DATA VISUALIZATION PROJECT

Master in Data Science and Advanced Analytics

NOVA Information Management School

Universidade Nova de Lisboa

From Vinyl to Streaming: The Sound Revolution from 1980 to 2020

Gonçalo Cardoso, 20230588

Inês Major, 20240486

Hugo Oliveira, 20230745

Luís Semedo, 20240852

Marisa Sequeira, 20230989

Rodrigo Miranda, 20240490

Index

1. Introduction

Music is a reflection of its time and just as society evolves, so does the way we create, produce, and consume sound. The past few decades have witnessed massive shifts in the music industry, from the dominance of physical albums to the rise of digital streaming platforms. These changes have not only influenced how we access music, but also how it is composed and structured.

In this project, we explore how the sonority of songs has evolved across two distinct time periods: 1980–1999 and 2000–2020. Rather than focusing on commercial performance or genre classification, our aim is to examine the musical characteristics themselves, the elements that shape how a song feels, sounds, and flows. By comparing variables such as loudness, duration, energy, and explicitness, we seek to understand whether there are identifiable patterns that mark a shift in musical direction.

Through data visualization, we aim to transform these audio metrics (often abstract or technical) into something visually intuitive and accessible, helping both casual listeners and music analysts grasp how music has changed at a structural level.

2. Data set and perspective

Since we aim to explore if there is a pattern or differences in the sonority of songs from 1980-1999 compared to 2000-2020, we used a data set from Spotify (refer to the Bibliography section for the link), containing detailed information on many songs (approximately 60000) released between 1980 and 2020. The dataset includes both objective audio features (such as loudness, tempo, danceability, acousticness, valence) and complementary information (such as year of release and whether the song is marked as explicit).

All features are presented and described in Figure 1 and Figure 2 of the Annex.

To analyse and communicate our findings, we decided to use Power BI to build an interactive dashboard, allowing users to explore and compare the evolution of musical characteristics across the two time periods. Our dashboard is available at: https://app.powerbi.com/view?r=eyJrIjoiYzc5N2JiNTItN2JjNi00ZWRjLWFmYzgtY2IwMmYzNTkyZWVkIiwidCI6ImU0YmQ2OWZmLWU2ZjctNGMyZS1iMjQ3LTQxYjU0YmEyNDkwZSIsImMiOjh9

In case of any problems regarding the visualization of our dashboard, we will make screenshot available at the annex - see Figures 7, 8 and 9.

3. Choice of project media, visual structure followed and its suitability to the theme of the work

Our choice of visual structure was guided by three questions:

. What is the need for the visualization being developed?

. What do people need the visualization for?

. What do we expect them to do from the visualization?

Addressing the first question, the goal of our visualizations is to reveal patterns and shifts in the sonority of music that would be difficult to identify from raw numbers alone. By using visual we make it possible to compare variables like loudness and duration, across decades in a clear and engaging way.

In relation to the second question, this project can be valuable to a wide range of users. It appeals to music enthusiasts who are curious about how music has evolved to producers, analysts, and researchers seeking to understand broader trends — such as the progressive increase in loudness (refer to Bibliography for information about the

Loudness War), the rise in explicit content, or the decrease in track duration in the streaming era.

Finally, we expect users to interact with the dashboard dynamically, comparing not only aggregated trends between the two periods, but also analysing individual artist trajectories. In the first page of our dashboard, we aimed to provide an immediate and intuitive comparison between the two selected periods (1980–1999 and 2000–2020) focusing on key audio features that reflect the evolution of music over time. These include average loudness, energy, duration, speechiness, and explicit content. The structure is supported by a grid system (see Figure 3 in the annex), which helped us organise the elements consistently and balance the visual hierarchy.

Initially, the top-left corner of the layout was occupied by the Spotify logo. However, since the project's goal is broader than the platform itself, we replaced it with a title ("The Sound Revolution"), aligning with the principle that humans tend to start scanning a screen from the top-left — a position of high visual attention. We placed the card elements at the top of the dashboard to provide users with an immediate overview of key indicators and right below the title, we placed the period selection buttons, reinforcing this natural reading flow.

