Exploring Music Rankings with Interactive Visualization

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ABSTRACT

Music rankings are mainly aimed at marketing purposes but also help users in discovering new music as well as comparing songs, artists, albums, etc. This work presents an interactive way to visualize, find and compare music rankings using different techniques, as well as displaying music attributes. The technique was conceived after a remote survey that collected data about how people choose music. Our visualization makes easier to obtain information about artists and tracks, and also to compare the data gathered from the two major music rankings, namely Billboard and Spotify. We also report the results of experiments with potential users.

CCS Concepts

•Human-centered computing → User interface design; Visual analytics; Information visualization;

Keywords

Music visualization; Music rankings; Music charts; Interactive visualization.

1. INTRODUCTION

People listen to music everyday, some of them even all day long. Music became a huge industry, with several artists and groups competing for popularity and recognition, which is likely to result in earnings. The more fans they conquer, the more influence they have.

Due to the worldwide internet access, the way people listen to music is changing. Some years ago, the success of a certain artist was mainly calculated by how many LPs or CDs were sold, which we call physical music sales. Nowadays, the main way of listening to music is using online streaming, like websites/players such as Youtube and Spotify. In fact, Liikkanen and Åman [12] found out that among on-demand music services, Spotify [15] and YouTube [18], are the most popular ones.

In general, rankings of many different things were always available and have been used to influence users' choices; music rankings (also called charts) would not be different. TV music channels, such as MTV and VH1, have most of their schedule based on music rankings: they show what most people want to see.

The Billboard [3] magazine produces the most famous music ranking, the "Hot 100" list, which shows the most played tracks (usually called singles, music that is being released on the media) based actually by streaming activity, radio airplay and sales data (respectively audience impressions measured and sales data compiled by Nielsen Music [6]). Spotify also produces rankings, which are based on users' streams, and can be filtered by location, daily or weekly. The data is available at Spotify Charts [16].

These popular rankings reflect the marketing strategy of record labels. When data are easier to observe and compare, new strategies can be planned and put into practice, contributing to improve marketing and music quality. Music rankings visualizations can help the analysis of data about artists and record labels, and also work as recommendation systems: users can use visualizations to compare and classify artists' information. For example, if the user prefers pop music, it is likely to be easier finding another pop music only looking at an interactive visualization. Regarding recommendation, a tool can analyze what the user is listening to and recommend other similar artists.

There are several works dealing with music visualization and analysis, but only a few are about music rankings. In our work we provide an interactive way to explore music rankings, through different visualization techniques integrated within a web application, aiming at supporting artists data and music exploration in general.

The rest of the paper is organized as follows. Section 2 briefly reviews related works. In Section 3, we firstly introduce the results of a remote user survey that we developed for requirement analysis; then we explain how we have chosen the current design, which data sets we decided to use, the implemented visualization techniques and the user interface provided by our web application. In Section 4, we describe and discuss the experiment with potential users, and finally, in Section 5, we discuss our findings and draw final comments including possibilities of future research.

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2. RELATED WORK

This section presents a brief review of works that range from exploration of music datasets to visualizing user's personal music listening history and automatic genre classification.

An interesting solution for the analysis of different rankings in general is LineUp [10]. The authors presented a ranking scalable multi-attribute visualization technique based on bar charts. The technique allows tabular data sets to be sorted for creating rankings, where the attributes values are represented by bars. Attributes can be grouped for sorting purposes, and different rankings for the same data set can be lined-up and compared.

One of the simplest tasks when dealing with music collections is navigation and/or exploration. Ono et al. use a similarity graph [13] to enable the exploration of data sets in terms of hierarchical similarities. They built a methodology for users to visually explore music collections considering that the similarity can take place only in small parts of the song. It uses Music Information Retrieval (MIR) to find similar segments between pairs of audio files and a graph metaphor to display the detected similarities.

