Country	Tracks	Users	Artists	Interactions Users	Interactions Artists
US	252,370	1,763	15,440	2,057,684	6,607,441
GB	99,911	890	5,271	1,095,637	2,767,202
DE	42,799	890	3,077	1,012,806	697,866
SE	29,108	348	1,970	393,348	672,944
CA	24,005	232	1,565	304,817	594,868
FR	17,718	281	1,815	337,739	357,730
AU	14,770	208	1,306	261,965	343,892
FI	14,673	448	1,093	508,934	286,145
BR	14,091	1,138	1,022	1,312,909	232,640
RU	11,779	1,288	848	1,202,064	155,409
JP	11,731	115	1,228	92,459	143,203
NO	11,282	224	765	256,921	238,427
PL	11,145	1,121	883	1,249,746	186,032
NL	10,958	406	1,018	573,307	186,117
IT	9,633	252	1,058	237,708	131,769
ES	6,115	257	765	297,364	71,862
BE	4,204	141	586	166,247	64,765
MX	2,881	213	323	295,140	33,887
UA	1,849	317	160	348,706	27,339
TR	1,478	115	286	113,165	14,868
Other	44,736	2,228	4,947	2,521,335	825,595
Total	637,236	12,875	45,426	14,640,001	14,640,001

Table 1: Basic statistics of the dataset. For each country, we report the number of users, tracks, artists, and interactions made by all users in the country as well as interactions made to artists from the country.

function, thanks to the multi-layer perceptron constituting a part of the model.

To estimate potential influence of the recommender algorithms on globalization patterns in different countries, we train them on subsamples of the dataset used to answer RQ1 and RQ2, and then analyze the recommendations they produce. To this end, we consider top 10 recommendations provided to each user and then calculate $IC_{c_u \to c_a}$ for $c_u = c_a$ and $c_a = US$ exactly like for RQ1.

Because the dataset under investigation contains a large number of items (see Table 1), we use its subsamples (containing around 100K items each) to run recommendation experiments, thereby avoiding computational limitations. For the subsamples, we enforce the following standard limitations: every track has to be interacted with at least 5 times and every user is required to have at least 5 interactions. To ensure robustness of the results, we conduct the experiment on three such random subsamples and report average recommendation levels.

2.4 Dataset

We conduct our experiments on the LFM-2b dataset [17] of listening events created by users of the online music platform Last.fm. [2] Unlike stand-alone streaming services such as Spotify or Deezer, Last.fm is based on the concept of "scrobbling", meaning that its users can share on the platform which music they are listening to, regardless of the actual service, device, or application they are using for music consumption. Therefore, Last.fm can be regarded as an aggregator that reflects the entire music consumption history of its users. This is desirable for our analysis since we aim at capturing in a more comprehensive way each listener's (and country's) music consumption behavior instead of focusing on one particular streaming platform.

The full LFM-2b dataset contains listening histories of ∼120K users, totaling to ∼2B interactions. Since the dataset's temporal coverages spans 15 years, from 2005 to 2020, and we intentionally leave out aspects of temporal dynamics from our analysis (see future work), we only consider a subset covering the years 2018-2019. Furthermore, we exclude potentially accidental interactions by removing listening events $< u, i >$ that only occurred once. [3]

Since our analysis necessitates country information of both users and artists, we first remove all users for which no such information is available in LFM-2b. We then collect information about artists' country from Musicbrainz [4] and only retain those artists for whom country data could be retrieved. After these steps we end up with a dataset of ∼14,640K interactions triggered by ∼13K users from 143 countries with ∼637K music tracks produced by ∼45K artists from 155 countries.

Finally, to reduce the complexity of the analysis and concentrate on reasonably represented countries, we select for the detailed analyses countries with at least 100 users and only countries whose artists created at least a total of 1,000 tracks. These filtering steps result in 20 countries [5] from all over the world (see Table 1 for basic statistics), which we further analyze. Note that the countries beyond these 20 still contribute to the results mentioned as a part of the aggregation over "other" countries.

