Globalization in music consumption

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Abstract

Globalization is one of those concepts that resonate in the mind of any social scientist. It is conventional wisdom for some and controversial for others. Because of the difficulty of its measurement and appropriation by postmodernist thinkers, the concept has a taint of unscientificness. In this paper, the aim is to show to what extent culture is globalized, more precisely music consumption. The data comes from Spotify, a music streaming platform and contains the 200 most listened songs each day, for a period of 3 and a half years and 31 countries.

Introduction

In general, we think of two main types of globalization of cultural products. The first possibility is that the same books, music, films, or artwork are popular in many different countries. The other is that cultural products are universal in most of their characteristics but slightly fitted to the particularities of a cultural environment. This is often referred to as glocalization. The latent variable that underlies both of these types of globalization is cultural taste. Similar preferences regarding cultural products are the driving force of globalization in this field, independently of whether these stem from a genuine interest in those products or are just a mere internalization of the logic of the market. The goal of this paper is to explore to what extent musical taste is uniform across countries. Can we say that "music is all the same" everywhere? How similar is the music that we listen to worldwide?

The music market is one of particular interest for the study of globalization because of the low barriers for its internationalization. It is difficult to think of another product that can travel from country to country so seamlessly. Unlike books, music does not have to be translated nor physically transported. It can be accessed from anywhere in the world with an internet connection. This has some consequences over the way we should think about music as a cultural product. By being a market with fewer barriers to entry, the popularity of a song across countries can be interpreted as a result of common preferences or shared musical tastes. Of course, the success of a song is still highly dependent on self-reinforcing dynamics (Salganik 2006), social valuation (Keuschnigg 2015), and intrinsic quality (van de Rijt 2019).

How similar is the music that we listen to?

There are probably as many ways to define and classify a musical piece as songs exist. One option would be to look at the sentiment that they transmit. Then we could say, for instance, that Rachmaninoff's prelude in C-sharp Minor resembles Chopin's Ballade No.1 in their intense poignancy (despite whatever Adorno has to say about the former). However, if we look at the structure of the piece those two are nothing alike. From the zillion attributes that can define a song, Spotify data includes only a handful of them. All the analysis will be based on them, so it should be noted that the results will be contingent on whatever these attributes can tell us about the songs they depict.

The audio features that Spotify provides are the following: duration of the song, key, mode, time signature, acousticness, danceability, energy, instrumentalness, liveness, loudness, speechiness, valence (a measure of positiveness) and tempo. For the analysis, I utilize these attributes in two different ways. First, training an algorithm to predict music genres, which is arguably the most traditional way of characterizing music similarity. Once every song is classified in one genre I characterize each country by how popular a genre is. This is a way of defining musical culture in broad strokes, but it can be informative nonetheless. The second method consists of clustering countries depending on their similarity in those attributes.

