Unveiling Spotify’s Playlist Dynamics

***Abstract*—In this work we studied a variety of prior research conducted within the domain of music recommendation network analysis. Utilising community detection algorithms pointed out within prior research such as Louvain Method allowed for the analysis of song attributes revealing how these factors influence recommendations addressing any prominent challenges in algorithm transparency. Examining patterns of song co-occurrence and clusters enables the uncovering of any biases empowering users with an enlightened understanding of their music consumption, potentially improving the user experience of streaming services.**

# Introduction

Music streaming platforms such as Spotify, Deezer, and Apple Music have transformed the way we access and enjoy music. However, the opaque nature of the recommendation algorithms that power these platforms often leaves users puzzled about the criteria for music selection. Addressing this lack of transparency in AI-driven platforms is essential to fostering a greater understanding and trust among users (Born et al., 2021).

Playlist continuation is a critical feature of these services, which extends beyond simply offering a vast catalogue of music. This aspect of the recommender system is designed to suggest tracks that not only align with, but also enhance the user's existing playlist, ensuring a coherent and enjoyable musical experience. Therefore, a deep understanding of the contextual and musical attributes that influence playlist recommendations is paramount in delivering relevant and engaging content.

## Research problem and motivation

The primary research problem focuses on the lack of transparency in playlist recommendation algorithms, leaving users uninformed about how music content is selected. Motivated by the need to address this concern, our study seeks to uncover the attributes and patterns shaping playlist dynamics. By understanding these factors, we aim to empower users to make informed decisions about their music consumption and enhance the overall user experience on music streaming platforms**.** By using community detection algorithms such as Louvain Method ‌(Jain et al., 2021) and analysing the distribution of key attributes like popularity, energy, danceability of each community, we aim to analyse the relationships/ correlations between these attributes and its effects on the songs that are recommended to users, answering question such as; ‘what attributes have the most weight in song recommendation?’, ‘how are these attributes used in order to generate song recommendations to users?’, ‘what biases may the song recommendation system have to certain attributes?, i.e. songs with popularity and danceability being promoted more’.

## Challenges to address

Several challenges must be overcome to achieve the objectives of this research. Firstly, the complexity of recommendation algorithms makes it challenging to dissect the factors influencing playlist recommendations. Additionally, the sheer volume of data within music streaming platforms necessitates robust methodologies for analysis. Moreover, the scalability and generalisability of findings across different platforms and user preferences presents further challenges. We also need to overcome the challenges related to research, looking into the challenges of music recommendation systems by (Velankar and Kulkarni, 2022) highlights the issues of data in-availability, overspecialisation and unreliable metadata which are all factors which can affect the reliability of our results. Furthermore, music recommendation systems face the challenges of personal emotions, as each person may react to songs differently (Assuncao, Piccolo and Zaina, 2022). Despite these obstacles, addressing these challenges is crucial for promoting transparency and accountability in playlist recommendation systems. To address the issue of data in-availability, we intend to take the approach of work done by (Scarratt RJ), through making use of a Spotify API to access a broader dataset for analysis. We aim to tackle the issues of overspecialisation through analysis of a range of different music features to get a full picture of the current processes.

# RELATED WORK

## Music Attributes

Much work has been conducted within the domain of analysing music attributes, regarding music recommendation. In particular research done by (Ochi et al., 2021) explores this domain by analysing features of songs such as the danceability, and popularity of songs and the relationship between these attributes and how songs with high scores in these aspects i.e. a song that is very danceable, has high energy and high popularity may be ranked against other songs that may have high scores in other aspects such as the BPM (beats per minute), energy and valence. Further related work done by (Duman et al., 2022), examined the impact that attributes such as energy, danceability, tempo have on music recommendation. The study employed a network centric approach, by extracting audio attributes from dance music using a Spotify API and comparing their findings to a baseline dataset, they found that the dance music had higher levels of energy, danceability, valence and loudness.