3. RESULTS

We illustrate our findings with a series of figures. Figure 1 shows how popular is domestic music, music produced by US artists, and music produced by artists from other countries in every of the 20 investigated countries. In case of DE, a little under 40% of listening events generated by German users are allocated to music produced by US artists (orange bar on the left). Under 20% of listening events generated by them is allocated to domestic music, i. e., produced by German artists (blue bar on the right). Figure 2 indicates the degree to which domestic music of different countries is consumed in the country of origin and outside. For example, BR has most of the listening events allocated to its domestic music coming from Brazilians, showing that it is not as popular in other countries. Figure 4 shows the spread of listening interactions with music from every country across other countries. In other words, this matrix shows how uniform the "export" of domestic music from every country to other countries is. Every row

[2] https://last.fm

[3] Since the dataset provides no information about the duration of a listening event, those single user–item interactions are often the result of a recommender engine starting to play a new track to the user, which the user skips after a few seconds. Therefore, we exclude those single interactions to remove this kind of noise.

[4] https://musicbrainz.org

[5] Throughout the paper, we use ISO codes to abbreviate countries. US: United States, GB: United Kingdom, DE: Germany, SE: Sweden, CA: Canada, FR: France, AU: Australia, FI: Finland, BR: Brazil, RU: Russia, JP: Japan, NO: Norway, PL: Poland, NL: Netherlands, IT: Italy, ES: Spain, BE: Belgium, MX: Mexico, UA: Ukraine, TR: Turkey

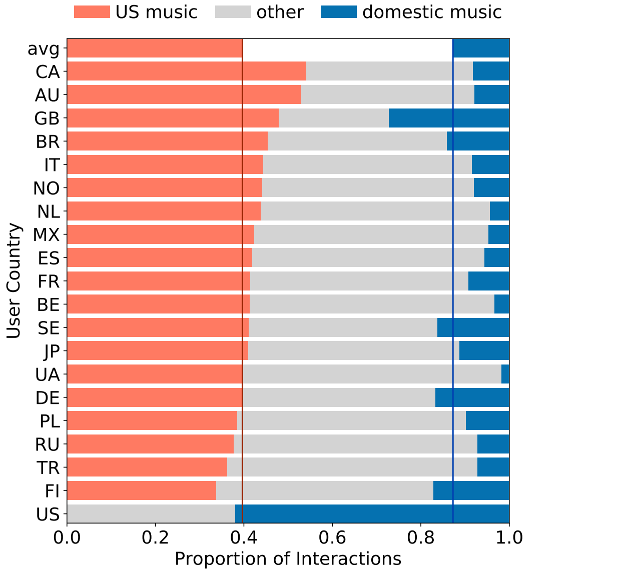


Figure 1: Distribution of listening activity over foreign (US and other) and domestic music. Every row corresponds to listeners of one country. Average proportions of interactions with music produced in the US (orange) and domestically (blue) are shown in the first row.

corresponds to the share, among all listening interactions, of the music produced in a single country. Every cell in the row shows the percentage of listening events coming from listeners of the corresponding country on the x-axis. For example, we can observe that 14.6% of listening interactions with JP music comes from US users (row JP, column US). Figure 3 demonstrates the potential impact two recommendation algorithms, ItemKNN and NeuMF, may have on the consumption balance in different countries. In each of the two subplots, empty bars reflect proportions of music actually consumed by the users (similar to Figure 1): orange bars on the left indicate listening events allocated to US artists, blue bars on the right refer to domestic artists. The filled bars illustrate the same concept applied to items recommended to users of different countries. For example, in Figure 3b, the row corresponding to DE shows that about 50% of items recommended to German users come from US artists, while at the same time only about 40% of their actual listening activity belongs to tracks from US.

