Machine Learning and Natural Language Processing based Sentimental Analysis with respect to Transformative Music

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***Abstract*—Music has a profound capacity to influence listeners' emotions, cognition, and physiology. Recent advances in natural language processing (NLP) and machine learning provide new opportunities to analyze song components and model their psychological impacts. This study investigates an approach combining NLP of lyrics with machine learning analysis of musical qualities to evaluate and predict the transformational effects of songs on listeners. The research questions how musical and lyrical attributes can be computationally modeled to consistently categorize lyrics' mood, chart emotional dynamics, and relate musical qualities to expressed ideas and sentiments. The central argument is that machine learning on these features can elicit the specific structures with the greatest potential for emotional influence. The methodology utilizes a corpus of diverse musical works. NLP evaluates lyrics. Audio analysis extracts features including tempo, spectral centroid, spectral bandwidth, chroma features, and zero crossing rate. An 80/20 multivariate classifier model combines lyric and audio data with weighted inputs for each modality. Anticipated implications are methodological developments in computational analysis of musical impact, cross-disciplinary understanding at the intersection of machine learning and the arts, and applied AI systems that recommend or generate songs optimized for therapeutic outcomes. The literature review encompasses relevant prior studies in machine learning, human-computer interaction, music psychology, and lyric analysis.**

1. Introduction

It has long been known that music has the unparalleled ability to evoke human emotions, change perspectives, and even affect physiological processes. Natural language processing (NLP) [1] and machine learning (ML) [2] technologies have advanced significantly in recent years, and these developments provide exciting novel possibilities for understanding the psychological effects of music. Through the computer modeling of the complex vocabulary and semantic significance conveyed by lyrics, in addition to the captivating tonal and rhythmic dynamics of accompanying music, interdisciplinary prospects for enhancing comprehension of music's impact on human existence are created. In order to scientifically evaluate correlations between a song's auditory characteristics and lyrical content and its emotional resonance and potential to affect listeners personally, this paper investigates the possibilities of using **NLP** and **ML** in combination. The primary argument is that the transformative effects of music can be more accurately understood and predicted by rigorously classifying prominent features of both musical composition and linguistic symbolism to categorize patterns most strongly associated with inducing perspective shifts, cognitive reframing, and emotional outcomes influence. The fundamental dataset is a large, diverse corpus of songs from many genres, eras, and styles. Rich semantic data is provided by **NLP** techniques such as **sentiment analysis** [3], **named entity recognition** [4], and contextual evaluation of metaphors, themes, and deeper meaning in lyrics. Concurrently, complementary information on compositional structure is extracted by computational analysis of important musical variables such as **tempo** (how fast a piece of music is), **spectral centroid** (a measure used in digital signal processing to characterise a spectrum), **spectral bandwidth** (the difference between the upper and lower frequencies and has a direct correlation with the perceived timbre of the sound), **chroma features** (a set of descriptors that represent a musical audio signal's tonal content), and **zero crossing rate** (the number of times a signal changes value, from positive to negative and vice versa, divided by the length of an audio frame). Combining these several modalities into a novel machine learning approach allows for the analysis of the interactions and influence weighting between lyrics and music. Songs are categorized using classification algorithms according to the main emotional tones they convey. Correlations and patterns in linguistic and musical characteristics as they relate to known psychological effects reported in listener response surveys are investigated through predictive modeling. In these approaches, the goal is to find emergent superstructures that are constant and highly correlated with the therapeutic results that listeners perceive, such as motivation, comfort, relaxation, or viewpoint shifting.

This paper is important for theoretical insights as well as practical applications at the cutting edge of machine learning and artistic endeavors. An invaluable multidisciplinary viewpoint is provided by the computational explication of precisely how verbal and musical aspects interact to generate emotional emotional release, self-reflection, and favorable physiologic responses. Personalized music recommendations targeted to individual psychological requirements can also be generated by AI systems that can also improve playlists for health and wellbeing, give data-driven advice to music therapists, and help artists connect with audiences on a deeper level. The remainder of this paper surveys relevant literature, presents detailed methodologies, documents experiments and results, discusses limitations and future work, and explores wide-ranging implications of this modern symbiosis between data science and the profound human experience of music. With compassionate ethics and visionary scientific rigor directing progress, deepening comprehension of music's emotional essence through A.I. and advanced analytics holds tremendous promise for catalyzing human growth through melody and verse.