One of the main structural decisions was to move the line charts (average duration and loudness per year) to the center of the page. This change ensured that they are positioned closer to the buttons that define the time period — allowing users to immediately associate the interaction (button click) with the result (updated line graph), minimizing cognitive effort.

The second page of the dashboard was designed to support individual artist analysis, allowing users to select specific artists who released music in both periods (1980–1999 and 2000–2020) to see the patterns that changes in the artist's songs. The visual structure (see grid system in Figure 4 in the annex) is basically the same as the first page and guides the user from the top left (where the artist is selected) through a sequence of relevant indicators and visualizations that describe the artist's musical profile over time.

4. Choice of visual elements and their combination

4.1 Shapes and pictures

We used a variety of chart types that support both comparison and exploration, depending on the nature of the variables.

Line charts were used to show the evolution of variables like loudness and duration over time, as they are effective at revealing long-term trends and changes in trajectory.

A donut chart was used to represent the percentage of speechiness in each period. We opted for a donut rather than a pie chart because the circular shape evokes musical elements (such as vinyls or CDs), and the central space allows for a cleaner display of labels.

Gauge charts were used to display energy levels on both pages, being particularly intuitive when working with fixed scales (e.g., 0 to 1). On the first page, the gauge does not change with button interaction because the graph was customized on photoshop.

We also included a waffle chart to represent the percentage of explicit tracks in each period. This chart type was chosen for its clear, grid-based representation of proportions, which makes it easier to compare values between periods. However, due to technical constraints in Power BI, we created this element in Photoshop, as well as the energy gauge mentioned above and stopwatch-style visualizations showing the percentage of short tracks (<4 minutes). These were designed externally to maintain full control over the colour palette and stylistic coherence, since Power BI did not offer enough flexibility for these visuals.

A bubble chart was introduced on the second page to represent average tempo per decade. Its design is visually engaging and easy to interpret: the larger the bubble, the higher the average tempo, allowing users to grasp both magnitude and temporal distribution at a glance.

Finally, we placed card elements at the top of each page to summarize key numeric indicators. On the first page, these include the number of tracks and number of artists per period; on the second, they include average values for popularity, danceability, and mode. Their position at the top provides users with a quick overview before engaging with the more detailed visualizations below.

Regarding our background (see Figures 5 and 6 in the annex), we opted for rounded-corner panels and containers throughout the dashboard. This stylistic choice was inspired by Spotify’s interface and logo, which often use soft, rounded shapes. The differences in the background of the second page compared to the first one are justified by the change of the line charts to the middle in the first page.

4.2 Type fonts and respective formatting

For most of the dashboard, we used the Gotham font, which is also Spotify's typeface. This choice was intentional, as it reinforces the visual connection to the platform and contributes to a coherent and recognizable aesthetic.

We applied bold formatting selectively, particularly in the card elements that display key numeric indicators. This decision helps users quickly identify and focus on relevant metrics, while the rest of the layout remains visually balanced. Titles were given a slightly larger font size to establish hierarchy, while axis labels, legends, and annotations were kept smaller and in regular weight to reduce visual noise.

On the second page of the dashboard, due to technical constraints within Power BI, we were unable to apply the imported Gotham font to specific visual elements, namely the bubble chart and energy gauge. In these cases, we used Segoe UI, a system-default font that we considered to be the most similar to Gotham.

4.3 Colors used

Our color palette was directly inspired by Spotify's brand identity, aiming to create a cohesive and thematically aligned visual experience. The dashboard adopts black as the dominant background color, complemented by Spotify Green (#1ED760) as the main highlight color, reinforcing the connection to the platform and providing strong contrast against the dark layout.

To distinguish the two periods under analysis, we chose two contrasting yet visually harmonious colors: the period from 2000 to 2020 is represented using Spotify's Green, while the period from 1980 to 1999 is represented using a vibrant orange (#FF8F33). Our first attempt was to use red for the 1980–1999 period, given its strong contrast with green. However, we replaced it with orange to avoid unintended associations with error or negativity, which red often carries. Orange maintains the contrast without conveying this meaning. We also used white (#FFFFFF) for typography, axis labels, and highlights in order to ensure high legibility and a clean contrast with the dark background.

