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A Study on the Sentiment Analysis of Contemporary Pop Musicians and Classical Music Composers

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Abstract

The study examined a sentiment analysis based on Tweeter messages between contemporary pop musicians and classical music composers. Musicians of each genre were carefully selected for the sentiment analysis. Many opinion messages on Tweets that users have discussed were collected, and the messages were evaluated by using Naïve Bayes Classifier. The results demonstrated that users showed high positive sentiments for the two different genres. However, on average, the positive sentiment values for classical music composers are higher than for contemporary pop musicians. In addition, the rankings of the highest positive sentiments among contemporary pop musicians and classical music composers did not coincide with the popularity of the two different genres of musicians. This study will contribute to the study of future sentimental analysis between music and musicians.

Keywords: *Sentiment Analysis, Twitter, Contemporary Pop Musicians, Classical Music Composers*

1. INTRODUCTION

The power of music to awaken emotions in listeners has long been recognized [1]. Lundqvist et al. found both positive physiological and perceptual responses to happy music [2]. They found that happy music created more zygomatic facial muscle activity, skin conductance, and lower finger temperature along with a greater perception of happiness than sad music. Moreover, Logeswaran and Bhattacharya found that music affects the way people evaluate visual images [3]. Priming with happy music enhanced the perception of happiness of a visual image of a happy face, while priming with sad music exaggerated the perception of depression associated with a visual image of a frown. Priming with happy or sad music influenced perceptions of a neutral face to an even greater degree. This research showed that music is emotionally evocative and affects perceptions that we form through our other senses.

With respect to music, this raises questions about how people who are listening to music react to the music or musicians. Do symphonies by Brahms or Does Stravinsky evoke more positive sentiments? How do emotional responses to Lopez and Beaver compare? Do people think more positively about contemporary pop or classical music? Modern technology makes it easier than ever to find the answers to these questions.

Nowadays, smartphones and other advances in technology not only increase opportunities for people to

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listen to music in their everyday lives [4] but also provide opinion-rich resources through social networking services.

In this context, studies concerning sentiment intensity have started to emerge [5, 6]. Generally, sentiment analysis is the process of determining whether comments (product or movie reviews, tweets) are positive, negative, or neutral, categorizing web comments, very often for marketing departments to analyze customer satisfaction. Pang, Lee, and Vaithyanathan used this approach to classify movie reviews into two classes, positive and negative, using unigrams, which are bags of individual words that serve as a classification feature that performs well with either Naïve Bayes Classifier (NBC) or Support Vector Machines (SVMs) [7]. Tweets have often been used in research for real-time sentiment analysis [8]. In addition, machine learning has been used for sentiment analysis, using emoticons and the NBC to achieve a high degree of accuracy [9].

The use of large computer data sets, called big data, has been used to research trends in the social sciences; sentiment analysis of tweets, specifically, has been conducted on a variety of subjects such as financial markets [10] and US elections [11]. However, little research has used big data to analyze the effect of music on emotions; although one study was done by Liikkanen, Jakubowski, and Toivanen to conduct sentiment analysis on involuntary musical imagery, referred to as "earworms," using over 80,000 tweets and finding that people expressed more negative than positive sentiments [12]. Music providers and listening platforms are starting to conduct sentiment analysis on music to recommend music to users.

Therefore, this study is to explore the sentimental analysis of contemporary pop musicians and classical music composers to get answers to the research questions as follows:

1) What feelings do people have about contemporary pop musicians and classical music composers?
2) Do people have more positive feelings for a group of contemporary pop musicians or classical music composers?
3) Who has the most positive feelings among contemporary pop musicians? And who has the most positive feelings among classical music composers?

This study will conduct an analysis using the Naive Bayes text classification to analyze the emotional strength score on the tweets referring to the two groups and analyze the overall positive and negative sentiments reflected in them.

