INVESTIGATING CROSS-COUNTRY RELATIONSHIP BETWEEN USERS' SOCIAL TIES AND MUSIC MAINSTREAMINESS

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ABSTRACT

We investigate the complex relationship between the factors (i) preference for music mainstream, (ii) social ties in an online music platform, and (iii) demographics. We define (i) on a global and a country level, (ii) by several network centrality measures such as Jaccard index among users' connections, closeness centrality, and betweenness centrality, and (iii) by country and age information. Using the LFM-1b dataset of listening events of Last.fm users, we are able to uncover country-dependent differences in consumption of mainstream music as well as in user behavior with respect to social ties and users' centrality. We could identify that users inclined to mainstream music tend to have stronger connections than the group of less mainstreamy users. Furthermore, our analysis revealed that users typically have less connections within a country than cross-country ones, with the first being stronger social ties, though. Results will help building better user models of listeners and in turn improve personalized music retrieval and recommendation algorithms.

1. INTRODUCTION

When meeting new people, they frequently tend to talk about their favorite music as conversation starter [30]. Indeed, several studies (e.g., [3, 23, 33, 43]) indicate that shared music preferences create and intensify social bonds. For instance, Boer et al. found in a study that participants liked others with the same music preferences more than those with different music preferences [3]. Based on this result, the authors conclude that shared music preferences can generate and increase social attraction.

In online social networks (OSN), such as Facebook, Instagram, or Twitter, the social bonding effects of shared music preferences are expected to follow similar patterns as the ones observed in offline settings, i.e., in the physical world. In the context of OSN, it is particularly interesting to consider that connections between users are not constrained to any single country, which is frequently the case in offline scenarios [5]; indeed, many social ties between users are cross-country connections [1]. Yet, sometimes individuals center their interactions within locally bounded social circles also in their online interaction behavior [10]. Whether they do so or rather not, however, strongly depends on the users' cultural backgrounds. For instance, Choi et al. found that American users maintained larger but looser networks, whereas Korean users had smaller but denser networks [9]. Barnett and Benefield analyzed cross-country friendship connections on Facebook and found that international ties tended to share borders, language, civilization, and migration aspects [1].

Similarly, it has been found that music preferences are highly influenced by the cultural background of listeners [40]. In particular, they strongly depend on the country the user lives in, and each country has its own characteristics with respect to which music is considered popular or mainstream in that very country [38].

In contrast to the above general studies on cross-country user connections and music preferences, little is known about how shared music preferences and social ties are related in OSN and how the social bonding effect varies for cross-country ties. Against this background, the research questions (RQ) we address are:

- RQ1: In which ways do listeners in different countries differ in terms of their inclination to listen to mainstream music (considering both global and country-specific mainstream)?
- RQ2: In which ways do listeners in different countries differ in terms of their social ties and connectedness in a music-related online social network (Last.fm)?
- RQ3: In which ways do the previous two aspects interrelate, i.e., does maintaining strong social ties (within or between countries) interrelate with a preference for mainstream music?

The answers to these questions will help building better models of listeners—individually and on a country level—and in turn improve personalized music retrieval and recommendation algorithms, as it has already been shown for other user characteristics, such as demographics [47], activity [49], or mood [26]. For instance, the intensity of cross-country ties of a user u together with information about the music mainstream of u's country and the countries u's friends originate from may be used to tailor recommendations for u. To give an example, if a Spanish user u maintains very strong ties to users in Brazil, a music recommender system may include in its recommendation list a few music items that are popular only in Brazil, to ideally provoke serendipitous music encounters for u.

The remainder of this article is organized as follows. Section 2 presents related work on music mainstream, social connectedness, and culture-aware listener analysis and modeling. Section 3 details the methodology we apply to answer the research questions. Section 4 presents and discusses the obtained results. Eventually, Section 5 rounds off this work with a conclusion and pointers to future research.

2. RELATED WORK

The work at hand connects to research on music preferences and mainstream, on user connectedness in social networks, and on culture-aware music and listener analysis. We briefly discuss the most important related literature in these areas and connect our work to it.