The background (see Figures 5 and 6 in the annex) features a subtle diagonal gradient composed of shades of grey and black with varying transparency. This was applied to create a sense of visual depth and to distinguish the foreground content without adding visual noise. Panels and containers were styled using slightly lighter or darker tones of grey and black to reinforce the layout structure.

On the second page, we used a monochromatic green gradient in the bubble chart that represents average tempo per decade. This gradient helps encode magnitude through color intensity: lighter tones indicate lower values and darker tones represent higher values. This approach aligns with the guidelines discussed in class for visualizing numerical data using color, ensuring the gradient functions as a coherent and interpretable indicator.

5. Intended meaning and success of the visualizations

As referred before, the main objective of our dashboard was to identify and highlight patterns in the evolution of musical characteristics between the periods 1980-1999 and 2000-2020. Rather than focusing on popularity or commercial success, given our doubts about how it was measured, we aimed to understand how the overall sound and structure of songs has changed over time.

The visualizations clearly communicate some of the most striking findings: a significant decrease in average song duration after 2010, suggesting a shift in how music is produced and consumed in the streaming era, a steady increase in loudness until 2010, a notable rise in the percentage of explicit tracks, particularly in the 2000-2020 period.

We believe the visualizations are successful because they transform abstract audio metrics into accessible visual narratives. The insights are visible at a glance, while the dashboard also supports deeper exploration, particularly through the second page, where users can interact with specific artists and compare their evolution across both periods. The clarity of the changes observed confirms that the project met its core goal: making the evolution of musical sonority over decades visible and understandable.

6. Conclusion

This project set out to explore how the sound of music has evolved by comparing two key periods: 1980–2000 and 1999–2020.

The patterns we found and described confirm that music has not only changed in terms of production techniques, but also in structure and tone, likely influenced by technological shifts, streaming culture, and changing audience preferences.

The project achieved its goal by making these abstract and technical changes visually accessible and easy to interpret, even for users without a background in audio analysis. Through clean layout, intuitive interaction and a coherent visual identity, the dashboard facilitates both quick insights and deeper exploration.

Looking forward, this work could be extended by including genre-specific trends, lyrics analysis, or even correlating features with chart performance to understand the connection between sound and success more deeply.

7. Bibliography

Kaggle. *Spotify Dataset*. Available at: https://www.kaggle.com/datasets/vatsalmavani/spotify-dataset

Spotify for Developers. Design & Branding Guidelines. Available at: https://developer.spotify.com/documentation/design#using-our-colors

Milner, G. (2009). *Imperfect Sound Forever: Loudness Wars, Listening Formations and the History of Sound Reproduction*. *Popular Music*. Cambridge University Press. Available at: https://www.cambridge.org/core/journals/popular-music/article/abs/imperfect-sound-forever-loudness-wars-listening-formations-and-the-history-of-sound-reproduction/0338AC967CC96021B8C053264029B188

NOVA IMS (2025). Data Visualization — Theoretical Class Slides.

8. Annex

Feature	Description
valence	A measure of the musical positiveness conveyed by a track (0.0 = sad or depressed, 1.0 = happy or euphoric).
year	The year the song was released (usually extracted from release_date)
acousticness	A confidence measure of whether the track is acoustic (0.0 = not acoustic, 1.0 = highly acoustic).
artists	The name(s) of the artist(s) who performed the track.
danceability	Describes how suitable a track is for dancing based on tempo, rhythm stability, beat strength, and overall regularity (0.0 to 1.0).
duration_ms	The duration of the track in milliseconds.
energy	A measure of intensity and activity. High values typically indicate fast, loud, and noisy tracks.
explicit	Indicates whether the track contains explicit content (1 = explicit, 0 = not explicit).
release_date	The date the track was released (typically in yyyy-mm-dd format).