We make the following observations answering **RQ1**. First, from the listening activity on Last.fm in 2018-2019, we see that 39.6% of all items interacted with were produced by US artists. Second, as Figure 1 shows, over 60% of listening events generated by US users are allocated to domestic music (bottom row, blue bar). This marks domestic superiority of US music, unmatched by any other country. The runner-up, being GB, shows only about 30% of listening events allocated to the domestic market. Third, on average, listeners of considered countries allocate 40% of their consumption to music produced by US artists (top row and vertical red line), with a maximum of about 50% shown by Australia and Canada. For many countries, above-average consumption of US music is combined with below-average consumption of domestic music, e. g., AU,

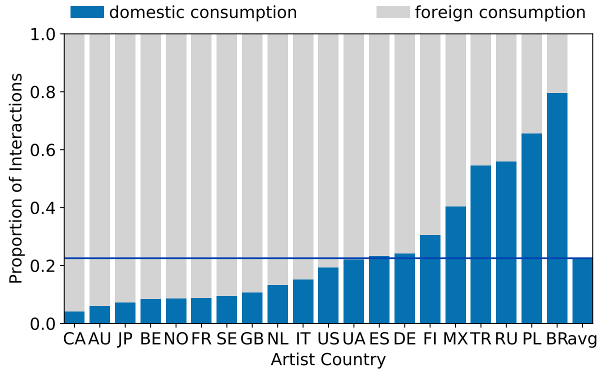


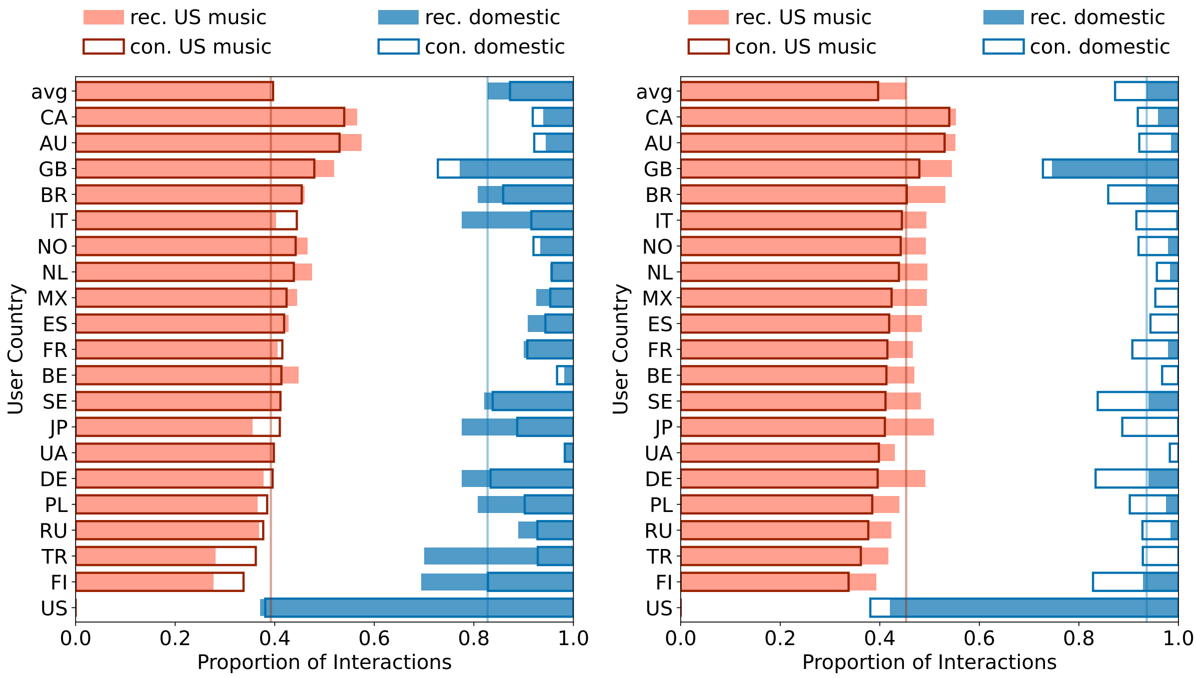
Figure 2: Consumption distribution of music produced in different countries, between local (blue) and international (gray) audiences.

