Characterization of the Brazilian musical landscape: A study of regional preferences based on the Spotify charts

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ABSTRACT

In the digital age, streaming services such as Spotify have changed the way people consume music, highlighting the enormous influence these platforms have on the market. In the highly competitive music industry, it is crucial for independent artists in particular to maintain their popularity. This is especially true in countries like Brazil, where geographical and cultural differences influence music consumption patterns. Understanding these patterns is essential for effective marketing and production strategies. Despite previous research on music consumption, genre preferences and user behavior, there is a lack of detailed studies on the geographical and cultural distribution of music preferences in Brazil. Our study fills this gap by examining musical genre preferences and acoustic features of tracks across Brazilian regions over two years. We collected Spotify chart data from 2022 and 2023, modeled bipartite genre-city networks, and used backbone extraction methods to highlight significant genre preferences. Temporal analysis revealed patterns and persistence of musical preferences across cities, while clustering techniques revealed regional and cultural differences in acoustic features. Our results show that genre preferences are stable across Brazilian regions, with important genres emphasized by backbone networks. Persistence analysis suggests minimal changes over time, except during major holidays. Furthermore, Brazilian city clusters exhibit distinct acoustic patterns regardless of music genres, with notable differences in features such as liveliness, speechiness, and valence. This research provides new insights into regional musical diversity in Brazil and paves the way for future studies on cultural and geographical influences on music preferences.

KEYWORDS

Music Preferences, Music Genre Networks, Regional Analysis, Spotify Charts, Music Data Mining

1 INTRODUCTION

In the digital era, streaming services have revolutionized the way people consume media content, particularly music [3, 8, 12]. The number of music streaming subscribers worldwide increased from 616 million at the end of the second quarter of 2022 to 713 million in the third quarter of 2023 [26]. As a result, paid music streaming subscriptions have become the norm for many music fans and have led to impressive growth in subscriber numbers in recent years. This surge in popularity has led to music streaming services accounting for a significant portion of the music industry's revenue, demonstrating their significant influence on the market and the steady global expansion of these platforms [4, 8, 36]. Among the various music streaming services, Spotify stands out as a profitable player. In 2023, Spotify paid out more than 9 billion dollars to artists, one of the highest annual payouts by a single provider in history[1]. What factors contribute to the persistence of these regional patterns?

In parallel, the music industry is highly competitive, and maintaining popularity and influence is crucial for artists, especially for independent ones [32]. Expertise in production and promotion offers substantial advantages in this landscape [5]. In large countries such as Brazil, this knowledge is even more important due to the great geographic and cultural diversity [45]. A music popular in the South may not resonate in the North, and vice versa. Thanks to extensive data from streaming platforms such as Spotify, it is now possible to understand the geographical distribution of music preferences [30]. Mapping regional popular music is the first step toward identifying the profile of a region and testing relevant marketing strategies [45]. This profiling, carried out through a temporal analysis, assesses the common characteristics associated with popular music and their cultural significance.

Indeed, several prior efforts have concentrated on studying music popularity within groups [2, 37], geographical distribution of music preferences [7, 25, 30, 45], user demographics and personality [6, 43], and music diversity [20, 31, 46]. However, these studies do not capture the regional behaviors of these groups in terms of genre preferences, especially in the Brazilian context. Given the significant role that music streaming platforms play in the distribution and consumption of music, it is important to understand the composition of musical preferences in different regions [6, 15]. In Brazil, with its diverse cultural landscape, this understanding is particularly important for artists, producers, and marketers who want to tailor their strategies to regional tastes [13, 17, 47]. With this in mind, this study seeks to fill this gap by examining and characterizing the musical genre preferences and audio features of tracks in different regions of Brazil over a two-year period on Spotify charts. In this way, we aim to gain valuable insights into the regional musical landscape that can improve marketing strategies, production decisions, and promotional activities. Our study aims to address the following research questions:

—**RQ1:** How do preferences for musical genres differ in different Brazilian cities over the years? What factors contribute to the persistence of these regional patterns?

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[1]Spotify royalty data 2023: https://apnews.com/article/spotify-loud-clear-report-8ddab5a6e03f65233b0f9ed80eb99e0c

—**RQ2:** To what extent do the acoustic features of the tracks reflect regional and cultural patterns in Brazil, independent of their musical genres? Furthermore, are there acoustic differences within the same musical genre across different regions?

To tackle these research questions, we collected data from Spotify charts for the years 2022 and 2023. We modeled genre-city bipartite networks and applied a state-of-the-art backbone extraction method to highlight significant genre preferences while respecting the heterogeneity of musical tastes across different cities. Using this refined topology, we conducted a temporal analysis to identify patterns and persistence in musical preferences, addressing RQ1. For RQ2, we generated features from the backbone network and applied clustering techniques to uncover regional and cultural variations in the intrinsic acoustic features of tracks. This involved profiling clusters based on their acoustic characteristics and identifying significant differences within the same genre in different regions. Our results show that preferences for musical genres in Brazilian cities exhibit a stable set of preferred genres, with backbone networks highlighting the most important ones. Moreover, we observed balanced preferences, while persistence analysis indicated minimal changes over time, except during important holidays. Regarding RQ2, Brazilian city clusters showed different audio patterns in tracks, regardless of musical genres. We found significant differences in features such as *liveness*, *speechiness*, and *valence* between clusters with similar genre preferences, indicating regional and cultural differences in musical preferences and acoustic nuances within the same genres in different regions.

