

# Spotify Playlists and Musical Genre Classification

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## 1 INTRODUCTION

- Introduce your topic.

I will focus on implicit genre classification of musical artists on Spotify. Genre classification based off of race is a potentially problematic phenomenon, that could be exacerbated by automatic playlist generation and playlist recommendation algorithms. For example, to include a black country singer's songs in an automatically generated playlist called "R&B beats."

I am interested in investigating these playlists at a large scale to see if this is a systemic problem within Spotify, particularly for R&B (Rhythm and Blues) and black artists..

- What is your motivation for working on this topic? Why should people care?

I read accounts from some famous black artists with their experience being boxed into the R&B category [11], and I want to see if this is a systemic issue that should be tackled in the music streaming community. Many white artists benefit from the ability to live within multiple musical genres or to shift to new genres throughout their careers. This provides an opportunity for new streams of revenue for white artists. Conversely, over-classification on the basis of race could present economic disadvantages to artists of color.

Historically R&B served as a space for black artists to rise to fame and claim more career opportunities within an industry with racist practices. However, to deny black artists as individuals with individual creative pursuits and unique musical intentions, could present social issues. Reducing black music to a monolith allows negatively-connotated generalizations about R&B to apply to an entire racial group of artists. Furthermore, over-classification in musical genre could serve as modern-day musical segregation.

- Formulate one or more specific research questions.

Does implicit over-classification on the basis of race occur for black artists in machine-generated playlists in Spotify?

## 2 BACKGROUND AND RELATED WORK

- What background information do people need to understand this research area and your research question?

With roots in blues and jazz, R&B came to popularity in the 20th century [5]. It was first recognized as "Race music" [7], and it was first formally recognized as R&B in the late 1940s. Its genesis occurred in parallel with the "second migration of African Americans" [9] and the social issue of segregation in America. As black populations of American cities increased in the 1940s, R&B became a culturally significant and unifying genre for the black community. It provided economic opportunity for black artist; with the grown black population in LA in the 1940s, "by decade's end would support no less than eight record labels specializing in R&B." [9].

In the early 1900s, a majority of music records were owned by white people, and rarely gave opportunity to black artists [7]. Additionally, self-producing music for black artists was often unrealistic in the face of historical economic oppression. "Recording equipment—still in its infancy—was bulky, expensive, and entirely owned by white people, and white people didn't listen to black music except for vaudeville songs that were sung by white people in blackface." [7] However between 1920 and 1940, black artists began producing under Race records, which created "music for and by black audiences." While these artist were often not compensated fairly, this allowed black musical artists to put their foot in the door, at least socially.

As Race Music came to popularity, and shifted to R&B, it continued to serve as a predominantly black safe space. R&B provided black artists an isolated musical genre to achieve recognition within the music industry. Awards like the Grammy's "Best R&B Song" and the American Music Award for "Favorite Album - Soul/R&B" have been awarded since the 1960s/1970s [10]. These awards have given predominantly black artists an opportunity for recognition when white artists had dominated the industry for so long.

Still, this genre has suffered from similar characterizations and stereotypes of hip-hop and rap music. In a study done by Simon Howard, they found that when listening to music by black rappers, participants activated negative stereotypes

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about Black people [8]. In a society with ingrained racial biases, musical genres associated with an entire race are likely to be subject to its same negative stereotypes. While racial biases and stereotypes are certainly important areas to tackle socially, it is also reasonable to recognize the disadvantage that may be posed to black artists that are unfairly categorized within a highly racially-associated musical genre.

FKA Twigs, a famous black artist talked about her experience being boxed to a musical category because of her race in the Guardian. "When I first released music and no one knew what I looked like, I would read comments like, 'I've never heard anything like this before, it's not in a genre, and then my picture came out six months later, now she's an R&B singer.'" [11]

Frank Ocean recounted a similar experience in the Quietes in 2011, "If you're a singer and you're black, you're an R&B artist. Period." [11]

Many white artists are not subjected to this same treatment, and are presented with an economic advantage. Miley Cyrus, renowned as a pop artist for the majority of her career made a strong social and economic transition from pop music to rock music in 2020, with her album "Plastic Hearts," [3] making over 3 million EAS (album equivalent sales), at par with the success of her previous albums. Taylor Swift, originally respected as a country artist, made also made a strong social and economic transition to pop music with her album, "Red." She made 4.5 million in sales [? ], and has maintained a consistent career in the new musical genre.

