MusEmoji: Music and Emoji Association

Randall Harris II
Northwestern University
1927 Orrington Ave.
Evanston, IL 60201
+1 (312) 208-0550
RandallHarris2017@u.northwestern.edu

Samantha Trippy
Northwestern University
1104 Garnett Place
Evanston, IL 60201
+1 (949) 309-7526
srtrippy@u.northwestern.edu

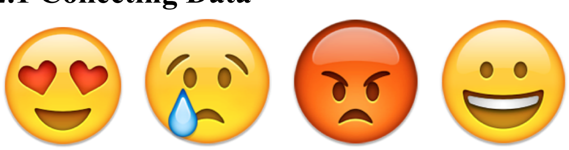
ABSTRACT
In this paper, we will describe the purpose, the process, and the future work to be done for our project, MusEmoji. MusEmoji seeks to incorporate Emoji or Emoticons into the characteristics typically used to classify or organize music. Our project will create links between certain types of music and associated Emoji so, eventually, people can utilize Emoji to generate playlists associated with a particular Emoji.

General Terms
Human Factors, Music Association

Keywords
Emoji, Music Playlists, Music Recommendation System, Music Association

1. INTRODUCTION
There exist many ways to classify associated music—from quantitative audio characteristics to qualitative genre classifications. We would like to incorporate Emoji, a new component of modern electronic communication, into these systems of classification/association. This is an interesting problem because Emoji has very recently and suddenly become highly integrated into media communication. First, music and emotion association is a subject that has been researched a lot. More importantly, understanding Emoji association with music can potentially tell us more about our collective connotations associated with different Emoji. Additionally, we would like to discover what similar qualities of music warrant similar Emoji classification for participants.

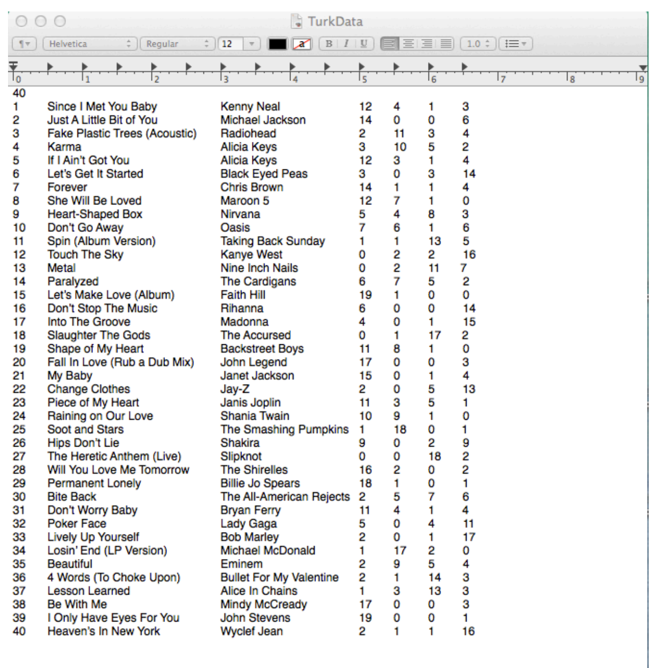
2. PROCESS
2.1 Collecting Data



We chose the four Emoji above to use as classifiers for our system. We then chose forty songs, which we believe were generally representative of the Emojis, ten songs for each Emoji. Using Amazon Mechanical Turk, we programmed surveys to be taken by Mechanical Turk Workers. Participants were instructed to listen to the at least one minute of a song via YouTube videos we provided on the survey and then chose which of the four Emojis they thought best fit the song. Each HIT on Mechanical Turk required a participant to assign one Emoji to a song for a total of two songs. We paid Mechanical Turk workers to incentivize participation. In the end, each song was manually assigned an Emoji by twenty participants, which gave us 800 total assignments. With regards to choosing songs, we used a 10,000 song subset of the Million Song Dataset developed by Echonest and Columbia's Lab ROSA.

2.2 How It Works
Our end-goal transformed over the course of our project. We originally wanted to build a page where users could select one of four Emoji and our system would output song suggestions for that Emoji. The first songs suggested being those for which the Emoji was manually assigned through user testing. Additional songs which have not been manually assigned an Emoji (from the 9,960 other songs within our subset of the Million Song Dataset) would then be listed under one of the Emoji in accordance to an automated, Nearest Neighbor Classification system we implemented. However, we were unable to work with the file formats of the Million Song Dataset and had to adapt our project accordingly.

2.3 Creating The System
As stated, we used Amazon Mechanical Turk to collect our data. The results of our data collected were provided by the interface in an Excel file, which we transferred into a text file to be used for C++ processing.



