Cultural Omnivorousness as a Result of Local Genre Network Structures

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1 Introduction

Over the last three decades, a debate around the concept of the cultural omnivore emerged (e.g., Peterson 1992, Peterson and Kern 1996, Peterson 2005, van Eijck and Lievens 2008, Vlegels and Lievens 2016). The concept describes socio-demographic status as a determining factor of cultural consumption patterns — where high-status groups consume a greater diversity and volume which includes both elite and popular cultural genres, while lower-status groups engage in few activities and strongly like one single non-elite form of culture (Maguire 2015).

Although many applications of the concept of cultural omnivorousness exist in quantitative research, it is rooted in the use of music genres (Hazir 2015). Researchers usually link music genres to construct cultural omnivorousness measures describing the volume or composition of a genre audience's consumption patterns (Vlegels and Lievens 2016). This process mostly rests upon survey-based data-collection on pre-defined music genre lists to gather music consumption patterns (e.g., Peterson 1992, Bryson 1996, Chan and Goldthorpe 2007). Specifically, survey participants are presented with a limited range of music genre options to state their cultural preferences — which has recently been criticized, because music genres have been found to be 'fuzzy' and constantly evolving (Beer and Taylor 2013, Sonnett 2016).

Instead of a survey-based approach limited by predefined lists of music genres, I utilize user-generated genre networks to identify music consumption patterns. This approach is inspired by Lamont's (2010) call to study classification systems from the ground up. The paper features two main analyses. A first analysis builds on existing methodologies in social network analysis to construct an undirected two-mode network of users and music genres to develop a set of metrics regarding the pattern of user genre choices and genre audience compositions (Lizardo 2018). In this analysis, I identify an exemplary genre pair (electronica and hip hop) that defies the above concept of cultural omnivorousness. A second analysis compares the user-generated with a professional music genre network via a percolation approach — describing the behavior of a network when edges are removed (Lambiotte and Ausloos 2006). This second analysis yields a set of general conclusions about the structural differences between professional and user-based genre networks necessary to inform the limitations of the concept of cultural omnivorousness found in the user-generated network. Subsequently, I will focus on electronica and hip hop to suggest that their local network structures systematically affect cultural consumption patterns. Employing this bottom-up approach, I obtain a more nuanced measurement of cultural consumption patterns and answer the following two research questions:

- **RQ1:** Do user-generated music genre networks exhibit patterns representative of the concept of cultural omnivorousness?
- **RQ2:** Do factors other than socio-demographic status affect user listening habits?

Hereinafter, Section 2 discusses existing theory. Section 3 introduces the data and Section 4 the methodologies applied. Section 5 presents and discusses the results. Section 6 concludes.

2 Existing Theory

Music tastes are important initial organizing tools for researchers to classify people and draw links between classifications and socio-demographic characteristics (Vlegels and Lievens 2016). Music genres shape boundaries within the music field and 'ultimately feed into sociology's conception of difference, class and inequality' (Beer and Taylor 2013; p. 2). The concept of cultural omnivorousness is the prime result of the utilization of music preferences to construct socio-demographic classifications of groups of people. As such, classifications of music genres are central to quantitative research on cultural omnivorousness (Beer 2013).

The problems with the construction of the concept of cultural omnivorousness within the existing literature are two-fold. First, Current research typically uses a predetermined array of music genres to measure differentiation in music taste (e.g., Bryson 1996, Peterson 2005, Chan and Goldthorpe 2007) —making the assumption that genres are rigid and stable concepts (Beer and Taylor 2013, Lena and Peterson 2008). This is at odds with research suggesting that music genres continually develop (Lamont and Molnár 2002, Lena and Peterson 2008). The emergence of decentralized social music streaming services (e.g., last.fm or Spotify) is supposed to have accelerated these dynamics (Vlegels and Lievens 2016). Further, genre labels may not be interpreted universally. Survey respondents can have different comprehensions of what type of music refers to which genre labels (Holt 1998, Savage 2006). Choosing from predefined lists of genres does not leave room for that 'fuzzyness' (Vliegels and Lievens 2016). Finally, survey-based genre preference research cannot guarantee that respondents actually know all elements on the list (Savage 2006, Vliegels and Lievens 2016). Research suggests that respondents have stereotypes over particular music genres without ever having listened to them (Rentfrow and Gosling 2007). Hence, the expressed preferences of survey respondents cannot be distinguished between stereotype and genuine taste. In sum, by using predefined genre lists to evaluate music taste, researchers risk missing important subgenres and styles within genre categories, which, in turn, may inform their conception of cultural omnivorousness. As a response, I follow Lamont's (2010) bottom-up approach to measuring music taste.

Second, problems exist regarding the exclusive focus on socio-demographic status as determining factors of cultural omnivorousness. Music genres with higher audience omnivorousness are said to pertain to audiences of higher socio-demographic status (Maguire 2015, Vliegels and Lievens 2016). Instead of a sole focus on socio-demographic characteristics, I propose to look at alternative network-based characteristics of music genres as a determining factor of a genre's audiences' omnivorousness. This proposition is motivated by recent work done by Lizardo (2018). He suggests a set of metrics to identify the cultural position of genres both in relation to their audiences and other (sub-)genres. This will elucidate the meaning of the structural positioning of a music genre within an umbrella genre category as an influential factor of their audiences' omnivorousness.

3 Data

Digital music service providers have established themselves as the primary sources of digital music streaming (Jacobson and Sandler 2008, Zhou et al 2018). Hence, I will use them as a source for data collection. For the two-mode analysis, I utilize a dataset collected from last.fm, an online music database and social networking service. For the comparative analysis, this paper utilizes the last.fm dataset and a dataset collected from Spotify, a music streaming service. See Table 1 for an overview of both datasets.

