Hip-Hop Culture incites Criminal Behavior: A Deep Learning Study

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Abstract. For centuries, music has been an inseparable part of many human cultures. The rise of the Hip Hop culture over the last 50 years has turned into a powerful movement, empowering people from various communities and making their voices heard. However, certain parts of Hip Hop and Rap music have started being associated with Misogyny, Substance Abuse and Violent behavior. This study aims to find a correlation between lyrics of Hip Hop and Rap songs that glorify such illicit behavior through their lyrics and the actual rate of criminal activity of individuals that are directly or indirectly influenced by Hip Hop culture. This research employs NLP concepts to build a model that detects song lyrics that falls into any of the 3 categories- 'Misogyny', 'Substance Abuse' and 'Violence'. A comparative study is conducted by training multiple models including Multinomial Naïve Bayes, Random Forest and LSTM on a manually collected and labeled dataset consisting of Rap song lyrics released between 1970 and 2020. The highest performing model (LSTM- 87% accuracy) was subsequently used to detect objectionable lyrics in popular Rap songs of the decade of 2010 to 2019. To obtain a correlation of these with the criminal activity of the target population, official data of criminal activity (2010-2019) of citizens aged 0-29 from the largest Hip Hop influenced areas in the world are compiled. This dataset is analyzed and to obtain strong evidence of a correlation between objectionable Rap song lyrics being promoted through song lyrics and the criminal tendencies of the youth that is primarily affected by it.

Keywords: Hip-Hop, LSTM, NLP, Criminal, Juvenile Crime, Rap, Misogyny, Substance Abuse, Violence.

1 Introduction

In the decade 1970, the streets of Bronx in New York saw an economic downfall, rising crime, gang violence, poverty and racial disparity. It was on these very streets, emerging from the powerlessness of the marginalized society, that the culture of Hip Hop was born- a movement of hope in an era of despair [2]. It was during these times that "Rap music", a form of music that incorporates masterful rhythmic verses and combinations of beats to deliver a message or a story was created. For the suppressed African American and Latino community of that time, Rap music told stories of pain, abandonment, poverty, hardships and vulnerability.

The Hip Hop culture over the next few decades grew rapidly, overcoming boundaries of colour, class and ethnicity. People across the globe found solace and freedom in Rap music, feeling a sense of belonging towards the Hip Hop culture. However, not long after this, a shift was seen in the way a part of Rap music was perceived over the world. Stories of vulnerability, pain, loss, anger turned into boasting of wealth, objectification of women, romanticizing drug abuse and justification of violence. Misogyny, Substance Abuse and Violence are now often portrayed as characteristics of the Hip Hop culture. Studies show that younger people who listen to rap and hip-hop are more likely to abuse alcohol and commit violent actions [12]. According to a survey conducted on individuals 25 years old or younger, two-fifths of the study sample (38%) reported use of marijuana and 13% use of club drugs. Moreover, 27% reported being engaging in at least one act of aggressive behavior. Most of the respondents (94%) reported listening to music "daily or almost daily." Among these "daily or almost daily" music listeners, 69% of them reported often listening to rap music [4]. Unfortunately, the movement that started as a means of empowerment and redemption of the people now persuades young minds towards alcoholism and addiction, stirs up aggressive behavior and a regressive mentality towards women [13].

This is a Machine Learning and Deep Learning-based study of the transformation of the Hip Hop genre, specifically rap music lyrics in the decade of 2010 to 2019 and its correlation with criminal tendencies of juveniles and young adults that are most likely to be influenced by these songs. A Neural Network has been built to detect objectionable lyrics in Rap songs and classification and in-depth analysis of 500 songs and juvenile criminal data from 2010 to 2019 has been conducted to find a strong correlation between objectionable Rap song lyrics and criminal tendencies of juveniles and young adults.

To date, several humanities and survey-based studies explore the prevalent detrimental traits of many parts of Hip-Hop culture [5,7,10,11]. This study aims to support these results using Natural Language Processing, Deep Learning and Machine Learning principles.

2 Methodology

The structure of this study is divided into two segments. The purpose of the first segment is to build a model using various Natural Language Processing, Machine Learning and Deep Learning techniques to automatically detect if the lyrics of a certain song promote illicit behavior falling under any of the three categories- Misogyny, Substance Abuse and Violence. Multiple NLP algorithms were trained on a manually collected dataset for this purpose- Random Forest Classifier, Support Vector Machine, Multinomial Naïve Bayes and LSTM. After the model was built, it was used on a compilation of 500 most popular rap songs of the years 2010 to 2019 to obtain outputs for each of these songs. Visualizations and analysis of these outputs are discussed in section 7 to gain deeper insights such as variation of slurs over the decade, streaming ratios of objectionable and non-objectionable songs etc.

