Unveiling the Music Graphs: Analyzing Spotify's Users and Artists

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We aim to empirically investigate, between listeners and musicians alike, whether music can bring individuals together and foster a sense of solidarity among those with similar musical preferences. To test this hypothesis, we first processed information on Spotify listening trends from a plethora of different sources (Kaggle, Spotify and Genius APIs). Then, we conducted extensive network and sentiment analysis of communities within Spotify networks. We show that different individuals within the same communities do indeed exude promising similarities in the realms of sentiment analysis and network properties. We found that the sentiment scores of the five most frequent genres appear similar. Furthermore, we discovered that artists and users are grouped according to their similarities. In the case of the artists' network, they collaborate or are related to artists from similar music genres. For the users, they gather with other users who share similar songs and music genres. Moreover, the most popular artists who are listened to by a community of users form communities within the artist networks. Our paper is expected to serve as a starting point for understanding users' and artists' behaviours. As technology and music intertwine and as more music gets distributed to consumers, the knowledge of our musical preferences will be beneficial and relevant for music recommendations.

social graphs| music industry | music streaming platforms| graph analysis | text analysis | sentiment analysis

A a constant in our lives, music has evolved rapidly in recent years from a technological perspective allowing new genres to emerge and creating more means of access for listeners to discover new artists and songs and create communities and social interactions around them.

In this paper, our purpose is to analyse the music industry, looking at how artists interact with each other, how they impact users, and how certain user groups interact and cluster together. Secondly, we want to analyse the sentiment of the lyrics, how that sentiment influences specific genres, and how specific words impact a genre.

Our musical behaviour can be easily depicted once we make public the music we are listening to, resulting in no need for users' confidential data from the streaming platforms to be used to define their behaviour. Twitter facilitates posting the music a Spotify user is currently listening to by using the hashtags #nowplaying, #listento or #listeningto. A group of researchers explored this opportunity by creating a dataset where pieces of information about the tracks a user is listening to have been gathered(1). We are particularly interested in this dataset since it is a sample of real Spotify users and offers the possibility to validate our expectations regarding the behaviour in the music industry. The dataset offered only the tracks and artists' names; since we were also interested in text analysis, we gathered the tracks' lyrics from Genius.

Our findings rely on studying the artists' and users' networks. We studied their characteristics using graph analysis tools and tested a series of hypotheses created based on our world understanding and expectations. All of these will be discussed in the first part of the Results. Furthermore, findings about the impact of the tracks' lyrics will be presented in the second part during the text analysis discussion.

Results

Our study relies on real user data gathered from Twitter, which comes with advantages and disadvantages. Firstly, we expect the data to be representative of the real users' distribution since it has been sampled from Twitter, and it gives an additional layer for the human social groups. That will result in more representative user communities in the users' network. However, the drawback is that the dataset is predisposed to human error and needs preprocessing. For instance, in the case of tracks performed by collaborating artists, there was no standard to separate the artists' names. As a result, users have chosen to separate them in as many different ways as possible, which made our preprocessing task difficult and susceptible to outliers.

Data Sampling. During the preprocessing, we encountered a fascinating natural phenomenon; the number of unique artists in the music industry has exceeded two hundred thousand. We attributed the high number of artists to the fact that it is now easier than ever to release new songs. Anyone can record and release a track without any intention of it being popular. In light of this, we reduced the number of artists by focusing on the most popular ones, as they will significantly influence the user network structure. Furthermore, since the artist's

Significance Statement

The results of this study will be beneficial to society since music is part of everyone's daily ritual. The need for song recommendations is growing as technology and music become more intertwined, and as more music is distributed to the users. Users who adopt the suggested strategy resulting from the study's findings will therefore have a better understanding of their own musical preferences. Users that share the music they are currently listening to will be guided on which artist, genres and moods they most emphasized with. Artists will be able to see how they are connected to one another based on their popularity from the users, how they collaborate, and how similar they are.

Author contributions

[1] Cristiana Lazar contributed to data cleaning and preprocessing, network generation, users' network analysis, and text analysis. Christian Bakos Leirvåg contributed to Spotify artist's network analysis. Wee Yang Sim contributed to the collaboration artist's network analysis and text analysis.

