Building a Chorus

Latent Value in Spotify Collaborative Networks

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Abstract

With an increasing demand for data literacy coupled with COVID-19's effects on the music industry, small to mid-sized independent artists face challenges of audience growth and value generation. Artists' collaborative networks present a pre-existing dataset which may represent latent value to the artist. This study aims to analyze Spotify artists' collaborative networks to determine aspects of these collaborative networks that may represent such insights, as well as how those patterns may reflect practices common across artists of similar genres or followings. In the context of this study, value is considered as any knowledge that informs artists' relationships with current or future musical collaborators. To address these aims, a set of ego artists of varying sizes and genres were selected through Spotify using consecutive sampling. Their extended collaborative networks were then gathered using snowball sampling out to a specified network size. The collected data was then analyzed using social network analysis and coded inductively. Analysis culminated in four major findings, which are congruent with similar trends identified in related studies. Results suggest that small to mid-sized independent artists' collaborative networks contain information on influential collaborators and collaborative trends across genres and artists following sizes. For this reason, artists' collaborative networks should be reviewed when pursuing audience growth or value generation.

Keywords: Spotify, artist collaboration, music collaborative network, music metadata

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Introduction

Modern musicians face a challenge of an industry that is increasingly data driven yet increasingly value obscured. Unlike other entertainment industries where one can draw fairly direct lines between platform, content, and payment (such as film, television, or gaming), music remains different. As a product, today's music is effectively free. And, with many music distributors working to ensure that every song is available on every platform, a sense of exclusivity that encourages music consumers to pay for more than one music streaming service subscription is nonexistent for all but the most popular artists.

This challenge is accentuated by dominant industry platforms which mediate the majority of industry revenue—Spotify, Apple Music, YouTube, and so on—who regularly have their payout practices called into question by market suppliers (Darville, 2021). The challenge for many small, medium, and independent artists becomes using their music to build an audience, then finding other ways to derive value from that audience. But, the resources needed to do that have a ways to go. It raises the question: in 2021—particularly with COVID-19's effects on live music and its related incomes—how do musicians build value that eventually becomes revenue?

As the world's music scene has gone virtual, access to—and understanding of—one's musical metadata is quickly becoming a prerequisite to building a following through which to generate additional revenue sources. One type of relationship which opens the door to not only additional content but also to new potential fans is musical collaborations. Indeed, with trends in recent years pointing not only to a rise in collaboration but a relationship between artist collaboration rates and revenues (Seekhao, 2020), the ability for artists to grow through collaboration is stronger than ever. And—where COVID-19 has hamstrung other methods of professional development for musicians—remote or virtual collaboration remains an option for many.

Background Information

Today's music streaming services (MSS) are a dominant force within the market. In the first half of 2019, 68% of US listeners across all genres used on-demand streaming as their preferred mode of listening, with even higher percentages in popular genres (Statista, 2020). Among MSS participants, Spotify lays claim to the majority market share at 36% in 2019, with the next largest presence in Apple (Apple Music) at 18%. In regards to revenue, 55.4% (US $11.2B) of all global music revenues in 2019 came from streaming services (paid and ad-supported) with the United States claiming the largest market demographic. In 2020, that revenue percentage jumped to 62.1% (US $13.4B), with many attributing the shift to the COVID-19 pandemic (IFPI, 2021). However, the payout rates of streaming are a topic of industry contention. Spotify's current payout rate is estimated to average around US $0.00318 per stream, and varying amounts are often reported due to Spotify's competitive top-down calculation of royalties which ranks and pays artists relative to all other artists' streaming numbers (Digital Music News, 2019; Soundcharts, 2019).

With these basic figures in mind, if an artist actively creating and promoting their music receives 100,000 streams per month on Spotify then they should receive an estimated payout of US $318.00. For comparison, an employee working at the US Federal minimum wage of ($7.25 per hour) full time (8 hours per day, 22 days per month) is estimated to make US $1276.00 over the same time period (U.S. Department of Labor, 2021). While other factors—such as payouts from other streaming platforms—should be considered, these rates of payment suggest that building a following by individually releasing, promoting and (when possible) performing musical material is prohibitive for small to mid-sized artists who wish to sustain themselves off of their music alone. As a result it becomes imperative for small and mid-sized artists to identify and develop other sources of value that build their audience and increase revenue opportunities.

Research Aims and Questions

My research aims to examine Spotify artists' collaborative networks for patterns which can be translated into valuable business intelligence for small to mid-sized artists of varying genres. Further, I aim to analyze the characteristics of these networks for indications of common and contested practices across other industry platforms and avenues. These aims use Spotify's platform as a critical lens to examine the state of the industry, while seeking generalizable trends that empower small and independent artists. With these goals in mind, I present the following research questions:

1. What forms of latent value (social, economic, and otherwise) exist in Spotify artists' collaborative networks?
2. How do patterns of musical collaboration present across different musical genres?
3. How do patterns of musical collaboration present across artists of different following sizes?
4. Where (if at all) do major music industry participants, such as major labels and prominent artists, appear in small to mid-sized artists collaborative networks?

Literature Review

The theoretical framework of this research breaks into five component pieces, each outlined below. (a) *Data and Information Availability* outlines the recent shifts redefining data's role in music, looking to Spotify as a herald of the sea change; (b) *Disruptive Tech and Music* reviews the music industry's turbulent history in adapting to technological disruption in ways that avoid consolidating existing power structures; (c) *Economics of Knowledge, Data, and Collaboration* reflects on evolving definitions of value within the knowledge economy as they relate to data and social networks; (d) *Network Attributes* summarizes the types of content and information present in the multimodal music collaborative networks, and their analyses, and; (e) *Data As Digital Literacy* contends with the importance of ensuring small and independent artists are informed participants of their respective discourse groups as part of an ever digital, ever changing market.

Data and Information Availability

The music industry, like many other digitally based or disrupted sectors, has seen a proliferation of data and metadata over the past 20 years. The online migration of music databases and exposure of music through MSS has not only increased the amount of data available to artists, listeners, and the platforms that connect them, but has also improved the visibility of previously existing music metadata in ways that are characteristic of Big Data in modern terms.

While this metadata has taken on various forms and evolutions (Riley, 2017) such as relational databases proprietary to various music streaming services, or the now-ubiquitous JSON data-interchange format, the availability of metadata in music has never been more standardized, centralized and visible to consumers and creators of music.

To many, these novel channels and types of data help pose new questions about music's influence on behavior, listeners' broader habits, and more areas of interest that would have been labeled as exceedingly difficult areas of inquiry even 20 years ago. However, standardization of traditional music metadata such as artist discography, genres, and collaborators also allows more direct and immediate inquiries into the networks that musical artists—and their content—create.

For artists listed on popular MSS such as Spotify, knowledge and understanding of the musical metadata and networks that surround them is not only interesting; it can help inform and guide business decisions. As Cantor and MacDonald's findings suggest, problem solving pertaining to supply chains is impacted by the amount of information available within a given system of operations. Too much system-wide information, and participants face overwhelm. Too little, and individuals may be making sub-optimal decisions (Cantor & MacDonald, 2009, p. 230). Thus, the ability to filter and present data—in this case, artists' collaborative networks—in a meaningful way becomes a matter of concern for optimizing artist costs and benefits. When considering the supply chain of tangible and intangible assets that go into the creation of an album, song or other piece of audio content, this insight becomes particularly salient. In the case of collaboration, an artist's understanding of their musical network and how prior collaborators (1^{st} degree connections) may help them find new collaborators ($\geq 2^{nd}$ degree connections) seems to have a direct impact on that artist's ability to make an informed managerial decision. This belief is corroborated by Huber's (1990) findings that increased information accessibility leads to "improvements in effective, intelligent decision making" (p. 65) but perhaps requires more selectivity than originally believed, as returns on information availability diminish and eventually reach a point of oversaturation.

Within this changing landscape one MSS, Spotify, stands above the rest in terms of enabling users—artists, listeners, and others—to readily access and manipulate musical metadata. Indicated by Haupt in 2012, and still very much true today in 2021, two prominent unique selling points (USPs) of Spotify are its large user base and developer platform, where technically able users can access various forms of publicly-visible metadata in JSON format via application programming interface (API) (Haupt, 2012). These attributes make Spotify one of the best publicly available databases for exploring latent forms of value in musical metadata, particularly those which can benefit artists. From the perspectives of database size, quality and accessibility, Spotify remains at the forefront of the industry.

Disruptive Tech and Music

Boons to data accessibility in the music industry have not been without busts or continued issues and imbalances of power in other areas of the industry. As Marshall points out, major labels remain in disproportionate positions of power despite the shift in standard forms of music consumption—from music sales dominating up until the start of the 21st century, to now the on-demand streaming of MSS being the preferred way to disseminate content (Marshall, 2015, pp. 184-185). These imbalances manifest on the surface level as issues of revenue through royalty payments. Popular artists who are signed to and supported by major labels such as Warner Music, Universal Music Group, and Sony find themselves disproportionately benefitting from representation and ownership of the underlying MSS platforms. However, this financial imbalance permeates into other aspects of artists' product and production lifecycles. Middleware tools that expedite various processes such as posting to social media, aggregating and reporting on analytics and outsourcing non-primary forms of creative content to support a musical release all come with costs attached. To a smaller artist who is seeing decreasing returns and revenue from their existing music catalogue, these tools spiral out of reach and artists find themselves suffering from an inability to keep pace with increasing output requirements of convenience (Slack & Wise, 2005, p. 34). In her conclusion, Marshall (2015) hints at this larger realization, noting that an MSS artist's "financial success depends upon scale and catalogue" (p. 186).

Additionally, willingness to adapt to technological change and trends has been an area of weakness in the music industry since (at least) the turn of the century. Moreau's analysis of the slow rate of adoption and digitization amongst majority firms in the music industry directly addresses this stance, speaking on the tendency for dominant market participants to remain change-averse in the face of significantly disruptive technologies (Moreau, 2013). When provided with the opportunities to be early adopters of various open, innovative solutions to the oncoming digitization and accessibility shift of music (and its data) in the early 2000s as a result of Napster and iTunes, dominant music industry players opted to double down on litigation and cling to old ways. Apple eventually claimed a "hegemonic market share" (Moreau, 2013, p. 28), forcing the industry to respond, but the trend of the music industry as a late adopter of new technologies, methods and modes of value creation continues. This is further bolstered by the December 2020 announcement of performance rights organizations ASCAP and BMI regarding 'Songview' (ASCAP, 2020). The database—originally scheduled for completion by Q4 2018 (ASCAP, 2017)—aims to track and reconcile records of musical works between the two PROs, finally ensuring that artists' royalties are tracked and not lost due to incongruent data between the two organizations (Songview, 2020). This progress pales in comparison to other industries, such as film and television, where SAG-AFTRA has provided centralized residual tracking (film's royalty equivalent) and reconciliation since the 1950s (SAG-AFTRA, 2021).

The above issues point to a compounding problem within the music industry stemming from two general themes: A disproportionate share of power and value remains in the hands of major labels despite the large proliferation of independent artists on Spotify and other MSS. And an industry-wide lack of will or determination to explore and utilize the latest data, technologies and applicable innovations in an open and constructive way to the industry as a whole. Within the scope of the data (and relevant tools) this poses an economic problem amongst market participants, mainly due to the general understanding that Big Data presents a form of knowledge

(Boyd & Crawford, 2012) that holds value to composers and performers within the Knowledge Economy (Tomé, 2020).

