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Beyond Acoustic Features: A Data-Driven Analysis of Music Consumption in Brazil

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Abstract: In the competitive streaming era, understanding regional music consumption is vital, particularly in culturally diverse nations like Brazil. While extensive research exists on national music trends, prior studies have overlooked the nuanced local variations in musical tastes and acoustic characteristics. This study addresses that gap with a data-driven methodology examining genre preferences and acoustic attributes across Brazilian regions using Spotify Charts data from 2022–2023. Our computational approach involved constructing bipartite genre-city networks, applying backbone extraction to identify key preferences, and using temporal analysis to assess their stability. We employed clustering techniques to uncover regional acoustic patterns independent of genre and association rules mining to pinpoint common and exceptional listening behaviors. Finally, we analyzed artist similarity to determine the influence of geography versus genre. Our findings reveal that while core genre preferences remain largely stable across regions and time, significant distinctions emerge from acoustic analysis. We identified distinct city clusters with unique sonic profiles, defined by variations in attributes like liveliness, speechiness, and valence. This demonstrates that regional identity is not solely shaped by genre. Furthermore, our analysis shows that artist similarity is strongly influenced by cultural and geographical proximity. Although many listening behaviors are shared nationally, unique patterns appear in specific clusters, especially during major holidays. This study contributes a robust computational framework for modeling music consumption at a granular geographical level. The results provide valuable insights for artists, digital platforms, and industry professionals, highlighting how regional musical identities are shaped by a complex interplay of genre, acoustic features, and cultural factors.

Keywords: Music Consumption, Music Networks, Backbone Extraction, Spotify Charts, Computational Music Analysis

1 Introduction

The music industry has been revolutionized in the digital era due to the new ways music is consumed today [Edmond, 2014; Barata and Coelho, 2021; Beuscart *et al.*, 2023]. One of the most popular approaches is streaming services, whose total number of subscribers has grown significantly in recent years, making them the default option for many fans [Statista, 2025]. Due to their popularity, these services account for a significant portion of the industry's revenue, demonstrating their influence on the market and their role in the globalization of music distribution [Barbosa *et al.*, 2021; Rahimi and Park, 2020; Beuscart *et al.*, 2023]. In 2023, Spotify emerged as one of the most profitable streaming services, disbursing over 9 billion dollars to artists[1], making it a valuable platform for studying digital music consumption.

At the same time, the music industry is highly competitive, making it essential for artists—especially independent ones—to maintain their popularity and influence [Murphy, 2020]. Expertise in production and promotion provides significant advantages in this field, particularly in large countries like Brazil, where vast geographic and cultural diversity plays a crucial role in shaping music preferences [Basaran and Ventura, 2022]. What is popular in the South may not necessarily resonate in the North, and vice versa. Thanks to the wealth of data available from streaming platforms such as Spotify, it is now possible to analyze the geographical and cultural impact of music preferences [Mondelli *et al.*, 2018]. Mapping regional popular music serves as a fundamental step in outlining a region's cultural profile and assessing relevant marketing strategies [Vaz de Melo *et al.*, 2020]. This profiling process, conducted through temporal analysis, aims to identify shared characteristics of popular music and their cultural implications, offering valuable comprehension to enhance audience engagement and support the commercialization of music in a way that reflects the diverse cultural landscape of the studied region.

Numerous previous studies have explored various aspects of music popularity within groups [Ren and Kaufman, 2017; Araujo *et al.*, 2019], the geographical distribution of music preferences [Mondelli *et al.*, 2018; Lee and Cunningham, 2012; Vaz de Melo *et al.*, 2020; Berkers, 2012], user demographics and personality traits [Tricomi *et al.*, 2024; Bello and Garcia, 2021], as well as music diversity [Way *et al.*, 2020; Hesmondhalgh, 2022; Morris, 2020]. However, these studies often overlook the regional dynamics of genre preferences and acoustic features, particularly in the Brazilian context. Given the crucial role of music streaming platforms in the distribution and consumption of music, understanding the composition of musical preferences across different regions is essential [Bello and Garcia, 2021; Ferraro *et al.*, 2021]. In a country as culturally and geographically diverse as Brazil, this knowledge is especially valuable for artists, producers, and marketers seeking to tailor their strategies to regional au-

[1] https://apnews.com/article/spotify-loud-clear-report-8ddab5a6e03f65233b0f9ed80eb99e0c. Access on 21 September 2025.

diences [Enriquez, 2022; Grasse, 2021; Wolbert, 2023].

While previous research has explored general trends in music consumption, a finer-grained regional analysis—particularly one that integrates both genre preferences and acoustic characteristics—remains limited. Most studies focus on broad geographical patterns or individual listening behaviors, yet little attention has been given to how these factors interact at a regional level over time. Additionally, existing research does not adequately address whether musical preferences are driven primarily by genre affiliation or if they are also influenced by intrinsic acoustic properties. To bridge this gap, this study aims to investigate and characterize musical genre preferences and acoustic features across various regions of Brazil over a two-year period using Spotify Charts data. Our objective is to provide a comprehensive, data-driven methodology for understanding regional music consumption, identifying both stable patterns and emergent trends. Specifically, we formulate 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?

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?

RQ3: What acoustic and genre patterns emerge from the preferences in each region?

RQ4: How acoustically similar are the artists within the previously identified city clusters? Does this similarity reflect genre preferences or geographical traits?