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popularity had a tail-heavy distribution, we chose our sampling threshold as the mean value of the artist's popularity, reducing the number to 22025. Ultimately, we let the nature of the artists' graph reduce the less important artists by extracting the largest connected component.

Due to computational limitations, we had to sample a subset of users. The initial number of 15267 users would have ended up in a very dense network that would be difficult to process since the dataset contains users listening to over two hundred thousand tracks. Therefore, we decide to keep around 90% of the users by removing the ones who listen to over 600 tracks. This decision has been made based on the assumption that if a user is listening to large numbers of various tracks, they cannot provide meaningful contributions to the community they are part of, and they might end up as link nodes between communities.

We base our findings on three networks. The first network is an artists' network based on artists' collaborations. Since we wanted to assess whether the sample on which the artist collaboration network was constructed reflects the real-world distribution and, consequently, whether the collaboration network is also real-world meaningful, we constructed a second artists network based on Spotify's related artists. The third network is the users' network, where the connections are made if users are listening to the same tracks.

Spotify Artist Network #1 (Links via collaboration).

Nodes and edges of the network. Each node represents a Spotify artist from the #nowplaying dataset. If there is a collaboration between two artists, we include an edge between the two nodes representing the artists. Hence, the network contains *4238* artists (nodes) and *9067* instances of artist collaborations (edges).

Density of the network. We observe that the density of the graph is very low at *0.001*, which tells us that artists don't necessarily collaborate as much as they could. This makes sense as an artist is likely to be selective with picking their collaborators as not all genres are able to mesh well with each other. The selective and intentional nature of collaboration would hence lead to a low artist network graph density.

Degree Distribution. Given the context, the degree of the nodes represents the number of collaborations an artist has with other artists. By examining the degree distribution (Figure 1a), we observe that most artists have few collaborations, around two, and a few exist with many collaborations, which might denote the presence of hubs. The artist's degrees also have a weak positive correlation with an artist's popularity. We cannot definitively determine whether one causes another, but one possible conclusion is that an artist that collaborates with other artists more (and has a higher degree) will have a higher popularity amongst fans as their songs would reach out to wider audiences.

The artist network's degree distribution obeys a power law. In other words, the artist network is a scale-free network. The power law coefficient we obtained from our analysis is about *3.60*. Hence, the artist network follows the small world rules since the degree exponent γ is greater than 3. Inherently, this tells us that the spread in terms of collaborations between artists is quantifiable and does not diverge. The average distance between the artists follows the small-world result that's derived for random networks. For scale-free networks where $\gamma > 3$, hubs continue to be present (as seen from some artists that have many collaborations). However, they are not sufficiently large and numerous to have a significant impact on the distance between the nodes. This means that the distances between each artist in the network are larger compared to another artist network with a smaller degree exponent γ.

Clustering Coefficient. The majority of the artists have a clustering coefficient between 0 and 0.2. This is likely due to most of the artists having a clustering coefficient of 0. This means that the collaborators of these artists are not linked to each other at all. On the contrary, we can see that there is a sizeable chunk of artists with clustering coefficients ranging from 0.8 - 1. This means that these artists are collaborating with other artists that are also likely to collaborate with each other. Node degree and clustering coefficient appear to have no correlation with each other. This means the artists that have a lot of collaborations are collaborating with artists that do not collaborate with each other. This is unsurprising as hubs (artists with lots of collaborations) may be linked to mostly nodes with low degrees (artists with a few collaborations).