2.1 Music Mainstream

A user's music preferences are shaped by various factors. Extant studies have investigated the relationship between music preferences and, amongst others, demographics (e.g., [4]), personality traits (e.g., [7]), or social influences (e.g., [3, 46]). Music tastes and preferences are measured in various ways, for instance, in terms of genre (e.g., [3, 29, 32, 40]), artist (e.g., [36, 48]), or mood (e.g., [14, 18]) preference.

Another approach to distinguish music preferences is to consider the degree of people's tendency to favor music that is considered *mainstream*, i.e., music that is most popular within the entire population [41]. In short, measuring music preferences in terms of a user's degree of mainstreaminess is a popularity-based approach that considers the degree to which a user prefers music items that are currently popular or rather ignores such trends [34]. Further studies revealed that people's preferences vary across countries, which holds true for both music genres [40] as well as mainstream music [38]. Early research with respect to music mainstreaminess for the use in music recommendation systems shows that the population which a user is compared to tremendously impacts the outcome with respect to recommendation performance [2,34]. More specifically, a user may be compared to the mainstream from a global perspective, but also from a country perspective. Yet, an in-depth analysis of country-specific differences concerning mainstreaminess—from a global perspective and a country perspective—is a research gap.

2.2 Social Connectedness

Research on the strength of social connections dates back to Granovetter's paper entitled "The Strength of Weak Ties" [15], describing the social network theory, which he later revisited in [16]. In OSN research, social connectedness has been a target of research since the early days of OSN. For instance, although theoretically not constrained to any single region [5, 9], social connections on OSN sometimes tend to center within locally bounded social circles [10,51], because social ties in OSN may follow the spatial, structural, and cultural perimeters of the societal system that OSN users belong to in offline settings, i.e., in the physical world [5].

Initially, designing measures of tie strength had been difficult as Granovetter [15, 16] had not given a precise conceptual definition for it [24]. A scale of measures has developed since then. Among the most common measures for tie strength and derived measures for node importance are the overlap in users' neighborhoods via Jaccard index (J), the closeness centrality (C), and the betweenness centrality (B), which we therefore also use in our work, and detail in Section 3.2.

Studies have revealed that music preferences play an important role in creating and intensifying social bonds [3, 23, 33, 43], because shared music preferences can generate and increase social attraction [3]. In other words, people tend to like people with the same music preferences more than people with different music preferences [3].

This fact has been exploited, among others, in [25], where a social approach for music recommendation is presented. It is based on the assumption that friendship relations in OSN are similar to those offline and that Facebook relationships are indicative of similar music tastes. The proposed system recommends YouTube music tracks to a target user, which have been positively rated (with at least 3 on a 5-point Likert scale) by the target users Facebook friends, but have not been rated by the target user him or herself.

While previous research on music and social bonding most often measures music preferences in terms of genre (e.g., [3,23,43]), we argue that music mainstreaminess may be an additional, insightful indicator for music preferences with regard to social bonding.

2.3 Culture-aware Music and Listener Analysis

Generally, human preferences have shown to be rooted and embodied in culture [20], and also listeners' music preferences are affected by cultural aspects (e.g., [11]). For instance, perception of music varies across cultures [22, 44, 45], which obviously influences music preferences. Furthermore, national market structures, including local airplay and subsidizing (e.g., local music quotas on radio) are different across countries [28, 31] and shape country-specific popularity of artists and songs. This results, among others, in the fact that pop music preferences disconverge rather than converge within European countries [8].

With the increasing popularity of personalized music recommender systems—i.e., systems that tailor recommendations for particular music items (e.g., artists, albums, or songs) to the preferences of individuals [42]—and the acknowledgement that tailoring recommendations to a listener's cultural specificities may substantially increase the performance of a music recommender system [2, 38, 47], research investigating and describing music and listener profiles from a culture perspective has received attention lately. To provide some examples, [27] show that incorporating cultural characteristics allows for more precise characterization of listeners; [50] integrate cultural aspects for modeling music similarity; [21] use culture-aware approaches describing and modeling intonation of audio music recordings. Comparisons of listener profiles across countries have been presented from many different angles [11, 37, 39], most frequently in terms of genres, while our work concentrates on mainstreaminess.

