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MFCSNet: A Musician–Follower Complex Social Network for Measuring Musical Influence

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ABSTRACT

Music, a significant and exquisite part of human culture, owns abundant features and enjoys a long-standing history. Music evolves in society over time, while artists' music gets influenced by personal experiences, external events, and inspirations from predecessors. In this paper, we propose a model named MFCSNet that measures musical influence by utilizing the data sets of musical characteristics and links between music influencers and followers. MFCSNet applies multiple indicators and has more analysis perspectives, and well reflects the influence of different kinds of music in various fields. Firstly, we analyze the influencer–follower relations by looking at the network of musical influence, observing the correlation between followers and influencers, and closely examining several sub-networks extracted from the entire network. Secondly, we propose measures that quantify the similarities within and between musical genres, using musical characteristics, such as danceability, energy, and valence, in order to measure the influence between artists and find the more influential characteristics. Furthermore, we apply MFCSNet on the whole timeline to analyze the evolutions and revolutions of music through time, with the goal of revealing the relation between music and culture, society, politics, and technologies.

1. Introduction

Humans have created many kinds of music, and it has continuously evolved and developed over time. This evolution and development are inseparable from the exchange and inheritance between artists. How to analyze the relationship between the artist's communication and the artist's musical influence has become a complex issue [1,2]. With the advent of data mining (DM) and machine learning (ML), many researchers have begun to use learning-based methods to analyze the influence of some entertainment fields such as music [3–7], video [8–10], interactive entertainment [11–13] and social media [14–17]. Those methods also have been applied in console [18–20], internet [21,22], and computer [23,24] games. For example, the Quest Pro recently released by Meta Company can introduce human actions based on human gestures through machine learning. It can also deduce the movement of the lower body according to the movement of the upper body of the person. These techniques have also been successfully used in the development of music-related software. For example, Spotify, which is now a big hit in Europe, the US, and Japan, analyses users' listening behavior to analyze their preferences and is supported by major record companies around the world, including Warner Music Group and Sony Music Entertainment. After analyzing the user's preferences, it suggests music to the user, a feature that makes it stand out from the crowd of music players. The study of the impact of music on people through modern technology has far-reaching implications and great significance. However, current methods for analyzing music features and musical influence have the following problems, and our motivation is to solve these issues.

- Many previous approaches have considered only a single indicator, but the musical influence is also affected by other indicators and they cannot be ignored.

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- Previous research measuring musical influence through modern data mining methods and machine learning algorithms is scarce, most of them aim to just analyze the characteristics of each music genre.

To ameliorate the aforementioned issues, we proposed MFCSNet. In our research, we combine network science and machine learning and carry out detailed analysis and mining of the evolution of music and its influence through various approaches. Moreover, music development is a time-based evolution, so the artist network is also a dynamic network. We categorized multiple attributes as indicators to be the parameters of the network, which are related to multiple factors including genres and artists in the dynamic network for analysis. For the evolution of the genre [25], we selected the popularity and the number of the communities of the network as the indicators. Furthermore, for the changes of artists, we selected average degree, average path length, and average cluster coefficient as the corresponding indicators. Finally, we integrated different indicators to reflect the changing process of the network more comprehensively and selected several big events that happened in human history such as the Great Depression, the Petrillo Ban, the development of electrical technology, and the booming of pop music to show that how the effects of changes in society, governance and innovation are identified within the network.

The main contribution of MFCSNet is threefold:

- We introduced a novel complex social network named MFCSNet, which analyzes scaling properties and establishes the relationship between music features and genres with dimension-reduction techniques and clustering algorithms.
- We proposed a novel method to measure similarity by combining Jaccard similarity coefficient and cluster analysis. We also proposed a novel algorithm adopting community-finding related algorithms and ML-based methods to conduct characteristic contagiousness analysis to measure the influence between artists and explore influential features.
- Through modeling and experiment, MFCSNet can precisely detect the characteristics of artist networks such as small-world effects and a scale-free network. MFCSNet also can keenly discover the connotation of music revolution and revolutionary artists by using anomaly detection and key node detection.

This paper is organized as follows. Section 2 analyzes and discusses the relevant research of musical analysis with its advantages and disadvantages. Section 3 describes the datasets used and the assumptions made to conduct experiments. Section 4 describes AMDCNet in detail and conducts experiments. Section 5 concludes this paper with future work.

2. Related works

2.1. Musical influence on human beings and other fields

In recent years, much research has been conducted on the influence of music on artists, as well as its relation to the external environment, and numerous relevant academic articles have been written. Franěk et al. [26] performed experiments to explore the influence of music on the perception of urban environments for young adults, and they suggested that the intensity of music could play a fundamental role. From qualitative perspectives, Buraga and Dospinescu [27] found a significant influence of music on students' cognitive abilities in various contexts, using human–computer interaction (HCI) methodology and semantic Web techniques. From quantitative perspectives, Liu et al. [28] proposed an evaluation model based on TOPSIS and defined the influence of music as the combination of the number of fans and the number of fans of the same genre as the influencer. Qin et al. [29] proposed the Spatial–Temporal Music Influence model based on Deepwalk and cosine similarity algorithm to analyze the influences among musicians. In addition, they proposed a musical similarity model based on principal component analysis and Euclidean distance. They used both models to predict trends in musical genres. The influence of music on human beings has also been supported and further confirmed by a large amount of research and those findings were even employed in clinical applications. For instance, while O'steen et al. [30] 's randomized controlled trial did not advocate that music relieved so much anxiety for women receiving radiation therapy for cancer, Herff et al. [31] stressed that music has the capability to aid therapeutic procedures associated with heart and brain operations. Kumarasinghe et al. [32], for example, explored the synchronicity of brain and heart exhibiting distinct responses to various auditory stimuli, suggesting that music is important for organ activation. The influence of music on the quality of human life has also become one of the topics. Gómez-Zapata et al. [33] used the quasi-experimental propensity score matching technique to find that students who received systematic music education achieved better academic performance, enhanced cultural consumption and participation in artistic activities. Fu et al. [34] conducted a comprehensive analysis of the impact of music and noise during surgical procedures. They found that while higher decibels affected the results of the surgery, music did not have a negative effect. Most medical professionals agree that music improves individual and team performance. Moreover, Xi [35] adopted the PSO-BP neural network algorithm and multidimensional data model to explore the music influence on emotional expression.

2.2. Research on the features determining musical influence

More and more researchers concentrated on selecting music characteristics and music factors to investigate music influence. By testing the influence of different styles of music on the purchase intention of craft beer and industrial beer, Paula et al. [36] found that only pop rock style had a positive effect on industrial beer, while most styles of music improved the acceptance of craft beer. Differences in music genres can also lead to dangerous accidents, and Babić et al. [37] found that genres affect speed and visual scanning of the environment, with more 'aggressive' and faster songs musically increasing driving errors. Because musician change-makers are likely to have a significant impact on music, it is meaningful to study it. Music has a wide range of effects on stress and anxiety, and Meyers et al. [38] studied these relevant influences in-depth. They found that as stress increases, people listen to music for longer periods of time, so music is a good way to de-stress. They focused on the types of music that people of different ages prefer when they use to decompress and the results showed that younger people preferred hip-hop music while older people preferred classical music. Zeng et al. [39] proposed a model based on musician influence and depth of adverse influence to find musician change-makers. They used the combinatorial weighting algorithm to introduce multiple groups of dimensions to describe musical influence. They also proposed a mutation-depth discriminating model based on the Pearson correlation coefficient to calculate the inverse influence depth. Banerjee et al. [40] studied the influence of different music's acoustics quantitatively using Multifractal Detrended Fluctuation Analysis (MFDFA). In particular, by dividing the music characteristics into pitch, loudness, and timbre of piano sound, this article revealed the cognition of the basic features of sound in human brains. Lévesque and Hurtut [41] proposed MuzLink, which is a tool that helps users explore and discover how different music artists have influenced and collaborated with each other by visually analyzing their musical adaptations. Li et al. [42] built a model of followers and influences of artists of targeted musical genres and analyzed the influence of music influenced by genres. The study found that 'influencers' influenced the music their followers created, making them more influential. Zeng et al. [43] studied the effects of different music on pedestrian dynamics and found that pedestrian speed can be controlled by adjusting the type, rhythm, and beat of the music to improve pedestrian flow. Musicians can also determine musical influence. Tao [44] calculated the music influence models of different musicians through the entropy weight method (EWM) and used the cosine similarity algorithm to model the music similarity using the theme model, so as to calculate the influence of each feature of music on the popularity of music through the similarity.

2.3. Network-based modern technology applied in musical influence study

It is worth noting that numerous modern computing technologies such as computer and network science have been utilized by many recent researchers for musical influence analysis. Early networks could be found in Cano et al. [45], in which the topology of several music networks is analyzed and the idea of complex networks regarding artists' relations is explored. In the work of Jacobson et al. [46], community detection methods from complex network theory, enhanced by audio-based analysis, were used to measure similarities among artists and build community structures. Collins [47] applied computational methods to plot the flow of musical influence, with the aid of MIR tools and web scraping and constructs charts of influence combining artist similarity and dates. Bryan and Ge [48] used the online music dataset to apply computational analysis on musical influence networks to quantify relevant features and trends and proposed an influence-ranking method to help recognize patterns of influence. Xue [49] gave a summary of the network-based analysis of musical networks, and experiments with the Document Influence Model to infer and also convolutional neural networks to predict artist influence. Cai et al. [50] established a music influence-oriented algorithm model that focuses on how influential people and their followers interact with each other, in which the principal component analysis (PCA) algorithm was used to determine the indicators reflecting the similarity of music, and finally got a globally directed network diagram about the differences and influences between genres. Liew et al. [51] made a quantitative analysis of the influence of British and American pop culture and global pop culture on pop music consumption through network analysis. They used the songs in the charts to build a network and took feature centrality as an indicator of the popularity of cross-cultural songs. Silva et al. [52] proposed a multimodal representation via heterogeneous networks, capable of combining different musical characteristics to construct representations and explore similarities at the same time, more accurately retrieving musical information than neural models.

