– Independent Work Report Spring 2019 –

Measuring Musical Sampling Impact Through Network Analysis

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Abstract

Musical sampling influence has only recently been studied through network structures through the basic analysis of artist-artist sampling relationships. In this paper, we integrate the use of additional properties of music sampling (such as genre, time period, and audio element sampled) to investigate patterns of influence in the musical community at large. Using the WhoSampled dataset, we investigate statistical metrics such as the most-sampled artists songs as well as the trend for musical sampling over time. we also take a more nuanced look at "influence" by providing a variety of graph centrality measurements for determining the influence of a node (representing an artist) on other nodes. This analysis resulted in a greater understanding of musical influence certain artists and genres had over other heavily-sampling artists and genres over time. The most influential genre was found to be Funk/Soul/Disco while the most influential artist of all time was James Brown. More specific influencers from different time periods were also found. We conclude with possible future research that can be applied to this network analysis of musical sampling.

1. Introduction

Music sampling is the act of taking a portion of another musical piece and reusing it as an element in a new recording. Musical sampling dates as far back as the 1890's which suggest that sampling may be a product of stylistic practices rather than being a modern trend. While certain genres of music are notable for utilizing sampling heavily during certain eras such as early 90's hip-hop, the use of sampling has spread far beyond hip-hop and is being employed by a variety of music producers across a variety of genres.

Sampling will be the measure of musical influence in this paper. Specifically, influence will be partially defined by the number of times a piece is sampled by other pieces. Sampling informs listeners of the artist's level of influence on other musicians within their expected sphere of influence within a genre or outside of it. With this in mind, we can ask, "Are there certain musicians or genres that exhibit a strong influence on others in the music community?"

The primary goal of this paper is to explore relationships between artists and genres and determine which utilize sampling the most in comparison to others. In addition, we can observe intra-genre and inter-genre sampling (having a sample be used by an artist from the same genre versus another genre, respectively). By noting the intra-genre relationships, we can identify whether artists tend to sample more from other artists within their genre or if they tend to extend their musical reach to unrelated genres instead. The secondary goal is to apply our network analysis on the sampling patterns of audio element (sample vocals, bass lines, drum beats, etc.) sampling across genres to different time periods. This time-based model of analyzing sampling can uncover specific sampling practices that arose during certain eras or possibly failed to exist after a certain period, an aspect of musical sampling that is often unconsidered in past related works.

1.1. Sampling Influence and Copyright Law

The importance of musical sampling influence takes on a controversial role in modern music due to the variety of lawsuits arising from unrestricted use of samples. Somoano notes that parties filing lawsuits for uncondoned sampling usage often cite the fact that their music has greatly influenced the music community to bolster the argument behind the importance of the possession of their song as billable property. [16] We can interpret these statements as saying that their sampling influence in the music community is both culturally noticeable and quantitatively measurable. By charting musical influence patterns with sampling based on a variety of factors such as time period, genre, and audio element sampled, one can better understand the artists and record companies filing lawsuits for uncondoned uses of a sample and observe whether their record does have a large influence on specific musical communities.

2. Related Work

2.1. Musical Sampling Influence Networks using WhoSampled

In past works, research has been performed on basic network analysis of sampled music that is grouped into genres at the very least. This is seen in a paper by Bryan and Wang from Stanford University's Department of Music. [7] The paper utilized the WhoSampled.com dataset to analyze musical influence and rank artists, songs, and genres based on their level of "sampling influence" throughout history then proceeded to rank the categories based on their amount of sampling analyzed via clustering and node degree. Overall, network analysis was used to indicate the relative flow of samples between genres. However, no intra-genre analysis was included which limited the potential findings that this dataset gives access to. The paper noted the complex nature of using network analysis to define "influence" in music but settled on using degree centrality as a sole measure of influence. They came to the conclusion that a unique power-law degree distribution is followed in the musical sampling world: Funk, soul, and disco music are heavily sampled by hip-hop, R&B, and electronic music when compared to the other genres that are sampled. A heavy focus was put on hip-hop, R&B, and electronic music as well while generally leaving the other sampling genres unanalyzed as the data for other genres was less rich. The paper also noticeably omits any analysis on any properties of the sampled or sampling music such as harmonics or audio elements.

Additional research by Stanford researchers Alban, Choksi, and Tsai attempted to investigate music sampling based on harmonic and timbral features such as dominant chords and qualitative emotional response. [4] It was a direct attempt to extend upon the work done by Bryan and Wang by placing a greater focus on features of the sampled works that are noticeable (but sometimes very subtle) to individuals with a deep background in music theory. The researchers identified the music by specific harmonic and timbral features rendered by the piece. Examples of "harmonic features" include "changes involving minor/major 7th chords" and "natural minor key changes". "Timbral features" include "calm, quiet, mellow". This paper's focus was clearly a far departure from the general sense of "influence" described by Bryan and Wang as this maps influence to preferential attachment in the network graph. Each edge was scored using a product of the degrees of each node to denote influence whereas our influence metrics include multiple types of centrality and degree measures rather than choosing a single model for influence.

The focus of Bryan et. al. and Alban et. al. varies from this paper as they mainly attempted to draw associations between the presence of harmonic and timbral features and their ability to make a song more likely to be sampled to form a ranking of top features. In addition, our paper does not touch on harmonic features because music theory would require additional knowledge that is not the focus of our "influence". Timbral features are not included in our paper either due to the need for granular data tagging that would be required in our dataset which was not provided by WhoSampled. Neither of the papers touched on the quantitative popularity of sampling over time much less the specific sampling techniques used over a set number of decades.

Brandford performed a unique solo analysis of sampling done by Kanye West and applied many analysis strategies that our paper also applies. [6] One of these unique areas of analysis is time period. Brandford sorted the songs Kanye West sampled into the decades they were created in and found that a disproportionate number of samples came from 1970's tracks. It is important to note that West's samples encompassed every decade back to the 1950's. Simpler data analysis that the previous two pieces of research employed were also used by Brandford. Basic statistics on the number of samples Kanye West has used and the number of artists these samples came from were cited to ensure the reader that researching Kanye West alone could provide a rich dataset. No analysis on genres was mentioned. It was clear that the focus of analysis was more limited in this investigation as most of the analysis was placed on time period and pure numbers of occurrences rather than forming a network (which, to Brandford's defense, would be quite limited for a single artist). Our paper does borrow the idea of investigating time period from Brandford's investigation as it provides a better understanding of the types of music that sampling producers find an interest in when sampling music.

2.2. Alternative Measures of Influence in Music Networks

Watson uses social network analyses from an economic and sociological perspective to pinpoint the connectivity of music networks between large metropolitan areas by analyzing their connectivity with music sampling. [21] Additionally, Watson's paper focuses on networks by looking at geographical areas as the nodes whereas all aforementioned works use a piece of music as a node. However, a sample usage still creates a link between nodes. Network graphs are where each node represents a metropolitan area and their number of links in the graph (amount of influence over the music industry as a whole) increases as more albums sample a song distinctly produced in their city. Nodes with greater degrees indicate more central metropolitan areas with greater influence in the music sampling network. This research applies the same principles we saw in Bryan and Wang's work but applies it to geographical areas and looks at these areas, rather than individual artists or genres, as the creators of musical influence. This is a large assumption that deviates from the popular belief that the reason a piece of music is sampled is due to the genre or artistic style provided by the track. Instead, the work believes that the unique characteristics of an area's musical community finds its way into its artists work and makes it more appealing to certain producers for sampling. Our paper deviates from this belief and analyzes influence through the traditional view of artists or genres as the creators of unique audio characteristics that make them more appealing for sampling.

A unique usage of networks was analyzed by Youngblood to analyze cultural transmission modes of music sampling in the modern era with the rise of the Internet. [22] Though the paper approaches the topic from a sociological perspective, there continues to be a focus on how sampling and how influence is spread across a network (i.e. how an artist or song becomes popular to sample). Youngblood specifically looks at the transmission of specific drum breaks through musical sampling in two different environments: Traditional cultural collaboration networks and online community networks with access to the collective knowledge of all members. The research looks at data through only three of the most (allegedly) popular sampled drum beats of all time and proceeds to analyze whether the music was sampled through a cultural collaboration network by noting time and distance. Based on the year the sample was made and the geographical location of the sampling song's production studio, they attempted to classify which of the two environments this sampling was inspired by. Results found that sampling is less influenced by geographical location and prior collaboration between artists due to the rise of internet networks. The author claims this has led to an increase in social interactions between artists and therefore sampling in general in the modern era. Like Watson's work, this use of networks is very different from ours but it provides an alternative way to look at how influence can be derived from a song's sampling usage.

Rather than looking at influence through sampling, one can also look at influence through the number of collaborations a musician has with other musicians. Zinoviev specifically analyzes the success of musical groups as a function of the amount of collaboration between them and other musical groups as represented in a social network. [23] He hypothesizes that groups with greater public popularity benefit the most from cultural cross-pollination caused by performers moving between working on different projects and collaborating with a variety of artists. The findings suggest that average neighbors' degree affects the success of a musical group node in a graph indirectly. Zinoviev found weak, but statistically significant correlations between degrees and and centrality in a collaborating network. Zinoviev also conclude that analyzing nodes with a higher centrality across multiple measures generally acted as a better predictor of success than simply making a prediction without these measures.