2. METHODOLOGY

2.1 Sentiment Analysis by Using Naïve Bayes Classifier

Sentiment analysis classifies opinion documents (product ratings, movie reviews, tweets) as expressing positive or negative opinions or sentiments. An important assumption about this document-level sentiment classification is that the opinion document (product rating, movie review, tweet) expresses opinions on a single subject, and the opinion is from a single individual. Most existing techniques for document-level sentiment classification are based on supervised learning such as NBC and SVMs.

To analyze the sentiment analysis for the selected musicians, this paper utilizes NBC on the collection of Twitter messages. The proposed method consists of three steps: data collection, feature extraction and selection, and classification and analysis.

First, the data collection fetches Twitter messages related to the top selected musicians. Twitter, one of the most popular social networking micro-blogging sites, allows users to post real-time messages, called tweets, resulting in an enormous number of text posts. Second, the collected Twitter messages are analyzed to extract features for sentiment analysis. Through Natural Language Processing (NLP), the method first collects a list of vocabularies to be used as a feature set in the training data. Finally, the extracted feature vectors will be evaluated by NBC to be classified into a negative or positive opinion.

Here is the detailed method for feature extraction and selection. The method uses the Bag-of-Words Model, one of the popular NLP methods, to extra features from the collected Twitter messages for the creation of feature vectors. First, a vocabulary list is collected from the training set, and each word is associated with how frequently it occurs. This vocabulary can be understood as a set of non-redundant items where the order doesn't matter. Let D1 (D1: "Each state has its own laws") and D2 (D2: "Every country has its own culture") be two documents in a training data set. The vocabulary can then be used to construct d-dimensional feature vectors for the individual documents where the dimensionality is equal to the number of different words in the vocabulary. The text document is treated as if it were a bag of words, that is, an unordered set of words without considering their position, tracking only the frequency of words in the document. In the example in Table 1, instead of representing the word order in all the phrases like "Each state has its own laws" and "Every country has its own culture," we simply note that the word 'its' occurred two times in the entire excerpt, the words 'each,' 'every,' and 'music' once, and so on.

Table 1. Bag of words representation of two sample documents D1 and D2

	each	state	has	its	own	laws	every	country	culture
xD1	1	1	1	1	1	1	0	0	0
xD1	0	0	1	1	1	0	1	1	1
Σ	1	1	2	2	2	1	1	1	1

2.2 Data Collection and Analysis

The Twitter micro-blogging service includes Application Programming Interfaces (APIs) that allow access to core Twitter data and interact with Twitter Search and trend data. This study used Twitter APIs to collect the most recent tweets that include the names of selected contemporary pop musicians and classical music composers. The Twitter APIs also allow the specification of a language parameter, which is set to English. The Twitter APIs limits responses to any particular request to 100 tweets. The application was set to avoid retweeting to increase the quality of collected data. For the test set, it selected tweets on the 100 most popular contemporary pop musicians as identified by a list in the Guardian [13]. Popularity was measured by the number of Twitter followers for each musician and thus identified the top ten contemporary pop musicians to use for the sentiment analysis. Figure 1 shows the distribution of followers of the top 100 musicians.

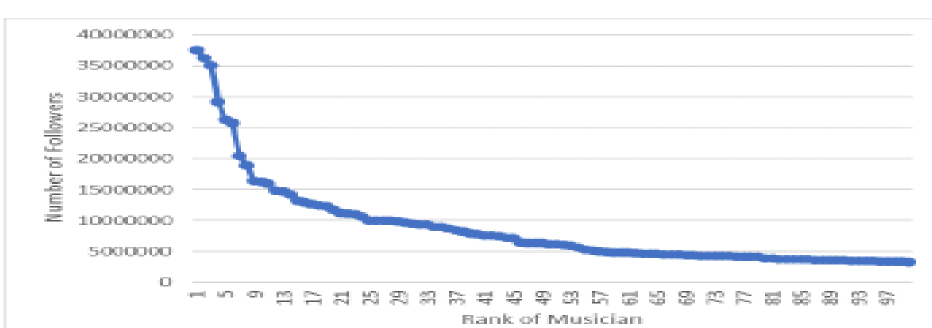

Figure 1. Distribution of Twitter followers of top 100 musicians

The top 10 musicians had more than 15 million followers, with an average of 1 million followers. Since no comparable list of the top 100 classical composers was available, the study used the ten most popular classical composers identified according to Discogs [14], a platform for music discovery and collection, and New York Times [15].

