

Original Paper

Research on the Influence of Music

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Abstract

As for question 1, based on the directed relationship between influencers and followers, we building a network of musicians based on influential relationships. A Music Influence Evaluation Model (MIEM) was also established, and the model formula is shown in the text. We then select the top 200 artists in the “music influence” ranking to build a subnet. The larger the subnet node, the more lines are extended. Indicating that the node represents the musician’s influence is large and extensive. From the graph, we can see that Bob Dylan is influential, but the breadth of influence is not enough; Miles Davis influenced a wide range of music factions.

As for question 2, we have developed a Music Similarity Evaluation Model (MSEM) to calculate the contribution parameters of fifteen different music metrics. Using fully connected neural networks combined with triple loss to solve the answer. According to the characteristics of Triple Loss, we can make the similar nodes in the space closer together and the dissimilar nodes further apart. After training, our neural network is able to distinguish artists very well. The results were obtained: artists within genres are far more similar than artists between genres, and a classification image of musicians from different genres was produced.

As for question 3, a comparative plot of characteristics revealed that music genres also have their own particular musical characteristics. The comprehensive analysis concludes that the difference between genres is mainly reflected by the six features of valence, tempo, mode, key, acousticness, and instrumentality, and this result is verified by k-means clustering. By plotting the percentage of influence as well as the change of musical characteristics, it was concluded that the influence of genres changes over time; some musical characteristics in genres also change over time. Finally, the similarity between each faction is calculated and plotted as a heat map, and the genres with high similarity must have interrelated relationships with each other.

As for question 4, we have developed a Music Influence T-test Model (MITM). We hypothesized that

“influencers” would not influence followers to create music, and a *t*-test using SPSS rejected the original hypothesis and concluded that “influencers” would influence followers to create music. Additionally, Contagious Evaluation Model (CEM) was also created. We established the “contagious” index and calculated the Pearson correlation coefficients between “contagious” and 15 musical characteristics, and obtained the results: energy, loudness, and acousticness are more “contagious” than other characteristics. Results: energy, loudness and acousticness are more “contagious” than other features.

As for question 5, a time series plot of the variation for each musical characteristic with year was plotted and the analysis yielded the following conclusion: There are characteristics that signify revolutions in musical evolution from these data. For example, the music after 1960s showed changes characterized by higher rhythmicity, faster tempo, and fewer spoken words. Based on these musical evolutionary changes, combined with the “musical influence” we calculated earlier, we select five musical change-makers: The Beatles, Bob Dylan, The Rolling Stones, Miles Davis and Jimi Hendrix.

As for question 6, we combined musical influences to identify the most influential musicians in each genre in each era as dynamic influencers to represent the music of the genre in that period. Creating images of their musical characteristics over time and analyzing them in relation to the history of musical development led to the conclusion that an artist’s musical identity changes with technology, social development, and changes in genre representation.

As for question 7, a Network Connectivity Evaluation Model (NCEM) was developed to measure which artists in the music network were heavily influenced by external factors during the time period. The first and middle of the 20th century were found to be highly connected online, and this period coincided with a period of social upheaval, with the Cold War, World War II, the Industrial Revolution, and the rapid development of the Internet having a great impact on music, from which many new musical styles were born.

Keywords

Weighted dynamic programming, Entropy method, Neural network, Time series analysis, Hypothesis testing, Pearson correlation coefficient.

1. Introduction

1.1 Statement of the Problems

1. Create a directed network of music influencers and establish the parameters of “music influencers” in this network. Explore a subset of music influencers by creating a subnet of the directed influencer network. Describe this subnetwork.
2. Develop a metric of musical similarity to explore whether artists in genres are more similar than artists in genres?
3. Compare the similarities and influences between and among genres. What distinguishes genres and how do genres change over time? Are some genres related to others?

4. Do “influencers” actually influence the music created by their followers? Are there certain musical characteristics that are more “contagious” than others?
5. Determine if there are characteristics that might mark a revolution in the development of music? Which artists represent the revolutionaries?
6. Analyze the influential processes of a genre of music over time. Reveal indicators of dynamic influencers and explain changes in genre or artist over time?
7. Identify the impact of social, political, or technological changes (e.g., the Internet) in the network.

1.2 Analysis

As for question 1, a network of musicians was first established based on the inter-influence relationships between musicians. A music influence evaluation model was then developed, determined by a combination of chronological span, number of followers, number of genres influenced, number of genres followed, and number of musicians followed. Based on the influence size, we filtered the top 200 musicians from the musician influence directed network to get the sub-network, and then described the sub-network in a multi-dimensional way.

As for question 2, the measure of similarity of musicians is actually defining the distance between two musicians. The weighted distances of fifteen musical features are considered to optimize the weighting coefficients by minimizing the sum of the maximum values of intra-genre distances and maximizing the minimum values of inter-genre distances. A fully connected feature extraction neural network based on Triple loss is used to extract the parameters obtained by solving the neural network using the neural network connection layer. The similarity of artists within and between genres was calculated separately for comparative analysis.

As for question 3, In the similarity measure will be the weight coefficients of each different feature, and the few features with the highest weights are the differences between genres. The key music networks of different genres are extracted from the musicians’ network, and the time series analysis of genres’ influence and musical characteristics over time is performed. The two-by-two similarity between the 20 genres is calculated, and the music genres with high similarity are related.

As for question 4, Assuming that “influencers” do not influence followers to create music, a t-test was conducted using SPSS. The Pearson correlation coefficients were then calculated separately for each musical indicator and infectiousness, so as to analyze which characteristics are more infectious.

As for question 5, We establish a time series of musical characteristics of different genres over time, and use these turning points and special points to determine whether there are revolutionary features of musical evolution. The revolutionaries are the first few whose music was most influential at these turning points in time.

As for question 6, Extract the most influential musicians of each decade of a genre and analyze the changing trends in characteristics. Identify the key characteristics that change, thus reflecting the changing trends from genre artists.

As for question 7, The “network connectivity” indicator was set to measure the time period in which artists in the music network were heavily influenced by external factors, and to analyze the relationship between music and culture in the context of social change, political influence and technological development at the corresponding time.

2. Model Preparation

2.1 Assumptions & Symbol Description

2.1.1 Assumptions

1. It is assumed that the given dataset is comprehensively detailed and authentic, i.e., there are no missing influencers and influenced persons. If there are followers who are not counted, this may cause errors in the calculation of music influence, similarity, etc.
2. It is assumed that the creative contribution of the two co-composed tracks is equal. There are many tracks in the dataset that were composed by two artists together, and it is obviously unreasonable to cleanse them directly, so it is assumed that each of them was involved in half of the composition.

2.1.2 Symbol Description

Table 1. Symbol Description

Symbols	Descriptions
z	Music Influence
x_i	Indicators that influence the impact of music
w_i	Weighting factor of music influence
s	Similarity
ω_i	Weighting of musical features

2.2 Data Pre-processing

2.2.1 Data Cleaning

First, we remove the musicians with the same ids but different names from the influence_data.csv, their data is invalid. Remove the 6 musicians data and then remove the case where follower’s age is smaller than influencer’s age. The number of original data is 42770, the number of duplicate ids is 42689, the cleaned data is 41956, and the new influence.csv is obtained.

We found that in data_by_artist.csv, full_music_data.csv there are some artist_id that cannot be found in influence_data.csv, so we cannot know the genre of these artists. They are not useful for our subsequent data analysis, and this part of the artist’s data is also deleted by us. data_by_artist.csv contains 5855 original data, 5564 after cleaning.