Figure 1 – Description of half of the features of the dataset

Feature	Description
id	A unique identifier for the track, often corresponding to the Spotify track ID.
instrumentalness	Predicts whether a track contains no vocals. Values closer to 1.0 indicate higher likelihood of being instrumental.
key	The key the track is in, represented as an integer (e.g., 0 = C, 1 = C#/Db, ..., 11 = B).
liveness	Detects the presence of an audience. Values above 0.8 typically indicate a live performance.
loudness	The overall loudness of a track in decibels (dB). Values are negative; closer to 0 indicates louder tracks.
mode	cates the modality of the track: 1 = major, 0 = minor.
name	The title of the track.
popularity	A popularity score provided by Spotify, ranging from 0 to 100.
speechiness	Detects the presence of spoken words in a track. Higher values indicate more speech-like content.
tempo	he tempo of the track in beats per minute (BPM).

Figure 2 – Description of the second half of the features of the dataset

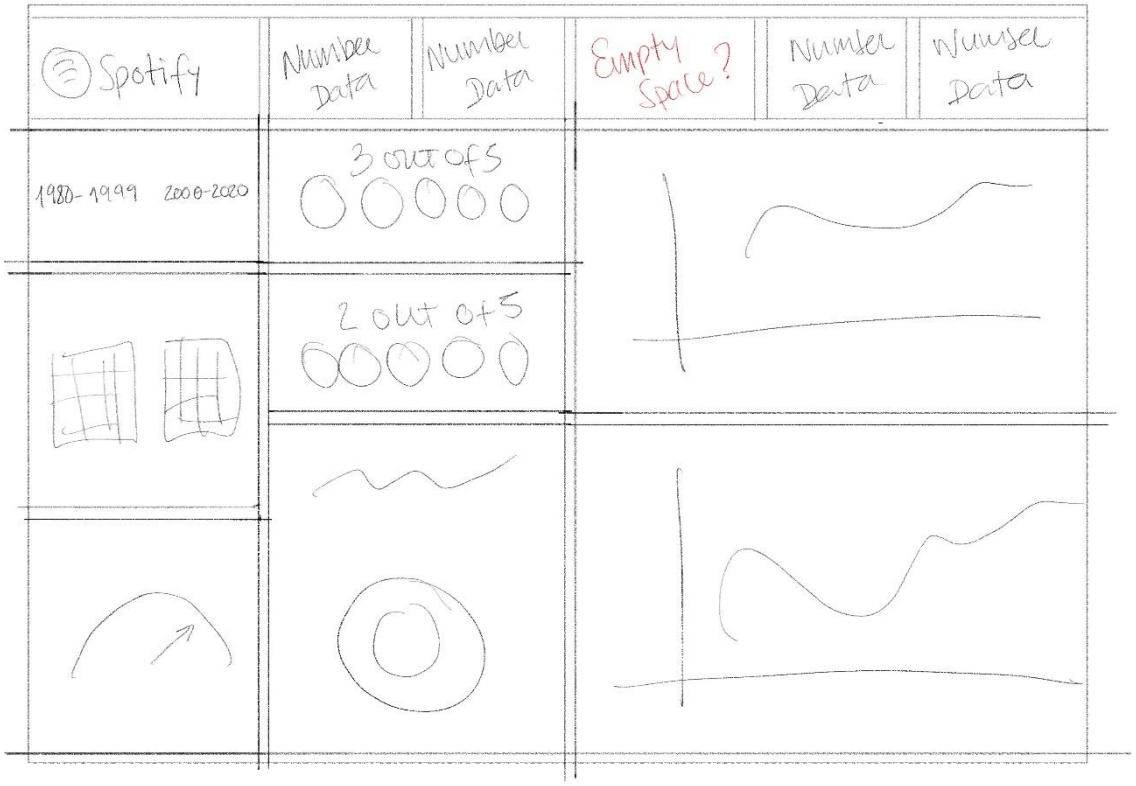