Economics of Knowledge, Data, Collaboration

Of course, the above points presuppose several economic characteristics and fundamentals of the music industry within the United States. Under the strictest capitalist definitions, recorded music and audio content available on demand through MSS represent a store of value within any given artist's repertoire. The size of that repertoire, in addition to other goods and services an artist and their brand might present contributes to market supply. Within a MSS such as Spotify, demand for a given artist is represented in the number of times their content is streamed, how many monthly listeners and engagements their content has, and—more broadly—how prevalent their content is among user- and algorithmically-generated playlists. Taking a traditional capitalist view, the transaction of value between listener and artist in the music streaming marketplace is that of musical content for streaming royalties, respectively.

However, if one adopts the perspective that knowledge is ultimately a store of value, then the system rapidly expands. Using the above points, we see the artists' and users' metadata become a source of knowledge and thus market participants who are aware (and able) to tap into its value will realize gains. Naturally, MSS metadata (and its emergent networks) are complex and interwoven. Here, we turn to Savage and Symonds argument that "the economic system is a social beast, based on interactions between collaborative players" (Savage & Symonds, 2018, p. 43), seeing not only the value contained within the larger information system of a MSS such as Spotify, but also that the interplay of that information creates value; a set of network externalities (to those capable of distilling the information into usable knowledge).

These network externalities appear to be an underutilized aspect of MSS metadata, particularly for small and independent artists who have a disproportionately low amount of representation on these MSS platforms. This scenario seems even more plausible by what we know about trends of late adoption and poor responses to disruptive technologies within the music industry over the past 20 years (Moreau, 2013).

One of these valuable network externalities appears to be direct connections (2^{nd} degree and beyond) an artist has access to through their immediate network of past collaborators. For any given Spotify artist, the effort and cost of collaborating with another Spotify artist is unique, but it is likely that the cost of collaborating (opportunity cost, time, and so on) is fixed and roughly linear. As Mason highlights, however, growth of a network (in this case a network of collaborators) returns exponential value per unit of cost (Mason, 2015), characteristic of a network effect. Thus, the value of connecting two or more Spotify artists via collaboration will likely exceed its cost at an exponentially increasing rate. In this way new collaborations between Spotify artists provide a unique selling proposition for all artists involved; mutual access and expansion of each others' collaborative networks. This interconnectivity upcycles, causing a positive feedback loop that—at first glance—appears to foster similar principles to those of wikinomics (Tapscott and Williams, 2008). Indeed, where the dominant players within the music industry can be said to be change-averse and cemented in orthodox modes of operation, independent artists and the networks they create serve as a foil that is constantly evolving, innovating and weaving webs of synergy.

Network Attributes

Naturally, in order to discern the types of value within a given network one must first categorize and understand the network itself. A musical collaboration resulting in a published song, album or other audio content generates a modal network—that is, a network in which the two or more collaborators share the common mode of content. The artists themselves are not directly linked but are linked through the art they've created, similar to how co-stars are modally connected in the common network-themed game "Six Degrees of Kevin Bacon". As Hogan (2017) cautions, one must be mindful not to readily assume meaning in modal networks (p. 9). The case of Spotify artists and collaborations is not different, and indeed we must be mindful to not automatically assume that an artist's collaborative network has meaning. Luckily, several prior studies have already explored and validated the underlying connections within these multimodal MSS networks.

Perhaps the most closely related exploration of collaborative networks in the music industry comes from a study of the same name published by Pascal Budner and Jorn Grahl in 2016. The pair leveraged another musical database, Discogs, that has retroactively added musical metadata and credits for songs, albums and more released before mass user and industry digitization in the early 2000s (Budner & Grahl, 2016). Performing two one-mode projections of the network while exploring the importance that collaborator role (Engineer, Photographer, Main Artist, and so on) plays, the pair found network characteristics congruent with common trends and patterns of social networks. Characteristics such as small world networks, high clustering coefficients, and collaborator (edge/node) weight variability were also noted (Budner & Grahl, 2016, p.11). This bolsters the theory that multimodal networks emerging from musical collaborations have inherent value and meaning that can be explored and analyzed, and are not simply happenstance connections.

One of the main differences between user-curated services such as Discogs (Discogs, 2018) and MSS such as Spotify, though, is that most popular MSS limit artists or those authorized to access their account to modify their own catalogue and corresponding metadata. Other users of the platform (artists, listeners, …) are unable to add, edit or remove (or suggest) canonical data changes within an artist's catalogue, leaving artists and the MSS platforms to self-enforce accuracy. This calls into question the veracity and consistency of artist metadata on MSS, particularly in instances where user-moderator community members would adjust or otherwise correct inaccurate entries. Fortunately, a 2020 study conducted by Mastumoto et al. indirectly tested the metadata accuracy and congruence within Spotify. In their proposed method using a context-aware network analysis, the group was able to accurately analyze latent relationships between artists using the artist-entered and automatically generated metadata available through the Spotify platform and API (Matsumoto et al., 2020). The group did, however, mention that future work should address any "situation in which the artist does not have information about 'related artists' or does not sufficiently have audio tracks or his/her biography" (p. 48682). In the scope of social network analysis and multi-modal network information, this indicates an area of potential weakness among new, unpopular, or artists with an otherwise small following and presence on the MSS platform used as a primary data source. Furthermore, both the Matsumoto and Budner studies chose to focus on popular or otherwise established artists in their respective datasets and networks. Budner and Grahl by choosing to select their dataset of albums (and endogenous collaborators/roles/content) from "Rolling Stone's 500 Greatest Albums of All Time" and Robert Dimery's "1001 Albums You Must Hear Before You Die" (pp. 2-3). Matsumoto by establishing a precedent in Dataset #1 by using 'Lady Gaga' as their "seed artist" and performing a breadth first search from that point of origin (p. 48677).

Both of these decisions—whether intentional or otherwise—reflect the disproportionately high amount of representation and leverage held by the dominant players (big labels, globally recognized artists, …) in the music industry at large. When recalling the assertion that metadata (and the distillation of it into usable, actionable business intelligence) represents knowledge and thus power within the MSS ecosystem, these analyses are useful but provide additional information to already oversaturated market participants (Cantor & Macdonald, 2009). Additionally, as mentioned previously, accessibility to tools and other forms of technological convenience is inordinately high amongst larger industry players (including artists). I suggest that these analyses and the systems that underpin them could provide exceptional value to smaller market participants, not only because they tend to be less visible in MSS dataset analyses, but also because they tend to sit further forward on the diffusion of innovation curve within the industry. Thus, the issue becomes inverting our understanding of these networks in a manner that allows us to build models from the bottom up; using small artists and their collaborative data as the networks' egos and expanding from there.

Data as Digital Literacy

One natural contention with the above points and arguments coincides with an issue that is becoming increasingly visible in popular culture and digital discourse: data literacy and privacy. Indeed, in their piece discussing the facts, fictions and considerations of big data, Boyd and Crawford (2012) underscore the importance of ethical considerations and privacy in accessing, interpreting and sharing big data (p. 672). More recently, developments such as GDPR in Europe and the CCPA in California have heightened awareness and sensitivity to the use of various forms of data across digital platforms. End User License Agreements (EULAs), such as Spotify's EULA allows artists' data to be shared to any user connected to Spotify's API, transitively enabling studies with low barriers to entry like the aforementioned studies or my own research. But, those attitudes, policies, and practices are changing.

To many aligned with the ideals of data privacy and ownership, the argument against sharing artist metadata via Spotify may be easy. It is owned by the data's subject (in this case, the artist) and therefore they have the ultimate say in how it is used. In this case, however, I disagree. I believe access to and understanding of this data falls into the category of digital literacy within the various discourse groups within Spotify and other music streaming services. Protections such as the California Consumer Privacy Act seem focused on redefining the relationship between consumer and service provider. Applying this focus to Spotify, the intention seems to keep the platform from selling user data to a third party without the user's consent. But, if we instead reframe around the goal of using existing data to help artists understand their own collaborative networks (in order to provide value), then an artist's data becomes a source of empowerment.

Further, using Gee's definition of literacy—the ability to understand and manipulate language(s) and symbols to convey or articulate meaning within a discourse—it is clear that the restriction of artists' ability to access, manipulate and better understand their own metadata impairs progress towards digital literacy (Gee, 1989). To the degree that dominant discourse is understood as a group engaging in an exchange of common meaning and value in a way that generates social good or capital, then attempts to model and share that information with the discourse's participants builds literacy amongst its members.

As mentioned, value and resource tends to disproportionately fall towards the dominant players within the music industry and—as they are part of industry infrastructure—music streaming services. One prominent critique throughout this literature review has been how previous studies of multi-modal artist networks emerging from music metadata and MSS have focused too heavily on popular artists that tend to be associated with dominant industry players.

Reconciling the above as I proceed, I would like to refocus the reader's attention around providing actionable knowledge to Spotify artists, their networks, and their discursive groups.

Methodology

This section outlines the steps taken to perform social network analyses, codings, and evaluation of findings for each source artist. Due to the nature of the study and analysis, this process was split into three distinct phases. (a) *Artist Selection* details the sampling criteria and size of the source (ego) artists; (b) *Artist Data Collection* introduces the tools and parameters used to survey each artist's network (including the final sample size); and (c) *Artist Network Analysis* presents the methods used to interpret, visualize and analyze each artist's collaborative network.

Artist Selection

To aggregate the data used in this study, I used consecutive sampling to gather 30 North American Spotify-listed artists from the publicly available Spotify app, with a heavy focus on US-based or US-presenting artists. To meet the criteria of selection, artists had to appear in search results or recommended lists for one of the five following genres: Hip-Hop (and subgenres such as Alternative/Indie), Rap (and Underground/Alt subgenres), Pop (and Alt Pop subgenres), Rhythm and Blues (R&B), or IDM/Beats. Additionally, artists were selected at increasing increments of followers with the goal of capturing 6 artists per genre in a range of 100 to approximately 250,000 followers, representing a gradient from newcomer to moderate success. For comparative purposes, established artists on Spotify's "Today's Top Hits" playlist consistently have more than 1,000,000 followers. Modern superstars such as Dua Lipa (approx. 24,200,000 followers), Lil Nas X (approx. 4,600,000 followers) and Travis Scott (approx. 16,200,000 followers) have significantly higher numbers. All artists had to have at least 1 collaboration. The resulting group of artists forms the ego sample **($N_A = 30$)**, where "ego" refers to the artist at the center of each collaborative network. All artists within the ego sample were listed on Spotify's United States application during the 2020-2021 period.

Table 1

Ego Artists by Genre Cohort and Size

Hip-Hop (Alt/Indie)	**Rap (Alt/Under.)**	**Pop (Alt Pop)**	**R&B**	**IDM/Beats**
Taylor*	Jay2	Somni	fika	Jobii
YTK	Pink Siifu	Billy Lemos	emawk	Prefuse 73
Ras G	redveil	Penguin Prison	Sylo Norzra	Daedelus
Elujay	CJ Fly	Healy	Melanie Faye	Shigeto
Jay Prince	Kirk Knight	RAC	Shay Lia	Nosaj Thing
Tobi Lou	Injury Reserve	Miami Horror	Yo Trane	TOKiMONSTA

Note. The 30 ego artists (N_A) sorted by following size (smallest to largest) and by cohort.