2.2.2 Data Normalization

For data_by_artist.csv and data_by_year.csv, these musician feature data are not of the same order of

magnitude, so they need to be unified to one order of magnitude. We used min-max scaling as a data normalization method to linearly transform the original musician feature data to map the original values to between [0,1]. min-max scaling function:

$$\frac{(x - \min)}{(x_{max} - x_{min})}$$

3. Problem 1: Musicians Network & Music Influence Evaluation Model (MIEM)

In the first question, we first used the data to create a network of musicians that represents the interactions between musicians. This network of musicians can better help us analyze the relationships between influencers and followers. In order to capture the parameters of “musical influence”, we developed a Musical Influence Evaluation Model to obtain the “musical influence” of all musicians. Finally, we analyze what “musical influence” reveals in a subnet by creating a subnet of the musicians’ network, for example.

3.1 Musicians Network

Here we use data from the “influence_data” dataset to build an influence network of musicians between influencers and followers. The data was first organized to derive two metrics for 5854 different musicians to create the musician network: 1. Number of other musicians influenced by that musician 2. Number of that musician influenced by other musicians.

In the image of the musician network we built, points of the same color represent musicians of the same category, a directed line segment between two points represents the connection between influencers and followers, and the color of the line connecting the two points is the same as the color corresponding to the influencer node. At the same time, the larger the number of nodes affecting the larger number of musicians, the final graph of the musician network obtained is shown below.

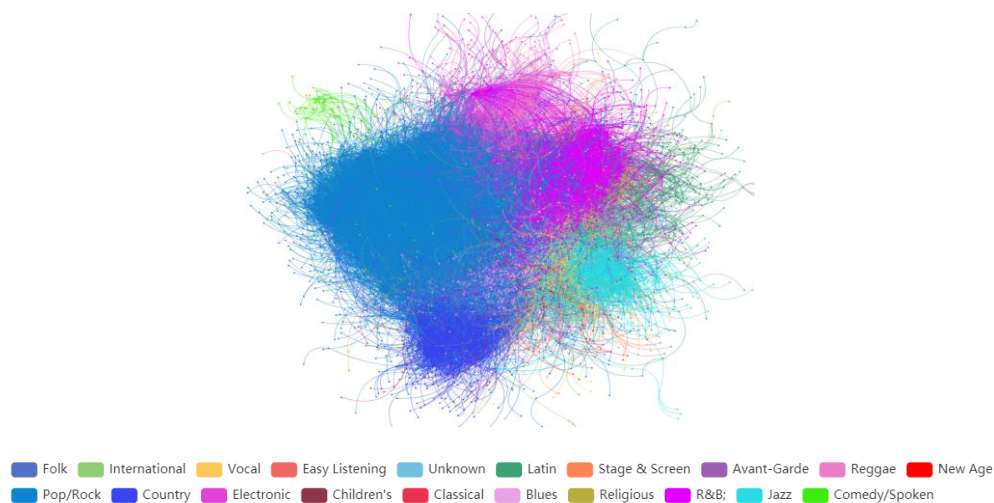


Figure 1. Musician Network Map

A. Overall analysis of the faction:

Pop/Rock has the largest share of the musician-oriented network and extends the largest number of connected lines, i.e., influences on other musicians, followed by the R&B category, followed by Jazz, country and Latin, respectively. From this ranking, we can see that the musical influence of a genre and its artists is directly proportional to the number of people in the genre, the more musicians in the genre, the more widespread and influential the genre is. Conversely, the smaller the number of musicians in the faction, then the more niche the faction is, then the less influential the faction and the musicians within the faction are.

B. Inter-factional analysis: We conducted targeted analysis for the top five music factions and obtained the following analysis table

Table 2. Faction Influence Number Table

	Total number	Same-genres	Dif-genres	Impact ratio
Pop/Rock	24141	22049	2092	0.913342
R&B	5530	3384	2146	0.611935
Jazz	2716	1769	947	0.651325
Country	3301	2502	799	0.757952
Latin	621	405	216	0.652174

From the table we can see that the total number of influences of musicians in Pop/Rock exceeds the total number of influences of the other four factions, which also shows that the Pop/Rock faction is the most influential faction among all factions.

At the same time, cross-factional influence can also reflect the influence of a faction. Nearly 40% of all musicians influenced by R&B faction musicians were influenced by musicians from outside the faction, then indicating that the music of the R&B faction is more portable and versatile. The fact that R&B has a better innovation and can attract a large number of musicians who are not of its faction to learn and imitate shows that musicians of the R&B faction play a great role in the spread of music culture across factions.

C. Statistical analysis of the number of people affected by different musicians:

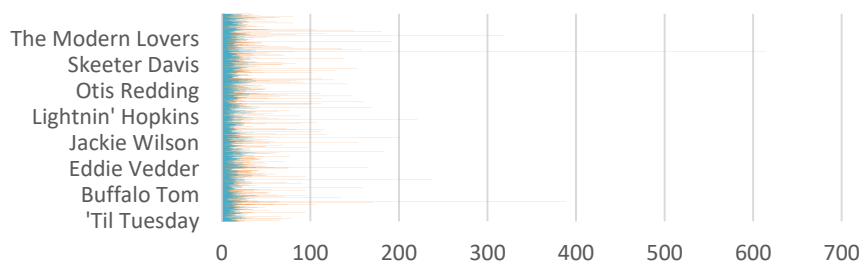


Figure 2. Influencers and Followers Quantities Histogram

According to the analysis of statistical charts, each musician has influenced an average of 11 musicians and each musician has been influenced by at least 10 other musicians. The musicians who influenced the largest number of other musicians were The Beatles, Bob Dylan and the Rolling Stones. They are all highly influential musicians in history, and at the same time the number of their influences by other musicians is largely above average, which suggests: The fact that great musicians have influenced a large number of subsequent generations of musicians and that these great musicians have been influenced by other musicians shows that there is a strong transmission and inheritance of music.

D. A Nightingale rose chart was created by counting the number of singers within the twenty genres, and the following results were obtained.

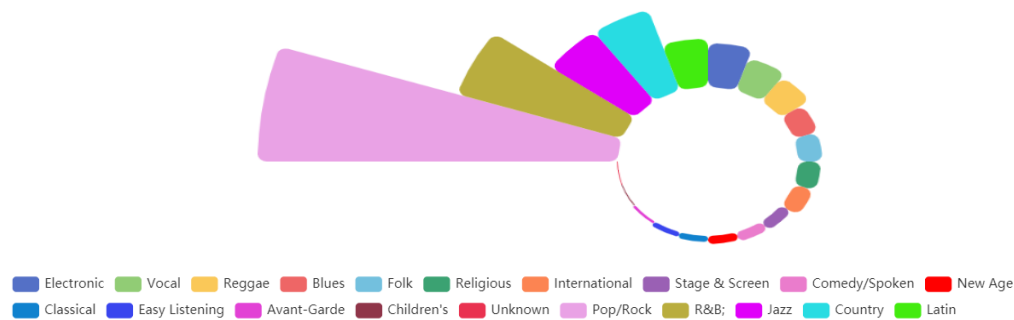


Figure 3. Nightingale Rose Chart

As you can see from the chart, Pop/Rock artists account for close to 50% of the total number of artists, followed closely by R&B, Jazz, Country, Latin and Electronic. In terms of historical musical influence, the influence of these genres with a large number of singers is indeed greater than that of genres with a small number of singers. The influence on other genres would be relatively greater, and it is these genres that have led the way in the development of music in the last hundred years.

3.2 Music Influence Evaluation Model (MIEM)

In order to develop parameters for capturing “musical influence” in a network of musicians, we developed a comprehensive evaluation model of musical influence that helps us evaluate the musical influence of musicians across generations and genres.