The remainder of this paper is organized as follows. In Section 2, we discuss related works. In Section 3, we describe the method of data crawling and the generated dataset. Section 4 details our methodology in four steps. In Section 5, we present our results in discuss our findings for RQ1 and RQ2. Finally, in Section 6, we conclude and propose ideas for future research.

2 RELATED WORKS

Some works aim to understand the distribution of music consumption in a population [7, 42, 43, 46], focusing on various aspects. These include consumption patterns [37, 42], genre preferences [22, 25, 27, 30, 45], user behavior [8, 14], the temporal evolution of music preferences [12, 41], the impact of marketing campaigns [5, 32], the influence of social events [10, 24], user demographics and personality [6, 43], the effects of algorithmic recommendations [33, 40], and musical diversity [20, 31].

Focusing on consumption patterns, Ren and Kauffman [37] built a machine learning model to predict the popularity of new releases on streaming platforms, uncovering patterns that remain common to popular music, such as tracks staying at the top of the charts for long periods. Similarly, Terroso-Saenz et al. [42] developed an algorithm to detect music propagation patterns on Spotify across different countries, finding strong correlations with cultural and social similarities. Our goal is different, as we want to identify the most popular music in each city, excluding national hits and making correlations between cities based on their popular music to describe possible geographical and cultural connections.

In terms of genre preferences, Mondelli et al. [30] used a network-based approach to analyze communities of countries with similar musical genre preferences, finding that most communities are culturally and/or geographically related. They also showed that Brazil is unique, with its top genres primarily originating from its own culture. Jiang et al. [22] found that new releases with functional purposes are less consumed, and popular genres like *pop* do not always equate to high consumption rates. Our study focuses on genre preferences in the different regions of Brazil. It emphasizes the country's cultural and geographical diversity and reinforces the idea that the most popular music genres in Brazil come from within the country.

Lee and Cunningham [25] presented hierarchical groups of countries with similar genre preferences, identifying leader-follower relations where leaders are defined by their historical production and consumption of a genre. Although determining the origin of genres in the Brazilian regions is not our primary research question, we address it by recognizing sub-genres that indicate regional origins and identifying national genres that are predominantly listened to in specific areas. Similarly, Vaz de Melo et al. [45] identified digital music consumption patterns in each state but did not reveal differences. Our goal is to highlight these differences by analyzing the track acoustic features of similar genres and sub-genres in different regions, connecting users geographically through similar preferences, and revealing regional differences.

Regarding user demographics and personality, Tricomi et al. [43] linked Spotify users' playlists to their demographic and personality traits, finding that similar playlists are created by users with similar profiles. Bello and Garcia [6] explored cross-country diversity in music charts over four years, revealing a trend towards greater diversity in global digital music consumption. In the area of musical diversity, Way et al. [46] found that the preference for local content increased in various genres from 2014 to 2019. Hesmondhalgh [20] argued that streaming platforms encourage music to have certain characteristics and thus influence the listener's aesthetic experience. Morris [31] investigated the "platform effects" on users' musical tastes and found that music acts like data, putting pressure on musicians and producers to adapt to platform trends.

Our study contributes to the literature by providing a longitudinal analysis of the geographical and cultural distribution of music preferences in Brazil. Using data from a two-year period, we examine how genre preferences and track acoustic features differ from region to region, offering new insights into the regional diversity of musical tastes in Brazil. Our research fills a gap in the understanding of regional music consumption and provides a basis for future studies on cultural and geographical influences on music preferences.

3 DATASET

To analyze Brazil's musical preferences geographically, we use the Spotify Charts[2]. This service summarizes the daily Top 200 most listened to songs in a specific region, referred to as a "chart". We collected the weekly rankings of all available Brazilian cities on the platform from 2022 to 2023. Each chart contains essential information about all tracks, including the track name, artist names, and the Spotify identifier for each track. Additionally, we used these identifiers to query for acoustic features and genres of each track

[2]Spotify Charts: https://charts.spotify.com/charts/overview/global

using the Spotify API for Developers[3]. Some core features described by Spotify are as follows:

—**Acousticness** measures from 0.0 to 1.0 whether the track is acoustic; 1.0 indicates an acoustic song, while 0.0 means a song without any acoustic elements.
—**Danceability** describes from 0.0 to 1.0 how suitable the track is for dancing based on a combination of musical elements; higher values indicate greater danceability.
—**Energy** measures from 0.0 to 1.0 how intense a track is.
—**Liveness** detects the presence of an audience in the recording on a scale between 0.0 and 1.0.
—**Speechiness** detects the presence of spoken words in a track; the more exclusively speech-like the recording, the closer to 1.0 the attribute value.
—**Valence** ranges from 0.0 to 1.0 describing the positivity of a track. Values close to 1.0 indicate happy, positive, and euphoric songs, while low values sound more negative, sad, depressed, or angry.

The dataset includes 5190 unique tracks, 487 genres, and 2056 artists. Geographically, we cover 17 cities across 16 states, namely: Belém, Belo Horizonte, Brasília, Campinas, Campo Grande, Cuiabá, Curitiba, Florianópolis, Fortaleza, Goiânia, Manaus, Porto Alegre, Recife, Rio de Janeiro, Salvador, São Paulo, and Uberlândia. Unfortunately, other cities – especially the countryside – could not be covered by this study due to their absence on the Spotify Charts platform. However, those mentioned above represent the five regions of Brazil (North, Northeast, Midwest, Southeast, and South), providing a comprehensive geographical perspective of the country's music preferences. Thus, we extend the literature with a detailed analysis of the temporal, geographical and cultural distribution of music preferences in Brazil across different regions.