3. Datasets & assumptions

The experimental datasets used in this paper are provided by Integrative Collective Music (ICM). All datasets related to this manuscript are available via our GitHub repository.[2] There are four files that contain different types of source data, including full music data, data by artist, data by year, and influence data. To be specific, full music data includes 98,340 songs' information in their respective artist names and artist IDs, and some musical features, such as danceability, tempo, loudness, and key. These data were obtained from Spotify's API. Data by artist and data by year are then derived, summarizing the mean values of musical features by artist or by yearly time horizon from 1921 to 2020. Lastly, the influence data contains musical influencers and followers for 5,854 artists in the last 90 years, which are reported by artists themselves and the opinion of industry experts. These data were scraped from a music website.[3]

In order to construct an effective model of the artist's social network and analyze the influence of music, we have to make several reasonable assumptions:

- **We assume that all works created by artists belonging to a certain genre also belong to the same genre.** This is well understood because the style of a certain artist is often fixed. All of Chopin's works belong to classical music and the works of The Beatles belong to pop music, which accords with our perception. Even if the individual works of a few artists may belong to other genres, this slight interference will not affect our analysis and conclusions based on this assumption.
- **We assume that the similarity of music characteristics cannot explain the similarity of genres. Similarly, the characteristics of music from the same genre may not be similar as well.** The characteristic of the genre cannot be completely determined by the given musical characteristics, and there are many influences such as chords, orchestration, and musical styles. Based on these assumptions, we cannot use the distance of the average song feature to compare the differences between genres.
- **We assume that the correlation between big events in social development and changes in music evolution can be explained by cause and effect.** There are many things in real life that may affect the evolution of music. Some things are positive and some are negative. However, the evolution of music also has its inherent motivation and contingency, which is a complicated process. For the convenience of analysis, we sometimes make causal explanations of the correlation between historical events and musical changes.

4. MFCSNet development

In this section, we will build the whole MFCSNet from one sub-network to another through different analysis angles using various methods. To measure the musical influence and obtain a convincing result, first, we built a complex social network, where the influencer–follower are denoted as the edges and the artists as nodes, and discover the small-world effect of the artist network. Furthermore, we found that this is a typical scale-free network with output degree nodes signifying influence and verified by the sub-networks of New Age music and Jazz music.

Secondly, we use the clustering approach [53] to divide the music similarity measurement into individual music similarity and similarity between two genres. For the former, we use the Euclidean distance of music characteristics to represent the degree of difference between specific music and apply the BIRCH clustering algorithm [54] to perform cluster analysis on artists. Then we use the obtained cluster labels to apply the Jaccard similarity coefficient which measures the similarity between artists. In this process, t-SNE is used as a tool for data dimension reduction. For the similarity between every two genres, we also use the Jaccard similarity coefficient to measure and visualize our results through heat maps. We also drew a heat map of genres and music characteristics to intuitively observe the difference between genres and tentatively applied the decision tree algorithm to visualize genre distinguishing based on music characteristics. In this way, the time series of music genre characteristics are analyzed.

Then, we analyze the specific mechanism by which influencers influence followers using community detection ideas. Through the Louvain algorithm [55], we found the community division in the artist network and used it as the label for the LightGBM ensemble learning model to obtain the feature importance of music characteristics, thus reflecting the contagiousness of characteristics during influence processes. Bob Dylan was selected as a representative artist to verify our conclusions through sub-network analysis.

Lastly, to explore the mechanism and representatives of the musical revolution, we first made it clear that the revolution is both anomalous and critical at the same time. We turn it into a composite task of anomaly detection and key node detection. We use an isolation forest algorithm for anomaly detection and an eigenvector for key node detection respectively. After obtaining the ranking of the artists after these two tasks, based on the TOPSIS method, we selected the top ten revolutionary figures and analyzed the rationality of the results based on reality.

[2] https://github.com/WangHewei16/Measure-Musical-Influence
[3] https://www.allmusic.com/

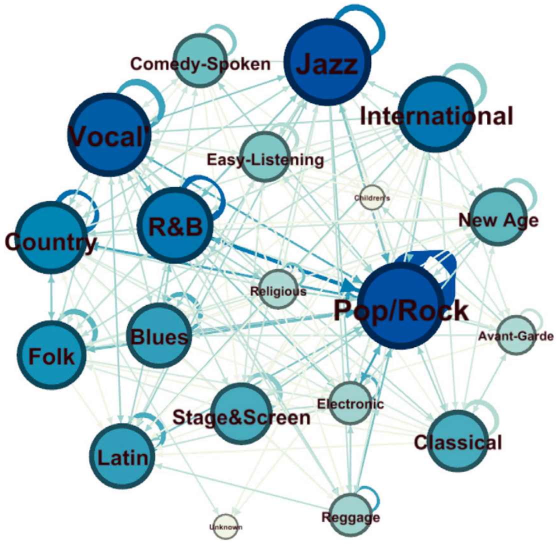

Fig. 1. The Network of Genre Influence.

4.1. Musician network and music influence

There are many music genres in the world, and there are many musicians for each music genre. For every musician, the formation of his/her personal style is influenced by many aspects. The most important one is the influence of the predecessors. The connection between influencers and followers is why the music genre continues to evolve. In this paper, we focus on the analysis of musicians, music genres, music characteristics, and other elements and aim to explain their internal laws of them. From the perspective of network science, such musician–follower social relations can be analyzed by building social networks. We regard each musician as a node and each pair of musician–follower as a directed edge of the graph. It should be noted each node has the attribute of a music genre.

We first aggregate the nodes of the same genre to observe more explicit rules, as shown in Fig. 1. The nodes in this network represent the genre and edges represent the number of pairs of influencer–follower between two genres. The node color, line segment thickness, and font size are all positively correlated with the node output degree. The obvious fact is that if a musician has a lot of followers, so it is natural that his social influence is high and the genres are similar. Then in the network, we can represent the musical influence of musicians by the degree of the node's output degree.

4.2. Small-world experiment and scale-free network

We select two sub-networks of all musicians' networks shown in Fig. 2 to analyze and find some interesting features related to music influence. We were visualizing the network, we noticed that the distribution of nodes is uneven and the group effect of the network is very significant. But even so, the connection between node to node is still very close which is a very significant feature of the small-world effect. The average distance between any two nodes in the network grows logarithmically as the number of nodes increases, that is $L \sim lnN$, and the local structure of the network still has a clear grouping character.

In order to verify our conclusion, we utilize the data in Table 1, then take the logarithm of the number of nodes and perform a linear regression with the average distance [56], as shown in Fig. 3.

Furthermore, we found that the number of followers of musicians is very unevenly distributed. The intuitive feeling is that most nodes have only a small output degree, while a few nodes, known as hubs, have a large degree. However, for a random network, the degree of nodes

Table 1
Average distance and number of nodes.

Genre	Average distance	Number of nodes
All Artists	6.119	5570
New Age	1.594	27
Comedy/Spoken	1.971	101
Electronic	2.426	168
Jazz	4.802	385

should obey a normal distribution. The influence of musicians should obey the Matthew effect from a sociological perspective which accords with the statistic of the output degree of the musician's network. Then we gain the number of followers and the number of nodes for each number of followers and plot them in double logarithmic coordinates. Fig. 4 shows that it has good linearity and we think the data obey power law distribution.

Based on the above experiments, we believe that the musician network is a typical scale-free network [57]. The scale-free network is a network model in which the node degree distribution follows a mathematical pattern called a power law distribution. The musical influence of a musician also obeys a power law distribution. If the probability distribution of node degree is used to represent the frequency of the occurrence of nodes with a degree in the network, then there is the following simple formula:

$$P(K) \sim K^{-\gamma} \tag{1}$$

Where $P(K)$ denotes the probability distribution of the occurrence of nodes with node degree K, and K represents the number of connections between nodes and other nodes. γ denotes the power-law exponent, which is the parameter that controls the shape of the power-law distribution.

4.3. Music similarity and metrics

Music as a form of art is very diverse. It is quite essential to develop a proper metric to reflect the music similarity. In the context of the question, music similarity can be understood in two ways: one is the similarity between two specific songs, and the other is the measurement of the overall similarity between two genres. For the former, it is easier to solve in the context of this question because we already have quantitative data on the characteristics of each specific music. Then we can think that the similarity of two specific music is the closeness of the two sets of data. For comparing the similarity between data and data, we can use the Euclid distance to represent.

Then how to measure the similarity between genres becomes herculean. Before that, we need to be clear about the fact that not all music in the same genre is similar. The similarity is the objective manifestation of data and genre is the subjective division of human beings. On this basis, if we can reflect the similarity of specific music through distance, we can perform cluster analysis and the music in the same cluster is objectively similar.

4.3.1. Cluster analysis: Data preprocessing and dimensionality reduction

We use all songs for cluster analysis. First, we build an unsupervised learning data set. For discrete features, we used one-hot encoding and standardized all the continuous features. In addition, our data dimension is up to 15, and To improve the effectiveness of learning, we need to reduce the dimensionality of the data.