TurkData

40						
1	Since I Met You Baby	Kenny Neal	12	4	1	3
2	Just A Little Bit of You	Michael Jackson	14	0	0	6
3	Fake Plastic Trees (Acoustic)	Radiohead	2	11	3	4
4	Karma	Alicia Keys	3	10	5	2
5	If I Ain't Got You	Alicia Keys	12	3	1	4
6	Let's Get It Started	Black Eyed Peas	3	0	3	14
7	Forever	Chris Brown	14	1	1	4
8	She Will Be Loved	Maroon 5	12	7	1	0
9	Heart-Shaped Box	Nirvana	5	4	8	3
10	Don't Go Away	Oasis	7	6	1	6
11	Spin (Album Version)	Taking Back Sunday	1	1	13	5
12	Touch The Sky	Kanye West	0	2	2	16
13	Metal	Nine Inch Nails	0	2	11	7
14	Paralyzed	The Cardigans	6	7	5	2
15	Let's Make Love (Album)	Faith Hill	19	1	0	0
16	Don't Stop The Music	Rihanna	6	0	0	14
17	Into The Groove	Madonna	4	0	1	15
18	Slaughter The Gods	The Accursed	0	1	17	2
19	Shape of My Heart	Backstreet Boys	11	8	1	0
20	Fall In Love (Rub a Dub Mix)	John Legend	17	0	0	3
21	My Baby	Janet Jackson	15	0	1	4
22	Change Clothes	Jay-Z	2	0	5	13
23	Piece of My Heart	Janis Joplin	11	3	5	1
24	Raining on Our Love	Shania Twain	10	9	1	0
25	Soot and Stars	The Smashing Pumpkins	1	18	0	1
26	Hips Don't Lie	Shakira	9	0	2	9
27	The Heretic Anthem (Live)	Slipknot	0	0	18	2
28	Will You Love Me Tomorrow	The Shirelles	16	2	0	2
29	Permanent Lonely	Billie Jo Spears	18	1	0	1
30	Bite Back	The All-American Rejects	2	5	7	6
31	Don't Worry Baby	Bryan Ferry	11	4	1	4
32	Poker Face	Lady Gaga	5	0	4	11
33	Lively Up Yourself	Bob Marley	2	0	1	17
34	Losin' End (LP Version)	Michael McDonald	1	17	2	0
35	Beautiful	Eminem	2	9	5	4
36	4 Words (To Choke Upon)	Bullet For My Valentine	2	1	14	3
37	Lesson Learned	Alice In Chains	1	3	13	3
38	Be With Me	Mindy McCready	17	0	0	3
39	I Only Have Eyes For You	John Stevens	19	0	0	1
40	Heaven's In New York	Wyclef Jean	2	1	1	16

Figure 1. Text file of songs and Mechanical Turk results.

We then built a Nearest Neighbor Classification system which takes a song as input and calculates the Euclidean distance of this song to every other song, making it possible to identify the "Nearest Neighbor" based on whatever characteristics we choose. We worked together using Microsoft Visual Studio to create a C++ program that takes an input file (e.g. of unassigned songs from the Database) and compares it to information about the manually assigned songs to calculate the Nearest Neighbor.

```
For this song, the best match is Song Number:  1
------------------------------------------------
Love Value:     12
Sad Value:      4
Angry Value:    1
Happy Value:    3
For this song, the best match is Song Number:  15
------------------------------------------------
Love Value:     19
Sad Value:      1
Angry Value:    0
Happy Value:    0
For this song, the best match is Song Number:  3
------------------------------------------------
Love Value:     2
Sad Value:      11
Angry Value:    3
Happy Value:    4
For this song, the best match is Song Number:  26
------------------------------------------------
Love Value:     9
Sad Value:      0
Angry Value:    2
Happy Value:    9
For this song, the best match is Song Number:  5
------------------------------------------------
Love Value:     12
Sad Value:      3
Angry Value:    1
Happy Value:    4
```

Figure 2. Output of our Nearest Neighbor System

The metrics provided by the Million Song Dataset were well encoded with specific quantitative and qualitative metrics such as key, loudness, tempo, and danceability. A list of up to 100 similar artists is also included for each track. More information about song metrics is available at: http://labrosa.ee.columbia.edu/millionsong/pages/example-track-description. While our system works for our manually assigned songs, we were unable to access the Million Song Dataset files to expand this system to the remaining songs based on chosen characteristics. We discuss steps we would take in the future to further expand this project in section 6. Additionally, we worked together to create a front end that displays the manually assigned songs, discusses different types of classifications we witnessed, and a few suggested songs for each of the four Emoji. Our project website is hosted on Github at: http://samtrippy.github.io/MusEmoji/.