3. METHODOLOGY

For our study, we use and extend the LFM-1b dataset [35], which comprises 1,088,161,692 listening events of 120,322 unique Last.fm users. Since our investigation aims at uncovering country-specific factors, we consider only the subset of the LFM-1b dataset that includes listening events of users who provide country information. To reduce the likelihood of less significant results due to a sample bias of users within a given country, we furthermore filter countries with less than 100 users, which results in a dataset of 53,258 users from 47 countries. Some of the users do not maintain any social ties on Last.fm. Excluding those (because we cannot compute the respective measures), we finally end up with a stable dataset of 5,680 users from 18 countries, on which we conduct our analysis.

3.1 Music Mainstreaminess

To quantify the proximity of a user to both the country-specific and the global mainstream, we employ the approach proposed in [2, 38]. Schedl and Bauer identified two rank-based measures as being best suited to estimate mainstreaminess of a user among his or her fellow citizens within the same country (Equation 1) and compared to a global mainstream (Equation 2). In the equations, which have been simplified from [2], where a complex framework is proposed, $M(u, c)$ denotes the rank-based mainstreaminess of user u in regard to country c (which is in our case always the country of the user); $M(u)$ denotes u's global mainstreaminess. Furthermore, τ denotes the rank-order correlation coefficient according to Kendall [19]; AF denotes a vector containing the global artist frequencies of all artists in the dataset, keeping a fixed order (i.e., the first element in vector AF is the total number of listening events to the artist who is most frequently listened to globally, and so on); $AF(c)$ is defined analogously, but only considers listening events in country c, maintaining the ordering of artists given by the global AF vector; $AF(u)$ analogously, but only considering listening events of user u (again maintaining the global ordering); $ranks(\cdot)$ represents the ranks of the real-valued artist frequencies given in vector $(\cdot)$.

Less formally, $M(u, c)$ measures how well user u's ranking of artist preferences corresponds to that of all users in country c; $M(u)$ measures how well u's ranking of artist preferences matches with the global ranking. Higher values indicate closer to the mainstream.

$$M(u,c) = \tau \left(ranks \left(AF(c) \right), ranks \left(AF(u) \right) \right) \quad (1)$$

$$M(u) = \tau \left(ranks \left(AF \right), ranks \left(AF(u) \right) \right) \quad (2)$$

3.2 Social Ties and Centrality Measures

To uncover social ties between users in the LFM-1b dataset, we first enrich the dataset using the Last.fm API endpoint *user.getFriends* [1] to obtain the connections of all users in LFM-1b. Since we are only interested in the intra-connectedness between users in the dataset, we exclude all friendship connections to users that are not contained in the LMF-1b dataset. This results in a total of 79,254 connections by 11,801 users (5,680 users only considering the 18 countries with at least 100 users). On the resulting network, we then compute tie strength and centrality scores that estimate the importance of nodes (users) in a network. More precisely, we use Jaccard index (J), closeness centrality (C), and betweenness centrality (B) since they are among the most common measures. Jaccard index (J) is defined as the fraction of shared neighbors among all neighbors of the two users u and v under consideration [17]. To obtain a single measure per user u, we compute the arithmetic mean of the Jaccard indices between u and all users connected to u. Closeness centrality (C) of user u is defined as the reciprocal of the sum of the shortest path distances between u and all other users in the network [13]. Higher values of closeness therefore indicate higher centrality. Betweenness centrality (B) of user u is defined as the sum of the fraction of all shortest paths between pairs of nodes v, w ($\neq u$) that pass through u [12]. Betweenness can therefore be regarded as how much in the way between two arbitrary users u lies. Users with high betweenness are assumed to have more control in the network, because more information will pass through them.

