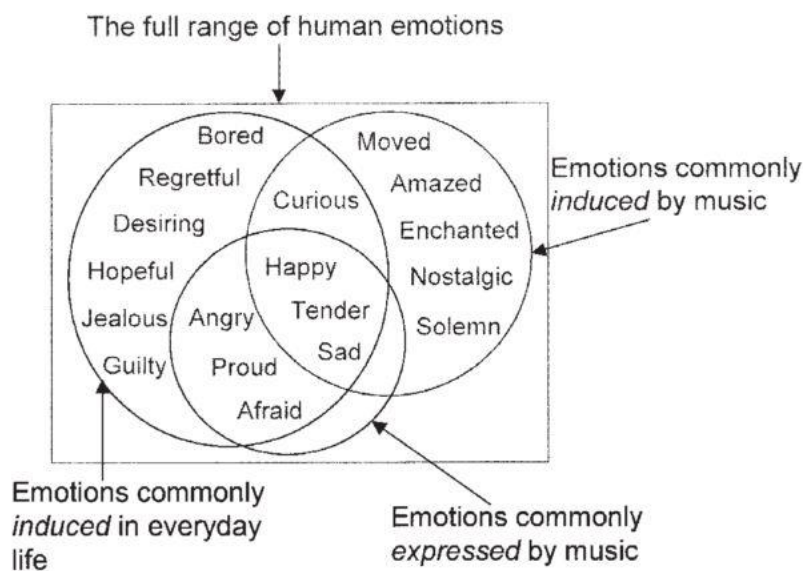


FIG. 1. HYPOTHESIZED RELATIONSHIPS BETWEEN (A) EMOTIONS COMMONLY INDUCED IN EVERYDAY LIFE, (B) EMOTIONS COMMONLY EXPRESSED BY MUSIC, (C) EMOTIONS COMMONLY INDUCED BY MUSIC (ILLUSTRATED BY A VENN DIAGRAM) (JUSLIN & LAUKKA, 2004)

The causal connections between music and emotion are not always clear (Thompson, 2009). On one hand, a person in the mood of dancing is more likely to turn on dance music (influence of mood on music selection). On the other hand, if a person on another occasion hears dance music, this might put this person in the mood for dancing (influence of music selection on

mood). This also raises the question whether the emotions that we feel when listening to music are evoked in the listener (emotivist position) or whether the listener is merely able to perceive the emotion which is expressed by the music (cognitivist position). As hypothesized by Juslin and Laukka (2004), there are different emotions associated with these two positions, as shown in figure 1. Lundqvist, Carlsson, Hilmersson, and Juslin (2008) investigated this matter and found evidence for the emotivist position, namely activation in the experiential, expressive, and physiological components of the emotional response system. However, among others, Kivy (1980) and Meyer (1956) (in Thompson, 2009) have questioned this view claiming that music expresses, but does not produce emotion. Thus the evidence, as found by Lundqvist et al. (2008), is not reliable for answering this question.

## MUSIC ELEMENTS AND EMOTION

---

According to Thompson (2009), emotions that we perceive from music are influenced by both the composition and the expression of the music. He examined several experiments in which the two factors were investigated separately and drew this conclusion. When melodies are stripped from all performance expression, for instance via a MIDI-sequencer, participants were still able to identify the intended emotion in the melodies. However, some emotions were more easy to detect than others (Thompson & Robitaille, 1992). On the other hand, when the experiment focusses on the expression of music, it is also found that listeners are able to detect the intended emotion of the performer, as described by Thompson (2009).

When we look further into how composition influences the perceived emotion, we can ask which specific features contribute most to this emotion. Herver (1935a, 1935b, 1936, 1937), performed multiple experiments to examine which musical features contributed most to this effect. She found that pitch and tempo were most influential for determining the affective character of music. Also important are modality (major or minor), harmony (simple or complex), and rhythm (simple or complex), respectively most to least important.

## MUSIC, EMOTION AND CULTURE

---

Hindustani music's classical theory outlines a connection between certain melodic forms (ragas) and moods (rasas), which makes it very suitable for music emotion research. In a study by Balkwill and Thompson (1991), it was found that western listeners, with no training or familiarity with the raga-rasa system, were still able to detect the intended emotion. They also found that this sensitivity was related to the basic structural aspects of music like tempo and complexity. These results provide evidence for connections between music and emotion which are universal.

Another source of emotion in music comes from extra musical associations. When a certain music is associated to a certain event for an individual, listening to the music may trigger an emotional response which is more related to the event than the music itself (Thompson, 2009). Thompson provides the following example:

*Elton John's "Candle in the wind 1997," performed at the funeral of Diana, Princess of Wales, has sold over 35 million copies and become the top-selling single of all time. Its popularity is undoubtedly related to its emotional resonance with a grieving public.*  
(Thompson, 2009, p149, sidenote)

Music taste and the reason why we listen is of influence on our emotional response as well (Juslin & Laukka, 2004). However, as Juslin and Laukka stress, there is very little research done to the relation between the motives and preferences of a listener and emotional responses to the music. Yet, as shown by Mohn, Argstatter, and Wilker (2010), musical background such as training or the ability to play an instrument are not of influence on the perception of the intended emotion of a music composer.

## AI GENERATED EXPRESSION

---

### AI AND EMOTION

---

Nowadays, we use computers on a daily basis. We interact with them very often and it is not unlikely that in the future robotic agents will assist our everyday lives. It is important that the communication between humans and computers is as natural and easy as possible. A large part of human-human communication is non-verbal and based on emotional expressions. Therefore, to enhance the communication between humans and computers, it is important to incorporate the recognition and production of emotions in computer systems. Many researchers are interested in this topic and working on such systems. For instance Nakatsu, Nicholson, & Tosa (2000), who focus on the recognition of emotion in human speech. They used a neural network trained on emotion recognition experiments, and had a recognition rate of 50% from eight different emotion states. Wang, Ai, Wu, & Huang (2004) created the Adaboost-system for recognizing different facial expressions.

This non-verbal communication of recognition and production of emotion  $\delta$  can be easily translated to the non-verbal communication of melodies. Therefore the two fields of human-computer interaction and AI-generated music are not that distend and it stresses the interest in emotional interactions imbedded in computer systems.

### AI AND MUSIC

---

AI generated music seems very easy to find on the web these days. However, since it is such a new field of study, I found it hard to find scientific documentation. Also, when one finds music which has been generated by a computer, often there is no description of how the music was generated. This means that it is hard to determine the amount of human input given to the system before it starts creating it's melodies. Such music can therefore not be used in controlled experiments. An option is to create the artificially composed music yourself –as a researcher. But the limited amount of time in a bachelor thesis, this was not an option for me.

Mantaras and Arcos (2002) identified different ways in which artificial music can be generated. The first is to focus on composition only, and avoid any emotion and feeling which until the melodic base sounds acceptable. The second is to focus on improvisation and the third type of program focusses on performance. This last type of programs has the goal to generate compositions that sounds good and expressive, and to a further extent, human-like.