CA, NL, IT, and UA. Forth, some countries such as GB, BR, and SE show above-average consumption of US music combined with also above-average consumption of domestic music. This is an indication of local musical culture comfortably coexisting and possibly interacting with the incoming US culture. Fifth, other countries such as TR, PL, FI, and RU consume below average of US music, remaining more open for music coming from other countries. In addition, FI also displays significant attention to domestic music.

From these observations, we conclude that music produced by US artists maintains strong positions in the considered countries. In particular, it dominates its own domestic market unlike domestic music of other countries. While there are countries combining low consumption of domestic with high consumption of US music, it is hard to call US music globally dominating. Many regions are also comparably influenced by other countries (if combined) and some, like FI or GB, show very strong positions of domestic artists. Thus, we hesitate to call US "cultural imperialism" absolute and homogeneous across countries.

We approach **RQ2** by defining three indicators related to domestic music in every country: *international consumption*, i. e., how big is the proportion of interactions with its domestic music coming from other countries (in other words, how widely exported domestic music is, see Figure 2 and 4); *domestic popularity*, i. e., the proportion of interactions from listeners of the country with domestic music (how popular domestic music is in its home region, see Figure 1); *popularity of US music* (used to detect hints of cultural dialog between US and considered country, see Figure 1). We analyze these indicators in terms of below/above average across considered countries for every particular country.

Using the indicators described above, we identify four patterns in behavior of domestic music scenes. First, glocalization through adaptation. Countries such as SE and GB score above average on all three indicators: their music is appreciated abroad while also being popular locally, and in addition these countries consume above average US music. We interpret this pattern as comfortable coexistence of global and domestic cultures with the latter likely adapt-



(a) Impact of ItemKNN

(b) Impact of NeuMF

Figure 3: Potential impact of recommender algorithms on music consumption balance in different countries. Empty boxes reflect actual consumption (denoted con.) extracted from the data. Filled boxes represent the output the two recommender algorithms produce (denoted rec.). Orange-tinted boxes on the left correspond to consumed / recommended music from US. Blue-tinted on the right - consumed / recommended domestic music.

ing and contributing to the former. Second, heavier adaptation of global trends. Domestic music is popular in BR as well as US music (both indicators above average). Domestic BR music receives most of its interactions from BR and little international attention. This pattern may imply even heavier adaptation of global influences to domestic circumstances. Third, non-US influenced. Countries such as PL, TR, and RU score below average on all three indicators: their music is predominantly consumed on domestic market while being less popular than US-produced music (which in turns enjoys below average popularity in these countries). We interpret this combination in a way that in these countries domestic music competes with a wide array of incoming music and US music is not necessarily the strongest influence there. Fourth, as the sole representative of this pattern, FI demonstrates high popularity of domestic music, combined with decent international consumption and lower popularity of US music. This pattern may express successful adaptation of less mainstream (beyond US) influences as well as strong distinct national culture.

We answer **RQ3** by analyzing results of the recommendation experiment detailed in Section 2.3. As shown in Figure 3b, NeuMF consistently recommends more US-produced items to listeners of every non-US country than these non-US listeners used to consume. This happens at the expense of the share of recommended domestic items. The character of the change implies that the share of recommended items from other countries is also larger than their actual consumption share (for all countries). We conclude that NeuMF amplifies globalization patterns and in particular dominance of an already dominant player, i. e., the US. On the contrary, ItemKNN (see Figure 3a) shows a different and less consistent behavior. Listeners in JP, TR, IT, and FI are recommended a considerably bigger share of domestic tracks than the share of listening events they actually allocate to domestic music. Interestingly, the shares of US music recommended to users in these four countries is lower than the share of US music consumed by them. The average share of recommended US tracks (see top row and red vertical line) is very close to the share of attention US music actually receives. On average, ItemKNN shows less changes than NeuMF. These observations are in line with the results of [14] where ItemKNN shows most calibrated recommendation results in terms of track popularity, especially when compared to methods with a higher number of trainable parameters, such as ALS and Variational Autoencoders. Our experiment shows that music recommendation algorithms can considerably contribute to the process of globalization, and the exact contribution largely depends on the algorithm. Therefore, recommender system designers need to be aware of such potential impacts.