4. RESULTS AND DISCUSSION

4.1 Country vs. Mainstreaminess

To answer the first research question, i.e., how listeners in different countries vary in terms of their inclination to listen to mainstream music, Table 2 shows basic statistics (mean and standard deviation) of country-specific and global mainstreaminess, for the top countries in the dataset (those with at least 100 users). The grand means and SD are 0.091 ± 0.060 for $\mathrm{M\_country}$ and 0.103 ± 0.062 for $\mathrm{M\_global}$. Additionally, mean, standard deviation, and median age of users are depicted. The countries with highest local mainstreaminess are the Netherlands, the United Kingdom, and Canada ($\mathrm{M\_country} = M(u, c) > 0.1$); those with highest global mainstreaminess are Finland, the Netherlands, and Mexico ($\mathrm{M\_global} = M(u) > 0.11$). This is in line with previous work [36], which used a different definition of mainstreaminess, nevertheless identified the Netherlands, the United Kingdom, Belgium, and Canada as most mainstreamy countries. [2] The high rank of Finland in our results may be surprising since many citizens of this country are know to have a preference for metal music, cf. [38], which is rather not considered mainstream. At the same time, however, also the standard deviation of

[1] `https://www.last.fm/api/show/user.getFriends`

[2] Note that Belgium is not included in our analysis because only 63 Belgian users remained after filtering.

Table 1. Top 20 global artists and their deviations of Finnish preference from the global preference in terms of artist frequency.

Artist	Global rank	Deviation
The Beatles	1	-47.44 %
Radiohead	2	-43.95 %
Pink Floyd	3	-25.80 %
Metallica	4	+126.72 %
Muse	5	+131.66 %
Arctic Monkeys	6	-55.71 %
Daft Punk	7	+96.84 %
Coldplay	8	-16.63 %
Linkin Park	9	-11.17 %
Red Hot Chili Peppers	10	-0.10 %
System of a Down	11	+152.54 %
Nirvana	12	-30.23 %
Iron Maiden	13	+170.77 %
Rammstein	14	+171.76 %
Depeche Mode	15	-22.87 %
Lana Del Rey	16	-28.33 %
Lady Gaga	17	+132.72 %
Led Zeppelin	18	-34.54 %
Florence + the Machine	19	-29.49 %
David Bowie	20	-19.43 %

mainstreaminess is very high for Finland, which indicates a strong dispersion over mainstream and non-mainstream music preferences among Fins. In fact, a deeper analysis reveals a large variety of music tastes in Finland, cf. Table 1. On the one hand, metal bands such as Metallica, System of a Down, and Iron Maiden are indeed more popular among Fins than globally. On the other hand, also artists such as Muse (top tags on Last.fm: alternative, rock), Daft Punk (electronic, house), and Lady Gaga (pop, dance) are highly popular in Finland.

According to our dataset, the least mainstreamy countries are Germany, Australia, and the Czech Republic, regardless of whether mainstreaminess is computed on the country level or globally.

Another observation is that the Scandinavian countries Norway and Sweden both show low standard deviations in their citizens' mainstreaminess level, indicating a stable inclination for a certain level of mainstream among the listeners in these countries. Interestingly, for Norway this goes together with a rather low mainstreaminess level (low tertile), while Sweden's level ranges in the high tertile.

We further investigate the correlation between all aspects in Table 2. Computing Pearson correlation coefficients between all pairs of aspects and a 2-tailed t-test to investigate significance, we identify the following significant correlations at $p \leq 0.05$: $\rho\,(\mathrm{M\_country\colon mean, M\_global\colon mean}) = 0.819$ ($p \approx 0.0$), $\rho\,(\mathrm{M\_global\colon mean, Age\colon mean}) = 0.280$ ($p = 0.05$).

4.2 Country vs. Social Ties and Centrality

Towards answering the second research question, i.e., how listeners in different countries vary in terms of their social ties and their connectedness within the Last.fm social network, Table 3 shows means and standard deviations of social tie strength (Jaccard index), closeness, and betweenness (cf. Section 3.2), again for the top 18 countries in the dataset. The grand means and SD for tie strength (J), closeness, and betweenness are 0.285 ± 0.101, 0.150 ± 0.067, and 0.027 ± 0.067, respectively. The countries with highest average tie strength are Sweden ($J = 0.319$) and Finland ($J = 0.301$), closely followed by Poland ($J = 0.299$) and the Netherlands ($J = 0.297$). These J values indicate that, on average, users in these countries share nearly one third of their neighbors with all users they are connected to. The lowest tie strength values are present for Ukraine and the Czech Republic ($J \approx 0.26$), closely followed by Italy, Spain, Russia, and Australia ($J \approx 0.27$).