4 METHODOLOGY

This section presents our methodology, including the steps for answering each RQ.

4.1 Modeling musical genre preferences

Aiming to answer our RQ's, we start by discretizing the two-year period into bimonthly windows. We then adopted network models for each period Δ_τ, specifically bipartite networks. Formally, the bipartite network $\mathbf{B}^{\Delta_\tau} = (V_{Genre}, V_{City}, E^{\Delta_\tau})$ consists of the following elements: V_{Genre} is the set of all music genres, V_{City} is the set of all cities, and E^{Δ_τ} is the set of directed edges $(g, c, w_{gc}^{\Delta_\tau})$, where $g \in V_{Genre}$ and $c \in V_{City}$. The weight $w_{gc}^{\Delta_\tau}$ represents the number of unique tracks of a genre g that appear in the Spotify chart of city c during the period Δ_τ.

Then, we use instances of $\mathbf{B}^{\Delta_\tau}$ to identify cities with common genre preferences. However, our analysis revealed that these networks often resulted in highly dense structures, where each node was strongly linked with many others. This density made it challenging to extract meaningful information about common preferences. This phenomenon is similar to the observations in prior efforts [30], who also faced difficulties due to the dense nature of their networks. They found that certain genres were universally popular, appearing in charts across multiple countries, resulting in an overly connected network.

To address the issue of overly dense networks, we employ a network backbone extraction method [16, 29, 34]. Since not all edges are equally significant for comprehension, as tracks and genres can be influenced by side effects such as singer popularity, we propose adopting *backbone* extraction algorithms to filter through the noise and unveil only the most relevant edges, resulting in a subset of the initial network [9]. There are several backbone extraction methods in the literature [16]. Some of these methods are used to explore network heterogeneity by identifying salient edges with significantly higher weights based on local individual patterns (e.g., Polya Urn Filter and Disparity Filter) or global network patterns (e.g., Thresholding), representing persistent and repetitive interactions [28, 39]. Local methods, in particular, are probabilistic methods that build *null models* for each node and can capture, from a local perspective, how salient an edge is according to its weight. A review of these methods for this context is available in the literature [16].

We determined that the most valuable edges – also called *salient* edges – in our context are not necessarily the weakest or strongest across all cities but those that have exceptional weights from the perspective of each city. In other words, these are the genres that appear most frequently in the charts of the individual cities, taking into account the popularity of the city and the genre. The main assumption is that these edges will not exhibit a uniform behavior across all cities but will show specific deviation patterns for smaller sets of cities. Thus, we employ the Polya Urn Filter [29], a backbone extraction method inspired by the Pólya urn combinatorial model. This method takes into account the reinforcement hypothesis of interactions between the same two nodes over time (i.e., a genre with a high presence in the listened genres of a city over the studied time windows is a salient link), presuming these edges are maintained and reinforced [29]. The method is controlled by a given *alpha*, which is used to determine the probability for the statistical significance of an edge according to the null model of the Pólya-Urn filter, and by a reinforcement parameter, which may be self-tuned.

We advocate the use of this method, as opposed to the thresholds used by other authors [1], because it is advantageous when observing cities and genre preferences, as it takes into account the heterogeneity of the data. For example, a genre may appear 10 times in the chart of one city and 100 times in another, creating edges with the corresponding weights. Both edges can remain in the backbone and connect the genre in both cities. This is possible because from the perspective of the first city, 10 occurrences may be significant when other genres only occur 1, 2 or 3 times. In this way, this approach respects the heterogeneity of edge weights in the networks.

The execution of the Polya Urn Filter reveals the most statistically significant edges of the network, and we retained edges with a *p-value* < 0.05, corresponding to a 95% confidence level. By extracting the backbone of $\mathbf{B}^{\Delta_\tau}$, we generated $\mathbf{B}^{\Delta_\tau}_{\mathbf{Backbone}}$, identifying the most listened-to genres in each city for each period. Overall, we aim to capture significant patterns in genre preferences across different cities using $\mathbf{B}^{\Delta_\tau}_{\mathbf{Backbone}}$.

Given the bimonthly sequence of bipartite backbone networks $\mathbf{B}^{\Delta_\tau}_{\mathbf{Backbone}}$, we start by analyzing how genre preferences vary and

[3]Spotify API for Developers: https://developer.spotify.com/documentation/web-api

persist across cities. We focus on the distribution of genre popularity in each city (i.e., whether all genres in the backbone are listened to with the same intensity). To measure this distribution variation, we calculated the Gini index, a well-established conventional measure of income inequality [11], for the genres in the backbone for each city. First, for each city and time window Δ_τ, we sorted the genre link weights in its corresponding backbone and used them as input to the following Gini equation $G = \frac{2\sum_{i=1}^{n} i \cdot y_i}{n\sum_{i=1}^{n} y_i} - \frac{n+1}{n}$.

In this definition, n is the total number of genres, y_i is the i-th link weight in the sorted set, $\sum_{i=1}^{n} y_i$ is the sum of all weights, and $\sum_{i=1}^{n} i \cdot y_i$ is the weighted sum of the values in the set, where i is the index of the value. The second term, $\frac{n+1}{n}$, is the normalization that guarantees that the value is between 0 and 1, where 0 means equally distributed and 1 means unequally distributed. In this way, we want to find out if the cities still have differences in these preferences according to their preferred genres in the backbone, essentially identifying the most preferred among the preferred genres.