3.1 last.fm dataset

Last.fm provides abundant online information about its users, including their music tastes and followers. The information is publicly available and can be downloaded via the last.fm API. To create the dataset, I first developed a crawler to collect usernames. I chose a random user as a seed and subsequently snowball sampled a list of usernames by downloading a user's list of followers and repeating this process for their followers,

Table 1: Dataset Overview

	last.fm	Spotify
User Observations (N)	Yes (37.156)	No
Artist Observations (N)	No	Yes (38.233)
Unique Genres	453	469
Additional Observations	User Playcount	No

etc. (Heckathorn 1997, Baltar and Brunet 2012). I employed snowball sampling, because crawling the entire last.fm network is not practically feasible. Previous research found that snowball sampling can produce a complete picture of a dense core of an entire network (Lee et al 2006, Mislove et al 2007), and that the collected local networks can sufficiently reflect the characteristics of the entire network (Heckathorn 1997).

The crawler yielded a total of 1.063.924 usernames. Subsequently, 397.250 usernames have been randomly selected from the entire dataset and inactive users (i.e., users who have not been active in 2021 as of 4th of April, 2021) deleted. Consider that active user accounts likely reflect current music taste more accurately. This process yielded a total of 105.875 active users in the dataset, which has been enriched with each user's total playcount and genre tags self-assigned to their music library. Since not all users have self-assigned genre tags to their music library, the final dataset has been reduced to 37.156 unique users and contains their username, genre tags, and playcount.

Because the last.fm network is user-generated, a range of genre tags exist that do not represent actual genres. To capture meaningful genre tags, the list of tags included has been restricted to tags mentioned more than 135 times — any genre tag mentioned by more than 0.5% of users. However, even among the restricted set of genre tags, some genres without proper meaning persist. Such tags include: 'seenlive', 'beautiful', 'awesome', 'epic', 'love', 'sexy', 'amazing', 'albumsiown', 'videogame', or 'favourites' and written varieties thereof. These tags have been manually deleted. Finally, some tags representing written varieties of identical genres (e.g., 'rocknroll', 'rockandroll', 'rock'n'roll') remain. These genre tags have been combined manually, yielding a total of 452 unique genre tags.

3.2 Spotify dataset

The Spotify API provides information on the streaming service's songs, artists and their professionally assigned genres, among other information. To gather an unbiased sample of genres on Spotify, I collected every song of Spotify's own playlists, which feature a range of genre, mood and era specific playlists as well as "This is:" playlists with a focus on particular artists. Subsequently, I collected the artists for each song and queried their related artists, which yields up to 20 unique artists per query. This crawling process yielded a total of 38.233 unique artists. Finally, I collected the ascribed genre tags for each artist. The final dataset contains 469 unique genre tags.

4 Methodology

To answer both research questions posed in the Introduction, this paper conducts two separate but related analyses. The first analysis consists of a two-mode network analysis. It utilizes a range of first-level metrics (e.g., user-level centrality) and mutually definitional second-level metrics (i.e., metrics based on first-level metrics). Second-level metrics are useful for (1) ranking users in terms of their genre choices and consumption volume and (2) describing genres in terms of their audience composition (Jacobson and Sandler 2008, Vliegels and Lievens 2016, Lizardo 2018). The second analysis features a percolation approach to compare genres across user-generated and professional networks (Lambiotte and Ausloos 2006, Celma and Cano 2008, Levy and Bosteels 2010, Bryan and Wang 2011).

4.1 Two-Mode Analysis

I begin the two-mode analysis by constructing a bipartite network of N users and K genres (generating a $N \times K$ matrix). Users connect to a genre by tagging the genre in their last.fm account. I derive the below metrics, which are also listed in Table 2.

4.1.1 First-level metrics

User-level centrality can be calculated by focusing on the rows of the $N \times K$ matrix, which corresponds to the traditional notion of degree centrality (Freeman 1978) — the sum of the number of genres a user tags:

$$d_{n0} = \sum_k a_{nk}$$

Where $a_{nk} = 1$ if user n tags a genre k and the sum is over all genres K. This metric measures cultural omnivorousness and will be used accordingly in subsequent analysis (Warde et al 2008, Fishman and Lizardo 2013).

Genre-level centrality is defined by the number of users who tag a particular genre (Lizardo 2018). It separates genres into relative popularity (Mark 2003), and is represented by the number of users tagging a genre (Faust 1997):

$$\delta_{k0} = \sum_n a_{nk}$$

Where $a_{nk} = 1$ if user n tags a genre k and the sum is over all users N.

4.1.2 Second-level metrics

User-level and genre-level centrality form the groundwork of research in the sociology of taste, especially regarding the omnivorousness literature (Warde et al 2008, Fishman and Lizardo 2013). Expanding on each, Hidalgo and Hausmann (2009) proposed a set of mutually definitional metrics to derive information about both the structure of genre choices (user-focused) and audience composition (genre-focused) (Lizardo 2018).

Average popularity of genre choice. Using genre-level centrality, I construct a second-order classification of users based on the average popularity of their genre choices:

$$d_{n1} = \frac{1}{d_{n0}} \left[\sum_k a_{nk} \delta_{k0} \right]$$

While d_{n0} separates users into omnivores (who tag a lot of genres) and univores (who tag only few genres), d_{n1} classifies users into popular genre seekers (i.e., users who tend to choose genres with a large number of followers) and niche genre seekers (i.e., users who tend to choose genres with a small number of followers) (Lizardo 2018). Thus, higher values of d_{n1} can be interpreted as a taste for popularity (Lieberson 2000).

Average omnivorousness of genre audience. Similarly to characterizing users into popular and niche genre seekers, a second-order metric can be computed that characterizes genres by the relative omnivorousness of their audience:

$$\delta_{k1} = \frac{1}{N_k} \left[\sum_n a_{nk} d_{n0} \right]$$

Where $N_k = \sum_n a_{nk}$. While δ_{k0} separates genres into popular and niche genres, δ_{k1} partitions genres into those preferred by omnivores and those preferred by univores. To see the difference, consider that a genre can be popular even though mostly univores choose it (Lizardo 2018).