3.2.1 Model Preparation

In this question, in order to determine the parameter of music influence, we have determined five evaluation indicators for evaluating “music influence”, which are all proportional to music influence, taking into account the characteristics of music dissemination, the influence of music dissemination over time, and the dispersion of music data: Chronological span between influencers and followers, number of followers of the musician, number of genres influenced by the musician, number of genres followed by the musician, number of musicians followed.

3.2.2 The Establishment and Solution of MIEM

1. Establishment of MIEM

Based on the standardized values of each evaluation index, expressed by x_i , and the corresponding dynamic weight function $w_i(x)$ ($i = 1, 2, 3, \dots, 5$), a comprehensive evaluation model is established to make a comprehensive evaluation of the five evaluation objects. Here, the comprehensive evaluation model is taken as the dynamic weighted sum of each evaluation index:

$$Z = \sum_{i=1}^5 w_i(x) \cdot x_i$$

This is used as a comprehensive evaluation index function of music influence.

2. Solution of MIEM

In the process of building the above weighted dynamic programming model, we use the entropy value method to determine the value of each weight. The entropy method is based on the degree of variation of each index value to determine the index weights, which is an objective weighting method that avoids the bias brought by human factors.

Firstly, a problem with n samples and m indicators for comprehensive evaluation is formed and the original data matrix x_{ij} is formed.

Calculate the weight of the j^{th} sample under the i^{th} indicator for that indicator.

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^n x_{ij}}$$

Calculate the entropy value of the i^{th} indicator.

$$e_i = -k \sum_{i=1}^n p_{ij} \ln(p_{ij}), \quad e_j \geq 0$$

$$k = \frac{1}{\ln(n)} > 0$$

Calculating the redundancy of information entropy.

$$d_i = 1 - e_i$$

Calculate the weights of each indicator.

$$w_i = \frac{d_i}{\sum_{j=1}^m d_i}$$

The above is the weight value in the weighted dynamic planning model. Based on the data in influence_data and the dynamic weighted evaluation equation, the formula for "Music Influence" is calculated as follows:

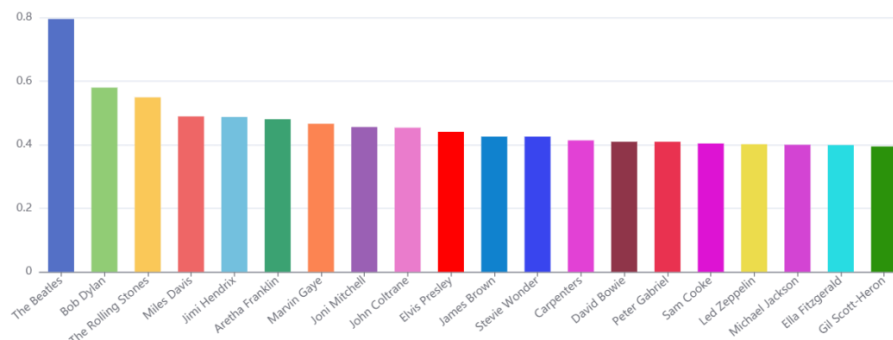
$$z = 0.29387 * x_1 + 0.32548 * x_2 + 0.39036 * x_3 + 0.12636x_4 + 0.099256x_5$$

The "Music Influence" of all musicians can be obtained by normalizing the five parameters of each musician and bringing them into the formula.

Table 3. Music Influence Ranking

Name	Genre	Music Influence
The Beatles	Pop/Rock	0.794851
Bob Dylan	Pop/Rock	0.579133
Rolling Stones	Pop/Rock	0.548584
Miles Davis	Jazz	0.488592
.....
King Krule	Pop/Rock	0
The Rivingtons	R&B;	0
LFO	Electronic	0

We extracted the top 20 musicians in terms of Music Influence and got the following ranking:

**Figure 4. Nightingale Rose Chart**

Among all musicians, The Beatles in the 1960s had the greatest Music Influence at 0.7948; the top 1000 musicians accounted for 53.26% of the total influence of all musicians, and the average value of all musicians' musical influence was 0.1115. Exceptionally, there were 38 musicians with a musical influence of 0. In particular, there are 38 musicians with 0 influence, because they have no influence on other musicians.

In addition, we can see from the graph that the top musicians are all familiar musicians who have influenced a large number of later generations of musicians, and that their Music Influence matches their musical attainments, which means that the obtained Music Influence indicator is correct.

3.3 Explore "Music Influence" in Key Musicians Network

We select the top 200 nodes in the influence ranking from the musician directed network to build the Key Musicians Network:

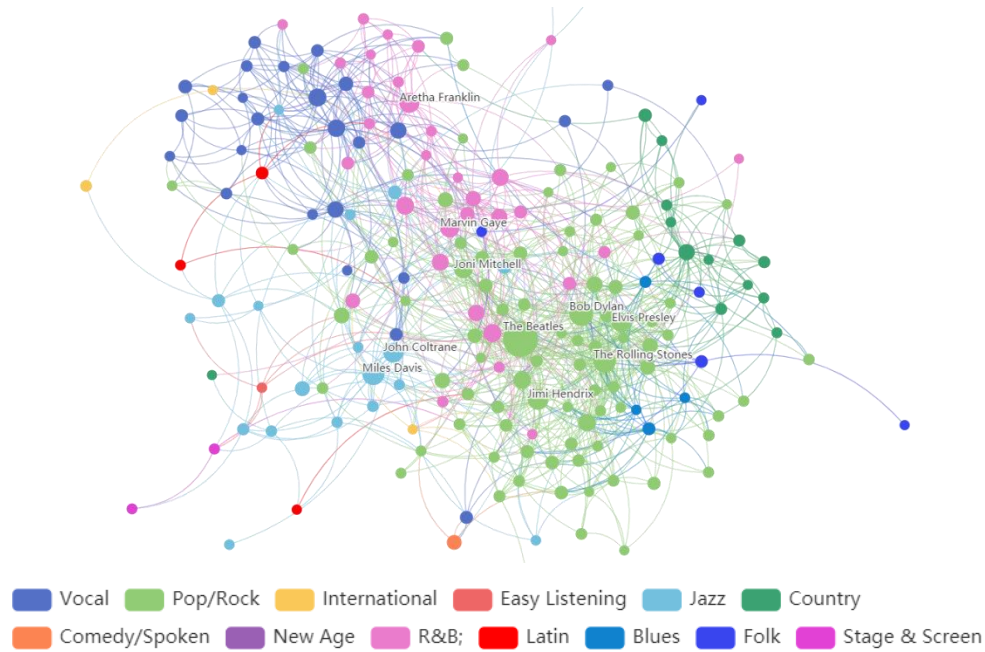


Figure 5. Key Musicians Network

In the image, points of the same color represent musicians of the same category, a directed line segment between two points indicates the connection between influencers and followers, and the color of the line connecting the two points is the same as the color corresponding to the influencer node. Extracting the percentage of different music genres in the subnet, the following pie chart is obtained.