Artist Data Collection

After artist selection, data for each ego artist's collaborative network was gathered with the aim of capturing all collaborations (1^{st} degree connections) released on Spotify between the ego artist and other artists. To increase total sample size and increase the likelihood of identifying trends within each artist's network, I extended my data collection to include collaborators of collaborators (2^{nd} degree connections) for each ego artist. I aimed to gather the following metadata for every artist: Spotify ID, name, follower count, genres, collaborations. Within collaborations, each item contains collaboration name, type (for example, track or album) and weight (where each track collaborated on has a weight of 1).

While Spotify's user interface presents all of the data necessary to construct an artist's collaborative network, to do so manually was untenable in the scope of this study. Additionally, the metadata I wished to collect is not centralized to any page within Spotify's app or application programming interface (API). Thus, an alternative mode of data collection was necessary.

To quickly and accurately capture surveys of each artist's collaborative network I developed korus.py (korus) using the programming language Python. To pull artist metadata, korus first connects to the Spotify API via the MIT-licensed spotipy.py module developed by Paul Lamere (Lamere et al., 2014). Upon connection to Spotify's servers, korus uses a provided artist alphanumeric identifier (Spotify ID) to perform a breadth first search (BFS) of that artist's collaborative network out to the desired degree. Each artist's metadata and collaborative data is then parsed as a Javascript Object Notation (JSON) file. The JSON Schema for this file can be found in Appendix A.

This process repeats for each artist within each ego's network, performing snowball sampling until data for all artists within the ego's network have been parsed. The resulting sample size of all artists within 2 degrees of the ego sample ($\mathbf{N_A}$) is 6,125 **($\mathbf{N_B}$ = 6125)**. Links to the korus code—including documentation—can be found in Appendix C.

Artist Network Analysis

After artist data was collected, the dataset was prepared for coding and analyses with additional Python libraries NetworkX and Plotly (NetworkX 2020; Plotly 2021). NetworkX was used to generate graphs for each ego artist's collaborative network as well as calculate various attributes of those graphs for social network analysis (SNA). Upon creating each ego artist's graph using NetworkX, a set of readout files were created and saved for reference and analysis. Plotly was used to visualize each ego artist's collaborative network as a graph, wherein each artist is represented by a node, artists' follower counts denoted by a node color, collaborations between artists denoted by an edge, and total number of collaborations between artists represented by edge thickness (weight). Each graph was saved as an interactive HTML file, allowing viewers to zoom in to portions of the graph as well as hover over nodes to view additional metadata (follower counts, genres, and so on). Samples of the NetworkX output files and Plotly graph visualizations are included below.

Figure 1

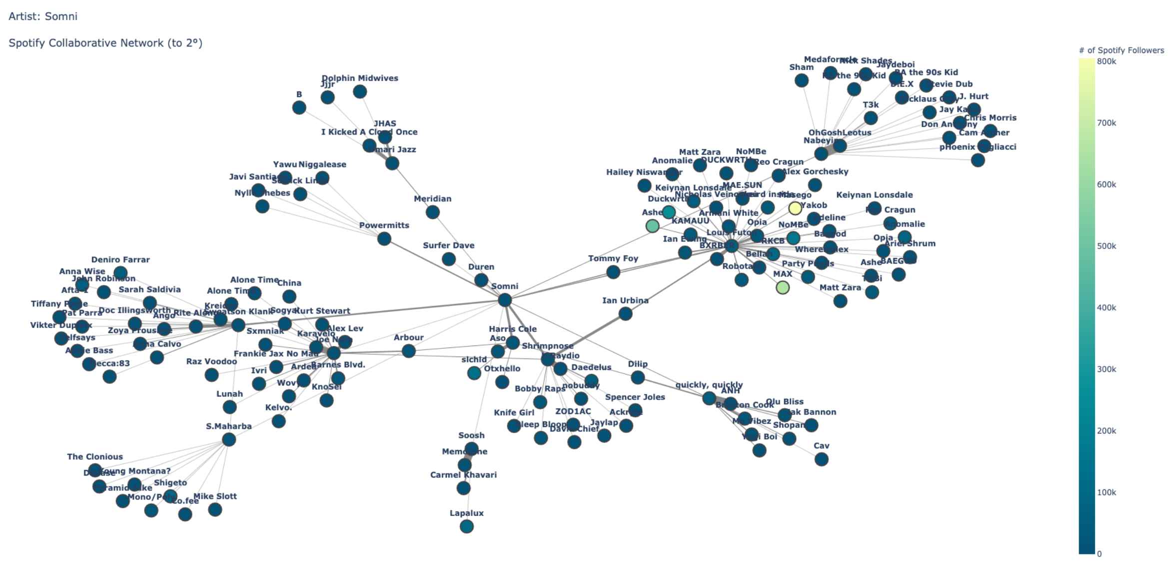
Somni Analysis Overview (Abridged)

```
Somni - Collaborator Graph (G)


METADATA
      Artist (Ego): Somni
      Followers   : 5294
      Degree      : 0

DEGREE CENTRALITY

> Max Degree Centrality
      Name      : Louis Futon
      Degree    : 1
      Followers : 61833
      Centrality: 0.2733

> Ego Degree Centrality
      Name      : Somni
      Degree    : 0
      Followers : 5294
      Centrality: 0.1000
```

```
COMPONENT ATTRIBUTES (G)
  Total Edges    : 157
  Total Nodes    : 151
  Radius         : 2
  Diameter       : 4
  Density        : 0.0139
  Center          : ['Somni']
  Avg. Clustering: 0.0153

EIGENVECTOR CENTRALITY (WEIGHTED)

> Max Eigenvector Centrality (Wt.)
      Name      : Nabeyin
      Degree    : 1
      Followers : 187
      Centrality: 0.7054

> Ego Eigenvector Centrality (Wt.)
      Name      : Somni
      Degree    : 0
      Followers : 5294
      Centrality: 0.0656
```

Figure 2

Somni Collaborative Network (to 2 degrees)



Note. Plotly visualization for the artist Somni of the Pop genre cohort, as rendered by korus. *Specific Note.* Somni can be found in the center of the graph visualization.

Once NetworkX and Plotly readouts were developed, each ego artist's collaborative network attributes and visualizations were studied for trends, which were then inductively coded and compared against other artists' data to identify noteworthy findings across the study. This approach resembles methods from previous studies on similar topics, such as those by Matsumoto et al. (2020) and Kaya et al. (2010).

Introduction to Findings

Over the course of artist data collection two distortions emerged whose impacts are visible within the findings. Distortions are defined as any aspect of the data collection that was unexpected *and* stood to impact the transcription of data.

Data Cleaning

Spotify’s API returns JSON data formatted to the standards described on their developer reference website (Spotify for Developers, 2021). However, this JSON data is not readily formatted for use by tools such as NetworkX and Plotly. Thus, preparing data for my analysis required me to aggregate, consolidate, and format (“clean”) artist data with korus. Where Spotify returns incomplete or duplicate data, korus attempts to preserve the data “as received” without interrupting code execution. For this reason, incomplete or duplicate data within Spotify’s database is also likely present in data generated by korus, but may differ slightly.

Superfluous Content Types

The initial surveys of each ego artist’s network returned an inordinately large number of collaborators compared to the expected amount. Looking further into the issue, I discovered that Spotify’s API returned two unexpected content types: “appears_on” and “compilations”. The labelling of these types appeared inconsistent, where albums and releases that were clearly “compilations” were marked as “appears_on”, making it hard to meaningfully discern between the two.

Content marked as “appears_on” regularly returned results of the source artist collaborating on another album through one or more singles. However, this list also included albums and singles that are marked as compilations; collections of musical content sourced from various artists and assembled together onto a single release. Many of these compilations—such as the long running “Now That’s What I Call Music” albums—are compiled by third parties and released with an artist name of “Various Artists”. Thus, the assumption that the included artists collaborated directly is challenged. This has the potential to lower the social significance of connections within an artist's collaborative network, while also inflating the number of connections encoded by korus.

As a result, content types of "compilation" and "appears_on" have been omitted from each artist's data and network analysis to better evince meaningful connections among collaborators.

Findings

With the above distortions in mind, completing network analyses on the selected 30 ego artists provided a range of insights. Where patterns relating to my research questions emerged across cohorts, I explored them further within their respective component attributes and graph visualizations. If necessary, I also referenced additional attributes (such as artist label affiliation) not captured in my primary surveys to better inform my analyses. From these patterns emerged four major findings: (a) *Collaborative Accretion* examines the propensity for ego artists' follower count and collaborative network size to increase in parallel; (b) *Clique Makers* investigates artists who are a combination of bridges and high-centrality nodes that appear in influential positions within networks; (c) *The Kendrick Effect* explores the tendency and significance of one or more highly followed artists to appear in a relatively low follower-count network and; (d) *Implied Networking* reconsiders the influence of non-traditional artists (producers, engineers, …) who rarely appear in all but the most popular artists' circles.

Collaborative Accretion

The most readily visible trend in the data and social network analysis is perhaps the most intuitive. Collaborative accretion refers to the correlation between the ego artist's follower count and the total number of artist collaborations (henceforth "nodes") within their 2 degree collaborative network (henceforth "component"). As a general trend, as an ego artist's following grows so does their component size. This trend has some notable exceptions, particularly with ego artists of higher following, such as Tobi Lou (Hip-Hop), Healy (Pop), and Yo Trane (R&B).

In instances where an ego artist's component is relatively small compared to their and other cohort members' following size, that artist can typically be found releasing music under a large label. For instance, the most followed ego artist within the Hip-Hop cohort (Tobi Lou) has the third smallest component. However, Tobi Lou's most recent project was released through Empire Records, a noteworthy music label with offices in major music cities across the U.S. (San Francisco, Atlanta, New York, Nashville) and other major talent on the label (EMPIRE, 2018). Within the Pop cohort, the ego artist Healy (103,115 followers with 18 nodes in their component) has released music under Braintrust Records, which is listed alongside the parent label of RCA Records.

The R&B cohort is a notable exception to this trend, where component size remained relatively small and did not exhibit a direct correlation between the ego artist's follower count and total nodes. Fika—the ego artist with the lowest follower count in the cohort at 4,293 followers—returned a component containing 193 nodes and an average clustering value of 0.0308 (3.08%), indicating not only a highest number of collaborations in Fika's collaborative network, but also that those collaborators are relatively interconnected. For comparison, Yo Trane—the ego artist with the highest follower count in the cohort at 142,893 followers—returned a component containing 39 total nodes and an average clustering value rounded to 0 (indicating no triadic connections between collaborators).

Additionally, select artists within the IDM/Beats genre cohort deviate from this correlation—namely Shigeto with 96,463 followers and 79 nodes within 2 degrees of connection. However, this cohort presents further interesting aspects for analysis as it contains the artist with the largest component—TOKiMONSTA (253,326 followers, 1216 nodes within 2 degrees)—and also provides a small window into what roles other musical content collaborators (such as producers) play within performing artists' networks. The IDM/Beats cohort's attributes are a topic of discussion in the *Implied Networking* subsection of the findings.

Collaborative accretion fits well with preexisting research and discussions surrounding network trends of similar nature as well as inquiries into the nature of collaboration in the music industry. From the perspective of network theory, the tendency for 2nd degree connections to increase as 1st degree connections increase has been explored in Scott Feld's research on the class size paradox, within which he presents the tendency for one's friends to have more friends than they do (Feld, 1991). If we consider musical collaborations to have social significance of a similar nature to friendship, then collaborative accretion is perhaps exhibiting a class size paradox—for most artists in the sample—to some extent.