This work builds upon and extends a previously published paper [Moura *et al.*, 2024], which focused solely on RQ1 and RQ2—examining regional genre preferences and the role of acoustic features in shaping music consumption. While that study established a foundational understanding of these aspects, it did not investigate how specific genre-acoustic patterns emerge across different regions (RQ3) nor whether artist similarity follows geographic or genre-based structures (RQ4). By incorporating these new perspectives, we enhance the analytical depth of the research, offering a more dynamic and computationally sophisticated approach to regional music analysis.

To tackle these research questions, we collected Spotify Charts data from 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 temporal analysis to identify patterns and persistence in musical preferences, addressing RQ1. For RQ2, we extracted features from the backbone network and applied clustering techniques to uncover regional and cultural variations in the intrinsic acoustic characteristics of tracks. This involved profiling clusters based on their acoustic properties and identifying significant differences within the same genre across different regions. Regarding RQ3, we employed data mining techniques to generate association rules, identifying frequent and exceptional patterns in genre preferences and acoustic attributes across regions. To answer RQ4, we computed the similarity of artists based on their acoustic features, constructing an artist-artist similarity network to analyze the relationships between favored artists in different regions. This network-based approach allowed us to examine whether artist similarity aligns more closely with genre preferences or with geographical distribution.

Our results show that preferences for musical genres in Brazilian cities exhibit a stable set of preferred genres, with backbone networks highlighting the most significant ones. Moreover, we observed balanced distribution patterns, while persistence analysis indicated minimal changes over time, except during major holidays. Regarding RQ2, Brazilian city clusters exhibited distinct audio patterns in tracks, independent 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 variations in musical preferences and acoustic nuances within the same genres across different regions. For RQ3, we identified common patterns across all cities, primarily involving sertanejo and its sub-genres. However, exceptional patterns emerged from specific combinations of genres and acoustic features that are unique to each cluster. Our approach to RQ4 demonstrates that clusters with similar archetypes of favorite genres tend to share acoustically similar artists, particularly in the case of funk. When genre-based differences exist, similarities among artists were not observed.

The remainder of this paper is organized as follows: In Section 2, we discuss related work. Section 3 describes the data collection process and the resulting dataset. Section 4 details our methodology in four steps. In Sections 5,6,7, and 8, we present our results and discuss our findings for all research questions. Finally, in Section 9, we conclude the study and propose directions for future research.

2 Related Works

Prior works related to our effort on the context of music preferences and listening habits have been focused on consumption patterns, genre preferences, user behavior, the temporal evolution of music preferences, the impact of market campaigns, the influence of social events, user demographics and personality, the effects of algorithmic recommendations, and musical diversity. We discuss the main contributions and the relevance of those previous studies, dividing them into three main areas: Consumption Patterns, Genre Preferences, and User Demographics/Personality, detailed as follows:

2.1 Consumption Patterns

Ren and Kaufman [2017] work aims 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.* [2023] developed and experimented with an algorithm to detect propagation patterns on Spotify across different countries, being capable of finding strong correlations with cultural and social aspects. Oliveira and Moro [2023a] tries to find subgroups that deviate from the standard that are described by a sequence of conditions. Oliveira and Moro [2023b] and Silva *et al.* [2023] used data mining techniques to discover exceptional patterns about musical genres in different markets on Spotify. Our goal is slightly 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, but also searching for patterns that involve musical genres and acoustic features.

2.2 Genre Preferences

Mondelli *et al.* [2018] employed a network-based approach to analyze communities of countries with similar musical genre preferences, revealing that these communities are often culturally and/or geographically interconnected. Notably, the study highlighted Brazil's uniqueness, as its predominant genres are largely derived from its own cultural roots. Conversely, Jiang *et al.* [2024] discovered that new releases designed for functional purposes tend to have lower consumption rates, and that popular genres, such as *pop*, do not necessarily perform well due to their production volume. Our study focuses on genre preferences in the different regions of Brazil. Our study centers on genre preferences across different regions of Brazil, underscoring the nation's rich cultural and geographical diversity. It reaffirms the notion that the most popular music genres in Brazil originate predominantly from within the country itself.

Lee and Cunningham [2012] presented a framework of hierarchical groups of countries characterized by similar genre preferences, establishing leader-follower relationships where leaders are defined by their historical production and consumption of particular genres. While examining the origins of genres within Brazilian regions is not the central focus of our research, we address this aspect by recognizing sub-genres that signify regional origins and identifying national genres that are predominantly popular in specific areas. Similarly, Vaz de Melo *et al.* [2020] explored digital music consumption patterns across states but did not highlight any distinctions. Our goal is to highlight these differences by analyzing the acoustic features of tracks belonging to similar genres and sub-genres across various regions, thereby connecting users geographically through shared preferences and uncovering regional variations.

2.3 User Demographics and Personality

Tricomi *et al.* [2024] established a connection between Spotify users' playlists and their demographic and personality traits, demonstrating that users with similar profiles tend to create comparable playlists. Bello and Garcia [2021] explored cross-country diversity in music charts over four years, revealing a trend towards greater diversity in global digital music consumption. Regarding musical diversity, Way *et al.* [2020] found that the preference for local content increased in various genres from 2014 to 2019. Hesmondhalgh [2022] argued that streaming platforms encourage music to have certain characteristics and thus influence the listener's aesthetic experience. Albuquerque *et al.* [2024] highlighted a case study about how manipulative design in social media platforms, especially how it affects children. Morris [2020] explored the "platform effects" on users' musical preferences, revealing that music behaves like data, exerting pressure on musicians and producers to conform to platform trends.