Next, we analyzed the persistence of genre preferences over time by examining the fraction of genres that remain in the backbone across sequential periods Δ_τ and $\Delta_{\tau+1}$ for each city. Our main idea here is to determine whether cities have a well-defined collection of preferred genres that persist over the entire period. These analyses allow us to understand how genre preferences vary across cities in Brazil over the years, addressing **RQ1**. They also help us to identify the regional factors that contribute to the persistence of these patterns, as described in the next section.

4.2 Modeling track acoustic features and regional patterns

Recall that the goal of RQ2 is to understand the track acoustic features to reveal regional patterns of the preferred tracks in different cities and even within a genre in different regions. To achieve this, we first use the information about music and genre preferences obtained from the backbones, as described in the previous section. However, the edges of such backbones do not encode the many dimensions that make up the track acoustic features (detailed in Section 3), so multivariate analysis is required. Given the persistence of the genres analyzed in RQ1, as we will discuss in Section 5, we assume that cities show very small variation of preferred genres listened to over time, making temporal analysis redundant. Therefore, we opted for analyzing a unique aggregated view of the regional time period on the track acoustic features. Then, we use the genre preference information from the backbones from RQ1, gather the track acoustic features, perform feature engineering, and use K-means clustering on these features to create clusters that tackle our RQ2, as detailed below.

From the backbones $\mathbf{B}^{\Delta_\tau}_{\mathbf{Backbone}}$, which capture the preferences of genres, for each city c_i a set of tracks S_{c_i} is built. This set S_{c_i} consists of the tracks from genres that belong to the backbone of genres linked to city c_i in V_{City}. However, we noticed that the same genre, preferred by two or more cities according to our backbone, may or may not have become preferred because of the same tracks. Thus, we observed that popular tracks of various genres appear in many cities, while others are exclusive to a given city. In the first case, these tracks are national hits of the genre, which do not contribute to revealing specific regional patterns. In the second case, they are tracks capable of revealing regional particularities, which are closely related to our objectives here. Based on this observation, for each city c_i, we have discarded instances of tracks that are listened to in at least one other city (e.g., a track is only kept in the set if it is exclusively represented in the chart by the city in question). Thus, each city has a representative and exclusive set of tracks that belong to different genres and were preferred by it over the entire period analyzed.

Nonetheless, we have retained a significant number of exclusive tracks for each city that are potentially capable of revealing the patterns of interest. More specifically, the number of tracks in the backbone for each city has decreased from 700–900 to 340–570. We found that most of the removed tracks belonged to very popular genres in Brazil, such as *sertanejo* and *funk*, including their sub-genres (e.g. *agronejo*, *funk-mtg*). These genres accounted for about 45% and 10% of the removed tracks for each city, respectively. Another frequently removed genre was *arrocha*, which accounted for 10% of the removed tracks.

After this, for each city c_i and each track in its respective set S_{c_i}, we gathered the values of the track acoustic features explained in Section 3, such as acousticness, valence, danceability, etc. From the distribution of values for each acoustic feature in the set S_{c_i} of city c_i, we extracted the four moments: *mean*, *variance*, *skewness*, and *kurtosis*. The intuition behind extracting these moments is to capture different aspects of the distribution of acoustic features for each city beyond the mean, allowing to obtain more consistent clusters [18, 35]. With this, we obtained a final feature matrix of 17 Cities x 28 features (7 acoustic features x 4 moments). By analyzing this matrix, we expected to identify regional and cultural patterns in track preferences, providing a detailed view of the predominant acoustic characteristics in cities aggregated by region.

To cluster the cities according to the audio characteristics of their preferred tracks, we started by applying Principal Component Analysis (PCA) to the final matrix of 17 Cities x 28 features (7 acoustic features x 4 moments) [18]. PCA was used to reduce the dimensionality of the data while retaining most of the explained variance [23]. Ultimately, we adopted 5 principal components, which corresponded to 82% of the explained variance. With the reduced data matrix, we then used the K-means clustering algorithm to group the cities based on the acoustic characteristics of their preferred tracks [18, 19]. Additionally, we used the silhouette index to determine the optimal number of clusters k, which was found to be $k = 6$, with a value of 0.38 indicating fair clustering [38].

Finally, we characterized each cluster based on the most popular genres and the track acoustic features. This alignment addresses **RQ2**: the first aspect illustrates the favorite genres of a group of cities, while the second aspect reveals the similarities in the track acoustic features between these clusters. However, clusters may exhibit statistically equivalent average acoustic properties. To distinguish statistically significant differences, we employed a one-way analysis of variance (ANOVA) [21, 44].

5 RESULTS

This section presents our results. First, we present a topological characterization of the networks modeled. Then we present the results for our RQ1 and finally for RQ2.

5.1 Topological analysis of genre preference networks

As described in Section 4, we extracted the backbone for all instances of $\mathbf{B}^{\Delta_\tau}$ with a *p-value* < 0.05 to determine the preferred genres of each city. Networks were grouped by year and the average and standard deviation for some metrics are displayed in Table 1 of six networks per year. On average, the backbone retained about 25% of the nodes and 11% of the edges. This significant reduction in network size allows us to focus on the most salient genre preferences for each city, as shown in Figure 1.

Table 1: Topology of the original and backbone networks for all instances of B^{Δ_τ} in 2022 and 2023.