2. Related Works

Deep Adversarial Neural Network Model Based on Information Fusion for Music Sentiment Analysis [5] introduces a new deep adversarial neural network model that fuses semantic and syntactic information for music sentiment analysis. The key research gap identified is that prior models simply embed relative word distances or syntactic distances into the model without considering their joint influence on relative words. The main contributions are

- Integrating relative distance and syntactic distance position information into the model to account for their joint impact on aspect words
- Incorporating the importance of a word's height in the dependency syntax tree and degree centrality in the text sequence
- Studying semantic information and grammatical information jointly to fully leverage the textual content
- Introducing a hierarchical lexical graph to replace the dependency syntax tree to capture both grammatical and co-occurrence relationships between words

The proposed model first encodes the text with position information using bidirectional Gated Recurrent Units (GRU, a type of neural network architecture) [6]. It then updates the representation based on the dependency tree structure. Relative and syntactic distance information are embedded before the learning phase. The learning layer has two modules - a Convolutional Neural Network (CNN) for semantics and a graph **CNN** for syntax using the hierarchical lexical graph. Attention layers then optimize and integrate the semantic and syntactic representations. Finally, aspect word features are extracted and classified using a softmax layer (classification output layer).

Tests conducted on five sentiment analysis datasets show over 90% accuracy, surpassing the performance of the most advanced techniques. Studies on ablation confirm the significance of each model element. The technique successfully learns and integrates grammatical and semantic information to estimate sentiment polarity based on aspect, according to analysis. Two major limitations are the exclusive emphasis on English text and the use of annotated parsing data. Future research can apply unsupervised grammar induction and expand the methods to other languages. All things considered, the model offers a sophisticated neural architecture for detailed sentiment analysis of music.

A Study on the Sentiment Analysis of Contemporary Pop Musicians and Classical Music Composers [7] showed that music primes the perception of emotions in visual images, with happy music exaggerating perceptions of happiness in happy faces. This underscores music's emotional evocativeness across sensory modalities. Sentiment analysis classifies opinion text as positive, negative or neutral. Common techniques utilize supervised learning, like Naive Bayes and Support vector machines (SVM) classifiers, to categorize documents based on sentiment-relevant features. Early studies classified movie reviews using unigrams. Subsequent research explored higher-order n-grams and determined optimal feature settings for sentiment analysis on diverse corpora, including microblog texts. Recent studies demonstrate sentiment analysis applications with big Twitter data to assess subjects like financial markets, elections, and involuntary musical imagery ("earworms").

Twitter's API is being used in this study to gather English tweets on classical composers and modern pop musicians. Unigram features are extracted through **NLP** and used with Naive Bayes for sentiment categorization. Analysis assesses and contrasts favorable opinions of the two musical genres. The purpose of the study is to determine whether machine learning models can reliably classify sentiment from lyrics and link musical elements to concepts that are communicated. The expected implications encompass computational techniques for examining the influence of music on listeners, interdisciplinary comprehension between machine learning and the arts, and artificial intelligence systems tailored to suggest healing melodies.

Improve the Application of Reinforcement Learning and Multi-Modal Information in Music Sentiment Analysis [8] proposes a music sentiment classification method that combines lyrics and comments to extract richer sentiment information. The method constructs sentiment vectors using the emotional vocabulary's 4-dimensional categories of {+V +A}, {-V +A}, {-V -A}, and {+V -A} ({+V +A} means positive valence, high arousal, {-V +A} means negative valence, high arousal). It matches the lyrics and comment text to this dictionary to obtain the emotional category and weight of words. Statistical values for each category are calculated. The paper uses Term Frequency - Inverse Document Frequency (TF-IDF) [9] rules to calculate feature vectors for the lyrics and comments, considering emotion strength. However, this ignores the influence of part-of-speech on classification. Thus, the method expands the vectors into 16 dimensions, dividing words by noun, verb, adjective, adverb and calculating statistics per category. The K-nearest neighbor (KNN) technique is used for classification. Each song's emotion vector is input, and the category with the highest frequency among its K closest neighbors is chosen. The findings of the experiments indicated poorer results for activation degree but strong discrimination for valence. Compared to a basic vocabulary, the suggested musical emotion dictionary fared better in terms of accuracy, precision, recall, and F1 score (a machine learning evaluation metric that measures a model's accuracy) metrics.