The second segment of the study focuses on finding a correlation between the degree of Misogyny, Substance Abuse and Violence in the songs detected by the model and the criminal tendencies of juveniles and young adults who are influenced by Hip- Hop or Rap music. Criminal or arrest data of juveniles and young adults in the largest Hip-Hop influenced areas in the world was compiled. Finally, the nature of the crimes and the conditioning of the popular Hip-Hop culture of that time are compared to understand if Hip-Hop culture has effects on the juvenile and young adult crime rates.

3 Song Lyrics Dataset

The lyrics data for training the model was collected manually by choosing Rap songs that glorify Misogyny, Substance Abuse and Violence. The lyrics which consisted of certain predefined keywords (eg. weed, stoned, high etc. for substance abuse) were targeted. The first step was to identify lyrics that fell under any of the three categories on which the study is focused upon. Moreover, songs of artists with criminal records or prior felonies, or those known to have objectionable lyrics in their songs were targeted. Following this, the lyrics of these songs were collected manually from reputable sources such as Genius and AZLyrics and arranged in a datasheet that was used for the models as training data. The final step involved sorting them into three different text categories- Misogyny, Substance Abuse and Violence.

4 Models

The following section elaborates various model architectures used for detection of song lyrics that consist of references to Misogyny, Substance Abuse and Violence.

4.1 Support Vector Machine

Support Vector Machine (SVM) classification algorithm is a type of supervised learning algorithm that takes labeled data and tries to classify among the given labels [6]. SVM is not limited to classification as it also does regression. SVM primarily tries to create a hyperplane that separates the classes. Data points from each class that are nearest to the hyperplane are called “Support Vectors”. For a multi-class classification problem like ours, the SVM has two approaches: Once versus One and One versus Rest. In this application, the latter is used. In the one to rest approach, one class is separated from the rest of the classes using a hyperplane. The classifier uses SVMs. A linear kernel is used and the default value of C(=1.0) is used.

4.2 Random Forest Classifier

Random Forest is an ensemble technique that constructs many individual decision trees for making predictions, of which the best performing is finalized [1]. Random Forest implements feature extraction to calculate the node impurity. A higher value of node probability implies higher importance of the feature. Each decision tree is provided with its respective training dataset. Random Sampling was used to create subsets of our main dataset. Each subset is used as a training set for its respective decision tree. Similarly, each decision tree is also provided with a test dataset to check the accuracy of each tree.

4.3 Multinomial Naive Bayes

Multinomial Naïve Bayes is a special form of the Naïve Bayes model [14]. The difference between Naïve Bayes and Multinomial Naïve Bayes is that Naïve Bayes essentially considers the presence or absence of a word in a document for its calculations but Multinomial Naïve Bayes takes not only the presence of a word but also its count into account.

$$P(A|x_1,\ldots x_n) \propto P(A)*P(x_1|A)\ldots P(x_n|A) \tag{1}$$

Here, 'A' is the variable that represents the classes, i.e., Misogyny, Substance Abuse and Violence. "x_n" represents the words in a sentence.

4.4 Long Short-Term Memory (LSTM)

LSTM is a state of the art deep learning model [8]. What makes the LSTM different from the RNN is the gated unit or cell present in the hidden layer. As the gates open and close, the information in LSTM is lost or retrieved as required.

Architecture. LSTM consists of three logistic sigmoid gates and two tanh layers. The tanh activation function maintains a value between -1 to 1 while the sigmoid activation function maintains a value between 0 and 1. The LSTM memory cell consists of three gates.

