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Conference Paper · October 2022

DOI: 10.1109/ACIIW57231.2022.10086019

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Music Charts for Approximating Everyday Emotions: A Dataset of Daily Charts with Music Features from 106 Cities

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***Abstract*—The music we listen to often reflects our emotional state. Accordingly, a city's music charts may reflect consistencies and patterns in the collective emotional experiences of its residents. In this paper, we report a dataset of arousal and valence-related music features collected from songs on Top-25 charts from 106 cities around the world, over a period of 158 days. Chart information was obtained from the Apple Music platform, and music features were obtained from Spotify. We visualize daily fluctuations of features corresponding to intensity arousal (energy, loudness), rhythmic arousal (danceability, tempo) and valence, highlighting trends in nine major cities across six continents, and conduct k-means clustering of all 106 cities from these five music features. Preliminary results suggest consistencies between our music feature data and previous literature, in reflecting cultural differences for preferred arousal levels in music. We also discuss possible implications of our paper and data in the use of music streaming charts as indicators for collective emotional experience.**

***Index Terms*—music, emotion, culture, surveillance**

I. Introduction

Music is often an indispensable part of people's everyday life. Despite globalization in recent years, music is diverse, and musical preference varies across individuals and geographical or cultural regions [1], [2]. Yet, one key reason why people listen to music is to regulate their emotions [3], ultimately contributing towards larger goals like enriching their well-being [4].

In focusing on emotion regulation as a primary reason for music listening, we propose that by tracking emotion-related music features of music consumed, we can estimate the temporal fluctuations in experienced emotions. This builds on research showing that music consumption, particularly on streaming platforms, reflect structural and cultural differences in emotions experienced by people around the world. In examining Spotify usage from 1 million users, Park and colleagues [5] found that preferences for arousal in music reflected known cultural trends of affect valuation [6]: Latin and North American users listened to more high arousal music, compared to East Asian users who listened to lower arousal music. One explanation could be that individuals experience differing amounts of negative emotions in daily life, and these can often be generalized to the cultural background they come from. Liew and colleagues [7] examined Spotify charts from 60 countries, and found that the level of rhythmic (danceability) and intensity (energy) arousal features of songs on these charts were correlated with the frequency of negative emotions experienced in these countries.

One psychological mechanism for this relationship could be due to the effect of cathartic listening, where individuals who feel high arousal negative emotions may use high arousal music to regulate their emotions [8], [9], and this is reflected in the rhythmic and intensity arousal of songs listened to for downregulate purposes [7]. Accordingly, our proposal assumes that the collective music preference of a geographical region (as observed in daily music charts), would reflect the fluctuating levels of day-to-day negative emotion experiences.

A. Related Work

Our approach borrows from commonly-used infodemiological approaches towards monitoring of mental health on social media, such as geographical comparisons of state-level prevalence [10], or longitudinal monitoring [11] of depression through relevant Tweets. These methods have also been applied to emotion detection from social media [12]. However, these approaches rely primarily on Twitter and natural language processing for data analysis. As such, these studies face limitations in cross-cultural generalizability, as linguistic differences make it difficult to compare social media posts across cultural and linguistic boundaries. By focusing our analyses on music features, we can examine a wider variation of cultures, without these limitations on language. In music research, the relationship between music consumption and emotion has been studied extensively at the individual-level, through tracking song playback and emotional experience via ecological momentary assessment or diary studies (see [13]). Several studies have also tried to relate Spotify feature data to manual annotations of recognized emotion in music, albeit with only limited success [14]. Charts have also been used to quantify music consumption at a macro, often country-level (e.g., billboard charts [15], [16], Spotify [17]. Our approach

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TABLE I
DISTRIBUTION OF CHARTS ACROSS CITIES

Region	Number of cities
North America	34
Europe	26
East Asia	14
South America	8
Africa	6
Southeast Asia	4
South Asia	4
Central America	3
Australia and New Zealand	3
Western Asia	3
Central Asia	1

differs in that we use data from Apple Music, which offers higher granularity by aggregating music consumption at the city level, rather than the country level. To our knowledge, we are the first to implement such an approach (of using Apple Music charts) in cross-cultural analyses of music consumption patterns.