Here, we adopt the t-distributed stochastic neighbor embedding (t-SNE) algorithm that can reduce dimension based on stochastic neighbor embedding [58]. The t-SNE algorithm comprises two main stages. First, t-SNE constructs a probability distribution over pairs of high-dimensional objects in such a way that similar objects are assigned a higher probability while dissimilar points are assigned a lower probability. Second, t-SNE defines a similar probability distribution over

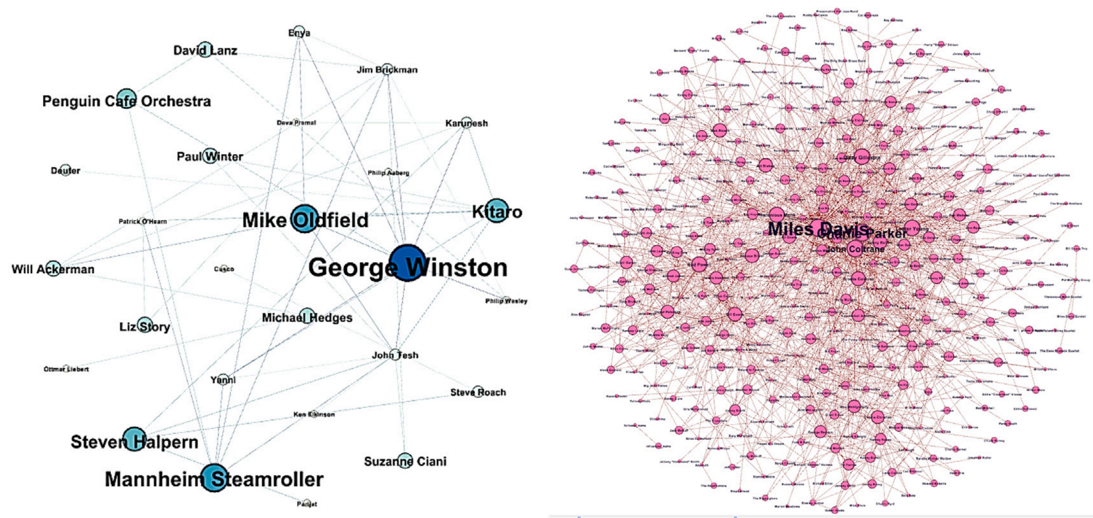

Fig. 2. The Network of New Age Music (left) and Jazz Music (right).

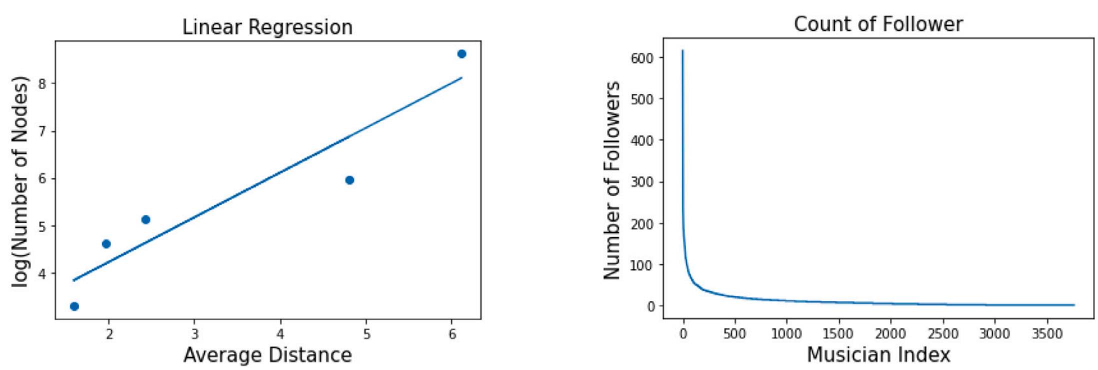

Fig. 3. Linear Regression to verify small-world effect (left) and Count of Follower (right).

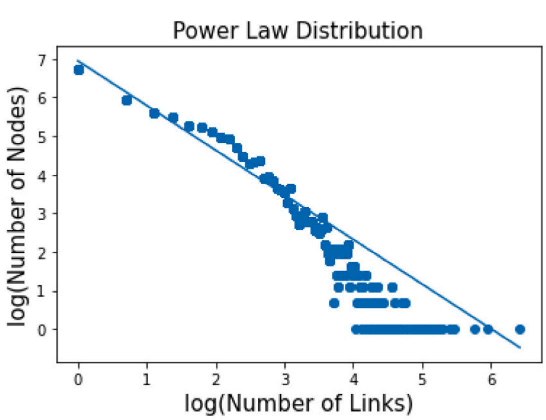

Fig. 4. Power law distribution.

the points in the low-dimensional map, and it minimizes the Kullback–Leibler divergence between the two distributions with respect to the location of the points in the map.

Given a set of N high-dimensional objects $x_1, \ldots, x_N$, t-SNE first computes probabilities p_{ij} that are proportional to the similarity of objects x_i and x_j. For $i \neq j$, define:

$$p_{i|j} = \frac{exp(-\left\|x_i - x_j\right\|^2 / 2\sigma_i^2)}{\sum_{k \neq i} exp(-\left\|x_i - x_j\right\|^2 / 2\sigma_i^2)} \tag{2}$$

And set $p_{i|j} = 0$. Note that $\sum_j p_{j|i} = 1$ for all i. Now define:

$$p_{ij} = \frac{p_{j|i} + p_{i|j}}{2N} \tag{3}$$

And note that $p_{ij} = p_{ji}$, $p_{ii} = 0$, $\sum_{i,j} p_{ij} = 1$. t-SNE aims to learn a d-dimensional map $y_1, \ldots, y_N$ (with $y_i \epsilon R^d$) that reflects the similarities p_{ij} as well as possible. To this end, it measures similarities q_{ij} between two points in the map y_i and y_j, using a very similar approach. Specifically, for $i \neq j$, define q_{ij} as:

$$q_{ij} = \frac{(1 + \left\|y_i - y_j\right\|^2)^{-1}}{\sum_k \sum_{\xi \neq k} (1 + \left\|y_i - y_\xi\right\|^2)^{-1}} \tag{4}$$

Herein a heavy-tailed Student t-distribution is used to measure similarities between low-dimensional points in order to allow dissimilar objects to be modeled far apart in the map. The location of the points y_i in the map is determined by minimizing the KL divergence using gradient descent. And now we have the two-dimensional data of the music representation.

4.3.2. Cluster analysis: Clustering and similarity measurement

After dimensionality reduction to 2, we applied the Balanced Iterative Reducing and Clustering using Hierarchies (BIRCH) algorithm [54] for clustering the data. BIRCH is a widely used and efficient clustering method in machine learning. It utilizes a structure called the Cluster Feature Tree, which helps optimize computational time and memory usage. Due to the complexity of music similarities with the presence of 19 music genres, we employed BIRCH to cluster the music data into

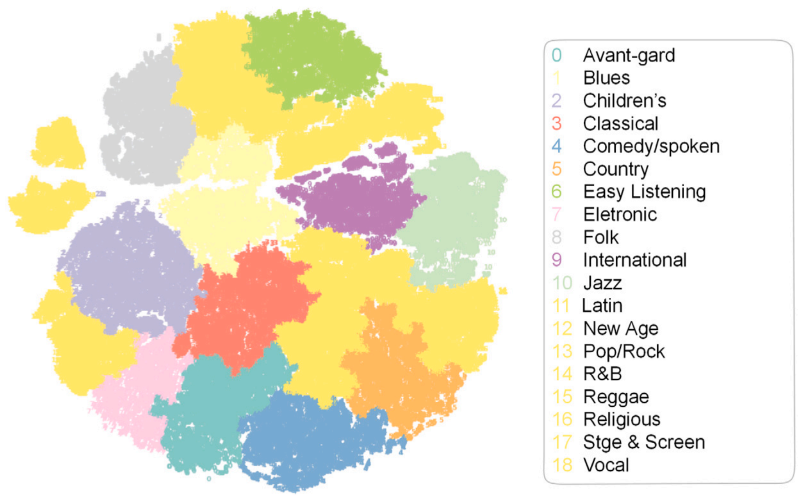

Fig. 5. t-SNE of cluster result of music data.

19 distinct clusters. This approach allows us to capture the intricate relationships and patterns within the music dataset. Fig. 5 shows the visualization result of clustering by t-SNE [59].

Therefore, it can be inferred that music within the same cluster exhibits higher similarity compared to music from different clusters. However, when considering unspecific music, it becomes challenging to determine the similarity between two musicians. To address this issue, we employ the Jaccard similarity coefficient, which is commonly used to quantify similarity and dissimilarity between limited sample sets [60]. The Jaccard similarity coefficient provides a suitable solution for comparing music similarity, and its formula is as follows:

$$J(A, B) = \frac{|A \cap B|}{|A \cup B|} \tag{5}$$

Where $J(A, B)$ is the Jaccard similarity coefficient, which represents the similarity between two finite sets A and B.

Based on this approach, we proceed by obtaining the clustering label sets for the works of two artists and calculate the Jaccard index to assess the degree of similarity between the two sets, representing different artists. To conduct a specific analysis of the similarities among musicians from the same genre and different genres, we select a few notable musicians from various genres, including Wolfgang Mozart from classical, Charles Mingus and Miles Davis from Jazz, U2 from Pop/Rock, and Queen from Pop/Rock. By tallying the frequency of each label, we can draw meaningful conclusions.

Among the selected musicians, it is observed that Charles Mingus and Miles Davis, both representatives of Jazz music, exhibit a Jaccard similarity coefficient of 0.802147, indicating a relatively high level of similarity between their works. In comparison, the similarity coefficients between Miles Davis and U2, Miles Davis and Queen, Charles Mingus and U2, Charles Mingus and Queen are 0.23546, 0.218201, 0.29039, and 0.247244 respectively, suggesting lower levels of similarity. Notably, U2 and Queen demonstrate a similarity coefficient of 0.5021, indicating a relatively higher degree of similarity between artists from the same genre. However, it is important to note that while artists within the same genre tend to exhibit greater similarity, this is not an absolute rule. An intriguing observation arises from the comparison between Wolfgang Mozart, a representative classical musician, and Charles Mingus, where the Jaccard similarity coefficient of 0.82724 surpasses the similarity between Miles Davis and Charles Mingus. This suggests that instances of artists from different genres exhibiting significant similarities do exist.