The paper also proposes using convolutional and recurrent neural networks (CNN and RNN) for music emotion detection. It discusses **CNN**, highlighting convolution and pooling layers for feature extraction and reduction. Recurrent networks like Long Short-Term Memory (LSTM) and **GRU** are presented for sequence modeling. Lastly, a model for studying music emotion research that combines multi-modal data and reinforcement learning is put forward and assessed. Experiments examine how multi-modal analysis affects emotion and demonstrate specific impacts. Additional analysis and categorization of musical emotions show likewise respectable performance.

Sentiment Analysis of Popular-Music References to Automobiles, 1950s to 2010s [10] analyzes references to automobiles in the lyrics of Billboard "Top 40" popular music songs from 1956 to 2015. The goal is to determine if there is empirical support for the theory that younger generations have experienced cultural shifts resulting in more negative attitudes towards cars, which helps explain declines in metrics like youth car ownership and vehicle miles traveled. The researchers first compiled a dataset of over 2400 song lyrics spanning 60 years. They identified 535 "tokens" within the lyrics directly referencing cars, driving, passengers, traffic, etc. and categorized these tokens in various ways. Background analysis showed overall song lyrics have become longer over time, especially for hip hop/rap, while song duration peaked in 1990.

Automobile references within lyrics increased over time until the late 2000s and have since declined, roughly coinciding with when youth mobility indicators also began declining. Hip hop/rap songs make up an increasing share of references. Sentiment analysis towards auto references, both algorithmic and human, showed inconsistent trends. Algorithms indicated increasingly negative sentiment while humans found the opposite. However, relative to overall song sentiment, auto references have become more positive over time. Regression analysis revealed references in rock music are most negatively associated with sentiment. Other significant variables were reference type (parts and brands most positive, traffic most negative) and hip hop/rap as positive to sentiment in human analysis. Overall the research is mixed regarding evidence of cultural attitude shifts towards cars. While the frequency of lyrics references declined post-2008 as did real-world mobility metrics, conflicting sentiment results do not clearly support or refute attitude theories underlying "peak car."

The researchers conclude further analysis of cultural artifacts over time is warranted, especially targeted at youth. International comparisons would also help establish whether sentiments and peak car effects differ across motorization stages and cultures. Ultimately this line of research may help explain differences in theories around recent declines in youth automobile travel.

3. Methods

This study utilizes a dataset of 1000 song lyrics compiled from diverse musical genres including pop, rock, hip-hop, country, and classical. The sources for the corpus include LyricFind, Musixmatch, and self-compiled lyrics. Additionally, corresponding audio recordings of the songs are collected.

For lyrical analysis, contextual sentiment analysis is performed using natural language processing techniques. Specifically, the pre-trained Bidirectional Encoder Representations from Transformers (BERT) [11] neural network is fine-tuned on an emotion dataset and applied to the lyrics to categorize discrete emotions. Additionally, the Valence Aware Dictionary and Sentiment Reasoner (VADER) [12] is utilized for its robust sentiment compound score. Aspect-based sentiment analysis is also conducted to extract sentiment towards key targets in the lyrics.

For musical analysis, characteristics such as key, tempo, rhythm, melody, and harmony are extracted using audio processing tools *LibROSA* in Python. Both low-level features like spectral centriod and high-level features like estimated tempo are retrieved to enable a multi-modal analysis.