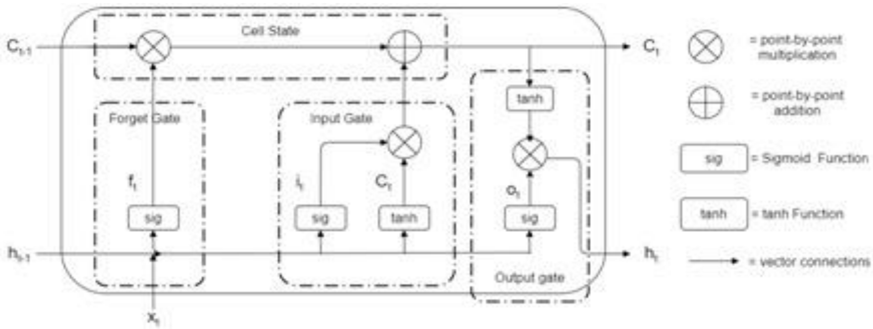

Fig. 1. LSTM Cell

Forget Gate. The forget gate has two inputs of h(t-1) and x(t). The information from the current input x(t) and hidden state h(t-1) are passed through the sigmoid function. A value of 1 denotes that the information is important and needs to be remembered while a value of 0 denotes that the information can be ignored.

$$f_t = \sigma \left(W_f \cdot [h_{t-1}, x_t] + b_t \right) \quad (2)$$

t = timestamp, f_t = forget gate, x_t = current input, h_{t-1} = previous hidden state, W_f = defined weight, b_t = Connection bias at t

Input Gate. The input gate has two inputs of x(t) and h(t-1) which are passed through the sigmoid and tanh activation units. The generated values are then passed on to calculate the point-by-point multiplication. The previous cell state C(t-1) gets multiplied with the forget vector f(t), and if the output is 0, then values will get dropped in the cell state, while an output of 1 retains the values.

$$C_t = f_t * C_{t-1} + i_t * C_t \quad (3)$$

t = timestamp, f_t = forget gate, C_t= cell state information, i_t= input gate at t, C_{t-1}= previous timestamp

Output Gate. The inputs of h_{t-1} and x_t are passed to the sigmoid function and the new cell state value is passed to the tanh function. A point by point multiplication of these outputs is performed to generate the information of the new hidden state.

$$o_t = \sigma \left(W_o [h_{t-1}, x_t] + b_o \right) \quad (4)$$

$$h_t = o_t * \tan h \left(C_t \right) \quad (5)$$

t = timestamp, o_t = output gate at t, W_o = Weight matrix of output gate, b_o= bias vector w.r.t W_o , h_t= LSTM output

The model built uses 70% of data for training and the other 30% of data for testing, with an embedding layer, spatial dropout of 0.4, an LSTM layer and a dense layer with 3 output neurons. A batch size of 32 was defined and 50 epochs were generated.

5 Model Evaluation

The accuracies and encoding techniques of the 4 models used are listed below.

Table 1. Model Accuracies

Sr. No.	Model	Encoding Technique	Accuracy
1	Support Vector Machine	Count Vectorizer	82 %
2	Random Forest Classifier	Count Vectorizer	76.87 %
3	Multinomial Naive Bayes	Count Vectorizer	85 %

4	Long Short-Term Memory	Index based Encoding	87 %

In the case of Multinomial Naive Bayes and SVM, a different testing file was made instead of splitting the dataset. This was done to separately 'fit_transform' the training data and only transform the test data.

For Random Forest, Grid Search method was employed to find the best hyperparameters. Different 'n_estimators' and depths of trees were tried. The best accuracy was found for n_estimators = 150 and max_depth = 60. The accuracy for these hyperparameters was 76.87%.

One of the key advantages of using LSTM over RNN networks is that they address the vanishing gradient problem [3]. Hence, LSTM is better suited to capture the long-term dependencies in song lyrics, giving the model a higher capability to understand context and repetitive phrases to aid classification. The LSTM model was found to be the most accurate and reliable model, the weights and results of which were used for the subsequent part of this study.

6 LSTM Application and Outputs

The LSTM model, hence built, was used to classify 500 song lyrics from the Genius top 50 rap song lyrics of each year from 2011 to 2019 into the three labels. These songs were scraped with an automated customized search engine made using the library lyrics_extractor. The 500 songs were thus compiled and fed into the model.

The output of the model comes in the form of three probabilities lying between 0 and 1 per category, each probability corresponding to a category showing how confidently the song lies in it. Only the songs with a probability of more than 0.8 in one particular category were considered to lie in it, otherwise, the song was labeled as 'Not Objectionable'. At the end of this step, each song had one of the labels- 'Misogyny', 'Substance Abuse', 'Violence' and 'Not Objectionable'.