Often, when dealing with rankings, time is an important attribute because rankings can vary in time. This is especially true for music rankings. Thus, it is rather common finding works that are based on time-line visualizations. For example, Dias et al. [7] combine a timeline-based visualization with a set of synchronized-views and an interactive filtering mechanism. Also, it is also interesting to observe how music taste evolved along time, and this has also drawn attention [14] and the visualization shown Billboard data. The data in that work is a time series starting in 1958: the top 5 artists for each week are shown in an interactive timeline and the tool plays automatically the number-one track of each week. It is also possible to search a precise week, artist or track.

As for user's personal music listening history, there are some interesting works. LastHistory [2] is an interactive visualization application for displaying Last.fm [11] data, the music listening stories, along with contextual information from personal photos and calendar entries. Last Chart! [8] also uses personal data from Last.fm, and displays Bubble, Cloud and other visualization charts on the web. Another example is Peter Gilks' site [9] that shows data from the tracking of his own music consumption on Spotify using Last.fm. He uses a handy script to download last.fm data into a CSV for building the visualization.

Another interesting analysis and visualization approach is reported by Zhang and Liu [19], which aimed at analyzing users' interests. The work revealed the underlying relevance of music tracks based on metadata and also on users' votes, as a collaborative relevance.

Automatic genre classification is crucial for the organization, search, retrieval and recommendation of music, and Valverde-Rebaza et al. [17] investigate two components of the music genre classification process using traditional and relational approaches.

As can be noticed, none of the mentioned works deal directly with visualization of music rankings. Our tool intends to fill this gap by providing visualizations of music rankings. We aim at supporting the comparison of rankings and, most important, showing attributes of the music tracks in the rankings, which is likely to make easier for a user to decide between listening a different music, exploring new alternatives based on genre, artist and position in the ranking, for example, or following the known path of listening the same music tracks.

3. MUSIC RANKINGS VISUALIZATION

People use rankings in general to compare data and get recommendations. Thus, the idea of using music datasets for building rankings is natural in the current streaming era. In 2015, at least two new big streaming services appeared, Apple Music and TIDAL, involving famous artists and record labels. This has impacted the traditional rankings. Playlists from these streaming services work as imperceptible merchandising. The users are attracted by titles such as "Top 100", "Hottest tracks", "The most played tracks", and start listening to brand new tracks, resulting in a recommendation cycle.

In this work, we decided to use two datasets acquired from Billboard and Spotify. Billboard data were acquired with a web crawler and stored in a MySQL database containing the track position, track name, artist, URL to listen on Spotify, last week position, weeks on chart and peak position. Spotify data were acquired from Spotify Charts as CSV files and also stored in the database, containing the track position, track name, artist, streams and URL. Music genre was an extra information mapped with iTunes [1] to handle data redundancy, and added to each artist data. We only considered the major music styles, so we would have a small amount of data to represent, making easier to identify genres by color.

3.1 Requirement Analysis

A remote user survey was set up for 13 days to obtain data about users' preferences and habits in listening music or selecting new music tracks to listen. A total of 377 people from 11 countries answered our questionnaire. They were 23 years old in average. Similarly to Liikkanen and Åman [12], we found out that Youtube (85%), download (67%) and Spotify (45%) are the most used services to listen to music. They are followed by Radio 35%, CD 21% and iTunes 18%. The preference for Youtube might be explained because it is easy to access as well as free.

People discover new music through the same services they use to listen to music, such as Youtube and Spotify (73%); through friends' recommendation (62%); music rankings (25%); and clubs/concerts (12%). So, the influence that music services have on users was confirmed, as the importance of friends' recommendation and music rankings.

Music genre influences most users choices for new music, with an influence rate of 93%, followed by artist (81%), music rankings (32%) and release date (22%). This influence affects how the music is chosen, as we expected. Music rankings are supposed to guide and rank general preferences, but not to influence so much the users' choices.