3. Approach

In this paper, we begin by creating and analyzing a standard network graph connecting artist nodes by an edge representing an instance of a sample. This can be used to analyze the sheer volume of samples and helps us form sampling communities (Louvain Communities) at a basic level to help us analyze smaller groups of sampling communities. This approach allows for standard analysis of metrics such as finding the most sampled artist or song throughout history.

However, the unique method by which we am investigating musical sampling networks is through analyzing changing sampling patterns over time periods, the type of audio element sampled, as well as within genres (intra-genre) and between genres (inter-genre). This adds a unique approach giving insight to the question of, “who samples what from which songs during which era”? The added element of analyzing the unique sampled audio elements of a song is something that has not been explored in past works.

This paper utilizes a combination of common statistical measures as well as network measures to determine influential genres and artists as well as the specific pattern of properties each of these may follow. All analyses were performed on the entire dataset encompassing all time periods in addition to analyses limited to specific decade-long time periods. This was done to study the "release date" property of the WhoSampled dataset and to view changing musical influence patterns over time. Combining all of these measures and analyzing the patterns of sampling properties allows us to identify the most influential parties in the music sampling community.

In fact, the inclusion of audio elements is made possible by the updated WhoSampled dataset that other researchers have not had access to in the past as former pieces of research did not have this property within their datasets. Others have not tackled the subject with the focus on sampled audio elements nor sampling over time, but my approach is adequate for investigating previously unnoticed factors/properties of sampling patterns as the dataset supports the cataloging of these attributes.

4. Implementation

Sampling usage is a directional relationship represented by a directed edge from the sampling artist to the sampled artist. While it is possible for an artist to sample another artist on multiple instances, our dataset does not have any of these occurrences. Had this occurred, each directed edge would contain a weight whereby an added weight of 1 would indicate an additional sample. But, our network is only directed and not weighted. We visualized the graphs and data with Matplotlib and carried out network measurements and operations using the NetworkX library for Python. [2, 1]

4.1. Data

The data needed to build a musical sampling network was acquired from the WhoSampled database. [3] This database contains approximately 300,000 instances of recorded samples as reported by volunteers and WhoSampled's sample identification algorithms. The dataset used for this project consisted of 30,000 instances of sampling selected from the entire database with uniformly random distribution. Each sample contained data on both the sampling and sampled artist names, song titles, genres, and release years. Furthermore, the type of audio element sampled was included for each sample. For the purposes of this project, we define sampling as music, speech, or sound that is reused from a recording with or without variations such as tempo or pitch. As such, "recordings" from before 1877 (before the existence of the first phonograph recording) were removed from the dataset. Additionally, sampling data for the 2010's is disproportionately lacking in the WhoSampled database as sampling data is simply slow to be registered onto the database. Samples including artists, "The Bible" and "Traditional Folk", were also removed as the former indicates written passages from The Bible and the latter indicates written material from traditional folk songs. The final dataset contained 29,667 samples. We created a directed graph where each node represents an artist. Each edge from Node A to Node B represents Artist A's usage of Artist B's song in a song (i.e. a sample). Each edge also contains a single edge property indicating the specific audio element sampled from Artist B's song. Furthermore, a single song may sample from multiple songs. This results in a network where there is a greater number of edges than nodes.

4.2. Statistical Measures and Patterns

The statistical measures amount to finding the correlation between two different properties of a sample. We look at the proportions of sampling usage while holding one of these properties stable to find possible patterns. For example, we hold a single genre stable and find the proportions of audio element types that are sampled from that genre. Or, we may hold a genre stable and find the proportions of audio elements that genre samples from others. For each of these measures, analysis is performed over the entire dataset but is then separated by time period to also discover any time-sensitive patterns. These findings are then combined into various tables for comprehension and plots for visual display.

4.3. Centrality and Influence (Network Measures)

Centrality is used to gain knowledge about how connected certain nodes are in relation to the entire network. We seek to identify influential nodes based on how connected they are to the rest of the network.

For some centrality measurements this can mean influence only in regards to being sampled by others (i.e. a node's in-degree). Other centrality measurements also take into account how often an artist samples others (i.e. a node's out-degree). Moreover, betweenness centrality, eigenvector centrality, and Katz centrality do not take into account the directionality of the edges. These measures tell us more about artists that are both heavily sampled by other artists and heavily sample other artists themselves. However PageRank is a measure that is derived from eigenvector centrality that takes edge directionality into account and is used in this analysis.

4.3.1. In-Degree Centrality is the conceptually simplest measure of centrality. The in-degree centrality for any node v is the fraction of nodes from the entire graph G that its edges are connected to. The centrality values are normalized by dividing by the maximum possible degree in a graph $n-1$, where n is the number of nodes in G. Despite being a simple measure of centrality, in-degree centrality returns the artists that have been sampled the most often from the dataset. This is a telling measure of influence as designated by our definition as a greater number of times sampled amounts to greater sampling influence.

4.3.2. Betweenness Centrality of a node v is the sum of the fraction of all-pairs shortest paths that pass through v. A higher betweenness centrality represents a node with greater influence over the network as more information passes through that node. The node acts as a "bridge" between other nodes in a network.

$$c_B(v) = \sum_{s,t \in V} \frac{\sigma(s,t|v)}{\sigma(s,t)}, \tag{1}$$

where V is the set of nodes, $\sigma(s,t)$ is the number of shortest paths from s to t, and $\sigma(s,t|v)$ is the number of those paths passing through some node v other than s,t. If $s = t$, $\sigma(s,t) = 1$, and if $v \in s,t$, $\sigma(s,t|v) = 0$. In the context of music sampling, an artist with higher betweenness centrality is either sampled by other artists often or samples other artists frequently. Removing an artist with high betweenness centrality would disconnect more subgraphs, exhibiting an artist's ability to act as a "bridge" between nodes in a network.

4.3.3. Closeness Centrality of a node u is the reciprocal of the average shortest path distance to u over all $n-1$ reachable nodes. A higher closeness centrality score implies an artist has more direct influence on all other nodes.

$$C(u) = \frac{n-1}{\sum_{v=1}^{n-1} d(v,u)}, \tag{2}$$

where $d(v,u)$ is the shortest-path incoming distance from v to u, and n is the number of nodes that can reach u. Because the graph is not completely connected, this algorithm computes the closeness centrality for each connected part separately scaled by that subgraph's size.

4.3.4. Eigenvector Centrality computes the centrality for a node based on the centrality of its neighbors. Much like in-degree centrality, eigenvector centrality measures a node's influence based on the number of incoming edges it has. Eigenvector centrality builds upon this by taking into account how connected their neighbors are to the rest of the network. The eigenvector centrality for node i is the i'th element of the vector x defined by the equation,

$$Ax = \lambda x \tag{3}$$

where A is the adjacency matrix of the graph G and λ is the largest eigenvalue of A as it is the eigenvalue associated with the dominant eigenvector. This largest eigenvalue results in the desired centrality measure.

The power iteration method used by NetworkX's eigenvector centrality algorithm guarantees that there is a unique solution x, all of whose entries are positive, if λ is the largest eigenvalue of the adjacency matrix A.

4.3.5. Katz Centrality computes the relative influence of a node within a network by measuring the number of the immediate neighbors (first degree nodes) and also all other nodes in the network that connect to the node under consideration through these immediate neighbors. Essentially, Katz centrality determines a node's centrality based on the centrality of its neighbors. It is procedurally similar to eigenvector centrality. The Katz centrality for a single node i is,

$$x_i = \alpha \sum_j A_{ij} x_j + \beta, \tag{4}$$

where A is graph G's adjacency matrix. All x_i's are centrality values of the current fixed point being analyzed (i.e. the point of convergence). The variable β provides greater weight to immediate neighbors. On the other hand, the factor α is strictly less than $\frac{1}{\lambda_{max}}$ (inverse of the largest eigenvalue in A) and acts as a penalization factor for connections with distant neighbors.

4.3.6. PageRank computes a ranking of the nodes in the graph G based on the structure of the incoming links much like eigenvector centrality. The main difference lies in PageRank's ability to account for edge direction which is important for finding the most influential sampled artists. Though originally used for ranking web-pages, it is included in network analysis modules like NetworkX due to its success in determining highly influential nodes. Eigenvector centrality and Katz centrality also attempt to keep the neighboring node importance in mind.

4.4. Groupings and Segmentation (Network Measures)

Clustering coefficients are normally used to group and identify how many tightly clustered groups are present in the entire network. Identifying communities in a graph allows us to determine subgroups of artists that primarily sample from each other and have the potential to display unique properties regarding the types of samples they employ in their music.

4.4.1. Louvain Modularity is a scale value between -1 and 1 that measures the density of edges inside communities to edges outside communities. Finding the Louvain Modularity involves a two-phase algorithm: First, small communities are found by optimizing modularity locally on all nodes. This is performed by computing the partition of the nodes which maximizes the modularity,

Q, which is defined as

$$Q = \frac{1}{2m}\sum_{ij}\left[A_{ij} - \frac{k_i k_j}{2m}\right]\delta(c_i, c_j), \tag{5}$$

where A_{ij} is the adjacency matrix where an edge between i, j is represented with a 1 and the absence of an edge is represented with 0; k_i and k_j are the sum of the weights of the edges attached to nodes i and j, respectively; $2m$ is the sum of all of the edge weights in the graph; c_i and c_j are the communities of the nodes; and δ is the Kronecker delta function which outputs 1 if $c_i = c_j$ and 0 if $c_i \neq c_j$. This first step is applied to all nodes until all nodes are placed into the optimal communities in which no modularity increase can occur. In the algorithm's second step, each small community is grouped into a single node and new edges are formed. Edges between nodes in the same community are represented as self-loops while links between nodes in different communities are represented normally. With this new network where the communities act as nodes, the second step finishes and the first step is repeated. The process continues until no new communities can be formed in the second step of the algorithm.