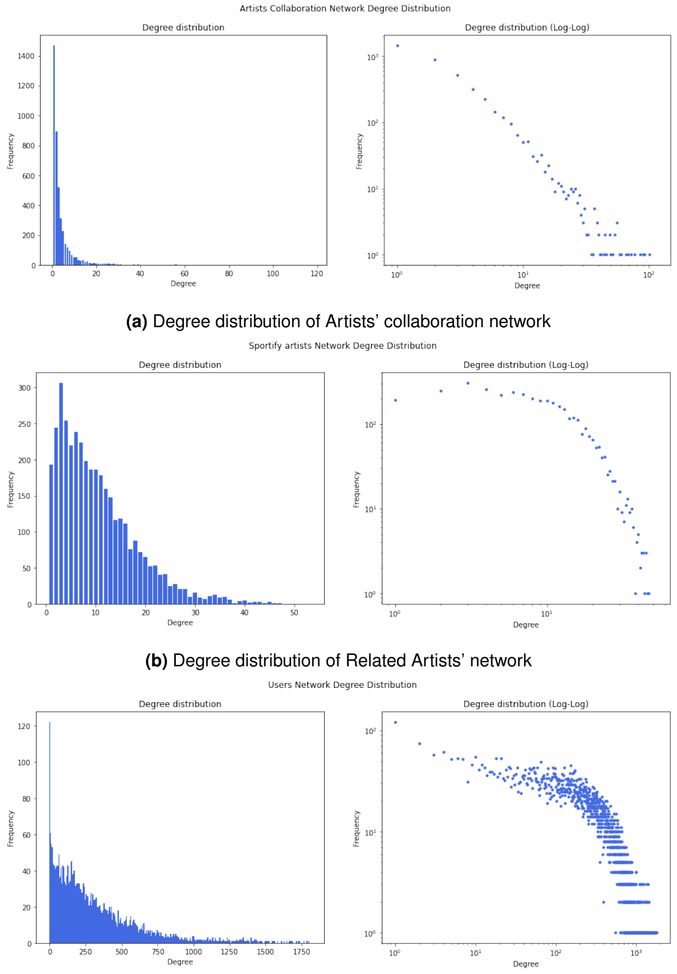
Centrality. We opt to use betweenness centrality as it determines the importance of artists based on the number of times they occur within the shortest paths between other nodes. The average betweenness centrality for the entire artist network is only*0.128%*. This means that most of the artists are not in the shortest paths between artists. This is expected given the large size of the scale-free network. Centrality is not correlated to degree distribution but has a weak positive correlation with the popularity of an artist. This is apt as a more popular artist would be more central and prominent amongst the shortest paths of other artists.

Spotify Artist Network #2 (Links via related artists).

Nodes and edges of the network. In contrast to the previous network, the *Spotify Artist Network 2* establishes links between artists based on their related artists we get from the *Spotipy API* call. By creating this network, we hope to supplement our understanding of the artists' communities by providing an alternative viewpoint. This network consists of 3778 nodes and 19524 edges.

Density of the network. An observation is that this network has significantly more edges than the network based on collaborations between the artists. This network has a density of *0.27%*, we can infer that the graph is not particularly dense. By having a higher density can we conclude that artists tend to be more related than collaborative with each other.

Degree distribution. Most artists have a degree equal to 3, in contrast with the first network, where the mode value of the degree distribution was 1, meaning that an artist would have more related artists than collaborations. As in the artists' collaboration network, the degree distribution (Figure 1b) follows the power law, with a power degree equal to 5.62, which will also place the network in the small world regime, like the first artists' network.



(a) Degree distribution of Artists' collaboration network

(b) Degree distribution of Related Artists' network

(c) Degree distribution of Users network

Fig. 1. The degree distribution of the networks plotted both on a linear scale (left) and a logarithmic scale (right). It might be noticed that all three networks' degree distribution follows a power-law distribution.

Clustering coefficient. The average clustering is around *0.40%*, can we draw the conclusion that artist's neighbours are not always related to each other. This implies some diversity among the artists in the communities. When examining each community's clustering coefficients we see that most communities have clustering coefficients in a range between *40% to 60%*. Overall are the communities sharing the same clustering, and there is also no significant correlation between the node degree and the clustering coefficient.

Centrality. The centrality of the network was measured by betweenness centrality. There is no correlation between centrality and degree distribution, which means that the number of related artists that an artist has will not influence their centrality. However, we discovered a slight positive correlation between the popularity and centrality of an artist. This means that an artist popular within the dataset tends to have a higher centrality. We see that the most central artists in the network are: *Amy Winehouse and Pharrell*, who are considered to be two fairly popular artists.

Spotify Users Network Analysis.

Nodes and edges of the network.. Each node represents a Spotify user from the #nowplaying dataset. Suppose two users are listening to the same tracks. In this case, we connect them by a link weighted with the sum of the inverse frequency of the tracks as we wanted to reduce the influence of the most popular tracks since a track that reached a notable position in a top chart can be listened to for biased considerations. The users' network consists of *13,130* nodes and *1,791,938* edges.