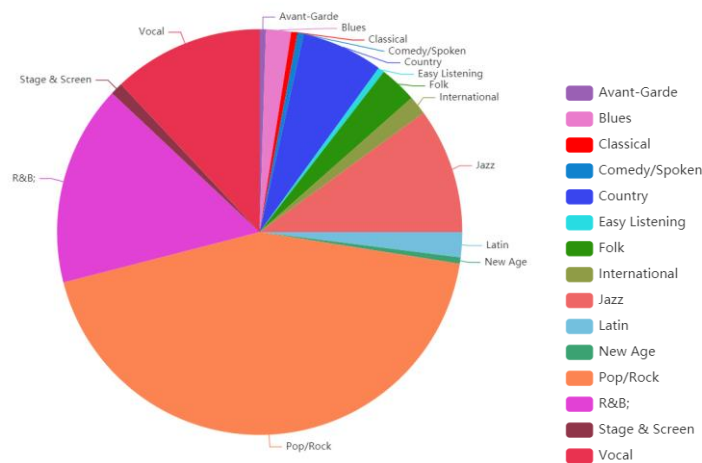


Figure 6. Pie Chart of Distribution Share

Among the top 200 sub-networks of musical influence, the Pop/Rock faction has the largest share of musicians, while the five genres with the smallest share are Avant-Garde and Comedy/Spoken, all of which have only one musician in the Key Musicians Network.

In the Key Musicians Network, the larger the node, the greater the influence of the musician; the connection between the nodes represents the connection between the influencer and the follower, if a node extends more lines, the wider the influence of the musician, which means more musicians are influenced by him.

Although only the top 200 nodes were extracted from the Key Musicians Network, the interconnectedness of thousands of nodes makes it impossible to analyze the influence of “Music Influence”. We extracted the second and fourth most influential musicians, Bob Dylan and Miles Davis, for example.

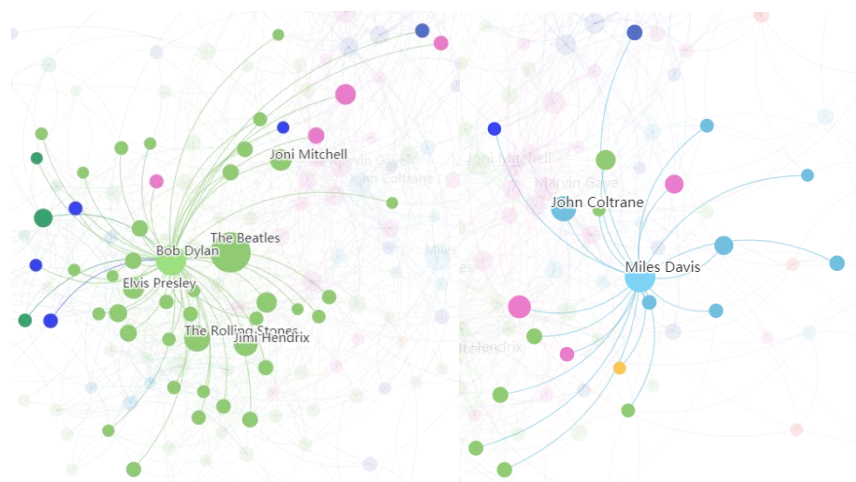


Figure 7. Influence Gravity Map

A. Bob Dylan’s musical influence remains strong among music masters, as seen in his network of influences. Fifty of the top 200 musicians have been influenced by him, and even The Beatles, who are ranked first in Music Influence, have been influenced by him. However, most of Bob Dylan’s Music Influences are concentrated in the same genre as his Pop/Rock, which may indicate that Bob Dylan’s musical style may be suitable for only one genre of Pop/Rock and not for some other genres, indicating that Bob Dylan’s Music Influence is great but the breadth of musical influence is average.

B. From Miles Davis’ influence network, we can see that although Miles Davis is the fourth most influential musician, his influence on the top 200 music masters is relatively small, and only 20 musicians in the lower ranking are influenced by Miles Davis’ music style, which means that most of Miles Davis’ Music Influence is concentrated in the small musicians, and there are many musicians who like to imitate Miles Davis’ music style. However, we can also see that Miles Davis has influenced a wide range of music genres, and among the top 200 musicians, there are 7 genres of music such as Jazz, R&B, and Latin that have been influenced by him. This suggests that his music is universal, resonating with musicians from other genres and guiding the music of musicians from different genres.

4. Problem 2: Music Similarity Evaluation Model (MSEM)

In order to measure music similarity as a metric, we developed a music similarity evaluation model. We use a fully connected feature extraction neural network based on Triple Loss (Because Triple Loss can make sample points of the same class become closer and points of different classes become more distant, in line with our assumptions about the optimization model, the results obtained from the model classification can also help us solve the problem: whether artists of the same genre are more similar than those between genres).

The musical features of all musicians were mapped, and a linear programming model for measuring the musical similarity between different musicians was developed using the parameters obtained from the connecting layer of the neural network, and the optimized cosine distance was used as the similarity between two musicians.

4.1 Establishment of MSEM

1. Objective function

A multi-objective linear programming model was developed with the goal of high similarity between artists of the same genre and low similarity between artists of different genres. A high degree of similarity among artists of the same genre is to make the minimum similarity among all artists of the same genre as large as possible, and a low degree of similarity among artists of different genres is to make the maximum similarity among all artists of different genres as small as possible. Thus, establishing the objective function that, S_{same_min} is similarity values of two artists with the least similarity in the same genre, $S'_{different_max}$ is the similarity value of the two artists with the greatest similarity in different genres, the formula is shown below:

$$\begin{cases} \max S_{same_min} \\ \min S'_{different_max} \end{cases}$$

2. Binding Conditions

A. The similarity between the two artists is S , expressed in terms of the modified cosine distance, a_i, b_i are the values of the i -th feature of the two artists, respectively, then S satisfies:

$$S = \frac{\sum_{i=1}^{15} \omega_i a_i b_i}{\sqrt{\sum_{i=1}^{15} (a_i)^2} \sqrt{\sum_{i=1}^{15} (b_i)^2}}$$

B. Limitation of weights

$$\sum_{i=1}^{15} \omega_i = 1$$

$$0 \leq \omega_i \leq 1, i = 1, 2, \dots, 15$$

In summary, the following linear programming model for measuring the similarity of musicians' music was developed:

$$\begin{cases} \max S_{same_min} \\ \min S'_{different_max} \end{cases}$$

$$s. t. \begin{cases} S = \frac{\sum_{i=1}^{15} \omega_i a_i b_i}{\sqrt{\sum_{i=1}^{15} (a_i)^2} \sqrt{\sum_{i=1}^{15} (b_i)^2}} \\ \sum_{i=1}^{15} \omega_i = 1 \\ 0 \leq \omega_i \leq 1, i = 1, 2, \dots, 15 \end{cases}$$

4.2 Solution of MSEM

In this problem, we use a fully-connected feature extraction neural network with Triple loss to extract feature similarity for several thousand artists in the data_by_artist dataset, so as to develop a measure of artist similarity and model the similarity between different musicians in the same genre and between genres to determine whether artists in a genre are more similar than those between genres.

4.2.1 Fully Connected Feature Extraction Neural Network

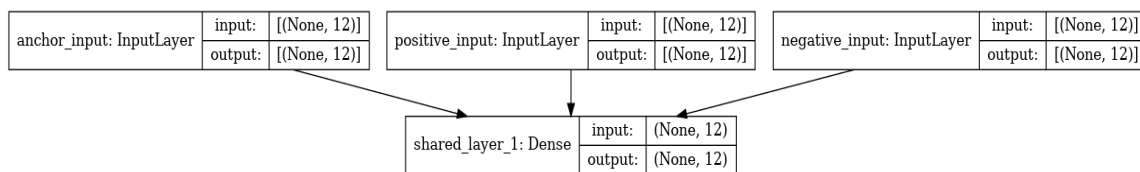


Figure 8. Schematic Diagram of Fully Connected Neural Network

Inspired by the face recognition system facenet, we build a neural network that maps musician features onto a Euclidean space. The core of this network is a shared model of anchor examples, positive examples, and negative examples, and the anchor examples are clustered with positive examples and away from negative examples by a supervised training method.