This study enhances the existing literature by presenting a longitudinal analysis of the geographical and cultural distribution of music preferences in Brazil. Utilizing data collected over a two-year period, we explore how genre preferences and track acoustic features vary across different regions, offering valuable awareness into the regional diversity of musical tastes within the country. Our research addresses a notable gap in the understanding of regional music consumption and lays the groundwork for future studies examining the 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 their Spotify identifier. Additionally, we used these IDs to query for acoustic features and genres of each track using the Spotify API for Developers[3]. The most prominent features present in this work are described by Table 1. Each one measures one specific aspect of the song, and their combination can be used to characterize the music descriptively.

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.

[2]https://charts.spotify.com/charts/overview/global. Access on 21 September 2025.

[3]https://developer.spotify.com/documentation/web-api. Access on 21 September 2025.

Table 1. Audio features collected from the Spotify API and their meaning, defined by Spotify

Feature	Description	Value Range
Acousticness	Measures whether the track is acoustic	[0,1]
Danceability	How suitable the track is for dancing based on a combination of musical elements	[0,1]
Liveness	The presence of an audience in the recording. Higher liveness values represent an increased probability that the track was performed live	[0,1]
Speechiness	The presence of spoken words in a track	[0,1]
Valence	Describes the musical positiveness conveyed by a track	[0,1]
Energy	Represents a perceptual measure of intensity and activity	[0,1]
Instrumentalness	Whether a track contains no vocals. “Ooh” and “aah” sounds are treated as instrumental in this context	[0,1]
Tempo	The overall estimated tempo of a track in beats per minute (BPM)	$[0, \infty]$
Key	The key the track is in. Integers map to pitches using standard Pitch Class notation	$[-1,11]$
Mode	Indicates the modality (major or minor) of a track, the type of scale from which its melodic content is derived	[0,1]
Duration_ms	The duration of the track in milliseconds	$[0, \infty]$

4 Methodology

This section presents our data-driven 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 $\mathbf{B}^{\mathbf{\Delta}_\tau} = (V_{Genre}, V_{City}, E^{\Delta_\tau})$ 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 $\mathbf{B}^{\mathbf{\Delta}_\tau}$ 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 [Mondelli *et al.*, 2018], 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 [Marcaccioli and Livan, 2019; Gomes Ferreira *et al.*, 2022; Neal, 2022]. 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 [Coscia, 2021]. There are several backbone extraction methods in the literature [Gomes Ferreira *et al.*, 2022]. 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 [Serrano *et al.*, 2009; Linhares *et al.*, 2022]. 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 [Gomes Ferreira *et al.*, 2022].

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 [Marcaccioli and Livan, 2019], 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 [Marcaccioli and Livan, 2019]. 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 Ali and Zannettou [2024], 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 $\mathbf{B}^{\mathbf{\Delta}_\tau}$, we generated $\mathbf{B}^{\mathbf{\Delta}_\tau}_{\mathbf{Backbone}}$, 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 $\mathbf{B}^{\mathbf{\Delta}_\tau}_{\mathbf{Backbone}}$.

Given the bimonthly sequence of bipartite backbone networks $\mathbf{B}^{\mathbf{\Delta}_\tau}_{\mathbf{Backbone}}$, we start by analyzing how genre preferences vary and 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 [Dorfman, 1979], 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:

$$G = \frac{2\sum_{i=1}^{n} i \cdot y_i}{n\sum_{i=1}^{n} y_i} - \frac{n+1}{n} \tag{1}$$

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 $\mathbf{B}^{\mathbf{\Delta}_\tau}_{\mathbf{Backbone}}$, 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 for obtaining more consistent clusters [Han *et al.*, 2011; Nisbet *et al.*, 2009]. 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) [Han *et al.*, 2011]. PCA was used to reduce the dimensionality of the data while retaining most of the explained variance [Jolliffe and Cadima, 2016]. 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 [Hartigan and Wong, 1979; Han *et al.*, 2011]. 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 [Rousseeuw, 1987].

Finally, we characterized each cluster based on the most popular genres and the track's 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) [Howell, 2007; van Belle, 2011].

4.3 Mining Association Rules

Concerning **RQ3**, to identify relevant patterns, we follow a similar pipeline provided by Oliveira and Moro [2023b], using the Apriori algorithm. As illustrated in Figure 1, we first obtained unique instances – in this case, tracks in the Charts of the whole period – of each cluster that was discovered in RQ2 and modeled the genres and acoustic features as transaction items. Furthermore, we discretized each acoustic feature using the interquartile range in three levels: Low, Medium, and High. At this point, we used the state-of-the-art Apriori algorithm to mine frequent itemsets of instances for each cluster [Agrawal and Srikant, 1994]. Our goal is to use the mined itemsets to generate Association Rules, which are denoted by the $X \rightarrow Y$ expression. It means that X has a co-occurrence with Y, and it can be qualified by classic data mining metrics [Oliveira and Moro, 2023b]. We used the three main metrics to evaluate Association Rules, described as follows:

- **Relative Support:** The frequency with which an itemset appears in the list of transactions. Values close to 0 indicate that the itemset rarely appears, while values close to 1 suggest it is very common across transactions.
- **Confidence:** The probability that itemset Y appears in a transaction, given that itemset X is present. It reflects the strength of the implication rule $X \rightarrow Y$.
- **Lift:** The ratio of the observed support of the rule $X \rightarrow Y$ to the expected support if X and Y were independent. Lift measures how much more often X and Y occur together than would be expected by chance. A value greater than 1 indicates a positive association (i.e., X and Y appear together more than expected), while a value lower than 1 implies a negative correlation (i.e., X occurrence implies a lower chance of Y also occurring). In cases when its value reaches exactly 1, it means that X and Y are independent. Lift is valuable in evaluating the least/most preferred associations of acoustic features and musical genres.