Additionally, I look to research conducted by Ordanini and associates, which examines the effects that collaboration between artists of different genres has on a song's popularity. In their 2018 study on the "featuring phenomenon," Ordanini et. al. came to the conclusion that a difference of genres between collaborators was of value in the marketability and co-branding of a song or musical content (Ordanini, 2018). This value is theorized to come from the cross pollination of one's audience with that of their out-of-genre collaborator, allowing each artist to realize the benefit of exposure to a new group of potential fans while also expanding their musical catalogue.

Considering the above, collaborative accretion then finds two likely explanations: One, that as ego artists gain collaborations, the likelihood for their collaborator to have more collaborations than them is high due to the class size paradox. And two, that artists who have a high number of collaborations across varying genres have likely been exposed to a larger number of audiences, and thus have had more opportunities—or impressions—to accumulate new followers.

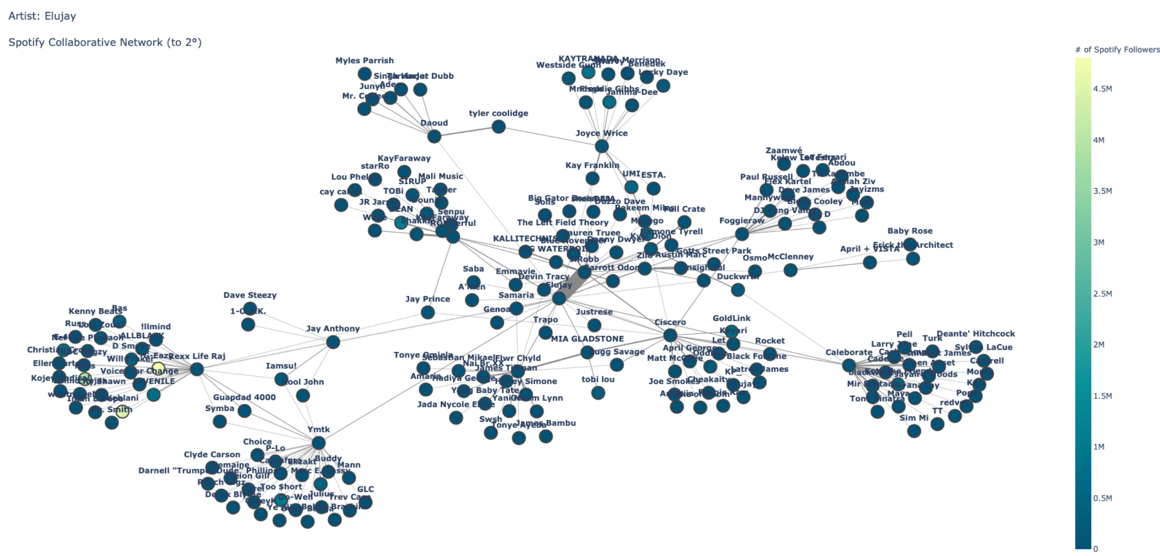
Clique Makers

The next tendency revealed through social network analysis is that of clique makers. This is the tendency for artists who act as bridges and highly influential individuals to increase in frequency as the ego artist's follower count increases. Clique makers were most prominent in the rap and hip-hop genre cohorts (relative to ego artists' followings) and may represent individuals who are—or are in close proximity to—key pieces of the ego artists' component.

These artists connect otherwise disparate groups of artists within the component, forming clusters around the ego artist as both 1^{st} degree nodes who have collaborated with other 1^{st} and 2^{nd} degree nodes, and as 2^{nd} degree nodes with edges that span multiple 1^{st} degree nodes. Elujay (49,035 followers, 205 nodes within 2 degrees) of the Hip-Hop cohort, exemplifies this with a set of edges between 1^{st} and 2^{nd} degree nodes.

Figure 3

Elujay Collaborative Network (to 2 degrees)



Note. Elujay sits at the center of the component, where they have distinct bridges and cliques developing between both 1st and 2nd degree nodes throughout their collaborative network.

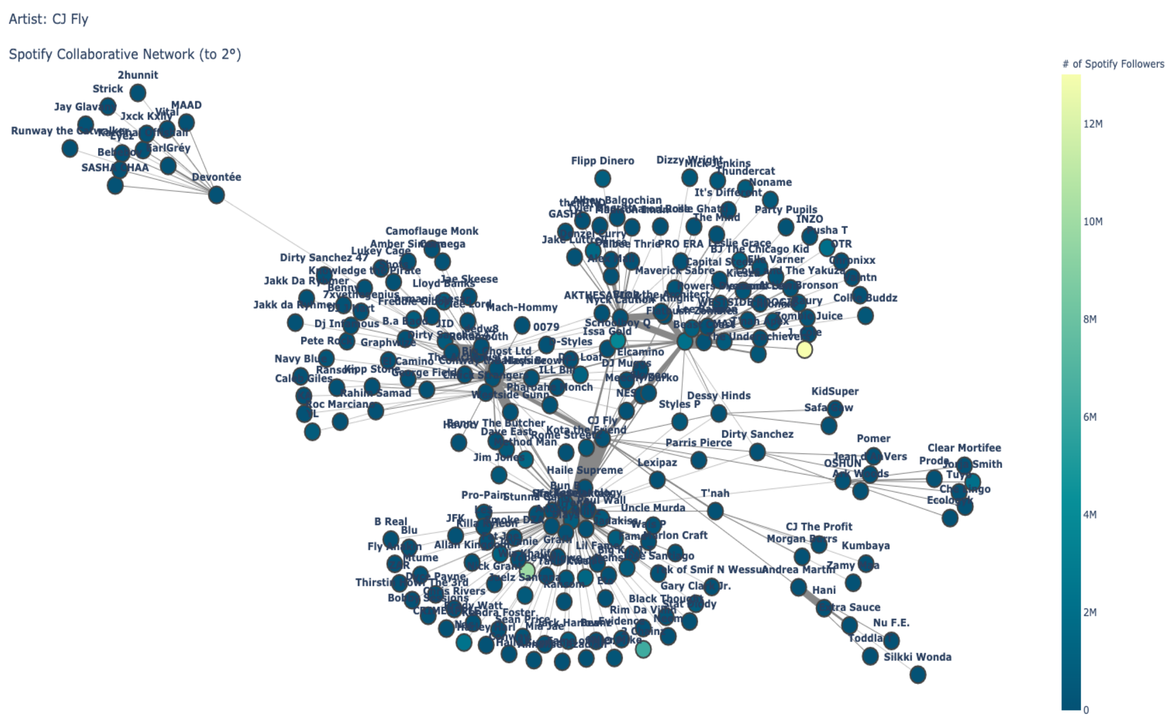
Comparatively, the smaller artists within the Hip-Hop cohort—having 25,000 followers or less—tend towards more disparate collaborations. 1st degree nodes have few edges (if any) between themselves and nodes that are not the ego artist. The same can be said for 2nd degree nodes. This suggests that these artists may or may not know each other and—more importantly—have not released any collaborative content on Spotify. The component for artist Ras G (26,500 followers, 185 nodes within 2 degrees) demonstrates this, where there is a small cluster created by bridges between 1st degree nodes, but next to no bridges spanning 2nd degree nodes. This trend is even more prevalent within the Rap cohort, where smaller ego artists had proportionately more nodes and edges within their component than in Hip-Hop.

Further, the clustering of these nodes is visible at earlier thresholds. Pink Siifu serves as an excellent example, where their component shows a large number of collaborations, high weights of edges (number of collaborative releases between the two artists), and connections between 1st degree nodes independent of the ego artist, Pink Siifu.

Indeed, the emergence of these patterns at lower follower counts may reveal a characteristic of the Hip-Hop and Rap genres—which is that collaborations and clusters form more readily regardless of an ego artist's following size. The number of collaborations between artists also potentially indicates that artists are forming stronger ties—that collaborations are emblematic of a continued relationship forming between the two artists. Smith, in his 2006 study on patterns in rap collaborative networks, reflects on similar possibilities stating that "in rap, the level of collaboration between two artists can help elucidate their actual community connections" (Smith, 2006, pp. 14-15). Tight-knit clusters of collaborators could serve a similar function as a recording label insofar as it allows artists to form a clique, using high density to strengthen ties within the group while also increasing the likelihood that the members of that clique could collectively serve as a bridge for other artists or groups of artists. These tendencies are well-demonstrated in the average clustering values of CJ Fly and Kirk Knight's networks, as well as the clustering visible in their respective network graphs below.

Figure 4

CJ Fly Collaborative Network (to 2 degrees)

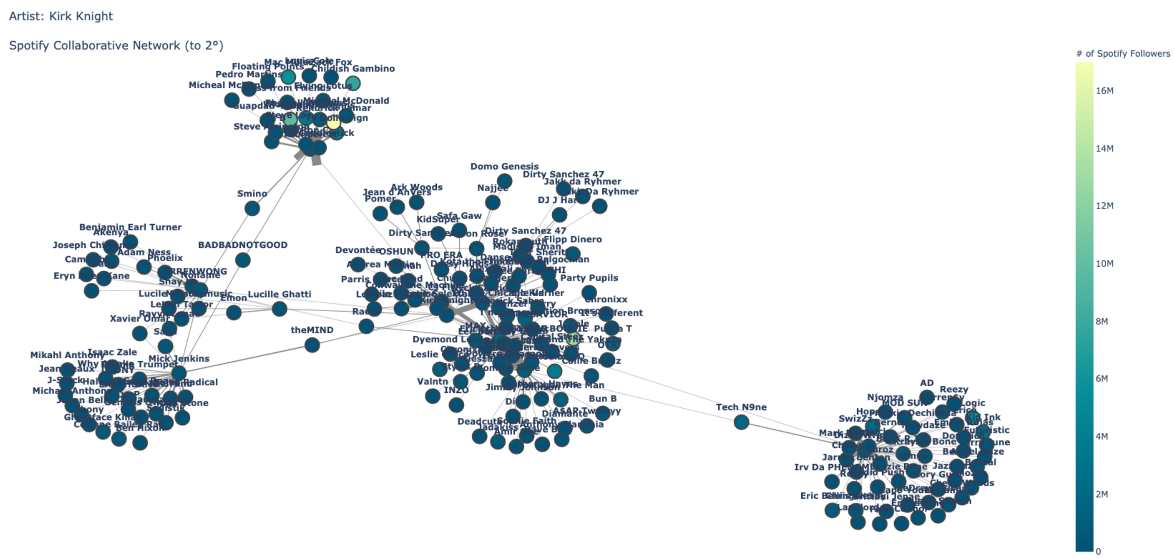


Note. CJ Fly's component has an average clustering of 0.0876 (8.76%) and total artist (node) count of 224.

Specific Note. Looking towards the center of the graph visualization, we see a number of interwoven nodes with a wide array of edges between 1st and 2nd degree nodes. The artists responsible for these nodes show potential to be clique makers.

Figure 5

Kirk Knight Collaborative Network (to 2 degrees)



Note. Kirk Knight's component has an average clustering of 0.072 (7.2%) and a total artist (node) count of 209.

Interestingly, another trend of influence—artist centrality—coincides with the increase of clique makers and the groups they connect. In some ways, this is expected. As the edges of bridges and cliques develop, the artists involved will have higher measures of centrality than artists with one-off collaborations. However, in other ways, these measures can provide interesting angles for examining bridges, cliques, and influence within the network—particularly when artists of high centrality are omitted from clusters.

