Exploring The Relationship Between Music and Migration: A Study of Spanish Demographics

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Abstract

This study examines the correlation between music and migration by analyzing the musical attributes of countries and their migration statistics. The study finds a correlation between some musical attributes, specifically those related to dance music, and the decision to migrate to Spain. The study suggests that the shared experience of dance music plays a part in migration decisions.

Keywords: Spotify; Culture; Demographics; Migration; Music.

1 Introduction

Music is recognized as integral to culture, with evidence of musical activity dating back to humanities earliest days. In both it's origins and today, it also finds itself inextricably tied to the movement of people and the musical traditions they bring with them. While it is believed that this relationship is reciprocal, and that music taste is a cultural element that feeds into the motivation behind migration, what specific elements of musical "style" play a part in this process remains to be explored. The purpose of this study is to examine this relationship through the lens of data analysis. By comparing the characteristics of the music most listened to by different countries in relation to the migration statistics of these countries, it aims to identify which are statistically most correlated with migratory choice.

2 Background

2.1 Migration

Many factors influence migration, including economic, political, social and environmental considerations. According to the World-Bank [2019], economic factors such as employment opportunities, wage differences and inequality drive migration. Political factors can also lead to individuals leaving their home in search of safety and security. Resource scarcity, natural disasters, and other environmental conditions also contribute to this decision.

Culture can also play a significant role in shaping migratory patterns. When it comes to voluntary migration, this can be factors such as language, religion and social norms, in addition to the cultural expectations of the destination [Huston 2020].

2.2 Music and Culture

Throughout history, music has played a part in ceremonies and social gatherings, but also revolts and protests. It continues to be studied in it's relation to contemporary politics and society [Alves 2020].

A nations shared musical tradition feeds into it's citizens national and individual identities [Epstein 2010]. While migration is generally understood as an economic phenomenon, ethnomusicologists have explored how a nations culture affects the decisions made by it's people when they move abroad. Culture has been observed through shared beliefs, customs, values and attitudes, but music is given little to no consideration.

2.3 Music Streaming

In recent decades, with the boom of online music sharing, torrenting and now streaming, more people than ever have immediate access to upwards of 80 million tracks [Peoples 2022]. With the digitisation of music consumption, it is also easier than ever to track what the people of a nation are playing on repeat. Curated national playlists, such as Spotify's weekly "Top 50's" can help track trends in not only the music industry, but in a nation's broader preferences in popular music.

Another consequence of the digitisation of music is the development of more practical ways to describe music. While musicians often use written forms of music, such as tab or sheet music, in the field of neural-creativity, researchers settle for encodings such as MIDI [Cífka et al. 2020]. These methods come with limitations, however, as without a robust set of meta-data, two identical representations are not assured to be musically similar in a way a human may recognize. The streaming industry has instead developed a series of abstract musical features that better lend themselves to being used in recommender systems. Given that these are feed-back systems, wherein a user's experience with the results provides data on which to learn, these features are a robust way to determine how similarly two songs will be perceived by us as being [Robley 2022].

3 Motivation

There is a lack of enquiry as to what about a countries music makes someone more inclined to move there. This report seeks to shine a light on this question through the lens of data analytics, with a focus on the emigrants to Spain from around

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the world. Being a Spanish native as influenced this decision. However, Spain is also positioned as noteworthy in this line of questioning for it's vast global cultural, economic and political ties. For one it is a former colonial-empire that administrated vast swathes of land in Africa, America and Asia, and brought to these places through the slave and commodity trade what is now one of the most spoken languages in the world. It is also a Schengen member state, meaning most European citizens have the right to move to and work in Spain without the need for additional Visas. Finally, it has one of the highest net-migration rates in Europe (that is difference between immigrants and emigrants) [EM and INE 2021] so migration data is plentiful and of easy access.