The following is a depiction of the format in which the outputs of the model were compiled. (NO = Not Objectionable)

Table 2. LSTM Output Format

Year	Song	Substance Abuse%	Misogyny%	Violence%	NO%	Label
2017	Love	0	17.39	0	82.60	NO
2011	Murder to Excellence	12.5	8.33	34.37	44.79	Violence
2015	Antidote	25.33	14.67	6.67	53.33	Substance Abuse

7 Visualizations

To perform analysis of hip hop songs over the past decade (2010-2019), top 100 songs of each year were scraped from popular music sites like Genius. All the songs were preprocessed prior to analysis. Note that all the visualizations and analysis are based on the outputs generated by the model.

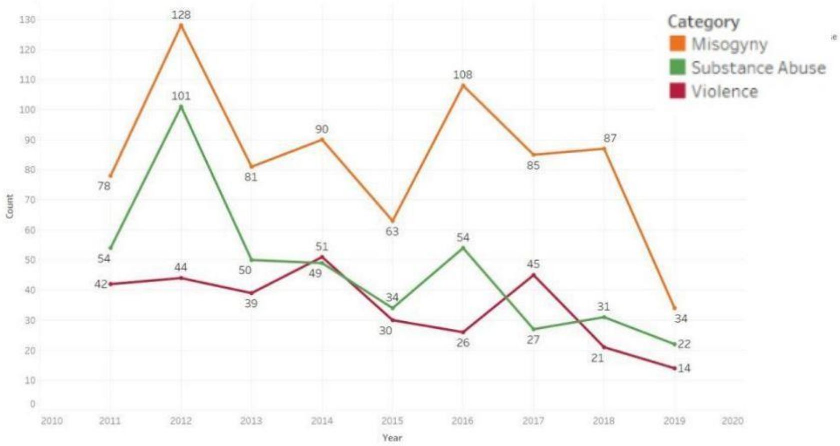

Fig. 2. Variation of significant slurs over the decade

TF-IDF values of each category were used to determine the important words under each label. A list of ten words was made for each of the labels. The occurrence of each of these words in the top 100 songs over the past 10 years was taken and plotted (see Fig. 2).

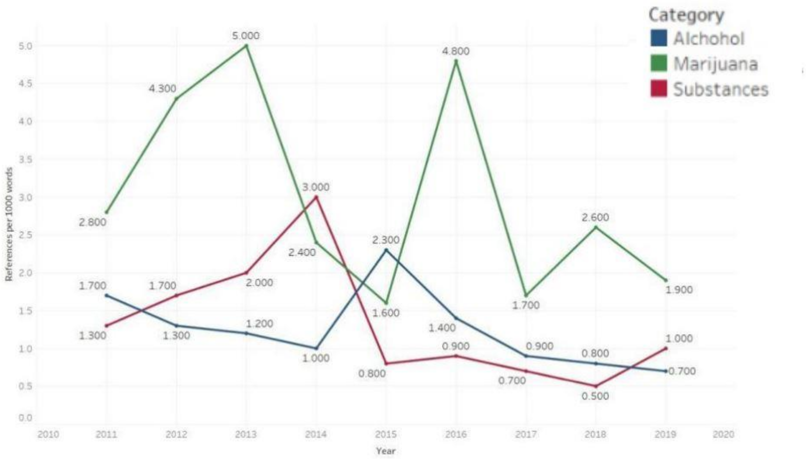

Fig. 3. Variation of individual substance per 1000 words

The Substance Abuse category is divided into three subclasses, namely ‘Hard Drugs’, ‘Alcohol’ and ‘Marijuana’ (see Fig. 3). Using the TF-IDF weights of the ‘Drugs’ category, the occurrence of these words per 1000 words was calculated. For instance, references to marijuana peaked in 2013 with 5 out of 1000 words in Rap songs as direct references to marijuana.