Average popular choice bias of genre audience. Further, this paper computes a metric that differentiates genres by the relative likelihood that their audiences are composed of users who choose genres which are popular or niche:

Table 2: User-Level and Genre-Level Metric Outline and Definitional Questions

	Name	Definitional Question
d_{n0}	User omnivorousness	How many genres are chosen by user n?
δ_{k0}	Genre popularity	How many users chose genre k?
d_{n1}	Average user popularity choice	How popular are the genres chosen by user n?
δ_{k1}	Average genre audience omnivorousness	How omnivorous are the users who chose genre k?
δ_{k2}	Average popular choice bias of genre audience	Are users who chose genre k likely to choose popular genres?
p_{k0}	Average genre playcount	How much music do users who chose genre k listen to?

$$\delta_{k2} = \frac{1}{N_k}\left[\sum_n a_{nk} d_{n1}\right]$$

This metric represents the two-step popularity of a given genre. Consider that even if not chosen by a large number of users, music genres may be indirectly popular if users choosing that genre also choose other popular genres, and vice versa for genres that have two-step niche status (Lizardo 2018).

4.1.3 Further metrics

Average genre playcount. Beyond the above recursively defined metrics regarding the user and genre degrees, I have collected user playcount as a variable. This allows me to further identify patterns related to the concept of cultural omnivorousness, which states that users of higher socio-demographic status do not only listen to a larger variety of music genres, but also tend to listen to higher volumes (Maguire 2015). As such, I have computed the average user playcount for each genre:

$$p_{k0} = \frac{1}{N_k}\left[\sum_n a_{nk} \rho_n\right]$$

Where ρ_n equals the playcount for user n.

4.1.4 Null comparison network

To evaluate which features of the user-generated network are due to cultural biases affecting users' genre choices, and which ones result merely from chance given the original distribution of both the number of genre choices at the user-level and the distribution of popularity across genres, I construct a randomized network. I implement a link-permutation procedure designed to preserve both the user-level and genre-level centrality but make everything else random (Maslov et al 2004). This procedure involves cycling through the original last.fm network, selecting two users at random and for each user selecting an existing edge connecting that user to a music genre and then swapping both edges (see

Figure 1: Link-Permutation Used to Generate Null Comparison Data

(a) Original Edges (b) Permuted Edges

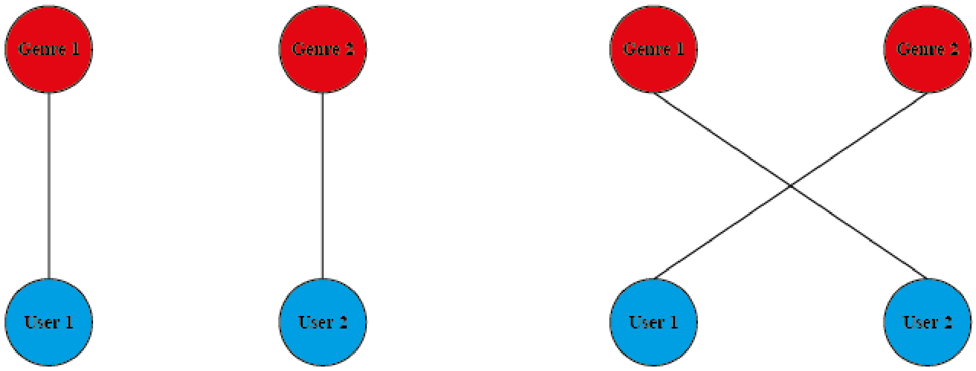


Figure 1). To construct the null comparison network, I take the original last.fm two-mode network and repeat the link-permutation procedure 100 times per edge.

4.2 Comparative Analysis

For the comparative analysis of this paper, I construct two undirected one-mode networks from the bipartite network data collected from last.fm and Spotify. To reiterate, both datasets consist of a network composed of two kinds of nodes called users/artists (for last.fm/Spotify respectively, subsequently referred to as users only) and music genres.

4.2.1 Percolation approach

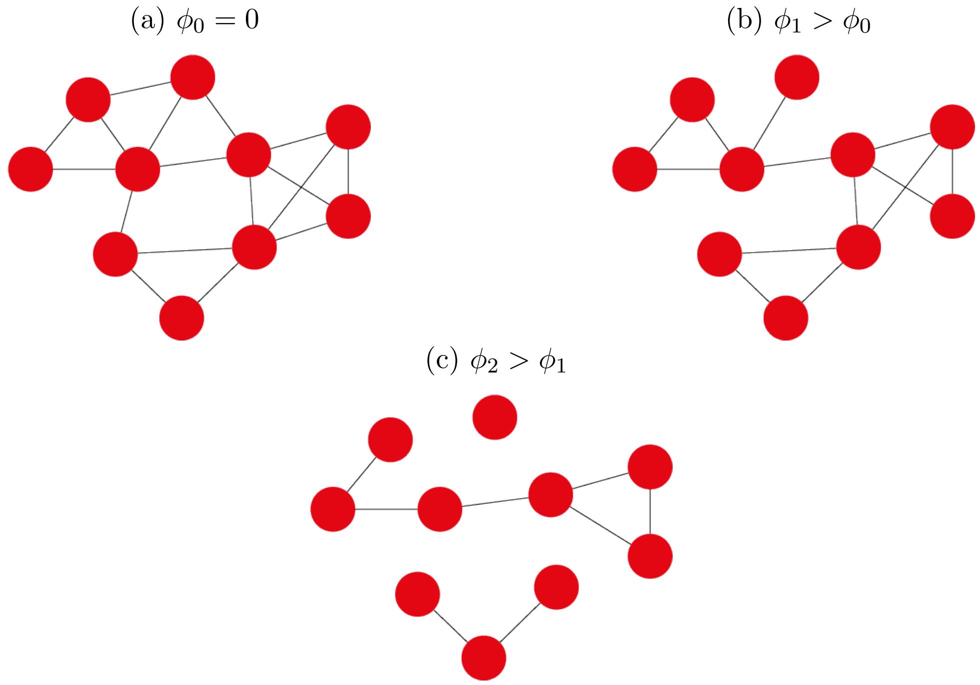
Motivated by Lambiotte and Ausloos (2006), I extract collective structures from the datasets by characterizing each music genre via its signature, which represents a vector consisting of the users subscribing to a specific genre.