These findings underscore the complex nature of musical similarities, indicating that while works within the same genre often share common characteristics, exceptions can occur, leading to intriguing resemblances between artists of different genres. By considering a diverse range of data, we gain a deeper understanding of the intricate relationships and patterns present in the world of music.

4.4. Analysis of the relationship between music characteristics and genres

The classification of music into different genres is subjective, often based on the perceived similarities in music characteristics within each genre. In this section, we aim to uncover the underlying patterns that connect music characteristics to specific genres. By examining these relationships, we can gain insights into the fundamental factors that define a particular genre. Our analysis will identify key features that distinguish one genre from another, providing a deeper understanding of the essence and identity of different genres.

Furthermore, we will explore the temporal dynamics of music characteristics within genres. By studying the patterns and trends exhibited by these characteristics over time, we can gain insights into how genres evolve and adapt to cultural and societal changes. This investigation will shed light on the dynamic nature of genres and the factors that shape their development over time. Understanding the temporal aspects of music characteristics within genres will contribute to a more comprehensive understanding of the evolution of music and its relationship with different genres.

Through our analysis, we will also examine the relationships between different genres. While genres often possess distinct characteristics, we acknowledge that there can be instances of overlap and cross-influences between genres. By uncovering these connections, we can better understand the interconnectedness and fluidity of music genres. This exploration will enrich our appreciation of the diverse and multifaceted nature of music, highlighting the intricate relationships that exist among different genres.

4.4.1. Genre distinction

In continuation of our exploration, we now delve into the relationship between music characteristics and genres. Determining genres based solely on music characteristics can be challenging, as even within the same genre, music can exhibit significant variations. However, by extracting the average characteristics from a variety of genre-specific music, we can potentially identify general trends that define each genre. Fig. 6 provides a visual representation [61] of the normalized average values of different characteristics for each genre, enabling us to discern distinct differences among them.

For instance, classical music is characterized by notably low values in danceability, energy, valence, tempo, and loudness, setting it apart from other genres. In contrast, comedy/spoken genre shows high values in liveness and speechiness. Both Pop/Rock and electronic

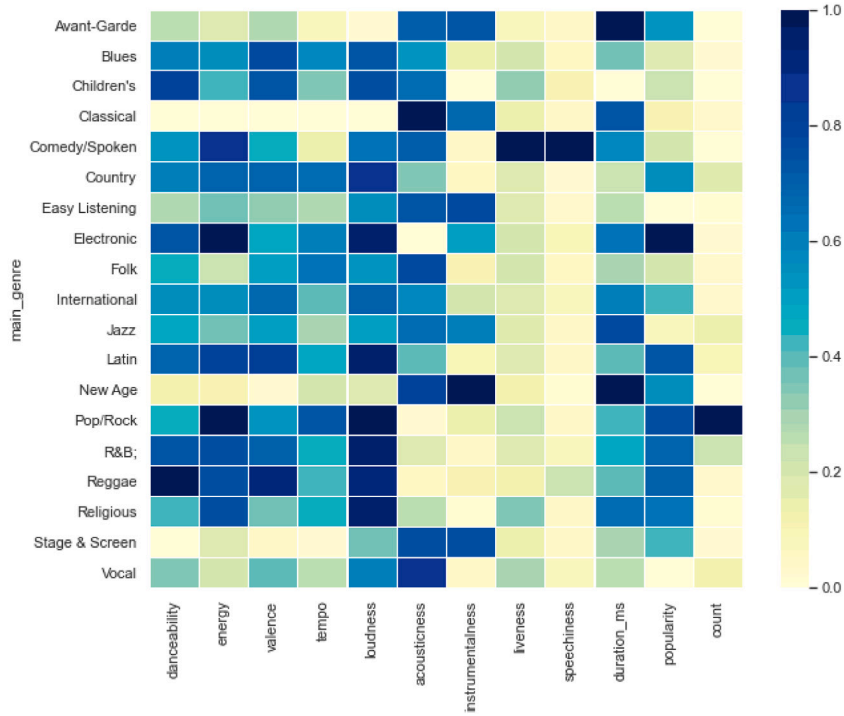

Fig. 6. Heat map of genres and characteristics.

genres exhibit high energy and loudness, but electronic music tends to have higher instrumental components compared to Pop/Rock. These observations align closely with our intuitive understanding of these genres, further validating the consistency between perceived genre characteristics and the analysis derived from the figure. These findings also reinforce the notion that music characteristics play a crucial role in defining and distinguishing various genres, providing valuable insights into the intrinsic qualities of different musical styles.

While these general tendencies can provide insights into the average characteristics associated with specific genres, it is crucial to recognize the diversity and individuality within each genre. Music, as an art form, encompasses a wide range of expressions, and there may be considerable variation even within a single genre. Therefore, while these average characteristics can serve as reference points, it is essential to consider the unique artistic choices and creativity that define individual compositions and artists within each genre.

4.4.2. Time series analysis of genres

Genres of music are not static entities; their characteristics evolve over time. Therefore, it is essential to analyze the time series of various music characteristics within genres. In this study, we have selected five representative mainstream genres for analysis. By examining the time series depicted in Fig. 7, we can derive the following insights:

- The popularity of all genres exhibits an upward trend. This observation aligns with the notion that newer music tends to garner more popularity compared to older compositions.
- Speechiness, energy, liveness, and valence exhibit overall stable trends throughout the entire time series. Although occasional peaks may indicate significant shifts or revolutions within specific genres, the overall patterns remain relatively consistent, showcasing the enduring nature of these characteristics over time.
- Acousticness, on the other hand, demonstrates a declining trend. This can be attributed to the widespread integration of modern technology and production techniques across most music genres, leading to a decrease in acoustic elements over time. Notably, the genres of classical, comedy/spoken, and stage/screen show a comparatively stable acousticness, likely due to their historical roots and preservation of traditional instrumentation.

4.4.3. Relation between genres

In Section 4.3, we mentioned that it is difficult to compare the similarity between two genres, but in Section 4.3.2 we compared the similarity of the artist's music by using the Jaccard similarity coefficient. We can also use the cluster labels obtained in Section 4.3 and use the same idea to compare the similarities between genres and genres.

The Fig. 8 is the correlation matrix [62] of the Jaccard similarity coefficient between genres which reflects the similarity between genres. We perform a simple analysis of the figure. There are several pairs of coefficients exceeding 0.9 which are classical and avant-garde, classical and easy listening, classical and stage screen, easy listening and stage screen, as well as vocal and folk. This is very consistent with perception. In the 20th century, the innovation of classical music creation techniques created the birth of avant-garde music; Classical music is very easy for listeners if it gets rid of complicated composition restrictions and even the two types themselves are crossed; A lot of stage music is derived from classical music, so the similarity is inevitable. The similarity between folk music and vocal music is that most folk music is expressed in the form of vocal music, and both have strong melodies and simple parts.

4.5. Analysis of the influence between influencer and follower

In the data we know, we can see pairs of influencers and followers. We subconsciously believe that the music of our followers is influenced by the influencer. However, we have not proven this statement. Even if it is true, how the influencer affected its followers' music became a question we have to solve.

As we mentioned in Section 4.2, the musician network has small-world effect [63], in which it can be expressed that musicians are often susceptible to the influence of musicians of the same genre. Under

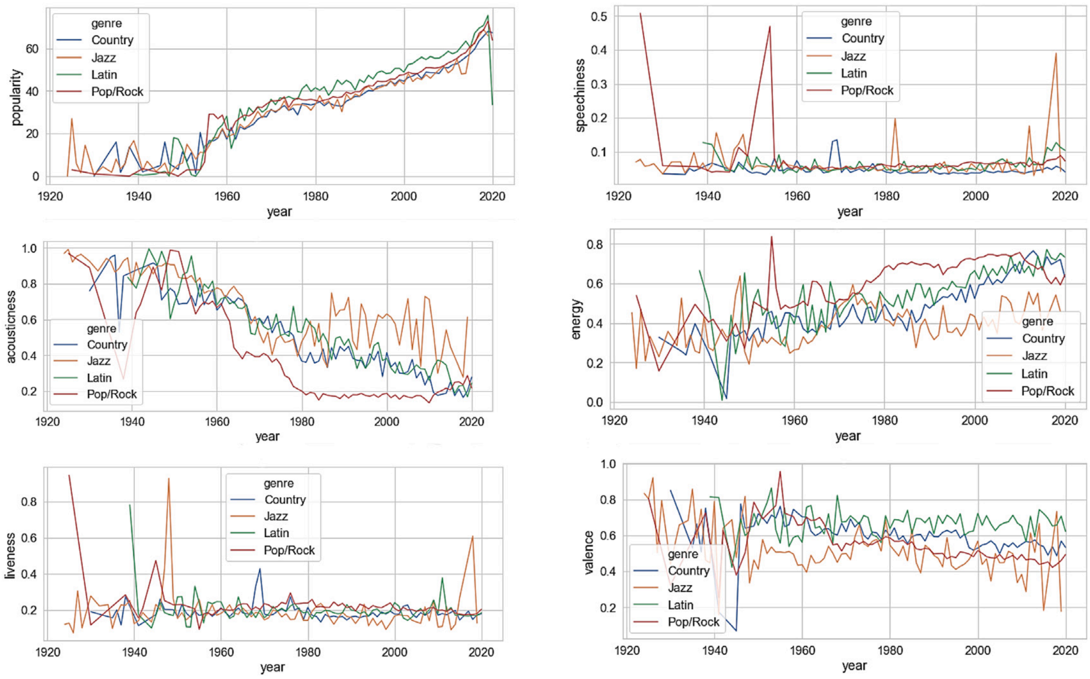

Fig. 7. Time Series Analysis of Various Characteristics for Five Representative Musical Genres (1920–2020). The characteristics consist of popularity, speechiness, acousticness, energy, liveness, and valence. The genres include country, jazz, Latin, and Pop/Rock.