4. LIMITATIONS

While our analysis captures listeners' behavior beyond pop charts, it bears a number of limitations. First, the data we base our analysis upon reflects a particular audience: Last.fm users (likely active internet and social media users), and therefore might not be representative of the population at large. Some countries and social groups are underrepresented on Last.fm (e. g., female users). In some

Artist Country \ Listener Country	US	GB	DE	SE	CA	FR	AU	FI	BR	RU	JP	NO	PL	NL	IT	ES	BE	MX	UA	TR
US	19.3	8.0	6.1	2.4	2.5	2.1	2.1	2.6	9.0	6.9	0.6	1.7	7.3	3.8	1.6	1.9	1.0	1.9	2.1	0.6
GB	11.1	10.8	6.0	2.3	1.8	2.3	1.6	2.8	8.0	8.5	0.7	1.7	9.1	4.5	1.9	2.1	1.1	2.1	2.4	0.8
DE	6.3	4.5	24.2	2.4	1.3	2.2	1.0	3.3	4.6	10.7	0.4	1.3	8.1	3.2	1.1	2.0	1.1	1.3	2.7	0.8
SE	8.4	5.0	7.7	9.5	1.6	2.3	1.2	6.1	5.6	9.4	0.4	2.3	8.4	3.4	1.2	2.3	1.1	1.3	3.2	0.9
CA	17.4	7.8	6.4	2.7	4.2	2.3	2.1	2.7	8.4	7.3	0.6	1.7	7.3	3.9	1.5	1.8	1.1	2.0	2.1	0.6
FR	9.8	5.5	5.9	2.5	1.5	8.7	1.4	3.0	6.0	9.0	0.6	2.0	9.8	3.8	1.6	2.1	2.3	2.4	2.5	1.4
AU	12.5	7.8	6.8	2.4	2.2	2.1	6.0	2.7	7.9	7.4	0.6	1.7	8.8	4.3	1.2	1.9	1.2	2.0	2.4	0.6
FI	5.4	2.7	6.3	1.7	1.4	1.7	0.6	30.5	3.9	10.1	0.4	0.8	6.4	3.1	0.7	1.9	0.8	1.3	3.3	0.7
BR	2.7	1.2	1.4	0.3	0.4	0.7	0.3	0.8	79.6	1.4	0.2	0.3	1.4	1.2	0.6	0.5	0.5	0.6	0.3	0.2
RU	2.4	1.4	2.0	0.5	0.4	0.5	0.3	1.3	1.9	55.9	0.2	0.6	3.0	0.9	0.3	0.5	0.2	0.6	8.9	0.3
JP	14.6	6.7	5.4	2.2	2.0	3.1	1.4	4.8	8.1	8.1	7.3	1.3	6.8	2.4	1.0	1.6	1.4	2.8	1.8	0.4
NO	8.3	5.1	6.2	3.6	1.6	2.7	1.5	5.3	4.8	8.3	0.5	8.6	8.9	5.0	1.4	2.1	1.3	1.2	2.6	1.0
PL	2.9	2.4	2.4	1.1	0.5	1.0	0.4	2.0	1.8	4.0	0.3	0.7	65.7	1.2	0.4	0.8	0.5	0.5	1.3	0.5
NL	7.8	5.2	7.8	2.7	1.5	2.2	0.9	4.2	6.8	8.7	0.5	1.8	8.9	13.4	0.8	1.5	1.6	1.5	3.1	1.1
IT	7.4	4.9	6.7	2.3	1.3	2.2	1.1	3.8	6.3	8.8	0.5	1.3	8.6	3.6	15.3	2.5	1.3	1.9	2.0	1.1
ES	7.0	4.6	4.5	1.5	0.8	1.5	0.7	1.9	5.4	4.9	0.4	0.8	6.0	2.7	1.3	23.3	0.9	10.2	1.2	0.6
BE	7.2	4.4	7.2	2.3	1.4	5.2	0.9	2.3	4.9	8.5	0.4	1.7	10.4	9.0	1.5	2.0	8.4	1.3	2.5	1.5
MX	7.3	2.4	3.2	1.3	0.9	0.9	0.4	1.0	9.6	4.4	0.1	0.6	2.7	1.7	0.5	3.6	0.2	40.5	0.7	0.2
UA	4.6	2.0	3.3	1.3	0.8	1.7	1.2	3.1	2.4	26.1	0.2	0.9	5.5	2.4	0.4	1.3	0.8	0.9	22.1	0.8
TR	4.7	2.2	4.1	1.4	0.3	1.1	0.4	1.4	2.1	3.5	0.0	0.6	5.6	2.4	0.3	0.5	0.7	0.9	0.7	54.5
avg	8.4	4.7	6.2	2.3	1.4	2.3	1.3	4.3	9.4	10.6	0.7	1.6	9.9	3.8	1.7	2.8	1.4	3.9	3.4	3.4

