Interactive, Spatiotemporal Visualization of Spotify Music Popularity

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1 Introduction and Problem Definition

Our team developed two interactive dashboards to visualize and analyze various aspects of popular music. The dashboards incorporate multiple interactive visualizations, including: (i) choropleth maps to visualize spatial popularity trends, (ii) line graphs to visualize temporal popularity trends, (iii) bar graphs to visualize song/artist popularity and audio characteristics, and (iv) word clouds to visualize words in popular lyrics. Furthermore, a clustering analysis based on audio characteristics is continually performed on the subset of songs selected by the user (via interactive filters), and bar graphs are color-coded to indicate cluster membership.

2 Literature Survey

2.1 ***Music Data Visualization [1-9]:*** Various data types are considered for this body of work, including audio features [1, 2], lyrics [3], popularity [4], listening history [5], and [6] considers all of the aforementioned data types. Our work will utilize popularity and lyrical data, so [3, 4, 6] will be more directly applicable to our work. Nonetheless, each paper contains useful visualization techniques for our group to consider: contour/landscape style visualizations for multi-dimensional data [2, 4]; TagPie graphics, which enable comparison of multiple word clouds [3]; and graph/network-style visualizations (to capture co-artist relationships) [5, 6]. However, none of [1-6] visualize geographical or temporal trends, so the proposed techniques will have to be adapted. Additionally, the exposition in [4] on data collection considerations, feature design, and clustering analysis will be valuable. Papers [7-9] form a sub-body of work related to the extraction of social tag information for music. In [7], listener-provided descriptive tags (e.g. “fast”, “funky”, “sad”) are extracted from Last.fm. In [8], similar information is obtained by performing sentiment analysis on Twitter data. The work in [9] establishes that certain social tags are strongly correlated with popularity. Therefore, these works provide an alternative to the lyrical analysis in our work. Additionally, geographical information is extracted from Twitter data in [8], so the discussion on geographical visualization remains relevant to our project.

2.2 ***Visualization in Other Domains, Domain-Agnostic Techniques [10-16]:*** Work from non-musical domains is also of value. Several strategies for jointly visualizing spatial and temporal aspects of numerical spatiotemporal data are available in [10-13]. Many of the proposed visualizations are rich in information but may be challenging for a novice to digest at first glance. [12] shows how interactivity can be used to separate visualizations of spatial and temporal aspects to aid the presentation. Additionally, the perceptual study in [14] is of particular value, as it provides guidance and comparative analysis of ranked-list data visualization considering space utilization, layout, and labeling strategies. Visualization of textual spatiotemporal data is discussed in [11, 15, 16]. The techniques herein can be considered for the word cloud visualization envisioned in our work. While several of the visualizations appear complex, [16] proposes a method to highlight trends, rather than treating time points independently, easing presentation.

2.3 ***Analysis and Visualization of Time Series [17-20]:*** The work in [17, 18] emphasizes detecting and analyzing latent evolutions in large ranking time series datasets. Both works compute similarities among ranked items to characterize ranking changes among groups of entries. However, the resultant visualization can be cluttered. Nonetheless, the ideas could be used in our project to find songs with similar ranking trends. The time-series clustering techniques of [19, 20] provide more strategies for computing similarities between ranking trends. While [19] provides a comprehensive review of recent techniques, [20] emphasizes a hierarchical clustering approach that also includes dynamic time warping (a distance measure between two time series which allows for the series to differ in length).

3 Proposed Method

Our team developed two interactive dashboards during the course of this project. Henceforth, these dashboards will be referred to as “Tableau Dashboard” and “D3 Dashboard”.

3.1 ***Innovations and Novelty:*** The innovative and novel aspects of our work are multiple. (i) To the best of our knowledge, spatial and temporal trends in song popularity have not been jointly and interactively visualized in prior work. (ii) Our tools compactly present multiple, jointly-interactive visualizations of interest in one location. (iii) Furthermore, our joint consideration of popularity and audio characteristics (Tableau Dashboard) or lyrical data (D3 Dashboard) are novel. Music enthusiasts will likely be interested in the spatial and temporal popularity trends, while music industry professionals will likely be *additionally* interested in trending audio characteristics and lyrical content. In addition to informing research, we anticipate that our proposed dashboard can be a decision-support tool for music industry professionals, who may sign new artists or target advertisements based on observed trends.