They (Mantaras & Arcos, 2002) also stress a main problem with generating music, which is to incorporate a composers "touch" to the music. This "touch" is something humans develop



over the years, by imitating and observing other musicians and by playing themselves. Similarly, as mentioned in the paper, the computer composer can learn musical style from human input. Yet, this does not achieve the sought result.

## PILOT STUDY

---

People are able to detect happy and sad emotions in melodies, even when they are not familiar with the style of music and effects of timbre are removed. I would like to find out how strong this emotional response is when listening to computer generated music. With the growing importance of human-computer interaction, recognition and production of emotions by computers becomes an important issue of researchers. I hypothesize that, given the information that a melody was generated by a computer, the listener will not have an emotional response as strong as when they believe the melody was composed by a human.

To test my hypothesis, I presented the same set of melodies to two different groups of participants. One group was informed the melodies are composed by humans, the other was told the melodies were computer generated. I firstly set up a pilot experiment to see whether participants believed that the melodies presented were indeed –depending on their group– made by humans or computers and whether the bias effect came up. And finally, to see whether the chosen set up led to validity and reliability, such as easy to understand questions and clear instructions.

## SET UP

---

Eight Participants were asked to answer 4 questions on each melody (10 in total) they listened to. Four of these participants were told the fragments had been composed by a human, the other 4 believed it was generated by a computer. This information was clearly stated to the participants; both in the introductory written text and the spoken word of welcome.

Given the review before, it was decided to test each melody with Likert scale questions on happy vs. sad emotion on a 7-point scale (since these basic emotions are easiest to identify), calm vs. energetic on a 7-point scale (since these hold a strong relation to the perceived emotion), naturalness on a 5-point scale, and the familiarity of the melody on a 3-point scale. Happy and sad (valence) and calm and energetic (energy level) were chosen to describe the perceived emotion of the melody. The last question on familiarity may answer whether a difference in emotional response between different melodies is correlated with how familiar a melody sounds to the participant. For instance, if a melody is rated as very happy or very sad but also as very familiar, it may be the link between the song we relate to that causes the emotional response instead of the actual melody. Also, there might be a correlation between the familiarity and whether the participant thinks the melody was made by a human or computer generated.

After answering the questions about the melodies, the participant was asked to answer some questions about musical education and every-day listening. The answers to these

questions were used as demographic information about the participant groups. Also, some questions were asked about the likeliness that the music was composed by a human or computer, and participants filled in a list of adjectives they found appropriate to the melodies they heard. This last question was asked to identify whether my four main adjectives (happy/sad/energetic/calm) were checked by most participants when they had the choice for different adjectives. All questions can be found in appendix I.

The music melodies that were used, were obtained from RWC Music Database (Popular Music). My supervisor, Makiko Sadakata, provided an edited version of this dataset, where only the repeating melody lines from each song were kept. This set contained 100 MIDI files, of which 15 were randomly selected. An advantage of using these melodies, is that they are royalty-free, specially developed for research, provided as a MIDI-format -to reduce the effects of timbre-, and the Popular Music set has a familiar sound to the listeners. The melodies were played by a guitar and the BPM of all fragments was normalized to 100. These melodies were all monophonic and 5-15 seconds long.

## RESULTS

---

One of the first changes made after the pilot was to remove the question about naturalness of the melody. Participants found this too hard to answer because they had to base their thought on such little information from the MIDI-file. For this reason I considered that the answers to this question would not contribute reliably to the research.

Also the scales of the Liker-scale questions were altered. In order to force participants to make a decision on the first two questions (identified valence and identified energy level), the scale was changed from 7 points to 6 points. This pushed the participants to choose a meaningful answer by eliminating the possibility to answer “neutral”.

Some melodies had a large variability in terms of pitch and tempo, which changed unexpectedly. These unexpected changes in the melody may lead the participant to answer differently after listening to the whole melody than when only the first part was attended to. To ensure the participants base their answers to the full melody, the participants were required to listen to a melody at least once before going to the next melody.

The adjective test at the end of the questionnaire showed some expected results. Most of the time the boxes for ‘happy’, ‘sad’, ‘calm’, and ‘energetic’ were checked as well as the box for ‘weird’. This is not strange since some of the melodies lay far from what the participants encounter daily, and also because the MIDI-format gives an artificial touch to the melody. For the final experiment, this question was removed, as it was only developed to test the clearness questions in the pilot.

A question was added to the end, asking the participant how well they believe computers can generate music compared to humans. The answer to this question was a 5-point Likert-scale going from 'worse than humans' to 'better than humans'. The answers to these questions might have an interesting correlation with the participants condition (human composed vs. computer generated).

Figure 2 shows the observed answers for each melody. According to the hypothesis, the group that believed to rate human composed music should provide stronger emotional responses than that believed to rate computer generated music. I computed the mean score on valence and energy level for each melody. In order to focus on response strength and not the direction of the response, I took the absolute value of the participants responses. By subtracting the means of the computer condition group from the means of the human condition group, I computed the response strength difference for each melody. If indeed the 'human composer' group has a stronger response to valence and energy, the bars in figure 2 should be positive given the mentioned subtraction. This would mean that the responses of the human group were more into the extremes (very happy - very sad) and the computer group was more close to the centre (neutral line). As can be seen in Figure 2, most spikes were positive with a mean value of 0.175, which was in favour of my hypothesis.