By isolating these Louvain communities, we are able to analyze the sampling makeup of these communities and view at a closer scale which artists and genres generally sample from each other. This can be used to verify the broader statistics we discover about the entire dataset.

4.4.2. Average Clustering Coefficient for the graph is the average,

$$C = \frac{1}{n}\sum_{v\in G} c_v, \tag{6}$$

where n is the number of nodes in graph G. c_v is the local clustering coefficient of a node v. The network average clustering coefficient is the average of the local clustering coefficients of all vertices and describes how tight-knit groups are in the entire network. To understand c_v, one must understand the description of a "neighborhood". A neighborhood for a node v is simply the set of all its directly connected neighbor nodes. Specifically, the local clustering coefficient c_v for a vertex v is given by the existing proportion of links between the vertices within its neighborhood divided by the number of links that could possibly exist between them. As an example, a node with a high local clustering coefficient would mean that every one of its neighbors is connected to each other, resulting in a coefficient of 1.

Local clustering coefficient measures are used to rank individual nodes and how close a node in the network is to forming a clique with its neighbors. This coefficient describes nothing about how many nodes in the graph are connected to some node v. Rather, this coefficient indicates the connectivity within a node v's neighborhood. An average of clustering coefficients over the entire network was analyzed because it indicates the amount of connectivity nodes have within their immediate musical communities. Our resulting measure therefore indicates on average of how connected all nodes are within their community.

5. Results

5.1. Verifying Historical Musical Sampling Beliefs

As a sanity check, we first verify that our network analysis implementation of the WhoSampled dataset supports popular sentiments regarding music sampling. These sentiments are easily verifiable given the sampled dataset the operations are performed on is accurate and reflective of the entire sampling community. By verifying these sentiments, there will be greater confidence in the dataset and other operations made on the dataset. Though statistical significance is still preferred when performing statistical operations, this verification gives significance to this project's approach and implementation. We verify the questions: "Does Hip-Hop sample music more often than other genres?" and "Did 'Grand Upright Music Ltd. v. Warner Bros. Records Inc.' slow the sampling trend?"

5.1.1. Does Hip-Hop sample music more often than other genres? We easily answer this question by analyzing the number of nodes with positive out-degrees and noting each node's genre. The outward-facing edge for some node x indicates a sample usage for node x. Over the entire dataset, there is a clear imbalance in which genres utilize sampling the most in their music.

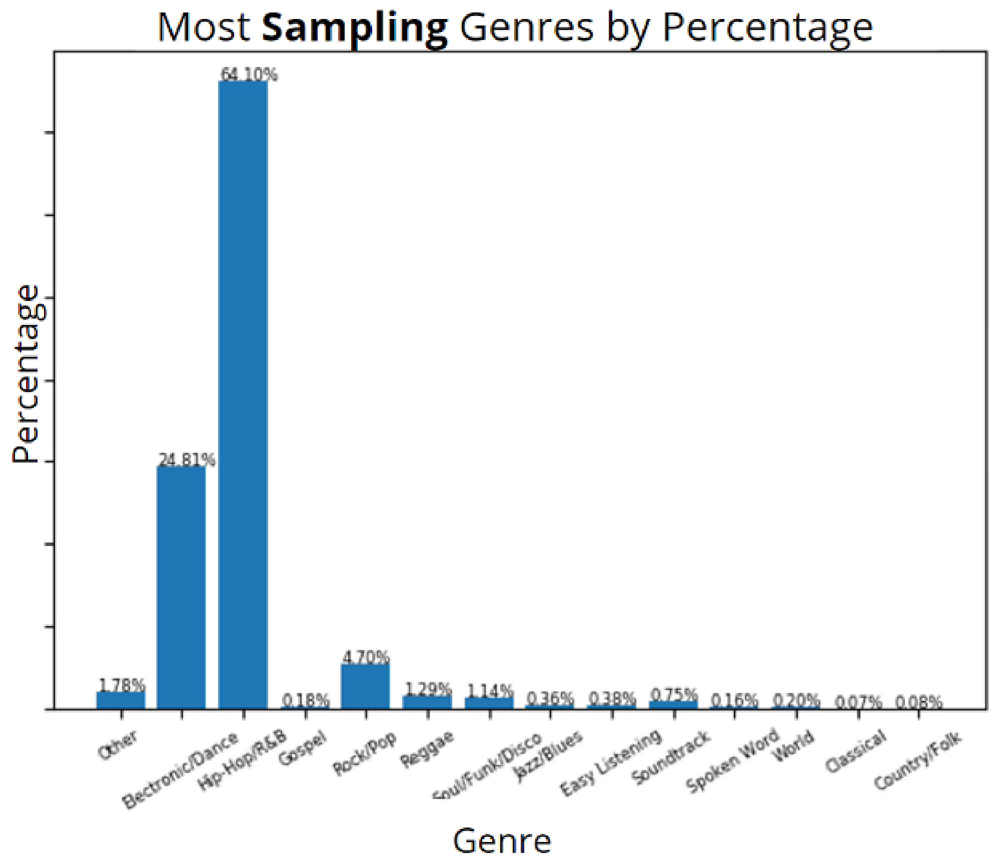


Figure 1: Most Sampling Genres Overall

From Figure 1, Hip-Hop/R&B artists make up 64.10% of all artists that use samples in their music. The second highest sampling genre is Electronic/Dance with 24.81% of all samples. Artists from these two genres alone make up 88.91% of all music samplers throughout all musical history. As originally claimed by the general public, Hip-Hop/R&B is clearly the highest-volume music sampler in the music community compared to all other genres.

5.1.2. Did "Grand Upright Music Ltd. v. Warner Bros. Records Inc." slow the sampling trend? The landmark court case in 1991 placed the first set of federal sampling laws upon artists, theoretically dissuading future artists from utilizing sampling in their music. It is not worth the time or money for many artists to attempt to clear an unlicensed sample.

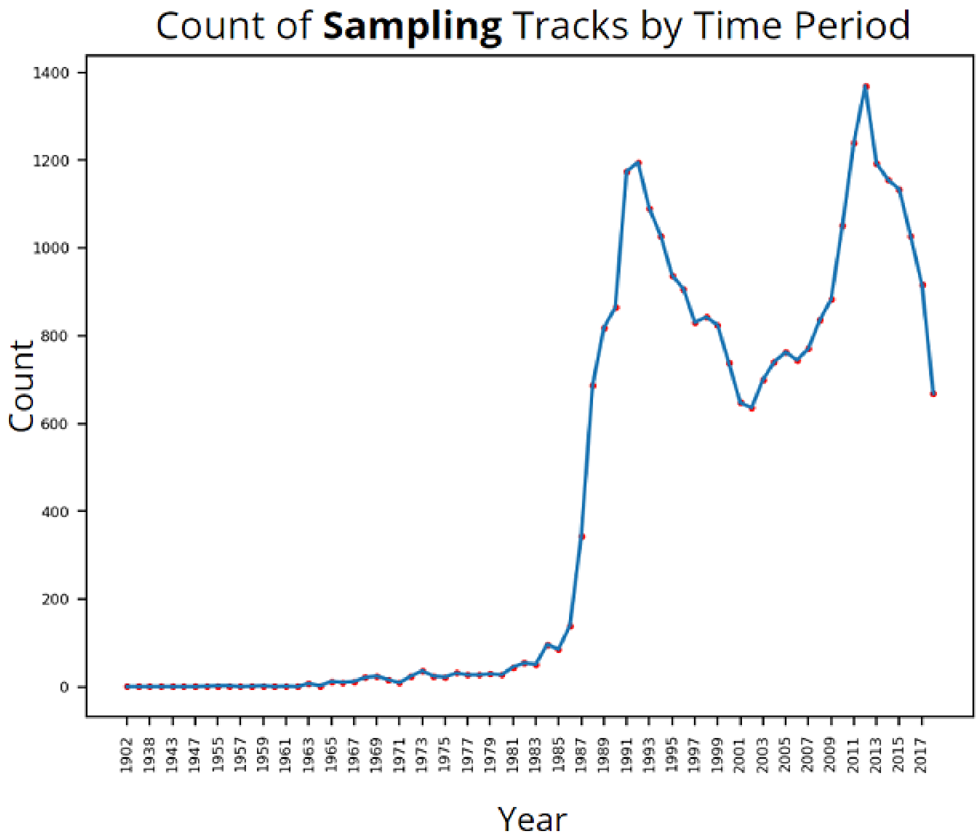


Figure 2: Count of Sampling Tracks by Time Period

Please note that the beginning section of the plot features a x-axis scale indicating "Year" that is not linear. Due to limited sampling practices, little to no data is included for large time periods in early years and is therefore omitted. In Figure 2, sampling volume saw a huge downturn from having approximately 1200 songs (in the dataset) with samples in year 1991 to approximately 600 samples by 2001. Sampling volume clearly became wildly popular in the late 1980's before it abruptly dropped around year 1991. This decrease in sampling volume occurred until 2001 when yearly sampling volume finally rose again until year 2011 when sampling volume equalized the levels seen in 1991.