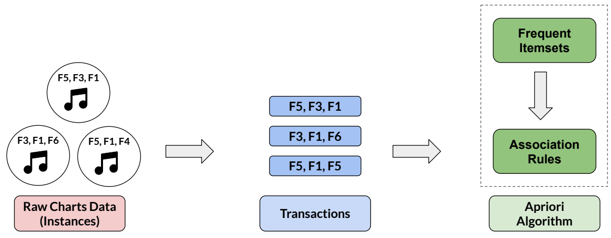

Figure 1. Pipeline to generate Association Rules using musical genres and acoustic features as itemsets.

The Apriori algorithm generated rules that describe shared patterns among all clusters and exceptional traits of each one for both genres and acoustic features.

4.4 Modeling Artists Similarity Network

As clusters were formed based on the acoustic features, **RQ4** regards the artist's context, especially in how similar they are. To explore this, we calculated the four moments of distribution (i.e.,*mean, variance, skewness, kurtosis*) of each feature for each artist. Then, we calculated the Cosine Similarity[4] of each artist with each other. The similarity value ranges between $[-1, 1]$, where 1 indicates that they are identical and -1 is the total opposite. To maintain the analysis context on the regional preferences, we only kept the artists that are exclusive to each cluster, which is necessary to highlight differences between exclusive preferences. Thus, we modeled an artist-artist similarity network $\mathbf{N} = (V_{Artists}, E)$ with exclusive artists from each cluster that is formed by the following elements: $V_{Artists}$ is the set of all unique artists of each cluster, and E is the set of undirected edges $(a_s, a_t, w^{cs}_{a_s,a_t})$, where $a^s, at \in V_{Artists}$. The weight $w^{cs}_{a_s,a_t}$ represents the similarity among two artists calculated by the Cosine Similarity, from their acoustic features. Furthermore, we performed an analytical and exploratory process to identify similarities and differences in artists' preferences between regions and how they are related to geographical and acoustic traits.

5 RQ1: Topological analysis of genre preference networks and temporal trends

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 constructed using bimonthly time windows and then grouped by year, resulting in six networks per year (2022 and 2023). Table 2 presents

[4] https://www.sciencedirect.com/topics/computer-science/cosine-similarity

the average and standard deviation for the following metrics: V_{City}, which corresponds to the number of nodes representing cities; V_{Genre}, the number of nodes representing musical genres; and the total number of edges, indicating the number of connections between cities and musical genres. The table also includes $\hat{k}_{in}(V_{City})$, the average in-degree of city nodes, which indicates how many different musical genres were consumed by each city during the respective year-instance, and $\hat{k}_{out}(V_{Genre})$, the average out-degree of genre nodes, representing how many cities each musical genre reached—an indicator of genre diffusion or popularity across cities.

Table 2. Topology of the original and backbone networks for all instances of $\mathbf{B}^{\Delta_\tau}$ 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

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 2. We observe that 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.

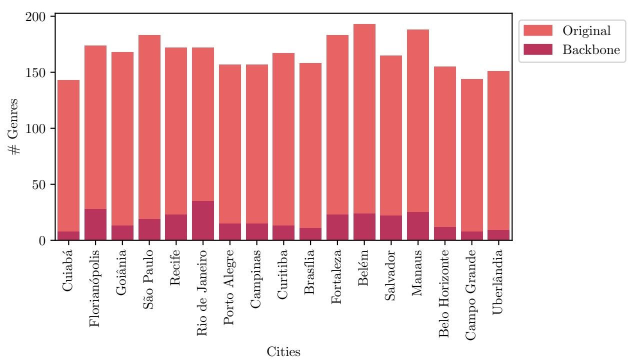

Figure 2. Genres present in the $\mathbf{B}^{\Delta_\tau}_{\mathbf{Backbone}}$ compared with all genres listened to in each city.

We also note that although most cities listened to 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 3 and 4 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.

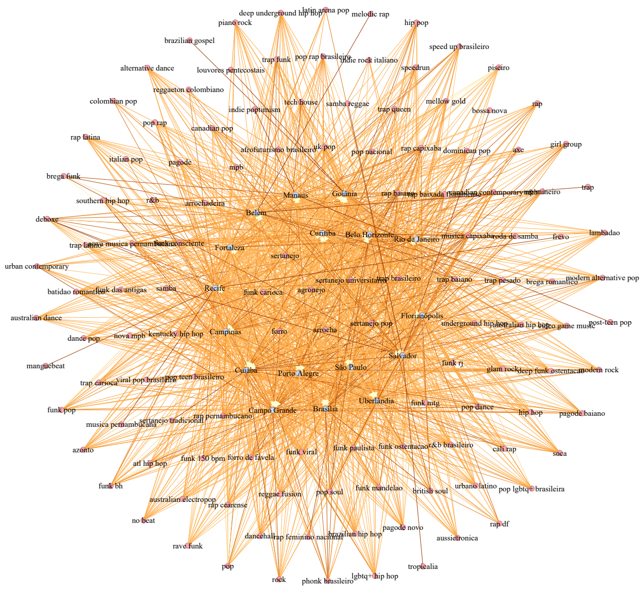

Figure 3. $\mathbf{B}^{\Delta_\tau}$, which represent the time windows of Δ_τ =January/February 2022.