3.2 *Datasets Used*

3.2.1 Popularity Data: Both the Tableau Dashboard and D3 Dashboard utilize popularity data from Spotify. This data is available via the Spotify Web API. The team used pre-scraped versions available online due to API usage limitations. Entries in the popularity dataset correspond to musical tracks; the dataset contains information about the top 200 most popular tracks (measured by stream count) for each day within a certain date range, and for each of several countries/geographical regions. The following information is provided for each track in the dataset: (i) Date, (ii) Spotify URL, (iii) Position in Top 200, (iv) Track Name, (v) Artist, (vi) Stream Count, and (vii) Country. Different, pre-scraped versions of this dataset were used in the two dashboards; differences are summarized in Table 1 below. Column headers in Table 1 contain links to CSV files containing pre-scraped data.

	Tableau Dashboard Version	**D3 Dashboard Version**
Date Range	1/1/2017 - 7/1/2019	1/1/2017 - 1/9/2018
Number of Countries	63	54
Total Number of Rows	8,469,130	3,441,197
File Size on Disk	941 MB	369 MB

Table 1: Summary of the two versions of the Spotify popularity dataset used in this project.

3.2.2 Audio Characteristics Data: The Tableau Dashboard joins the popularity dataset with an audio characteristics dataset. Data on audio characteristics is available via the Spotify Web API, but the team utilized the pre-scraped version linked here, which was processed to remove duplicates. The audio characteristics dataset contains the following information about 216,842 songs: (i) Genre, (ii) Track Name, (iii) Danceability [0-1], (iv) Energy [0-1], (v) Loudness [dB], (vi) Speechiness [0-1], (vii) Acousticness [0-1], (viii) Instrumentalness [0-1], (ix) Liveness [0-1], (x) Valence [0-1], (xi) Tempo [bpm], (xii) Duration [ms], and (xii) Language. The file size of the audio characteristics dataset is 22.4 MB.

3.2.3 Lyrical Data: The D3 Dashboard also utilizes lyrical data in addition to popularity data in order to produce word clouds. This data is available via the Musixmatch Developer API. The Musixmatch database is extensive, and contains much information about the tracks contained therein. However, the team only uses Track Name and Artist information to look up lyrics. Musixmatch's free API imposes the following limitations on the team: (i) only 30% of the lyrics for each track can be accessed, and (ii) each API key is limited to 2000 API calls per day.

3.3 *Approach #1: Tableau Dashboard*

An interactive dashboard has been developed using Tableau Desktop, and the home screen is shown in Figure 1. The dashboard consists of six visualizations, which also have interactive features that serve to limit the body of songs summarized by the visualizations. Each visualization is described below, in the context of an *arbitrary* selection of songs:

1. **"Spatial Popularity Trends"** is a choropleth map, where stream counts are aggregated by country (i.e. across time, artist, and song), and countries are shaded according to the total number of streams in that country. Individual countries may be selected by clicking on the map, or by using a search bar.
2. **"Most Popular Artists"** is a bar chart, where stream counts are aggregated by artist (i.e. across time, country, and song), and artists are presented in order of popularity. Furthermore, a clustering analysis

is *continually* performed on the selected corpus of songs (determined by filter settings), and bars are colored according to cluster membership. Clustering analysis is based on audio characteristics (specifically Danceability [0-1], Energy [0-1], Speechiness [0-1], Acousticness [0-1], Instrumentalness [0-1], Valence [0-1], and Tempo [bpm]), and employs K-means clustering where the number of clusters (K) is automatically determined by maximizing a measure of clustering quality (specifically, the Calinski-Harabasz criterion, for more details, see here).