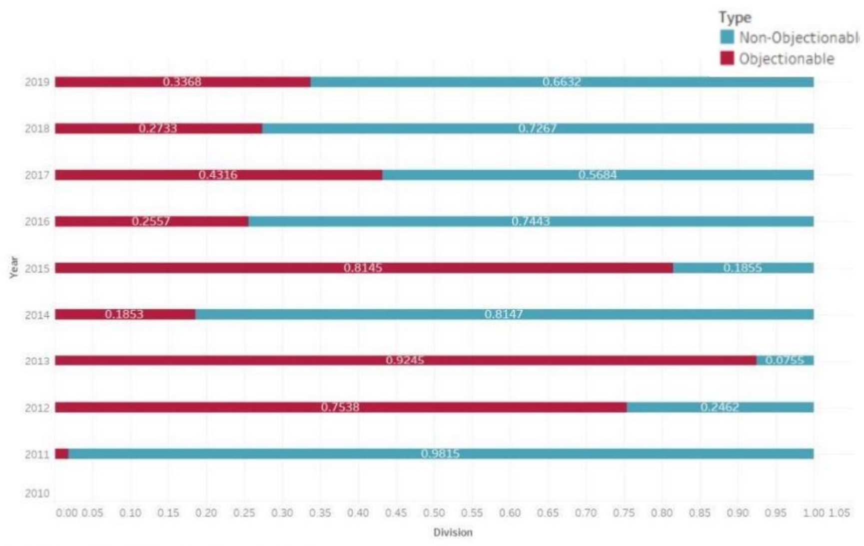

Fig. 4. Streaming ratios of Objectionable and Non Objectionable songs

A major part of analyzing the transformation of Rap music involves understanding what audiences accept and like.

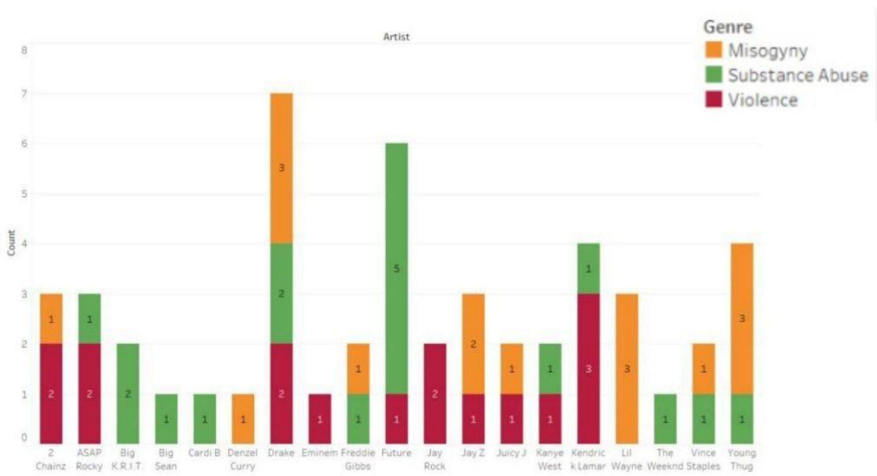

Fig. 5. Distribution of categories of artists with the most objectionable lyrics

Streaming data of 10 most objectionable and 10 least objectionable songs of each year in the decade is collected from Youtube and plotted year-wise (see Fig. 4). The year of 2013 saw the largest ratio of streams of objectionable songs (0.92). The tastes of Hip-Hop audiences have changed for the better over the decade as this ratio sees a general decline until 2019 (0.33).

The prominent rap artists of the decade 2010-2020 that repeatedly had songs in the categories of Misogyny, Substance Abuse and Violence as analyzed by the model are plotted (see Fig. 5).

8 Crime Data

The target population of this study is individuals aged 10-29 who are heavily influenced by the Hip-Hop culture. As no data directly recording the crime rate of the global hip-hop audience is available, three factors were considered to maximize the proportion of hip-hop listeners in our dataset.

1. The dataset contains criminal records of cities with the largest hip-hop listening population in the world.
2. The data is further narrowed down into the age group that is most impressionable and likely to follow, listen to and be influenced by the Hip-Hop culture, which is 10-29 [9].
3. The kind of criminal activity that was taken into account is directly promoted by a part of hip hop culture through song lyrics and music videos.

To maintain the veracity of the data, arrest data provided on the official state government websites were collected and narrowed down according to the three filters mentioned above. In multiple cases, the arrest data for the target age group (10-29) of the 'Target City' is not made publicly available, and hence the arrest data of the county or state in which the city lies is considered instead. The types of crimes in the data are categorized into Misogyny, Substance Abuse and Violence as stated below:

1. Misogyny- Sex offences, Prostitution, Rape.
2. Substance Abuse- Possession and Manufacturing of Narcotics (Opium, Cocaine, Marijuana etc.), Driving in an intoxicated state, Violating Liquor laws.
3. Violence- Assault, Aggravated Assault, Homicide, Murder, Illegal possession of weapons, Damage to property, Robbery.

The final dataset is 10 years of criminal records of impressionable juveniles or young adults living in cities with the strongest rooted hip-hop cultures in the world.