Figure 4: Music export matrix. Every cell shows the proportion of interactions with music from a given artist country allocated to users from a given listener country. For instance, 19.3% of all the music created by US artists is consumed by US listeners, while 14.6% of interactions with the entirety of Japanese music are made by US users.

countries Last.fm is not very popular and their listeners are likely to use different channels of music consumption. Therefore, our dataset may overrepresent listeners who are open to and interested in global culture, in particular in countries where Last.fm is not popular. Furthermore, the data gathered in the LFM-2b dataset are already affected by recommender systems of different platforms users connect to their Last.fm accounts, which means that our insights about "actual music preference" can be, to a certain degree, distorted.

5. CONCLUSION AND FUTURE WORK

We addressed three research questions related to patterns of music consumption on online music platforms. Regarding the dominance of US vs. domestic music (RQ1), we found that the former maintains strong positions in all considered countries. However, the US does not display signs of absolute and homogeneous "cultural imperialism". While it dominates its domestic market, in other countries, US music shows various levels of coexistence with domestic music. While some countries such as Australia and Canada find their domestic music competing with US music, others, such as Great Britain, Brazil, and Sweden, display high consumption levels of both US and domestic music. Countries like Finland and Germany, on the other hand, are open to music both from other countries and domestically created.

Looking for traces of glocalization (RQ2), we distinguish several ways domestic music can behave under the pressure of global cultural trends. Music from countries like Great Britain and Sweden shows signs of adaptation of global cultural trends, with their music coexisting with US music and being greatly listened to outside their domestic markets. Music from Brazil appears to be highly influenced by global trends but mostly consumed locally. Countries like Poland and Turkey also display signs of their music being localized and influenced by global trends, however, to a lesser extent influenced by US music than others. Finland combines competitive "export" of their music with high local consumption and relatively low consumption of US music, showing signs of a strong and distinctive musical culture.

Finally, we show that recommender systems may have a considerable impact on globalization patterns (RQ3). We investigate this for a traditional ItemKNN approach and the deep-learning-based NeuMF algorithm. While the former fosters consumption of local music in most of the considered countries, the latter supports internationalization and, in particular, cultural imperialism of the US.

Directions for future research include temporal analysis of consumption trends over the 15-year-span covered by the LFM-2b dataset, in particular considering possible alterations caused by the global pandemic [18, 19]. Other directions include exploring the link between globalization amplification and popularity bias, and investigating the effectiveness of different mitigation strategies.