When users are interested in music rankings, they mainly

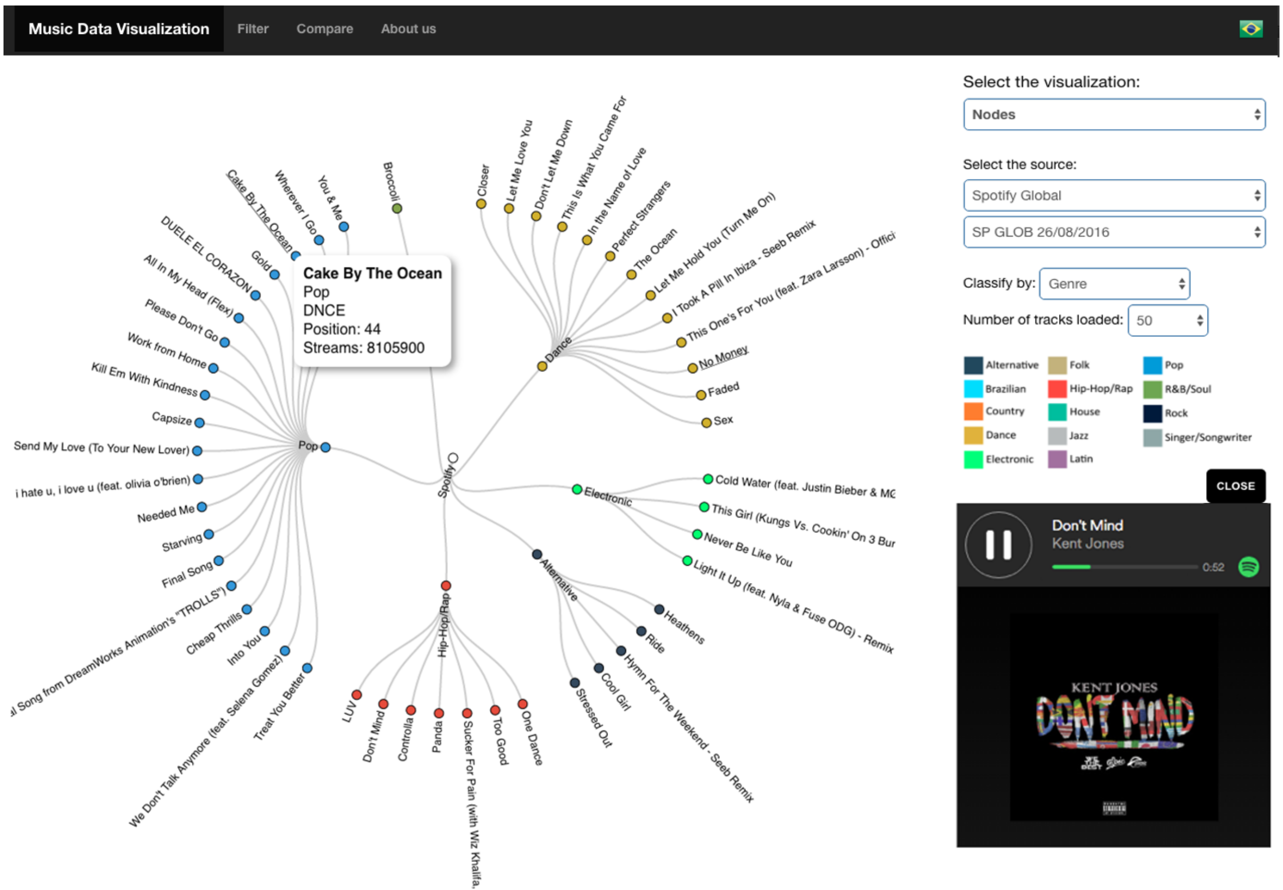


Figure 1: MusicVis Tool Interface: Data from Top 50 Spotify Global on August 26th week is exhibited by Genre in the Node-Link Tree visualization. Also, there is a tooltip showing more information about each track and when clicked, a Spotify player appears to listen to it.

look at Billboard (27%), followed by Spotify Charts (22%), and 37% of the people look at one of them at least. The classification criteria preferred by users when looking at rankings are: recommended artists (52%), followed by total number of executions per track (52%), recommended tracks (51%) and total number of executions per artist (31%).