Specifically, each music genre k is characterised by the vector $\overline{\Gamma}^k = (..., 1, ..., 0, ..., 1, ...)$ of N components, where N equals the number of users in each network (i.e., $N_{lf} = 37.156$ for last.fm and $N_s = 38.233$ for Spotify). $\overline{\Gamma}^k_n = 1$ if user n subscribes to genre k and $\overline{\Gamma}^k_n = 0$ otherwise. Hence, a genre's audience defines its signature. To quantify the correlations between two genres k_1 and k_2, I compute the cosine distance:

$$C^{k_1 k_2} = 1 - \frac{\overline{\Gamma}^{k_1} . \overline{\Gamma}^{k_2}}{||\overline{\Gamma}^{k_1}|| ||\overline{\Gamma}^{k_2}||}$$

Where $\overline{\Gamma}^{k_1} \cdot \overline{\Gamma}^{k_2}$ denotes the dot product between the two N-vectors, and $||$ their associated norm. $C^{k_1 k_2}$ increases when audiences are relatively similar and vice versa. Thus, $C^{k_1 k_2} = 1$ if their audiences strictly overlap and 0 if their audiences are strictly disconnected.

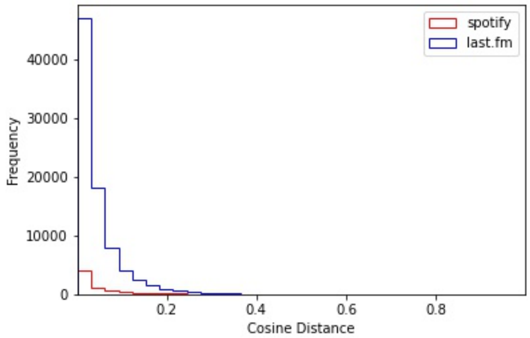
Figure 2: Branching Representation of Percolation Approach



To extract a network of alike music genres from the entire correlation matrix C^{ij}, where $i \neq j$ and $i, j \in [0, K]$, I define a filter coefficient $\phi \, \epsilon \, [0, 1]$ so that $C_\phi^{ij} = 1$ if $C^{ij} > \phi$ and $C_\phi^{ij} = 0$ otherwise (Lambiotte and Ausloos 2005). Increasing the filter coefficient ϕ removes less correlated links between music genres and leads to the shaping of well-defined genre classifications — a percolation approach (see Figure 2).

Figure 3 depicts the frequency of cosine distances for the last.fm and Spotify genre network for $\phi > 0$, i.e., any genres that are not strictly disconnected. Note that the last.fm network has vastly more connections between genres, which is due to the fact that the last.fm network is based on users tagging their entire music library while the Spotify network is based on at most three genre labels ascribed to each artist. Last.fm users likely exhibit a greater variety in music taste than Spotify ascribes to its artists. In fact, at $\phi > 0$, the last.fm network exhibits 92146 edges between genres, while the Spotify network only exhibits 8104 edges. Hence, the last.fm network naturally tends towards a greater amount of connections between genres. However, these connections are likely to be less meaningful, as they represent both the connection between genres and variety in cultural taste for a given user. To create comparable networks, this paper continues with the last.fm network at a filter coefficient $\phi = 0.1125$ while leaving the Spotify network unchanged. This restriction reduces the amount of edges in the last.fm network to 8161, which is roughly equal to the amount of edges in the Spotify network. This decision is further supported by relatively similar cosine distance frequency patterns for the last.fm network from a cosine distance of 0.1125 onward as compared to the Spotify network

Figure 3: Cosine Distance Distribution



(see Figure 3). Additionally, restricting the last.fm network leads to a reduction of edges to 8.85% of the original level, while only reducing the amount of nodes in the largest connected component to 94.2% — indicating that the restriction mostly reduces noise in the last.fm network instead of meaningful network structure.

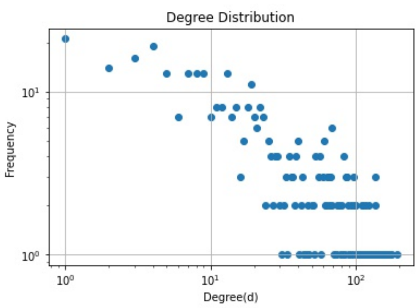
4.2.2 Whole-network descriptive metrics

To further ensure that no systematic differences in the last.fm and Spotify network emerge due to the above restriction, this paper computes a range of descriptive metrics. These include the network density, genre-degree centrality (Celma and Cano 2008), average shortest path length (Bryan and Wang 2011), Gini coefficient (Levy and Bosteels 2010), and assortativity (Watts and Strogatz 1998).