Metric	Original		Backbone	
	2022	2023	2022	2023
# V_{City}	17	17	17	17
# V_{Genre}	118±6.6	112±20.7	25.6±2.6	28.3±4.2
# Edges	1422±176.8	1211.5±203.7	161.8±12.7	154.5±23.3
$\hat{k}_{in}(V_{City})$	76.8±12.8	63.8±12.7	9.4±3.4	8.9±3.3
$\hat{k}_{out}(V_{Genre})$	11.3±6.4	9.9±6.6	6.19±6.18	5.4±5.8

We observe the number of nodes and averaged metrics in the bimonthly original networks is quite similar between the two years, with 118±6.6 in 2022 and 112±20.7 in 2023. There is a significant decrease in the backbone networks, with an average of 25.6±2.6 nodes in 2022 and 28.3±4.2 nodes in 2023. The average number of edges also decreased from 1422±176.8 and 1211.5±203.7 in the original networks to 161.8±12.7 and 154.5±23.3 in the backbone networks for 2022 and 2023, respectively. The average in-degree ($\hat{k}_{in}$) for V_{City} (cities) decreased from 76.8±12.8 and 63.8±12.7 in the original networks to 9.4±3.4 and 8.9±3.3 in the backbone networks, respectively. Similarly, the average out-degree ($\hat{k}_{out}$) for V_{Genre} (genres) decreased from 11.3±6.4 and 9.9±6.6 to 6.19±6.18 and 5.4±5.8, respectively. The significant reduction in the number of nodes and edges in the backbone networks emphasises the sparsity and more focused nature of the backbone, which is essential for identifying the most relevant genre preferences for each city.

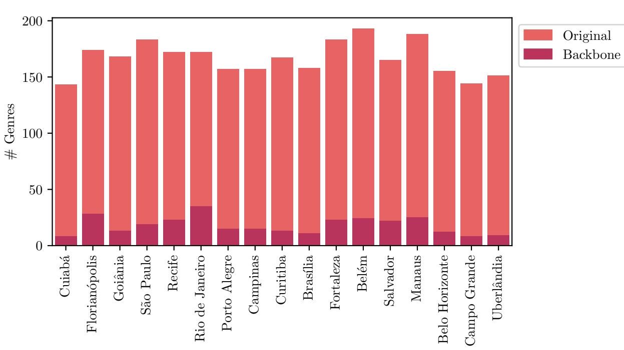

Figure 1: Genres present in the $\mathrm{B}^{\Delta_\tau}_{\mathrm{Backbone}}$ compared with all genres listened to in each city.

We also note that although most cities listened more than 150 unique genres, only a maximum of 30 were considered urban preferences in the two years. To illustrate these topological patterns of revealed genre preferences, we show in Figures 2 and 3 the original network view for our first bipartite network corresponding to the period January/February 2022. The darker the edge, the stronger the preference of this genre for the connected city. If we follow our hypothesis that such genres are maintained and reinforced in the network behavior, we see that out of the 142 genres in the original network, only 17 remain in the backbone network, indicating that each city has a limited number of genres that are consistently preferred over time.

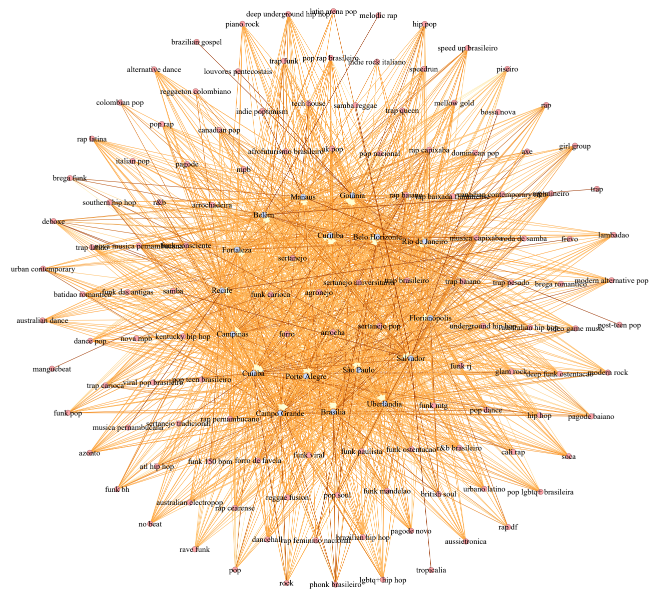

Figure 2: B^{Δ_τ}, which represent the time windows of Δ_τ =January/February 2022.

5.2 Analysis of musical genre preferences

We then move on to analyze the distributed preference of genres in the backbone via the Gini index to determine whether cities listen to their favorite genres with similar intensity in the months analyzed. Figure 4 shows these results in the form of a heatmap. In this heatmap, the x-axis represents the different cities and the y-axis represents the bimonthly time windows from January/February 2022 to November/December 2023. Each cell in the heatmap shows the Gini index for a specific city and time window, with the color intensity indicating the degree of inequality in genre preferences. The Gini index values range from 0 to 1, with values closer to 0 indicating a more even distribution of genre preferences and values closer to 1 indicating a more uneven distribution.