In 2017, pop music made up 31.1% of Global, recorded-music retail sales, followed by rock music at 24.1% and R&B at 11.9% [2]. For this reason, it is clear that there is a benefit to having the ability to shift into these musical genres and also immense economic opportunity in musical genres outside of R&B.

Spotify provides an array of playlists and other ways of delivering curated or genre-specific music. There is a wide variety of playlists that are curated by Spotify employees, these are often in line with specific music genres, moods, or themes. There are also algorithmically generated playlists, like the "Discover Weekly" playlist, which uses your listening data to pick a playlist catered to your preferences.

While transparency is limited, there are multiple ways in which these algorithmic playlists are generated [4].

- Collaborative Filtering: Spotify analyzes data from many listeners and uses listening patterns to motivate recommendations. For example: listeners who like Rihanna often also

listen to Nicki Minaj, so Rihanna listeners will also be recommended Nicki Minaj.

- Natural Language Processing: Spotify uses metadata from songs to understand the meaning of songs and motivate recommendations. For example: listeners who like an artist with sad and mellow NLP analysis will be recommended other artists with similar sentiments.

- Machine Learning: Spotify tracks listening history of all listeners and uses these patterns to motivate recommendations.

- User Retention Rate: Spotify tracks user engagement to motivate recommendations. For example: listeners who frequently skip a particular song will not likely be recommended the song again.

- What previous work exists that is relevant to your research question?

In "Algorithmic Effects on the Diversity of Consumption on Spotify," researchers at the University of Toronto work to understand Spotify's recommendation algorithm [6]. They find that users with lower levels of listening diversity are provided better recommendations.

- How does your research question interact with this previous work? Are there questions previous work left unanswered? What limitations does previous work have?

I am not particularly focused on personal algorithm-based recommendations. However, if playlists produced by Spotify do over-classify artist based on race, this could affect user listening habits, which is related to the algorithm-based recommendations. From a more social-perspective, existing playlists on the platform are extremely relevant to users' listening choices.

I am curious about the different quality of music recommendations in terms of users with specific musical genre listening habits. For example, is a non-diverse pop music listener more likely to be provided with quality recommendations?

Additionally, I am curious if listeners of genres with a large number of sub-genres are benefited by the findings from their study. R&B is often used as an umbrella term for genres such as soul, blues, and hip-hop. Do listeners of broader genres benefit from low-diversity listening habits in their recommendations?

### 3 METHODS

Describe your methodological approach in detail. This section will look slightly different in each paper. However, it will likely include descriptions of one or more of these things:

- data collection

For my data collection, I used the Spotify API to collect song and playlist data, and I used a Bing API in Python to help me with manual race labeling.

Initially I knew I wanted to collect data that was free of influence from listening data, so that Spotify provided playlist classification that were true to their generic recommendations. I did this by setting up 3 Spotify accounts so that I could create separate Web App API clients. I then decided on the quantity and type of data I would collect.

I set up a series of queries querying the API. My data collection methods downloaded a number of playlists for a number of user-specified genres. These playlists are collected from the first results of a specific genre's "Mixes." Mixes are Spotify's algorithm generated, personalized genre playlists. For each Mix I downloaded all artist and track data for each playlist. This data was set up to be downloaded to json files locally.

I decided which genres to include in my query with this source [1]. I chose to include r&b, rock, house, edm, rap, hip hop, pop, country, jazz because these were all listed as popular genres and were not sub-genres. In my initial data download, I collected 10 playlists for each of these 10 genres for my 3 dummy Spotify accounts, and also my personal Spotify account's API client.

After doing this download, I realized that all of the data from each of these 4 clients was identical. I did not come to a conclusion why this occurred, but upon future work I might reach out to Spotify Developers to get more insights. Because of this, I decided to only pursue analysis from one of the dummy accounts.

After a brief analysis of the data and the number of artists in the data (over 2500), I decided to cut down the number of playlists collected in order to ensure that manual labeling was feasible. I performed my data download again, this time with 5 playlists per genre (50 songs per playlist).

After determining which artists were in the dataset (1440 total), I set up a method in Python in order to quickly label the races of these artists. First, I downloaded 5 images locally

using the Bing API with the query "artist name musician." I then entered a race label for each artist, prompting my method to return a new image if the image was unclear or the face was obstructed.