Starting with Figure 4, note that the last.fm network is closer to a scale-free (power-law) distribution than the Spotify network. However, both networks have very similar degree distributions for nodes of degree 30 or higher. This is expected, since most empirical distributions only fit a power law in the tail (Bar-Yam 2016). Next, Figure 5 plots the assortativity for both networks. It is apparent that the last.fm network is more assortative with respect to genre degree than the Spotify network — meaning that in the last.fm network genres of high degree are more likely to be connected to other genres of high

Figure 4: Last.fm/Spotify genre-level centrality

(a) Last.fm degree distribution



(b) Spotify degree distribution

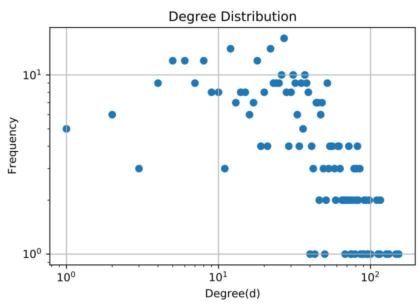


Figure 5: Last.fm/Spotify Assortativity

(a) Last.fm Assortativity (b) Spotify Assortativity

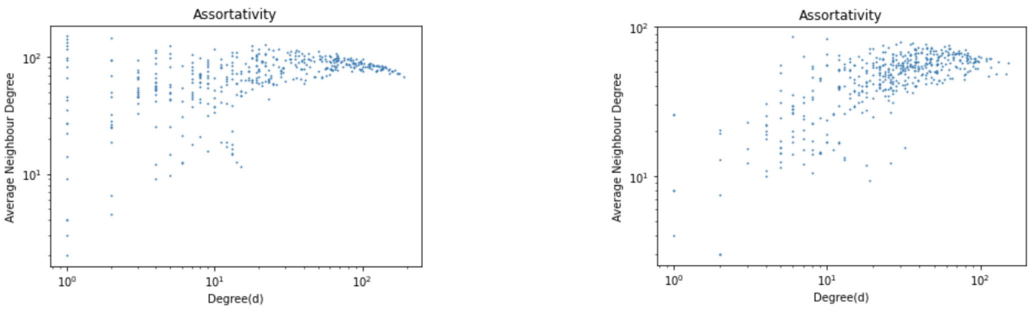
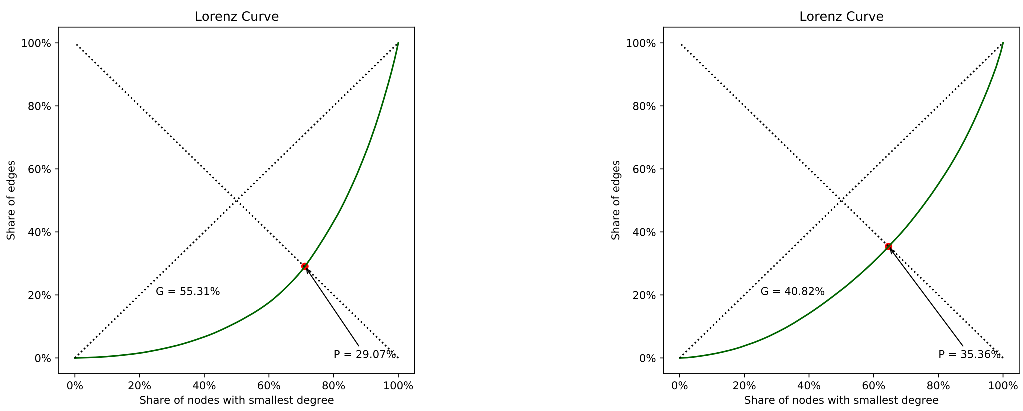


Figure 6: Last.fm/Spotify Gini coefficient

(a) Last.fm Lorentz curve (b) Spotify Lorentz curve



degree. This may be because more popular genres are easier to recall for last.fm users, which, in turn, leads more popular genres to be recalled together more often. The Spotify network, in contrast, represents a professional genre network, for which genre recall is likely to be higher. Overall, however, both networks are clearly assortative. Similarly, Figure 6 shows that the last.fm network exhibits greater popularity bias than the Spotify network. This is in line with the above argument that the last.fm network may be more biased toward popular genres because its users have stronger awareness of more popular genres (Levy and Boostel 2010).

Table 3 reports further descriptive network metrics. First, the average shortest path length of both networks is almost identical and low. This means that both networks allow its users to reach any given music genre with relatively high efficiency. Next, the network density of both networks is relatively low. This may hint at the conclusion that the noise level in both networks is low.

Table 3: Last.fm/Spotify Network Descriptive Metrics

	last.fm	Spotify
Average Shortest Path	2.43	2.55
Network Density	0.09015	0.07384

4.2.3 Genre in-depth analysis

Taking the above metrics together, I conclude that the restriction on the last.fm network has made the two networks comparable. I now introduce the comparative analysis, which will focus on two music genres in-depth. Each exhibits opposing divergence from the concept of omnivorousness. This part of the analysis aims to detect whether some patterns regarding the concept of omnivorousness are due to the existing music genre network structure as exhibited by professional music networks, or whether the existing explanations based on socio-demographic audience characteristics sufficiently explain the omnivore-univore duality.

This in-depth analysis is based on creating a local network around a particular genre, presenting the genre's edges in a circular bar plot. The plot uses cosine distance of a genre's connections as a measure of bar height and has been manually categorized into connection belonging to the same overarching genre category and connections of different overarching genre type. Circular bar plots have been created to study the genre's local network structures and compare these structures across user-generated and professional music networks.