To illustrate this, I look back to CJ Fly's component (69,352 followers, 224 nodes) due to the high average clustering (7.2%). To identify the most unique collaborator and most frequent collaborator within each component, I use measures of degree centrality (often just "centrality") and weighted Eigenvector centrality (eigencentrality). These illustrate a node's number of edges (relative to the total edges) and a node's influence (as a function of node edges and edge weights) respectively.

Both the highest centrality and the highest eigencentrality in the component belong to Statik Selektah (a 1st degree connection), at 39.91% and 70.4% respectively. Referring back to CJ Fly's graph visualization, we see that CJ Fly and Statik Selektah have a high edge weight, indicating a high number of collaborations between the two. Looking at other artists of high eigencentrality within the component, we see that Bun B, Curren$y, Termanology, and UFO Fev all have values lower than Statik Selektah but higher than CJ Fly and—importantly—they are all 2nd degree nodes.

Table 2

CJ Fly Component Nodes Sorted by Weighted Eigencentrality (Abridged)

Artist Name	**Degrees from Ego**	**Artist Followers**	**Eigencentrality (Wtd.)**
Statik Selektah	1°	93,917	0.7049
Bun B	2°	629,255	0.4141
Curren$y	2°	779,916	0.2923
Termanology	2°	32,602	0.2777
UFO Fev	2°	2,089	0.2095
CJ Fly	0° (Ego Artist)	69,352	0.2012

Note. Behind Statik Selektah, we see that the remaining artists with higher eigencentrality than the ego artist (CJ Fly) are all 2nd degree connections.

Looking down the list for high centrality values, we see that the artists with the largest number of unique edges within CJ Fly's network are all 1st degree connections between the component maximum and the component ego artist.

Table 3

CJ Fly Component Nodes Sorted by Degree Centrality (Abridged)

Artist Name	**Degrees from Ego**	**Artist Followers**	**Degree Centrality**
Statik Selektah	1°	93,917	0.3991
Conway the Machine	1°	115,138	0.2063
Joey Bada$$	1°	2,113,138	0.1928
Nyck Caution	1°	65,832	0.0987
Kirk Knight	1°	120,646	0.0717
CJ Fly	0° (Ego Artist)	69,352	0.0717

Note. The artists with the highest number of unique connections are all 1st degree collaborators, keeping with Feld's theory that one's connections will likely have more connections than them.

The identification of clique makers within ego artists' components coincides with recent studies that also examine the importance of centrality (and eigencentrality) in Spotify musical networks. Notably, research that lends itself to explanations of collaborative accretion also remains relevant within this trend.

In a study on popularity and centrality in Spotify networks, South et. al. address the trends of influence exhibited by artists and a critical inflection point. Their study finds two types of network influencers. Community leaders, who are individuals similar to clique makers who have a high number of connections and utilize those connections to grow in popularity and celebrities, who are highly influential yet only interact with a small number of artists within the network (South, 2020). South and colleagues also identify that these celebrities tend to exist within hip-hop, rap, and associated genres, with artists such as Lil Wayne and Rick Ross emerging as some of the most popular artists also possessing high eigencentrality.

Thus, clique makers may represent potential or emerging community leaders (under South's definitions) who are in the process of pursuing collaborations, building audiences, and amassing influence among their immediate neighbors. And, as was noted when exploring rationale for collaborative accretion, these clique makers' ability to bridge genres—as well as cliques—may directly impact their followers, influence, and popularity as they amass more collaborative content.

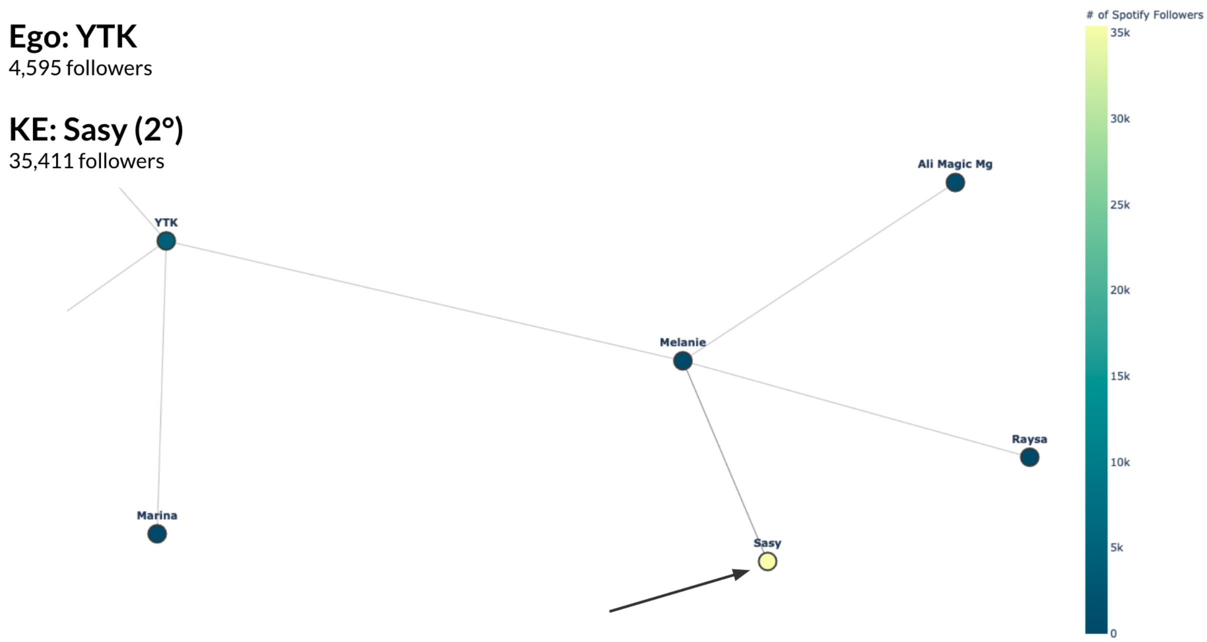
The Kendrick Effect

The next major finding is coded as the Kendrick Effect, which can be summarized as the tendency for ego artists' components—irrespective of ego artist following—to have one or a few "superstar" artists whose followings vastly outnumber the rest of the artists in the component. The coding "Kendrick Effect" was given because Kendrick Lamar was the first artist from whom I noticed this trend (in the ego artist Kirk Knight's network).

The Kendrick Effect was visible within nearly all 30 ego artists' networks with the least visible effect among the R&B genre cohort, which is also the genre cohort with the lowest total artists within 2 degrees ($N_{R\&B} = 471$, 7.69% of N_B). The effect displayed a slight inverse correlation with ego artist following size, such that a decrease in the disparity between the average number of followers in the component and the component's most followed artist was observed as ego artist size increased. Also of note is the tendency for the "Kendrick Effect" artists (where more than one appeared in a component) to occur in close proximity, often connected to the same node. And—equally as significant—was the tendency for the Kendrick Effect artists to have low centrality (degree or eigencentrality) within the network as a whole.

Figure 6

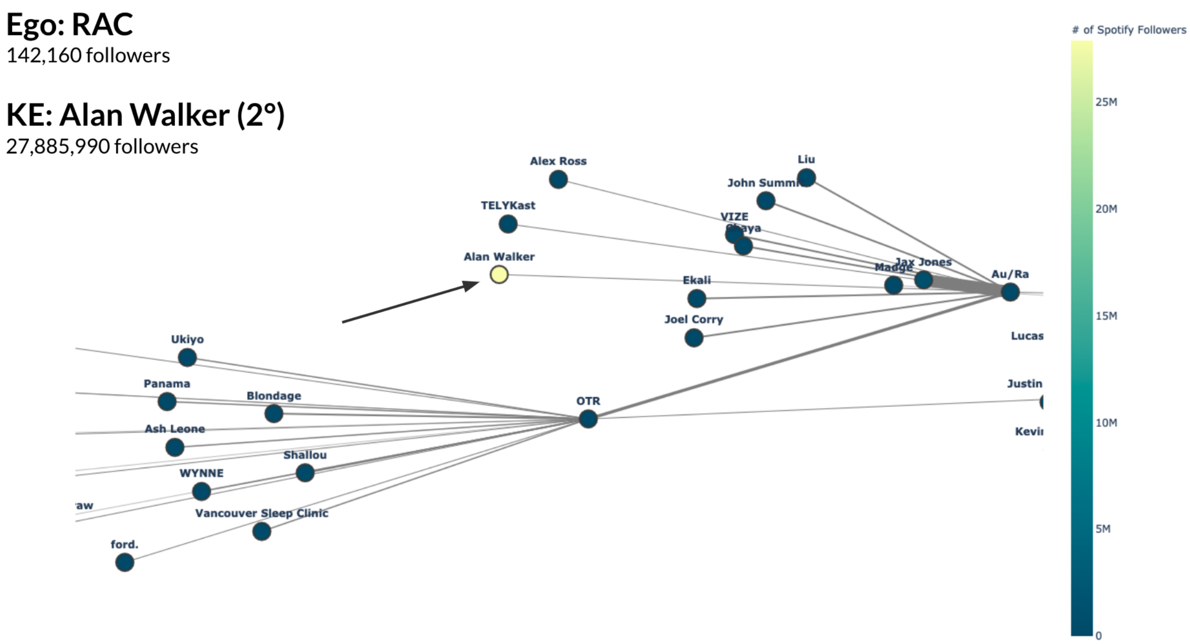
YTK Kendrick Effect Visualization



Note. In ego artist YTK's component, they have 4,595 followers. Standing well over that number is Sasy, at 35,411 followers with the largest audience in the component.

Figure 7

RAC Kendrick Effect Visualization

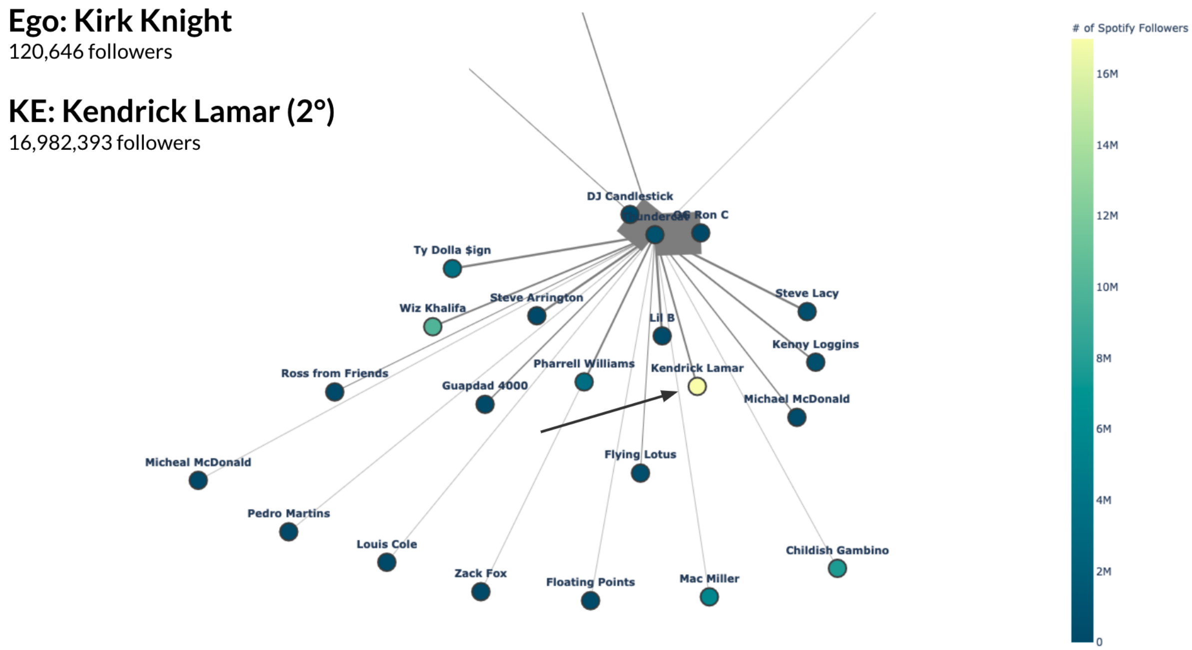


Note. In ego artist RAC's component, they have 142,160 followers. The Kendrick Effect is observed in the 2nd degree node Alan Walker, who has 27,885,990 followers.