Considering the results of our survey, we decided to investigate visualization techniques for music rankings following different criteria, as well as integrating different attributes of the music tracks. Moreover, although the rankings visualization should include some of the attributes of the tracks, we also propose an alternative visualization to show the distribution of artists (and tracks) per genre. The following sections describe our design choices and the visualization techniques.

3.2 Design Choices

As mentioned before, we have chosen Billboard and Spotify as main data sources. However, any service that provides the data we employ in our visualizations can be used as source.

With the data from rankings acquired and treated, we analysed carefully the results from the remote users survey to check what would be the best choice in visualizations.

Nowadays, the rankings on Billboard and Spotify are displayed as ordered lists of tracks based on the position in the ranking of the most listened music tracks/artists. As for Billboard, the interaction is basically, for some tracks, the possibility to get a link to the music video on Youtube and a link to the streaming on Spotify. The Chart Highlights section brings us some important events in the ranking. Regarding Spotify, the list is even simpler, exhibiting the position, track and artist, and the number of streams. The interaction is just the possibility of click on one of the tracks and listen to it. In the beginning of 2015, they stopped sharing gender and age information from users.

Since we found out 93% of the users are interested on the music genre, it became really important to add this information to the data. We chose to use colors for representing genres. All of the colors have similar tones and try to express the feeling or the major album colors of the music genres. The artist is also important to users, thus the visualizations explicitly represent them.

Finally, we have implemented the following data visualizations techniques: Sunburst, Node-Link Tree, Bubble Chart and Treemap, all being able to represent music data content and music genre. They were chosen because they mix traditional and modern visualizations. They were implemented using D3.js [4]. Herein we give more details about Sunburst and Node-link Tree, mainly because our experiment showed they are the ones preferred by potential users.

3.3 Node-Link Tree Music Visualization

This visualization is a radial Reingold-Tilford tree, with tidy arrangement of layered nodes. The central node represents the music ranking source. The depth of the nodes is computed by the distance from the root and the number of layers.

In our technique (Figure 1), the Node-Link Tree (NLT) visualization is ordered by music genre. Each genre is represented by a node, and has one or more music tracks, which are the leaves connected to the music genre node.

The tooltip is available at all visualization techniques, appearing in NLT when the user hovers the mouse over each node or text. It displays the music track name, music genre, artist, position and streams (Spotify) or last week position (Billboard). Also, all nodes and text are clickable: clicking on an outer node (music track) it will open a Spotify online music player with the album cover. Clicking on an inner node (Music genre, Artist or Position), it will search this term on the web to give more information. This is useful when users are curious about where is the artist from, who are other famous artists of that music genre, and so on.

When ordered by artists, the inner nodes become the artists and the leaves are the music tracks. The same method is used when it is ordered by position, adding the position number beside the artist name.

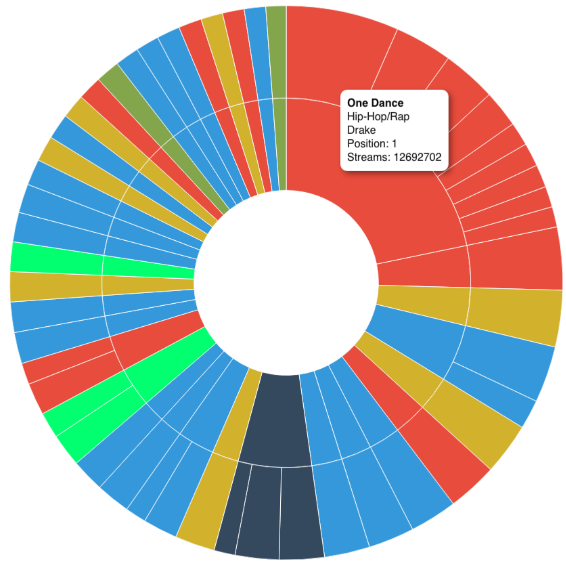
3.4 Sunburst Music Visualization

A Sunburst chart displays a hierarchy of items layered in a circular arrangement. We created a Sunburst interactive visualization to display and allow comparison of Billboard and Spotify rankings. Figure 2a presents a visual representation built with this technique.