Density of the network. A density of 2% for our users' network's backbone indicates that there are very few connections among the users. In this case, we expect only the most meaningful connections were kept after the backbone extraction, resulting in a more meaningful conclusion about the users' network structure and the users' interactions.

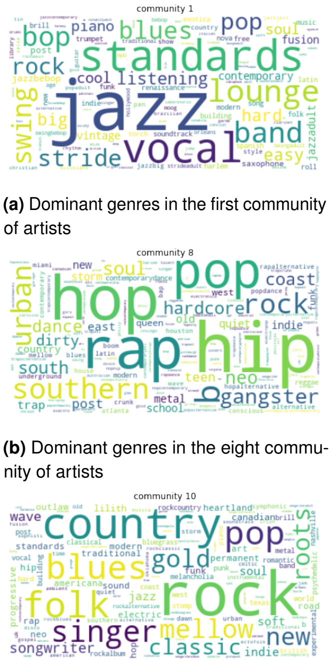
Degree distribution. In this network's case, the nodes' degree represents the number of tracks that a user has in common with other users. Analysing the degree distribution (Figure 1c), we observe that it follows the power law, with an exponent degree γ equal to 4.41, indicating that the users' network follows the small world's rules. An interesting observation about the users' network is that the degree distribution positively correlates with the number of tracks a user listens to. This observation is not surprising since we expect a user listening to a higher number of tracks to have a higher probability of having more in common with other users.

Clustering coefficient. The average clustering coefficient has a relatively low value, only 22.5%, which means that the neighbours of a user do not necessarily share the same tracks or, to a certain extent, the same music tastes. With this observation, we expect a higher diversity of artists and music genres in users' communities.

Centrality. As a centrality measure, we have used eigenvector centrality since we are interested in measuring the user's influence on the network by the music they are listening to. In our analysis, we discover that centrality is strongly positively correlated with the degree and also with the number of tracks a user listens to. This means that a user is more influential, the more he is connected to other users and the more songs he listens to.

A. Findings and Testing of hypotheses.

Artists with similar music genres should form communities.. We would expect artists that perform music of similar genres to form communities. Intuitively, this makes sense as artists within the same genre can collaborate on new songs easily. To investigate this, we plotted the genre word clouds of different communities within the artist network. If we could identify underlying themes in the genres of each community, it would validate our hypothesis. Our results show that each community had artists that were *distinctly* of several related genres. For example, community 10 (Figure 3c) was undoubtedly an old-school rock, country and folk community. On the other hand, community 1 3a had jazz-oriented artists, with words like 'jazz', 'standards' and 'swing' being prominent throughout the community's artist genres. As such, we can say, with high confidence, that artists are generally grouped together according to the genres of their music.

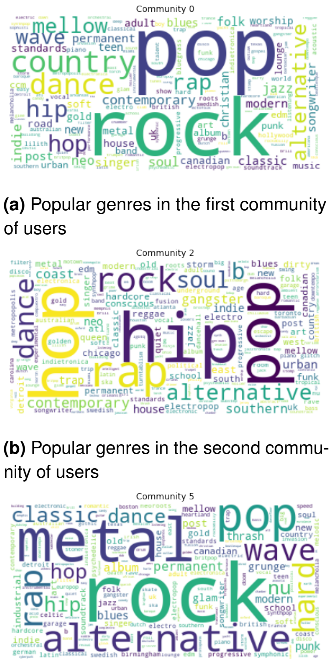


(a) Dominant genres in the first community of artists

(b) Dominant genres in the eight community of artists

(c) Dominant genres in the tenth community of artists

Fig. 2. A subset of communities from collaboration artists' network where the dominant genres are displayed in the form of a wordcloud. (a) community of jazz-oriented artists (b) community of hip-hop-oriented artists (c) community of rock-oriented artists



(a) Popular genres in the first community of users

(b) Popular genres in the second community of users

(c) Popular genres in the fifth community of users

Fig. 3. A subset of communities from users' network where the popular genres are displayed in the form of a wordcloud. (a) community of pop-rock-oriented users (b) community of hip-hop-oriented users (c) community of rock-metal-oriented users

Users with similar preferences should form communities. A common expectation for the users' network is that users with similar musical tastes cluster. We validated this hypothesis in two different ways. Firstly, we computed the average percentage of a user's tracks that are also listened to by other users in the same community. The results show that in the majority of communities, in the case of more than 50% of users, over 80% of their songs are listened to by other users from the same community. The hypothesis also was validated by computing wordclouds which emphasise the most dominant genres in a user's community. Since an artist can belong to multiple genres was expected that a genre is repeated in the genres' wordclouds. However, we can distinguish the difference between communities, which means that users are grouped according to musical preferences.