However, the limitations of (Duman et al., 2022) approach are found particularly in the sample size and the lack of data for contextual listening experiences. Since data for this study was collected as part of a much larger survey the details about the specific listening situations of the user are not obtained with the study suggesting that future iterations considering the mood, energy level and specific habits would allow for a better understanding of how often people listen to music from certain subgroups. The lack of data on the contextual listening experience of users suggests a more nuanced network analysis injecting user preference. Since this study investigated the particular reasons associated with songs that people moved to requiring a questionnaire limiting the amount of data for dance music. This only provided a snapshot of the network dynamics and a more comprehensive understanding of how these attributes for clusters and sub-communities within a larger network of genres remain undeveloped. Previous studies (Scarratt RJ, 2021) collected data solely for Spotify and thus were able to gather substantial amounts of data, similar to our project, thus the issue of data in-availability will not be as much of a limitation compared to this related study. Comparatively our project seeks in expanding this approach by constructing and analysing a song co-occurrence network mapping the relationship between song attributes across a wide variety of genres. We intend to address the apparent data limitations encountered in prior studies by adapting a broader data set akin to (Scarratt RJ, 2021) Spotify centric study.

## Algorithms for Customisable Reccomendations

The article "Recommendation Algorithm for Spotify Users: Exploring the Quest for New Music" (Curtis, 2022) investigates the nuanced process of utilising song attributes to provide personalised music recommendations. Curtis's research aims to bridge the gap between user preferences and algorithmic suggestions. This study implements the use of the K-Means clustering algorithm, supplemented by experiments with diverse data types—including numeric, and ordinal.

Curtis takes a user-centric strategy through the use of user input, seeking to refine the personalisation of recommendations to better align with individual preferences, thereby enhancing the overall user experience. Preliminary results from a controlled experiment, which utilised assorted music playlists and active participant involvement, indicate a potential increase in user satisfaction through this bespoke method.

The study acknowledges certain constraints, notably the reliance on Spotify's API, which limits the breadth of data available for analysis and thereby impacts the algorithm's depth of insight. A particular shortfall noted is the lack of song language data, highlighting its potential importance in fine-tuning music recommendations. Additionally, the research points to the challenge of accurately capturing a user's musical preferences solely through their saved tracks and listening history, suggesting a fertile ground for further investigation. This exploration into customizable algorithms links with our project's aim to scrutinise the mechanics of music recommendation systems, emphasising the critical role of user input in the evolution of personalised music discovery.

## Community Detection

Many studies have undergone research when understanding the structure of music recommendation systems. Network analysis methods have shown to be very valuable in this regard, injecting techniques such as centrality measures [12][13] or community detection algorithms [14], to identify some of the influential songs and community detections algorithms in order to find out some of the underlying structures in the network of song interactions.

The study titled “Personalised Recommendation System using Community detection and Markov model” (A personalised Next-Song recommendation system using community detection and Markov model, 2017b), (PRCM) makes use of community detection with Markov chain framework in order to refine the music recommendation systems. The approach entails mapping user networks on the basis of interactions with songs and in order to differentiate communities that have similar tastes. It also utilised historical data to personalise the sequence of prediction through calculating community-based transition matrices, and PRCM adapting to both the long-standing preferences and the changes in user behaviour to enhance the precision of recommendations. However, the PRCM has several challenges relating to the short-term and long-term behavioural changes, accurately detecting the user communities that have shared music tastes and integrating these components into a Markov model. This work aligns with our project to understand the dynamics in playlist creation and focusing on the networked relationships of song attributes.

# DATASET AND NETWORK PRESENTATION

The dataset used for network construction is sourced from the Million Playlist Dataset Remastered, available on Spotify's research platform. Random playlists from this dataset were selected, excluding those with too few songs (e.g., 2-5 tracks). This approach ensures a meaningful representation of song co-occurrences within playlists, offering insights into music consumption behaviour and playlist dynamics on music streaming platforms. The data then was used to an undirected graph representing a co-occurrence network of songs in different Spotify playlists. In the network the nodes represent the songs, the edges represent the co-occurrence relationships between the songs in playlists. The weight of the edges is the number of times two songs have appeared together in playlists and the edges also have a list of playlist IDs where the two songs have co-occurred. We had a large and a smaller dataset(subset) shown in table 1. You can see the network visualisation for the larger dataset in Figure 1. The dataset of songs' co-occurrence within Spotify playlists addresses the research problem of playlist recommendation algorithms as we can use the dataset to start analysing the patterns and attributes shaping playlist dynamics, this data shows the associations between songs, thereby enhancing our understanding of Spotify's playlist dynamics.