The race labels I chose to include were black, white, latino, asian, indigenous, other/mixed, and unknown. This process took much longer than expected, but avoided the dangers of bias that exist in AI race labeling services.

Only 237/1440 artists were labeled as "unknown." The race breakdown of the artists:

White: 721

Black: 375

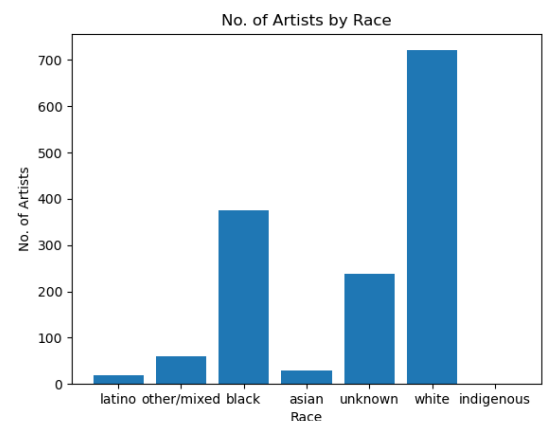
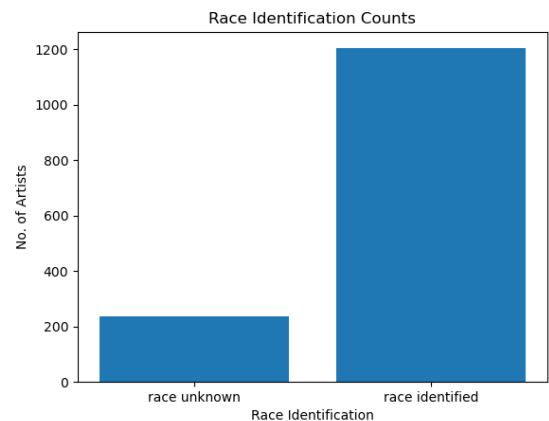
Unknown: 237

Other/Mixed: 59

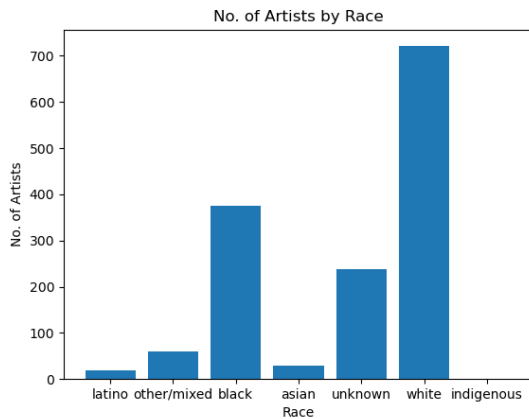
Asian: 29

Latino: 18

Indigenous: 1



The genre breakdown of the songs:



- measurement of variables

I decided to focus on four metrics to compare on the basis of race: genre representation, exposure, correct-genre classification, and pop-possibility.

I calculated genre representation by counting the number of artists that had tracks within playlists of multiple genres. I hoped that this metric would reveal inequality in the diversity of genre representation on the basis of race. I also calculated this multiple playlist metric with hip hop, r&b and rap grouped. I did this to account for social grouping of these genres and to see if this affected the analysis.

I calculated exposure by counting the number of artists that had tracks within multiple primary playlists (EX: artist has a song in the Spotify mix that is the first search result). I also counted the number of artists that had tracks within multiple non-primary playlists (playlists that were not the first searched Mix). I hoped that this metric would reveal bias in ranking for artists with diverse genre representation. I calculated this metric with hip hop, r&b and rap grouped.

I calculated correct-genre classification by seeing if the word tokens that artists' genres matched the genre labels that Spotify had given each artist. I hoped to determine whether Spotify genre labels matched the actual placement of their songs within Mix playlists.