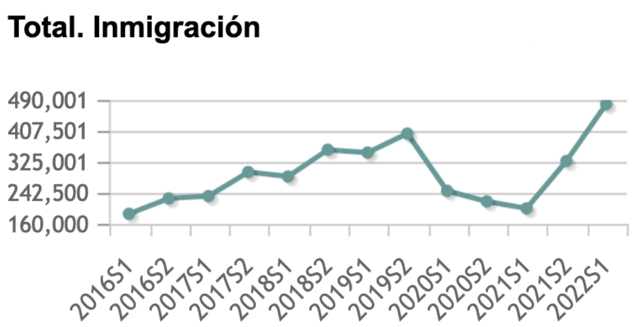

Figure 1: Total immigration numbers to Spain over the course of six 2-semester years. Of note is the gradual rise throughout the early 2010's with a steep dip at the beginning of the COVID-19 epidemic and now explosive growth, contributing to Spain's high net-migration.

4 Initial Proposal

This project began with the objective of identifying a similarity metric for a playlist of songs. If the "Top 50" playlists for two countries render a high similarity metric, this would indicate that the two countries share some semblance of taste in popular music. This metric would then be calculated for every country from which people emigrate to Spain to. Any correlation between this metric and a given country's total emigration numbers to Spain would suggest that taste in music (or overall musical similarity) influences where someone chooses to migrate to. Other national statistics, such as population and percentage of Spanish speakers would be taken into account as rough stand-ins for other cultural and economic reasons for migration. The correlation of these features with total emigration would act as a benchmark for the above mentioned metric.

5 Collecting Data

All data collected is available publicly and it's use did not require the acceptance of additional terms of conditions beyond those required to access the data.

5.1 Spotify

As previously mentioned, Spotify maintains numerous "curated" playlists, some of which are generated on the basis of popular listening data from geographic regions. This includes the "Top 50" national playlists.

Collecting data from Spotify involves the use of the Developer API that allows for the extraction of user listening data, playlist meta data and, importantly, musical meta data. This latter information is what is used to determine the musical similarity of two tracks, which along with meta-data similarity, contributes to a recommendation being generated. Data scraping from Spotify's API is subject to their terms of service that outlines the correct uses for said data.

For the purposes of this project, three CSV files were sampled from a publicly available repository on Kaggle [u/BwandoWando 2021]. It queries a variety of both official and unofficial "Top 50" national playlists every day over the course of a month. Data is stored in three CSV files.

5.1.1 *Playlist Metadata*

At only around 300kb, it stores information about the playlists sampled, including the owner, the data created, the total listeners, description and name.

5.1.2 *Playlist Track Metadata*

This dataset is around 4mb. For every time a song was extracted from a playlist over the course of a month, there is an entry on this table. It includes attributes such as track popularity, the track name, the playlist it was extracted from, and when it was added to and read from the playlist.

5.1.3 *Track Metadata*

This dataset is around 10mb. This table contains a more complete set of characteristics for every song that has been read from any given playlist. This means there is only one entry per song. The characteristics that are of interest include some related to meta-similarity:

- The artists on each song.
- The markets on which the song is available.
- The album the song belongs to.
- Track duration.
- Track explicitness.

Aswell as some related to musical similarity:

- "Danceability".
- "Energy".
- "Speechiness".
- "Accousticness".
- "Instrumentalness".
- "Liveness".
- Valence.
- Tempo.
- Key.
- Loudness.