The Gini index values for cities are mostly between 0.1 and 0.4, suggesting overall balanced genre preferences. However, this balance could mask nuances in the distribution. For example, a Gini index of 0.1 could mean that there are two sets of genres that are very popular, while others are leveled down. The heatmap allows

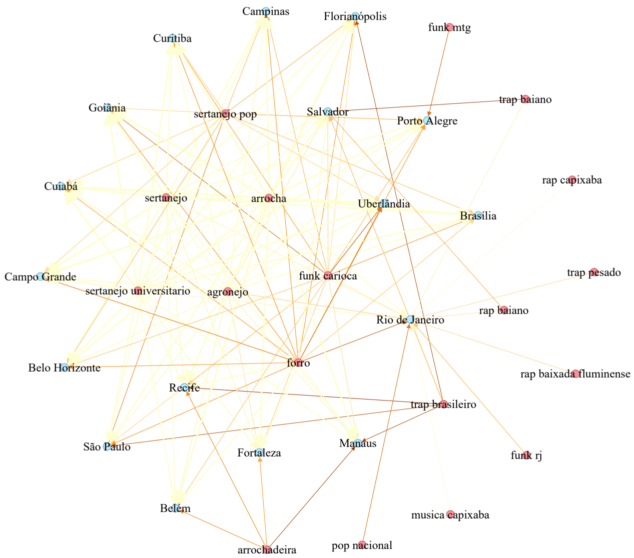

Figure 3: $B^{\Delta_\tau}_{\text{Backbone}}$, which represent the time windows of Δ_τ =January/February 2022.

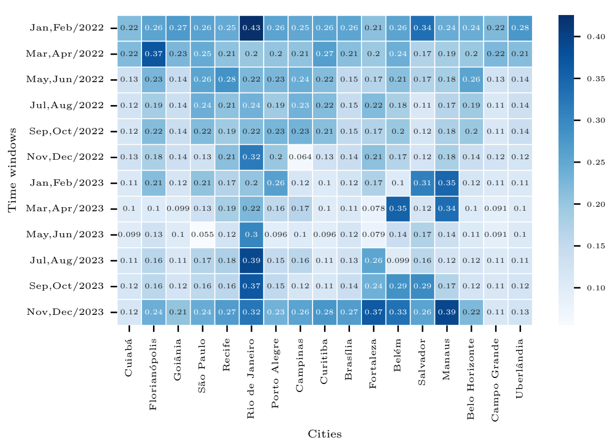

Figure 4: Heatmap of the Gini index for each city across bimonthly time windows.

us to observe patterns and changes in the distribution of genre preferences over time and in different cities. From the heatmap, we can see that certain cities such as Rio de Janeiro, Manaus and Belém have relatively higher Gini index values, indicating a more unequal distribution of genre preferences in some time windows. On the other hand, cities such as Cuiabá, Campo Grande and Uberlândia show more balanced genre preferences with lower Gini index values throughout the analyzed period. We thus observe sometimes consistency, sometimes variation in genre preferences between different cities and time windows, which helps us to understand the distribution of music tastes in the Brazilian cities analyzed.

We analyzed the persistence of genres in the backbone over time, aiming to identify whether cities listen to the same genres with

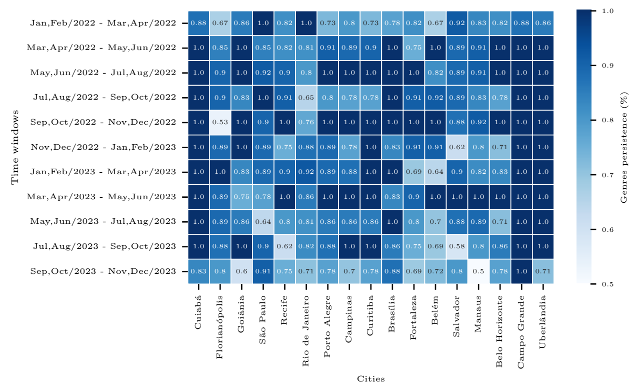

Figure 5: Heatmap of the genre persistence (%) of Δ_τ in $\Delta_{\tau+1}$ for each city

consistent intensity, as shown in Figure 5. In this heatmap, the *x-axis* represent the cities and the *y-axis* represent the compared bimonthly time windows Δ_τ and $\Delta_{\tau+1}$. Each cell shows the percentage of genres from Δ_τ that are still present in $\Delta_{\tau+1}$ for each city. This persistence analysis revealed two main findings. First, all cities have a well-defined group of preferred genres, indicated by a high persistence degree. Second, certain months showed significant changes in genre preferences compared to the previous months in most cities, except for Cuiabá, Campo Grande, and Uberlândia. These months are January/February, March/April, September/October, and November/December, which correspond to popular holidays in Brazil. January/February and March/April coincide with the carnival period, characterized by nationwide parties and specific music genres. September/October and November/December are the last four months of the year, associated with Christmas and New Year's Eve celebrations. These holidays could increase the popularity of certain genres or change the acoustic characteristics of genres during these periods.

Although we found seasonal differences, we did not formally establish a causal connection between the genres in these seasonal windows and the acoustic features, but a potential link could exist. Based on these findings, we divided the cities into two groups: those that consistently listen to the same genres over the years and those with seasonal variations. Cuiabá, Campo Grande, and Uberlândia stand out as cities with no significant changes in both years. These cities are geographically close, but other geographically close cities, such as São Paulo, Campinas, and Belo Horizonte, do not exhibit the same behavior. Besides Cuiabá, Campo Grande, and Uberlândia, all other cities show seasonal variances, mostly between 10% and 30% in different genres. Overall, the favorite genres of each city vary very little, indicating that the preferences are stable with some seasonal influences.