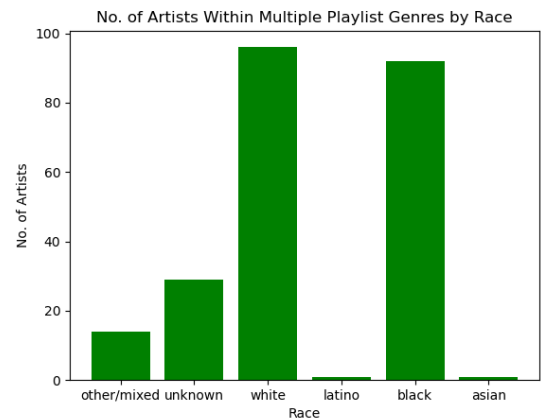
I calculated pop-possibility by counting the number songs that artists had in pop playlists. I plotted this count against popularity and number of followers, and calculated correlation of these success metrics against number of pop songs. I hoped to find if artists of certain races were less capable

of achieving representation in the pop genre despite higher levels of popularity.

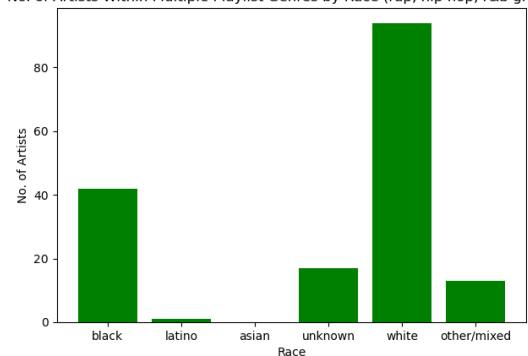
## 4 RESULTS

- Show your reader what your learned!

Genre representation:



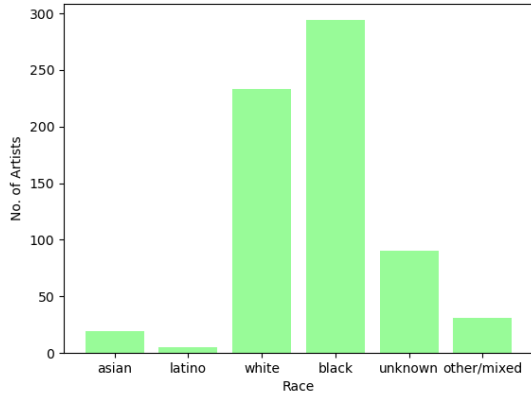
No. of Artists Within Multiple Playlist Genres by Race (rap, hip hop, r&b grouped)



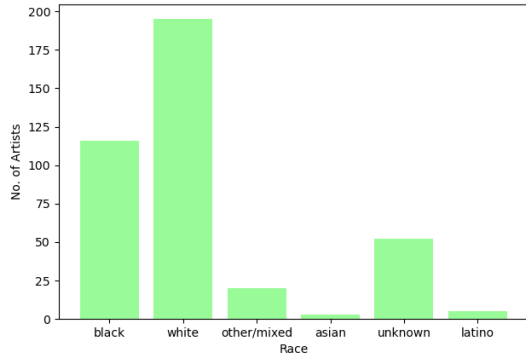
In the grouped genres plot, I found that there was some difference in the proportions of artist count and their actual population in the dataset: 11.2% of black artists, 13% of white artists, 22% of other/mixed artists, .06% of latino artists.

Exposure:

Artists Within Multiple Primary Playlists by Race (rap, hip hop, r&b grouped)



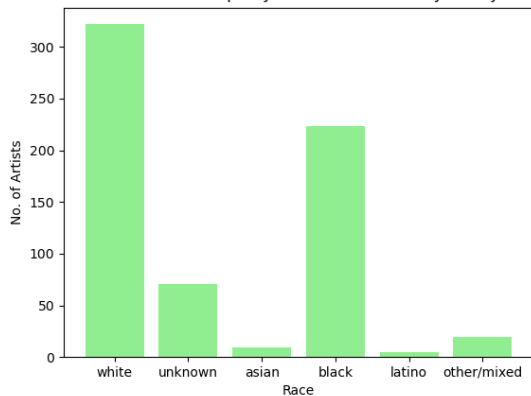
Artists Within Multiple Non-Primary Playlists by Race (rap, hip hop, r&b grouped)



I found that the number of artists for each race (in the non-primary playlist plot) were relatively proportional to their populations: 30.9% of black artists 27% of white artists 28% of latino artists 10.3% of asian artists.

#### Correct Genre Classification:

No. of Artists Within Spotify-Identified Genre Playlists by Race



I found that artists of each race were correctly implicitly classified by their songs' appearances in genre playlists at surprisingly high rates across the board: 44.7% of white artists

59.5% of black artists 27.8% of latino artists 31% of asian artists.