B. The Present Research

To estimate city-level fluctuations in daily emotions, we collected city-level Top-25 charts as compiled by Apple Music over a half-year period. As Apple Music does not provide music feature information, we obtained scores for indicators of rhythmic and intensity arousal, and valence, from Spotify's database. We then visualize these indicators over time and cluster the cities according to the similarity of their charts. Following previous research, we expect the visualization and clustering analyses to show some degree of variation in music-emotion features across cultural boundaries.

II. DATA COLLECTION

A. Music Dataset

Since April 27, 2021, Apple Music began listing the Top-25 songs from 106 major cities around the world. These are organized into playlists, and updated daily with songs "making the waves" in cities worldwide. By recording songs on these playlists, which can reflect the collective music preference of users within these cities, we created a dataset of Top-25 songs at the city-level. As playlists were updated daily, we designed a simple web crawler to record the titles and artists of these songs on a daily basis. The collection period ranged from July 28, 2021 to January 19, 2022. However, we encountered unexpected server shutdowns during the collection process, and had 18 days of missing data: 2 August 2021, 15 August 2021, 7 September 2021, 8 September 2021, 16 October 2021, 17 October 2021, 13 November 2021 and 10 December, 2021 to 20 December, 2021. This resulted in 158 days of usable data. A list of cities included in this data is shown in Table I, North America has the most cities with 34, followed by Europe with 26 and East Asia with 14, while in all other regions there were no more than 10 cities.

TABLE II
DESCRIPTIONS OF ACOUSTIC FEATURES

Features	Description
Danceability	How suitable a track is for dancing
Energy	A perceptual measure of intensity
Loudness	The overall loudness of a track
Valence	The positiveness conveyed by a track
Tempo	The average speed or pace of a track

Next, we collected the music features of these tracks that represented arousal and valence. Through the Spotify API[1], we first matched the song names of our database with that listed on the Spotify database. Relying on the corresponding ID, with the exception of a small number of songs that could not be retrieved, we extracted 11 music features (all the openly accessible music features) provided by Spotify. We then focused specifically on features that reflect emotional arousal and valence. We selected five acoustic features: danceability (rhythmic arousal: [7]), energy (intensity arousal: [18]), loudness (intensity arousal), valence, and tempo (rhythmic arousal), as shown in Table II. Unfortunately, the detailed process employed by Spotify in the development of these features is not publicly available, but a description each feature is available on the Spotify platform[2].

III. DATA ANALYSIS

A. K-means Clustering

Our second step was to conduct a broad clustering of cities according to their arousal and valence-related features. We used the k-means algorithm to cluster cities based on all the Spotify-obtained musical features of tracks their Top-25 charts on Apple Music. A fundamental step for k-means algorithm is to determine the optimal number of clusters into which the data may be clustered. To ensure the robustness of the selected k value, we utilized two methods (elbow method and silhouette method) to select the optimal value of k.

The elbow method runs k-means clustering on the dataset for a range of values of k (from 2 to 8), and for each value of k, it calculates the squared errors of each data point $i \in C_I$ and its cluster center and sums them up to get the sum squared error (SSE).

$$SSE = \sum_{i \in C_I} dist(i - \text{center of } C_I)^2 \tag{1}$$

where $dist$ is a function to calculate a distance between two points. Then, by plotting a line chart of the SSE for each value of k, we select the k value that has a small value and a low SSE as the optimal k value, which looks like an "elbow" on the line chart.

The silhouette method measures the extent to which a point is similar to its own cluster compared to other clusters,

[1]https://developer.spotify.com/console/

[2]https://developer.spotify.com/documentation/web-api/reference/#/operations/get-audio-features