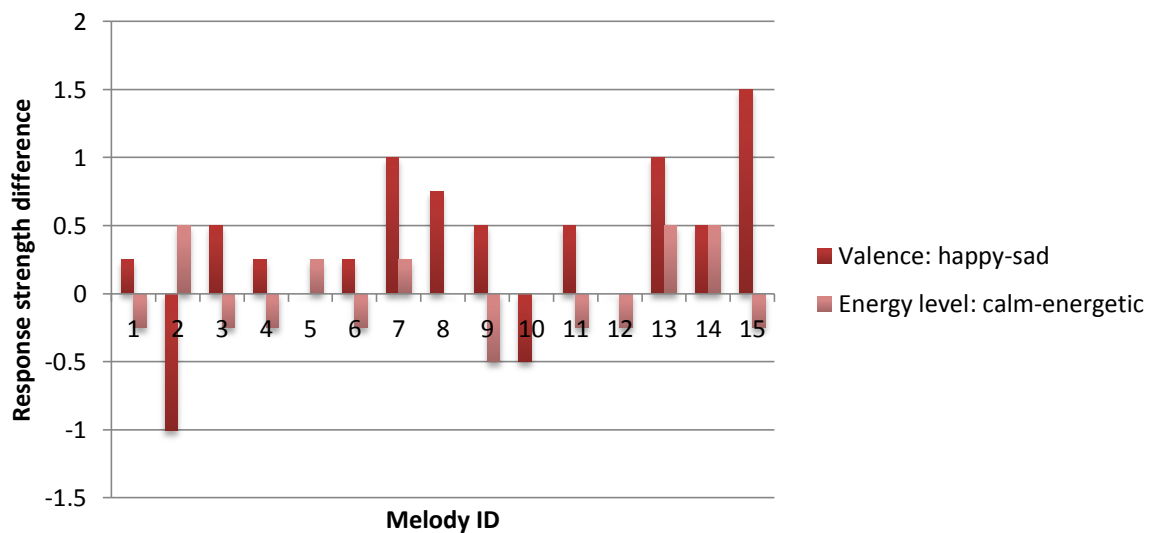


FIG. 2 DIFFERENCES BETWEEN THE TWO GROUPS. ONLY THE STRENGTH OF THE RESPONSE IS COUNTED, NOT THE DIRECTION

## MAIN EXPERIMENT

---

For the main experiment, I tested a larger group of participants on the same database of melodies as with the pilot. As mentioned in the Pilot-Results section, some changes were made to ensure a more valid and reliable experiment. The aim of the experiment was to test the hypothesis that the group with the ‘human composer’ condition had a stronger emotional response to the melodies than the ‘computer generated’ conditioned group. Also, I tested effects of familiarity of a melody and analysed which specific musical features contribute to emotional responses.

## METHODS

---

For the main experiment, 20 participants answered the questions (see appendix II for the full questionnaire). Ten of these formed the first group, who were informed they were going to listen to melodies which were composed by humans. The other ten formed the second group whom were told that the melodies were generated by a revolutionary computer program. The participants were all between 18 and 25 years old students at the Radboud University Nijmegen. They had different music educational backgrounds, for example whether they played an instrument or not, received musical education, and the amount of hours spend listening to music per week. Participants were randomly assigned to either of the two groups.

Participants answered the first set of questions from appendix II for each melody they listened to (scoring happy/sad, calm/energetic and familiarity). These melodies were –same as for the pilot– all in MIDI format with a normalized pitch and bpm of 100. The melodies came from the same database as the pilot experiment. I used a random set of 40 melodies from this database –including the 15 melodies used in the pilot experiment–, of which each participant listened to a random subset of 20. This was decided based on feedback about concentration and clear perception of the melodies, which the pilot group provided.

The participants sat in a quiet room facing a wall while answering the questions. The audio was presented to them via a headphone, and the questions appeared on a computer screen. The participants were allowed to listen to a melody as often as they wanted. In order to continue to the next melody, the current melody had to be completely listened to at least once, and all the questions had to be answered.

Not only their responses to the questions were saved, but also the number of times they listened to a particular melody and also the time spend answering the questions for a melody. This ‘reaction time’ was used to compute outliers.

The responses of the participants to the different melodies were used for multiple correlation tests. Also, the responses were used for a FANTASTIC analysis (Müllensiefen, 2009).

FANTASTIC is a software toolbox in R developed by Müllensiefen which can identify 83 different features of melodies and forms a set of principal components which describe the set of melodies it was given. These features incorporate for instance pitch change, tempo, and uniqueness of note sequences. The analysis takes into account the m-types of a melody, which are small sets of 3-5 notes. These are formed as if a frame was moved over the notes of the melody, each time selecting a small set. All the features were used to analyse the type of emotional responses. More information about the toolbox and explanation of all features is provided in the technical report on FANTASTIC (Müllensiefen, 2009).

## RESULTS

---

### PRE-PROCESSING

---

To determine outliers, I used the dispersion of the reaction times. An outlier was identified when the reaction time was larger/smaller than the mean reaction time for that melody  $\pm 3$  the standard deviation. One outlier was found, and this data point was removed from the data. Other responses by this participant were all kept.

After removing the outlier, the mean ratings of identified valence (happy vs. sad) and identified energy level (calm vs. energetic) for each of the 40 melodies were computed. This was done for all participants, the subset with the 'human composer' condition and the subset with the 'computer generated' condition. A mean value was calculated for the valence score, the energy-level score, and the familiarity score. Based on the Likert-scale, answers were rated -3 (sad and calm) to 3 (happy and energetic). The familiarity score varied between -1 and 1, unfamiliar and familiar respectively.

### IDENTIFIED VALENCE AND IDENTIFIED ENERGY LEVEL

---

Figure 3 shows the value for the mean identified energy level and the mean identified valence. The regression lines for both groups are drawn in the figure. We can see that both groups showed a positive correlation between these two variables (Human composed,  $r=0.8415$ ,  $p<.0001$  and Computer generated  $r=0.6769$ ,  $p<.0001$ ). Since the effect was evident in both groups, which means that, despite information about the composer, happy and energetic music features were present in the same melodies, but also sad and calm features occurred simultaneously in the melodies.