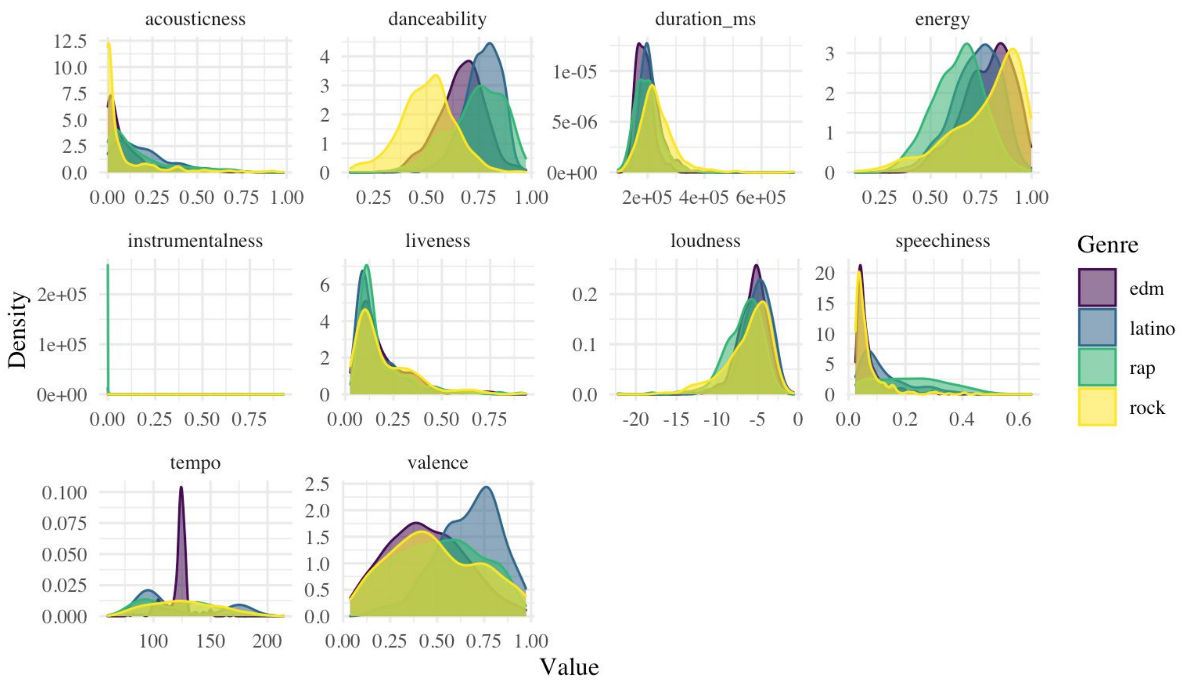
Data and Methods

The data consists of the daily charts including the 200 most popular songs on Spotify for 31 countries between January of 2017 and May of 2020. The countries are simply those in which Spotify is most popular as a streaming platform including countries from Asia, Europe, North America, South America, and Oceania. It should be noted that merely because of the fact that Spotify, a Swedish company, is popular in those countries, they already consist of a biased sample. If the musical catalog of Spotify is attractive in a country that should tell us something about how westernized music is in that country.

In order to sort songs by genre, I utilize a random forest algorithm for classification. Random forest, first described by Breiman (2001), consists of multiple decision trees, each one of them fitted on a bootstrapped sample of the data using only part of the attributes. The decision of how to classify an observation is then taken by bagging (aggregating the results of each tree and selecting the most popular category). To maximize the performance of the algorithm I tune the mtry parameter (the size of the sample of attributes used by each tree) but not the number of trees, which is not recommended (Probst and Boulesteix 2017).

In order to make predictions, the algorithm has to be trained with labeled data. For that matter, I use a training dataset that consists of Spotify playlists containing music of a single genre. I select those playlists that are more popular, preferably created by Spotify, and revise them one by one to make sure that the included songs are of the alleged genre. The result is a dataset with 1,444 labeled songs and a balanced share for each genre. One source of arbitrariness in the analysis comes from the selection of genres to be introduced. The genres included are Rock, Latin, Rap, and EDM (electronic dance music). One obvious absence is that of Pop, but there is a reason for it. As its name indicates Pop or popular music, is not characterized by a sound, structure, or style. Pop drinks from other genres and creates songs fitted for the general public. If I were to include into the classification problem it would result in all kinds of issues. Unlike pop, the genres included all have something characteristic that defines them and that has some representation of the features that are included in the data. Rap has the speechiness, EDM has the tempo, Latin music has the valence and Rock the danceability and instrumentals (figure 1). It is also true that other genres could have been included, like EDM subgenres which similar analyses have proven to be easily classifiable with almost perfect accuracy (Wolf 2020). However, that would require a more extensive training dataset, and the gains in regards to answering our research question would be marginal. Thus, the selection of genres done here is an effort to improve identifiability and parsimony, or, from a machine learning perspective, getting the best bang for your buck.