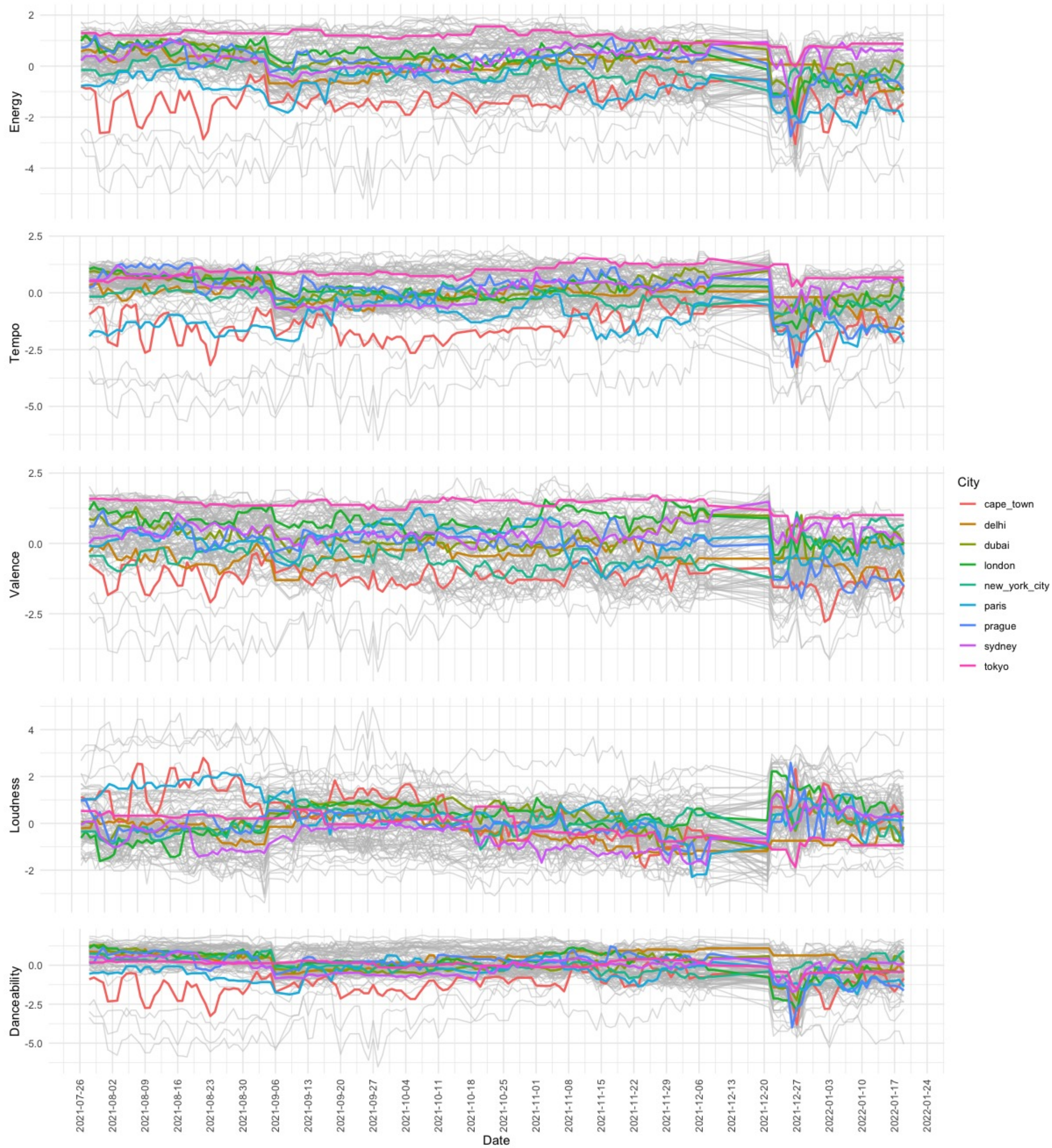

Fig. 1. A visualization of mean energy, tempo, valence, loudness, and danceability scores per city Top-25 chart per day. Nine representative cities (Cape Town, Delhi, Dubai, London, New York City, Paris, Sydney Tokyo) corresponding to the different geographical regions from the data, are highlighted in color.