The user's network would be impacted by the communities from the artist's network. By creating a wordcloud for the most popular artists in the user's communities, we could potentiallydetermine whether the artists' communities affect what the users listen to. This is done by comparing the wordcloud from the users' network to the wordcloud with the most popular artists in the artists' communities. Considering that we have two different networks for artists we compared the wordcloud of popular artists in the user's communities with both networks. By inspecting the figure 4 we concluded that a significant number of artists belonging to the same community are found among the artists listened to in a community of users. This means users from the same community tend to listen to artists who collaborate or are related (since we found this pattern in both artists' networks). Currently, it is difficult to say if the listeners influence how artists collaborate or if the artists' collaborations impact how listeners gather together. On the other hand, Spotify computes the related artists based on the community's listening history, which means that, in this case, the users' preferences could influence whether the two artists are related. However, the conclusion is unmistakable, the network of artists reflects the network of users and vice versa.

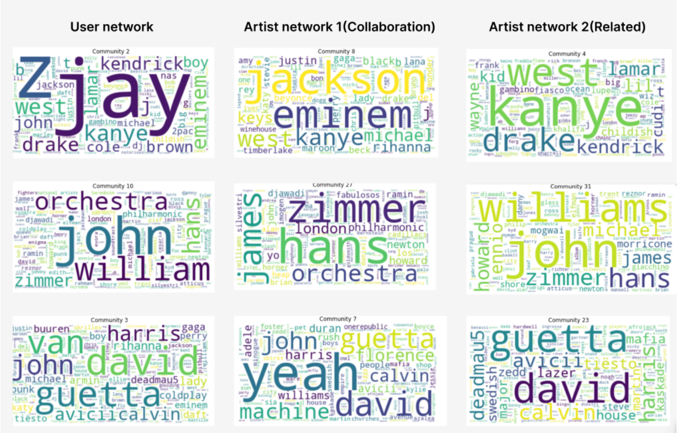


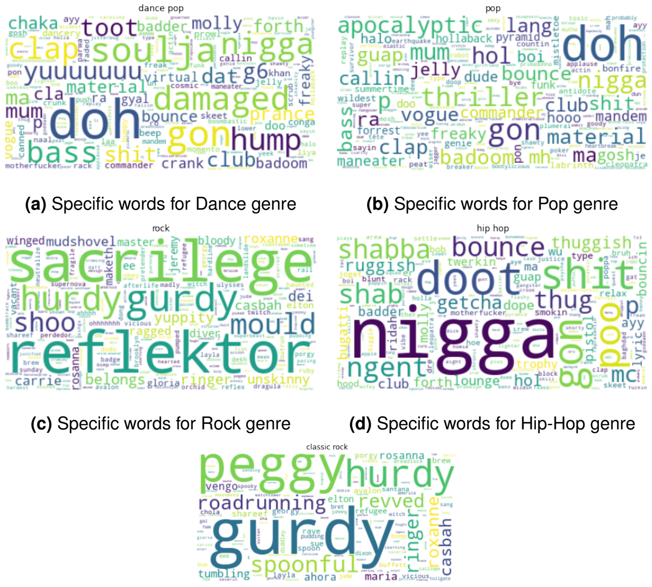
Fig. 4. Wordclouds over popular artists in the communities. The user network is shown in column 1, the collaborative artist network is represented in column 2, and the related artists' network is represented in column 3. Communities, where they share similar artists, can be found in the rows.

The words specific to each genre. Considering the TF-IDF method used to find each gender-specific word amonst the most frequent genres in our dataset, we can see that Dance-Pop (Figure 5a) and Pop (Figure 5b) share a significant number of words such as "clap", "club", "bass", which emphasises the similarity of the two, Hip-Hop (Figure 5d) seems to be the best depicted one, using a large number of swearing and jargon words used to describe the thug-like nature and Rock (Figure 5c) and Classic Rock (Figure 5e) which address a larger pallet of themes are not necessarily defined by specific words.