Of note is that while some of these are features are used in formal music theory, others are more broader terms for musical style that best capture what it is people like about a given song.

	country	total.migration2spain	mean.track.duration_ms	mean.track.explicit	mean.danceability	mean.energy	mean.key	mean.loudness	mean.speechiness	mean.acousticness	mean.instrumentalness	mean.liveness	mean.valence	mean.tempo	mean.musicalsim2spain	total.population	percentage.spanishSpkrs
0	Germany	0.748392	-0.294000	2.019939e-01	-0.047689	-0.006323	-0.105379	-0.021009	0.162974	-0.179195	-0.096342	0.088513	0.053745	0.239069	0.052012	-0.082150	-0.672210
1	Austria	-0.430038	-0.235747	5.160428e-02	-0.105610	-0.026073	-0.068669	-0.061476	-0.100272	-0.134660	-0.093759	0.199159	0.098436	0.145142	-0.097335	-0.167964	-0.672210
2	Belgium	-0.125465	-0.081920	1.747588e-01	-0.027318	-0.023923	0.167068	0.048163	0.202919	-0.182273	-0.141152	0.029511	-0.107283	0.128007	0.117438	-0.164859	-0.648100
3	Denmark	-0.414804	0.000040	5.581411e-02	-0.162756	-0.072331	-0.128441	-0.036668	-0.179867	-0.242771	-0.171200	0.044751	0.097562	0.133555	-0.176315	-0.171078	-0.672210
4	Estonia	-0.462221	-0.080415	1.939499e-01	-0.350033	-0.176391	-0.005400	-0.242109	-0.035931	-0.120439	0.149581	0.173366	-0.489054	0.223119	-0.577067	-0.175831	-0.744541
5	Finland	-0.396455	-0.119209	-4.668727e-02	0.072207	0.153195	-0.095586	0.207222	-0.145499	-0.406836	-0.075046	0.056606	0.143524	0.084433	0.546735	-0.171352	-0.696320
6	France	1.090758	-0.245229	6.745485e-01	0.076398	0.030461	0.264129	0.058926	0.461620	0.094667	-0.093846	-0.199854	-0.017618	0.153449	0.212950	-0.100213	-0.431107
7	Hungary	-0.406080	-0.385236	4.158698e-01	0.107091	-0.058732	-0.010352	-0.126307	0.122152	-0.124467	-0.162271	-0.028365	-0.097023	0.097057	0.110174	-0.165959	-0.744541
8	Ireland	-0.367006	0.107682	-6.147641e-02	-0.386857	-0.211418	-0.159765	-0.235715	-0.204179	0.011640	-0.047440	0.113286	-0.072841	0.223010	-0.775024	-0.172112	-0.672210
9	Italy	0.579880	-0.235675	5.174792e-01	-0.157882	0.384247	0.032167	0.433036	0.344735	-0.369834	-0.165954	0.092995	-0.335068	0.027667	0.500536	-0.108069	-0.503438
10	Netherlands	-0.126120	-0.114787	1.368346e-01	0.002984	-0.054757	0.059295	-0.024176	0.084893	-0.338110	0.021687	0.103041	0.109671	-0.049809	0.121282	-0.158282	-0.648100
11	Portugal	0.218577	0.021974	4.523131e-17	-0.079320	-0.285825	0.059183	-0.040724	0.174912	0.165081	-0.030787	0.135283	-0.209428	0.201521	-0.521687	-0.165182	-0.527548
12	Slovakia	-0.439611	-0.146537	4.404129e-01	-0.154866	-0.021592	-0.020062	-0.144394	0.141654	-0.166997	-0.067332	0.083869	-0.147197	0.159046	-0.183893	-0.171111	-0.744541
13	Romania	3.662586	-0.126187	3.425567e-01	0.217959	0.025509	0.029297	-0.098874	0.130962	-0.287840	-0.105299	0.098086	-0.298066	0.176839	0.124450	-0.152915	-0.648100
14	Sweden	-0.340947	-0.268237	-1.178298e-01	-0.472420	-0.351139	-0.020750	-0.254189	-0.205046	0.225911	-0.056051	0.097268	0.005228	0.129831	-0.667992	-0.166419	-0.623989
15	Norway	-0.401409	-0.217594	-6.374398e-02	-0.521782	-0.293983	-0.074832	-0.128106	-0.223862	0.016557	-0.152267	0.099179	-0.292887	0.200005	-0.554402	-0.171443	-0.708375
16	United Kingdom	1.664935	0.225140	3.927659e-02	-0.391863	-0.126654	-0.152591	-0.206391	-0.066188	-0.098463	-0.049782	0.145971	-0.173789	0.157884	-0.713001	-0.100586	-0.623989