Specific Note. The color of Alan Walker's node can also be used to infer this effect, as it maps to the follower count legend on the right hand side of the graph.

Figure 8

Kirk Knight Kendrick Effect Visualization



Note. In ego artist Kirk Knight's component, they have 120,646 followers. The Kendrick Effect is observed in the trend's namesake—Kendrick Lamar—a 2nd degree node with 16,982,393 followers.

Specific Note. Notice that Childish Gambino and Wiz Khalifa also have higher followings, demonstrating a proximity effect of the "superstars" in the component around the same node.

This effect stands opposed to several intuitions I had at the outset of my analysis. Where my expectations were that follower counts would tend towards an even distribution, or be relatively similar across a network, the analysis revealed the contrary. With respect to audience size, the Kendrick Effect demonstrates how ego artists experience winner-take-all behavior within their collaborative network. Interestingly, this finding is presaged by a similar study by

2010, which examined the propensity for highly popular artists to take the "lion's share" of digital music sales (Stratchan, 2010). Stratchan's inquiry found evidence that corroborated the presence of a "superstar effect" of digital music sales among the top 1% of artists, indicating concentration of a similar nature. Thus, the Kendrick Effect and its alignment with previous inquiry symbolizes a few things. For the more successful of the ego artists, it illuminates the challenge of attracting followers on Spotify even as a relatively close collaborator to a superstar artist while themselves being established. For the newcomers of small following, the Kendrick Effect shows that even small artists face the challenge of competing with a relative superstar. Several possible explanations can be introduced from the observation of this pattern, but let us look at two in particular: algorithmic influence, and playlist influence.

Algorithmic influence. Algorithmic influence may play a role in the presence of the Kendrick Effect, as previous studies such as Werner's have identified ways in which Spotify's recommendation system tends to exhibit certain biases such as gender bias (Werner, 2018). In turn, these biases affect which music is presented to listeners, who may default to the use of Spotify's recommendation algorithms to find and consume music Spotify deems similar to their pre-existing listening habits. The extent of this is hard to pin down though, as Spotify—like many large tech platforms—doesn't openly disclose a wealth of information on how their algorithm(s) work; a common challenge faced by researchers examining these types of systems (Christin, 2020). However, arguments and discussions surrounding algorithmic culture as an attribute of many modern media platforms—of which Spotify and MSS are included—provide a compelling case and rationale for why the Kendrick Effect may be a manifestation of Spotify's recommendation algorithm's behavior.

Naturally, music consumer behavior must also be considered in this equation. Though to the degree that recommendation algorithms are a reflection of current consumption behavior, an algorithmic bias towards quantifiably popular artists stands to amplify existing listening habits and—over time—could manifest as the observed Kendrick Effect(s).

Playlist influence. Playlist influence is another likely explanation or contributor to the Kendrick Effect, due to what is known about Spotify's editorial playlists (which are curated and promoted by the platform) and their impacts on the artists which they feature. Maria Eriksson provides one of the best academic inquiries into the state of playlists on Spotify, citing it as a highly visible source of both order and disorder on the MSS platform (Eriksson, 2019).

Perhaps one of the most important distinctions about editorial playlists is that they are created, curated, and promoted by Spotify's internal teams and not by regular users of the platform. They are available to explore and discover more readily in-app under the 'Browse' and 'Genres' sections, as well as on the homepage, and are reported to account for roughly thirty percent of the total streams generated in 2018 (Spotify, 2018). Spotify has made many assertions that artists cannot pay to get placed on editorial playlists, even going so far as to add comments on the policy to their "Spotify for Artists" frequently asked questions (Spotify, 2021).

However, these assertions have been challenged by both Spotify users and artists alike. One of the most noteworthy occurrences of this was the platform-wide promotion of Canadian artist Drake's album *Scorpion* on its release in 2018, in which the album appeared atop nearly all users' home screens and recommended playlists, regardless of that user's listening habits and playlist preferences. The campaign prompted heavy pushback from users of the platform and even led to subscription refunds to some users who filed complaints under the premise that they had paid for an ad-free experience (Techcrunch, 2018).

Considering this, the dichotomy of Spotify's statements versus its actions as a MSS suggest that there may be a conscious or unconscious bias benefitting popular or otherwise prominent artists (such as those presented by labels with direct ties to the platform) within Spotify's editorial playlist teams. Placing this potential preference back in the context of the Kendrick Effect then helps explain why the most popular artists seem to find themselves on editorial playlists more frequently, in turn accumulating more followers.

Implied Networking

The last major finding is a mixture of patterns observed among the more followed artists of the study and the IDM/Beats genre cohort. Implied networking refers to the non-traditional performing artists—such as producers, beatmakers, and instrumentalists—appearing as clique makers and other high influence artists in the larger ego artists' networks among the Rap, Hip-Hop, and Pop cohorts.

The term "non-traditional performing artist" defines an artist whose mode of performance defies the contemporary expectation of their genre. In Pop, where a performing artist would likely be considered a singer or songwriter, a producer would qualify as a non-traditional performing artist. In rap, where the performing artist is assumed to be an emcee, a beatmaker would have the same designation. This is an important distinction, because many popular modern music genres and MSS only list the performing artist(s) as the 'Artist' alongside the track and album name. For instance, Spotify has an additional credits menu that is available in the app by clicking on the 'See More' button of a song and then selecting "Show Credits". This disparity in visibility is not only present in the Spotify app, but is also extant in the platform's API, which returns "performers" credited on a collaboration while omitting other contributors.

These contributing individuals are—by every available definition—collaborators on the final song or release, and yet are not included in the artist data returned by Spotify. Further, the artists listed within the IDM/Beats genre cohort would likely be considered as producers or beatmakers within other popular genres, as IDM/Beats music is typically instrumentals in the style of popular modern genres. And—perhaps not coincidentally—the total artists in the IDM/Beats cohort equated to 2305 (or 37.63%) of the total 6125 sampled artists. This is where the implicit networking effect emerges; not as a visible trend across the entire analysis, but one that implies the presence of highly influential networks not fully represented in the data.

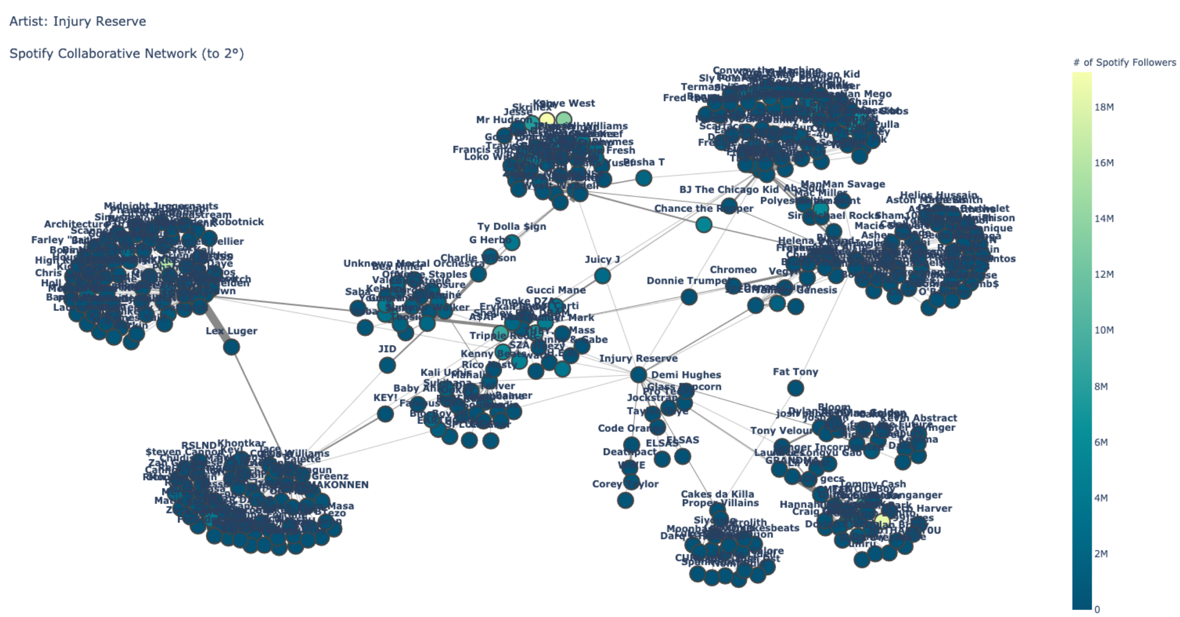
Interestingly, the two genres where these non-traditional performing artists most readily appeared, giving rise to the theory of implied networking, were hip-hop and rap. Both genres are known for the common presence of songs containing beat tags, short snippets of audio that typically play at the start of the song indicating who the song was produced by. In his 2020 paper on the topic, Christopher Greene details how these beat tags are used to identify the producer or beatmaker who created the instrumental that then becomes the foundation for a vocal performance by an emcee or vocalist. He then explores how common practice is to remove these tags once an instrumental has been purchased, but artists began requesting that the beat tags for popular producers be left in the final song, growing from "a subtle to the frequently uncredited musician behind the instrumentals… into an important part of the music itself" (Greene, 2020, p. 605).

With Greene's arguments reflecting much of the common practice surrounding beat tags, producers, and these genres, we see how less known hip-hop and rap producers may literally have their name or signature removed from a song after the instrumental is purchased. Of course, practices surrounding beat tags only provide a small window into one explanation in two genres.

However, this convention suggests that other contributors of similar roles such as songwriters, additional singers, and instrumentalists may also hold influence in these networks and not receive fully visible credit as collaborators. For instance, consider the presence of Kenny Beats and Lex Luger—both notable producers—in the Injury Reserve network as artists with highly weighted edges (numerous collaborations) bridging two or more groups of 2nd degree nodes.