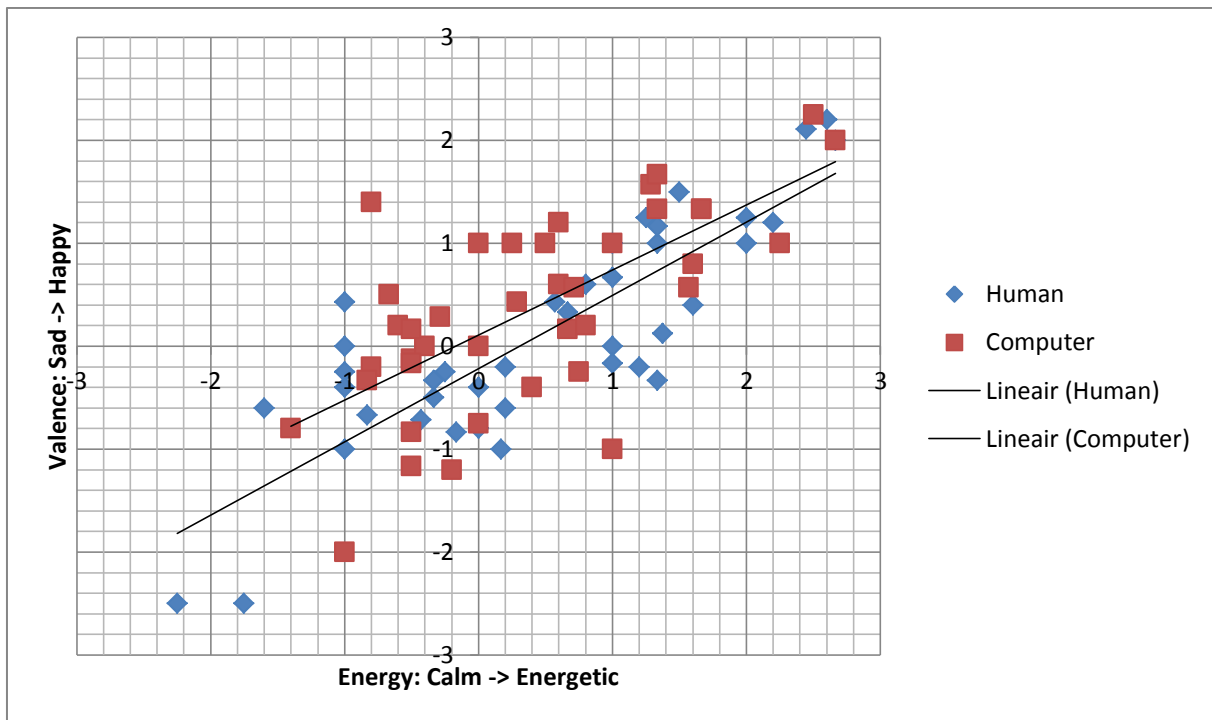


FIG. 3 CORRELATION BETWEEN ENERGY AND IDENTIFIED VALENCE

---

### FAMILIARITY

---

As mentioned before, there is a possibility that a participant responded to a melody based on similar, more familiar songs. To identify if this was indeed the case, correlations were computed between the familiarity rating and the mean scores on both identified valence and identified energy level. To also check a possible effect for the strength of the response, these means were squared to neglect the direction of the answer. As a result, correlations were computed for four different situations, but in none of these cases were the correlations significant. This suggests no significant correlation between the emotional response to a melody and the familiarity. Hence, the hypothesis that a participant's response is based more on the familiar melody than on the actual melody can be rejected.

Also, to check whether the condition had an influence on the perceived familiarity of a melody, the mean familiarity ratings of both groups were computed. For the 'human composed' conditioned group, this mean was -0.11 and for the 'computer generated' group this mean was 0.05. Thus there was no effect between condition and how familiar a melody tended to sound.

---

### RESPONSE STRENGTH DIFFERENCES

---

To compute the strength in response for a melody, the mean values for identified valence and identified energy level were squared to neglect the direction of the response and focus purely on the strength of the response. Then, the means of the 'computer generated' conditioned group

were subtracted from the ‘human composer’ conditioned group. Therefore, if the result was positive the ‘human composer’ conditioned group had a stronger response to the melody. In figure 4 we see the results of these subtractions per melody for both the identified valence and the identified energy level, respectively. In order to confirm my hypothesis, the mean value for both figures should be positive. These means were 0.10 and 0.58 for identified valence and identified energy level respectively. Which are indeed positive, but are rather small.

We see that a lot of peaks in figure 4 per melody are in the same direction. The correlation between the two bars in the graphs was highly significant ( $r=0.5738$ ,  $p<.001$ ). This means that if a group had a strong response to a melody, this response was reflected in both questions about perceived emotion.

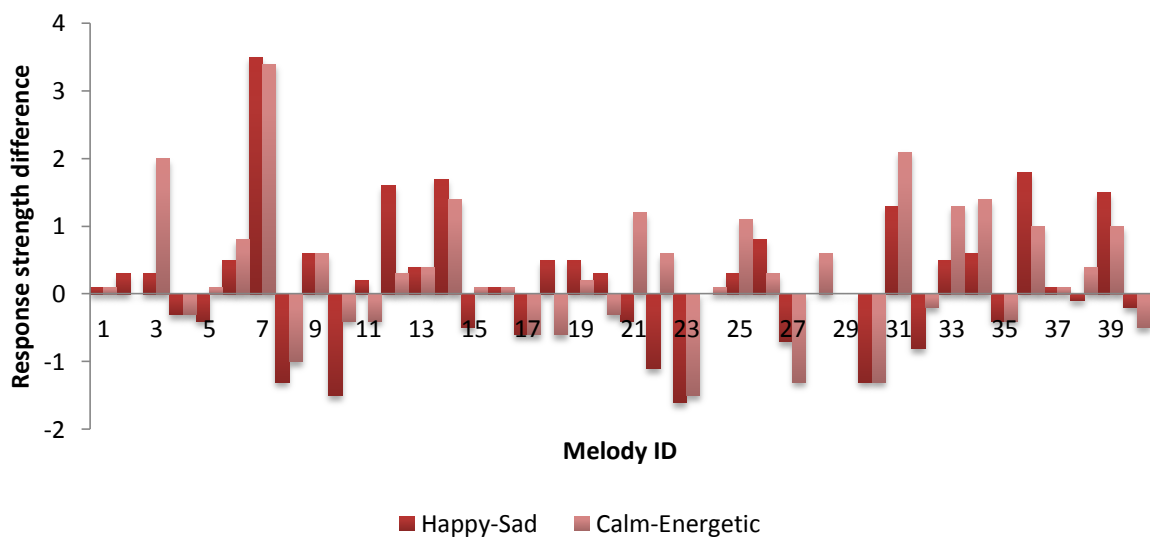


FIG. 4 DIFFERENCE IN RESPONSE STRENGTH FOR IDENTIFIED VALENCE AND IDENTIFIED ENERGY LEVEL

Finally, I tested the difference of response strength between participants of the two groups with a T-test. For independent variable I chose the assigned group, and the total emotion score for a participant was used as dependent variable. This total emotion score was computed as the sum of all the absolute values of their responses. I used the absolute values of the responses to only look into the strength of response, and neglected the direction. This results in the following formula, where n is the number of melodies per participant (20).

$$Total\ emotion\ score = \sum_n |valence\ score| + |energy\ score|$$

The T-test –one tailed- comparison did not indicate significant group differences ( $t(18) = 0.20$ ,  $p>.1$ ). This means that there was no significant difference between the two groups on how strong their emotional response was to the melodies.



---

## FANTASTIC MELODY ANALYSIS

---

In order to determine which musical features contributed to the identification of valence and energy level, I used the FANTASTIC toolbox (Müllensiefen, 2009). All the 40 melodies were submitted to the FANTASTIC music feature analysis, which resulted in the 83 feature values for each melody. These data can be described as a point cloud within a 84 dimensional coordinate system. A principle component analysis (PCA) was used to describe this point cloud. The parallel analysis suggested nine principal components to describe the dataset of 40 melodies. Which means nine principal components were 'drawn' through the long axes of the (standardized) point cloud. For each of the nine components, features that contributed more than .60 were considered important when interpreting them. The final factor construction can be found in Appendix III - FANTASTIC analysis, table 3. Using the information from the Technical report (Müllensiefen, 2009), I tried to best describe the nine factors based on their most contributing features. Interpretation of the components: (1) Repetition and uniqueness of m-types with relation to the corpus, (2) Repetition of m-types in the melody, (3) Pitch changes within m-types, (4) Correlation between tempo and change in pitch in a melody, where higher tempo also has larger pitch change and vice versa, (5) Expectancy of changes in pitch, (6) Level of tonality, (7) Variability for note length, (8) Uniqueness of an m-type, (9) Duration contrast. For all feature definitions see (Müllensiefen, 2009).