Figure 1. Description of the train/test dataset

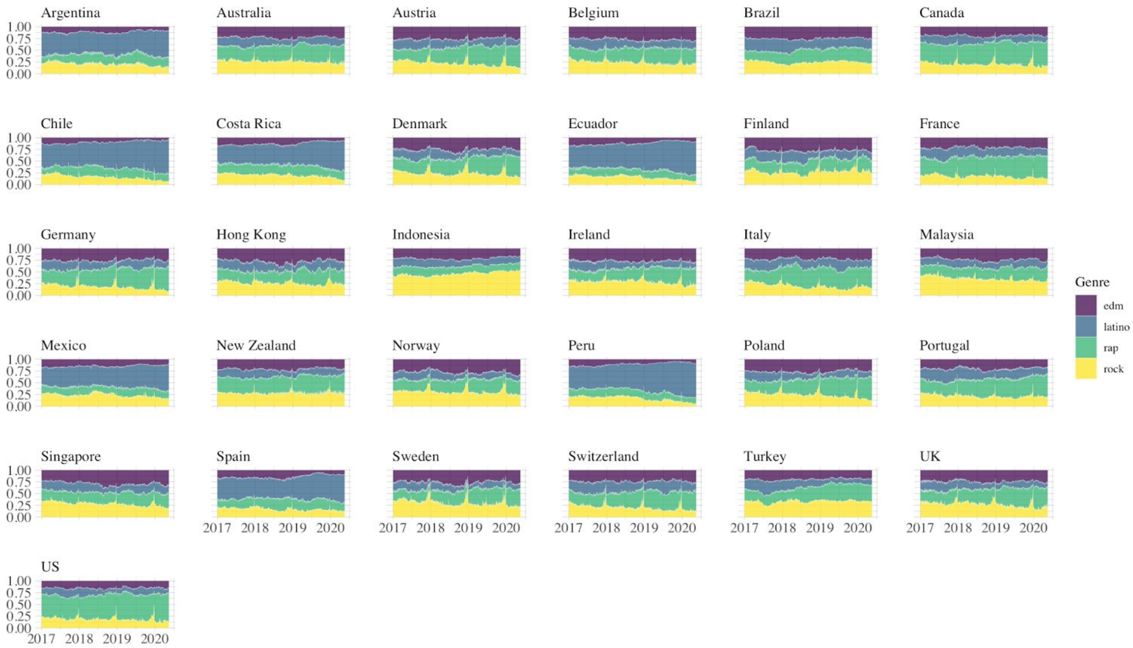


For the second part of the analysis, I use hierarchical clustering to group countries according to the characteristics of the music that is more popular in them. Although only the hierarchical clustering is presented, results with other clustering algorithms (k-means and k-medoids) were qualitatively similar. Hierarchical clustering, although computationally more intensive than other methods, has the advantage of being explicit about the distances between elements, forcing the analyst to make a decision on the number of clusters after looking at them in the dendrogram. In this case, in which the elements to be clustered are few (31 countries) the computational inefficiencies do not suppose an issue and the dendrogram presents a clear visualization of distances between elements. Hierarchical clustering operates over a matrix of Euclidean distances. Also, elements or clusters to be merged at each step are chosen according to Ward's method, which proceeds by minimizing within-cluster variance. Other options exist, but under typical circumstances, Ward's method is the most accurate (Ferreira and Hitchcock 2009). Lastly, to decide the number of clusters several metrics were consulted but results were conflicting. The decision was finally based on the visual exploration of the dendrogram alone. Therefore, more attention should be paid to the continuous distances between elements than to the discrete representation of clusters given that the latter was discretionary.

Results

After training the random forest algorithm the performance in predicting music genres is acceptable but far from perfect. On the test dataset, which has ¼ of the song of the training dataset, it correctly classifies 82.8% of the songs and the area under the ROC curve is 0.95. In general, classification is not biased except in the case of Latin music, which is often misclassified as Rap (but not the other way around). Thus, we should expect our predictions to overestimate the number of rap songs and underestimate the amount of Latin music. For further developments, this bias could be tackled by a refinement of the training dataset and accuracy could be improved by using an XGboost algorithm, which has been shown to outperform random forest in music genre classification (Bahuleyan 2018).