There was a clear drop in sampling volume post-1991 that didn't begin to recover for another decade around 2001, as indicated in Figure 2. We cannot say that the downturn was a direct result of the Grand Upright Music Ltd. v. Warner Bros. Records Inc. ruling despite it being correlated with the year of the case. To answer the claim, we can say that the volume of sampling tracks post-1991 do correspond with a slowing in sampling usage in music overall.

As an aside, there was a large dip in sampling data post-2010. This can be attributed to the lack of sampling data from the 2010's in the WhoSampled database which is mentioned earlier in the Implementation.

5.2. Most Influential Genres

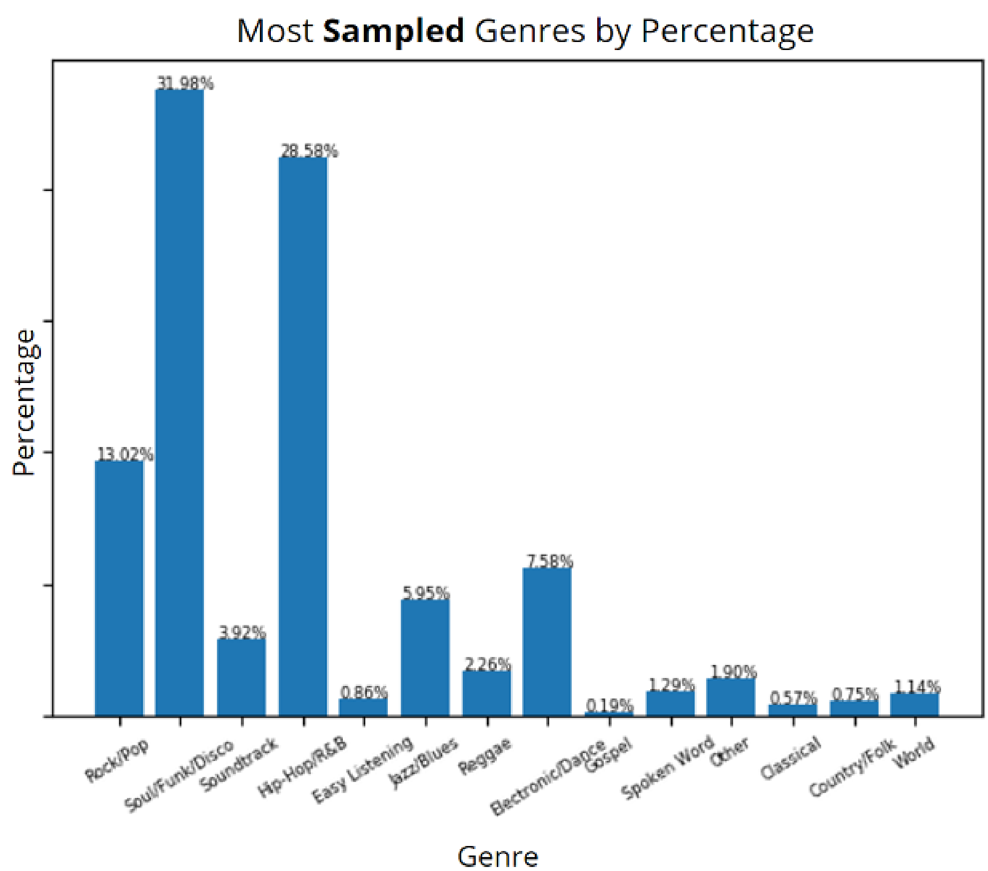


Figure 3: Most Sampled Genres Overall

Recall that being sampled by more artists implies greater influence in our model. Analysis of influential genres entails summing the in-degrees of all nodes in a genre to determine the number of samples. The more nodes of a single genre that were sampled, the greater proportion of samples that came from that genre. In Figure 3, we see two genres that are deemed highly influential and are sampled above all other genres. Soul/Funk/Disco was the sampled genre of choice for 31.98% of artists while Hip-Hop/R&B was sampled 28.58% of the time. It appeared that Soul/Funk/Disco was slightly more influential than Hip-Hop/R&B overall, but the two genres were clearly more influential than all other genres.

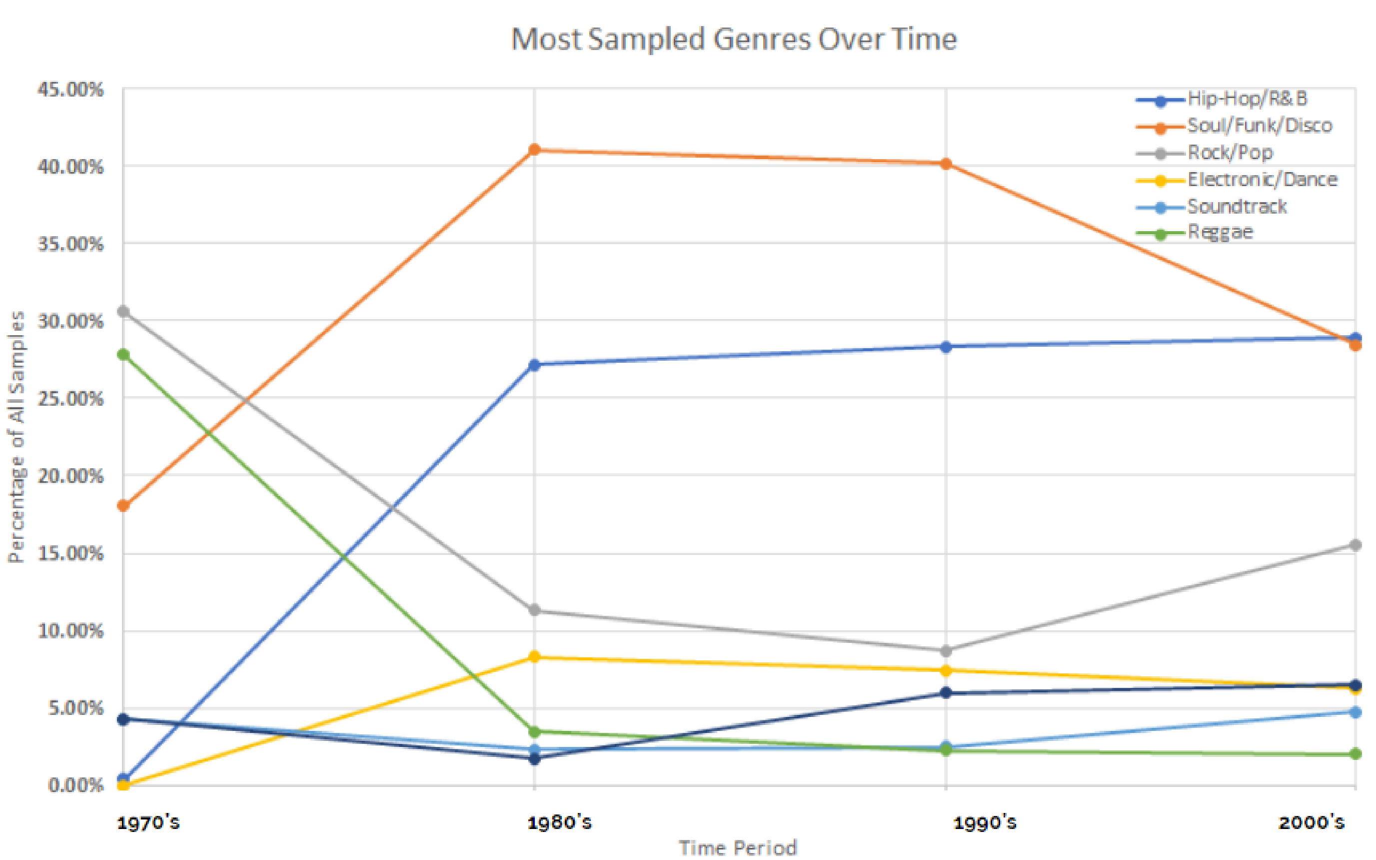


Figure 4: Most Sampled Genres Over Time

Understanding genre influence over time can provide stronger evidence detailing whether certain genres were always the most influential. From Figure 4, the early era of music sampling in the 1970's did not display a heavy influence by Soul/Funk/Disco or Hip-Hop/R&B (which was arguably not invented at the time). Instead, Rock/Pop and Reggae were the genres of choice by samplers that saw a decline in every time period since the 1970's. From the 1980's onwards, Hip-Hop/R&B and Soul/Funk/Disco established their strong influence. At its peak, Soul/Funk/Disco was sampled by over 40% of all sampling artists in the 1980's before falling to under 30% in the 2000's. Hip-Hop/R&B's popularity as a sampled genre rose dramatically from 0% in the 1970's to over 25% in the 1980's and has made minor increases in sampled proportion since. By being sampled roughly 27% of the time in the 1980's to 29% of the time in the 2000's, it has stabilized while Soul/Funk/Disco's sampled proportion dropped. Hip-Hop/R&B during the 2000's took over Soul/Funk/Disco as the most influential genre by a small margin. We can gather that the two aforementioned genres continue to be highly influential but Soul/Funk/Disco's influence may be lessening in the current and future time periods.

5.3. Intra-genre and Inter-genre Sampling Strength

Artists that sample music from within their own genre perform intra-genre sampling. Exactly 32.6% of all samples by artists were found to be from other artists within their genre when viewing the entire dataset. Considering one might expect an artist to sample from all genres equally and uniformly, 32.6% is a significant proportion. Clearly, artists are inclined to sample from other artists in their genre because it may align more closely to their musical goals.