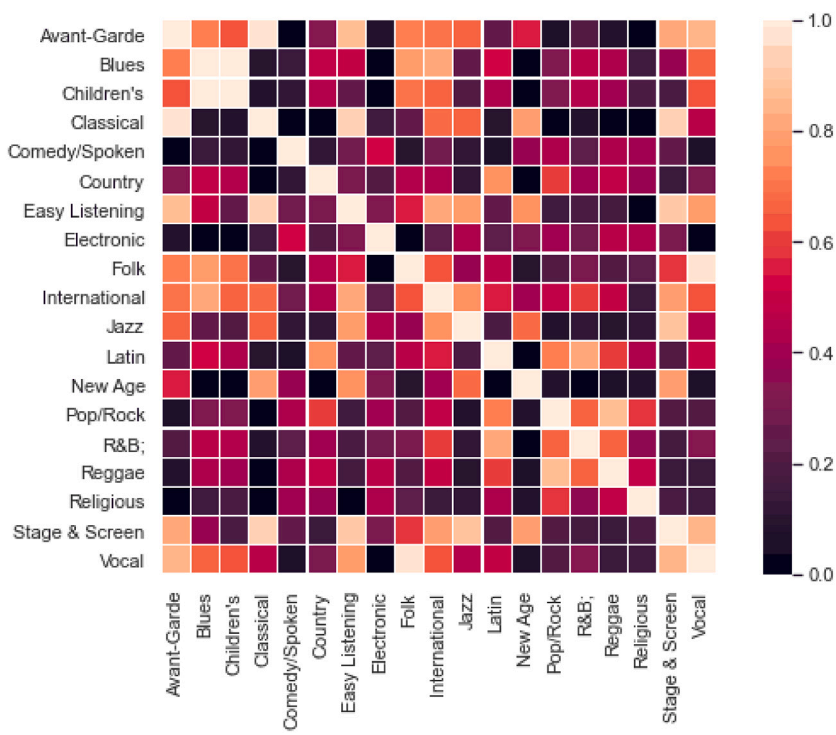

Fig. 8. Heat map of Jaccard similarity coefficient between genres.

such circumstances, the network often forms several communities in the end. Analyzing the influence mechanism of influencers on followers, we can do community mining and classify nodes according to the network structure. Then we can construct a classification task with node classification as the label and the artist's music characteristics as the features. The impact can be considered significant if the task can be learned well. By comparing the importance of music features in the machine learning process, we can compare the different roles that feature play in the process of influencers affecting followers.

4.5.1. Community finding through Louvain algorithm

Louvain algorithm [64] is an unsupervised algorithm used for community finding. Modularity, which is optimized during the process, is defined as a value in the range $[\frac{1}{2}, 1]$ which measures the density of

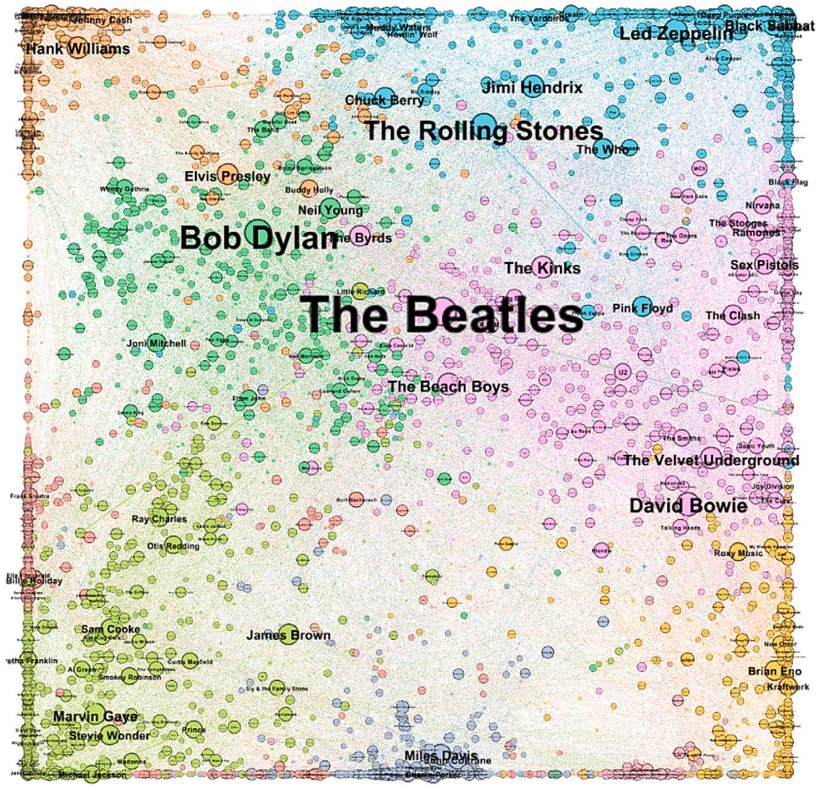

Fig. 9. Artists network after community findings.

edges inside communities compared to edges between communities. For a weighted graph, modularity is defined as:

$$Q = \frac{1}{2m} \sum_{ij} \left[A_{ij} - \frac{k_i k_j}{2m} \right] \delta\left(c_i, c_j\right) \tag{6}$$

Where A_{ij} represents the edge weight between nodes i and j; K_i and K_j are the sum of the weights of the edges attached to nodes i and j, respectively; m is the sum of all of the edge weights in the graph; c_i and c_j are the communities of the nodes; $\delta(x, y) = 1$ if $x = y$, 0 otherwise [65].

This algorithm is divided into 2 phases repeated iteratively: Modularity Optimization and Community Aggregation. Initially, every individual node in the network is placed into its own community. For each neighboring node j of i, we remove node i from its original community and add it to the community of j. We can then calculate the network's modularity with this new community structure. This value is easily calculated by two steps: removing i from its own community and inserting it into the community of j. The two equations are quite similar and the equation for the later step is:

$$\Delta Q = \left[\frac{\sum in + 2k_{i,in}}{2m} - \left(\frac{\sum tot + k_i}{2m} \right)^2 \right] - \left[\frac{\sum in}{2m} - \left(\frac{\sum tot}{2m} \right)^2 - \left(\frac{k_i}{2m} \right)^2 \right] \tag{7}$$

Where $\sum$ is the sum of all the weights of the links inside the community i is moving into, $\sum tot$ is the sum of all the weights of the links. We use this algorithm for the artist network.

As shown in Fig. 9, the size of the node is positively correlated with the label size and the out-degree of the node which means that it is positively correlated with the influence of the artist. And nodes with different colors represent belong to different communities according to the results of the Louvain algorithm.

4.5.2. Comparing characteristics contagiousness through machine learning

In order to explore the differences between the various characteristics of music in their influence, we can use the characteristics to learn the community labels and popularity of artists to compare relatively more contagious characteristics. We use the LightGBM [66, 67], a powerful machine learning technique based on decision tree integration, which can efficiently handle large datasets, offers fast training speed, and achieves high accuracy. After proper data preprocessing and parameter setting, we learned the classification and regression tasks with the community as the label and popularity as the goal with 68.702% (accuracy) and 0.74433 (r2 score). The effect is very significant, which means that music characteristics are strongly explanatory for the classification of the community and the popularity of artists. By leveraging LightGBM, we can examine the relative importance of different music characteristics. Given its tendency to assign higher importance to frequently used features in branch nodes, we gain valuable insights into the significance of certain traits compared to less frequently utilized ones. This enables us to better comprehend the impact and contagiousness of specific characteristics within the artist network, ultimately enhancing our understanding of its dynamics and influence. Fig. 10 shows the result of feature importance [68].

It can be observed from the results that the mode and key of an artist's music have almost nothing influence on the communities and popularity so we can ignore it. On the contrary, danceability, duration, and acousticness have a great impact on the artist's community and music popularity. We can say that danceability, duration, and acousticness are more contagious characteristics than others. We can also find some interesting things. Energy has a great influence on the popularity of songs, but the energy in the same community is not consistent while liveness is just the opposite. It can also be inferred that the influence of an artist in the community is not exactly the same as the influence of the entire music field, which leads to the small-world effect in the artist network.

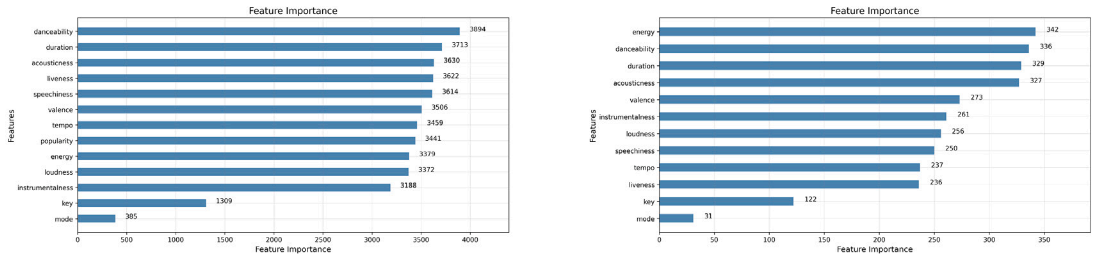

Fig. 10. Feature importance.