9 Results

The hypothesis that rap songs have a direct effect on the criminal tendencies of juveniles and young adults is explored in this section.

Table 3 demonstrates the overall rise or drop percentages in each of the measured value of Misogyny, Substance Abuse and Violence level of song lyrics as recorded by the model and the overall rise or drop percentage of juvenile or young adult crime over the same period.

Table 3. Song Lyrics and Crime Correlation

Years	Area	Crime Category	Criminal Age Group	Song Variation	Crime Variation	Correla-tion
2013-17	Detroit (Wayne County)	Misogyny	10 - 16	17.03 % Decrease	19.04 % Decrease	**Positive**
2013-17	Detroit (Wayne County)	Substance Abuse	10 - 16	17.17 % Decrease	24.48 % Decrease	**Positive**
2013-17	Detroit (Wayne County)	Violence	10 - 16	14.27 % Decrease	50.55 % Decrease	**Positive**
2011-18	Atlanta	Misogyny	0 - 29	28.03 % Decrease	31.00 % Decrease	**Positive**
2011-18	Atlanta	Violence	0 - 29	14.63 % Decrease	44.60 % Decrease	**Positive**
2011-18	Atlanta	Substance Abuse	0 - 29	8.25 % Decrease	13.19 % Decrease	**Positive**
2010-18	California	Substance Abuse	10 - 17	8.25 % Decrease	86.96 % Decrease	**Positive**
2010-18	California	Violence	10 - 17	14.63 % Decrease	69.52 % Decrease	**Positive**
2010-18	Pennsylvania	Substance Abuse	10 - 17	8.25 % Decrease	35.10 % Decrease	**Positive**
2010-18	Pennsylvania	Violence	10 - 17	14.63 % Decrease	52.71 % Decrease	**Positive**
2014-18	Bronx	Misogyny	0 - 16	20.56 % Decrease	26.58 % Decrease	**Positive**
2014-18	Bronx	Substance Abuse	0 - 16	1.7 % Increase	86.53 % Decrease	Negative
2014-18	Bronx	Violence	0 - 16	26.57 % Decrease	53.34 % Decrease	**Positive**
2014-18	New York County	Misogyny	0 - 16	20.56 % Decrease	42.00 % Decrease	**Positive**
2014-18	New York County	Substance Abuse	0 - 16	1.70 % Increase	78.57 % Decrease	Negative
2014-18	New York County	Violence	0 - 16	26.57 % Decrease	45.54 % Decrease	**Positive**

The 14 positive correlations out of 16 records provide strong support to the theory that criminal activities of juveniles and young adults in areas that are influenced by the Hip Hop culture are closely linked to the kind of rap songs that were popular in those years.

10 Future Scope

Very few computational works of research have been conducted that provide strong evidence of the effect of the Hip-Hop culture on the psychology of the youth. More efforts are required to record and enhance the dataset so as to promote research in this unexplored field. For instance, this study uses criminal data of Hip-Hop influenced states and cities to draw results due to lack of publicly available arrest data, but targeting smaller individual areas with greater Hip-Hop influence will make the results more specific and precise.

One of the major challenges faced in this study was to associate the motive behind the crime with cultural influences. Factors such as the environment in which a child is brought up, crimes committed in the heat of the moment or for self-defense, the judicial system and literacy rates of the targeted areas all contribute to the crime rate.

To address these challenges, a more comprehensive juvenile arrest data can be obtained by conducting interviews, surveys or by taking into account the circumstances of the crime to provide future researchers with a more relevant and insightful dataset for computational studies.

11 Conclusion

This study provides a comprehensive overview of the evolution of Rap music, a major part of Hip-Hop culture in the decade of 2010 to 2019. The analysis and visualizations of the rap lyrics over the years provide deeper insights into the psychological effect it may have on juveniles and young adults. Finally, juvenile and young adult arrest data for each category is analyzed and a correlation is obtained between the arrest rates and the variation of song lyrics over the decade. These results suggest strong evidence of a psychological effect of rap songs promoting Misogyny, Substance Abuse and Violence on young people. This study does not aim to undermine the real Hip Hop culture that has been a thread of art, music and stories connecting various communities and people all over the globe. Instead, it aims to demonstrate the power that words and music hold over the human psyche. Music artists and songwriters need to understand that their music is heard by millions of people over the world and their fame must be used responsibly- not to spread hatred, addiction or to degrade lives but to heal wounds, share pain and to inspire love and kindness.

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