- Model inputs: three inputs, i.e., anchor example, positive example, negative example, different examples, i.e., vectors of eigenvalues for different musicians in data_by_artist.
- Model: a shared model, which we construct using a fully connected neural network.
- Model output: three outputs, i.e., the output obtained from three examples by sharing the model calculation.

Because our musician data has only 12 feature values, we use a fully connected neural network as the shared_layer, and the output of the neural network is optimized using the triplet loss feature, so that the cosine similarity of the vector output after the same genre musician feature passes through the model is higher, and the cosine similarity of the vector output after different genre musician features passes through the model is lower, so that the musician similarity can be calculated.

Note that the model in the above figure is the model used for training. After training, only the middle shared_layer needs to be extracted as the final model to calculate the mapping of music features to Euclidean space.

4.2.2 Triple Loss

The input of this loss function is a triplet, i.e., the triplet input of the neural network model extracted by the model computation, including Anchor example, Positive example, Negative example, where Anchor and Positive are data of the same genre, and Anchor and Negative are data of different genre.

The supervised clustering model is achieved by optimizing the distance between the anchor example and the positive example to be smaller than the distance between the anchor example and the negative example. The similarity calculation of musician sample feature values is achieved by comparing the cosine distance of the vectors output by the features of two musicians after model calculation.

Loss function formula ^[1]:

$$L = \max(d(a,p) - d(a,n) + margin, 0)$$

a : anchor, the anchor example; p : positive, the same music type as a ; n : negative, a different music type from a ; $margin$ is a constant greater than 0. The final optimization goal is to bring the distance between a and p closer and the distance between a and n farther, i.e., to achieve a small cosine distance between the output values of two models with the same genre musicians and a large cosine distance between the output values of different genre musicians.

where the sample can be divided into three categories:

- easy triplets: $L = 0$, i.e., $d(a,p) + margin < d(a,n)$, this situation does not require optimization, natural a and p are very close together, a and n are very far apart.
- hard triplets: $L > margin$, i.e., $d(a,n) > d(a,p)$, a and n are close together and a and p are far apart, this case has the greatest loss and needs to be optimized.
- semi-hard triplets: $L < margin$, i.e., $d(a,p) < d(a,n) < d(a,p) + margin$, distance between a and p is closer than distance between a and n , but not close enough, did not meet $margin$, there are losses in this case, but they are smaller than hard triplets and also need to be optimized.

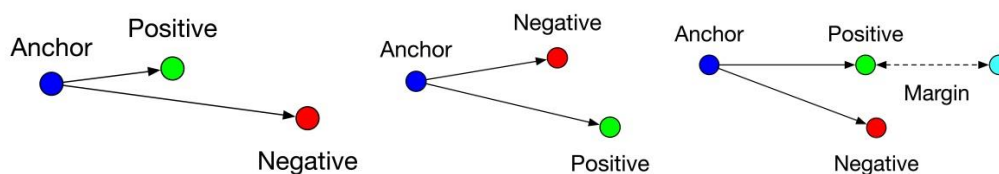


Figure 9. Schematic Diagram of Triple Loss Principle

By learning from these three kinds of data, the neural network can map the features of one musician onto another space. By comparing the cosine distance between two features on this space, we can compare their similarity.

4.2.3 Data Set Construction

Our model input is a triad: (anchor, positive, negative), where anchor and positive are musicians of the same genre, and anchor and negative are musicians of different genres. We can get the genre of the musician ids by using the influence_data dataset, and combine it with the data_by_artist dataset, we can

get the musician features we need.

The data construction process is as follows:

1. randomly select a musician as Anchor
2. choose a musician Positive who has the same genre as Anchor
3. choose a musician Negative who is different from Anchor
4. form the model input (a, p, n)
5. repeat the above operations until the data set is large enough

4.2.4 Model Training and Solution

Using the above data and the model for training, we obtain the following loss plot, which illustrates the effective convergence of our model.

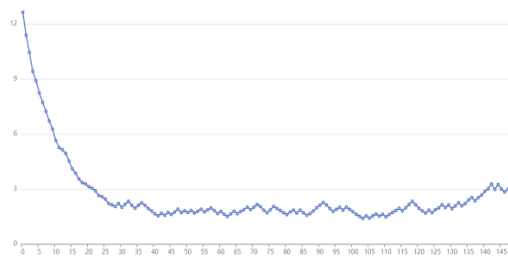


Figure 10. Loss

Based on the trained model, get each ω :

$$\begin{aligned} \omega_1 &= 0.7382, \omega_2 = 1.238, \omega_3 = 3.165, \omega_4 = 3.573, \omega_5 = 1.093, \omega_6 = 4.837, \omega_7 = 7.284, \omega_8 \\ &= 6.837, \omega_9 = 4.128, \omega_{10} = 0.9737, \omega_{11} = 1.273, \omega_{12} = 1.0234, \omega_{13} \\ &= 1.3276, \omega_{14} = 0.5283, \omega_{15} = 1.0128 \end{aligned}$$

The musical features of all the musicians were extracted by the above model, the similarity between each musician was calculated by bringing in the above formula, and the results were classified by using the clustering method, and the scatter plot of musical similarity between musicians was obtained as shown below.



Figure 11. Scatterplot of Similarity

In the above scatter plot, points of the same color represent musicians in the same faction, while different colors represent different musical factions. It can be seen that the scattered points of the same color are basically clustered together and they are closer together, which means that they are more similar; And most of the points with different colors are not clustered together, indicating that they are less similar. This leads to the conclusion that the musical similarity of artists in the same genre is greater than the musical similarity of artists between genres.

5. Problem 3: Contact & Change between Genres

5.1 The Differences between Genres

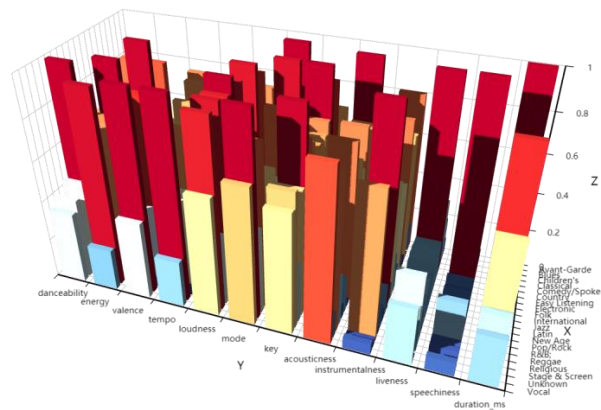


Figure 12. Genre Characteristics Relationship

In the 3D histogram, the Y-axis represents the different music features, the X-axis represents the different music genres, and the Z-axis represents the music feature data after normalization. From the graph we can see that the different musical characteristics of different music genres are very different, so it can be determined: the difference between genres is mainly reflected by 15 musical characteristics. For example, the musical characteristics of Speechiness, Loudness and Energy are much higher in Comedy/Spoken compared to other music genres, because the musical characteristics of Comedy/Spoken are having strong verbal expression as well as having strong infectious power; however, Comedy/Spoken is mainly based on vocal performance, so it is weaker than other music genres in terms of instrumentalness and danceability. The importance ranking of all music features, ω_n , obtained from the music feature weights calculated in the second question is shown below.