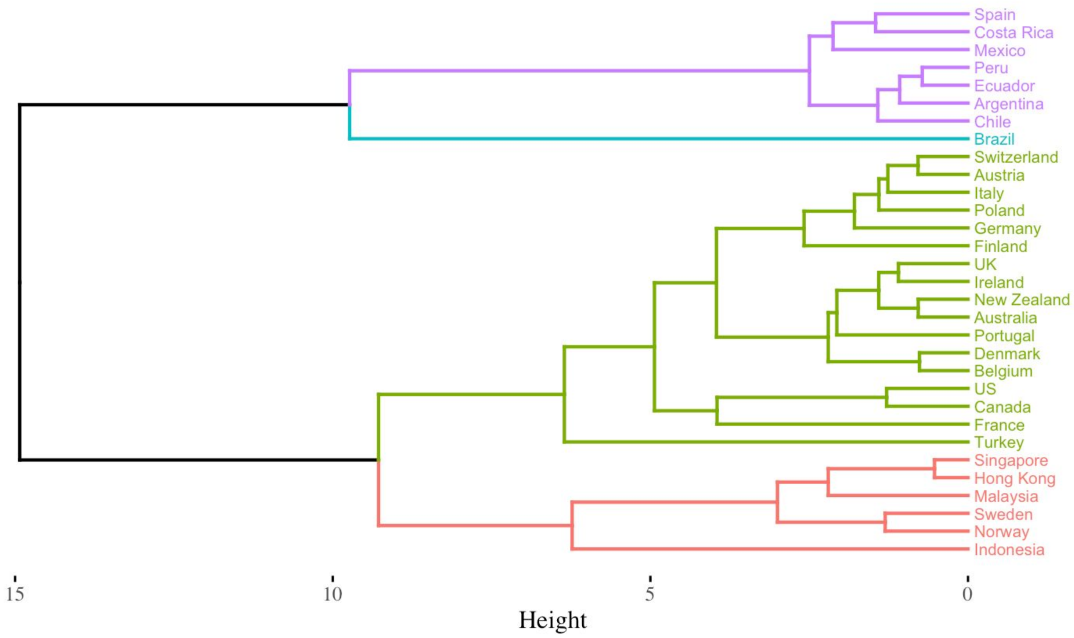
Figure 2. Popularity of musical genres by country (2017 - 2020)



The results of applying the trained algorithm on the original dataset are shown in figure 1. The first thing that catches attention is the presence of sudden spikes of rock music in countries like Sweden, Denmark, or Austria. The spikes occur every year during Christmas and they are due to the extreme popularity of Christmas songs in those countries (especially in Sweden). In a more careful inspection, we can discern clear similarities between countries. For instance in Latin American countries, Mexico and Spain Latin music is the most popular genre, and its dominance has been growing throughout this period. In other countries like the US, Canada, and France Rap music is the most prominent genre.

Figure 3. Hierarchical Clustering

Ward method



The clustering of countries confirms these observations. The dendrogram (figure 3) has been partitioned in 4 clusters, represented by colors. The first cluster, in purple, is comprised of all the Spanish speaking countries in the data. Brazil sits alone in a cluster, far from any other country but closest to the Spanish-speaking cluster. The third cluster is mainly formed by western countries. Within this cluster, there is a clear correlation between geographical proximity and similarity in musical taste. For instance, Switzerland, Austria, and Italy are merged at a small distance in the dendrogram. Same with the UK and Ireland (geographical neighbors) which then are merged with New Zealand and Australia (linguistic neighbors). The US and Canada are also fairly similar in musical taste. The fourth cluster is the most implausible, combining the Asian countries and two Nordics, Sweden and Norway. If we plot the clusters over the two main PCA axis (figure 4, in the appendix) we can see how the clustering does a good job in separating the Spanish-speaking countries from the rest and isolating Brazil. The particularities of the Spanish-speaking countries are clear just by looking at the valence of their songs (figure 5, in the appendix), which is higher than that of any other country.