#### Correlation between genre and success metrics:

|                   | artist_popularity | artist_followers |
|-------------------|-------------------|------------------|
| r&b               | 0.134078          | 0.064529         |
| rock              | 0.168767          | 0.088047         |
| house             | 0.053377          | -0.040437        |
| edm               | 0.127160          | 0.040814         |
| rap               | 0.257834          | 0.207440         |
| hip hop           | 0.227711          | 0.264587         |
| pop               | 0.368709          | 0.523756         |
| country           | 0.071450          | -0.039914        |
| jazz              | -0.293961         | -0.103869        |
| multiple          | 0.234052          | 0.101396         |
| black_grouped     | 0.302355          | 0.264588         |
| artist_popularity | 1.000000          | 0.533830         |
| artist_followers  | 0.533830          | 1.000000         |

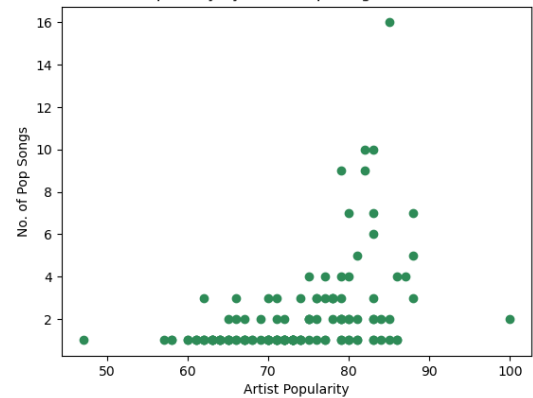
I used the aggregated counts of artists' songs in each genre and their correlation with Spotify's two built-in success metrics to motivate the next section.

I confirmed that artists' number of songs in pop playlists was the highest correlated with both popularity and number of followers.

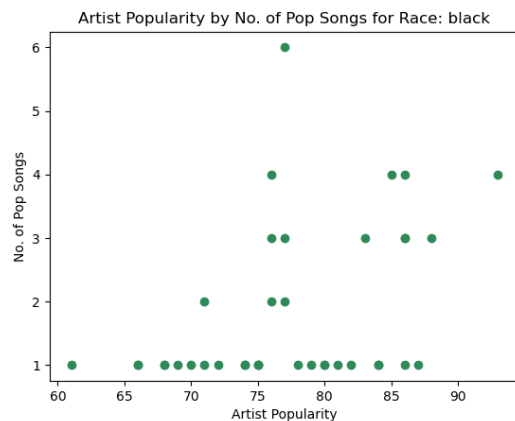
#### Pop Possibility:

I chose to only do this analysis for black and white artists, because they were the only race groups with enough pop songs to do meaningful analysis. I plotted both number of followers and popularity against number of pop songs.

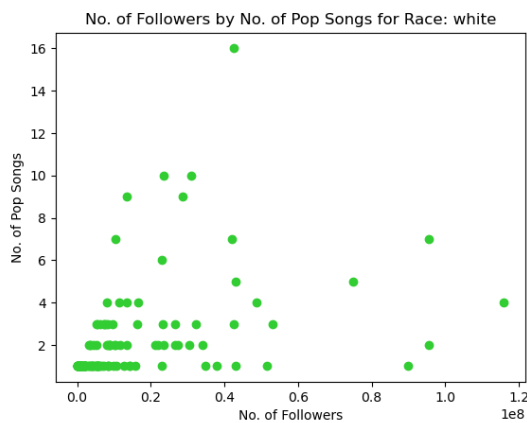
Artist Popularity by No. of Pop Songs for Race: white



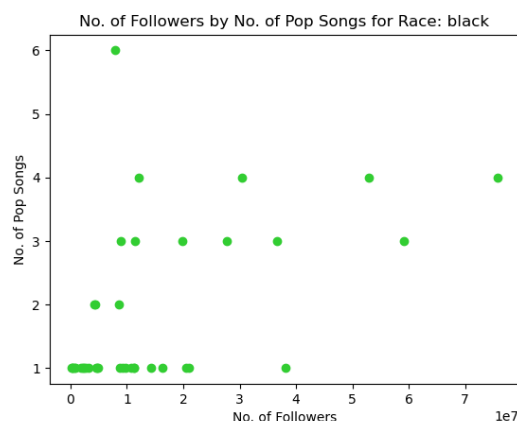
Correlation for white artists (popularity vs. num pop songs): 0.43