With respect to closeness centrality, the countries with highest C value are Ukraine, Italy, Spain, Russia, and Mexico ($C > 0.16$), those with lowest closeness are Sweden ($C = 0.117$), Poland, Finland, and the Netherlands ($C \approx 0.13$). Interestingly, in the case of Sweden, the lowest mean closeness centrality is paired with the highest standard deviation ($C = 0.117 \pm 0.084$). Investigating the reason for this, we find that there are many Swedish outliers with very low closeness centralities. Quantitatively, the 25-, 50-, and 75-percentiles for closeness in Sweden are 0.0002, 0.1500, and 0.1790, respectively, while being 0.1248, 0.1672, and 0.1910, on average, among all other countries.

As for betweenness, the countries with highest values ($B > 0.0004$) are Mexico and Italy, while lowest scores ($B < 0.0002$) are realized by users in the Netherlands, Sweden, and France. Mexico and Italy, however, also show the largest standard deviations. In fact, the median of their B values approaches zero. About half of Italian and Mexican users therefore have no or very few connections. Still, these countries' 75-percentile as well as maximum B is at the same time the highest among all countries, $B \approx 0.0003$ and $B \approx 0.01$, respectively. A few users in Italy and Mexico are hence extremely well connected and can be assumed to have a high level of influence in the entire analyzed network, i.e., sub-network of Last.fm [6].

Investigating which of the aspects in Table 3 correlate, Pearson correlation coefficients are significant at $p \leq 0.05$ for the following pairs of aspects: $\rho\,(\mathrm{B\colon mean, J\colon mean}) = -0.363$ ($p = 0.01$) and $\rho\,(\mathrm{C\colon mean, J\colon mean}) = -0.637$ ($p \approx 0.0$). The negative correlations between tie strength and centrality measures indicate that while direct neighbors between connected users show significant overlaps, this does not generalize to the whole network. Our assumption, which we test in the next section, is that these local neighbors who are well connected are rather users in the same country.

Table 2. Statistics of country-specific and global mainstreaminess as well as age for countries with at least 100 users. Country names are abbreviated according to ISO 3166-1 alpha-2.

		M_country		M_global		Age		
Country	Users	mean	std	mean	std	mean	std	median
US	927	0.091	0.062	0.096	0.067	20.8	13.6	22.0
RU	789	0.093	0.057	0.102	0.061	18.9	12.0	21.0
PL	775	0.095	0.066	0.104	0.070	19.2	10.3	20.0
BR	531	0.091	0.065	0.107	0.069	19.7	10.0	21.0
UK	470	0.102	0.057	0.107	0.057	21.2	13.8	23.0
DE	463	0.081	0.062	0.088	0.066	20.7	13.3	22.0
FI	217	0.092	0.094	0.112	0.065	20.2	10.3	22.0
UA	207	0.097	0.052	0.108	0.052	19.3	11.5	22.0
IT	175	0.090	0.058	0.106	0.067	23.1	14.0	23.0
ES	157	0.088	0.053	0.104	0.059	21.9	12.1	24.0
NL	155	0.106	0.058	0.112	0.059	25.6	16.0	23.0
SE	132	0.094	0.049	0.105	0.053	21.6	13.9	22.0
CA	127	0.101	0.059	0.108	0.061	19.3	11.3	22.0
CZ	124	0.075	0.057	0.093	0.063	19.2	10.4	22.0
MX	109	0.087	0.060	0.110	0.062	21.7	11.4	23.0
FR	108	0.088	0.055	0.101	0.058	22.3	11.8	25.0
AU	107	0.085	0.061	0.092	0.070	20.0	11.4	21.0
NO	107	0.090	0.048	0.100	0.058	20.6	13.9	22.0

Table 3. Statistics of social tie strength and centrality measures for countries with at least 100 users. Country names are abbreviated according to ISO 3166-1 alpha-2.