6. ACKNOWLEDGMENTS

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NETWORK ANALYSES FOR CROSS-CULTURAL MUSIC POPULARITY

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ABSTRACT

Anglo-American popular culture has been said to be intricately connected to global popular culture, both shaping and being shaped by popular trends worldwide, yet few research has examined this issue empirically. Our research quantitatively maps the extent of these cultural influences in popular music consumption, by using network analyses to explore cross-cultural popularity in music from 30 countries corresponding to 6 cultural regions (N = 4863 unique songs over six timepoints from 2019-2021). Using Top100 charts from these countries, we constructed a network based on the co-occurrence of songs in charts, and used eigencentrality as an indicator of cross-cultural song popularity. We then compared the country-of-origin of the artists, arousal music features, and socioeconomic indicators. Songs from artists with Anglo-American backgrounds tended to have higher eigencentrality overall, and mixed effects regressions showed that eigencentrality was negatively associated with danceability, and positively associated with spectral energy, and the migrant population of the country (of the charts). Next, using community detection, we observed 11 separate 'communities' in the network. Most communities appeared to be limited by region/culture, but Anglo-American music seemed disproportionally able to transcend cultural boundaries far beyond their geographical borders. We also discuss implications pertaining to cultural hegemony, and the effectiveness of our method in estimating cross-cultural popularity.

1. INTRODUCTION

How do songs become international hits? To some extent, research suggests that one answer is simply being based in America, and singing in English [1]. Numerous studies have documented the prevalence of Anglo-American artists on the charts of 'foreign' countries throughout the 1960s to the 2000s [2, 3]. Yet, at the same time, the 1980s saw a nationalistic increase in the consumption of domestic, and localized artists alongside widely dominant Anglo-American music [1, 4]. However, these papers rely on country-determined charts as indicators of music-popularity, which raises problems of irregularity. For example, the metrics/methods used to determine rankings on national top charts may differ between countries. Moreover, charts may also be defined through radio plays (e.g., Billboard), which biases the consumption pattern towards the distributor of the music, rather than bottom-up listening preferences. The advent of music streaming services in recent years provides a possible solution to both these issues: within a platform, charts are calculated through consistent metrics. Secondly, users choose the songs they want to listen to. While music recommendation systems do provide suggestions on songs for the user, these are still largely based on the users' preferences and listening history [5], and users still retain agency in choosing whether or not to listen to a recommended song. This is a shift away from the music-purchase model [6], allowing for greater flexibility and choice. Accordingly, streaming charts offer increased granularity, whereas music-purchase models only monitor sales. In this regard, country charts from music streaming services may be more representative of bottom-up music consumption.

In assessing the global top charts provided by streaming services, we are unable to decompose the cultural contribution of individual countries in determining overall global popularity, as such information is typically not made public. We thus needed a method to combine music from various country-charts to composite a marker of global popularity. To this end, we constructed a network from Top 100 charts from 30 countries (over 6 cultural regions), and relied on the co-occurence of songs within and across charts to determine its cross-cultural popularity through centrality. Constructing a network would also allow us to quantify the cultural diversity and clusters present across these 30 charts through community detection algorithms. More information on how networks are used in this paper is available in Section 2 (Methods).

Accordingly, our research aims to use network analyses to model the cultural 'Communities' present across these charts, and in doing so, assess the dynamics of cultural influences in music consumption around the world. We identified 11 Communities, most bounded by shared cultures, with the exception of the largely Anglo-American Community, which was prevalent across charts from all cultural regions.