**Network Terminology:**

* **Nodes:** The number of nodes (or vertices) in the network, representing individual elements.
* **Edges:** The number of edges (or links) connecting pairs of modes in the network.
* **Average Clustering Coefficient:** Measures the degree to which nodes in the network cluster together.
* **Average Degree:** represents the average number of edges connected to each node in the network.
* **Betweenness Centrality**: Measures the extent to which a node lies on the shortest paths between other nodes in the network.
* **Closeness Centrality:** Measures the average distance from a node to all other nodes in the network.
* A colorful brushstrokes on a white background

  Description automatically generated**Eigenvector Centrality:** Assigns relative scores to nodes based on the concept that connections to high-scoring nodes contribute more to the node's score.

Figure 1 - Larger Network Visualisation in Gephi

|  |  |  |
| --- | --- | --- |
| Networks Statistics | Smaller Network | Larger Network |
| Number of Nodes | 537 | 2767 |
| Number of Edges | 7715 | 229384 |
| Average Clustering Coefficient | 0.935 | 0.582 |
| Average Degree | 28.734 | 165.8 |
| Betweenness Centrality | 0.004 | 0.467 |
| Closeness Centrality | 0.310 | 0.0004 |
| Eigenvector Centrality | 0.0179 | 0.0142 |

Table 1 - Network Statistics

Using Gephi we calculated the different network statistics from the smaller and larger network, and we used the statistics we had calculated and compared them both. Comparing the small and large graphs shows differences in their structural properties and connectivity patterns. The small graph has more denser clustering and higher average degree, indicating stronger communities and more interconnected nodes. However, the large graph demonstrates a lower average clustering coefficient and average degree, suggesting a more spread out and less densely connected network. Additionally, centrality measures such as betweenness, eigenvector, and degree centrality show variations between the two graphs, indicating differences in the presence of influential nodes and overall network structure. These findings have implications for understanding the structural properties and dynamics of co-occurrence networks of songs, which can inform further analysis and modelling of the playlist dynamics. By analysing the structural properties of these co-occurrence networks, we can gain insights into the underlying dynamics of playlist construction, which are contributing to the recommendation system.

# Network Analysis & methodology

Our objective is to carry out analysis of the song co-occurrence network by using additional attribute information obtained from the Spotify API. The methodology involves several key steps. Firstly, we utilise the Louvain community detection algorithm to partition the network into distinct communities based on connectivity patterns. This allows us to identify similar groups of songs that frequently co-occur in playlists, revealing underlying structural patterns within the network. Subsequently, we further conduct our analysis by computing a network metric, in this case we choose betweenness centrality and eigenvector centrality. The betweenness centrality highlights nodes that act as bridges or intermediaries between different parts of the network (clusters), which could be crucial for understanding network dynamics and identifying influential nodes. Eigenvector centrality highlights songs that are not only frequently featured in playlists but also commonly appear alongside other highly featured songs, indicating their importance and influence. Additionally, we analyse attribute information, including danceability and popularity, for nodes within communities to identify any patterns or clusters based on these attributes. We then compare them with the metrics calculated within each community. This enables us to explore the relationship between song attributes and network connectivity, focusing on what musical characteristics contribute to playlist dynamics. Therefore, songs that have a high betweenness centrality may bridge communities due to the characteristics within both while songs that have a higher eigen vector suggests a higher popularity community sharing attributes such as high energy in the dance music genre. This analysis will provide us insight into how songs with specific attributes connect with different communities, providing us a foundation on how we can improve music recommendation systems through suggesting songs that align closely with user’s preferences and explore genre connections. In addition, this shed light on the structure of music consumption showing how different genres connect and the driving force of song popularity within those genres. Finally, we calculate the top 3 songs that have a high betweenness centrality and eigenvector centrality, doing so will pinpoint some of the influential songs within the network. We can then further investigate attributes of each of these tracks and understand what common attributes of songs tend to bridge different communities that have a high betweenness centrality. Deep diving into the attributes of these key songs may reveal specific characteristics that may contribute to the bridging of communities i.e. high betweenness or the most influential songs in the community i.e. high eigen vector. Thus, uncovering patterns like highly consistent influential songs in a dance music community.

# Results & Discussion

In this section, we discuss the findings from our network analysis of song co-occurrence within Spotify playlists. Our investigation started in the application of the Louvain community detection algorithm, alongside the calculation of betweenness and eigenvector centrality measures, to reveal the dynamics in playlists and song interactions. By integrating these network metrics with song attributes; specifically, danceability, energy, and popularity using the Spotify API, we aim to uncover patterns that show the characteristics of songs that play different roles within the network. Our analysis not only identifies songs that serve as bridges across diverse music playlists but also highlights those that have influence within their communities. This exploration allows us to better understand the underlying factors that guide the algorithmic recommendations on Spotify, offering insights into how certain attributes may affect a song's presence within playlists.