Figure 9

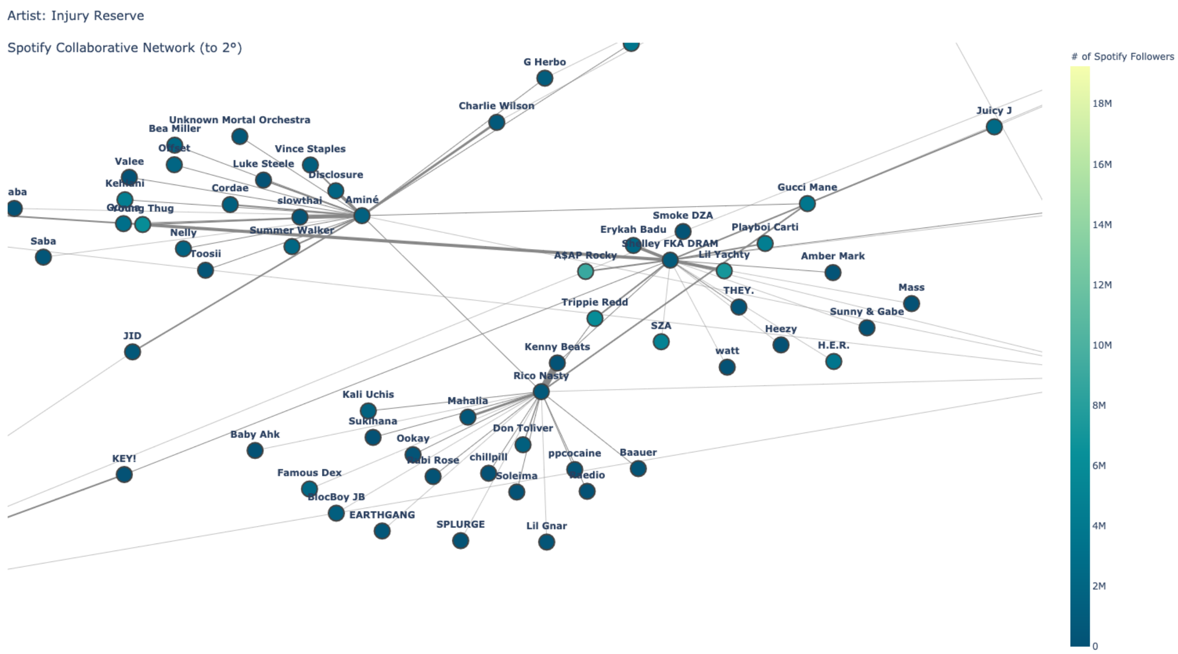
Injury Reserve Collaborative Network (to 2 degrees)



Specific Note. Due to the number of nodes, the purpose of this graph is simply to illustrate the bridges built between the definite groups of nodes within the graph. Note the collaborations (edges) that connect the outer groups to one another independently of Injury Reserve (who are located just down and to the right from the center of the component).

Figure 10

Injury Reserve Subsection — Kenny Beats

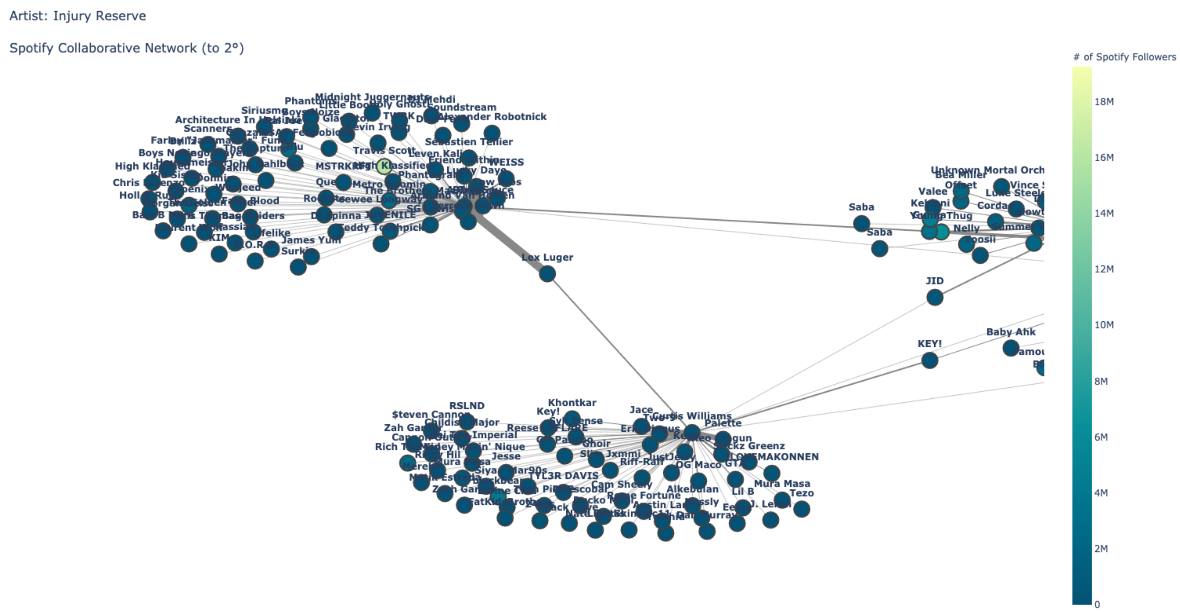


Note. Zooming in on the central collaborators, we see Kenny Beats (a producer) as a bridging artist between a handful of 1st and 2nd degree nodes.

Specific Note. Kenny Beats' node can be located near the center of the graph, inbetween Rico nasty and Trippie Redd.

Figure 11

Injury Reserve Subsection — Lex Luger



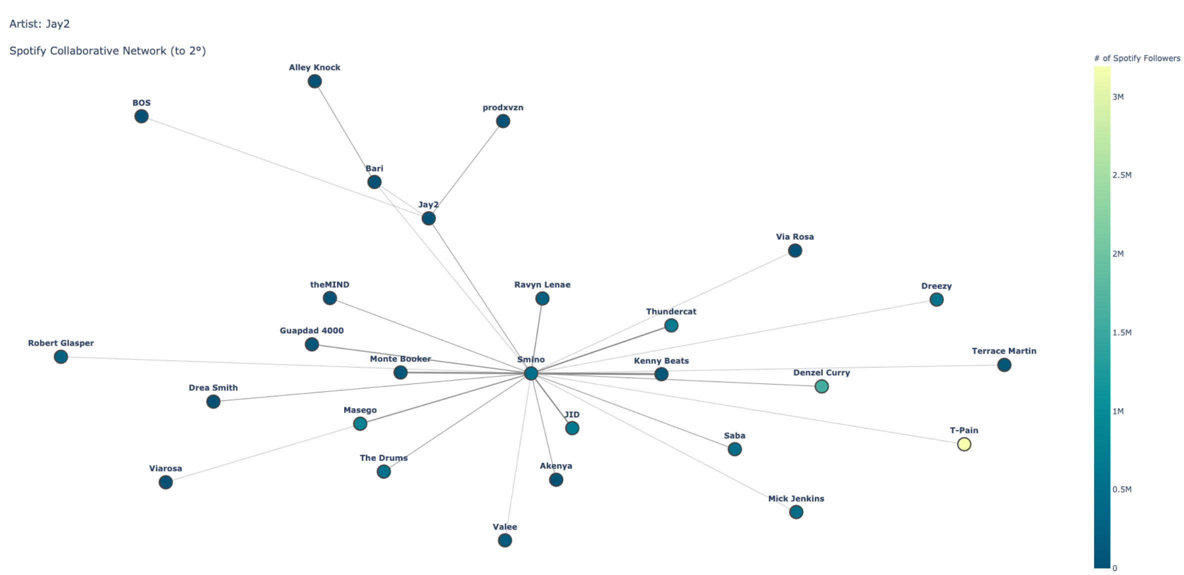
Note. Similarly, we see Lex Luger serving as the only bridge—and a highly weighted one at that—between two separate groups of artists.

Specific Note. Lex Luger can be seen as the single node between the top and bottom groups of nodes, acting as a bridge between two large groups of artists.

Now consider the network generated by an ego artist of smaller following such as Jay2. If we pull data on the other artists listed in their collaborative network, we find that they are traditional performing or recording artists, rather than producers, beatmakers, or songwriters. This raises an important question about hidden individuals in Jay2's network: how do other collaborators who produce, contribute to instrumentals, or provide additional vocals manifest in this component's graph? And what degree of centrality and influence do those individuals possess? If the influence seen in non-traditional artists of similar role in larger networks serves as any indication, then some of the most influential individuals within small artists' networks may be underrepresented in the data despite their high impact. And, because MSS such as Spotify choose not to readily reveal this data both in app and through their public database (via API), it is hard to discover these artists where they may have less leverage to ensure they are credited alongside the recording artist(s).

Figure 12

Jay 2 Collaborative Network (to 2 degrees)



Note. Notice artist names such as Kenny Beats, Monte Booker and prodxvzn in Jay2's small network, all of whom are more noteworthy as instrumental producers than vocal artists.

In many ways, this pattern ties back to the biases that may be responsible for the Kendrick Effect. As these implied networks and their contributors only appear with larger ego artists and notable non-traditional performers, it follows that the ability to negotiate a "performer" credit may be reserved for only the already-successful among the group. For lesser known or upcoming collaborators who aren't traditional performing artists, this stands to increase the difficulty of building one's reputation in a preexisting network of music professionals.

Conclusions

To conclude, let us look at the significance of each major finding in relation to the initial research questions as well as pertinent information from other studies. *Collaborative Accretion* may be of interest to artists and their teams when considering ways to increase audience size. As Feld's class size paradox suggests, each new collaboration with a unique artist presents a likelihood that the new collaborator will have more collaborations than the ego artist. And, in keeping with Ordanini's studies, seeking collaborations across genres likely exposes the ego artist to a wider audience and thus more opportunities for audience growth. As a form of value to artists or other musical collaborators, a visible trend of collaborative accretion within one's own genre provides insight into how many collaborators (and 2^{nd} degree nodes) the ego artist has relative to other artists of their size and genre. In the case of an artist with a modest following who has a relatively small collaborative network compared to their peers, additional collaborations may generate strong audience growth. Conversely, an artist who has a comparatively large number of collaborations for their following may wish to seek other methods of growth, or perhaps collaborate outside of their genre.

Clique Makers present another unique set of insights to artists wishing to better understand their collaborative networks. Artists—particularly those who may exhibit traits of community leaders—with high centrality and eigencentrality within an ego artist's network represent individuals with a high propensity to collaborate (relative to the rest of the group). These clique makers could then be approached for collaboration with that influence in mind. Similarly, artists with high centrality indicate a high number of unique connections relative to the rest of the network, suggesting that those artists may be able to provide references even if they themselves are not available for collaboration. For small artists in particular, the successful identification and collaboration with these burgeoning leaders could vastly increase the number of close connections to the ego artist while also adding value to the clique maker's network.

The Kendrick Effect and its consistency with past trends identified within digital music sales suggests both opportunities and challenges for artists to address. Broadly speaking, knowing where the "superstars" are within any artists network provides a degree of cognizance which allows ego artists to build towards or away from connections with those artists and their immediate collaborative networks. Where these highly followed artists may have access to major label resources, knowledge of the location(s) of Kendrick Effects in network could increase one's own access to these resources over time. Additionally, to the degree that the Kendrick Effect may represent algorithmic or playlist bias on the Spotify platform—as suggested by Eriksson and Werner's arguments—smaller artists gain foresight and forewarning into the challenges presented to them by these biases. Whether they are looking to overcome these biases with their latest releases or to address and improve platform conditions in these regards, an understanding of the Kendrick Effect provides a strong basis for informed action.

Finally, *Implied Networking* illuminates both an added, less visible store of value within artists' networks and a fantastic starting point for future research into the variety of collaborators—not just traditional performers—that contribute to musical releases. Not only do these markers for implicit networks seem to appear as bridges between groups of otherwise disparate artists, but also their high centrality or eigencentrality implies that these partially visible collaborators are also highly influential. For artists looking to build their following, implied networking suggests that perhaps the best collaborators to seek out are non-traditional performing artists such as beat makers, producers, songwriters, and so on. Indeed, ego artists who are willing to not only bridge genres but are also able to bridge roles may realize some of the largest gains of centrality, audience visibility, and future connections when tapping into these implied networks.