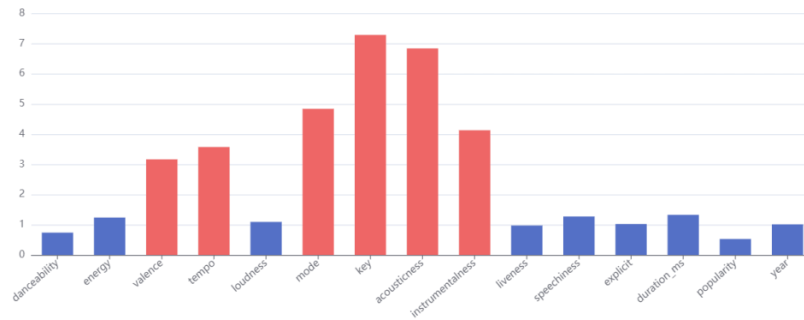


Figure 13. Music Characteristics Contribution

We use the six musical features with the largest weights to distinguish between genres: valence, tempo, mode, key, acousticness, and instrumentalness - they are obtained using an optimization model, and the difference between these six features The difference between these six features represents the difference between the genres to the greatest extent.

After that, we used the k-means clustering algorithm to cluster the musical features of all musicians in the 20 genres, and the obtained genre clustering results are shown in Figure 14.

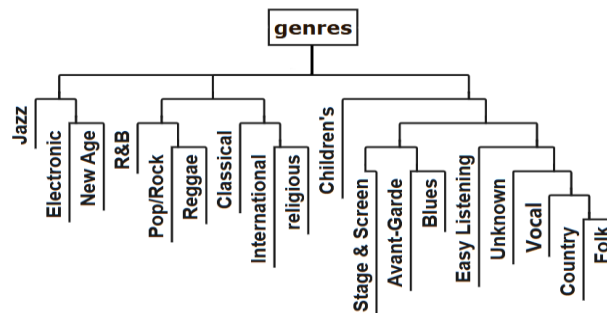


Figure 14. Music Genres Clustering

From the merging distances in the above clustering diagram, the children’s genre is very different from other music genres, mainly in that the characteristic values of danceability, valence and acousticness are greater than those of other genres; however, its song duration and instrumentation values are much lower than those of other genres. These characteristics coincide with the characteristics of children’s songs which are light and lively, with more backing vocals and suitable for dancing. In contrast, jazz and electronic music are classified into the same category as New Age, which is characterized as danceable and less active in the dataset, which is consistent with the lazy and romantic characteristics of jazz.

5.2 The Variation of Genres over Time

A. Part I: Changes in the musical influence of genres over time

The share of the weight of the major genres in the music world changes over time, and the larger the share, the more dominant that form of music was in the music world at the time. We calculated - based

on the difference between the chronological span of influencers and followers - that the average chronological span over which musicians of one decade can influence is 15.8 years. Since the chronological span in the title is measured in decades, we set this chronological span of influence to 20 years, and when calculating the influence of genres, we superimposed the data from the first two decades to obtain the annual percentage of musical influence for each genre as shown below.

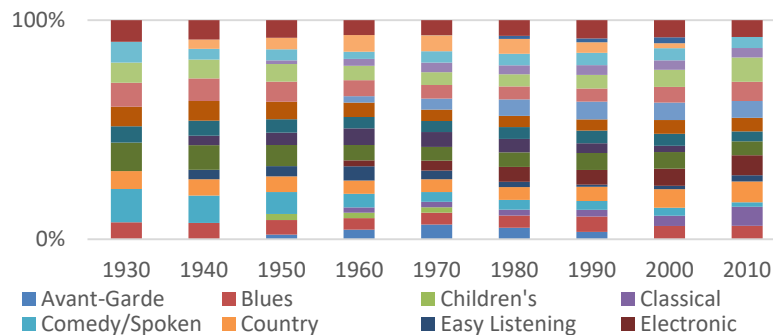


Figure 15. Music Genre Influence Change

The horizontal axis represents time and the vertical axis represents percentages. Each bar represents the percentage of influence of each music genre in this decade, and the larger the percentage in a bar indicates the greater the influence of that genre in this decade.

From the chart, it can be seen that Comedy/Spoken was a dominant musical genre during the three decades of 1930, 1940 and 1950, because during this period, transportation and communication technology were not yet developed, and the main way for people to enjoy music was to go to the movie theater or opera house to enjoy music, and the main form of Comedy/Spoken interpretation was also in that era. This led to the dominance of Comedy/Spoken in the music world during these thirty years; however, although Comedy/Spoken dominated the top of the influence list, its influence declined gradually during these thirty years.

Of course, there are emerging genres that have declined in influence, such as international music, which began to emerge in the 1930s and reached its peak of influence around 1960, because with the outbreak of World War II, cultures spread as the war unfolded and different cultures around the world began to intermingle, leading to cultural clashes between different cultures. This led to the prevalence of international music, showing that the dominance of music genres changes with world politics. Other music genres also have similar characteristics, and for the sake of space, I will not cite them here.

B. Part II: Changes in the musical characteristics of genres over time

Over time, the musical characteristics of different musical forms change in different ways. We analyzed all 15 types of musical characteristics (danceability, vocals, beats, etc.) of the twenty genres, mapping out the different musical characteristics of each genre over time, and because of the large number of musical characteristics, here we take the typical acousticness as an example.

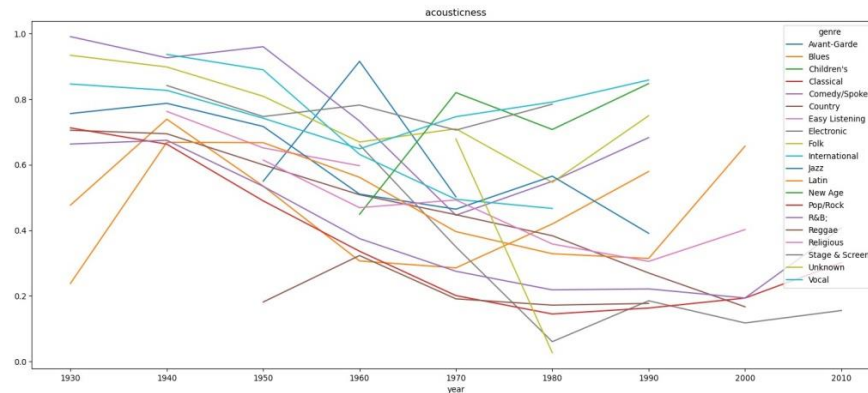


Figure 16. Acousticness with Time

In the line graph, the horizontal axis represents time, the vertical axis represents the music characteristic data after normalization, and the different colored lines indicate the direction of the acousticness metrics of different genres over time.

As can be seen from the graph, the changes in acousticness indicators for each genre are relatively large over time, and acousticness shows whether a piece of music has been technically enhanced or electronically amplified. Before the 1950s, the acousticness values of basically all genres were above 0.6, indicating that most of the music did not use technical enhancement or electronic amplification techniques because the technology was more backward at that time and these techniques were not yet widespread, so that only some musicians of individual genres used these techniques in their music. In the 1970s, when electronic enhancement techniques became more popular, many musicians began to use these electronic amplification techniques, resulting in acousticness values for basically all genres dropping to varying degrees, with the average coming in at around 0.5. In the 1980s, it seems that these electronic enhancement techniques became too popular, and Folk, Latin In the 1980s, it seemed that these electronic enhancement techniques were too popular, and Folk, Latin, and others started a round of “back to basics” movement, they began to abandon the use of electronic enhancement techniques, and therefore their acousticness values began to rise, and led Religious, Blues, and several other genres in the 1990s also began to “Back to the basics”.

5.3 The Genres are Interrelated

The mutuality between the streams, which we obtained from the model established in the second question, the central value of the musician’s scatter within a particular stream is the eigenvalue of that stream, and the similarity between each stream is obtained by calculating the optimized cosine distance of the central value between each stream, plotted as a heat map, and the image obtained is shown below.