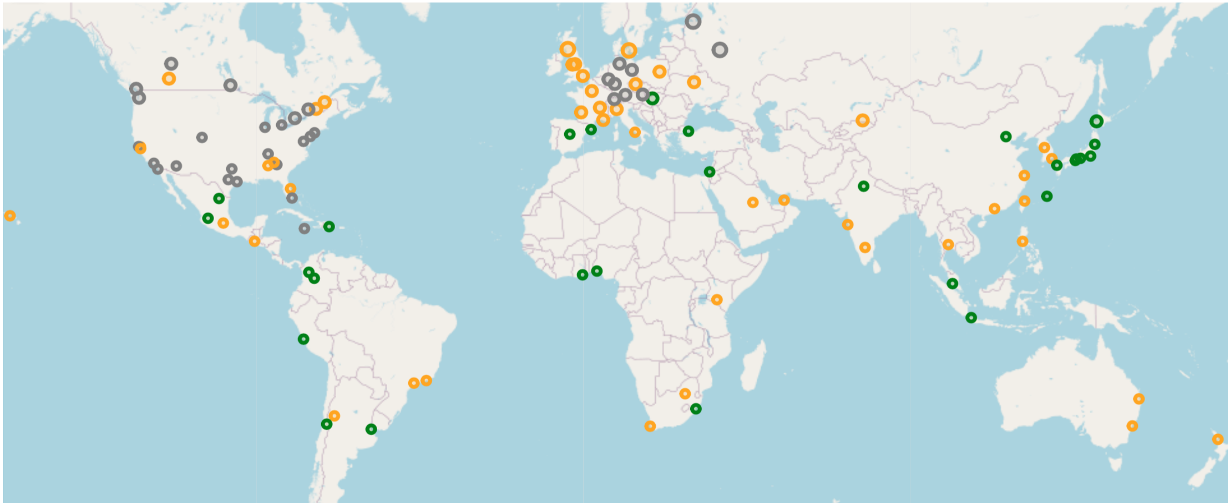

Fig. 2. K-means clustering of cities according to arousal and valence-related music features of songs on their Top-25 charts. Gray dots correspond to Cluster 1, green to Cluster 2, and yellow to Custer 3.

TABLE III
CITY CLUSTERS ACCORDING TO K-MEANS CLUSTERING

Cluster	City
Cluster 1	New York, Atlanta, Austin, Berlin, Chicago, Cologne, Dallas, Denver, Detroit, Edmonton, Frankfurt, Hamburg, Houston, Kingston, Los Angeles, Miami, Moscow, Munich, Nashville, Ottawa, Philadelphia, Phoenix, Saint Petersburg, San Diego, San Francisco, Seattle, Toronto, Vancouver, Vienna, Washington DC, Winnipeg, Zürich.
Cluster 2	Tokyo, Osaka, Nagoya, Sapporo, Fukuoka, Kyoto, Sendai, Naha, Accra, Barcelona, Beijing, Bogota, Budapest, Buenos Aires, Delhi, Durban, Guadalajara, Istanbul, Jakarta, Kuala Lumpur, Lagos, Lima, Madrid, Medellin, Monterrey, Santiago De Compostela, Chile, Santo Domingo, Tel Aviv-Yafo.
Cluster 3	London, Paris, Seoul, Almaty, Auckland, Bangkok, Bengaluru, Birmingham, Bordeaux, Brisbane, Busan, Calgary, Cape town, Copenhagen, Dubai, Dublin, Glasgow, Guangzhou, Guatemala City, Honolulu, Johannesburg, Kyiv, Liverpool, Lyon, Manchester, Manila, Marseille, Melbourne, Mexico City, Milan, Montreal, Nairobi, Prague, Quebec City, Rio de Janeiro, Riyadh, Roma, San Jose, San Juan, São Paulo, Shanghai, Sydney, Taipei, Warsaw.

TABLE IV
MEAN VALUES OF CLUSTER ACOUSTIC FEATURES

	Danceability	Energy	Loudness	Valence	Tempo
Cluster1	0.609	0.555	-6.147	0.435	112.225
Cluster2	0.64	0.629	-5.62	0.523	119.224
Cluster3	0.611	0.595	-5.572	0.49	113.566

by computing the silhouette coefficient for each point and averaging it out of all the samples to obtain a silhouette score, which ranges from -1 to 1: a high score indicates that the object is well matched to its own cluster and poorly matched to neighboring clusters. Therefore, the highest silhouette score suggests the optimal k value for clustering. In "(2)", $S(i)$ is the silhouette coefficient of the data point i.

$$S(i) = \frac{b(i) - a(i)}{\max(b(i), a(i))} \tag{2}$$

where $a(i)$ is the average distance between i and all other data points in the cluster to which i belongs. $b(i)$ is the average distance from i to all clusters to which i does not belong.

To cluster cities based on the music features of tracks, we counted the list of songs that ranked in the top-25 in each city during the collection period firstly. We then calculated the average of the acoustic features of the tracks for each city during the collection period. So each city had one score (Average of the collection period) for each acoustic feature. Acoustic features included danceability, energy, loudness, valence and tempo. Finally, we clustered the cities by using these acoustic features as features for C_{music}.