The number of tweets for each musician each month was relatively constant, with a median of 50 tweets and distribution as shown in Figure 2. This study collected up to 100 tweets for each of the twenty composers during the selected July 2017. For some pop musicians, there were fewer than 100 tweets.

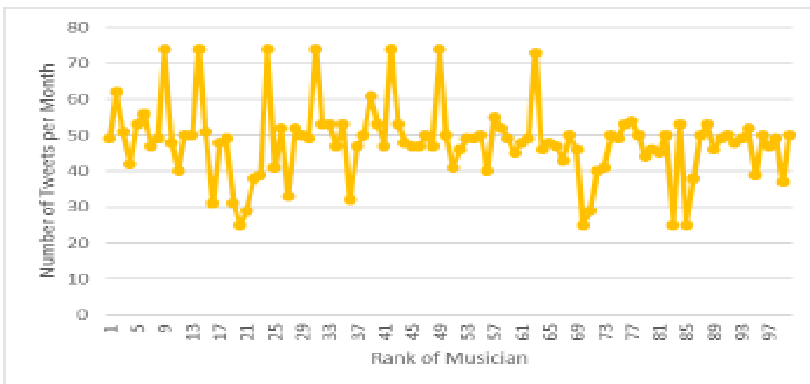

Figure 2. Distribution of monthly tweets of top 100 musicians

Tweets have many unique characteristics, which present unique challenges that were taken into account in designing our sentiment analysis. The nature of micro-blogging services results in people using acronyms, making spelling mistakes, and inserting emoticons and other characters to express special meanings. Sample tweets are shown in Figure 3.

u'RT @MitchellJoachim: Mozart Beethoven Chopin never died they simply became music u'@ARTPOPGR @GagasAnus Mozart etc are older and everyone, even from the youngest generation knows their name, real legends
u"@fiercynn I haven't seen Call the Midwife but a bunch of my friends love it! And I'm enjoying Mozart in the Jungle but am on late s1

Figure 3. Sample of tweets data

3. RESULTS OF FEATURE EXTRACTION

This study used a sample data set of 2000 real tweets (1000 positive + 1000 negative) as our algorithm training set. The collected data set was used to extract features that would be used to train our sentiment classifier. This study used the presence of a unigram as a binary feature. While for general information retrieval purposes, the frequency of a keyword's occurrence is tracked, in this study, keyword frequency was not counted since the overall sentiment would not necessarily be affected by the repeated use of keywords. Pang et al. obtained better results for sentiment analysis by using term presence rather than term frequency. Higher-order n-grams might better capture patterns of sentiment expressions. However, unigrams provide sufficiently good coverage of the data. They also reported that unigrams outperform bigrams when performing sentiment classification for movie reviews [7]. Dave et al. obtained results showing the contrary that bigrams and trigrams worked better for the product-review polarity classification [16]. Pak et al. experimented with unigrams, bigrams, and trigrams and determined the best settings for micro-blogging data [17]. Hence, this study used unigrams. The process of obtaining unigrams from a Twitter post is as follows in Table 2: filtering, tokenization, and removing stop-words.

Table 2. The process of obtaining unigrams

Step	Contents
Filtering	Removed URL links (e.g. http://example.com), Twitter user names (e.g. @alex – with symbol @ indicating a user name), Twitter special words (such as "RT"6), and emoticons.
Tokenization	Segmented text by splitting it where there were spaces or punctuation marks to form a bag of words; however, this study made sure that contractions such as "don't", "I'll", and "she'd" would remain as one word.
Removing stop words	Removed articles ("a", "an", "the") from the bag of words.