		Social Ties (J)		Closeness		Betweenness (x100)	
Country	Users	mean	std	mean	std	mean	std
US	927	0.287	0.102	0.152	0.066	0.023	0.061
RU	789	0.270	0.103	0.162	0.064	0.031	0.073
PL	775	0.299	0.106	0.132	0.072	0.023	0.061
BR	531	0.287	0.102	0.159	0.060	0.028	0.075
UK	470	0.290	0.098	0.149	0.067	0.028	0.069
DE	463	0.286	0.106	0.145	0.072	0.024	0.056
FI	217	0.301	0.112	0.133	0.080	0.022	0.057
UA	207	0.261	0.098	0.165	0.054	0.027	0.055
IT	175	0.268	0.086	0.163	0.059	0.040	0.125
ES	157	0.269	0.092	0.163	0.055	0.032	0.067
NL	155	0.297	0.113	0.135	0.080	0.017	0.053
SE	132	0.319	0.104	0.117	0.084	0.019	0.044
CA	127	0.294	0.105	0.156	0.067	0.023	0.058
CZ	124	0.265	0.098	0.152	0.063	0.027	0.065
MX	109	0.295	0.100	0.161	0.064	0.042	0.122
FR	108	0.282	0.100	0.154	0.062	0.019	0.039
AU	107	0.270	0.096	0.157	0.060	0.025	0.060
NO	107	0.291	0.103	0.142	0.068	0.026	0.067

4.3 Mainstreaminess vs. Social Ties and Centrality

Regarding RQ3, i.e., in which ways do mainstream and social connectedness interrelate, we analyzed various aspects with respect to the 33,974 connections between the users in our sample. Most connections in our sample are cross-country (26,914 connections, i.e. 79%), while only 21% (or 7,060) are between users of the same country.

In a detailed analysis for differences between different degrees of mainstreaminess vs. social ties and centrality, we found two significant differences: As conjectured, the social tie strength of users within the same country (measured by the Jaccard index between the connections of the two users to compare, cf. Section 3.2) differs from the social tie strength of cross-country connections. In a 2-tailed t-test, the difference between connections within a country ($mean = 0.241$, $std = 0.109$) and cross-country connections ($mean = 0.219$, $std = 0.095$) is highly significant ($t = 17.154$; $df = 33972$, $p = 0.000$).

Comparing each user's social tie strength (averaged over all his or her connections with his or her respective mainstreaminess level), in a t-test, we found that the difference between the group of users with a low preference for mainstream ($mean = 0.281$, $std = 0.102$) and the group of high mainstream users ($mean = 0.289$, $std = 0.104$) is highly significant ($t = -2.819$, $df = 3777.883$, $p = 0.005$), when using the $\mathrm{M\_global}$ measure. When using the $\mathrm{M\_country}$ measurement, this effect disappears. We conjecture that from a country perspective of mainstreaminess, the different forms of mainstream per country and the more focused music preference within a country levels the effect that can be seen from a global perspective.

Investigating individual countries, Table 4 shows that for all countries, the social tie strength between users within the country is higher than for connections spanning two countries. The difference is highly significant ($p \leq 0.001$) for BR, CA, DE, FI, NO, PL, SE, UA, UK, and US; the difference is significant ($p \leq 0.05$) for ES, NL, and RU. So, although the number of cross-country connections is higher than the number of connections within a country, the social tie strength for inner-country connections is higher for all countries under investigation.

5. CONCLUSION

Using the LFM-1b dataset of country-specific listener and listening information, we set out to answer three research questions: In which ways do listeners in different countries differ in terms of their inclination to listen to mainstream, on a global and a country level (RQ1)? In which ways do listeners in different countries differ in terms of their social ties and connectedness in Last.fm (RQ2)? In which ways do mainstream and social connectedness interrelate (RQ3)?

We found large differences between countries in terms of the level of global and regional mainstream consumption of listeners as well as their fluctuations, i.e., standard deviations (RQ1). A particularly interesting example is Finland with a mid (regional) to high (global) mainstreaminess level. While seeming surprising at first glance, a high standard deviation in mainstreaminess reveals that there is a group of Finnish listeners that largely follows the trend, whereas another large group established their own preferences, far away from the mainstream. Further analysis showed that this group's influence foremost stems from metal music. In contrast, Finland's neighbors Sweden and Norway show a very stable level of preference for mainstream.