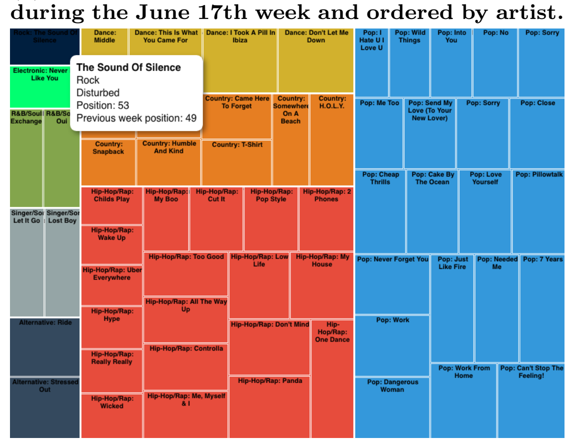
The outer layer represents the music tracks, while the inner layer depends on the criteria used to order the data: when ordered by artist or position in the ranking, the inner sections represent the artists; when ordered by music genre, they represent the music genre. Color is used to represent music genre in both cases (there is a legend at the right side, not shown here).

The section size means the position (Billboard) or the streams (Spotify). When ordered by artist, the tracks from the same artists are clustered no matter what are their position in the ranking.

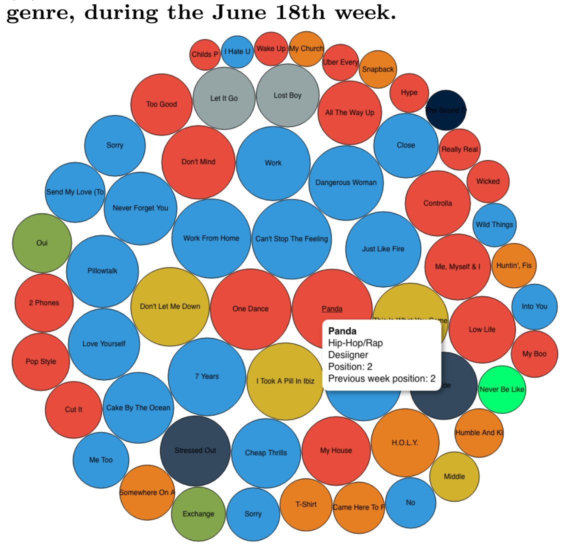
The usual Sunburst behavior in response to the selection of a section is implemented: when clicking on a section, the visualization changes for showing that specific music genre or artist occupying all the inner circle along with the related tracks in the outer sections. A tooltip shows details about items. If the mouse is on a section of the inner circle, the tooltip will display the artist name or the music genre; if it is on the external circle, it will show the track name, music genre, position, and streams (Spotify) or last week position (Billboard).



(a) Sunburst applied to Spotify's USA Top 50 during the June 17th week and ordered by artist.