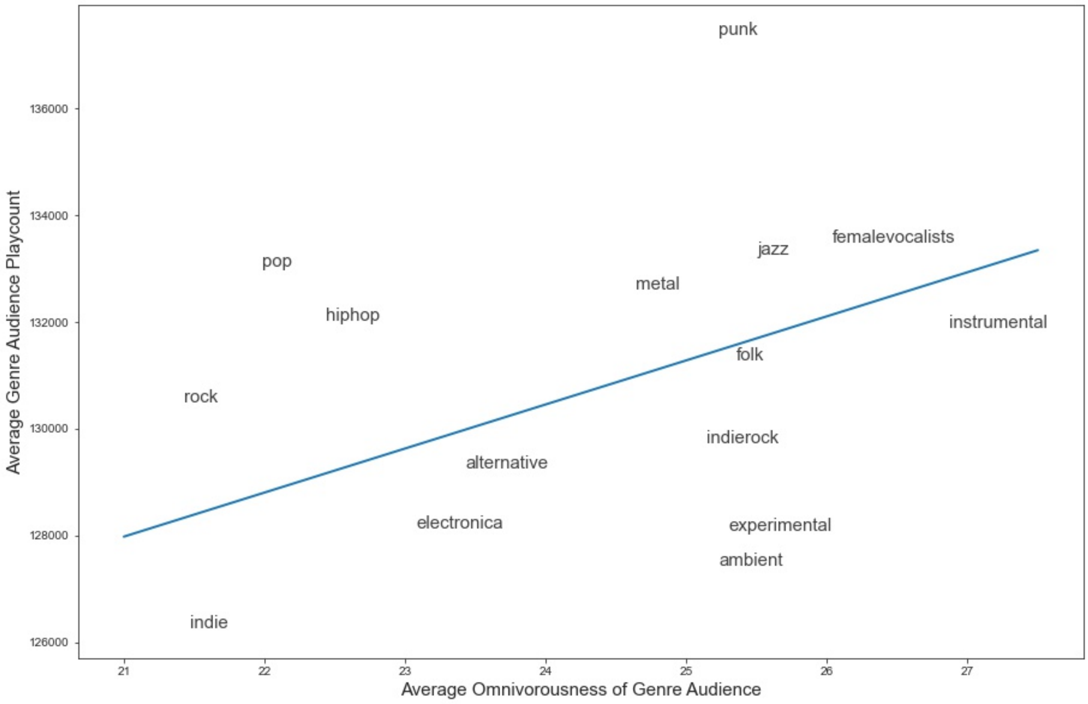
5 Results and Discussion

5.1 User-generated network results

The first analysis begins with a $\delta_{k1} - p_{k0}$ plot. Figure 7 represents the relationship between a genre audience's omnivorousness and its average playcount. The genre tags show the $\delta_{k1} - p_{k0}$ relationship for the top 15 genres of the original data and the regression line represents the linear $\delta_{k1} - p_{k0}$ relationship for the randomized version of the network. As such, deviations from the null comparison data are informative, i.e., they represent structural biases regarding cultural consumption patterns in the user-generated network.

Figure 7 directly corresponds to statements drawn from the concept of omnivorousness, i.e., a socio-demographic group's variety and volume of cultural consumption should be positively correlated (Maguire 2015). In line with the concept of omnivorousness, the null network exhibits a significant positive relationship between a genre audiences' omnivorousness and its average playcount (slope coefficient = 826.44 at p-value = 0.027). As

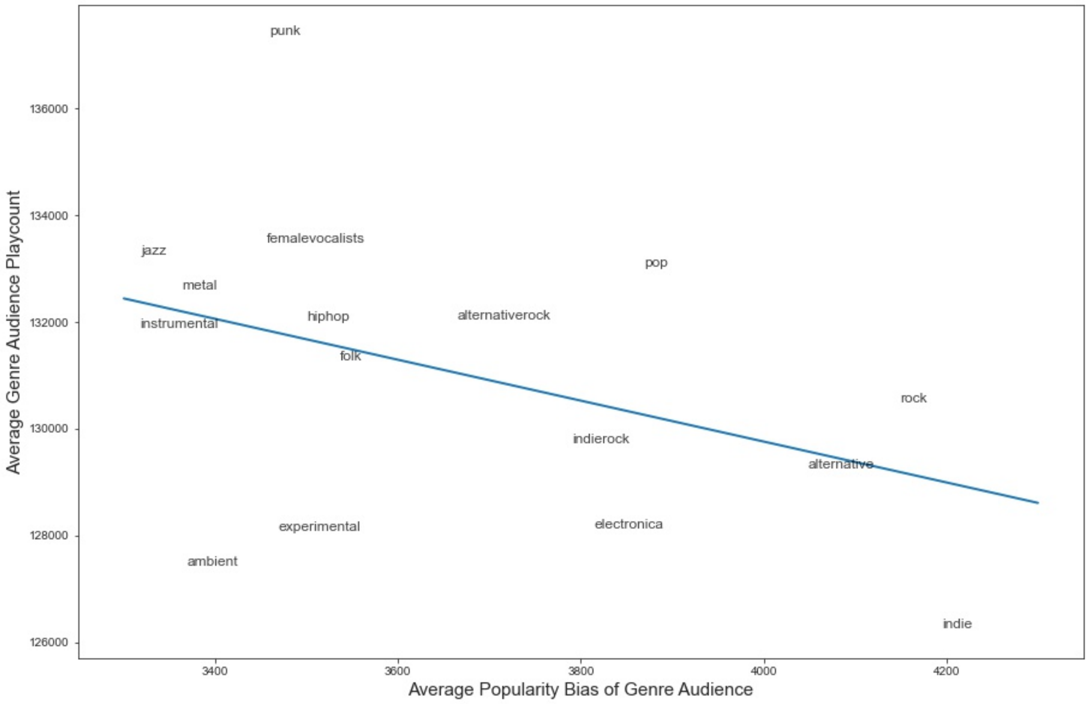
Figure 7: Average Playcount by Genre Omnivorousness



such, the concept of omnivorousness is embedded in the null network. However, the original network does not exhibit a meaningful positive $\delta_{k1} - p_{k0}$ relationship (slope coefficient = 505.85 at p-value = 0.22). This suggests that a structural bias against the concept of cultural omnivorousness exists in the user-generated network. Regarding particular genres in the original data, note that while electronica and hip hop exhibit similar genre audience omnivorousness, the electronica audience has a considerably lower average playcount than the hip hop audience. The same contrast (with different levels of genre omnivorousness and playcount) applies to indie and rock, as well as ambient/experimental/indierock and jazz/metal/punk.