Conclusions

What the results presented here suggest is that whether we are more similar or not than a few decades ago, some cultural particularities in dominant cultural taste persist. When Henry Wadsworth Longfellow said that "music is the universal language of mankind" maybe he was not completely right. Musical tastes are still attached to other cultural elements. Language and physical proximity, which were arguably the main source of cultural diffusion until the advent of the internet, seem to play a role in determining what kind of music is more popular in a country.

These observations, however, do not rule out the possibility that sharing a language and being in close contact could just be confounders in the relationship between musical taste and nationality. A more careful examination and a causal design would be necessary in order to determine that. Also, obvious exceptions exist like Brazil and Portugal, countries that despite sharing a language and past seem to have very little in common when it comes to popular music. Also, the fact that musical taste is not as globalized as we could expect does not mean that the music market is not. For instance, Latin music, which is not so popular in the US but dominates in Spanish-speaking countries is still produced in large quantities in the US (this could be considered a form of glocalization). Thus, in cultural markets, it is important to note the difference between globalization of production and of consumption.

References

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Appendix

Figure 4. Results of hierarchical clustering over PCA axis

Ward Method

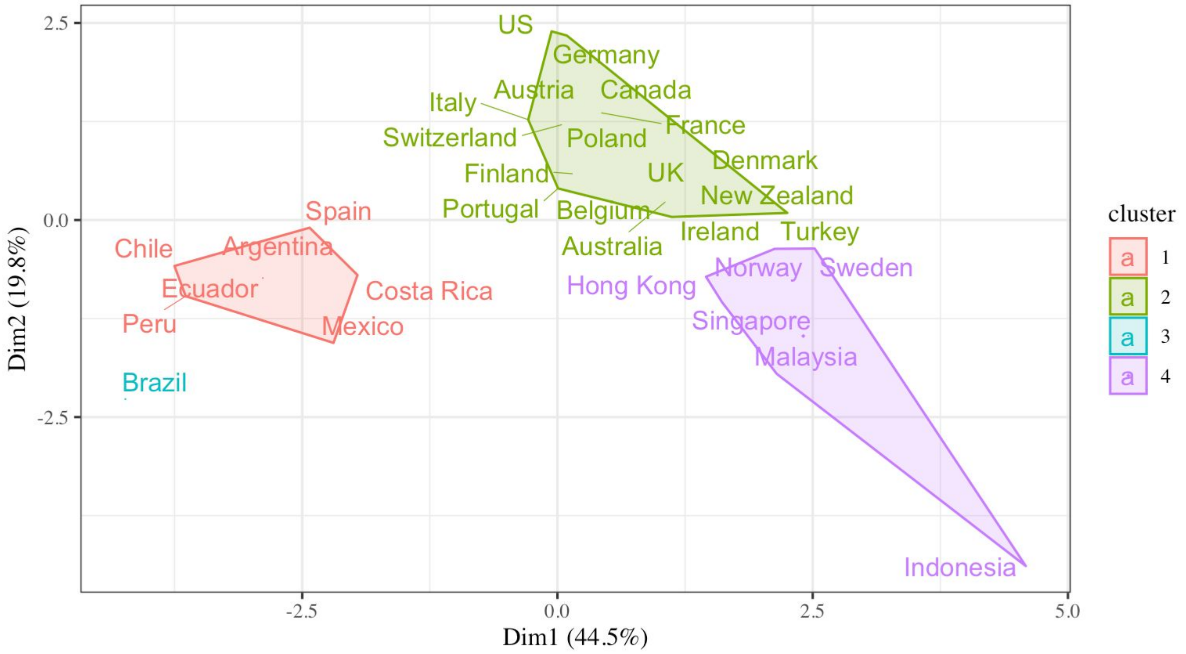

Figure 5. Valence Distribution across countries