##### A graph of a bar graph Description automatically generated with medium confidence

Figure 5 - Popularity Distribution

Figure 2 - Average Betweenness Centrality

##### A diagram of a danceability distribution Description automatically generated

Figure 3 - Danceability Distribution

A graph of green bars

Description automatically generated

Figure 4 - Average Eigenvector Centrality

A graph of different colored lines

Description automatically generated

The Average Betweenness Centrality Graph shows the average betweenness centrality for six different communities within the network. Communities with higher average betweenness centrality, like the one represented by the third bar (Community 2), may be considered as crucial connectors within the network. On the other hand, communities with lower betweenness centrality, such as the first bar (Community 0), may have songs that are more niche or less central in connecting diverse parts of the network. In the eigenvector centrality graph, we see significant variation in how communities rank in terms of their songs' influence within the network. High eigenvector centrality, as shown by the tallest bar (Community 0), indicates a community where songs are likely influential among each other. The danceability distribution graph illustrates the variation in the attribute of danceability across the same six communities. Each community has a different distribution curve, suggesting that some communities have a selection of songs that are consistently more danceable than others. For example, community 4 represented by the red curve seems to peak at higher danceability scores, indicating a cluster of songs with high danceability. The popularity distribution curves for each community indicate how songs' popularity (Mesnage *et al.*, 2011) varies within them. The peaks of these curves show that each community has a different central tendency in terms of popularity, and the width of the curves illustrates the diversity within each community. Some communities have a broader distribution of popularity, suggesting a mix of both high and low popularity songs, while others are more narrowly distributed.

## Discussion of Findings

Now we investigate using a combined analysis, we can see that community 2 has a high danceability distribution we can see that community 2 has the highest average betweenness centrality score but the lowest eigenvector centrality score. This suggests that while these songs are often used to connect different songs within playlists (acting as bridges), they are not central nodes. This indicates that they might be popular and versatile choices for diverse playlists but are not the most influential songs within any specific music community. Community 0's high average eigenvector centrality and one of the lowest betweenness centrality, paired with a high peak in danceability, suggest that this community contains songs that are particularly influential within their own group and are highly danceable, yet they may not serve as broad connectors between different musical communities. We can see that the two centrality measures show communities with high eigenvector centrality tend to have a low betweenness centrality and vice versa.  Community 4 has a very high popularity distribution but one of the lowest danceability distributions. It has a fairly low average betweenness and eigenvector centrality which suggests that while these songs are widely known and possibly commercially successful, they are less likely to be bridges between other playlists or popular within that community. This could be the case as community 4 may have a group of popular songs within a specific genre that resides with listeners for reasons other than danceability. Thus, they may be individually successful but may not have strong connections within the network.

Now we are going to further investigate community 2 as it has the highest average betweenness centrality. From that community we can get top 3 songs with the highest betweenness centrality and the top 3 songs with the average highest eigenvector centrality. However, community 2 on average has the lowest eigenvector centrality scores compared to others.

|  |  |  |  |
| --- | --- | --- | --- |
| Average Betweenness Centrality Ranking (Community 2) | Name of Song | Genres | Energy |
| 1 | Chicken Fried - Zac Brown Band | Contemporary Country | 0.713 |
| 2 | This Is How We Roll - Florida Georgia | Contemporary Country | 0.931 |
| 3 | Wanted - Hunter Hayes | Contemporary Country | 0.476 |

|  |  |  |  |
| --- | --- | --- | --- |
| Highest Average Eigenvector Centrality Ranking (Community 2) | Name of song | Genres | Energy |
| 1 | House Party- Sam Hunt | Contemporary Country | 0.853 |
| 2 | Wanted - Hunter Hayes | Contemporary Country | 0.476 |
| 3 | Take your time - Sam Hunt | Contemporary Country | 0.723 |

Table 2 - Average Betweenness Centrality Ranking (Community 2)

Table 3 - Highest Average Eigenvector Centrality Ranking (Community 2)