To identify which factors contribute to the identified emotion in the melody, I firstly computed the loading of each factor for each melody. This allowed me to test whether different factors were contributing more to the identified emotion in a melody than others. The resulting table of factor loads, as shown in Appendix III - FANTASTIC analysis table 4, was used to find different contributing factors to the identified emotion in the melody. First I used a Unit Step function on the data where for each participant the scores on identified valence and identified energy level for each melody were transformed to either 0 (sad or calm) or 1 (happy or energetic). This data and the contribution of the factors to the melodies –resulting in a 11\*400 data matrix– were used to compute which factors were most important to the identified emotion in a melody. This was done by using type II Wald chi-square tests ANOVA on both the Unit Step data of the identified valence, as the identified energy level. For both valence(V) and energy level(E) the most influential factors can be found in Table 1. Given these important factors and their meaning, identified emotion thus depends mainly on the combination of pitch change and the variability of note length. A higher tempo and unexpected changes in note duration occur together with larger changes in pitch the melody which gives a happy-energetic feel to the melody, and vice versa. We see that valence and energy differ on components 7 and 8. This means that for identified valence note length was a contributing factor and for identified energy level the uniqueness of an m-type was a contributing factor.

<b>Valence (V)</b>		<b>Energy Level (E)</b>	
(1) Repetition and uniqueness of m-types with relation to the corpus	$\chi^2=11.5792$ $p<.001$	(1) Repetition and uniqueness of m-types with relation to the corpus	$\chi^2=28.8244$ $p<.001$
(4) Correlation between tempo and change in pitch in a melody, where higher tempo also has larger pitch change and vice versa	$\chi^2=28.8467$ $p<.001$	(4) Correlation between tempo and change in pitch in a melody, where higher tempo also has larger pitch change and vice versa	$\chi^2=47.9388$ $p<.001$
(9) Duration contrast	$\chi^2=12.9337$ $p<.001$	(9) Duration contrast	$\chi^2=7.8788$ $p<.01$
(7) Variability for note length	$\chi^2=4.4327$ $p<.05$	(8) Uniqueness of an m-type	$\chi^2=5.766$ $p<.05$

TABLE 1 INFLUENTIAL FACTORS TO VALENCE AND ENERGY

I also tested whether there was a difference in contributing factors to the identified emotion for the two groups. The results can be found in Table 2. As can be concluded from this table, the contributing factors to the identified emotion for both groups were very similar, meaning that the two groups did not base their responds on contrasting features of the melody.

	<b>Valence (V)</b>		<b>Energy Level (E)</b>	
<b>“Human composed” -condition</b>	(1) Repetition and uniqueness of m-types with relation to the corpus	$\chi^2=11.2204$ $p<.001$	(1) Repetition and uniqueness of m-types with relation to the corpus	$\chi^2=16.0694$ $p<.001$
	(4) Correlation between tempo and change in pitch in a melody, where higher tempo also has larger pitch change and vice versa	$\chi^2=13.2306$ $p<.001$	(4) Correlation between tempo and change in pitch in a melody, where higher tempo also has larger pitch change and vice versa	$\chi^2=25.3692$ $p<.001$
	(9) Duration contrast	$\chi^2=5.3129$ $p<.05$	(9) Duration contrast	$\chi^2=6.9137$ $p<.01$
<b>“Computer generated” -condition</b>	(4) Correlation between tempo and change in pitch in a melody, where higher tempo also has larger pitch change and vice versa	$\chi^2=15.0669$ $p<.001$	(4) Correlation between tempo and change in pitch in a melody, where higher tempo also has larger pitch change and vice versa	$\chi^2=18.9992$ $p<.001$
	(9) Duration contrast	$\chi^2=7.3349$ $p<.01$	(1) Repetition and uniqueness of m-types with relation to the corpus	$\chi^2=11.7804$ $p<.001$
			(8) Uniqueness of an m-type	$\chi^2=4.6443$ $p<.05$

TABLE 2 FACTOR CONTRIBUTION DEPENDING ON GROUP AND IDENTIFIED EMOTION

## CONCLUSION AND DISCUSSION

---

The main question for this research was whether respond –emotionally- different to music when they were told it was either composed by a human or generated by a computer. I hypothesized that the listener would not have an emotional response as strong when listening to computer generated music as when they believe the melody was composed by a human. However, given the results from the experiment, there was no significant difference between the groups in strength of emotional response. This means that the emotional response to the melodies were similar irrespectively of the assigned group. Still, given my own experience, I believe that people are biased by the information that the music they listen to is computer generated. This experiment has shown that the bias I believe is present, is not as strong as I expected. It could be interesting in a follow-up study to test this expected bias with a stronger and more trustworthy prime. For instance, when told the melody was computer generated, also provide additional information about the -fictive- software or –fictive- developers and keep providing this prime throughout the experiment. For the ‘human composed’ condition the participant could be primed by giving more information about the –fictive- artist or be set in a music-studio environment.

Familiarity of a melody had no significant effect on the emotional response to the melody. Also, there was no significant difference in the familiarity scores given by the two groups. This means that the familiarity of a melody did not contribute to any effects that were found, and that the effects were –mainly- based on the provided melodies.

One main effect which was found was the positive correlation between identified valence and identified energy level suggesting that melodies which are experienced as happy are also experienced as energetic and the same holds for sad-calm melodies. Using FANTASTIC, it was found that the contributing features for valence and energy were very similar. Therefore it could be concluded that the identified emotion of a melody, as the union of the identified valence and identified energy level, was mainly based on these similar factors, namely; the combination of pitch change and the variability of note length. This means that a high tempo is associated with happy, and a slow tempo with sad. This seems to correspond to the finding of the first analysis that happy and energetic features were experienced together but also sad and calm features were experienced together.

To conclude, I would recommend to extend this research with a larger group of participants and stronger primed conditions. If it is true that people respond differently to artificially composed music -and so artificially created emotions-, this should be kept in mind when developing not only computer generated music, but also robotic –emotional- mediators.