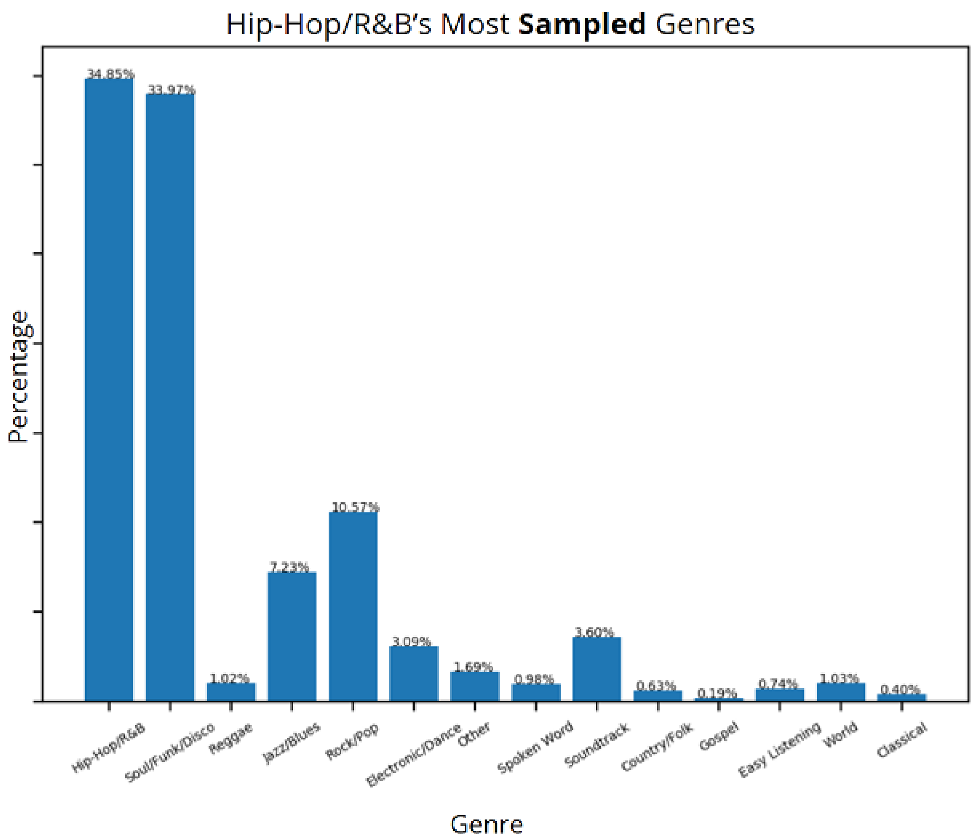
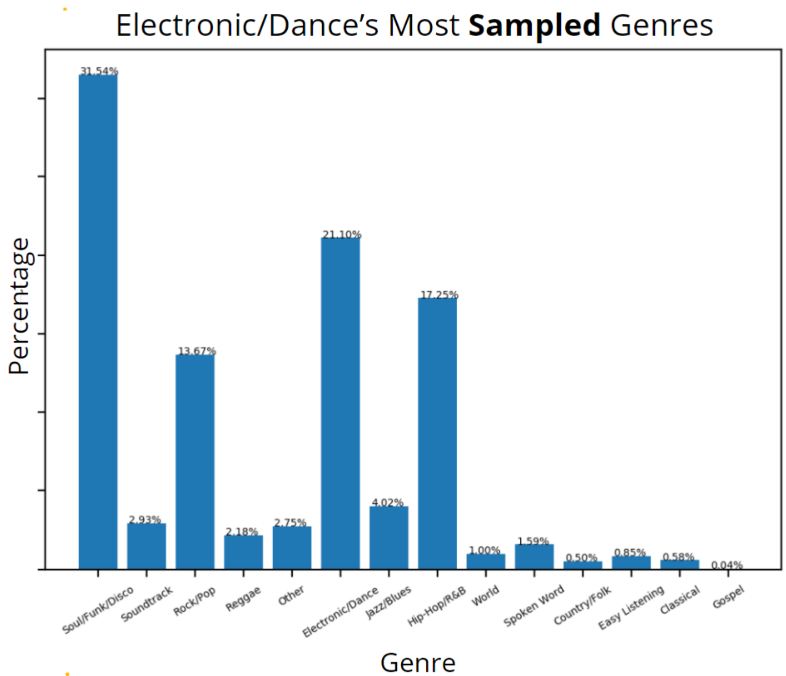


Figure 5: Hip-Hop Sampling Proportions

When viewing Figure 5's display of Hip-Hop Sampling Proportions, one can see that Hip-Hop/R&B artists sample heavily from other artists in their genre in addition to Soul/Funk/Disco artists. These two genres comprise over two-thirds of the genres sampled by Hip-Hop/R&B artists. However, wouldn't one already expect this because Hip-Hop/R&B and Soul/Funk/Disco are the two most influential genres in music?



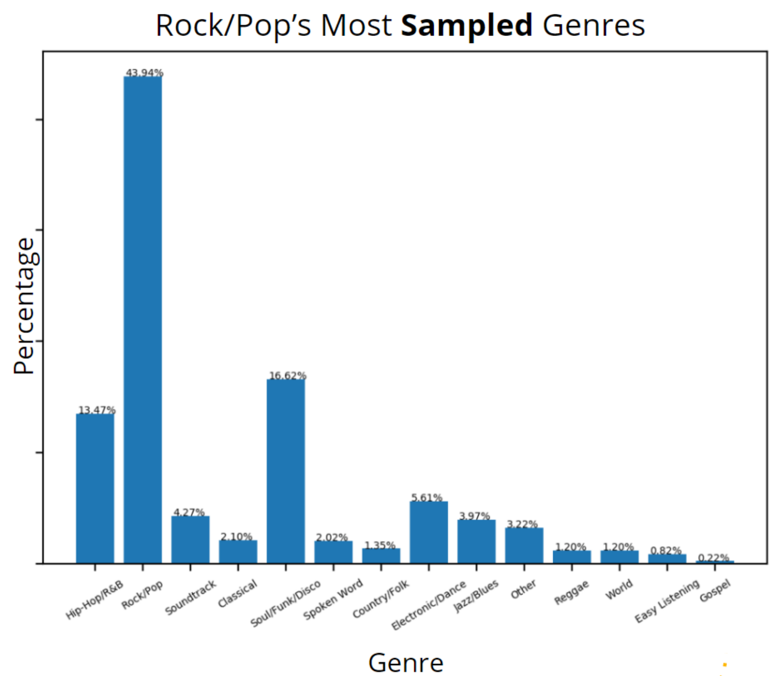


Figure 6: Electronic/Dance Sampling Proportions

Figure 7: Rock/Pop Sampling Proportions

Despite the strong genre influence of Hip-Hop/R&B and Soul/Funk/Disco, we are able to observe the effects of artists that sample from within their genre in Figures 6 and 7. Electronic/Dance artists sample Soul/Funk/Disco the most (31.51% of the time) and Hip-Hop/R&B third-most (17.25% of the time) but also sample their own genre second-most. We see this same effect in which Rock/Pop artists sample other Rock/Pop artists most often (43.94% of the time). This same pattern is observed in every other genre's intra-genre sampling proportions. Some genres display the effect more strongly than others.

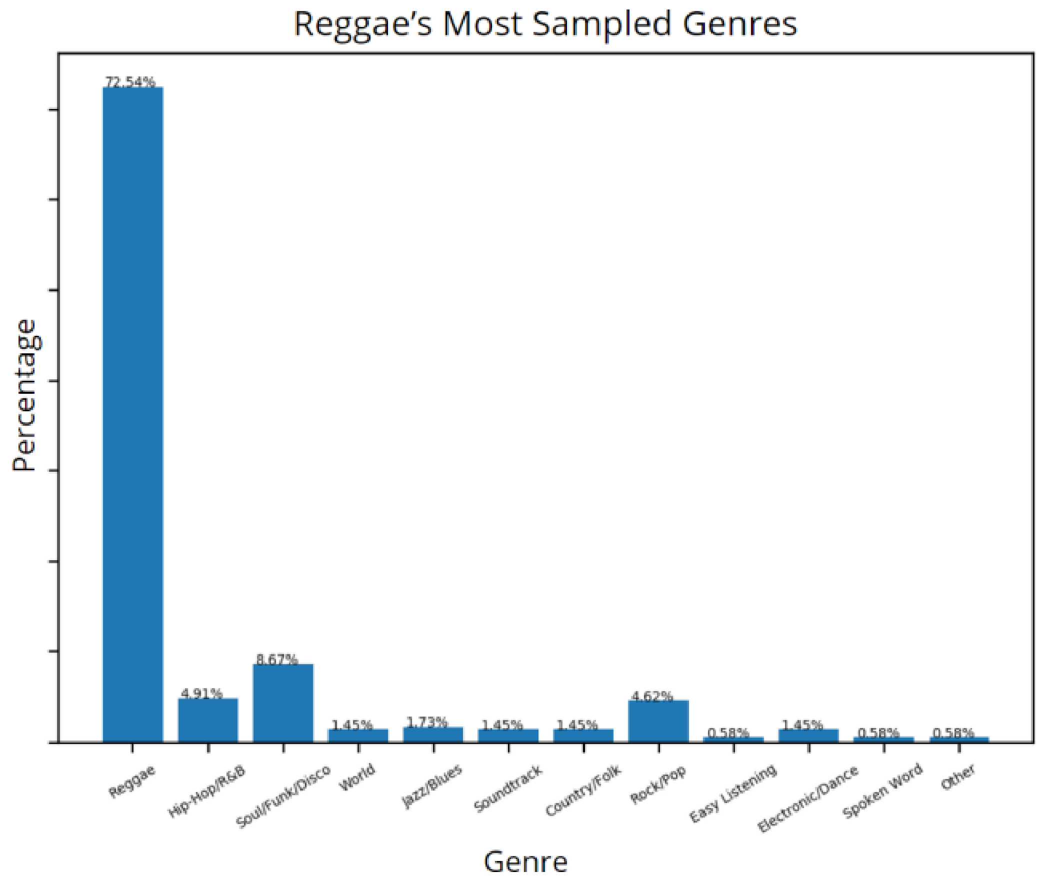


Figure 8: Reggae Sampling Proportions

From Figure 8, 72.54% of the samples found in Reggae are also by Reggae artists! From these results it appears that it is common to observe artists sampling others in their genre despite the heavy influence of major sampled genres.