17	Switzerland	-0.029274	-0.137873	1.753307e-01	-0.055970	-0.053984	-0.035617	-0.064121	0.104090	-0.138324	-0.115893	0.061643	-0.023664	0.089092	-0.102927	-0.167547	-0.708375
18	Turkey	-0.431789	-0.465438	-7.069787e-02	-0.256999	-0.040923	-0.055662	-0.450831	0.041940	-0.132133	0.165657	0.020269	-0.342845	-0.275242	-0.429386	-0.081665	-0.763829
19	Morocco	6.604314	0.012533	3.876980e-01	0.057143	-0.133593	0.027861	-0.424056	0.610529	0.097068	0.008312	-0.109713	0.018685	0.039524	-0.366872	-0.136612	-0.527548
20	Costa Rica	-0.439075	0.033331	2.209308e-01	0.377496	0.222912	-0.218650	0.556189	0.089560	-0.199356	-0.150683	0.051715	0.045200	-0.022637	0.875635	-0.171332	1.625500
21	Guatemala	-0.370284	0.050996	6.797872e-02	0.453115	0.415359	-0.255906	0.749457	-0.254665	-0.284812	-0.127109	0.023705	0.096973	-0.377734	0.898710	-0.157490	1.314478
22	Nicaragua	0.031970	0.151815	1.716948e-01	0.495531	0.389610	-0.262483	0.549701	-0.024065	-0.230046	-0.141133	0.073409	0.156124	-0.082815	0.858847	-0.169806	1.572458
23	Panama	-0.434255	0.015666	1.784606e-01	0.314494	0.317674	-0.124860	0.559392	0.103115	-0.148618	-0.154092	0.000787	0.144639	-0.028879	0.922197	-0.172458	1.447084
24	Canada	-0.420950	0.041444	6.059817e-02	-0.357014	-0.409004	0.103431	-0.420370	-0.131294	0.138897	-0.092334	0.106839	-0.209725	0.180619	-0.848262	-0.137752	-0.703553
25	Mexico	-0.016453	-0.066836	-3.073820e-02	0.313658	0.134803	0.130753	0.472979	-0.234601	-0.127629	-0.026659	0.120399	0.212820	0.006161	0.830854	-0.028446	1.623089
26	Argentina	1.771868	-0.126464	1.065310e-01	0.498974	0.141811	-0.168553	0.454863	0.107099	-0.294782	-0.143051	-0.083789	0.048991	-0.292810	0.863485	-0.124443	1.630322
27	Bolivia	0.847987	-0.072411	6.291264e-17	0.479422	0.309031	-0.222710	0.772752	-0.183933	-0.389416	-0.117144	0.026366	0.055247	-0.225874	0.908686	-0.163615	1.350643
28	Brazil	0.687409	-0.215964	-1.413957e-01	-0.047695	0.623034	0.011157	0.813725	0.001724	0.382918	-0.050560	1.455776	0.511415	0.243688	0.389299	0.067664	-0.708375
29	Chile	-0.014166	0.133659	3.676289e-01	0.790126	0.493939	-0.107633	0.628577	-0.045367	-0.374202	-0.088349	-0.059664	0.337642	-0.519385	0.860642	-0.154663	1.625500
30	Colombia	3.533557	0.104234	2.326765e-01	0.663331	0.432996	0.043720	0.718706	0.204891	-0.198789	-0.119902	-0.011491	0.283002	-0.048899	0.896198	-0.118292	1.623089
31	Ecuador	2.625075	0.101712	3.073820e-02	0.510076	0.340430	-0.337303	0.665483	0.000380	-0.240114	-0.145158	-0.081880	0.054240	-0.247946	0.872669	-0.157414	1.596568
32	Peru	1.403593	0.106206	1.140288e-02	0.512109	0.482013	-0.290966	0.843323	-0.070048	-0.314911	-0.164270	-0.079018	0.119864	-0.253812	0.905229	-0.139050	1.319300
33	India	-0.048763	0.307017	-5.692556e-01	-0.249487	-0.178469	-0.042646	-0.223714	-0.255190	0.320168	-0.121481	-0.118803	-0.208961	-0.118203	-0.537855	1.409650	-0.768579
34	Israel	-0.452797	0.030494	-1.767447e-01	-0.243528	-0.176310	-0.045609	-0.019721	-0.233738	0.100893	-0.136491	0.245880	-0.341563	0.132230	-0.427223	-0.169215	-0.708375
35	Japan	-0.428794	0.588499	-7.069787e-01	-0.388930	0.780124	-0.280814	0.879198	-0.509516	-0.471241	-0.172004	0.165694	0.226760	-0.054964	0.380715	-0.031684	-0.766240
36	Australia	-0.427215	0.121359	1.860470e-01	-0.328382	-0.348473	-0.085702	-0.178443	0.008992	-0.021807	-0.050652	0.055406	-0.386298	0.128355	-0.654669	-0.152741	-0.708375
37	New Zealand	-0.471503	0.120845	2.592255e-01	-0.049784	-0.277812	0.052609	-0.117499	0.067716	-0.170828	0.016933	-0.102812	-0.325875	0.105471	-0.398635	-0.171492	-0.742130