3. "**Temporal Popularity Trends"** is a line plot, where stream counts are aggregated by day (i.e. across artist, song, and country), and plotted over the date range specified by the slider immediately underneath the line plot. The two ends of the slider can be moved, or dates can be entered using a calendar tooltip. Furthermore, the selected range can be dragged once the width is fixed, for example, to conveniently examine different six-month periods of time.
4. **"Most Popular Songs"**, a bar chart, where stream counts are aggregated by song (i.e. across time and country), and songs are presented in order of popularity. As in **"Most Popular Artists"**, clustering analysis (same as described above) is *continually* performed on the selected corpus of songs (determined by filter settings), and bars are colored according to cluster membership.
5. **"Popular Audio Characteristics"** is a bar chart that shows the average values of multiple audio characteristics of songs in the selected corpus.
6. **"Most Popular Genres"** is a tree map that shows the genres with which songs in the selected corpus are associated. Cell size and color are proportional to popularity.

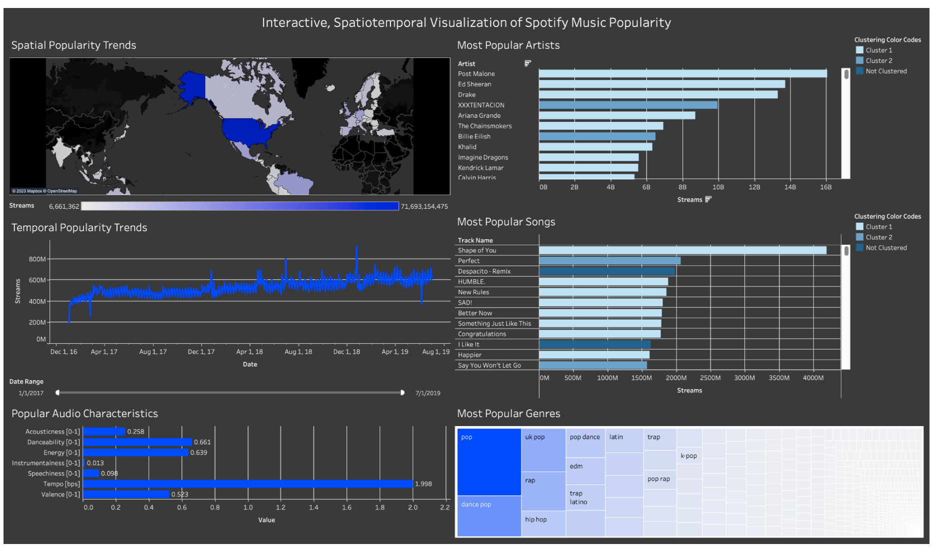

Figure 1: Homepage of the Tableau Dashboard, containing six dynamic, interactive visualizations. Please zoom in as required.

Interactive capabilities of the Tableau Dashboard are as follows, and are demonstrated in more detail here:

- Selecting a country in the **"Spatial Popularity Trends"** restricts the corpus of songs selected for visualization and analysis to be those from one country. All visualizations are now to be interpreted in the context of the selected country. To be explicit, after a country is selected, the dashboard shows (1) the most popular artists in that country in **"Most Popular Artists"**, (2) the most popular songs in that country in **"Most Popular Songs"**, (3) the aggregate number of streams over time in that country in **"Streams Over Time"**, (4) the average values of various audio characteristics of the most popular songs in that country in **"Popular Audio Characteristics"**, and (5) the most popular musical genres in that country in **"Most Popular Genres"**.
- Selecting an artist in the **"Most Popular Artists"** will update visualizations, which should now be interpreted in the context of the selected artist. Note that **"Spatial Popularity Trends"** would now be shaded based on streams corresponding to the selected artist.