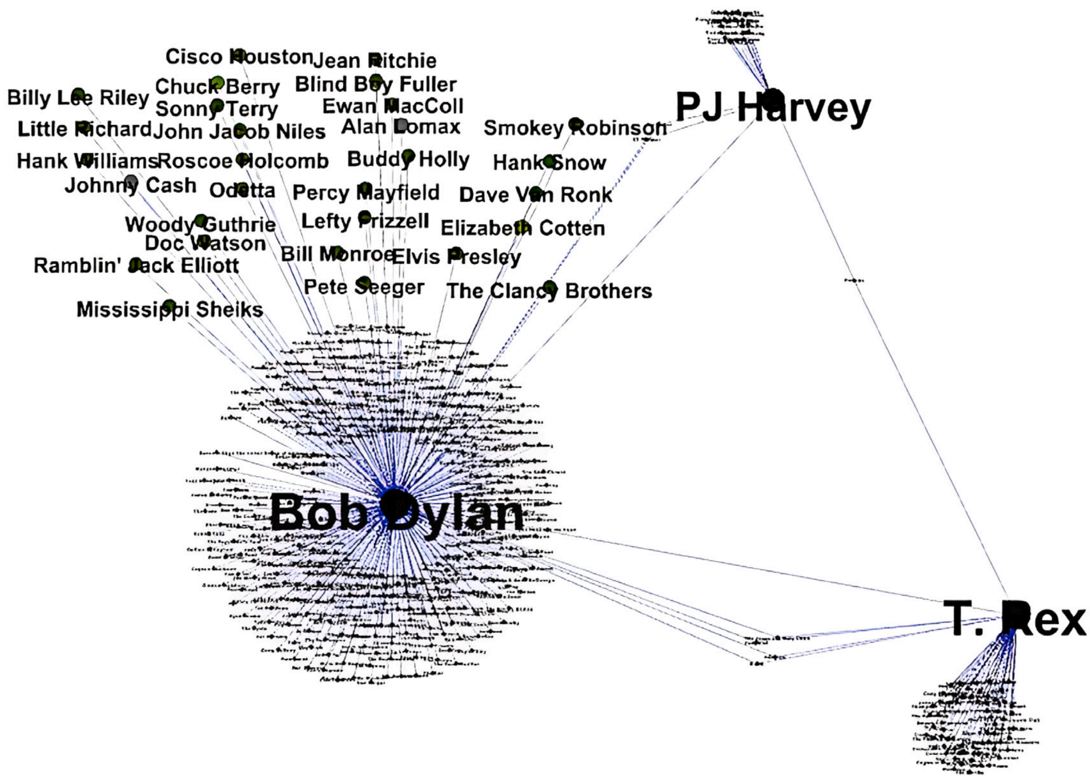

Fig. 11. Network of Bob Dylan and relative artists.

4.5.3. *Analysis of particular musician: Bob Dylan*

Bob Dylan, a great singer, and songwriter, won the Nobel Prize in Literature. His music is widely spread and his influence is huge. Fig. 11 shows the huge network of Bob Dylan and relative artists and Table 2 shows part of this data. As we can see from the network, there were lots of artists who influenced Bob Dylan and he also influenced lots of artists. We compare the musical characteristic between Bob Dylan's influencers and Bob Dylan. We choose five typical influencers as the representatives. We can see that the variance of each characteristic between Bob Dylan and his influencer is much lower than the average variance between genres except loudness. Note that most of Bob Dylan's influencers belong to different genres with Bob Dylan. Among them, danceability and acousticness are the most prominent and we can prove our conclusion mentioned above.

4.6. *Revolution detection in music genre*

Before studying which features can signify the revolution best or how to find them when the revolution happened in music development, we need to clarify what a revolution is. In our understanding, the revolution in an artist's genre implies two notable features: one is that the artist's musical characteristics have changed significantly from the previous characteristics of the same genre and the other one is that the artist must have a strong influence at the same time, otherwise it cannot be called a revolution of the genre. Based on the above analysis, we can find the revolution through the combination of two methods. On the one hand, it is anomaly detection of artists in the genre, and on the other hand, it is the key node detection of the artist network, which has anomalous and critical nodes that can be considered revolutionary artists.

4.6.1. *Anomaly detection via isolation forest*

Isolation forest is an unsupervised anomaly detection method [69] suitable for continuous numerical data. It does not require labeled samples for training and can efficiently identify isolated points using a random partitioning strategy. The dataset is recursively divided until all samples are isolated. Abnormal points typically have shorter paths in this random segmentation process, making isolation forest particularly effective for high-dimensional data. The average path length of a tree in isolation forest can be computed using the harmonic number. By normalizing the path length of a sample, an anomaly score can be calculated. Given a dataset containing n samples, the average path length of the tree is:

$$c(n) = 2H(n-1) - \frac{2(n-1)}{n} \tag{8}$$

Table 2
Result of Artists. It includes each characteristic value of Bob Dylan and influencer, their variance and average variance between genres.

Artist name	Danceability	Energy	Valence	Tempo	Loudness	Liveness	Speechiness
Bob Dylan	0.512598	0.477932	0.551934	126.1601	−11.1843	0.308978	0.064535
Mississippi Sheiks	0.5565	0.32465	0.55045	106.0978	−7.42905	0.207875	0.040025
The Clancy Brothers	0.627137	0.378902	0.626686	113.9226	−13.776	0.336761	0.205653
Cisco Houston	0.583757	0.089468	0.590405	115.869	−21.3409	0.114024	0.123124
Johnny Cash	0.619803	0.449381	0.680662	115.0377	−11.5931	0.242243	0.098216
Dave Van Ronk	0.539267	0.110505	0.41947	115.3997	−18.159	0.15623	0.060457
Elizabeth Cotten	0.4378	0.2788	0.6702	114.8968	−18.7476	0.115	0.0333
Pete Seeger	0.566084	0.194964	0.554519	108.7208	−17.9479	0.181601	0.103027
Doc Watson	0.51814	0.294644	0.7273	119.6732	−17.1408	0.183124	0.03984
Variance	0.003041	0.016825	0.007531	29.67627	17.98782	0.005483	0.002696
Average Variance between Genres	0.010416	0.02177	0.02349	38.87972	11.96357	0.007038	0.010995

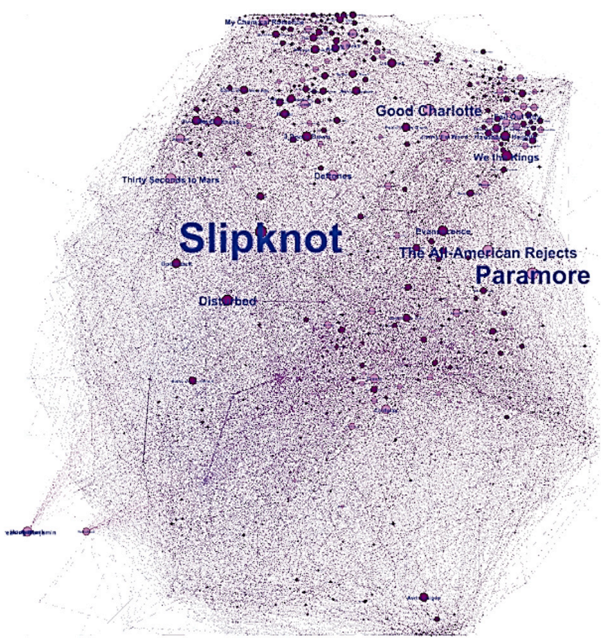

Fig. 12. Visualization of eigenvector centrality.

Where $H(i)$ is the harmonic number and the value can be estimated as $ln(i) + 0.57721$. $c(n)$ is the average value of the path length when the number of samples is given, used to normalize the path length $h(x)$ of the sample x. E stands for the expected value. The anomaly score of sample x is defined as:

$$s(x, n) = 2^{-\frac{E(h(x))}{c(n)}} \tag{9}$$

4.6.2. Key node detection via eigenvector centrality

In graph theory, eigenvector centrality is a measure of the importance of network nodes [70]. Relative scores are assigned to all nodes in the network based on the following concept: connections with high-score nodes contribute more to the score of the node in question than equal connections with low-score nodes. A high eigenvector score means that a node is connected to many nodes that themselves have high scores. Fig. 12 shows that node size and font size are positively correlated with eigenvector centrality. For a given graph $G := (V, E)$ with $|V|$ vertices let $A = (a_{v,t})$ be the adjacency matrix, i.e. $a_{v,t} = 1$ if vertex v is linked to vertex t, and $a_{v,t} = 0$ otherwise. The relative centrality, x, score of vertex v can be defined as:

$$x_v = \frac{1}{\lambda} \sum_{t \in M(v)} x_t = \frac{1}{\lambda} \sum_{t \in G} a_{v,t} x_t \tag{10}$$

Where $M(v)$ is a set of the neighbors of v and λ is a constant. With a little rearrangement, this can be written in vector form as an eigenvector equation $Ax = \lambda x$.

Table 3
The Rank of Artist who Revolutionized Pop/Rock Music. The rank is based on the anomalous values and centrality of eigenvectors of Pop/Rock artists.

Rank	Artists
1	DragonForce
2	Otep
3	Killswitch Engage
4	Sigur Ros
5	Cradle of Filth
6	The Dillinger Escape Plan
7	Dillinger Four
8	Asking Alexandria
9	Biohazard
10	Doves

4.6.3. Revolution detection via TOPSIS

After obtaining the anomalous value and eigenvector centrality of artists from Pop/Rock, we use the technique for order of preference by similarity to the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), a multi-criteria decision analysis method used to determine the best alternative from a set of options. It considers the similarity of each alternative to the ideal solution based on multiple criteria. In the context of the research, TOPSIS was employed to rank artists in Pop/Rock music based on their anomalous values and centrality of eigenvectors, identifying the top artists who may have revolutionized the genre. By leveraging this technique, we get top artists who may create a revolution in Pop/Rock music. Table 3 shows part of the data of the top 10 artists.

In order to confirm the rationality of our method, we look up the relevant materials of the top artists. DragonForce is a typical, famous energy metal band known as "The World's Fastest Melodic Speed Power Metal"; Otep is a band of alternative metal that said they would break all the numb truths taught by traditional culture and society, break people's hypocritical faces and corrupt moral values, and carry out a turbulent revolution; Killswitch Engage is a heavy metal band from the United States and they were recently named one of the representatives of the New Wave of American Heavy Metal by some domestic media, that is, the New Wave of America Heavy Metal movement and were named one of the representatives of the New Thrash. Although music is subjective and the evaluation of art is subjective, our results are reasonable to understand intuitively. By observing their musical characteristics in Table 4, it can be found that the differences are mainly concentrated in energy, valence, loudness, and acousticness, which shows that these characteristics can signify a revolution.