Correlation for black artists (popularity vs. num pop songs):  
0.41



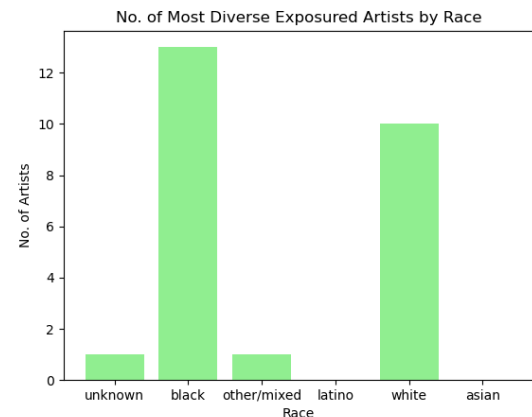
Correlation for white artists (followers vs. num pop songs):  
0.41



Correlation for black artists (followers vs. num pop songs):  
0.51

I found that the correlations were similar for both races, implying that popular artists from either race are capable of producing songs in the pop genre.

Exposed Artists:



In this plot I compared the top 25 artists who showed up in the most playlists by race. I did not find anything glaringly unfair, but in general this lead me to find some statistics about diversely exposed artists.

I confirmed that being diversely exposed is good for artist success. Artists in the top 25 most diversely exposed appeared in 9-12 playlists each compared to average 1.7 playlists for artists.

These top artists has an average popularity of 84.6, compared to 60.43472222222222 for entire dataset.

Additionally, top artists had an average followers of 31,654,654 compared to 3,705,676 for entire dataset.

## 5 CONCLUSION

- What are your main conclusions? Connect these back to your motivation.

My main conclusion is that there is not obvious that Spotify does implicit genre classification on the basis of race. Across each of my metrics, I found that both black and white artists had similar metrics regarding exposure, genre representation, rank, and pop-possibility. Still, I believe that there are some interesting insights.

Firstly, this project did confirm that artists' ability to live within multiple genres certainly correlates with success. Additionally, pop as a musical genre is highly correlated with musician success.

One disparity that I did notice was diverse genre representation of latino artists, where only 0.06% of latino artists lived within multiple types of genre playlists. This may be indicative of not enough data.

- What limitations does your project have?

The first subject of limitations that I had was in labeling. Labeling was far too time-consuming to do manually and individually, and if I were to collect data at a larger scale in the future, I would certainly need access to outside labelers. Additionally, classification was difficult for multiple reasons. Firstly, some artists were groups, and I had to classify based on majority race, which was imperfect. Also many artists were hard to identify, and were left to my own error, or placed in other/mixed. As a race category, other/mixed is hard to analyze, because you cannot attribute it to some group with specific social treatment.

The second limitation was in the data itself. Initially, I think that the data was skewed towards music that is typically aligned with black groups and that is highly interactive in its existence in the music industry. Including r&b, hip hop, and rap, made analysis a bit difficult, because in some ways some combination of these genres are the same (EX: r&b contains elements of rap). I also do not feel that I had enough data to accurately generalize trends within the streaming platform. Additionally, another limitation is that it is somewhat impossible to get "true" genre labels at a larger scale. Most artists do not officially identify as a singular musical genre, and even if they all did, scraping this information would be an extremely difficult process. One final limitation is the Spotify API itself. I was unable to determine how they choose the data to return when you query for Mix playlists, but the ones I received were not accurate to the actual Spotify accounts I created the clients for.

The third limitation was with my analysis. As I mentioned, I feel that my analysis would be more meaningful if I had more data that accurately represented all races and musical genres. Additionally, a lot of the analysis was difficult to come to definite conclusions about because of chicken/egg issues. For example: Do artists make pop music because they are popular, or does making pop music turn you into a popular musician.

- What would future work entail?

For future work I would certainly like to acquire more data that is representative of all the populations I plan to analyze. In order to do this I might consider outsourcing labeling or combining it with some AI race labeling service.

I would also like to determine an outside data source to give me more confidence about artists' "True genre."

I would also consider expanding this analysis to another music streaming platform.

Finally, I would like to perform some type of case study analysis on specific artists that I can acquire confident race, genre, economic data, and streaming statistics for. This would allow me to explore specific instances of potential bias.

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