Figure 2: Final dataset to be analysed after pre-processing

5.2 Spanish Emigration Statistics

The National Institute for Statistics (INE in Castilian Spanish) is responsible for the accumulation and storage of various nation-wide data, as well as for facilitating access to this data. The Migration Statistics (EM) department surveys all legal migration into and out of Spain by continent and country. The dataset used was constructed from data available on the INE website `ine.es`, last updated in 2021.

5.3 Spanish Language Statistics

The data on the total number of Spanish language speakers in each country, and total population of that country was scraped from the Wikipedia article on the *Spanish language* [2023]. It has cites numerous sources for both of these metrics, and so is demonstrably trustworthy. However, it serves as a rough indicator of how common Spanish speaking is in the countries of interest.

6 Cleaning Data

Every dataset required at least some cleaning in order to prepare it for use in data analysis routines. Cleaning took the form of, firstly, removing all unwanted or unnecessary attributes. This was mainly done in the Spotify CSV files, as included in every song and playlist meta-data entry is information corresponding to artwork, URLs and access URIs. Given that these values are unique to every song (or every release of a song, given that some songs appeared as both singles and as one track in an album), they can be considered neither categorical nor nominal and so do not serve for statistical analysis.

Similarly, more pertinent information (such as song artists) was stored, by default, as a string containing a JSON containing the name of the artist, but also meta-data relating to them. This unnecessary information was dropped from the table entries leaving cleaned data.

A functional limitation of Python (the language used to conduct analysis) necessitated further cleaning of individual entry features. Because of how CSV variables are read into Pandas `DataFrames`, artist names or song titles with apostrophes or quotation marks would interfere with how the parser.

The Spanish language dataset was missing the total population values for some countries. One additional step that had to be taken to allow for it's use was to manually enter the missing values, to allow for the calculation of the percentage of Spanish speakers.

There were some cases where entries were missing or had null attribute values, and where the correct value could not be either found elsewhere or gleaned from another entry. In such cases the entry was discarded.

7 Combining Data

Once the data had been cleaned, the following pre-processing routines were followed to normalise and prepare the data for combination and subsequent analysis.