- Clicking on a song in **"Most Popular Songs"** will update visualizations, which should now be interpreted in the context of the selected song.
- Modifying “Date Range” under **“Streams Over Time”** will update visualizations, which should now be interpreted in the context of the selected date range.
- Filters can be combined, for example, by clicking on the United States in **"Spatial Popularity Trends"**, the artist "Ed Sheeran" in **"Most Popular Artists"**, and the song "Shape of You" in **"Most Popular Songs"** to see a chart of streaming trends for that song (and artist) within the United States in **"Temporal Popularity Trends"**. The escape key can be pressed to clear any applied filters.

3.4 *Approach #2: D3 Dashboard*

A second interactive dashboard has been developed using Flask, Python, SQLite and D3.js, with sample visualizations provided in Figure 2. Flask and Python are used on the server-side to filter the selected corpus of songs based on user interactions and retrieve lyrics through the Musixmatch API. SQLite is used to expedite data loading instead of using the Pandas framework. D3.js is then used to visualize data corresponding to a user-selectable geographical region. On the home page, an animated world map displays the total number of streams in each country on each day, as the date marches forward. When users click on a country, they are navigated to a page that visualizes data *from the selected date and country*. This page contains (i) a bar graph and (ii) a word cloud, which are described below:

- The **bar graph** shows the top *N* songs (by stream count), where *N* is user-adjustable.
- The **word cloud** shows words appearing in the lyrics of the top 20 songs *from the selected date and country.* To make results more meaningful, a threshold is applied such that only words that account for more than *70%* of the total corpus of text are visualized. Additionally, non-English-language words, English-language profanity, and common-but-uninsightful words (e.g. ‘a/an’, ‘the’, ‘and’, etc.) are filtered out in an attempt to visualize the *sentiment* conveyed by popular song lyrics.

Other features of this dashboard include:

- **Smooth Transitions in Bar Graph:** When the user selects a new region or updates the date, bars smoothly transition from their previous state to the new state, improving the visual aesthetics and overall user experience. Additionally, when the mouse hovers over a bar, that bar becomes slightly larger to indicate to the user that it is interactive.
- **Page Redirection in Bar Graph:** When the user clicks on a bar, it will open the corresponding Spotify song page, allowing the user to access more information about that song quickly.
- **Circular Progress Bar:** A circular progress bar is displayed while the data is being fetched from the server, providing users with visual feedback about the loading status. This feature ensures that users are aware that the data is being processed, enhancing the user experience.

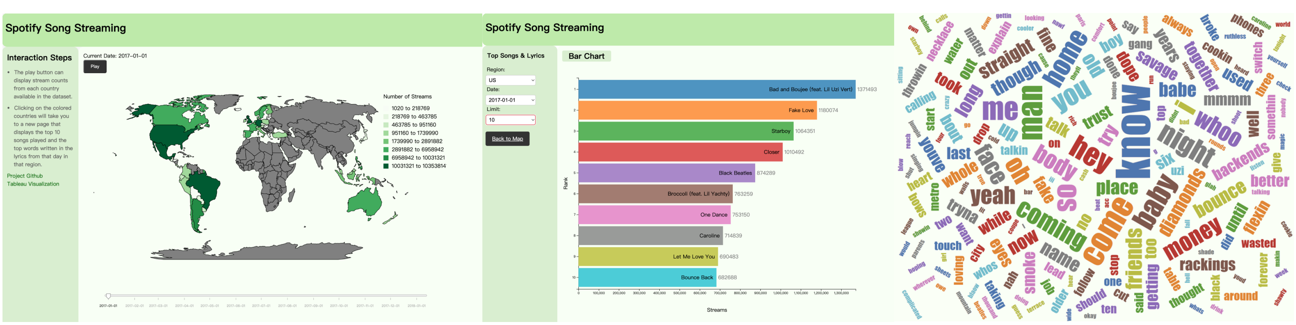

Figure 2: Homepage of the D3 Dashboard containing an animated, interactive heat map, as well as ranked bar chart and word cloud visualizations of popular songs in the US on one day. Please zoom in as required.