IV. RESULTS

A. Descriptives and Visualizations

A visualization of the daily fluctations for each of the five Spotify indicators is provided in Figure 1. For ease of interpretation, we highlight nine cities, that broadly represented the geographical regions data was collected from: Cape Town, Delhi, Dubai, London, New York, Paris, Prague, Sydney, and Tokyo. The missing dates in the dataset were linearly interpolated. Descriptively, we noticed certain trends common in the data. For tempo, danceability and energy, a large drop was observed during the Christmas period. As this holiday season is often associated with a set of traditional songs (carols), that have since become representative of festivities beyond religious Christian communities. In comparing across cities broadly, past research has also suggested that Energy is associated with collectivism, and is also more prominent in Japanese music [16]. Accordingly, Tokyo was highest amongst the nine cities on Energy, and Cape Town and Paris, that are individualistic societies were amongst the lowest. However, these are preliminary descriptive observations of the data, and future studies would need statistical analyses and comparisons to other datasets in order to demonstrate the ecological and external validity of this method (music features as macro-level emotion indicators).

B. Observed Clusters

We first calculated the optimal k value of k-means through the elbow method and silhouette method, respectively. For both methods, the optimal k value was 3. Therefore, considering these two results, we chosen 3 as the optimal k value for the k-means analysis. These clusters are visualized in Figure 2, and detailed in Table III. The means for each acoustic feature of the three clusters is shown in Table IV. We observed that, broadly, Cluster 1 comprised mostly North American and Eastern European cities, Cluster 2 comprised mostly East Asian and Latin American countries, and Cluster 3 comprised cities that were evenly spread-out across the globe. On one hand, these clusters appear to only somewhat represent theoretical understandings of cultural difference. For example, Cluster 2 comprised several East and South Asian cities and Latin American cities, that have arguably collectivistic societies (see [19]), and certain types of music may be more commonly used in these societies for community rituals or collective activities (see [20]). Cluster 1, with many Northern cities, may represent music preference stemming from climate and weather, which are known antecedents of music preference [21]. On the other hand, these clusters provide a bottom-up grouping of cities by music preference, and current literature may not be sufficient in interpreting these relationships, especially across sociolingusitic boundaries.

V. Discussion

In this work, we describe a dataset we collected of Top-25 charts from 106 cities, over the period of 158 days. We included music features corresponding to valence, intensity, and rhythmic arousal in music. Ultimately, our aim is to show the feasibility of music features from charts as indicators of collective societal moods, and we believe that this paper provides an initial step in that direction. Thus far, we found descriptive evidence that between-city variations in Energy, appear to coincide with previous research on the use of Energy in representing prevailing negative emotions at a societal level. Next, our clustering of city-level music preferences around the world identifies consumption patterns for music based on arousal and valence features. Given that these features are known to reflect societal norms towards emotions, we think that these patterns may be representative of some form of collective values, norms, or aesthetics.

A. Limitations and Future Directions

One limitation of our research is our reliance on a closed (Apple Music's) ranking system for identifying popular music. Apple has broadly defined them as a combination of play counts and local popularity[3], but the specific details in the ranking process are not made public. As such, we cannot discount the possibility that external influences (e.g., music labels or local radio stations) may have exerted a top-down effect in manipulating chart data. One solution would be to corroborate the constitution of local charts with charts from other streaming platforms (e.g., Spotify), but they generally lack the city-level granularity of Apple Music, providing country-based charts instead that may not necessarily reflect city-level trends. Secondly, local music consumption might also be influenced by local media or events, such as songs used in product commercials or patriotic songs at national events, beyond collective cultural tendencies or collective emotions. On the other hand, these events are also products of local culture and also represent local values and aesthetics, are charts may still be representative of localized music preferences.

Finally, our research lacks a quantitative comparisons of longitudinal trends and regional variations with a similarly structured 'gold-standard' emotion dataset to verify our claims on emotion representation via music features. While it is indeed challenging to construct such a dataset, we think that follow-up research can test the patterns observed in this dataset with other indicators of emotion at the city level, which could be through web-based or digital data sources (e.g., search queries and trends, weather information, social media), or through participant self-reports in cross-cultural surveys. Doing so would establish the validity of music as sociocultural indicators of everyday emotion experience, thus allowing researchers to take advantage of widely available data from music streaming platforms, to infer cultural variation in emotional experience around the world. All data used in this study are also available online on our Github repository[4].

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