7.1 Pre-Processing

7.1.1 *Spotify Data*

After extracting the playlist track meta-data and the track meta-data, we choose a subset of attributes to consider when finding similarity. These are the above mentioned musical-attributes with the addition of the meta-attributes for track duration and track explicitness. These (and subsequent attributes of interest) are mean-normalized:

$$\text{normalize}(\text{value}) = \frac{\text{value} - \text{mean}}{\text{standard deviation}}$$

To determine the similarity between two playlists, firstly all the songs belonging to a playlist must be extracted. This is achieved by joining the playlist track meta-data with the track meta-data on the track ID attribute. Because there can various entries for one song in the same playlist (one entry for every time the song is read), we further reduce it to one entry per song with an additional `times_added`.

To determine the similarity between two playlists, firstly the mean values for the attributes of interest are calculated. Cosine distance is then used to determine how similar the two sets of average music characteristics are:

$$\text{cosine similarity}(A, B) := \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}}$$

Given the above routine, the similarity between every country's "Top 50" playlist with Spain's is calculated and stored (along with their mean musical attributes) as an attribute to every country's playlist.

7.1.2 *Emigration Data*

The pre-processing here is minimal. Given that, during cleaning, all invalid or nonessential entries have been removed (notably those that indicate the emigration numbers for wider regions and continents), the only pre-processing done is mean-normalisation.

7.1.3 *Language Data*

From this language data we want to extract both the total number of inhabitants per country and the percentage of of residents who speak Spanish. The latter is calculated by dividing the total number of Spanish speakers (including limited competence speakers) and divide it by the total population. As above, these values are then mean-normalised.

7.2 Merging Data

Once all datasets have been pre-processed, they are merged with an inner join on the `country` attribute. The resulting dataset has 37 columns and 17 rows (see fig. 2).

8 Observations

8.1 Outliers

Given that the stated goal is to examine how overall musical similarity affects emigration, a simple linear regression model is run on the constructed data. The resulting coefficient is −3.25, indicating that while there is some correlation it seems to be a negative correlation, which might indicate that the initial hypothesis is incorrect. However, visualising this plot reveals that the this negative correlation stems from Morocco, an substantial outlier that has the highest emigration rate to Spain but is below average with regards to similarity

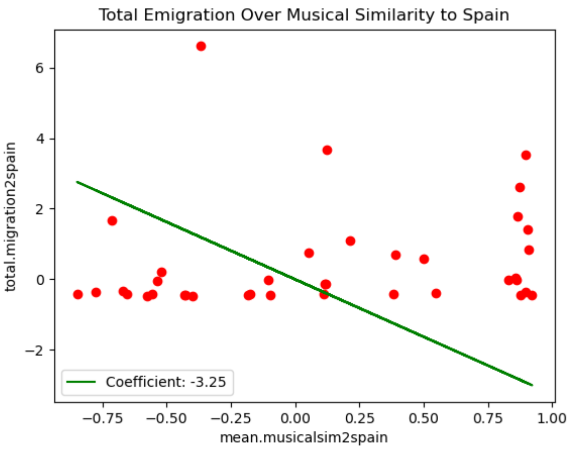

Figure 3: Scatter plot of migration over similarity with corresponding linear regression line.

(see fig 3). While certainly this would indicate that musical similarity is not the *most* correlated attribute to the target, it also does not suggest that it is unimportant. The other two outliers correspond to the UK and Romania (left-most to right-most respectively). Some outliers were to be expected because, as mentioned above, there are many factors that motivate migration. In the case of Morocco, close borders and centuries of overlapping history and reciprocal migration likely overcome any musical differences. Spanish-Romanian diplomatic relations have likewise persisted for over 135 years, throughout which both have amassed numerous bilateral agreements [*Embassy of Romania in Spain. Madrid* no date]. Spain currently ranks 10th for foreign investment in Romania [Moncloa 2022] and Romania is set to join the Schengen zone soon.

While there are reasons for there to be outliers, their presence indicates that the similarity metric being used was either insufficient or incomplete.