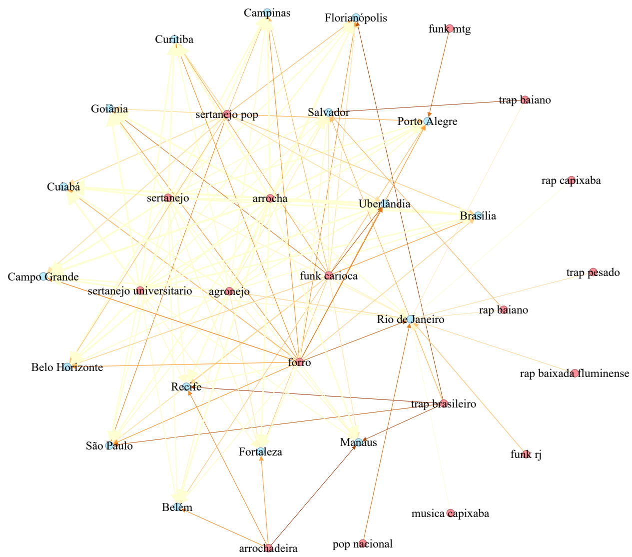

Figure 4. $\mathbf{B}^{\Delta_\tau}_{\mathbf{Backbone}}$, which represent the time windows of Δ_τ =January/February 2022.

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 5 shows these results in the form of a heatmap. In this heatmap, the x-axis represents the different cities and the y-axis represents

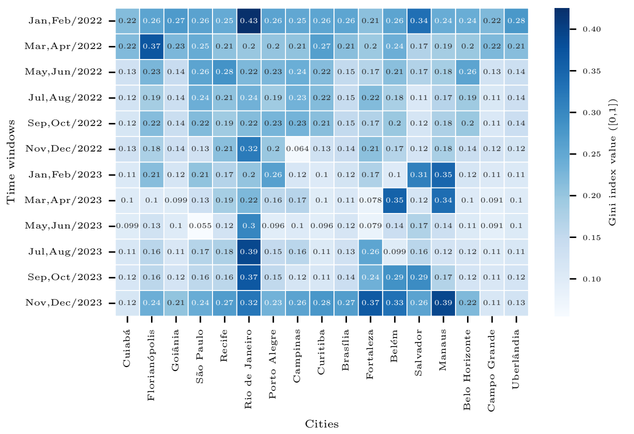

Figure 5. Heatmap of the Gini index for each city across bimonthly time windows.

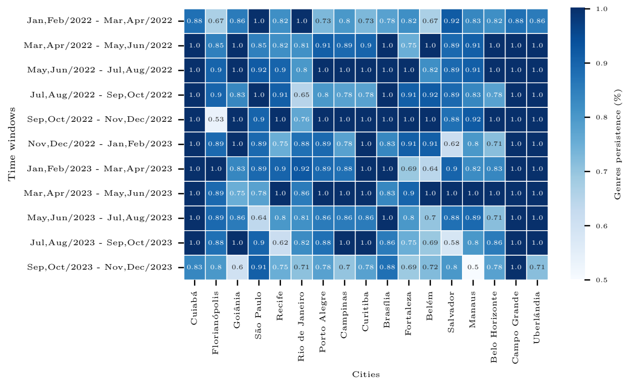

Figure 6. Heatmap of the genre persistence (%) of Δ_τ in $\Delta_{\tau+1}$ for each city

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 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 consistent intensity, as shown in Figure 6. 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.

6 RQ2: 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;

Figure 7. Geographical distribution of the cities in the individual clusters, with each color representing a cluster.

- **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 7 the geographic distribution of each cluster in the Brazilian territory. Geographically, we can characterize Cluster 1 as the Southern part 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 8. 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

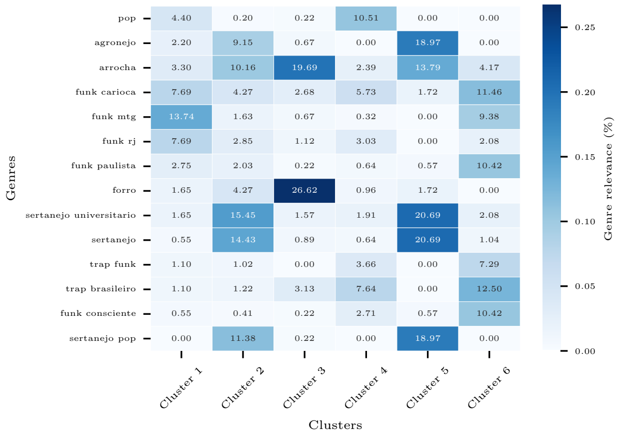

Figure 8. Most relevant genres in each cluster (%).

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 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 9.

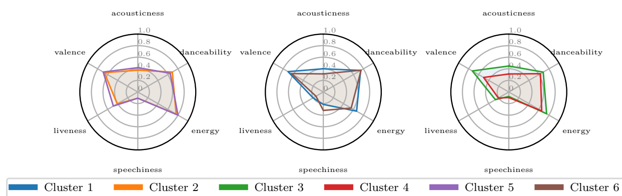

Figure 9. Average tracks' audio features across clusters.

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 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*, *acoustic-*

ness, 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 9, as shown in Figure 10. 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.