This study only used the positive and negative. Table 3 lists positive sentiment samples. Frequently appearing positive words included "funny," "enjoy," "beautiful," "love," "hope," "best," "amazing," "perfect," and "thank." On the other hand, negative samples contained words such as "bad," "mad," "back off," "crazy," "surgery," "pain," "doubt," "rubbish," "crying," "hurt," "serious," "empty," and "bore," as shown in Table 4.

Table 3. Sample of positive tweets

Sample string	Sentiment
17 Again! The movie looks so funny!!! I cannot wait!!! I just need to get my tush outt17 Again! The movie looks so funny!!! I cannot wait!!! I just need to get my tush outta bed. lol bed. lol	positive
enjoying this beautiful sunny day... just wish it was a bit warmer	positive
enjoying this beautiful sunny day... just wish it was a bit warmerenjoying this beautiful sunny day... just wish it was a bit warmer	positive
Beautiful Day! enjoy it	positive
I really don't deserve him. Isn't it funny how you realize who really cares? He says he \"wuvs\" me, well I think I might love him.	positive
@OfficalJonasBro i love you nick...hope i see you in germany...world tour 2009!!!it would be the best day for me in my life... O-O	positive

Table 4. Sample of negative tweets

Sample string	Sentiment
Is it bad I get mad when people say Britney can't sing? Back off my Queen.	negative
@Uncle_Trav I know... Its my crazy phone. I've tried and can't figure it out.	negative
feels like crying. i can't go to @mileycyrus concert in london in december	negative
Beautiful Day! enjoy it	negative
@Awesome_Tie i know, i wanna see them in nottingham soooo much but i doubt that will ever happen	negative
oh no it's gonna rain all weekend. Rubbish!	negative

4. EXPERIENTIAL RESULTS

The results were obtained from tweets for the 10 contemporary pop musicians and the 10 classical music composers most often appearing in tweets. The sentiments expressed in each tweet were analyzed using NBC.

The sentiment scores for contemporary pop musicians revealed positive sentiments in the range of 59~97%.

Table 5 lists the ten contemporary pop musicians' order of popularity as measured by the number of tweets reported by the Guardian. The right column in Table 5 shows the sentiment score for the recent tweets this study collected for each of these contemporary pop musicians. As shown in Table 5, tweets for Perry's music showed the highest positive sentiment, and those for Gomez and Bieber followed. Shakira was the only non-USA musician among the 10 contemporary pop musicians and showed the lowest score in positive sentiment.

The average sentiment score was 76.1% with a standard deviation of .11. The top five most contemporary pop musicians have higher sentiment scores than the bottom five. The average sentiment score for the top five contemporary pop musicians is 80%, while the bottom five have an average sentiment score of 70%. However, in this study, we did not find a direct correlation between the degree of positive sentiment and popularity ranking.

Table 5. Top 10 contemporary pop musicians

Popularity Ranking	Name	Country	Sentiment Score
1	J. Bieber	USA	81%
2	S. Gomez	USA	83%
3	K. Perry	USA	97%
4	Rihanna	USA	80%
5	T. Swift	USA	78%
6	B. Spears	USA	77%
7	Shakira	Columbia	59%
8	J. Timberlake	USA	71%
9	J. Lopez	USA	69%
10	M. Mathers	USA	65%
	Mean		76.1%

Tweets for the most popular classical music composers were collected and analyzed for user sentiment. The results are summarized in Table 6. Tweets expressed the most positive sentiments for Vivaldi, Brahms, Stravinsky, and Wagner, while sentiment scores were relatively low for Beethoven, Schubert, and Chopin. Vivaldi received the highest positive sentiment scores, and Beethoven received the lowest positive sentimental scores. For classical music composers, the degree of positive sentiment was not found to be directly correlated with the list of popularity rankings that this study used.