In terms of social ties and centrality measures (RQ2), we found that, on average, Last.fm users share between one fourth (Italy, Spain, Russia, and Australia) and one third (Sweden and Finland) of their neighbors. Moreover, social tie strength is negatively correlated with betweenness and closeness centrality, which indicates that direct neighbors between connected users show significant overlaps,

Table 4. Differences in social tie strength between connections within a country and cross-country connections. Country names are abbreviated according to ISO 3166-1 alpha-2. Significance levels are: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

country		connections	mean social ties (J)	std	t	df	p	
AU	within country	34	0.25620	0.11058	1.784	35.268	0.083	
	cross-country	760	0.22181	0.09615				
BR	within country	1075	0.25639	0.11569	7.736	3622.000	0.000	***
	cross-country	2549	0.22605	0.10438				
CA	within country	28	0.29538	0.12547	3.259	874.000	0.001	***
	cross-country	848	0.23501	0.09537				
CZ	within country	110	0.22807	0.09750	0.051	184.758	0.959	
	cross-country	315	0.22753	0.09416				
DE	within country	369	0.25107	0.11538	7.542	2704.000	0.000	***
	cross-country	2337	0.21144	0.08993				
ES	within country	180	0.23885	0.09972	2.730	248.262	0.007	*
	cross-country	880	0.21680	0.09397				
FI	within country	171	0.26051	0.12002	4.761	1252.000	0.000	***
	cross-country	1083	0.22110	0.09719				
FR	within country	42	0.25933	0.12916	1.114	44.620	0.271	
	cross-country	673	0.23666	0.10755				
IT	within country	246	0.24656	0.08706	1.856	1261.000	0.064	
	cross-country	1017	0.23359	0.10085				
MX	within country	108	0.22272	0.11188	0.002	128.309	0.998	
	cross-country	908	0.22270	0.10033				
NL	within country	67	0.26510	0.12334	2.113	75.556	0.038	*
	cross-country	717	0.23217	0.10690				
NO	within country	84	0.26555	0.10218	4.769	105.179	0.000	***
	cross-country	578	0.20911	0.09553				
PL	within country	958	0.25610	0.11539	12.336	3270.000	0.000	***
	cross-country	2314	0.20937	0.09075				
RU	within country	1596	0.21208	0.09940	2.201	5299.000	0.028	*
	cross-country	3705	0.20598	0.08945				
SE	within country	50	0.32686	0.11978	5.880	57.000	0.000	***
	cross-country	474	0.22339	0.10359				
UA	within country	160	0.22599	0.11370	3.547	1228.000	0.000	***
	cross-country	1070	0.19947	0.08376				
UK	within country	513	0.25545	0.11070	7.558	2869.000	0.000	***
	cross-country	2358	0.22043	0.09135				
US	within country	1269	0.23737	0.10070	4.474	5595.000	0.000	***
	cross-country	4328	0.22367	0.09456				

but this does not generalize to the whole network.

Our hypothesis that users whose neighborhoods are well connected are likely from the same country could be verified (RQ3). For most analyzed countries, our analysis revealed significantly higher social tie strength for connections within the same country compared to cross-country connections. In other words, although users have less connections within the same country than cross-country ones, the social ties are stronger for inner-country connections. Furthermore, our analysis identified that the group of mainstreamy users have stronger social ties compared to the group of users less inclined to mainstream music concerning tie strength.

The logical next step in this line of research is to integrate the findings into a music recommendation system. The mainstreaminess and country information is highly useful to alleviate cold-start; the information about cross-country social ties can be exploited to personalize recommendations depending on the tie strength between the target user and connections to users in other countries. For instance, collaborative filtering techniques could be extended by a mainstreaminess or social tie filtering component, in a fashion similar to [38].

Finally, it would be worth investigating whether results generalize to platforms other than Last.fm. However, this research question may be hard to investigate externally and independently in the absence of publicly available datasets from the big players.

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