5.4. Patterns in Audio Element Sampling

The inclusion of sampled audio elements allowed the attempt to derive patterns between genres, sampling time periods, and the specific types of audio elements chosen for samples. We hoped for a detailed set of audio elements but the reality of the dataset was a less-nuanced set of variables to describe audio elements. If more than one audio element was sampled by a song, the audio element sampled was labeled as "Multiple Elements" rather than displaying the individual audio elements. This led to the inability to develop any noticeable correlations between combinations of audio elements that were sampled together by specific genres.

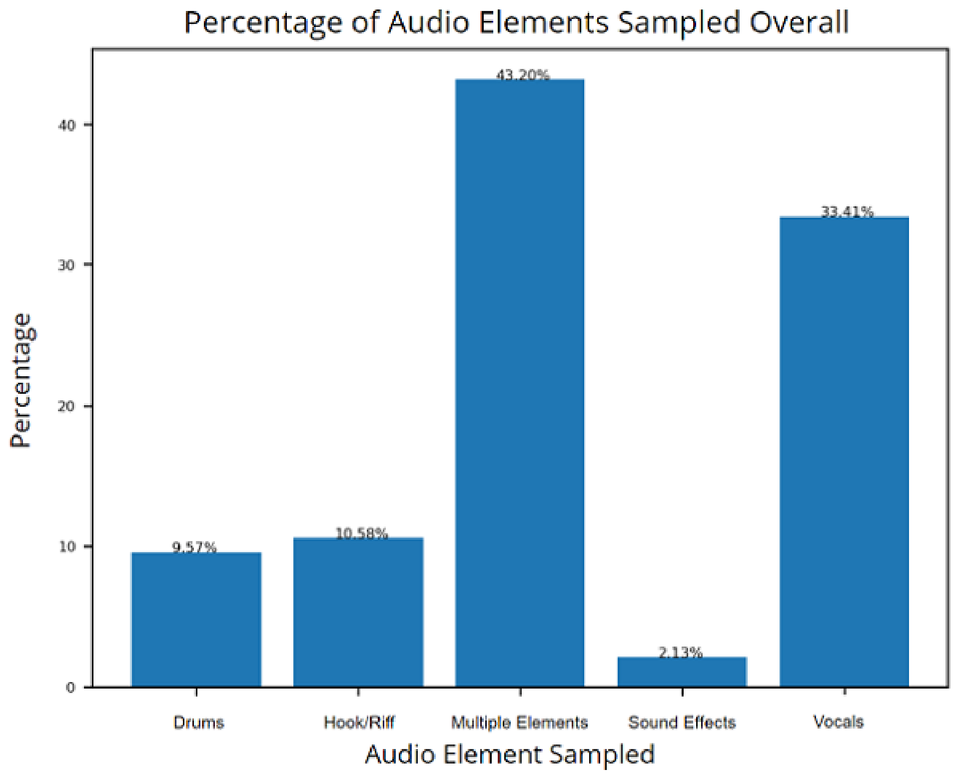
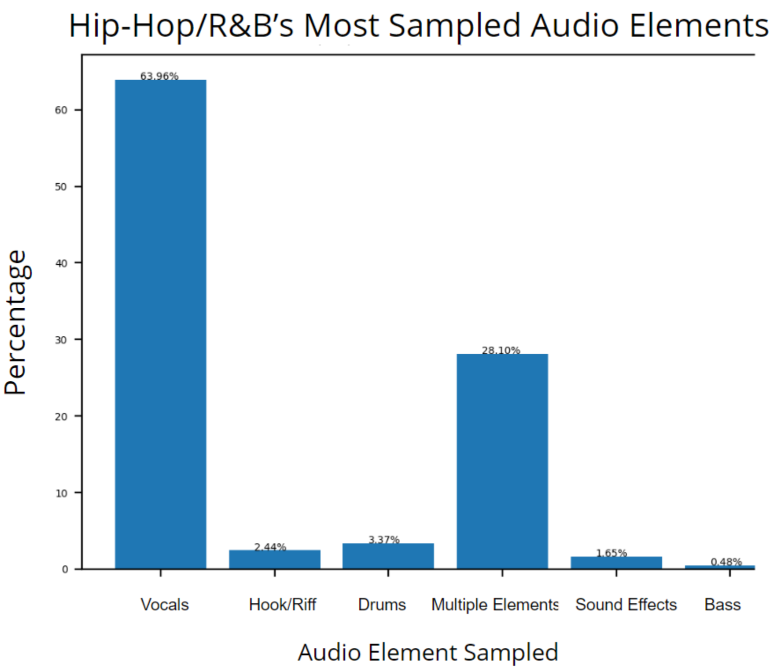


Figure 9: Most Sampled Audio Elements Overall

However, the analysis of audio elements did show that artists across all genres tended to sample either Vocals alone, or Multiple Elements. In Figure 9, 43.20% of all audio elements sampled are Multiple Elements while 33.41% are Vocals.



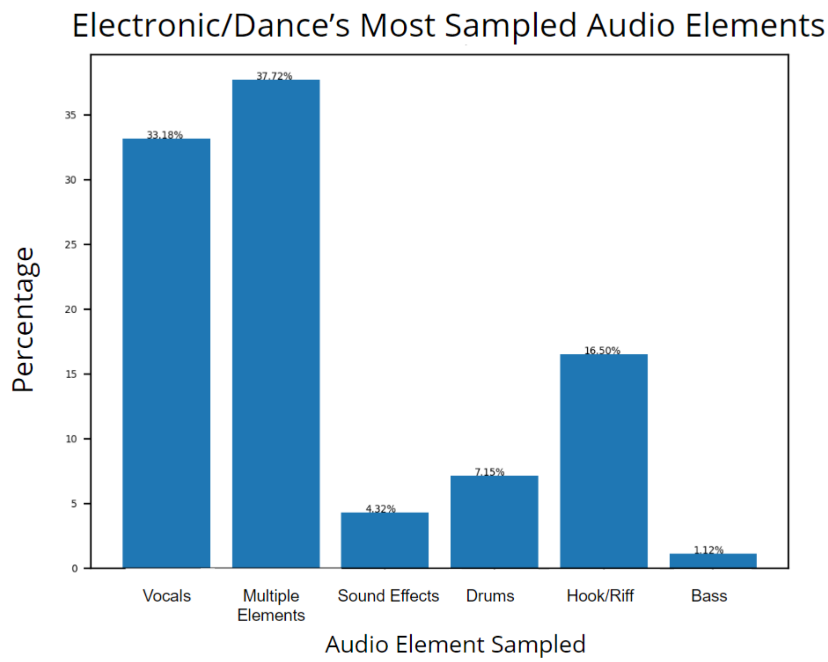


Figure 10: Most Sampled Audio Elements by Hip-Hop/R&B

Figure 11: Most Sampled Audio Elements by Electronic/Dance

First we view the audio elements sampled by the major sampling genres: Hip-Hop/R&B and Electronic/Dance. 46.13% of audio elements that Hip-Hop/R&B artists sampled were Multiple Elements and 32.96% were Vocals while 35.53% of audio elements that Electronic/Dance artists sampled were Multiple Elements and 35.30% were Vocals. This follows the pattern in which Multiple Elements and Vocals are always the two most-sampled audio elements. The sampled audio elements were dominated by Multiple Elements and Vocals for every genre analyzed.

Though it is a weak result compared to what a more detailed dataset could have provided, the data appears to reflect a sampling pattern where artists across all genres either sample Multiple Elements of recordings, or just Vocals.