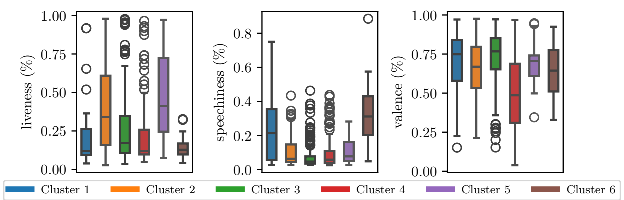

Figure 10. Distribution of values for the features *liveness*, *speechiness*, and *valence* across clusters.

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.

7 RQ3: Analysis of regular and exceptional patterns of musical genres and acoustic characteristics

As detailed in Section 4, we generated Association Rules that represent frequent patterns in each region formed by the clustering analyses. Table 3 describes patterns about the *sertanejo* and its sub-genres for each cluster. The ‘pattern’ column describes a pair (X, Y) of two musical genres related to *sertanejo*. The ‘support’ measures how frequently this pair appears in the dataset of such a cluster. Values next to 0 mean that such a pair is not so much popular, while values closer to 1 describe the most common pairs. We found that all clusters have strong rules that indicate whether an artist is present in a *sertanejo* track; he may be present in all other sub-genres of this musical style. In other words, *sertanejo* artists hold a significant position across all clusters. Regardless of the regional preference degrees for *sertanejo* music, when it appears on the city Charts, these artists may be situated alongside those from other *sertanejo* sub-genres (e.g., *agronejo*, *sertanejo universitário*, etc). This phenomenon underscores the interconnectivity of musical preferences within diverse clusters. The most proficient genres and acoustic rules for each cluster are summarized in Table 4. The ‘rule’ column describes an instance of the implication $X \rightarrow Y$ on such a cluster (i.e., X co-occurs with Y). ‘Lift’ measures the strength of the relationship between two items in terms of correlation. Values greater than 1 represent positive correlation, while values very close to 1 indicate independent variables. The ‘Confidence’ metric reflects the probability of the item Y appearing in a transaction given that item X appeared. The most frequent patterns of each cluster are discussed as follows:

Cluster 1: Region characterized by happy and danceable songs, with high preference to *funk*, which is represented by the features *valence, danceability* and *energy*. As shown by Table 4, these three attributes have joint variance (i.e., their values are commonly on the same level: low, medium, or high). The combination of *funks* from different states in this region is not frequent, highlighting the unicity of these variants. The combination of *arrocha* and *forró* is a great surprise since neither of them is preferred in this region, but it’s always listened to together.

Cluster 2: Region with explicit preference to *sertanejo* and its sub-genres, but with slightly traits of *forró* and *funk*. Multi-regional *funks* are also not listened to together here, but genres like *pop nacional* and *trap* are preferred, especially within *funk carioca*. The main acoustic features of this region’s variance imply the *instrumentalness* and *valence*, which indicates that happier songs have a higher presence of instruments and vice versa.

Cluster 3: Composed by cities of the Northeast, has high preference to *arrocha* and *forró*, but it is also the region with the lowest acceptance of the *sertanejo*. However, when a *sertanejo* song is listened, it’s probably also a *arrocha* or *arrochadeira* music. Other exceptional patterns of this region are that *pop_nacional* is preferred alongside *pagode baiano*, which is a regional genre. The *piseiro* is not one of the favorites, but has high coexistence with *forró*, the favorite one.

Cluster 4: The group formed with the cities of the North region, in addition to Rio de Janeiro. It has genres patterns similar to Cluster 3, but with acoustic variances related to *liveness*.

Cluster 5: Region totally dominated by *sertanejo* and its sub-genres. The frequent patterns are all about *sertanejo*, and acoustic rules show a linear behavior between *instrumentalness, valence, energy,* and *danceability*.

Cluster 6: Represented by the two cities of São Paulo present in our dataset. This cluster presents rules that are favorable to *speechiness*, a major attribute for this region. About musical genres, *funk paulista* is not strongly related to *funk consciente*, although both are from the same region.

The usage of the Apriori algorithm resulted in rules that describe patterns that involve all cities included in this study, the scope of the *sertanejo* and its sub-genres. Exceptional patterns were mined in each region, with valuable information about genre and acoustic features combinations.

8 RQ4: Analysis of preferred artists similarity based on acoustic features and musical genres

To investigate the similarity between artists of different contexts/regions and address RQ4, we calculated the Cosine Similarity of the four moments of distribution (*mean, variance, skewness, kurtosis*) and modeled a many-to-many network of the exclusive artists of the regions previously found. With that approach, it is possible to discern differences and similarities of the content highlighted by the backbone in Table 2. By analyzing the topology in Table 5, it's perceptible that the high presence of exclusive artists from Cluster 4 and the total absence of artists from Cluster 5. It means that the region of the North with Rio de Janeiro has a diverse pool of artists, while Cuiabá and Campo Grande don't have any exclusive artists. It could be explained by the extreme preference of *sertanejo* in both cities and the mainstream behavior of this genre across the whole country, making it difficult to identify uniqueness in this Cluster.