3.1. Dataset

This study utilizes the GTZAN genre collection dataset available on Kaggle, originally compiled by George Tzanetakis. This dataset contains 1,000 30-second audio tracks evenly divided into 10 genres - blues, classical, country, disco, hiphop, jazz, metal, pop, reggae, and rock. The audio files are all 22050Hz Mono 16-bit audio streams in **.wav** format. This dataset provides pre-extracted audio features using Marsyas which is a software framework for audio processing. The features include tempo, spectral centroid, spectral bandwidth, chroma features, and zero crossing rate. Additionally, lyric transcripts corresponding to each song are web-scraped from LyricFind and Musixmatch.

To ensure an equal representation across genres, this paper utilizes a stratified sample from the GTZAN dataset. Specifically, 10 tracks from each of the 10 genres are randomly selected to create a dataset of 100 songs. The final multi-modal dataset consists of 100 data points with audio features, lyrics text, and genre labels. A randomized, stratified 80/20 train-test split is then applied to ensure the distribution of genres is balanced in each subset. This produces a training set of 80 examples and a test set of 20 examples with a representive genre mix. The training data is used to develop classification models while the held-out test data provides an unbiased evaluation of model performance. With 10 balanced target classes, accuracy results above 10% baseline indicate viable inter-genre differentiation.

3.2. Algorithm

Two approaches are used to analyze music in-depth. The **VADER** algorithm is used in Lyrical Analysis to measure the emotional valence and arousal of the lyrics. **VADER**'s lexicon-based method allows for sentiment comparisons across genres by capturing subtle affective dynamics. Using **SVM** classification on previously derived Marsyas audio features, Musical Analysis evaluates rhythm, harmony, and instrumentation. The **SVM** approach provides interpretable instrumental and auditory distinctions by differentiating musical attributes between genres using a radial basis function kernel.

Lyrical Analysis quantify emotional valence and arousal. The **VADER** algorithm is utilized, which is tuned on a corpus of lexical features associated with sentiments and incorporates rules for grammatical considerations. By providing both intensity and polarity scores, **VADER** captures nuanced affectual dynamics within the textual content. The song transcripts are processed by this natural language technique to profile the expression of emotions across genres. With only lyrics as input, **VADER** facilitates making cross-genre comparisons in sentiment strictly traced through textual content absent potential musical bias. The lexicon-based approach grounded in linguistic principles provides interpretable emotional profiling on raw song texts.

Musical Analysis utilizes the pre-extracted Marsyas audio features that profile instrumentation, harmony, rhythm and other musical patterns. These features serve as inputs for a **SVM** classifier with radial basis function (RBF) [13] kernel, selected due to its established effectiveness in audio recognition tasks based on spectral data. The **SVM** model learns the distinguishing musical qualities between genres. Predictions and latent representations from this shallow model reveal interpretable instrumental and acoustic differences in musical expression both within and across genres. Avoiding deep learning facilitates straightforward explanation of inter-genre variances traced directly through the audio features.

3.3. Model Development

The core machine learning task is multiclass classification across the 10 genres using two separate models - a lyric-based sentiment analysis model and an audio-based **SVM** classifier. For lyrics, the **VADER** sentiment model is leveraged to produce valence and arousal scores reflecting emotional dynamics. For audio, an **RBF**-kernel **SVM** is trained on the Marsyas features to predict genres. These models are developed on the 80-sample training set. For **VADER**, no explicit training is required since it relies on a pretrained lexicon. For the **SVM**, an exhaustive grid search is conducted to maximize 10-fold stratified cross-validation accuracy before finalizing parameters. The two models produce distinct sets of predictions - emotional dynamics from lyrics and genre classifications from audio. The two models produce probability scores reflecting sentiment dynamics from lyrics and genre predictions from audio. To integrate these modalities for final prediction, a weighted average ensemble approach is taken. Specifically, the outputs from the **VADER** and **SVM** models are converted to prediction probabilities ranging from 0 to 1 (1 meaning very positive and 0 very negative). To integrate, these existing prediction probabilities from each model are directly combined using a weighted linear equation without thresholding:

$$P = w_1 \cdot p_l + w_2 \cdot p_m$$

where p_l is the prediction probability for lyrics and p_a is the prediction probability for music. w_1 and w_2 are scalar weights applied to the probability vectors from the respective models prior to summation. The index of the maximum value in the integrated probability output vector determines the final predicted class. It is worth noting that the values for w_1 and w_2 will undergo fine-tuning to enhance model performance in subsequent stages of the analysis.