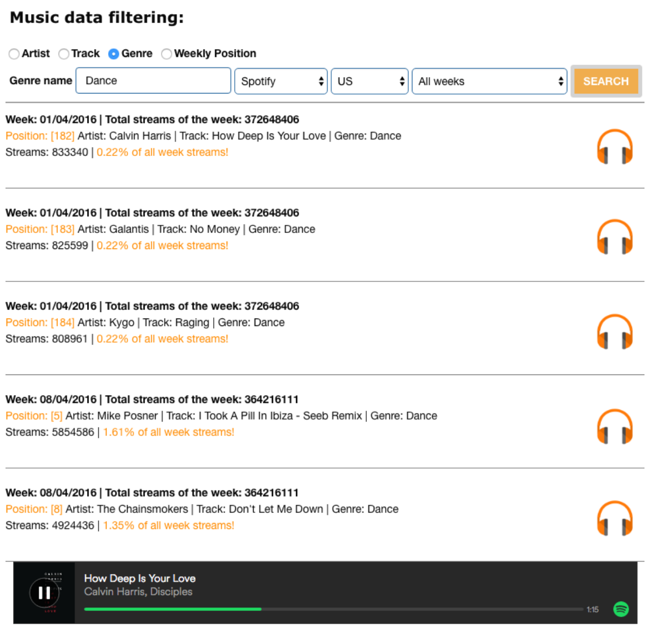


(b) Treemap applied to Billboard Top 60 by genre, during the June 18th week.

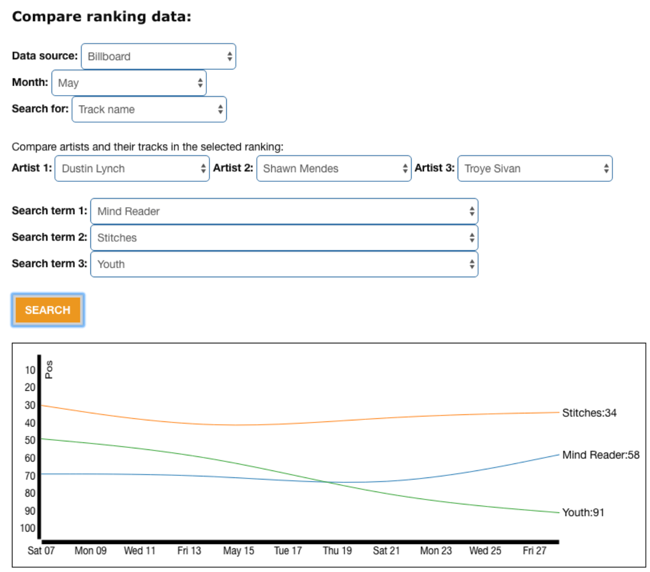


(c) Bubble Chart applied to Billboard Top 60 by position, during the May 18th week.

Figure 2: MusicVis visualization techniques.



(a) Filtering Dance music data from all Spotify USA ranking.



(b) Comparison between 3 artists that appear in Billboard rankings of May. They are all compared in a Multi-Series Line Chart.

Figure 3: MusicVis interactive features: Filtering and Comparison.

3.5 Treemap

Treemap is a method for displaying hierarchical data by using nested rectangles. Figure 2b shows an example of this visualization applied to our dataset.

As in Sunburst, when selecting Spotify data, the size of each section represents the amount of streams. The dataset shown in Figure 2b is classified by genre, which make easier to notice the proportion of each music genre on that specific week. Each rectangle can be clicked on to open a player.

3.6 Bubble Chart

Bubble charts represent data by circles of different sizes and colors. In Figure 2c we can see such visualization as implemented in our work. It starts ordering the circles from the center and then spiralling data around, classifying by position or clustering by artist and music genre. The bubbles are clickable, so they allow listening each track. Tooltip and colors representing music genres are also available.

3.7 Interactive features

Filtering and **searching** (Fig.3a) are used to obtain data from all of our database. The query can be from Artist, Track, Genre or Position. Once the type is selected and the name is typed, the user can filter specific ranking, country and week, or check the full results.

The results are shown as a list, with the following information: Week, Position, Artist, Track, Genre, Streams and Total number of streams on that week (Spotify) and the amount of listeners (in %) on that specific week.

The user can also order the result by new/old or relevance (representing the most listened results). When clicking on the headphone icon, a Spotify player is shown and the user can listen to that track.