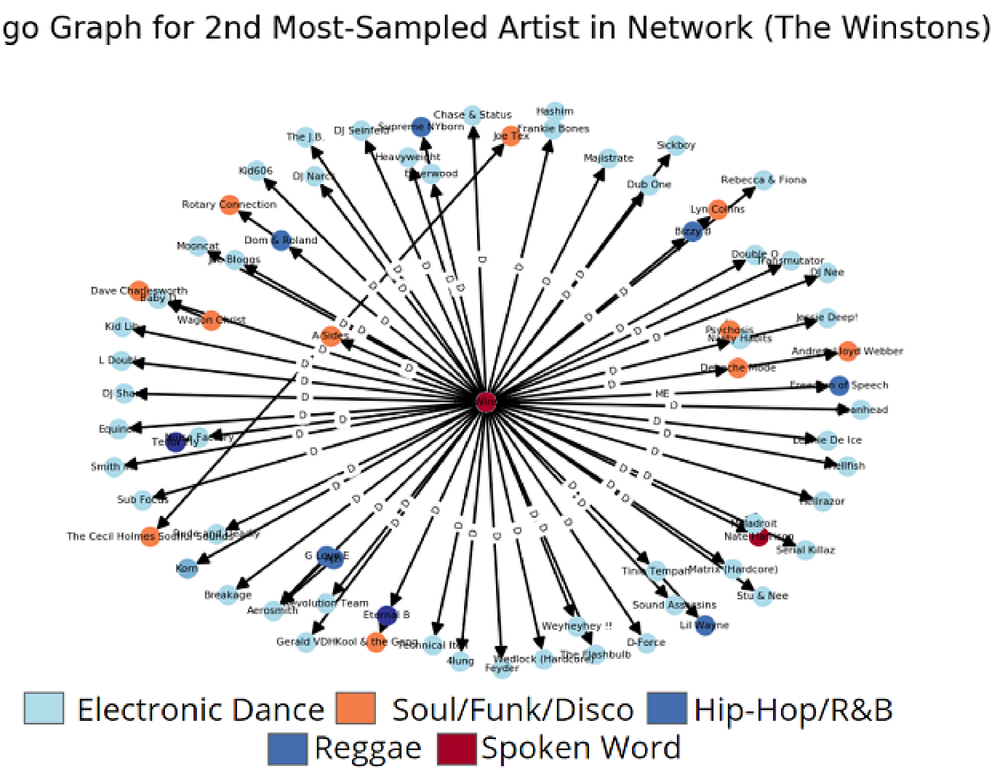


Figure 12: The Winstons' Ego Graph

Despite this failure to find a distinct audio element sampling pattern, it is clear that some artists have a specific element of their music sampled for distinct reasons. Take The Winstons and their widely sampled song "Amen Brother" as an example. In the Ego Graph seen in Figure 12, nearly all existing samples of The Winstons were specifically Drum samples. An Ego Graph is a network consisting of an "ego" node (The Winstons in this case) and the neighboring nodes to whom the "ego" is directly connected to in addition to any edges between the neighboring nodes. Few other audio elements of their music were sampled. Despite this pattern with The Winstons, general sampling patterns do not follow such a blatant sampling pattern and are much more varied.

5.5. Most Influential Artists

Recall that "in-degree centrality" returns the artists that have been sampled the most often from the dataset, "betweenness centrality" returns the artists that are either sampled by other artists often or sample other artists frequently, and "closeness centrality" describes artists that have greater direct influence on all other reachable nodes. "Eigenvector centrality" computes an artist's influence based on the connectivity of their neighbors to the rest of the network. "Katz centrality" improves upon this by weighing greater influence upon neighbors that are immediately closer to the current node v. "PageRank" is very similar to Eigenvector centrality and Katz centrality but takes directionality of edges into account, thus providing a stronger measure of influence based on how often an artist is sampled.

Artist Rank	In-Degree Centrality	Betweenness Centrality	Closeness Centrality	Eigenvector Centrality	Katz Centrality	PageRank
1.	James Brown	Public Enemy	James Brown	James Brown	James Brown	James Brown
2.	The Winstons	Beastie Boys	Lyn Collins	LL Cool J	Public Enemy	Lyn Collins
3.	Public Enemy	LL Cool J	The J.B.'s	Run-DMC	Lyn Collins	Afrika Bambaataa
4.	Lyn Collins	De La Soul	Fred Wesley	Lyn Collins	Run-DMC	Public Enemy
5.	Beside	Jay-Z	Beside	Public Enemy	LL Cool J	The Winstons

Table 1: Top Artists by Centralities (All Time Periods)

Note that in Tables 1-4, no artist appears in the top 5 for all centrality measures. This is evidence that no artist can be pinpointed to be the most influential artist throughout all time periods. Their influence (however it may be measured) wavers during different time periods based on trends during the period. But aside from James Brown's missing presence in Betweenness Centrality in the overall centrality ranking seen in Table 1, he is ranked in the number one position in every other centrality ranking. This indicates his great influence in each of the ways influence can be defined.

It is important to note the strong presence of James Brown in every centrality measure except for betweenness centrality over all time periods. Recall that betweenness centrality only refers to the ability of an artist to "bridge" communities due to the samples they use in their music or the music that samples them. Therefore an artist like Public Enemy that is sampled by a diverse set of artists from different genres and sample others in high volumes would display a high betweenness centrality.

Moreover, nearly every artist displayed Table 1 is a Soul/Funk/Disco or Hip-Hop/R&B artist. This further confirms that these are the two most influential genres in music. Observe that 19 of the 20 artists in Tables 1-4 of the Betweenness Centrality column are Hip-Hop/R&B artists except for James Brown, a Soul/Funk/Disco artist. This reflects the earlier statement that Hip-Hop/R&B

artists in general are sampled by a diverse set of artists from different genres and Hip-Hop/R&B artists themselves sample in higher volumes, leading to a higher betweenness centrality.

Artist Rank	In-Degree Centrality	Betweenness Centrality	Closeness Centrality	Eigenvector Centrality	Katz Centrality	PageRank
1.	James Brown	Public Enemy	James Brown	James Brown	James Brown	James Brown
2.	Beside	Kurtis Blow	The J.B.'s	John Davis and the Monster Orchestra	Beside	Fred Wesley
3.	Run-DMC	Beastie Boys	Fred Wesley	Kurtis Blow	Run-DMC	The J.B.'s
4.	Public Enemy	Run-DMC	Beside	Run-DMC	Kurtis Blow	Afrika Bambaataa
5.	Kurtis Blow	James Brown	Afrika Bambaataa	The J.B.'s	Public Enemy	Beside

Table 2: Top Artists by Centrality (1980's)

Artist Rank	In-Degree Centrality	Betweenness Centrality	Closeness Centrality	Eigenvector Centrality	Katz Centrality	PageRank
1.	James Brown	Public Enemy	James Brown	James Brown	James Brown	James Brown
2.	Public Enemy	Masta Ace Incorporated	Lyn Collins	Lyn Collins	Public Enemy	Lyn Collins
3.	The Winstons	LL Cool J	Fred Wesley	Fred Wesley	Lyn Collins	Fred Wesley
4.	Lyn Collins	Beastie Boys	Melvin Bliss	Parliament	N.W.A.	Public Enemy
5.	Run-DMC	De La Soul	Parliament	LL Cool J	Run-DMC	The Winstons

Table 3: Top Artists by Centrality (1990's)

Artist Rank	In-Degree Centrality	Betweenness Centrality	Closeness Centrality	Eigenvector Centrality	Katz Centrality	PageRank
1.	James Brown	Jay-Z	The Notorious B.I.G	The Notorious B.I.G.	The Notorious B.I.G.	Run-DMC
2.	The Winstons	Public Enemy	James Brown	Public Enemy	James Brown	Public Enemy
3.	The Notorious B.I.G.	Kanye West	Public Enemy	EPMD	Public Enemy	The Notorious B.I.G.
4.	Beside	50 Cent	Beside	Run-DMC	Beside	James Brown
5.	Public Enemy	Nas	Run-DMC	James Brown	The Winstons	Beside

Table 4: Top Artists by Centrality (2000's)

Observe that James Brown's domination of the centrality rankings in each time period weakens in the 2000's (seen in Table 4) when he is relegated to positions below rank 1. Though he still appears in the top 5 of every centrality measure (besides betweenness centrality), it appears that his influence lessens in the modern sampling environment. The music sampling community in the 2000's appears to be centralized greatly around Hip-Hop/R&B artists such as The Notorious B.I.G. But, this should come as no surprise because one can observe Figure 4 which depicts the weakening hold of Soul/Funk/Disco samples in the 2000's where it is replaced by Hip-Hop/R&B.

Despite this lowered ranking for James Brown in the 2000's, his appearance in nearly every top 5 temporal centrality ranking over the time periods indicates his strong influence. The only other artists that appear in each of these time periods in addition to the overall centrality ranking are Public Enemy and Run-DMC. This indicates that these artists have strong sampling influence over many time periods and continue to be sampled.

5.6. Average Clustering Coefficients

Over all time periods, the average clustering coefficient for the entire graph appears to be extremely small indicating that groups of samplers tend to be small and are rarely tight-knit with respect to an artist or set of artists.

Time Period	Average Clustering Coefficient
Overall	0.003854434
1980's	0.004470729
1990's	0.003857424
2000's	0.001085667

Table 5: Average Local Clustering Coefficients Over Time

Referring to Table 5, the clustering coefficient appears to decrease from the 1980's to the 2000's but this absolute change in the clustering coefficient is small. The low clustering coefficient overall demonstrates the tendency for artists to not cluster together with all other artists in their neighborhood. Because of the nature of sampling data and the wide variety of artists a single artist could possibly sample from, a low average clustering coefficient is not unexpected. However, the trend of a lowering average clustering coefficient over time means artists tend to form fewer tightly knit groups that sample primarily from each other, possibly indicating artists sampling from unique artists that are outside of their "neighborhood".