Figure 3 – Grid System of the first page of the Power BI dashboard

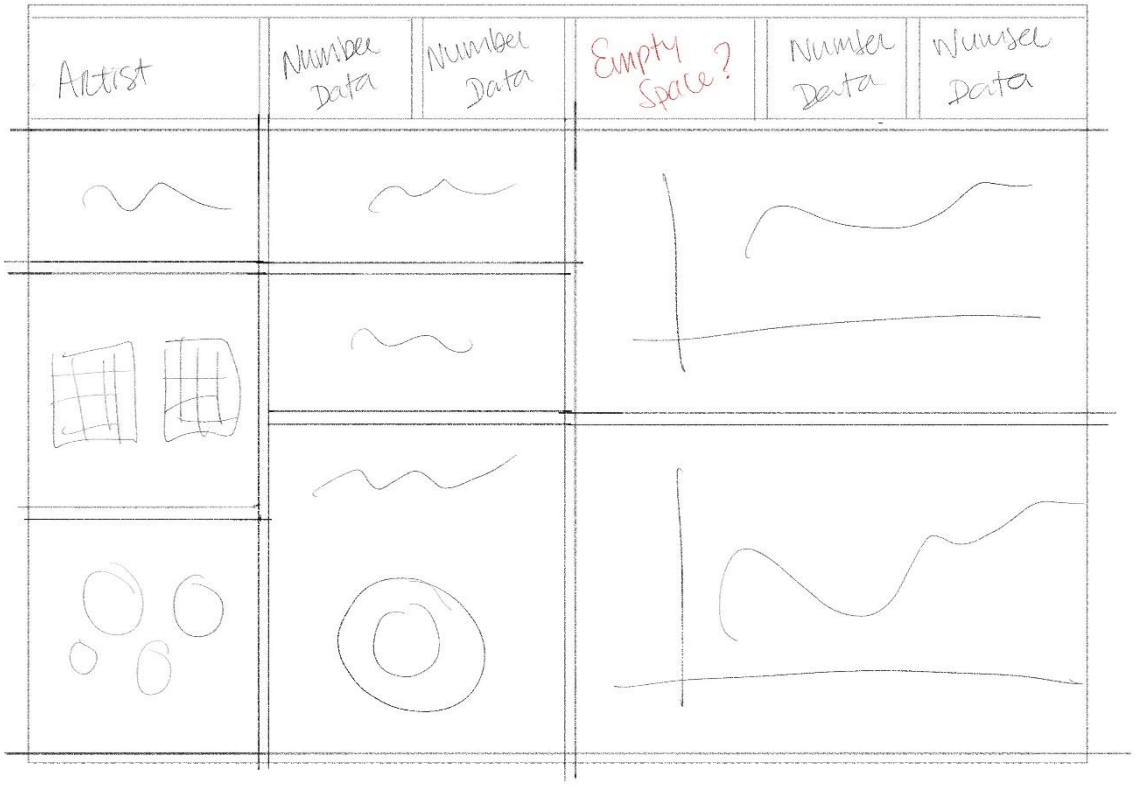

Figure 4 – Grid System of the second page of the Power BI dashboard

Figure 5 – Background of the first page of the Power BI dashboard

Figure 6 – Background of the second page of the Power BI dashboard

Figure 7 – Cover of our Dashboard

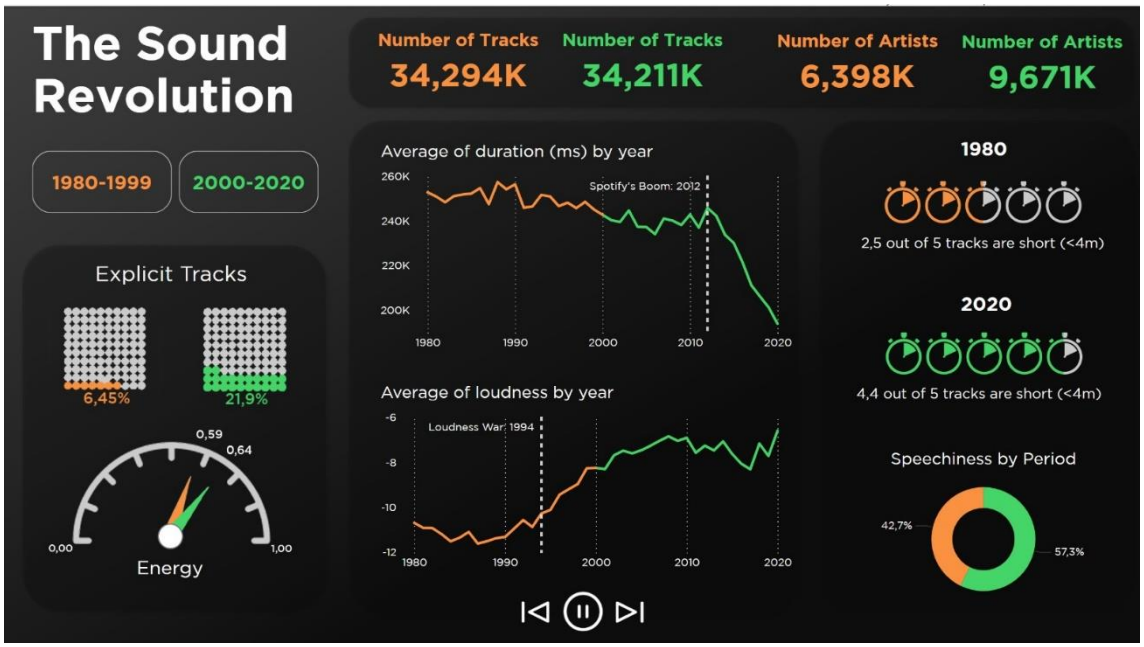

Figure 8 – Page 1 of our Dashboard

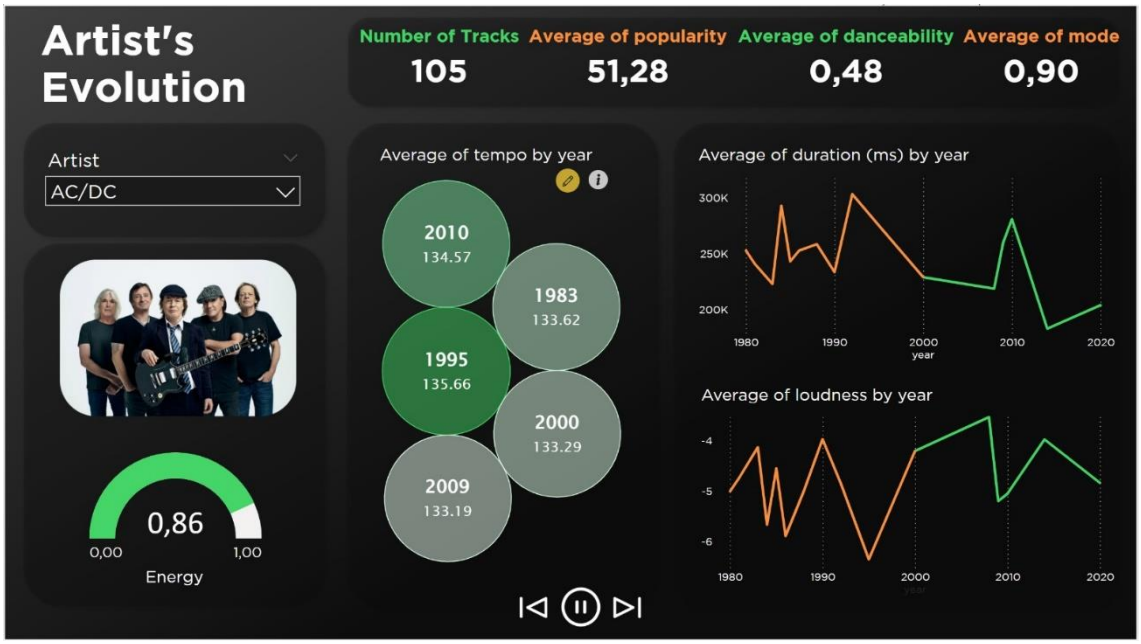

Figure 9 – Page 2 of our Dashboard