2.4 Testing

Since we were working with emotions and many people's subjective opinions on music, we expected that people might classify the same songs differently. Due to the multidimensionality of music, we understood that a song can represent many different things concurrently (e.g. sadness and anger) and we expected our data to reflect this. If time permitted, we would have liked to test the output of our system by creating more surveys that would ask participants to rate on a scale of 1-10 how well their emotions match with the Emoji determined to match a song by our system. Then if the average is high enough, we could assume it works well. If the rating is too low, we could make appropriate adjustments or explore why this may be the case. Furthermore, if we conducted this experiment again, we would include some error checking in our surveys to ensure users are not blindly answering the questions. We would ask the same question two times with the Emoji listed in different orders to see whether users do provide the same answer. If users do not provide corresponding answers to the same question, an indicator that they are not faithfully completing the survey, we could eliminate these answers. The MusEmoji project is something that has not been done before. There is not an existing system that we could compare to, and the results could be different with every input. Thus, there is not a baseline approach that we can truly compare to. Most of the testing for accuracy in a future project would have to come from the average Emoji accuracy method or duplicate question-asking method described above.

3. RELATED WORK

Music classification systems have become increasingly important due to the popularity of online media streaming services. Thus, the amount of research completed on the topic has boomed over the past decade or so. Additionally, as Emojis and Emoticons become increasingly popular with computer-mediated communication, research on our perceptions of these images has grown over the past few years. We know that music is multidimensional and can represent a number of different themes, emotions, etc. concurrently. Furthermore, we also understand that music is subjective. The same song can have different associations for different people.

While one study has been completed based upon a similar idea of exploring the link between emoticons and musical genres [1], this research focused more on mapping genre and mood. With our study, we hoped to explore and determine which characteristics of a song were likely predictors of which Emoji a listener would characterize the song by.

4. COLLABORATORS

Samantha and Randall worked together on every component of the project. All components of our work—data collection, data processing, producing the Nearest Neighbor Classifier, creating the website, and creating the poster to present our project—were contributed to by both members, ensuring we both have an understanding of every component of the project.

5. TIMELINE

The following table outlines our milestones, the group members who worked on each task, and our proposed and actual completion dates.

Milestones	Group Members	Proposed Date	Actual Date Completed
Test Mechanical Turk	Both	2/23	2/23
Choose Songs and Emoji	Both	2/25	2/25
Develop and Post HITs	Both	2/27	3/2
Data Collected	Both	3/6	3/8

(target)			
Write Nearest Neighbor Classifier	Both	3/9	3/16
Create Front-End System	Both	3/13	3/18
System Testing	Both	3/16	3/19
Finish Poster	Both	3/18	3/19
Final System/Poster/ Presentation	Both	3/20	3/20

6. FUTURE WORK

Due to the time constraints of the course, we were unable to complete all of the tasks we would have liked to for this project. Thus, there are many interesting tasks that we could complete for this project if given more time.

6.1.1 Data Collection

First, we would like to improve our data collection method with error checking, as mentioned in section 2.4. If users were provided two of the same survey questions to answer for a song (i.e. Which of the following Emojis do you believe best represents the song?) with the possible answers in different order, we could error check by making sure every user's two answers are in agreement. This will avoid using data which users may have carelessly provided without actually completing the task properly by listening to the song.

6.1.2 Million Song Dataset

Perhaps the largest and most important component of future work we would like to carry out is full utilization of the Million Song Dataset with all of its characteristics. The trouble we faced in accessing these files was a large obstacle in our project which we did not anticipate. If we had more time, we could have opened these files to compare the metrics for the manually assigned songs by making histograms of different characteristics. Thus, we could determine the most popular characteristics of songs which were assigned to each Emoji. This is where past research completed on Emojis as well as music classification systems comes into play, as we could look at which metrics of a song are commonly used by other studies [1, 2, 3, 4]. After choosing the metrics, we could use these in our Nearest Neighbor Classifier to extrapolate the known information about manually assigned Emojis to systematically assign other songs in the dataset to a particular Emoji with our program.

7. REFERENCES

[1] J. Holm, H. Holm, and J. Seppanen. Associating Emoticons with Musical Genres. In Proc. of Conference on New Interfaces for Musical Expression, Sydney, Australia. n.p. http://www.nime.org/proceedings/2010/nime2010_383.pdf

[2] Y. A. Sari, E. K. Ratnasari, S. Mutrofin, and A. Z. Arifin. User Emotion Identification in Twitter Using Specific Features: Hashtag, Emoji, Emoticon, and Adjective Term. In *Jurnal Ilmu Komputer Dan Informasi* 7.1 (2014): n.p. http://jiki.cs.ui.ac.id/index.php/jiki/article/viewArticle/252

[3] R. Yashamita and K. Tani. A Method of Deducing the User's State of Mind by Analyzing Pictographic Characters and Emoticons in Mobile Phone Emails and a Method of Selecting Music Suitable for the User's State of Mind. Proc. of IEEE TENCON, Region 10. n.p. http://ieeexplore.ieee.org/xpl/login.jsp?tp=&arnumber=4766457&url=http%3A%2F%2Fieeexplore.ieee.org%2Fxpls%2Fabs_all.jsp%3Farnumber%3D4766457

[4] L. Lebduska. Emoji, Emoji, What for Art Thou? *HARLOT* 12 (2014): n.p.http://harlotofthearts.org/index.php/harlot/article/view/186/157