The user can **compare** artists and music tracks in a Multi-Series Line Chart (Fig. 3b). Firstly, one selects the data source (Billboard or Spotify) and Month, and then Search for Track Name or Artist. A drop-down list is shown with Artists to select. If we are searching for tracks, Search terms are available along the track names of each artist. After clicking on the search button, a Multi-Series Line Chart displays how the track oscillated during the month. In this graph, colors do not represent music genres, but are used to differentiate each result.

4. USER STUDY

This study aimed at evaluating the visualizations, filtering and comparison techniques, usability and learnability of our application. In this section we briefly describe participants, procedure and results.

4.1 Participants

After invitation on the mail list of our University and Technical High School, an amount of 94 Brazilian people volunteered to the experiment: 44 males (46.8%) and 50 (53.2%) females, ranging from 15 to 33 years old, with mean and mode as 18 years old. Concerning to education, 86 (91.5%) are students in a computing-oriented high school course, 3 (3.2%) had already graduated in CS, 3 (3.2%) had a M.Sc. degree in CS and 2 (2.1%) are Ph.D. in CS. Among all, 85.1% consider important or very important to listen to music; 53.2% have already follow music rankings; 79.8% know Billboard, Spotify Charts or both rankings. And, finally, 53.2% are acquainted to data visualization.

4.2 Procedure

The experiment was performed on a local network, taking around 15 minutes each. Only few information were given in person. At first, they were told to sign an agreement statement, and fill a profile questionnaire. Then, they were invited to surf on Billboard, Spotify Charts, and our tool, freely. At the same time, they were able to answer our questionnaire, which evaluated the visualization of music rankings. The participants had to give their level of agreement to positive sentences using a 5-point Likert scale ranging for 1 (strongly disagree) to 5 (strongly agree). The last step was to answer a System Usability Scale (SUS) [5] questionnaire.

4.3 Results

Aggregating 4 and 5 as positive feelings, we found out that: (i) 56.3% surely preferred using our tool instead of Billboard; (ii) 54.3% preferred instead of Spotify Charts; (iii) 70.2% totally liked the colors; (iv) 67% found the layout attractive; (v) 85.1% found that the tool is very interesting.

Specifically evaluating the tool, the results show: (i) 66% liked Sunburst; (ii) 61.7% liked Node-Link Tree; (iii) 48.9% liked Bubble chart; (iv) 44.7% liked Treemap; (v) 81.9% liked the data filtering feature and (vi) 75.5% liked the comparison feature.

These findings were confirmed by a SUS overall score of 79.2. Considering learnability, the score is 90.4. If we analyze only the group of those subjects acquainted to data visualization, the scores are: SUS=82 and learnability=90.5.

The analysis of additional comments made by 18 participants allowed us to better understand what participants found about this work. Noteworthy comments are about Treemap being confusing and not intuitive (2 users) and complains about the chosen colors, that did not match what one user expected.

5. DISCUSSION AND FINAL COMMENTS

From the analysis of the questionnaires we were able to obtain interesting insights about our project. Sunburst and Node-Link Tree were successful visualizations for our purpose. They are able to exhibit a large amount of data, and at the same time are pleasant. The traditional visualizations, Bubble Chart and Treemap were not efficient, in users' opinion: it was not easy to follow the ranking path in Bubble Chart, and Treemap was confusing, both non-intuitive.

Another important issue is that some artists are not available in Spotify, which makes the rankings different from one data source to another. Billboard considers radio, physical sales and other stream services, which make an artists like Beyoncé appear in this ranking and not in Spotify. Her new album was only available for streaming at TIDAL, for example.

In all, our results show that our work presented a new interactive way to present, find and compare music rankings, making easier for users to infer and become interested in music based on music genres and artists.

As future work we want to compare personal data (such as Last.fm tracking) with these rankings, and improve the comparison feature. We also want to provide new visualizations and obtain data from other music rankings.

6. ACKNOWLEDGMENTS

We thank all the volunteers involved in this project.

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