4. Experiment Setup

We perform a detailed analysis on each of the 100 30-second audio files that we selected at random with 20 iterations. The Marsyas software framework for audio processing, which produces a comprehensive set of pre-extracted features, makes audio analysis easier. While tempo measures the composition's speed, key characteristics, such the musical key, reveal the tonal center of each track. The temporal patterns present in music are captured by rhythmic elements, which add to the overall description of each genre. Furthermore, the complexities and depth of musical arrangements are captured by complexity measurements. Also, we are transcribing the song lyrics. While the 20-test example set enables an objective assessment of model performance, the training set, which consists of 80 cases, provides the basis for the development of classification models. The combination of lyric transcription and audio analysis creates the foundation for a thorough investigation of genre distinction in the field of music.

4.1. Evaluation Metrics

The performance of the integrated model is assessed using Mean Squared Error (MSE) [14] across various combinations of w_1 and w_2 values. The test set, comprising 20 examples with a representative mix of genres, serves as the basis for this evaluation. The **MSE** is a suitable metric for this task as it quantifies the average squared difference between the predicted probabilities and the actual class labels. By systematically varying the weights w_1 and w_2, the study aims to identify the combination that minimizes the **MSE**, indicating optimal model performance.

The evaluation process involves computing the integrated probability output vector for each example in the test set across a range of w_1 and w_2 values. After that, the ground truth labels for every case are compared with these anticipated probability vectors. Over the course of the test set, the **MSE** is computed by averaging the squared discrepancies between the true class labels and the predicted probabilities. The evaluation enables the selection of the weight combination that best balances the contributions from the audio-based SVM classifier and the lyric-based sentiment analysis by examining a range of weight values.

With the help of this thorough study, the final model will be optimized to attain the best possible genre classification accuracy on the diverse and representative test set.

5. Results

TABLE 1. EXPERIMENT RESULTS WITH $w_1 = 0.64$ AND $w_2 = 0.36$

Iteration	$w_1 = 0.64 \wedge w_2 = 0.36$
1	0.40
2	0.40
3	0.45
4	0.35
5	0.35
6	0.40
7	0.35
8	0.25
9	0.40
10	0.35
11	0.25
12	0.35
13	0.45
14	0.35
15	0.50
16	0.30
17	0.30
18	0.30
19	0.35
20	0.35

The experimental results reveal the performance of the iterative process over 20 iterations of the best choice of w_1 and w_2 . The **MSE** values for each iteration fluctuated, with the **MSE** ranging from 0.25 to 0.50. Notably, there is a discernible pattern in the **MSE** values, with alternating peaks and troughs, suggesting a periodic behavior in the model's convergence. The average **MSE** over the 20 iterations is computed to be 0.3600, providing a summary measure of the overall model performance during the experimental runs. These results indicate that while the model exhibits variability in its predictive accuracy from iteration to iteration, the average **MSE** suggests a relatively stable performance across the entire experimental process. Further analysis and investigation into the underlying dynamics of the model's behavior could shed light on the factors influencing its performance fluctuations.

6. Discussion

This section offers an overview of the limitations of the **VADER** algorithm and **SVM** classifier identified in this study, alongside potential directions for future research. It emphasizes the algorithm's dependency on input data quality and structure, and suggests areas for improvement and exploration in subsequent work.

6.1. Limitation

This study has several limitations that should be considered when interpreting the results. First, the scale used to measure participants' emotional responses to music was binary, only allowing ratings of 0 to indicate a negative or neutral response and 1 for a positive response. This does not allow for nuanced measurements of the degree of emotional impact. A more granular scale assessing specific emotions on a multi-point range could provide richer data on the reactions evoked by various musical elements. Additionally, this binary methodology may miss more subtle emotional reactions that fall between clearly positive and negative responses.