Next Steps

These major findings and their implications present a wide variety of next steps and future research. Among the most immediate would be to increase the scope of the study in a second iteration, expanding the number of ego artists sampled or the degrees out from the ego parsed for each component and perhaps attempting to build a complete (or near complete) graph of all collaborative data available through Spotify. Further, to the extent that other MSS make similar data available, additional research may examine collaborative networks on other platforms such as Soundcloud or Bandcamp, comparing and contrasting the differences in trends based on the types of artists present on each platform.

Another potential direction of this research exists in the intersections of these findings with other relevant data, such as social media activity, royalty payouts, artist locations, and so on. With the complements of additional dimensions for data analysis, discussion surrounding artist cliques, label influence, platform payouts, and other areas of interest may become more informed. These attributes could also be analyzed across artist size in order to draw conclusions about endogenous and exogenous factors that contribute to a rise or fall in artist popularity.

Finally, the findings presented within this research may provide a valuable stepping stone into future activism within the music industry, particularly surrounding Spotify and popular practices across music streaming services. The recent formation of the Union of Musicians and Allied Workers aligns heavily with this direction, and among their core values are that of better artist compensation, contributor visibility, and industry transparency surrounding the influence of major players (UMAW, 2021). This study only scratches the surface of collaborative networks' value for artists, and I hope it represents a shifting of the tides within the larger industry, as there is certainly more to be seen.

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Appendix A

Korus Generated JSON Schema (Artists)

Figure A1

Korus Generated JSON Schema for Artists


```json
{
    "id": "21M2ze8jdDJnLL90bzipq",
    "name": "The Source Artist",
    "accessed": "01 Jan 2020 22:20:21 +0000",
    "followers": 578,
    "genres": [
        "indie", "alternative"
    ],
    "collabs": {
        "2HOjzMceunaiolBmG65YD": {
            "id": "2HOjzMceunaiolBmG65YD",
            "name": "Collaborator Name",
            "followers": 407,
            "genres": ["alternative", "hip-hop"],
            "collabs": {
                "0jvjuFmLe7LPC7avh44BzM": {
                    "title": "Anything is Possible (Single)",
                    "type": "track",
                    "weight": 1
                }
            }
        }
    }
}
```


Note. The JSON Schema for artist data collected by korus.py. Each file is named procedurally, based on the artist's Spotify ID.

Appendix B

Korus Analysis Output Files

Figure B1

Artist Analysis Overview File (Korus)

```
{EGO ARTIST} - Collaborator Graph (G) Metadata

Artist (Ego): {EGO ARTIST NAME}
Followers   : 4595
Genres      : ['indie hip hop']
Degree      : 0

COMPONENT ATTRIBUTES (G)

Total Edges (G sub-e)  : 11
Total Nodes (G sub-n)  : 12

Radius      (Gr)       : 2
Diameter    (Gd)       : 4
Density     (G sub-d)  : 0.16666
Center      (G center) : [{CENTER ARTIST}]
Avg. Clustering (C-bar): 0.0

DEGREE CENTRALITY (G sub-n)

> Max Degree Centrality

Name      : {MAX CENTRALITY ARTIST}
Degree    : 1
Genres    : []
Followers : 9
Centrality: 0.4545

> Ego Degree Centrality

Name      : {EGO ARTIST}
Degree    : 0
Genres    : ['indie hip hop']
Followers : 4595
Centrality: 0.3636

EIGENVECTOR CENTRALITY (WEIGHTED)

> Max Eigencentrality (Weighted)

Name      : {MAX EIGEN ARTIST}
Degree    : 1
Genres    : []
Followers : 9
Centrality: 0.705048792888462

> Ego EigenCentrality (Weighted)

Name      : {EGO ARTIST}
Degree    : 0
Genres    : ['indie hip hop']
Followers : 4595
Centrality: 0.1504198763379304
```

Specific Note. Files are named procedurally as `{artist-name}_overview.txt` where artist name is filled with the artist's name. This is a sample file from artist YTK.

Figure B2

Artist Degree Centrality Output File (Korus)

```
(1°) Marina
Followers : 9
Genres    : []
Centrality: 0.0909

(1°) The Eighth
Followers : 0
Genres    : []
Centrality: 0.0909

(2°) Ali Magic Mg
Followers : 803
Genres    : ['persian hip hop']
Centrality: 0.0909

(2°) Raysa
Followers : 6
Genres    : []
Centrality: 0.0909

(2°) Sasy
Followers : 35411
Genres    : ['persian pop']
Centrality: 0.0909

(2°) Crowned Papi
Followers : 0
Genres    : []
Centrality: 0.0909

(2°) Ron Tas
Followers : 23
Genres    : []
Centrality: 0.0909

(2°) Dedré Jackson
Followers : 20
Genres    : []
Centrality: 0.0909

(2°) DreadheadJae
Followers : 37
Genres    : []
Centrality: 0.0909

(0°) YTK
Followers : 4595
Genres    : ['indie hip hop']
Centrality: 0.3636

(1°) Melanie
Followers : 224
Genres    : []
Centrality: 0.3636

(1°) CM$
Followers : 9
Genres    : []
Centrality: 0.4545
```

Note. Artists are sorted lowest to highest by degree centrality.

Specific Note. Files are named procedurally as `{artist-name}_degree_centrality.txt` where artist name is filled with the artist's name. This is a sample file from artist YTK.

Figure B3

Artist Weighted Eigenvector Centrality Output File (Korus)

```
(2°) Ali Magic Mg
Followers : 803
Genres    : ['persian hip hop']
Weighted Eigen Centrality: 0.0068

(2°) Raysa
Followers : 6
Genres    : []
Weighted Eigen Centrality: 0.0068

2°) Sasy
Followers : 35411
Genres    : ['persian pop']
Weighted Eigen Centrality: 0.0136

(1°) Marina
Followers : 9
Genres    : []
Weighted Eigen Centrality: 0.0284

(1°) The Eighth
Followers : 0
Genres    : []
Weighted Eigen Centrality: 0.0284

(1°) Melanie
Followers : 224
Genres    : []
Weighted Eigen Centrality: 0.0360

(2°) Crowned Papi
Followers : 0
Genres    : []
Weighted Eigen Centrality: 0.1329

(2°) DreadheadJae
Followers : 37
Genres    : []
Weighted Eigen Centrality: 0.1329

(0°) YTK
Followers : 4595
Genres    : ['indie hip hop']
Weighted Eigen Centrality: 0.1504

(2°) Dedré Jackson
Followers : 20
Genres    : []
Weighted Eigen Centrality: 0.3988

(2°) Ron Tas
Followers : 23
Genres    : []
Weighted Eigen Centrality: 0.5317

(1°) CM$
Followers : 9
Genres    : []
Weighted Eigen Centrality: 0.7050
```

Note. Artists are sorted lowest to highest by weighted eigenvector centrality.

Specific Note. Files are named procedurally as `{artist-name}_eigen_centrality.txt` where artist name is filled with the artist's name. This is a sample file from artist YTK.

Appendix C

Korus Documentation

Overview

Korus is an application written in Python 3 that allows a user to input a Spotify artist's unique identifier (Spotify ID) and retrieve that artist's collaborative network out to a specified degree. Additionally, Korus leverages the powerful Plotly and NetworkX libraries to allow users to analyze and visualize Spotify artists' collaborative networks.

Dependencies

Korus uses the `pyenv` and `pipenv` Python modules for virtual environment and dependency management. These can be installed using a package manager such as Homebrew, and will need to be installed prior to running korus.

Codebase

Due to Spotify's Terms of Use and the user-linked nature of Spotify's API access keys, Korus' code repository can only be obtained on request—and at the discretion of—myself (Jameson Lyon) by contacting jameson.lyon@berkeley.edu.

Data Processing

Korus retrieves and parses Spotify artists' data in realtime (up to a maximum, rate-limited API request speed), and does not make use of saved instances of Spotify's data and/or database. In order to complete artists' network analyses, Korus isolates and reformats strictly necessary data to construct the relevant graphs and visualizations.

Using Korus

To use Korus observe the following steps, in order:

1. Obtain the unique Spotify ID for the ego artist you wish to analyze
2. Open and run `korus.py` (when prompted, enter the ego artist's Spotify ID)
3. Wait for `korus.py` to finish executing*
4. Open and run graphData.py (when prompted, enter the ego artist's Spotify ID)
5. Upon completion of `graphData.py`, a visualization of your generated component should open a new tab in your default internet browser
6. You can access the generated analysis files in the data directory; the subdirectory is named identically to the ego artist's Spotify ID
7. To update an ego artist's data, simply rerun `korus.py` and `graphData.py` **

* Artists' collaborative network size scales in an exponential fashion. Thus, an artist with a large number of 1st degree connections will have an exponentially longer parse time for their 2nd degree connections than an artist with few 1st degree connections. This runtime complexity also increases with degrees from the ego.

** Reruning `korus.py` on an artist that you've previously parsed data for will overwrite any existing data on that artist. Only one instance of artist data can exist per artist in Korus at any given time.

Appendix D

Ego Artists Sample List

Table D1

Ego Artists (Sorted by Genre and Followers)

Genre Cohort	Artist Name	Spotify ID	Followers
Hip Hop	Taylor*	5zcgTnL7jjir7HRsDfGgZM	96
	YTK	4QsNZ1JTLzhVSAzMxjLe7b	4,595
	Ras G	3PU8Ju4WBYNY5xvJE3DMfV	26,500
	Elujay	1CgbNAF3Stnz1Tpipu3xdO	49,035
	Jay Prince	2TLYSzGyVYkxAgYSCqUnQj	113,558
	Tobi Lou	4T8NIfZmVY6TJFqVzN6X49	268,454
Rap	Jay2	5RoJ70jcjGUibtNjye7DwO	4,579
	Pink Siifu	40ZElxHldNyvn7x8WRC6fh	20,671
	redveil	5BwsX8bXOFC1YnqSlyfOKM	37,598
	CJ Fly	41yEdWozNYEzA2RfgYQHgr	69,352
	Kirk Knight	1nSpOxq3pcgomrfpXudQuq	120,646
	Injury Reserve	3nf2EaHj8HikLNdaiW3v73	177,644
R&B	fika	4nJPiUgLhO1HcK13jBkAqX	4,293
	emawk	2zAshenjqDlcL4pudfySBY	22,959
	Sylo Norzra	0QitJHI0ZwMa5F9TR6EYSl	24,417
	Melanie Faye	4pcfFC9isxezJyTwbV1nIp	40,211
	Shay Lia	3sJQwG0SsGRyv5C5kh4o9a	53,250
	Yo Trane	4W49e48G0gg1pucAN6JiGH	142,893

IDM/Beats	Jobii	2MGL4XU2LCJC47c7VvSwuE	9,107
	Prefuse 73	0ZsnKPvBsvvycnET2GZMrG	53,415
	Daedelus	1YRGQOk4Mk9EpM6nTJhXtK	60,439
	Shigeto	48C2RLG6w7o4jAJjCJKZM8	96,436
	Nosaj Thing	0IVapwlnM3dEOiMsHXsghT	179,888
	TOKiMONSTA	3VwKSHAfgzV1DOHV0aANCI	253,326
Pop	Somni	7qFssj4KoOxd1IOPfv9iT7	5,294
	Billy Lemos	7ebBg3BuRFa2satTcY8whC	35,221
	Penguin Prison	5VsOThWOagH8C8gCvIy13k	61,213
	Healy	2Yhge9MsE7qKcV0eWsuuHM	103,115
	RAC	4AGwPDdh1y8hochNzHy5HC	142,160
	Miami Horror	0Z5pcmXDCKTrFWLnDChC37	219,390