To further investigate the structural bias against the concept of omnivorousness in the last.fm network, I plot the $\delta_{k2} - p_{k0}$ relationship in Figure 8. This figure portrays the relationship between a genre audience's bias toward listening to popular music and its average playcount. Remember that the concept of omnivorousness states that users of higher socio-demographic status tend to listen to popular and elite music genres (e.g., classical) while users of lower socio-demographic status only listen to popular music genres (Peterson 1992, Hazir 2015). Thus, the relationship between a genre audience's average popularity bias and its playcount should be negative, given that elite genres are less popular than non-elite genres (Peterson 2005, Maguire 2015). Indeed, the null network, again, exhibits alignment with the concept of omnivorousness (slope coefficient = -3.82 at p-value = 0.025). However, the user-generated network lacks alignment with the concept of omnivorousness (slope coefficient = -4.21 at p-value = 0.084). Hence, there is no

Figure 8: Average Playcount by Genre Audience Popularity Bias



meaningful relationship between a genre audience's popular choice bias and its average playcount. Regarding particular genres represented, note that experimental, ambient, electronica and indie all exhibit lower than random popularity bias given their playcount. In contrast, punk, femalevocalists, pop and rock exhibit higher than random popularity bias given their playcount.

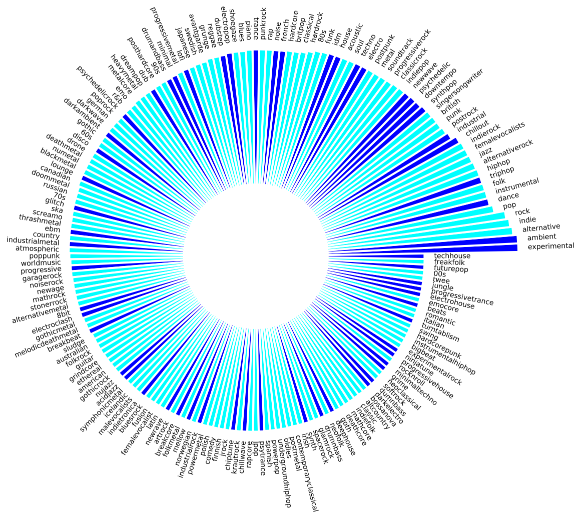
Because the null network in Figure 7 and Figure 8 represents a network structure corresponding to the concept of omnivorousness, but the original data does not, this paper suggests that user-generated networks exhibit structural biases contrary to the concept of omnivorousness. In other words, if no structural biases existed in the last.fm data, its network structure would correspond to the concept of omnivorousness simply by chance. But since no meaningful relationships exist between a genre audience's playcount and their omnivorousness or popularity bias, the structural biases in the last.fm network must be contrary to the one suggested by the concept of omnivorousness.

5.2 Local network results

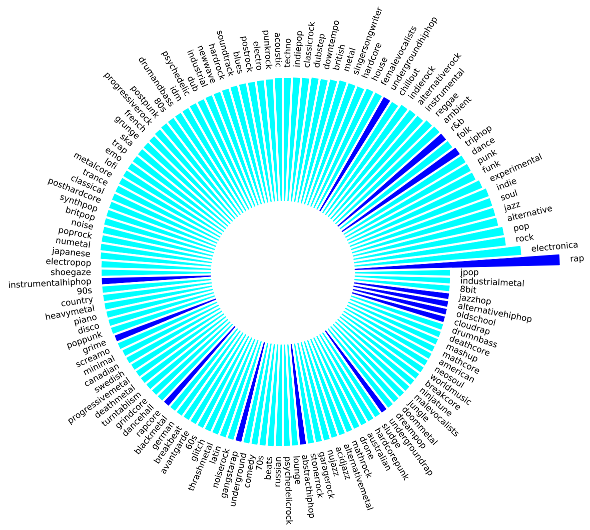
To investigate what may cause the above anomalies, this paper analyzes the genres electronica and hip hop in-depth. These genres have been chosen because, first, they represent the two deviating forces from the concept of omnivorousness. Electronica exhibits a lower than random playcount on average given its audience omnivorousness and popularity bias — meaning that given the amount of music its audience listen to, electronica users deviate

Figure 9: Last.fm In-Depth Genre Cosine Distances

(a) Electronica Circular Bar Plot



(b) Hip Hop Circular Bar Plot



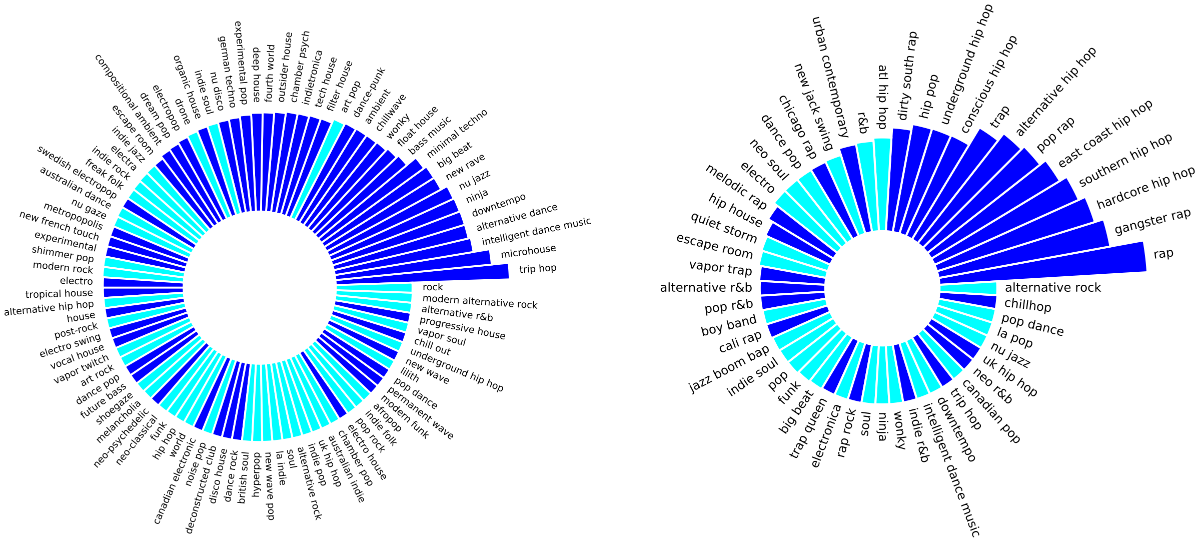
from the concept of omnivorousness by listening to a higher variety and less popular music than expected. Hip hop exhibits contrasting patterns, also systematically defying the concept of omnivorousness. Second, both genres represent overarching genre categories featuring a plethora of connected genres belonging to the same genre category (Campbell 2018). Because the comparative analysis results depend on the ability to categorize connected genres into an overarching genre category, electronica and hip hop lend themselves to further in-depth analysis.