The generated network is illustrated by Figure 11. Each node is painted with its related color in the clustering method. In other words, blue nodes represent favorite unique artists of Cluster 1, while the yellow, green, red, and brown nodes represent Clusters 2, 3, 4, and 6, respectively. The darker the edge, the higher the similarity degree between two artists. To identify the significantly different artists based on the Cosine Similarity, a strong threshold was defined in the interval $[-1, -0.5]$, which is the range that includes the most dissimilar vectors. Such filtering resulted in the network illustrated in Figure 12, where the darkness of the edge represents the dissimilarity degree. Through an analytical process, the generated component highlights the singularity of artists in Clusters 3 and 4, due to high dissimilarity with artists of other clusters. The North Cluster (represented by the red nodes), which also has a light preference for the *funk*, is statistically different from the artists of Cluster 1 (blue nodes), which prefer the *mtg funk* and *pop*. Moreover, the geographical gap was not a problem in clustering Rio de Janeiro with the cities in the North, but it could reflect cultural assignments of the exclusive artists. The inverse situation is represented by Figure 13, which emphasizes a strict proximity of Cluster 4 (red nodes) with Cluster 6 (brown nodes) and Cluster 2 (yellow nodes). However, Cluster 2 has far greater distance genre preferences than Cluster 6 when compared with the North region. The network topology shows that it is harder to find similar artists in different Clusters, since that version of the network has less than 10% of the original edges. Finally, our results exhibit that artists from the same group of

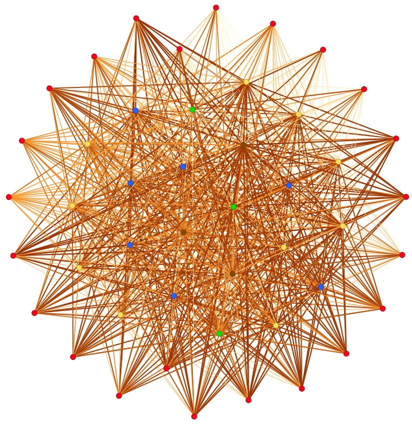

Figure 11. Original artist-artist similarity network.

sub-genres (e.g., *funk mtg, funk, carioca, funk paulista, etc*) are unique, with a small degree of similarity with other artists. The comparison between artists of different genres resulted in various artists with opposite traits. Cluster 5 has no special artists' preferences, which means these cities are out of that concern.

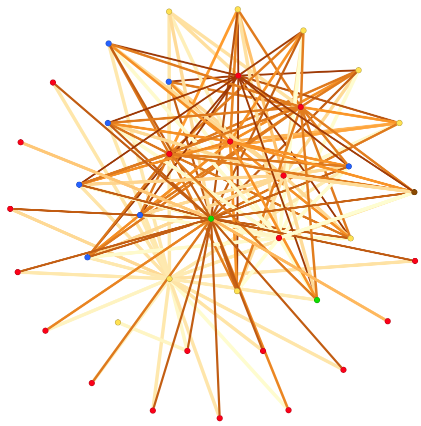

Figure 12. Filtered network with the significantly different artists.

9 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, which form a complete data-driven methodology.

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

Table 3. The *sertanejo* phenomenon patterns that emerges from all clusters.

Cluster	Pattern	Support	Cluster	Pattern	Support
Cluster 1	('agronejo', 'arrocha')	0.308	Cluster 2	('sertanejo_universitario', 'sertanejo')	0.567
	('agronejo', 'sertanejo')	0.317		('sertanejo', 'agronejo')	0.363
	('sertanejo_pop', 'agronejo')	0.152		('sertanejo', 'sertanejo_universitario')	0.370
	('agronejo', 'sertanejo_universitario')	0.301		('agronejo', 'arrocha')	0.373
	('arrocha', 'sertanejo')	0.419		('sertanejo_pop', 'agronejo')	0.189
Cluster 3	('agronejo', 'arrocha')	0.219	Cluster 4	('agronejo', 'arrocha')	0.208
	('sertanejo_universitario', 'arrocha')	0.307		('sertanejo_universitario', 'arrocha')	0.302
	('sertanejo', 'agronejo')	0.193		('sertanejo', 'arrocha')	0.292
	('sertanejo_universitario', 'agronejo')	0.185		('agronejo', 'sertanejo_universitario')	0.189
	('sertanejo', 'arrocha')	0.295		('sertanejo_pop', 'sertanejo')	0.111
Cluster 5	('arrocha', 'sertanejo')	0.420	Cluster 6	('sertanejo_universitario', 'sertanejo')	0.426
	('sertanejo_pop', 'arrocha')	0.188		('sertanejo', 'sertanejo')	0.417
	('sertanejo_universitario', 'agronejo')	0.196		('agronejo', 'arrocha')	0.298

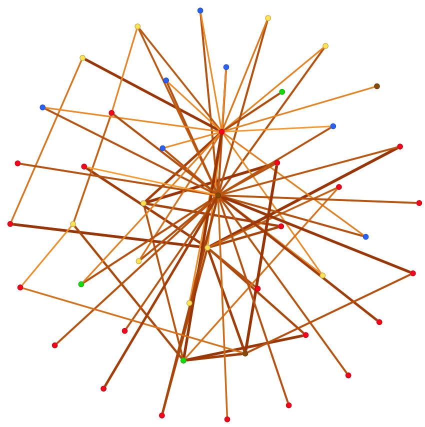

Figure 13. Filtered network with the significantly similar artists.