4 Experiments/Evaluation

4.1 Scalability Evaluation

4.1.1 Question: How does the tool perform when visualizing data at the daily, monthly, and yearly scales?

4.1.2 Observations (Tableau Dashboard): Various latencies associated with the Tableau Dashboard were measured to understand its ability to handle a large dataset. The most significant latency was observed to be the initial loading time, during which required datasets are loaded, joined, and initial visualizations and calculations are performed. Of the two datasets used in the Tableau Dashboard (popularity and audio characteristics), the popularity dataset dominates in size (see Sections 3.2.1-3.2.2), and affects loading time more. Therefore, an experiment was performed, where the time required to load, join, and show initial visualizations was logged as a function of the number of rows present in the popularity dataset. This time is reported to the nearest second by a pop-up window in Tableau Desktop, and was recorded manually over five trials for each size-altered version of the popularity dataset. Results are presented in Table 2, which indicate that initial loading time is roughly proportional (obviously) to the size of the popularity dataset, but also that (i) an 8-9 second offset is likely dominant component of all loading times, and (ii) even when all rows in the dataset are retained, loading time is still (a very modest) 15 seconds.

% of Rows Retained	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Average
20%	9	10	9	10	10	**9.6**
40%	10	11	11	11	11	**10.8**
60%	13	11	12	12	12	**12**
80%	14	13	14	13	13	**13.4**
100%	15	15	15	15	14	**14.8**

Table 2: Characterization of initial loading latency in Tableau Dashboard.

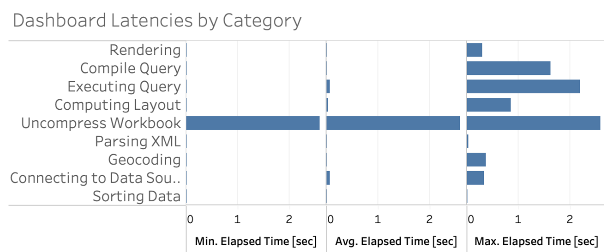

Figure 3: Characterization of other latencies in Tableau Dashboard.

Other latencies associated with interactive operations in the Tableau Dashboard were measured using the "Performance Recording" feature in Tableau Desktop. A three-hour interactive session (comprising numerous interactive events) was conducted between invocations of "Start Performance Recording" and "Stop Performance Recording". Various latencies associated with generating graphics and performing calculations were measured automatically by Tableau, and measurement statistics are shown in Figure 3. For each latency category, the minimum, maximum, and average latencies are shown - note that average latencies (besides the one-time uncompress action) are on the order of tens of milliseconds, with maximum latencies, which are likely one-time and startup-related events, on the order of one second. We conclude that the Tableau Dashboard is responsive, and handles the large popularity dataset well. All tests were performed using a MacBook Pro (2.3 GHz Intel Core i9 core), and Tableau Desktop 2022.4.1.

4.2 Usability Evaluation

4.2.1 Questions: How do peers feel about the usability of the tool? Are filters easy to apply and remove? Are visualizations sufficiently clear? What additional features might users want to have?

4.2.2 Observations (Tableau Dashboard):

The final form of the Tableau Dashboard is shown in Figure 1. For reference, the home page of Tableau Dashboard as of the project midterm, before external feedback was solicited, is available here. The inputs of seven peers was solicited, and resulted in improvements to (i) functionality (consideration of audio characteristics, genre, and clustering analysis), (ii) interface design (note the changes in layout and color scheme), and (iii) wording/labeling (note that clarity in labeling was improved upon).

4.3 Utility Evaluation

4.3.1 Question: What non-trivial, domain-specific insights were obtained by employing the tool?

4.3.2 Observations (Tableau Dashboard): Numerous insights can be obtained from the Tableau Dashboard. As just one example (in the interest of space), insights into the transformation of rap and pop music between 1/1/2017 and 7/1/2019 (a transformative period) are provided below. In the interest of space again, supporting figures are omitted. However, these results can be reproduced by interacting with the Tableau Dashboard, which is available as a package (including data) here.