Figure 9 displays a circular bar plot for each of the genres from the last.fm network. The bar height corresponds to the cosine distance of each connected genre. The dark blue bars represent connected genres belonging to each umbrella category. Note three main findings. First, electronica ($N = 60$) features a much larger number of connected genres belonging to the same genre category than hip hop ($N = 14$). Second, electronica (60/132) also exhibits a higher proportion of connected genres of the same umbrella category than hip hop (14/121). Third, hip hop has a very close connected genre (i.e., rap) while other connected genres are relatively more disconnected than for electronica, where the transition is much smoother. This can be seen by comparing the difference in bar height between the most connected and least connected partner genres. Also, remember that hip hop and electronica exhibit similar audience omnivorousness while hip hop's audience exhibits higher playcount than electronica (see Figure 7 and Figure 8). As such, the results suggest that the hip hop audience listens to a smaller range of connected genres more intensely than the electronica audience. In other words, the hip hop audience

Figure 10: Spotify In-Depth Genre Cosine Distances

(a) Electronica Circular Bar Plot

(b) Hip Hop Circular Bar Plot



is more likely to listen to similar connected genres, while the electronica audience taps on a wide range of connected genres (while both audiences listen to similar numbers of connected genres).

Above, I alluded to the fact that the difference in assortativity between the last.fm and Spotify network may be because last.fm users are more likely to remember popular genre tags (or even know them in the first place). This may lead last.fm users to tag their libraries with more popular genre tags for each of their music taste patterns. Similarly, it may be that last.fm users are more likely to recall (or know) a range of electronica sub-genres as opposed to hip hop sub-genres, which may lead to the electronica audience tagging their libraries with a larger variety of genre tags. Thus, although the number of connected genres outside of the respective umbrella genre is very similar for both electronica ($N = 132$) and hip hop ($N = 121$) — meaning that both genre audiences exhibit similar genre recall rates outside of their umbrella category — the deviations of both genre audiences from the concept of omnivorousness may be due to differential genre recall rates for electronica and hip hop sub-genres, respectively. To investigate this hypothesis, I implement circular bar plots for either genre category from the Spotify network.

To be clear, if the professional local genre networks exhibit a similar amount of connected genres belonging to either electronica or hip hop, differential genre recall rates for either genre category may cause each to defy the concept of omnivorousness. If, on the other hand, the networks exhibit a similar pattern to the last.fm network (i.e., differential number of connected genres belonging to the same umbrella category as electronica and hip hop), the local network structures may affect the cultural consumption patterns of each genre category's audience to an extent that the concept of cultural omnivorousness fails.

Figure 10 shows the circular bar plots for the Spotify network. Even in a professional music genre network, electronica ($N = 92$) features a larger number of connected genres belonging to the same umbrella category than hip hop ($N = 51$). Further, electronica (55/37) exhibits a higher proportion of connected genres of the same umbrella category than hip hop (28/23). Finally, hip hop, again, has very close connected genres (e.g., rap) while other connected genres are relatively more disconnected than for electronica. As such, the professional music genre network closely mirrors the user-generated one. Hence, differential within-genre recall rates can, to some extent, be ruled out as an explanation for structural biases against the concept of omnivorousness. Instead, the results suggest that the number of sub-genres belonging to an umbrella category affect a given genre audience's omnivorousness. This corresponds to the results of the two-mode analysis in the following way. Electronica exhibits higher than random audience omnivorousness and a large number of sub-genres, while hip hop exhibits a lower than random audience omnivorousness and a low number of sub-genres.

A possible explanation for why the concept of omnivorousness may still hold is that it has been established by contrasting classical music to pop-culture (Peterson 1992). Given that classical music is a well-established and fragmented music genre, while modern pop-culture does not feature similar granularity (Campbell 2018), this paper suggests that the concept of cultural omnivorousness is potentially confounded by the local network structures of the studied genres. Consider that higher-status socio-demographic groups tend to listen to well-established and fragmented music genres (e.g., classical music) (Peterson 2005, Van Eijck and Lievens 2008). According to the above results, this group is likely to listen to a higher variety of music genres, while also being of higher socio-demographic status. On the other hand, lower-status socio-demographic groups tend to listen to pop-culture, which exhibits less granularity (Savage 2006, Van Eijck and Lievens 2008). Following the above results again, this group is likely to listen to a lower variety of music genres, while also being of lower socio-demographic status. In sum, either group does not listen to a higher or lower variety of music genres because of their socio-demographic status, but rather due to the given local network structures of their respective cultural choices.

6 Conclusion

Peterson (1992) claimed to have found that higher-status socio-demographic groups are more likely to like symphonic music alongside a wide range of other kinds of music, while lower-status socio-demographic groups tend to listen to only a few music genres. He interprets the results as showing an omnivore-univore divide based on status hierarchy. In this paper, I showed that user-generated music genre networks do not exhibit such omnivore-univore divide. In fact, while random genre networks follow the divide, user-generated data exhibits contrary structural bias. I found that the existing number of sub-genres under an overarching umbrella genre category (e.g., classical, electronica, hip hop, pop, rock) may be the driving force behind an audience's omnivorousness. This result is plausible, given that Peterson's study focused on classical music (a well-established and granular music genre), which also happens to be listened to by higher-status socio-demographic groups. Hence, this study concludes that the concept of omnivorousness may be confounded and future research should study the granularity of genre categories as driving forces for their audience's omnivorousness.

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