To summarize, preferences for music genres in Brazilian cities show a stable set of preferred genres, with backbone networks highlighting the most important ones. The Gini index indicates balanced preferences, while persistence analysis reveals minimal changes over time, except during major holidays. Overall, genre preferences remain consistent, with cultural events contributing to occasional variations.

5.3 Analysis of track acoustic features and regional patterns

In our RQ2, we wanted to understand to what extent the intrinsic acoustic features of tracks are independent of their musical genre and whether there are acoustic differences between different regions within the same musical genre. As explained in Section 4, we applied K-means clustering and used the average silhouette score to evaluate the quality of the resulting clusters on track acoustic features, uncovering 6 clusters composed of the following cities:

- **Cluster 1:** Florianópolis, Porto Alegre, Curitiba, and Belo Horizonte
- **Cluster 2:** Goiânia, Brasília, and Uberlândia
- **Cluster 3:** Recife, Fortaleza, and Salvador
- **Cluster 4:** Rio de Janeiro, Belém, and Manaus
- **Cluster 5:** Cuiabá and Campo Grande
- **Cluster 6:** São Paulo and Campinas

We start by presenting in Figure 6 the geographic distribution of each cluster in the Brazilian territory. Geographically, we can characterize Cluster 1 as the Southern of Brazil, with the addition of Belo Horizonte. This is a distinctive pattern since Belo Horizonte is in the Southeast but clusters with Southern cities. Cluster 2 likely represents the Central region, including part of the Midwest and the city of Uberlândia, bridging the Midwest and Southeast. Cluster 3, consisting of Recife, Fortaleza, and Salvador, aligns well with expectations as these are Northeastern cities, showing regional acoustic similarities. Cluster 4 contains Rio de Janeiro along with Belém and Manaus, indicating a notable divergence as Rio de Janeiro typically aligns with Southeastern cities. This cluster suggests that geographic distance was not a barrier to grouping these cities acoustically. Cluster 5 represents part of Brazil's Midwest with Cuiabá and Campo Grande, reflecting acoustic similarities within this region. Finally, Cluster 6 includes São Paulo and Campinas, suggesting that these two cities from the state of São Paulo have unique acoustic features that set them apart from other Southeastern cities, further emphasizing the distinctiveness within the Southeast region itself. These clusters reveal both expected and unexpected patterns, illustrating the complex regional and cultural variations in the acoustic features of tracks across Brazilian cities.

We move to our analysis of the exclusive tracks in each cluster, resulting in the classification of the genre preferences, as shown in Figure 7. The heatmap illustrates the distribution of genre preferences across different clusters. The x-axis represents the clusters, while the y-axis represents the genres. Each cell shows the percentage of tracks in the cluster that belong to a particular genre. For visualization purposes, we selected genres for the heatmap where the sum of all cells in a given row (genre) is at least 10% of what is listened to in the clusters. This threshold provided a good trade-off between highlighting the most popular genres of the clusters and including the sub-genres of these top genres. A higher threshold would have resulted in only the top genres being displayed, obscuring sub-genres, while a lower threshold would have displayed less popular genres, complicating visualization and interpretation.

We found that Clusters 2 and 5 share similar genre preferences, focused on *sertanejo* and related styles. Similarly, Cluster 1 and Cluster 6 both prefer *funk* and its sub-genres. Although these clusters are geographically close, they suggest track acoustic features

Figure 6: Geographical distribution of the cities in the individual clusters, with each color representing a cluster.

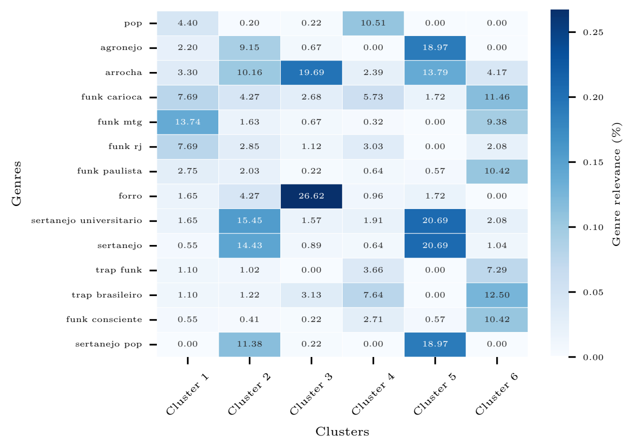

Figure 7: Most relevant genres in each cluster (%).

differences within the same group of genres. In contrast, Cluster 3 and Cluster 4 did not show significant similarities with any other cluster, despite their proximity to each other. Cluster 3 strongly prefers *forró* and *arrocha*, while Cluster 4 has a more general genre preference.

Given the identified genre patterns, we analyzed significant differences in track acoustic features between clusters with similar genre preferences. We used one-way ANOVA with a *p-value* of 0.05 to identify differences. This analysis revealed significant differences in 9 of 13 track acoustic features between at least two clusters. We used the average of these features to profile and compare clusters with similar genre preferences, as shown in Figure 8.

In these radar plots, each axis represents one of the acoustic features (e.g., acousticness, valence, danceability). The values on the axes indicate the average feature value for each cluster. The

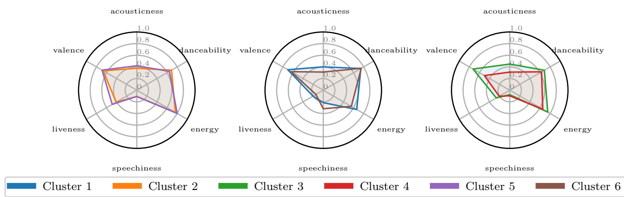

Figure 8: Average tracks' audio features across clusters.