Historically, rap and pop are the popular music genres in the US. However, it is interesting to note that the leading category oscillates, when six-month intervals are examined between 1/1/2017 to 7/1/2019, due to the emergence of new *sub-genres* within rap and pop. Within the rap genre, this time period sees the rise of the trap and DFW rap, and the decline of the hip hop and ATL hip hop sub-genres. Within the pop genre, this time period sees the rise of the UK pop, and dance pop sub-genres, and the decline of the EDM, and Canadian pop sub-genres. This transition can also be observed via dominant audio characteristics within each genre over time. Figure 4 shows the dominant audio characteristics in rap and pop songs over 5 6-month intervals between 1/1/2017 and 7/1/2019. One notes the dramatic trend (fall, then rise) in "Instrumentalness" within pop music, and the rise of "Acousticness" within rap and pop.

4.3.3 Observations (D3 Dashboard): We conducted an analysis to identify regional similarities in music preferences, as measured by cosine similarity. For analysis, each region is represented by a vector containing stream counts for each track played in that region. To correct for population variations between regions, each vector is normalized to sum to one, i.e. entries represent the *proportion* of total streams allocated to each track. The cosine similarity score between two regions is computed by taking the inner product of the two corresponding vectors. Similarity scores range from -1 to 1, where 1 means the vectors are identical, 0 means the vectors are orthogonal (i.e., have no similarity), and -1 means the vectors are diametrically opposed. The five most-similar and five least-similar region-pairs emerging from this analysis are listed in Table 3. According to Table 3, our findings suggest that regions with similar music preferences tend to share a common language, whereas regions with different preferences often face language barriers. This analysis provides insights into the music preferences of different regions and can be used to inform marketing and promotional strategies for music artists and streaming services.

5 Most-Similar Pairs of Regions			5 Least-Similar Pairs of Regions		
Region 1	**Region 2**	**Similarity**	**Region 1**	**Region 2**	**Similarity**
Honduras	El Salvador	0.9778	Chile	Iceland	0.1740
Uruguay	Argentina	0.9774	Paraguay	Iceland	0.1776
Guatemala	El Salvador	0.9668	USA	Chile	0.1819
Ecuador	Bolivia	0.9651	Chile	Finland	0.1834
Hungary	Czechia	0.9634	Peru	Iceland	0.1871

Table 3: Regional similarities in music preferences

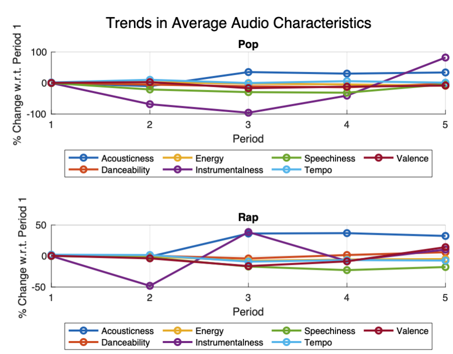

Figure 4: Trends in audio characteristics within rap and pop.

6 Conclusion

Our team developed dashboards in Tableau and D3 to visualize and analyze various aspects of popular music. The dashboards incorporated multiple interactive visualizations (including choropleth maps, line and bar graphs, and word clouds). The Tableau Dashboard also included a clustering analysis based on audio characteristics, which provides non-trivial insight into the co-evolution of musically-similar songs, and correlation of audio features with popularity. By visualizing and analyzing tabular-form data (and combining other datasets), our tools provide insights that may prove valuable to music industry professionals, particularly regarding emergent sub-genres within popular genres, trending audio characteristics, and similarities between geographical regions.

6.1 Contribution Statement

(UA) developed the interactive choropleth map; **(JC)** helped with developing the D3-based bar graph; **(RC)** assisted in implementing the Tableau dashboard's clustering feature and helped prepare the poster; **(KS)** developed the Tableau-based dashboard, performed experiments using the Tableau dashboard, led the preparation of this report, and contributed to debugging the D3-based word cloud and poster preparation; **(YT)** developed the D3-based word cloud; and **(YY)** developed the D3-based bar graph and performed similarity analysis.

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