## REFERENCES

---

- Balkwill, L., & Thompson, W. F. (1991). A Cross-Cultural Investigation of the Perception of and Cultural Cues Emotion in Music: Psychophysical and Cultural Cues. *Music Perception, 17*(1), 43–64. <http://doi.org/10.2307/40285811>
- Cope, D. (1991). *Computers and Musical Style* (Vol. 6).
- Ekman, P. (1992). An argument for basic emotions. *Cognition and Emotion, 6*(3-4), 169–200. <http://doi.org/10.1080/02699939208411068>
- Hevner, K. (1935a). Expression in Music : a Discussion of Experimental Studies and Theories. *Psychological Review, 42*, 186–204.
- Hevner, K. (1935b). The Affective Character of the Major and Minor Modes in Music. *The American Journal of Psychology, 47*(1), 103–118.
- Hevner, K. (1936). Experimental Studies of the Elements of Expression in Music, *48*(2), 246–268.
- Hevner, K. (1937). The Affective Value of Pitch and Tempo in Music. *American Journal of Psychology, 49*(4), 621–630.
- Juslin, P. N., & Laukka, P. (2004). Expression, Perception, and Induction of Musical Emotions: A Review and a Questionnaire Study of Everyday Listening. *Journal of New Music Research, 33*(3), 217–238. <http://doi.org/10.1080/0929821042000317813>
- Koelsch, S., Fritz, T., Cramon, D. Y., Müller, K., & Friederici, A. D. (2006). Investigating Emotion With Music : An fMRI Study. *Human Brain Mapping, 27*, 239–250. <http://doi.org/10.1002/hbm.20180>
- Logeswaran, N., & Bhattacharya, J. (2009). Neuroscience Letters Crossmodal transfer of emotion by music, *455*, 129–133. <http://doi.org/10.1016/j.neulet.2009.03.044>
- Lundqvist, L.-O., Carlsson, F., Hilmersson, P., & Juslin, P. N. (2008). Emotional responses to music: experience, expression, and physiology. *Psychology of Music, 37*(1), 61–90. <http://doi.org/10.1177/0305735607086048>
- Mantaras, R. De, & Arcos, J. (2002). AI and music: From composition to expressive performance. *AI Magazine, 23*(3), 43–58. Retrieved from <http://www.aaai.org/ojs/index.php/aimagazine/article/viewArticle/1656>
- Melomics. (n.d.). Retrieved February 1, 2016, from <http://geb.uma.es/melomics/melomics.html>
- Mohn, C., Argstatter, H., & Wilker, F.-W. (2010). Perception of six basic emotions in music. *Psychology of Music, 39*(4), 503–517. <http://doi.org/10.1177/0305735610378183>
- Moss, R. (2015). Creative AI: Computer composers are changing how music is made. Retrieved January 2, 2016, from [//www.gizmag.com/creative-artificial-intelligence-computer-algorithmic-music/35764/](http://www.gizmag.com/creative-artificial-intelligence-computer-algorithmic-music/35764/)
- Müllensiefen, D. (2009). Fantastic : Feature ANalysis Technology Accessing STatistics (In a

Corpus): Technical Report v1.5.

Nakatsu, R., Nicholson, J., & Tosa, N. (2000). Emotion recognition and its application to computer agents with spontaneous interactive capabilities q. *Elsevier, Knowledge-Based Systems*, 13(7-8), 497–504.

Service, T. (2012). Iamus's Hello World! review. *The Guardian*. Retrieved from <http://www.theguardian.com/music/2012/jul/01/iamus-hello-world-review?newsfeed=true>

Thompson, W. F. (2009). *Music, Thought, and Feeling. Understanding the Psychology of Music*. Oxford university press.

Thompson, W. F., & Robitaille, B. (1992). Can composers express emotions through music? *Empirical Studies of the Arts*, 10(1), 79–89.

Wang, Y., Ai, H., Wu, B., & Huang, C. (2004). Real Time Facial Expression Recognition with Adaboost. *Pattern Recognition, Proceedings of the 17th International Conference on*, 3, 926 – 929.

## APPENDIX

---

---

### I - PILOT QUESTIONS

---

For each melody:

1. How happy or sad is this music?  
Very sad – Sad - Little sad – Neutral - Little happy – Happy - Very happy
2. How energetic or calm is this music?  
Very calm – Calm – Little calm – Neutral – Little energetic – Energetic – Very energetic
3. How familiar is this music?  
Unfamiliar – Neutral – Familiar
4. How natural is this music?  
Artificial – A bit artificial – Neutral – A bit natural – Natural

After listening to all melodies:

1. How long do you listen to music, per week? (in hours)  
Open ended
2. Do you play an instrument?  
Yes – A little – No
3. Did you ever receive any theoretical or practical music lessons?  
Yes – No
4. Which of these words did you experience while listening?  
Angry – Funny – Light – Sad – Other  
Calm – Happy – Melodic – Scary  
Energetic – Heavy – Random – Sharp  
Exciting - Joyful – Rhythmic – Weird
5. Where the questions difficult to answer?  
Open ended
6. Do you think it is probable that these samples were created by a computer?  
Open ended
7. Do you have any recommendations?  
Open ended

## II – EXPERIMENT QUESTIONS

---

For each melody:

1. How happy or sad is this music?  
Very sad – Sad - Little sad – Little happy – Happy - Very happy
2. How energetic or calm is this music?  
Very calm – Calm – Little calm – Little energetic – Energetic – Very energetic
3. How familiar is this music?  
Unfamiliar – Neutral – Familiar

After listening to all melodies:

4. Please fill in your gender and age  
Male – Female            age-scrollbar
5. How long do you listen to music, per week? (in hours)  
Open ended
6. Do you play an instrument?  
Yes – A little – No
7. Did you ever receive any theoretical or practical music lessons?  
Yes – No
8. How well do you think that computers can make music compared to a human like music?  
Worse – A bit worse – Alike – A bit better - Better
9. Where the questions difficult to answer?  
Open ended
10. Do you think it is probable that these samples were created by a computer?  
Open ended
11. Do you have any recommendations?  
Open ended



Features	Factors								
	1	2	3	4	5	6	7	8	9
mean.entropy	-0.08	<b>0.93</b>	-0.04	-0.15	0.05	0.04	0.15	0	0.11
mean.productivity	-0.04	<b>0.95</b>	-0.08	-0.17	0.04	0.09	0.08	-0.04	0.12
mean.Simpsons.D	0.26	<b>-0.79</b>	0.05	-0.1	0.04	0.17	0.12	-0.27	-0.01
mean.Yules.K	0.27	<b>-0.73</b>	0.09	-0.1	0.04	0.2	0.13	-0.33	0
mean.Sichels.S	0.01	<b>-0.88</b>	0.02	-0.02	-0.06	-0.1	0.11	-0.04	-0.12
mean.Honores.H	-0.15	-0.09	0.31	0.19	0.01	0.18	-0.15	<b>-0.64</b>	0.12
p.range	0.14	0.21	0.12	0.05	<b>0.76</b>	-0.21	0.17	0.06	0.24
p.entropy	0.17	0.16	0.21	0.11	<b>0.75</b>	-0.15	0.42	0.01	-0.07
p.std	0.04	-0.02	-0.22	0.1	<b>0.87</b>	-0.02	-0.01	0	0.02
i.abs.range	-0.16	0.24	-0.44	0.25	0.25	-0.33	-0.04	-0.09	0.2
i.abs.mean	0.14	-0.19	-0.41	0.28	0.33	0.26	-0.02	0.03	0.44
i.abs.std	-0.08	0.23	<b>-0.74</b>	0.24	0.19	-0.04	-0.02	-0.14	0.22
i.mode	0.25	0.25	-0.03	0.2	0.33	0.32	-0.14	0.12	-0.08
i.entropy	0.18	0.07	0.06	0.32	0.35	0.08	0.11	0.02	0.51
d.range	0.24	0.22	-0.15	-0.28	-0.16	-0.22	0.34	0.06	0.59
d.median	-0.01	0.07	-0.05	<b>-0.71</b>	0.08	0.28	0.09	0.21	0.18
d.mode	-0.21	-0.18	-0.12	0.04	-0.02	0.14	<b>0.73</b>	-0.14	0.24
d.entropy	-0.22	0.09	0.01	-0.14	0.03	-0.16	<b>0.83</b>	0.06	0.22
d.eq.trans	0.27	0.06	-0.09	0.17	-0.04	0.01	<b>-0.78</b>	-0.28	-0.08
d.half.trans	-0.08	-0.38	0.28	0.05	0.01	-0.03	-0.01	0.49	0.04
d.dotted.trans	-0.38	-0.02	0.07	-0.45	0.1	-0.13	0.35	-0.11	0.07
len	-0.56	-0.32	0.19	0.47	0.05	-0.28	-0.18	-0.09	0.11
glob.duration	-0.43	-0.16	0.24	-0.38	0.04	-0.28	-0.38	-0.03	0.37
note.dens	-0.26	-0.2	0.03	<b>0.81</b>	0.04	-0.04	0.17	-0.11	-0.21
tonalness	-0.13	0.21	0.05	0.01	0.47	0.6	-0.3	0.03	-0.26
tonal.clarity	-0.24	-0.02	0.4	0.01	-0.03	<b>0.66</b>	0.05	0.14	0.21
tonal.spike	-0.1	-0.01	0.02	-0.02	-0.1	<b>0.85</b>	0.05	-0.13	-0.09
int.cont.grad.mean	0.09	0	-0.11	<b>0.85</b>	0.19	0	-0.01	0.16	0.06
int.cont.grad.std	-0.01	0.11	-0.26	<b>0.79</b>	0.14	-0.06	-0.01	0.13	0.03
int.cont.dir.change	0.05	-0.07	0.21	0.48	-0.13	-0.16	-0.22	0.23	-0.08
step.cont.glob.var	0.01	-0.09	-0.13	-0.08	<b>0.9</b>	0.1	-0.11	-0.08	-0.06
step.cont.glob.dir	0	0.13	0.07	0.45	-0.05	0.39	0.03	0.42	-0.02
step.cont.loc.var	-0.23	-0.32	-0.14	0.49	0.27	0.03	-0.34	-0.02	0.35