8.2 Most Correlated Attributes

To overcome this issue, a multiple-linear regression model was trained on the full dataset (excluding the country and target attributes). The result of this procedure is an array of coefficients or weights that are applied to the value of each attribute before using it's value (along with other rest) to predict the target. Coefficients that are closer to 0 show fewer signs of correlation, while those with larger magnitude indicate either positive or negative correlation (see fig 5). For ease of analysis, the best six coefficients are picked (those with the highest value aside from the musical similarity attribute). Here we see that our regression lines seem to be more resilient to outliers, and we see that they all do follow the general trend of the plot. The most positively correlated attributes `speechiness`, `danceability` and `energy` are attributes characteristically attributed to Reggaeton, a genre of Caribbean and Latin-American origin that is typically regarded as one of the most popular forms of dance music

Attributes	Coefficients
mean.track.duration_ms	-0.311436
mean.track.explicit	-4.321761
mean.danceability	4.213655
mean.energy	4.499870
mean.key	-0.069229
mean.loudness	-1.705097
mean.speechiness	6.621505
mean.acousticness	-1.315734
mean.instrumentalness	-2.865513
mean.liveness	-0.322570
mean.valence	-0.188734
mean.tempo	2.694332
mean.musicalsim2spain	-3.251988
total.population	-0.397842
percentage.spanishSpkrs	0.711636

Figure 4: All tested attributes and their respective coefficients.

both within and without the Spanish speaking world [Pineda 2022].

The negatively correlated attributes are `instrumentalness` and `explicitness` and seem to suggest that Spain attracts fans of more synthetic or synthesized music with less swearing. Conducting visual analysis on the plots indicates however that outliers seem to affect `explicitness` more given that most playlist feature above average explicitness in general.

9 Conclusions

We can conclude from this analysis that there is some degree of correlation between the average musical-style attributes of Spotify "Top 50" playlists and the decision to migrate to Spain. Furthermore, most of the attributes originating from the Spotify data outperform those relating to either total population or the percentage of Spanish speakers per country, indicating that correlations found are robust and are not simply due to skewed data.

Not all attributes seem to be equally important, however, and those that are are those that would be pertinent to most forms of dance music and in particular Spanish dance music; energy, danceability and speechiness. This might suggest that dance music (and more-so the kind of dance music someone can listen to) in a place plays a part in that persons decision to emigrate. This conclusion would be supported by the literature as dance music is often enjoyed communally in social gatherings such as those traditionally treated as cultural markers when discussing migration.

9.1 Limitations

Because of where some data (in particular the Spotify data) was sourced from, there were numerous formatting and compatibility errors associated with the raw data files. This required lengthy cleaning and re-formatting to allow for use with Pandas. Furthermore, this research's scope is limited by looking specifically at Spain, and at a period of 1 year. Ideally access to other streaming services "Top 50" equivalent playlists would have been used to compare and contrast the results provided by Spotify's, however as most of these are either premium-services or do not have robust API support we were limited to only one demographics perspective. Many Apple users use Apple Music exclusively, and while there is no guarantee that Apple's playlist data would have been any different to Spotify's it would have added another level of reliability to the analysis conducted. This being one academic endeavour of many that students must undergo has also meant that there was a limited amount of time that could be dedicated to this research.

9.2 Future Work

Further experimentation with the style-similarity metric could still prove the initial hypothesis of similarity being ultimately correlated to emigration totals. Other similarity metrics such as Jaccard or Manhattan could be tested. Additional song attributes (particularly additional meta-attributes) could be taken into account, or even used to determine a secondary meta-similarity score that could be used in conjunction to the musical similarity for finding a line of best fit. Furthermore other regression types could be investigated, as it seems that linear don't perfectly capture the relationship between some of these attributes and migration, and alternative regression types might render far more closer fitting lines.