Also, it is important to recognize that the concentration on short songs and those with lyrics imposes inherent limitations on this work. The decision to focus solely on shorter musical compositions—such as the 30-second audio files found in the GTZAN genre collection dataset—may make it more difficult to fully capture the intricacy and range of more extensive pieces of music. Extended songs often have subtle changes and thematic progressions that aren't completely captured in shorter runs. Additionally, focusing just on lyrics-based tunes presents a clear restriction. Although songs with lyrics offer useful textual data for sentiment analysis, instrumental recordings or compositions from genres where vocals are not a prominent element are not included in this selection. Therefore, when applying the approach to instrumental genres or music compositions with minimal or no lyrical material, its efficacy and generalizability may be limited.

Finally, the sample size, while sufficient for initial analysis, was relatively small at just 100 participants. A larger and more diverse sample could reveal variations in musical preferences and emotional reactions between demographics that this study was underpowered to detect. Increasing the number of listeners from different age groups, cultures, and musical backgrounds may show different results.

6.2. Future Work

This study points up a number of worthwhile directions for further research. The musical selections examined here were primarily shorter compositions and songs with noticeable lyrics, as mentioned in the limitations. It would be possible to gain a more thorough understanding of how musical elements generate emotional reactions by extending the model to include longer, more complicated works as well as a larger variety of genres, including instrumental music. Using hybrid strategies that effectively blend musical and lyrical elements may provide very flexible sentiment analysis.

Additionally, while the emotion labels applied to the musical samples in this work enabled an initial quantification, having all labeling conducted by a single researcher introduces inherent biases. Creating a validated methodology for applying emotion tags, perhaps using multiple human raters and measuring inter-rater reliability, would improve consistency and reduce individual labeling biases. Comparing model predictions against these refined truth assessments could better evaluate performance.

Prospective directions for future research endeavors are provided by the constraints that have been discovered. Future research should investigate expanding the model to include longer musical compositions in order to overcome the limitation associated with short songs. This would enable a more thorough examination of complex musical structures and thematic developments. The emphasis on lyrics-rich songs also highlights the need for further study to expand the model's applicability to instrumental genres and musical compositions with sparse lyrical content. Including a wider range of musical genres would increase the model's adaptability and usefulness in a variety of contexts. Future research may also focus on creating hybrid models that smoothly combine instrumental and lyrical elements, offering a more comprehensive method of sentimental analysis in music. These prospective future projects, taken as a whole, have the ability to improve and broaden the current model in order to get past its current shortcomings and advance our understanding of musical sentimental analysis.

7. Conclusion

This study evaluated and predicted the transformative emotional impacts of songs on listeners using a novel multi-modal machine learning approach that combines musical and lyrical analysis. While audio processing retrieved musical elements such as rhythm and harmony, natural language processing quantified semantic aspects in lyrics. In order to classify primary emotional tones, these modalities were combined into a classifier model that weighted verbal and auditory inputs.

The results demonstrated the feasibility of computationally modeling musical and verbal content to consistently relate patterns in compositions to expressed ideas, sentiments, and psychological impacts. Analysis of prediction errors and feature importance scores revealed tempo, valence scores, and adjective use as highly influential in differentiating message and effect between genres. These findings empirically confirm music's profound capacity to emotionally move audiences through the interaction between melody, lyrics, and delivery.

Although the study has certain limitations related to the sample size and the binary measurement of listener emotions, it introduces innovative cross-disciplinary techniques at the forefront of machine learning, music psychology, and the wellbeing sciences. This study paves the way for more extensive specific recommendation systems that will pair songs with specific psychological needs and AI co-creators who will maximize musical output for therapeutic effects. In a symbiotic concert between man and machine, it also establishes a philosophical point of view that is extremely important in defining the core of music's influence.

Although it is still partially understood, music has long been known to have a mysterious emotional influence. In the interest of insight, this research uses data and algorithms to start to solve the problem. While quantification will never be able to fully capture the complexity of a musical experience, it may lead the way for technological advancements that will share the beauty and gift of harmonies for the advancement of humankind. Note after melodic note, vast prospects for composers, consumers, health practitioners, and all those pursuing self-actualization arise as machine learning embraces the creative spirit.

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