4.7. Analysis of Pop/Rock music evolution

The social network composed of artists is actually a dynamic network because the influence on followers has a starting point. Then, the dynamic changes of the artist network shown in Fig. 13 can be seen as the evolution of the genre. We need to select different indicators, count the values at different time points and find out the underlying laws.

Table 4
Characteristics for different genres.

Main genre	Pop/Rock average	DragonForce	Otep	Killswitch engage
Danceability	0.514731164	0.215714	0.427	0.40776
Energy	0.679092273	0.945	0.986	0.9722
Valence	0.528098704	0.245429	0.3294	0.27704
Tempo	124.2515474	175.6751	95.788	139.40176
Loudness	−8.622568483	−4.60657	−3.6995	−3.3938
Mode	1	0	1	0
Key	7	11	1	0
Acousticness	0.211001661	0.001201	0.000168	0.000123915
Instrumentalness	0.106300431	0.073807	0.8465	0.05106676
Liveness	0.20087188	0.276986	0.1775	0.254288
Speechiness	0.061926938	0.103214	0.0682	0.089512
Duration_ms	239614.4851	436733.4	252786.5	230326.88
Popularity	42.93024632	44.85714	41.5	48.6

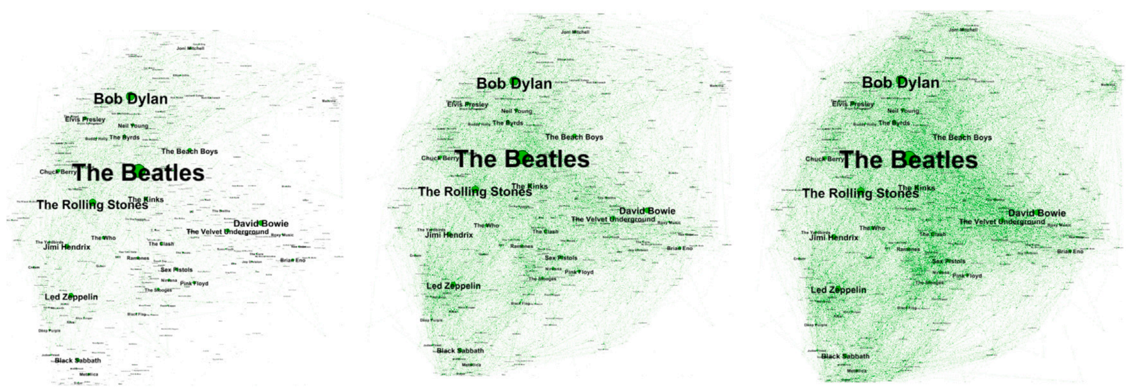

Fig. 13. Change of Pop/Rock artist network (1960–1980–2000).

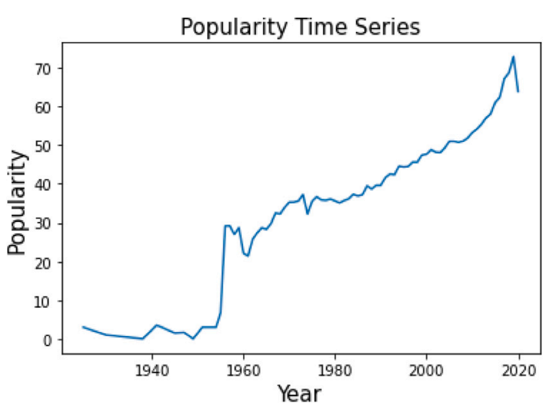

Fig. 14. Time series of popularity.

4.7.1. Indicator selected to reflect genre evolution

i. Popularity: Popularity given in the data is calculated by algorithm and is based, for the most part, on the total number of plays the track has had and how recent those plays are. As popularity increases with time, the genre of Pop/Rock evolves. Data is collected through "full_music_data.csv" statistics. Fig. 14 shows the time series of popularity.

ii. Number of Communities or Number of Weakly Connected Components: As we mentioned in Section 4.5.1, we can use the community detection algorithm to obtain a regional division of the artist network. In MFCSNet, such as the artist influence network, the smaller the number of communities, the more mature the genre is because artists tend to unite and communicate. In a similar way, we can count the weakly connected components of the network (artist networks are directed graphs and the edges that represent influence are often one-way), and we can get results consistent with the community detection method. Fig. 15 shows the time series of the number of communities and average degree.

4.7.2. Indicator selected to reflect artist influence

i. Average Degree: As we mentioned in Section 4.1, the out-degree of a node indicates the number of followers of the artist, which can also reflect the influence of the artist.

ii. Average Path Length: The average path is the average graph distance between any two points in the graph, as mentioned in Section 4.2. It shows how closely the artist is connected. The left subfigure in Fig. 16 shows the time series of average path length.

iii. Average Cluster Coefficient: In graph theory, the clustering coefficient [71] is a measure used to describe the level of clustering among the vertices in a graph. Specifically, it quantifies the extent to which the neighbors of a vertex are connected to each other. For example, it reflects how well your friends know each other on a social network. The clustering coefficient can be divided into local and global clustering coefficients, with the average cluster coefficient representing the average of the local cluster coefficients across all nodes in a graph. The local cluster coefficient $C(i)$ of a vertex v_i in the graph is equal to the number of edges between all the vertices connected to v_i, divided by the maximum number of edges that could possibly exist between those vertices. In directed graphs, the maximum number of edges is $k_i(k_i-1)$, as each vertex can have two edges between them. k_i represents the total number of edges pointing to vertex v_i and the number of edges pointing from vertex v_i. The right subfigure in Fig. 16 illustrates the time series of the average cluster coefficient, and the formula is as follows:

$$C(i) = \frac{\left|\left\{e_{jk} : v_j, v_k \epsilon L(i), e_{jk} \epsilon E\right\}\right|}{k_i\left(k_i-1\right)} \tag{11}$$

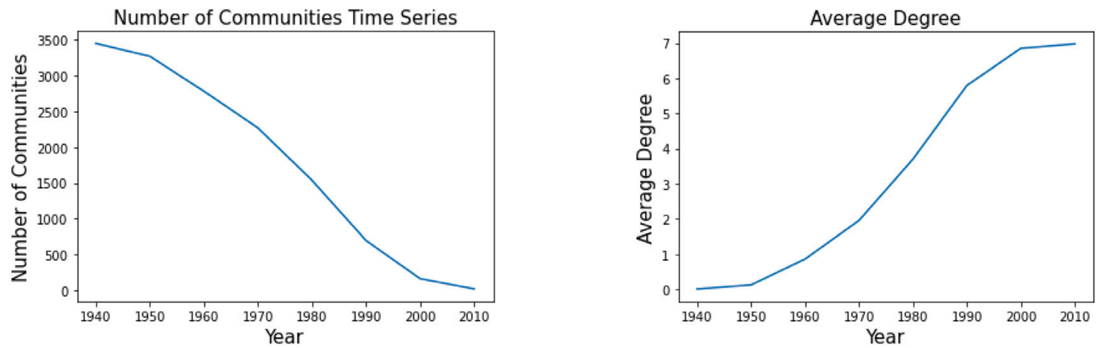

Fig. 15. Time series of number of communities and average degree.

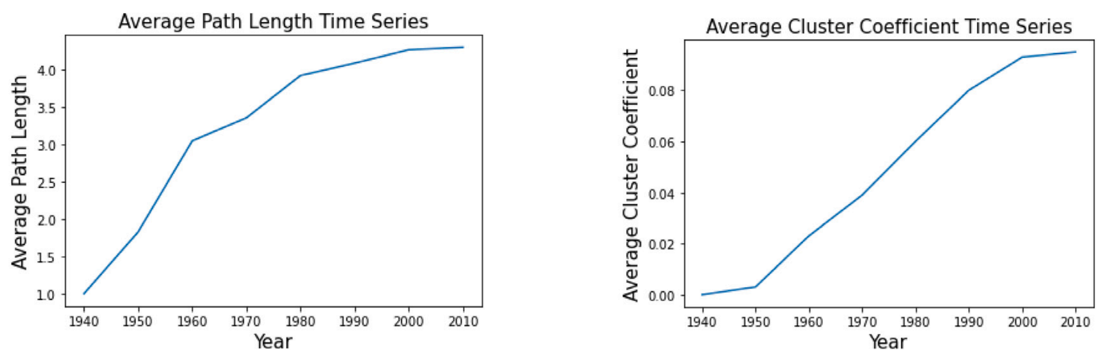

Fig. 16. Time series of average path length and average cluster coefficient.

4.8. Identification of social, technological, and political influences in music

Music, as an integral part of human society, has consistently evolved and undergone revolutions, often in conjunction with shifts in the external environment. The impact of culture, society, technology, politics, and other factors can be observed throughout the history of music, and our work aims to identify and analyze these influences. In this section, we will explore several significant trends or changes in music that correspond to historic events, shedding light on the interconnectedness between music and its social, technological, and political contexts.

4.8.1. The great depression

In 1929, the United States was struck by the Great Depression, resulting in widespread unemployment and a sense of panic across the nation. However, by the mid-1930s, the country began to emerge from the depths of the economic downturn, and a newfound optimism began to take hold. People gradually adapted to their circumstances and sought solace in joyful activities, including dancing and embracing the pleasures of life. This shift in societal mood is reflected in our data visualization. Fig. 17 clearly illustrates the impact of this event on the average danceability of various music genres. Following the mid-1930s, there is a noticeable increase in the average danceability scores across the genres, indicating a growing preference for more upbeat and rhythmic music that resonated with the revived sense of optimism during that period.