Eve, and Carnival. It follows the results of previous studies, which show Brazil as one of the countries that listen to national genres and how diverse their preference can be over different regions [Mondelli *et al.*, 2018; Lee and Cunningham, 2012; Bello and Garcia, 2021]. Our analysis has shown that the cities can be divided into two groups: one group, which includes Cuiabá, Campo Grande, and Uberlândia, consumes 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 though their genres consumption is significantly different, as shown by previous authors [Vaz de Melo *et al.*, 2020; Lee and Cunningham, 2012; Mondelli *et al.*, 2018]. 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. The association rules task revealed national traits that overcome genres and acoustic preferences, with the *sertanejo* and its sub-genres. Each cluster has exceptional patterns that involve sets of its most important acoustic features and the occurrence of genres less preferred, answering RQ3. In RQ4, the similarity analysis verifies the hypothesis that similar sub-genres have similar artists, aligning geographical and cultural factors as influential for the uniqueness of artists' characteristics, besides musical genres. 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 formalize our data-driven methodology into a framework that encompasses a wide range of study cases related to music preferences. Moreover, a natural next step is to dive into text/lyrics mining to uncover new patterns – especially on songs and genres with a high 'speechiness' ratio – or reinforce our results. Increase the data dimensionality with demographics (e.g., users' age and gender), other music platforms (e.g., YouTube for streaming and Radio Charts for traditional music consumption), and a wide longitudinal space is planned to provide a broader view of Brazil's musical landscape. Surveys with those involved in music production (e.g., DJs, solo artists, etc) to conduct a qualitative evaluation of this study to explore cultural and demographic factors could provide a valuable insight not covered in this work. Furthermore, we want to test the current methodology with more robust datasets to evaluate its computational cost and performance.

Declarations

Acknowledgements

The authors would like to thank the Universidade Federal de Ouro Preto for ceding laboratories for the execution of this

Table 4. Exceptional acoustic and genre patterns of each cluster.

Cluster	Rule	Lift	Confidence
	funk_mtg → funk carioca	2.27	0.482
Cluster 1	funk_paulista → funk carioca	3.08	0.655
	pop_nacional → funk carioca	2.25	0.479
	forró → arrocha	1.71	0.879
	(‘valence_high’, ’instrumentallness_High‘) → danceability_High	1.50	0.492
	danceability_Low → (‘energy_High’, ‘instrumentallness_Medium’)	1.57	0.380
	(‘energy_High’, ‘instrumentallness_Medium’) → liveness_High	1.85	0.612
	funk_mtg → funk carioca	2.61	0.496
Cluster 2	funk_paulista → funk carioca	3.08	0.655
	arrocha → (‘arrocha’, ‘agronejo’)	1.59	0.09
	(‘liveness_Low’, ‘valence_High’) → danceability_High	2.09	0.682
	danceability_Low → (‘valence_Low’, ‘instrumentallness_Medium’)	1.87	0.51
	instrumentallness_High → danceability_High	1.76	0.579
	arrochadeira → agronejo	2.18	0.533
Cluster 3	piseiro → forró	2.72	0.966
	pagode_baiano → pop_nacional	6.19	0.897
	valence_Low → (‘instrumentalness_Medium’, ‘energy_Low’)	1.86	0.615
	valence_Low → energy_Low	1.69	0.553
	(‘danceability_Low’, ’instrumentallness_Medium‘) → valence_Low	1.69	0.558
	forró → arrocha	1.87	0.712
Cluster 4	funk_rj → pop_nacional	3.25	0.422
	pop_nacional → pagode_baiano	7.37	0.403
	(‘valence_Medium’, ‘instrumentallness_Medium’) → liveness_High	1.57	0.518
	liveness_High → (‘danceability_Low’, ‘instrumentallness_Medium’)	1.54	0.390
	liveness_High → (‘energy_High’, ‘instrumentallness_Medium’)	2.09	0.456
	arrochadeira → forró	4.14	0.752
Cluster 5	(‘forró’, ‘arrocha’) → arrochadeira	4.33	0.302
	(‘liveness_Low’, ‘valence_High’) → danceability_High	2.14	0.701
	(‘instrumentalness_Medium’, ‘liveness_Low’) → energy_Low	1.59	0.522
	(‘danceability_High’, ‘liveness_Low’) → valence_High	1.90	0.625
	funk_consciente → funk_paulista	6.34	0.766
Cluster 6	funk_paulista → funk_consciente	6.34	0.522
	pop_nacional → funk carioca	2.25	0.479
	forró → arrocha	1.71	0.879
	speechiness_High → valence_Low	1.58	0.522
	energy_Low → (‘speechiness_High’, ‘instrumentalness_Medium’)	1.70	0.417
	(‘liveness_High’, ‘instrumentallness_Medium’) → danceability_Low	1.58	0.519

Table 5. Topology of the original and filtered artist-artist similarity network.

Metric	Original	Differential Filter	Similarity Filter
# Nodes	46	39	45
# Edges	710	140	73
Avg. Degree	30.87	7.38	3.24
# Nodes (C1)	7	7	7
# Nodes (C2)	10	9	10
# Nodes (C3)	3	2	3
# Nodes (C4)	23	20	22
# Nodes (C5)	0	0	0
# Nodes (C6)	3	1	3

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Authors’ Contributions

The conceptualization and methodology were led by F.A.S.M., C.H.G.F., and H.C.S.C.L. The investigation and data analysis were conducted by F.A.S.M., C.H.G.F., and H.C.S.C.L. F.A.S.M. and C.H.G.F. wrote the original draft, while C.H.G.F. and H.C.S.C.L. contributed to review and editing. The supervision and project administration were carried out by F.A.S.M., C.H.G.F., and H.C.S.C.L.

Competing interests

The authors declare that they have no competing interests.

Availability of data and materials

The collected dataset is available on Kaggle (https://doi.org/10.34740/kaggle/ds/4791865)

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