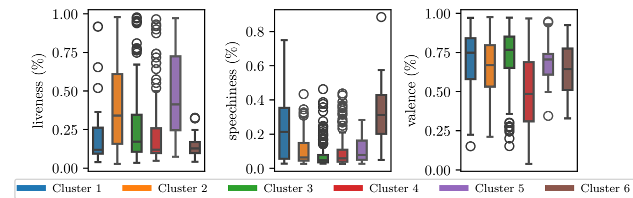

Figure 9: Distribution of values for the features *liveness*, *speechiness*, and *valence* across clusters.

first plot compares Cluster 2 (Goiânia, Brasília, and Uberlândia) and Cluster 5 (Cuiabá and Campo Grande), which have preferences for *sertanejo* and related styles. The notable difference is in *liveness*, while other features are relatively similar. Both clusters show high *energy*, indicating a preference for energetic national country music. The second plot compares Cluster 1 (Florianópolis, Porto Alegre, Curitiba, and Belo Horizonte) and Cluster 6 (São Paulo and Campinas), which are associated with *funk* and its sub-genres. The main differences are in *speechiness*, *acousticness*, and *energy*. However, *danceability* stands out as a core feature for *funk* across both clusters. Finally, the third plot compares Cluster 3 (Recife, Fortaleza, and Salvador) and Cluster 4 (Rio de Janeiro, Belém, and Manaus), which do not share common genre preferences. Cluster 3 has higher values for most features than Cluster 4, but both clusters characterize their regions — the North with Rio de Janeiro and the Northeast — as very energetic and dance-oriented.

Lastly, we deeply explored the distribution of the outstanding track acoustic features of each comparison made in Figure 8, as shown in Figure 9. These boxplots provide a detailed view of the distribution for *liveness*, *speechiness*, and *valence* in all clusters. The first plot illustrates the *liveness* feature for all clusters. Clusters 2 (Goiânia, Brasília, and Uberlândia) and 5 (Cuiabá and Campo Grande), which share similar *sertanejo* preferences, contrast significantly with the other clusters. This suggests that *sertanejo* tracks are more associated with live performances compared to other genres. The second plot presents the *speechiness* feature. Clusters 1 (Florianópolis, Porto Alegre, Curitiba and Belo Horizonte) and 6 (São Paulo and Campinas), the *funk* clusters, show a higher lyrical presence in their favorite tracks. This suggests that these clusters value lyrical content more and differentiate the types of *funk* they prefer. The *funk* of Cluster 1 (*mtg, bh, carioca*) focuses on rhythm and energy, while Cluster 6 emphasizes a more lyrical funk (*paulista, consciente*). The third plot shows the *valence* feature. Cluster 4 (Rio de Janeiro, Belém, and Manaus) shows a more dispersed distribution, indicating a preference for more "negative" music compared to the other clusters.

To summarise, the Brazilian city clusters show different acoustic patterns in the tracks, regardless of the musical genres. Significant differences were observed in features such as *liveness*, *speechiness*, and *valence* between clusters with similar genre preferences. This reveals regional and cultural differences in musical preferences and acoustic nuances within the same genres in different regions.

6 CONCLUSION AND FUTURE WORKS

In this study, we collected and analyzed data on digital music consumption from Spotify, focusing on various cities in Brazil over the period from 2022 to 2023. This analysis aimed to understand the regional and cultural patterns in musical preferences and how these preferences are reflected in both genre and acoustic characteristics. Our approach involved modeling bipartite networks of genres and cities, extracting their backbones to highlight significant preferences, and performing detailed temporal and cluster analyses.

The primary objectives were to address two research questions. In response to RQ1, we discovered that each city has a well-defined set of favorite genres that remain relatively stable over time. These favorite genres are consistently preferred, but there are occasional seasonal variations influenced by major holidays like Christmas, New Year's Eve, and Carnival. It follows the results of previous studies which shows Brazil as one of the countries that most listen to national genres and how diverse their preference can be over different regions [6, 25, 30]. Our analysis has shown that the cities can be divided into two groups: one group, which includes Cuiabá, Campo Grande, and Uberlândia, consume their strict favorite genres throughout the year, while the other group has seasonal preferences in addition to their favorite genres. This distinction sheds light on how cultural events influence musical tastes in different regions of Brazil.

Regarding RQ2, our clustering based on track acoustic features revealed distinct regional patterns. We identified six clusters of cities, some of which showed strong geographical ties, while others, such as the cluster including Rio de Janeiro, Belém, and Manaus, demonstrated that geographical distance was not a barrier to similar acoustic preferences, even their genre consumption are significantly different, as shown by previous authors [25, 30, 45]. Notably, we found that clusters with similar genre preferences could exhibit significant acoustic differences. For example, Cluster 5 (Cuiabá and Campo Grande) and Cluster 2 (Goiânia, Brasília, and Uberlândia) both prefer *sertanejo*, but with different acoustic profiles. This suggests that even within the same genre, there are regional differences in acoustic preferences that reflect broader cultural and regional influences. Our results show the importance of considering both genre and acoustic features to understand regional musical preferences. These findings can be valuable for the development of targeted marketing strategies and the improvement of music recommendation systems.

For future work, we plan to scale the analysis to a global level to gain even deeper insights into the cultural and regional diversity of musical preferences and to use the backbone extraction methodology to cope with the heterogeneity of global music data.

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