dens.p.entropy	0.35	0.12	0	0.03	0.4	-0.07	0.44	0.14	-0.33
dens.p.std	-0.07	-0.03	0.15	0.14	<b>-0.68</b>	0.04	0.19	0.01	-0.06
dens.i.abs.mean	0.39	0.12	-0.06	0.32	-0.12	0.19	-0.04	0.07	0.16
dens.i.abs.std	-0.12	0.21	<b>-0.66</b>	0.2	0.11	-0.18	0.06	0.02	0.19
dens.i.entropy	0.26	0.17	0.2	0.48	0	0.14	0.46	-0.18	-0.01
dens.d.range	-0.41	-0.22	0.1	0.16	0.16	0.05	-0.27	0.12	<b>-0.63</b>
dens.d.median	0.24	-0.06	0.05	0.45	-0.16	-0.51	-0.16	-0.22	-0.08
dens.d.entropy	-0.25	0.21	-0.05	0.09	-0.14	-0.21	<b>0.68</b>	-0.15	-0.09
dens.d.eq.trans	0.01	-0.26	0.18	0.02	-0.09	0.1	<b>0.83</b>	0.2	-0.03
dens.d.half.trans	-0.18	-0.02	0.15	0.25	-0.08	0.22	0.37	-0.15	0.08
dens.d.dotted.trans	0.46	0	-0.08	0.37	-0.16	0.4	-0.3	0.11	-0.03
dens.glob.duration	0.28	0.14	-0.22	0.43	-0.17	0.15	<b>0.61</b>	0.02	-0.26
dens.note.dens	-0.13	-0.19	0.09	<b>0.82</b>	-0.06	-0.12	-0.05	-0.13	-0.11
dens.tonalness	-0.04	0.17	-0.15	0.15	-0.45	-0.2	0.21	-0.19	-0.06
dens.tonal.clarity	0.28	-0.1	-0.35	0.09	0.26	-0.38	-0.02	-0.26	-0.33
dens.tonal.spike	-0.09	-0.09	-0.06	-0.08	-0.14	<b>0.81</b>	0.02	-0.12	0.01
dens.int.cont.grad.mean	0	0.06	0	<b>0.72</b>	-0.12	0.22	0.12	-0.04	0.24
dens.int.cont.grad.std	0.18	0.02	-0.27	0.46	-0.08	-0.24	0.44	0.24	-0.22
dens.step.cont.glob.var	0.24	0.09	0.07	0.1	<b>-0.85</b>	0.04	0.07	0.08	0.08
dens.step.cont.glob.dir	-0.15	0	-0.03	0.52	-0.02	0.23	0.08	0.48	0
dens.step.cont.loc.var	0.14	0.24	0.09	-0.21	-0.22	0.02	0.21	0.14	-0.46
dens.mode	0.22	0.2	-0.07	-0.26	-0.11	0.09	0.19	-0.19	0.01
dens.h.contour	0.01	-0.11	-0.07	0	-0.11	-0.07	-0.15	0.36	0.28
dens.int.contour.class	0	-0.14	-0.04	-0.51	0.14	0.16	0.15	-0.02	0.08
dens.p.range	-0.12	-0.04	0.11	-0.4	0.48	0.05	-0.06	0.29	-0.16
dens.i.abs.range	-0.32	0.13	-0.08	0.15	-0.27	-0.16	-0.09	0.23	-0.18
dens.i.mode	-0.21	0.2	-0.43	0.05	-0.21	-0.11	-0.08	-0.32	-0.22
dens.d.mode	0.15	0.12	0.19	-0.11	0.03	-0.19	<b>-0.73</b>	0.15	0.1
dens.len	0.28	0.11	0.23	0.18	0.23	0.18	-0.11	-0.29	-0.09
dens.int.cont.dir.change	-0.09	0.04	0.07	0.01	0.17	-0.01	0.18	-0.44	-0.44
mtcf.TFDF.spearman	-0.09	<b>0.8</b>	0.09	0.15	0.01	-0.09	-0.06	0.14	-0.24
mtcf.TFDF.kendall	-0.12	<b>0.81</b>	0.07	0.14	0	-0.07	-0.06	0.13	-0.23
mtcf.mean.log.TFDF	0.44	0.25	-0.38	-0.24	-0.1	0.25	0.32	0.23	-0.11
mtcf.norm.log.dist	0.42	-0.28	-0.39	-0.41	-0.05	0.15	0.34	0.18	0.09
mtcf.log.max.DF	0.04	0.32	0.52	0.24	0.06	-0.25	0.11	0.41	-0.03
mtcf.mean.log.DF	<b>0.78</b>	-0.16	0.25	-0.27	-0.01	-0.2	0.06	0.02	-0.04
mtcf.mean.g.weight	<b>-0.78</b>	0.14	-0.26	0.27	0.01	0.2	-0.05	-0.01	0.03
mtcf.std.g.weight	0.42	-0.32	0.08	-0.47	0.01	-0.1	0.33	0.18	-0.07
mtcf.mean.gl.weight	-0.26	<b>-0.87</b>	-0.13	0.2	-0.01	-0.09	-0.03	0.24	-0.03
mtcf.std.gl.weight	0.1	<b>-0.94</b>	0	0.03	0.05	-0.04	0.01	0.14	0.02
mtcf.mean.entropy	<b>-0.83</b>	0.25	-0.03	0.1	-0.01	0.04	0.24	-0.01	0.07
mtcf.mean.productivity	<b>-0.8</b>	0.04	-0.21	-0.09	0.04	0.17	0.28	0.05	-0.06
mtcf.mean.Simpsons.D	<b>0.84</b>	-0.28	-0.04	0.06	0.07	0.01	-0.07	0.02	0.12
mtcf.mean.Yules.K	<b>0.82</b>	-0.22	0.01	0.12	0.08	-0.03	-0.09	0	0.15
mtcf.mean.Sichels.S	<b>0.64</b>	0.09	0.04	0.26	0	-0.17	-0.17	0.21	0.15