The results on table 2 and 3 show the top 3 songs with the highest average betweenness centrality and the lowest eigenvector centrality are all contemporary country songs; it shows a possible aspect of playlist recommendation systems. The high betweenness centrality signifies these tracks' role as bridges in the musical network, facilitating connections across diverse listening preferences through the contemporary country genre. This bridging function suggests that despite their niche appeal within their immediate community as indicated by low eigenvector centrality these songs are important in linking different genres shown by a high betweenness centrality. The exclusive presence of contemporary country music within this community underscores a strong genre-specific identity, potentially reflecting both user preferences for genre diversity and the algorithms' strategies in curating personalised music experiences. This subtle correlation between song centrality and genre highlights the mechanisms behind music recommendations, where certain tracks emerge as bridges across playlists. We also investigated the energy of each track however they were all at different levels. This randomness in energy levels within a specific genre-focused community suggests that the recommendation algorithms prioritise connectivity over consistency in song attributes like energy.

Now we are going to further investigate community 0 as it has the lowest average betweenness centrality compared to other communities. From that community we can get top 3 songs with the highest betweenness centrality and the top 3 songs with the average highest eigenvector centrality. However, community 2 on average has the highest eigenvector centrality scores compared to others.

|  |  |  |  |
| --- | --- | --- | --- |
| Average Betweenness Centrality Ranking (Community 0) | Name of Song | Genres | Energy |
| 1 | Gold Digger - Kanye West | Hip hop | 0.696 |
| 2 | Tennessee Whiskey - Chris Stapleton | Contemporary Country | 0.37 |
| 3 | One Dance - Drake | Hip hop | 0.619 |

Table 4 - Average Betweenness Centrality Ranking (Community 0)

|  |  |  |  |
| --- | --- | --- | --- |
| Average Eigenvector Centrality Ranking (Community 0) | Name of song | Genres | Energy |
| 1 | In Paris - Jay Z | Hip hop | 0.882 |
| 2 | One Dance - Drake | Hip hop | 0.619 |
| 3 | Trap Queen- Fetty Wap | Hip hop | 0.873 |

Table 5 - Average Eigenvector Centrality Ranking (Community 0)

The songs with the highest betweenness centrality in Community 0 ("Gold Digger," "Tennessee Whiskey," "One Dance") act as bridges within the network to other communities, facilitating connections between different clusters or musical genres. Despite having the lowest average betweenness centrality compared to other communities, these songs play a crucial role in linking diverse musical tastes, which might not directly reflect their popularity but rather their connectivity within the playlist network. We can see that the contemporary country genre is still one of the genres that act as a bridge even in a community with low average betweenness centrality further strengthening our results as discussed in community 2. In contrast, the high eigenvector centrality scores for songs like "In Paris," "One Dance," and "Trap Queen" suggest these tracks are not only popular within their community but also frequently appear alongside other popular songs. This indicates a strong influence within their immediate network, highlighting their central role in shaping the listening habits within Community 0. Looking at the energy levels in table 4 we can see that they vary however we can see on both tables 4 and 5 hip hop songs tend to have high energy levels especially in a community with high connectivity and influence as shown by a high eigenvector centrality.

Limitations

Considering the scale and complexity of Spotify's entire network, the use of the Million Playlist Dataset Remastered for investigating playlist dynamics, while comprehensive, introduces certain limitations. First, the dataset, although large, represents only a subset of Spotify's global user interactions, potentially missing a large number of listening patterns and emerging trends outside its reach. This limitation suggests that findings might not fully capture the diverse music consumption on the platform. Second, the study's focus on quantifiable attributes like danceability, energy, and genre might not account for the subjective and contextual factors influencing music preference, such as mood or personal experiences, which are challenging to quantify but crucial for understanding user behaviour. Lastly, the dynamic aspect of music trends and user preferences over time is another area that this dataset cannot fully address as it offers a static snapshot of playlist compositions, thus limiting the ability to track changes in listening habits or the impact of new music releases. Together, these limitations underscore the importance of continuous data collection and analysis to refine our understanding of Spotify's recommendation system.

# Conclusion & Perspectives

The study addresses the unclear workings of Spotify's playlist recommendations through network analysis and community detection, examining song connections and attributes to reveal how songs are recommended.

The analysis uncovers that certain songs link diverse musical tastes due to features like danceability and genre, pointing out genre biases and the importance of song connections over popularity in the recommendation process.

It highlights the need for more transparent algorithms to increase user trust and satisfaction, suggesting future research on factors like lyrics and overcoming data challenges for improved recommendations.

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