The average sentiment score was 80.6% with a standard deviation of .09. The distribution of sentiment scores for classical music composers was different from that of pop musicians. The sentiment scores among the 10 most popular classical music composers ranged from 70% to 93% while the range for contemporary pop musicians was wider, from 59% to 97%. In other words, classical music composers received more consistently positive sentiment scores than contemporary pop musicians. In addition, while the top six contemporary pop musicians all received sentiment scores substantially higher than the bottom four musicians, the same was not true for the sentiment scores of classical music composers. Vivaldi was 7th most popular in terms of the number of tweets yet was the first in sentiment score. Indeed, the average sentiment scores for the top five most tweeted classical music composers (78%) were lower than the average for the bottom five least tweeted classical music composers (83%). Moreover, five of the 10 classical music composers had sentiment scores of the 80%. For contemporary pop musicians, no more than three sentiment scores fell in any given ten percent cut-off. In this sense, individual differences in sentiment scores were less notable among classical music composers than among contemporary pop musicians.

Table 6. Top ten classical music composers

Popularity Ranking	Name	Country	Sentiment Score
1	S. Bach	Germany	82%
2	A. Mozart	Austrian	81%
3	L. Beethoven	Germany	69%
4	F. Schubert	Italy	70%
5	R. Wagner	Germany	88%
6	F. Chopin	Poland	70%
7	A. Vivaldi	Italy	93%
8	J. Brahms	Germany	88%
9	F. Hendel	England	77%
10	I. Stravinsky	Russia	88%
Mean			80.6%

This study compared sentiment scores for contemporary pop musicians and classical music composers in Figure 4. Classical music composers show higher average sentiment scores with more even distribution than those of contemporary pop musicians. These results also show that the average sentiment score for all 10 contemporary pop musicians was 76.1% while the average sentiment score for all ten classical music composers was 80.6%. This result indicates that people get positive feelings when they listen to music and is consistent with the generally accepted perception that "listening to music makes feel good."

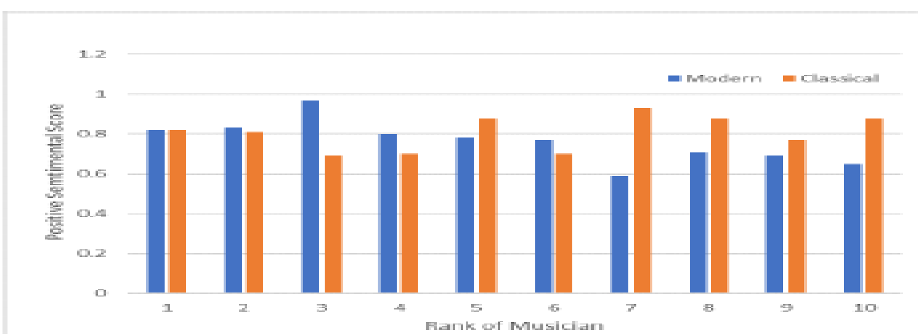

Figure 4. Compares sentiment scores for contemporary pop musicians and classical music composers

5. CONCLUSION

This study analyzed the sentiments expressed in tweets by contemporary pop musicians and classical music composers. The sentiment analysis techniques by using NBC were used on recent tweets for 10 selected musicians in each of the two categories. Our results show that tweets for both contemporary pop musicians and classical music composers show a high degree of positive sentiments, on average greater than 75 percent. Moreover, while positive sentiment about contemporary pop musicians averaged 76.1 percent, people had a high positive sentiment of 81 percent on average for classical music composers. Among the classical musicians, people had more positive sentiments toward Vivaldi and less positive sentiments toward Beethoven. For pop singers, Perry was ranked highest, and Shakira was ranked lowest. Moreover, on average, people had more positive sentiments toward classical music composers than toward contemporary pop musicians. This suggests that people react positively to music and support the study of Olsen et al. that participants experience more positive emotions than negative emotions when listening to music, regardless of the genre of music (violent music (extreme metal, violent rap), nonviolent (classic) music, or classical music [18].

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