5.7. Louvain Communities

We analyzed isolated sampling communities that sample purely from each other using Louvain Communities which are subgraphs of the entire dataset. We found that the largest Louvain Communities contained a single genre that proportionally dominated all other genres.

n'th Largest Louvain Community (# of Artists)	Genre (% in n'th Largest Community)			
	Hip-Hop/R&B	Electronic/Dance	Rock/Pop	Soul/Funk/Disco
1. (1420 Artists)	55.56%	14.23%	10.35%	7.46%
2. (1384 Artists)	59.68%	20.45%	5.56%	7.44%
3. (1024 Artists)	56.84%	19.04%	6.64%	8.11%
4. (754 Artists)	55.57%	14.06%	7.29%	9.42%
5. (746 Artists)	12.20%	60.59%	8.71%	2.41%

Table 6: Top Genre Makeup in n'th Largest Louvain Communities Overall

The proportional makeup of each of the largest Louvain communities was unsurprising given our observations with intra-genre sampling: Each of the partitioned communities were dominated by a single genre. For four of the five largest Louvain communities, Hip-Hop/R&B was the genre making up the majority of the community, as observed in Table 6. Electronic/Dance came 2nd to Hip-Hop/R&B in each of these 4 communities and was the most prevalent genre in the 5th largest Louvain community.

This single-genre dominance is the result of a genre that has a high sampling volume in its music. Based on our results from investigating intra-genre sampling, this same genre with high sampling volume frequently samples from artists within its own genre which leads to an insular Louvain community.

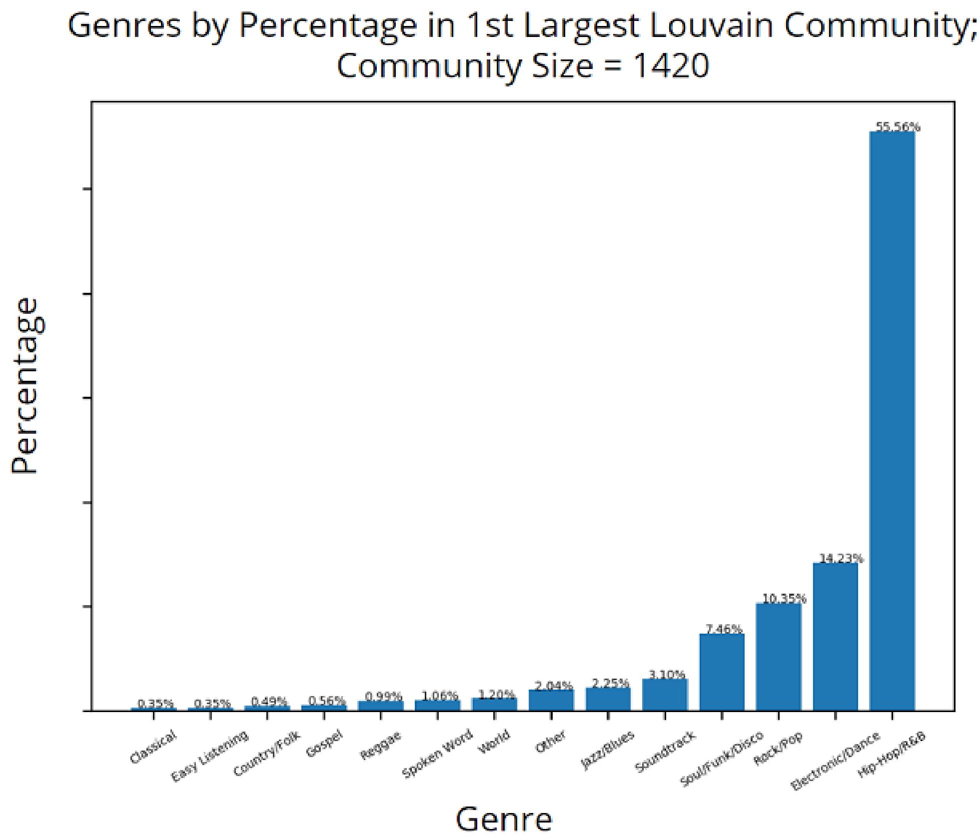


Figure 13: Genre Makeup of Largest Louvain Community

As shown in Figure 13, 55.56% of artists in the largest Louvain Community are Hip-Hop/R&B artists, indicating a high level of intra-level sampling and an insular sampling pattern. This percentage indicates a high level of intra-genre sampling in the Louvain Community because reaching a majority proportion in the community would require some sampling from other artists in your genre. Take this extreme case as an example: If a genre g makes up 50% of a community's nodes and there was no intra-genre sampling, all of g's nodes are sampling or sampled by artists from other genres. This is extremely unlikely and we can reason that for a genre to take the majority in an ego graph, high levels of intra-genre sampling must be involved. This result is also strongly supported by the fact that other genres have low proportions compared to Hip-Hop/R&B. Observe that the 2nd highest proportion genre (Electronic/Dance) only makes up 14.23% of the community.

The most prevalent genres in this community are a combination of the top sampling genres and the most sampled genres over all time periods. Genres that are found most often in the Louvain communities are those that have a greater presence in the sampling community either by being sampled by many artists or by sampling many artists themselves.

Of the top 5 Louvain communities (in terms of size), the top 4 communities have Hip-Hop/R&B as the dominant genre with the 5th community having Electronic/Dance as the dominant genre. Though this does show a difference between the top Louvain communities, it supports the result that the communities are dominated by genres that sample heavily from others (Hip-Hop/R&B and Electronic/Dance) and are sampled heavily by others (Hip-Hop/R&B).

6. Conclusion and Future Work

6.1. Conclusion

Through network analysis of the sampling network, we first verified the historical musical sampling claims perpetuated in modern media and found them to be quantitatively verified. Hip-Hop/R&B does sample music dramatically more often than other genres with Electronic/Dance following it. Though we couldn't form a causative relationship between the sampling laws that arose from "Grand Upright Music Ltd. v. Warner Bros. Records Inc." and the decrease in sampling volume in 1991, there was a noticeable correlation in the period after 1991 with a decreased sampling volume.

We then analyzed the dataset for the most influential genres which are the genres sampled the most often by artists. Soul/Funk/Disco was the most influential genre overall but Hip-Hop/R&B has recently challenged this. After performing a temporal analysis, it appears that Hip-Hop/R&B has consistently been sampled by artists 25-30% of the time while Soul/Funk/Disco has seen a decrease in the proportion of sampled genres since the 1980's.

Intra-genre influences were found to be strong and artists noticeably sampled from other artists within their genre just as much as they sampled from the most influential genres (if not more). Some genres displayed higher proportions of intra-genre sampling but the greatest takeaway was that all genres do show a strong tendency to sample from within their genre.

James Brown was and continues to be one of the most influential artists throughout all eras of music as indicated by numerous types of centrality measurements. He is without a doubt the most influential artist but other artists such as Public Enemy and Run-DMC also display noticeably strong influences throughout all time periods of music. These two artists are the only other artists to appear in the top 5 of the overall and time-divided centrality rankings. Centrality measurements also reinforced the strength of Hip-Hop/R&B and Soul/Funk/Disco as the most influential genres in music sampling.

The average clustering coefficient of the entire network was found to be very low throughout all time periods as expected due to the nature of music sampling. The low average clustering coefficient indicates a low tendency to mutually sample among a group of artists. This coefficient thus tells us communities of artists that exist tend to not sample from each other heavily. Sampling between neighborhoods of artists tends to be influenced by genre only. In addition, a decrease in the average clustering coefficient over time periods since the 1980's may indicate fewer tightly knit groups of artists that sample primarily from each other.

Louvain communities also helped reinforce the notion of strong intra-genre sampling and the dominance of Hip-Hop/R&B and Electronic/Dance as the highest volume samplers across all genres of music. By being highly sampling genres found in these communities, their majority proportion in each of the largest Louvain communities occurred as a result of strong intra-genre sampling. The more Hip-Hop/R&B or Electronic/Dance samplers are in a community, the more they sample from their own genre resulting in a compounding effect.

The greatest limitation in the analysis of the sampling network was the lack of granularity in the Audio Element property of the WhoSampled dataset. Due to the labeling scheme in which the sampling of multiple audio elements leads to a sample being categorized as "Multiple Elements" rather than listing each of the audio elements, we were unable to notice any patterns that arose from certain genres or time periods. The only conclusion that could be drawn was that artists tend to sample Vocals if they do not sample Multiple Elements.

Another limitation stemming from the dataset was the lack of sampling data for music released in the 2010's. Much of the sample data in the dataset was concentrated in the 1980's-2000's. Though these eras are indicative of the peak in sampling popularity as a musical device, it is unclear if the data for the most recent decade is lacking due to lack of valid data or actual lack of sampling in the music community. As a result, we did not perform temporal analysis on this time period. Future research could be performed at a later date to observe if the data for this time period is entered into WhoSampled.

6.2. Future Work

Future studies of musical sampling influence networks can look towards the patterns established by this paper to create an application capable of making predictions about the types of samples likely to be found in a song containing the specific defining characteristics we researched in this project. This predictive analysis could potentially aid developers such as WhoSampled with their music sampling identification software by acting as a false positive check.

From a legal perspective, the sampling patterns that establish the potential for a predictive algorithm could be used for ground truth facts during legal proceedings of musical sampling lawsuits. There are often initial arguments from parties debating whether a song was actually sampled by another song and a predictive algorithm could help determine the likelihood this is true based on an artist's past behaviors within the current musical community's trends.

Legal and historical scholars could also perform a deeper analysis of the dip in sampling volume post-1991 that is correlated with the Grand Upright Music v. Warner Bros. Records copyright case that famously ruled the specifics behind what constitutes a legal sample.

7. Acknowledgments

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