4.8.2. The Petrillo Ban

In 1942, James Petrillo, the President of the American Federation of Musicians (AFM), implemented a ban on commercial music recordings, leading to a significant strike by numerous musicians. This move had a profound impact on the music industry at the time. However, after 26 months of negotiations, major record companies eventually yielded and agreed to adjust the fees associated with recording copyrights, effectively ending the strike in 1944. The Petrillo Ban resulted in a noticeable decline in the circulation of music during this period. Fig. 18 illustrates the trend in the number of releases across various genres from 1940 to 1945, clearly indicating a downward trajectory following the implementation of the ban.

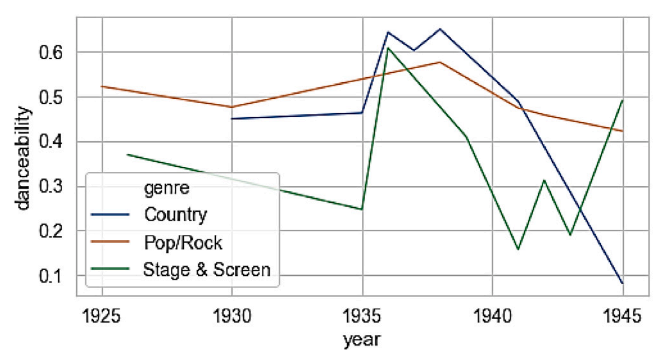

Fig. 17. Average danceability of several genres from 1925 to 1945.

4.8.3. Electric musical technologies

Electric technologies have played a pivotal role in the evolution of music. The 1930s marked the emergence of various electric musical instruments, such as the electric piano (invented in 1929), the electric guitar (invented in 1931), and the electro-mechanical Hammond organ (invented in 1934). These innovations revolutionized the way music was created and performed, ushering in a new era of sonic possibilities. During World War II, advancements in electric technologies found their way into the design and development of electric instruments in the late 1940s and 1950s. This period saw the rise of iconic solid-body electric guitars by renowned manufacturers like Fender and Gibson, leaving an indelible mark on the trajectory of music. One notable impact of electric technologies can be observed in the average acousticness of music, as depicted in Fig. 19. Starting from the late 1940s, there has been a consistent downward trend in the average acousticness of music.

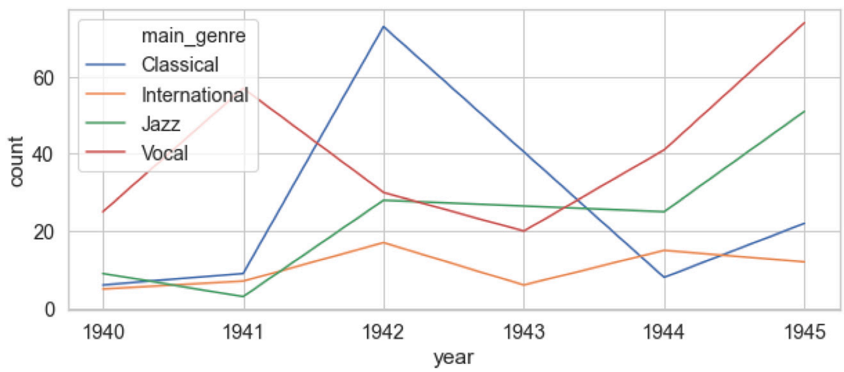

Fig. 18. Release counts of several genres from 1940 to 1945.

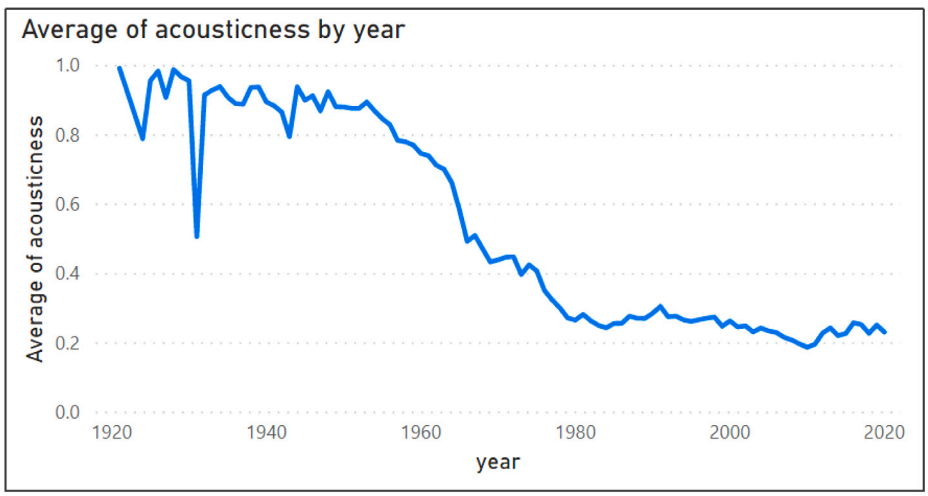

Fig. 19. Average of acousticness by year.

This decline can be attributed to the increasing adoption of electric instruments, which offer amplified sound, enhanced versatility, and the ability to explore new soundscapes and tonal possibilities.

4.8.4. *Pop/Rock boom in the 1960s*

During the 1960s, a significant shift occurred in the socio-political landscape, with the end of Eisenhower's era of repression and the emergence of the Kennedy era. This coincided with the coming of age of the post-war baby-boom generation, who began to express their discontent and challenge the societal norms inherited from previous generations. This spirit of rebellion and social change found its reflection in the music of the time. The rise of rock 'n' roll and pop music became synonymous with the youth rebellion movement, the sexual revolution, and a decade of political activism. Iconic songs like Bob Dylan's "Blowin in the Wind", which became a civil rights anthem, questioned the societal norms and called for a reevaluation of deeply ingrained prejudices. The arrival of the Beatles in the United States in 1964 sparked a phenomenon known as Beatlemania, further igniting the popularity of pop/rock music.

Our network analysis reinforces the cultural significance of this era, as many influential artists such as Bob Dylan, the Beatles, the Rolling Stones, Led Zeppelin, and David Bowie emerged during the 1960s within the genre of pop/rock. In Fig. 20, we observe a substantial increase in the percentage of pop/rock releases since the late 1950s, indicating its growing dominance in the music industry. These observations underscore the profound impact of society on the evolution of music and the pivotal role that pop/rock genre played in capturing the spirit of the era. It serves as a testament to the power of music as a medium for social commentary and transformation.

5. Conclusion and future work

This paper provided valuable insights into the analysis of musicians, music genres, and music features, shedding light on the underlying patterns and laws that govern the music landscape. Through the development of MFCSNet, a comprehensive network model, we were able to measure musical influence, visualize network dynamics, and identify key factors driving the evolution of music schools. By defining revolution as a period characterized by significant change and strong influence, we successfully identified transformative moments in music history. Our findings also highlighted the impact of social, political, and technological changes on the musician network, emphasizing the interplay between music and its broader socio-cultural context. From a practical standpoint, our research has implications for various stakeholders in the music industry. Talent scouts can utilize our findings to identify promising artists and facilitate their career growth. Researchers can further explore the intricacies of music communities using our network model and analysis techniques. Additionally, policymakers can draw insights from our study to inform decisions regarding music education, genre promotion, and cultural preservation. In summary, this study has contributed to a deeper understanding of musicians, music genres, and music features, providing valuable insights into the complex dynamics of the music world. Our findings have practical applications and offer a broader perspective on the role of music within society and cultural evolution.

For future work, we will address the limitation regarding the design of the dynamic network. This work's current focus has primarily been on time intervals for edges, while nodes have not been extensively processed due to their continuous influence. This limits our comprehensive

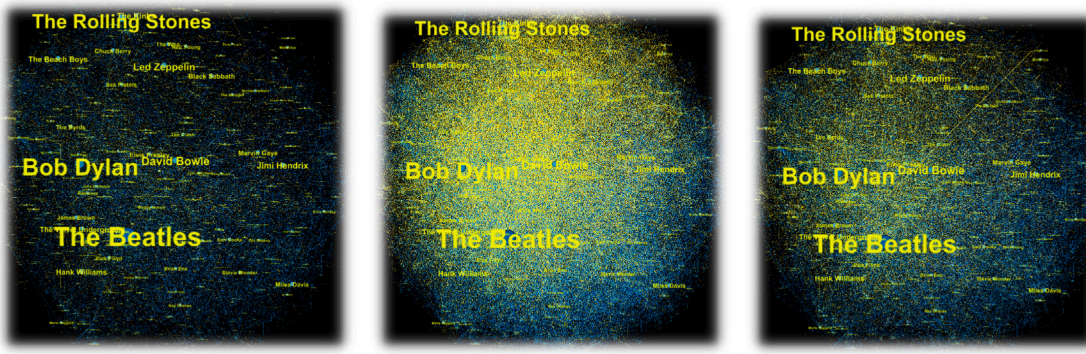

Fig. 20. The Boom of Pop/Rock Music (1950s-1960s-1980s) Yellow edge means that the follower is a Pop/Rock artist and blue is not. The yellow part gradually occupying the mainstream illustrates the booming of Pop/Rock music. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

analysis of the evolution and dynamics of individual artists within the network. To overcome this, future research can explore methods to incorporate the temporal aspects of both edges and nodes [72], allowing for a deeper understanding of how artists evolve and interact over time. This would provide valuable insights into the dynamics of artistic influence and its impact on society. Additionally, we plan to utilize some deep learning models such as graph neural networks (GNNs) to analyze the complex artist network. GNNs have the potential to capture intricate patterns of musical influence and uncover deeper insights into the dynamics of the network. By leveraging such a deep learning network, we can enhance our understanding of the impact of music on society, politics, and technology, providing a more comprehensive analysis of the data.

Declaration of competing interest

On behalf of all the authors, I declare that the authors have no conflict of interest.

Data availability

Data will be made available on request.

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