1.1 Network analyses

Network analyses model the complex relational structures present in a data, and have been used in a diverse range of applications, from web search engines [7], to modeling language evolution [8], and are used widely in the social sciences [9, 10]. They examine relationships between nodes in a network: nodes refer to any entity that is treated as fundamental in the analysis. For example, in a study on social networks, individuals are often treated as nodes. The relationships between nodes are represented by edges. edges may be weighted, to reflect the strength of a connection between two nodes. For example, two individuals (nodes) that frequently interact with each other, may have a higher weight for that relationship (edge), than between two strangers. Accordingly, some nodes may be more strongly connected with other nodes in a network. These nodes exert a greater influence on the network, and are more 'central': centrality refers to the relative importance of a node to all other nodes within the network [11].

In this paper, we rely strongly on the notion of eigencentrality, which additionally accounts for the corresponding centrality of linked nodes in determining the centrality of a given node [12]. For our analysis, we define nodes to be unique songs, and the edge weights as the frequency by which they co-occur on any country's Top 100 charts. Songs with high eigancentrality scores are more influential within the network, which means that they carry a greater presence across the various country-based Top 100 charts used in this analysis, which could be in turn indicative of greater cross-cultural popularity.

1.2 Contextualizing factors

For interpretation, we also compared the eigencentrality of songs on countries' charts with socioeconomic indicators, as well as song-level information on the country-of-origin or residence of its artist, and features of rhythmic and intensity arousal.

1.2.1 Artists' Country-of-residence and origin

While constructing a network of music charts would allow us to visualize and compare the influence of individual songs, we still needed to compare this information to the cultural background of these songs. As such, we obtained the country-of-residence (where possible) or country-of-origin of all artists that were represented on the charts. We then grouped these countries according to their cultural region to facilitate cultural comparison.

1.2.2 Gross Domestic Product (GDP), income inequality, and migration

Going beyond the network, we wanted to examine if economic development, social inequality, and migration could offer explanations for cross-cultural popularity. Past research has identified links between music preferences, and socialeconomic status (SES; [13]), such as social class [14]. At a country-level, Woolhouse and Bansal [15] found a direct relationship between economic development and music consumption patterns. Accordingly, we examined economic development through GDP per capita, and income inequality (Gini coefficient). Finally, we also examined migration statistics, as music has strong functions for identity formation in immigrants (see [16, 17]), who may bring with them differing music consumption patterns into the country they relocate to. Moreover, societies with high openness may be more accepting of immigrants and more open towards foreign cultures [18], and consequently, may be more receptive towards music from beyond their cultural region.

1.2.3 Arousal features in music

Rhythmic (danceability) and intensity (energy) arousal features of songs in national charts has been shown to reflect that country's affordances for high-arousal negative emotional experiences in daily life [19]. Energy, in particular, has been shown to reflect the use of cathartic emotional downregulation of anger experiences [20]. Given that past research has found links between music popularity and arousal features (e.g., [21, 22], we also examined eigencentrality in the context of musical arousal.

1.3 Related work: Network analyses in music research

Networks have long been used to analyze and visualize relationship structures in music. In predicting artist popularity, Matsumoto et al. [23] constructed a context-aware network combining Spotify-based audio features with biographic metadata and 'related artist' lists. South et al. [24] examined a dataset of musical collaborations on Spotify, and used eigencentrality to estimate the influence of artists on that dataset. Zinoviev [25] similarly examined the mobility of individual musicians amongst music groups in the Russian music industry. Finally, Ortega [21] examined music covers to estimate the influence of the original artist. While these projects largely used network analyses to estimate the popularity or influence of an artist or song, our research is unique in using chart co-ocurrence to derive cross-cultural popularity, through accounting for the relative popularity of songs from different regions around the world.

2. METHODS

2.1 Data Acquisition

Our analysis utilized consumption charts of Top 100 songs (by monthly play count on Deezer) from 30 countries (see Table 1: Chart Country) for March 2019, September 2019, March 2020, September 2020, March 2021, and September 2021, for a total $N_{songs} = 16998$ (unique $N_{songs} = 4863$ from $N_{artists} = 1001$).

For each song, we obtained the titles, artists, and ISRC codes from the Deezer Application Program Interface