mtcf.mean.Honores.H	-0.38	0.02	0.05	0.11	0.24	0.04	-0.06	-0.39	0.26
mtcf.TFIDF.m.entropy	-0.21	<b>0.73</b>	0.44	0.12	-0.04	-0.13	-0.17	-0.11	-0.05
mtcf.TFIDF.m.K	0.18	0.24	<b>0.8</b>	0.1	-0.11	0.01	0.03	-0.16	0.06
mtcf.TFIDF.m.D	0.29	0.27	<b>0.77</b>	0.04	-0.13	0.03	0.04	-0.14	0

TABLE 3 FEATURE CONTRIBUTIONS TO THE COMPUTED FACTORS<sup>2</sup>

Melody ID	Factors								
	1	2	3	4	5	6	7	8	9
0	0.637411	0.336302	-1.20443	-1.18821	-1.29296	-0.80506	0.213545	0.060288	0.661942
1	-0.35807	1.072001	-0.04089	0.156214	-0.33837	-0.22921	-0.76243	0.483317	0.729755
2	1.734393	0.95599	1.928228	0.67681	-1.43488	0.9671	2.901085	-1.75678	0.01932
3	0.668089	-0.66267	-0.48608	-1.20508	1.457358	-0.10762	-0.08077	0.576306	-2.16309
4	0.113875	-0.29961	1.251689	0.044348	-0.2235	0.393383	-1.36062	1.352151	-1.07522
5	0.764137	-0.95965	-1.11768	-1.64757	-1.81806	-0.75794	-0.00188	0.104992	-0.62012
6	-0.73797	0.946303	-0.43083	1.680371	-1.08715	1.396349	2.471659	0.497439	-1.84059
7	1.513419	-1.73721	-0.77975	0.764924	1.044216	1.384231	-0.83619	-0.6507	0.151951
8	-0.68783	-1.90313	0.672588	0.902006	0.280177	-2.13647	-0.04058	-3.61853	-0.66723
9	-0.15598	1.091149	0.838213	-1.46853	0.175703	2.00626	-0.42343	-2.18123	1.285197
10	-1.13005	0.757087	-0.97213	-0.91661	-0.46885	1.25969	0.326822	-0.99	-0.02137
11	-0.47199	-0.17027	1.62271	0.231862	-0.21903	1.118811	-1.52326	1.084217	0.158877
12	0.196493	-0.51529	-1.68469	0.79829	-1.20324	-0.36928	-0.16438	0.504147	1.170502
13	0.005691	-3.39001	1.504245	-2.51647	0.704931	1.454531	2.225584	0.447833	2.031727
14	-0.01433	1.091386	0.0393	-0.63477	0.27516	0.186207	-0.41309	-0.88719	-0.87645
15	0.125892	0.412298	-0.01224	-0.25406	-1.84663	-0.10359	-1.26515	-0.36025	-1.38871
16	-1.3004	0.719113	-1.54338	-0.03141	-0.36521	0.012892	0.434047	0.894764	0.296262
17	0.162802	-0.38174	-1.28315	-0.10971	0.712921	-0.61704	-0.51903	0.717287	-0.21448
18	-1.32695	-0.10606	-1.61806	0.131423	-0.98731	1.830522	-0.21568	-0.95228	0.368333
19	0.434157	1.063907	0.224157	0.222908	0.683737	-1.35161	0.632547	1.309366	1.251535
20	0.390368	0.869181	-0.19905	-1.67851	0.956439	0.399498	0.577725	-0.23903	-0.88512
21	-0.99447	1.13782	0.840968	0.050308	0.223439	-0.83118	0.691797	0.852708	1.102424
22	-1.55528	0.413403	0.426796	0.880424	1.776081	-0.19716	0.606997	1.038523	0.651255
23	-1.02198	-0.54929	0.820684	1.455849	1.137568	0.247115	-0.95018	0.699011	-0.48632
24	-1.49258	0.335365	0.557764	0.194586	-1.55945	0.150025	0.179849	0.842956	-0.5011
25	0.731356	-1.07946	-0.99188	0.927814	-1.3133	0.271099	-0.53663	0.250482	1.880362
26	-0.3099	0.54226	0.026885	0.063872	0.166135	-1.90936	-0.03073	-0.4033	-0.64553
27	0.371631	-0.93315	1.234498	0.508586	-1.33357	0.019558	-1.51077	1.464069	-0.4892
28	-0.46759	-0.45129	0.669313	1.405357	1.328478	-0.11885	-1.03082	-0.69737	0.887595
29	-0.14926	0.58427	-1.08135	0.07365	0.3678	0.514757	-0.13956	-0.08518	-0.88992
30	-1.05421	-0.23112	1.438229	1.139998	1.17912	0.623331	-0.6336	-0.30533	0.111915
31	1.615772	0.15051	1.02716	1.462597	0.138484	-0.23614	1.843045	0.156802	-1.16404
32	-1.00624	-0.14786	-0.02697	-0.24418	0.302867	-1.1274	-0.28627	0.466897	-0.42529
33	2.863219	0.164235	-0.26616	0.824322	0.321127	-0.22089	-0.234	-0.37047	0.36562

<sup>2</sup>Contributions >.60 or <-.60 are in boldface. These factors account for 62 % of the variance in the underlying data.

<b>34</b>	1.331914	-0.06353	-0.14215	-0.75449	0.028528	-0.87134	-0.19309	0.415736	1.234778
<b>35</b>	1.058105	1.104622	0.703722	-2.03566	0.291998	-0.26229	0.377836	-0.73883	0.157477
<b>36</b>	-0.94138	-1.32973	-0.20688	-0.50636	-1.14976	-1.6403	0.774765	0.046412	-0.7807
<b>37</b>	1.0039	-0.72118	-1.89702	0.183434	1.02332	0.755916	-0.39388	0.41334	-1.20231
<b>38</b>	-0.5222	0.646353	0.025224	0.227733	1.1025	0.451131	-0.5839	-0.02883	0.3793
<b>39</b>	-0.02396	1.238708	0.132388	0.183958	0.9632	-1.54968	-0.12739	-0.41375	1.440663

TABLE 4 FACTOR CONTRIBUTION TO THE MELODY