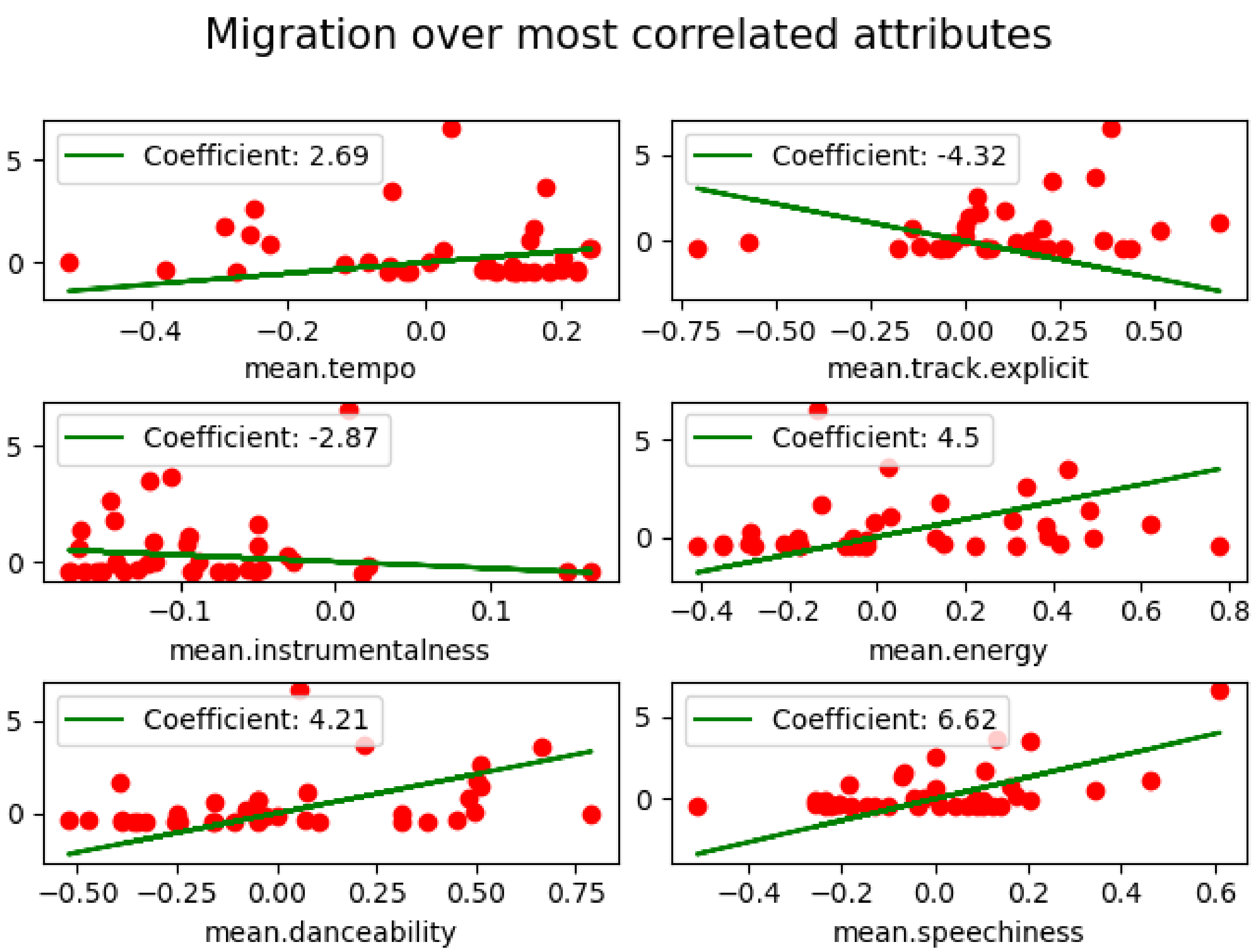

Figure 5: Multi-plot for each of the highest magnitude coefficients consisting of scatter plots where every y-axis is the total migration but each plot has a different x-axis. Every plot includes the regression line given by the coefficient of it's x-axis attribute. This is over all data, including the outliers.

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