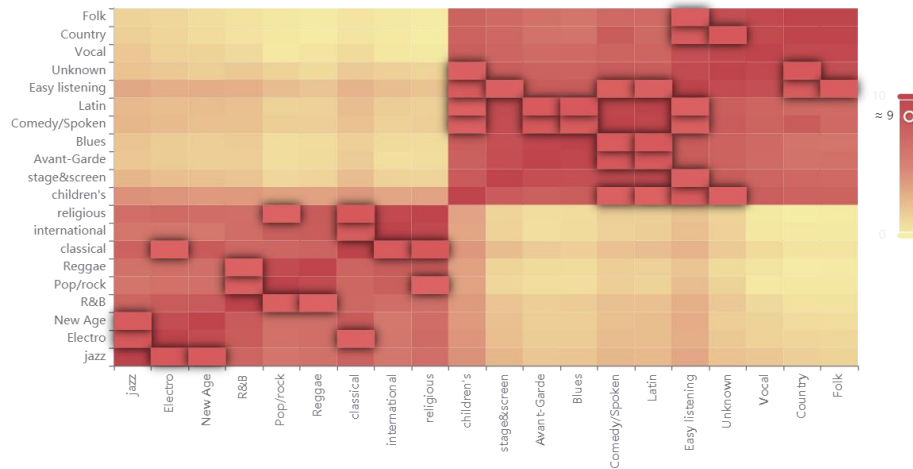


Figure 17. Stream Similarity Heat Map

In the heat map, the horizontal and vertical axes represent different music genres. The darker the color of the points in the map, the more similar the two genres are, and the lighter the color, the less related the two genres are.

From the heat map, we can find that there are interrelationships between genres, and some genres even lead to the creation and development of other genres. For example, Blues was mainly a vocal narrative at first, but later added instrumental accompaniment, and it made considerable contributions to jazz, rock, country and western music; with the increasing popularity of Pop/Rock, Folk music was influenced by With the growing popularity of Pop/Rock, Folk music was influenced by Pop/Rock music and formed the music category of Folk Rock.

6. Problem 4: Musical Influence & Contagious

6.1 Music Influence T-test Model (MITM)

In this question, the mean \bar{s} of the similarity between all influencers and followers is calculated separately. The similarity between all “influencers” and non-influencers is calculated separately, and it follows a normal distribution. Establish the test.

H_0 : “Influencers” do not influence the music created by their followers

H_1 : “Influencers” influence the music created by their followers

A T-test was performed using SPSS software with confidence interval set at 95% and the results were obtained as shown below:

One-Sample Test						
Test Value = 7						
	t	df	Sig. (2-tailed)	Mean Difference	95% Confidence Interval of the Difference	
					Lower	Upper
Similarity	-3.785	9616	.002	-3.24977	-5.0700	-1.4295

Figure 18: Hypothesis Testing Results

The p-value was $0.002 < 0.05$, so the original hypothesis was rejected and the alternative hypothesis was that the “influencers” would influence the music created by the followers.

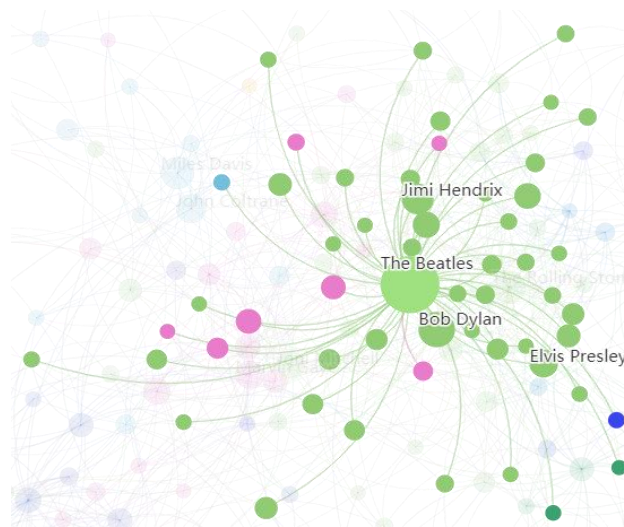


Figure 19. Key Influence Subgraphs

We used the network graph of the top 200 musicians in terms of music influence obtained from the second question as the basis for the relationship, with the musicians influenced by The Beatles as a sub-graph. From the sub-graph, that is, those musicians who are in the same genre as The Beatles, filtered from the followers of The Beatles, their eleven key musical indicators are averaged and brought into the formula in the second question.

$$S = \frac{\sum_{i=1}^{15} \omega_i a_i b_i}{\sqrt{\sum_{i=1}^{15} (a_i)^2} \sqrt{\sum_{i=1}^{15} (b_i)^2}}$$

The follower similarity value $S_{similar}$ is obtained.

Similarly, in the network graph of the top 200 musicians, the followers of The Beatles were eliminated, and musicians in the same genre as The Beatles were selected and brought into the formula to obtain the non-follower similarity value S_{unlike} :

Table 4. Similarity Table

	Non-follower	Follower	The Beatles
S	0.7293	0.7823	1

As can be seen from the table, followers of The Beatles are more similar to The Beatles than followers who are not The Beatles. Also, we visualized 11 individual musical characteristics for these three categories and obtained the following radar plot.

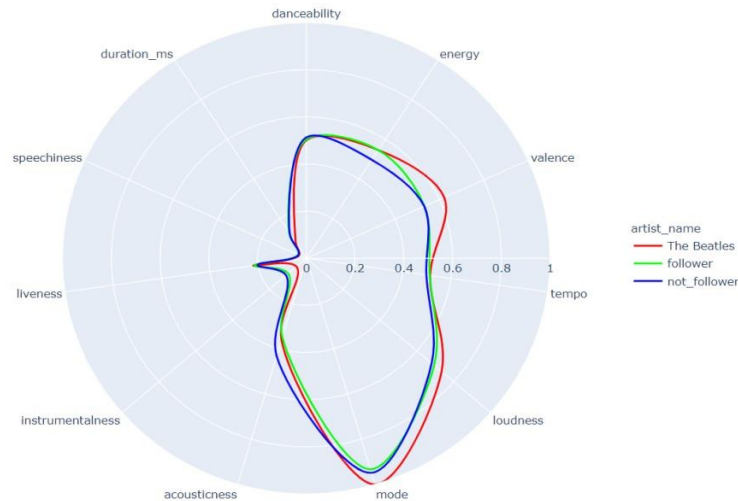


Figure 20. Similarity Radar Chart

As you can see from the radar chart: In characteristics such as liveness, tempo, energy, followers are more similar to The Beatles, although there is no particularly large gap, this is because all samples are of one genre of Pop/Rock and the gap between genre and genre is not too large. But there is a certain gap indicating that the influencer has had a great influence on the follower, bringing the musical characteristics of the follower closer to the follower.

6.2 Contagious Evaluation Model (CEM)

In this paper, a new metric is developed to measure “contagious”, which is considered to be influenced by both “musical influence” and popularity with equal weighting, resulting in the definition of contagious:

$$\text{Contagious} = \text{Popularity} + \text{Music Influence}$$

The value of “contagious” is calculated specifically. The Pearson correlation coefficients between “contagious” and different musical characteristics of the artist’s compositions were then calculated using SPSS software, and the results are shown in the following table.