The sentiment value by genres. We discovered that the sentiment scores for each of the five most frequent genres appear to be similar. The rarity of words may have contributed to this outcome. As we saw in the lyrics word clouds for each genre, the showed words tend to be rare, and they might not be found in the LabMT dataset (which was used for computing the sentiment for each track). However, more negative sentiments can be associated with Hip-Hop which may be anticipated since we can notice words like "pistol", which have a negative association in its lyrics' wordcloud.

Discussion

In the course of our investigation, we encountered certain limitations. Firstly, We had issues extracting all the unique artists from the given string due to the diverse different expressions for an artist to indicate collaboration with another artist. We used a complex RegEx pattern to detect as many mainstream ways as possible, 'featuring', 'with', 'and', and



(a) Specific words for Dance genre

(b) Specific words for Pop genre

(c) Specific words for Rock genre

(d) Specific words for Hip-Hop genre

(e) Specific words for Clasic Rock genre

Fig. 5. Wordclouds which depict the most significant words for each most frequent genres in our dataset

so on. However, this has led to a few shortcomings in terms of the artists extracted, which may end with a network not fully representative of the real world. Another issue was that some of the 'artists' extracted were not artists. For example, 'His Orchestra' refers to a specific artist's Orchestra, not a stand-alone artist. This is an artefact from our approach to extracting collaborations from tweets. However, the same confusion was made by Spotify since it considers His Orchestra as an artist, but on a closer look, all the songs in the playlist are played by an established artist and his Orchestra.

On the other hand, it was challenging to sample the dataset to generate graphs that could generalize to real-world trends and behaviours, given our limited computational resources. Therefore, we applied multiple layers of sampling, from using a threshold to extracting the largest connected component or the backbone from a graph.

A future extension of our project may include a recommendation system based on community detection, where tracks, artists and genres could be recommended since we discovered that users in a community tend to have similar tastes.

Methods

The explainer notebook can be found at https://github.com/bakos97/Final-project-Social-Graphs/blob/chris/notebooks/Explainer_Notebook.ipynb

The project repository can be found at https://github.com/bakos97/Final-project-Social-Graphs

Disparity filter. To reduce the density of users' networks, we extracted the backbone using the disparity filter approach, which has been discussed in Extracting the multiscale backbone of complex weighted networks (2). The disparity filter is a way to identify which connections in a network should be preserved. It removes the weakest ones based on a user-defined threshold value. The process is iterative and continues until only the strongest connections remain - the network's backbone.

Louvain's Algorithm. Louvain's algorithm is a popular choice for partitioning communities in a network because it is fast and effective at identifying relatively clear and distinct communities within a network. The algorithm works by iteratively optimizing this measure, starting with each node in its own community and then merging and splitting communities in a way that maximizes modularity. This is useful for a variety of applications, such as identifying groups of users in a social network or understanding how different parts of a complex system are connected.

Given that our network was essentially a social network of artists and users bound together by the music they listened to, we found Louvain's algorithm apt for our use case. We did consider other community detection algorithms like hierarchical clustering algorithm and Girvan-Newman algorithm. However, those algorithms tend to be computationally expensive, especially for large networks with many nodes and edges. We are working with large networks of many nodes, so we decided to prioritize computational efficiency when choosing the algorithm.

Betweenness centrality. Betweenness centrality is a centrality measure that is used in network analysis to identify the importance of a node in a network. This measure is calculated by determining the number of times a node lies on the shortest path between two other nodes in the network. Nodes with a high betweenness centrality are considered to be important because they have the potential to control the flow of information or resources between other nodes in the network.

In the context of our Spotify networks, betweenness centrality could be used to identify the most important users or artists in terms of their ability to connect different listeners or music genres. For example, an artist with a high betweenness centrality in our artist network may be considered a "bridge" between different musical genres or listener demographics, and could be used by the company to recommend music to users or to tailor its algorithms for personalized playlists. Additionally, identifying artists with high betweenness centrality in a Spotify network could be useful for understanding the overall structure and dynamics of the network, and could provide insight into how different musical genres or listeners are connected.

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