The research question that I am interested in solving deals with the genre classification of a particular artist in the musical canon. Echo Nest, whose parent company is Spotify, classifies artists as having some genre labels. In many cases, artists can be represented by a few different genres which distinguish them from other artists. Echo Nest uses semantic labeling to establish a more granular perspective into the world of genre, focusing less on the genre, and more the worlds which describe the sound (The Echo Nest, 2014). This information is available to Spotify users through the Spotify API. What's not clear, however, is the way in which these artist labels are accounted for through time. For example, consider Bob Dylan who some might consider a folk artist in his early career transitioning to a more rock-filled sound in the later part of his career. Spotify classifies Dylan by both genres, among others like "country rock" and "mellow-gold" which is described by pop, soul, and easy-listening (Mrarroyo, 2017). This might be an easy sentiment to handle considering the huge popularity that Dylan has seen since he first became popular in the early sixties. But how can we classify one artist in the canonical context of that genre? Can Bob Dylan really be lumped into the same category as the likes of Joni Mitchell and AC/DC in the folk and rock genres, respectively? In other words, can artists be described under an umbrella of genres? This question is difficult, regardless of whether an artist's repertoire has changed, but not impossible to answer using the Spotify API.

To alleviate some of the challenges of this question, I will limit myself to a single broad genre. This would allow me to take a random sample of artists in that genre that I expect to be broadly reaching. As far as quantitative assessment goes, the only claim I will be able to make is that some musical characteristic is particularly important to genre. For example, pitch is important in the characterization of music being rock music. I won't be able to make broad general claims using this method of analysis, so my research will be idiographic and pertaining to the case of one genre.

The question that I am attempting to answer is whether we can use the features of an artist's repertoire to explore which genres they fit into. The Spotify API provides plenty of information to describe the audio features of a song like Pitch, Tempo, and Timbre. As I mentioned above, I will be limiting myself to one genre. The sampling technique that I will use will consist of compiling a list of Spotify Artist IDs (what the API uses to search and provide artist genre) of artists who are classified into a broad genre such as jazz or rock. This technique will ideally provide a wide variety of results with new and old, popular and unpopular, and mainstream and experimental artists. The data itself will be generated using the "spotifyr" library in R, which is an abstraction of the Spotify API in R. My research meets the terms and condition for fair use of the Spotify API in this project. Below is a tabular representation of the most important variables in my research. Most are self-explanatory, but some others like timbre or key are a bit more tedious to figure out but are explained below. There are two aspects to the dataset which are a bit interesting. First, is that timbre and pitch are measured over the duration of the song, and not a single value. This created opportunities to compare the timbre vectors of one song with another over the course of the song or multidimensionally scale the entire timbral variable for comparison to other songs (Savelsberg, 2021). Also worth noting is the small bit of wrangling that will be necessary. Once an artist is a part of the sample, it will become necessary to compile various audio attributes of their songs. These are int the audio analysis part of the API. I will also need to use a different pull from the API to gather the release date to determine changes over time.

Variable	Type	Notes
timbre	Continuous (array)	These are the coefficients which “build” timbre. Timbre is a linear combination of 12 different musical characteristics which shape the sound. This is an array because timbre is recalculated over non-overlapping segments of the song.
pitch	Continuous (array)	An array of relative values of pitch of a song by pitch classes (key). It is normalized to be on a 0-1 scale describing the relative pitch of a single pitch class. Again, this is an array since pitch is recalculated over segments of the song.
duration	Continuous	The length of time (in seconds) that timbre and pitch are measured over.
tempo	Continuous	Speed or pace of song.
time_signature	Discrete	$3 \leq$ time_signature ≤ 7; corresponds to time signature of “3/4”, “4/4”, “5/4”, “6/4” or “7/4”.
key	Discrete	$-1 \leq$ key ≤ 11; corresponds to the key the song is played in. It is formatted in standard pitch class notation (i.e., C=0).
loudness	Continuous	Measured in decibels (dB). Typical range about -60 to 0.
Spotify ID	Nominal	Measured in base-62 and identifier of unique song, artist, album, playlist, user, etc.
genres [artist]	Nominal	Genres assigned by Echo Nest.
release_date [track]	Ordinal	Release dates of songs by year, month, and day.

The potential bias that I have considered is most largely the selection bias in my sample. I think that I have alleviated some concern by reducing my scope to one genre, but I can’t help but think I will be limited by the popularity of certain artists. I could argue that popular artists have been around longer and would hold out a better opportunity to analyze the change of the genre in canon over time, but the idea doesn’t seem bulletproof. Another sampling option that I have thought about would be to randomly sample the entire list of Spotify artists and filter those down by those who share the genre I'm interested in. This would alleviate concerns with selection bias but would be much more burdensome computationally.

The intention of my project in the literature review stage was to conduct music recommendation based on multidimensional feature spaces that songs have (Oramas, 2017). While this new research question won't consider recommendation, it will consider song features. It will consider the song features over a particular genre, hopefully consolidating the feature space just a little bit more. I would then perform clustering on this feature space to see whether certain genres or artists have changed over time. This may also be made easier with an even bigger simplification down to just a few artists. If over time I can observe a change in a particular genre, this may further lend itself to the idea that broad genres like I propose to study are rarely characteristic of anything clear, but rather, something that has been created to somewhat simplify the immense volume of music available to a user.

Another option that I have would be to change my sampling procedure to simply random sample the population of Spotify artists and use the feature space I build with these artists to classify the presence or lack of a certain genre in that artists repertoire. Two intriguing classification algorithms would be a support vector machine (SVM) and a decision tree. Both offer different benefits. SVM works well with high dimensional data but lack interpretability (Nalini, 2016). Decision trees could help solve the interpretability problem in understanding music but might not offer as precise of predictions as the SVM would (Schedl et al., 2013). Both techniques would need to be refined in the context of the data. I would likely validate my models effectiveness using K-fold cross validation and optimize for F1 score. Testing in these ways would allow me to measure what kind of musical descriptors are used to define a particular genre.

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