Table 5. Pearson Correlation Coefficient

danceability	energy	valence	tempo	loudness	mode
0.155	0.279	0.071	0.086	0.333	0.023
key	acousticness	instrumentalness	liveness	speechiness	duration_ms
0.002	0.392	0.165	0.077	0.049	0.061

As can be seen from the above table, the Pearson correlation coefficients of energy, loudness, and acousticness are larger and more relevant than those of other musical features, indicating that these three features are more “contagious” than other features.

7. Problem 5: Revolutions in Musical Evolution

7.1 Signify Revolutions in Musical Evolution

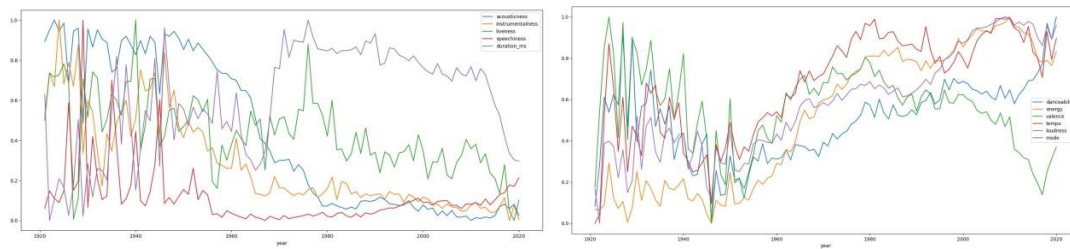


Figure 21 & 22. Music Features over the Years

We plotted the trend of each music feature over the years based on the data_by_year dataset, where the horizontal axis indicates time, the vertical axis indicates the data values of music features after normalization, and the different colored lines indicate the direction of the integrated music indicators of different generations over time.

As can be seen visually from the above line graph, the musical character of the pre-1940 period swung dramatically, music was in a wave of globalization, and musicians discovered that musical diversity could make melodies more moving. During the period 1940-1960, great changes took place; the music after 1960 showed changes characterized by higher rhythmicity, faster speed, increased loudness, more technical enhancements, and fewer spoken words.

7.2 Musical Revolutionaries

Table 6. Musical Revolutionaries

name	genre	start_year	danceability	energy	valence	tempo	loudness	mode	key	acousticness	instrumentalness	liveness	speechiness	duration_ms	popularity	
The Beatles	Pop/Rock	1960	0.7574	0.5008796	0.5462	0.6216	0.513	0.73427	1	0	0.3618025	0.053346487	0.2199	0.03230105	0.08066326	0.593343
Bob Dylan	Pop/Rock	1960	0.5166	0.49024272	0.4771	0.5504	0.542	0.69808	1	0.64	0.56482565	0.035160771	0.3093	0.0442179	0.13235109	0.380998
The Rolling St	Pop/Rock	1960	0.4861	0.50368237	0.7197	0.659	0.528	0.77892	1	0	0.29496734	0.181024725	0.2672	0.03020957	0.11541101	0.426838
Miles Davis	Jazz	1940	0.4761	0.43083099	0.307	0.4096	0.47	0.61752	0	0	0.65834384	0.21076362	0.2165	0.03355912	0.22474943	0.28025
Jimi Hendrix	Pop/Rock	1960	0.4494	0.39041378	0.7163	0.5371	0.508	0.75773	1	0.73	0.21198646	0.17814105	0.265	0.08072295	0.12681569	0.522788

This article is based on a selection of the top five most influential musicians between 1940 and 1960, namely The Beatles, Bob Dylan, The Rolling Stones, Miles Davis and Jimi Hendrix. Analysis reveals that four of these five artists belong to the Pop/Rock genre. The characteristics of their music also coincide with the direction of change of each musical characteristic at the inflection point, such as energy, valence and tempo are relatively high, while acousticness, instrumentalness and speechiness indicators are relatively low. The musical characteristics of the following years also changed in the above direction, thus also side-by-side confirming the great influence of the music of the change-makers. In my network, these five artists can represent the revolutionaries.

The changing musical character of the revolutionaries was ahead of its time. For example: The Beatles' danceability, energy, and valence are strong indicators of their expressiveness, creating their carefree mood of "leave tomorrow far behind, may you have much joy". Unlike the cliché, sentimental,

archaic and old-fashioned atmosphere that filled the British scene at the time, thus almost driving the younger British generation wild. The rise and revolution of The Beatles signaled the end of the dominance of American pop music in Britain, and a large group of followers began to learn the musical characteristics of The Beatles. Each element of The Beatles' fiery popularity had an impact on the fashion trends of society at the time.

8. Problem 6: Dynamic Influencers & Time series of Genre Changes

8.1 Dynamic Influencer Metrics

In this question, we analyze the musical evolution of R&B as a genre of music over time. For the indicators of dynamic influencers, we design as follows.

1. from each era, we select the artist that best represents the musical genre of R&B to represent the musical characteristics of R&B music in that one era
2. The musician who best represents a genre is defined as the musician with the greatest "musical influence" in that era.
3. A comprehensive analysis of the 14 musical characteristics of each era

8.2 Time Series of Genre Changes

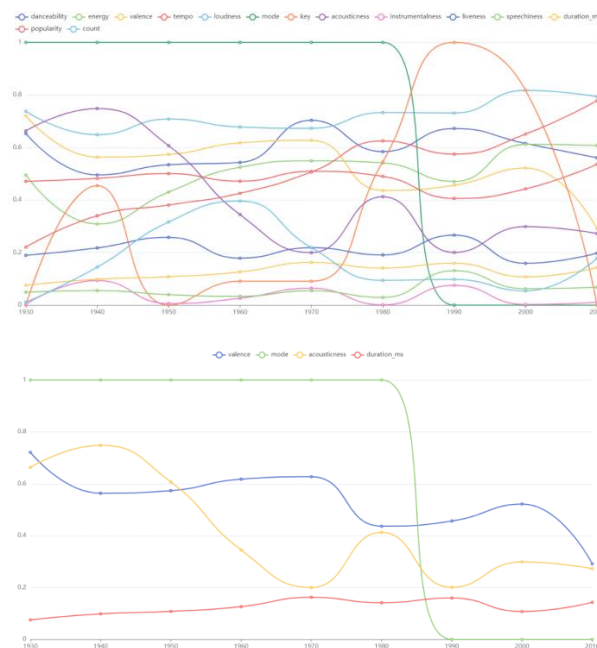


Figure 23 & 24. Music Features over the Years

In the line graph, the horizontal axis indicates time, and the vertical axis indicates the music feature data after normalization. The lines of different colors indicate the direction of the music indicators of different genres over time, showing the trend of the genre over time. It can be seen that most of the indicators are not particularly dramatic changes, but only float in a small range, so we extract the four indicators with relatively more dramatic changes.

It can be seen that the biggest change is the mode indicator of R&B music, which directly changes from Major to Minor, indicating that the volume, tone and timbre of the performance has changed relatively significantly in this era, and the emotional expression of the music has changed from bright and open to soft and dark. The change in the mode indicator also corresponds to a decline in the valence indicator. In the early 20th century, music expressed more positive and optimistic emotions, while at the end of the 20th century, music expressed more negative and sad emotions. At the same time, the development of electronic music technology and the use of electronic tuning in R&B led to a decline in the indicator of acousticness.

9. Problem 7: Network Connectivity Evaluation Model (NCEM)

9.1 Establishment of NCEM

The 20th century was a milestone in the development of music in the West, and in fact, in the world at large. The 20th century was different in that the variety of music changed radically, and it was during this century that the modernization of music took place. This musical explosion was felt then no less than the technological explosion and information explosion we feel today.

We started with network connectivity and calculated it separately for the period 1930-2010. The higher the network connectivity, the greater the changes that occurred, indicating that external factors had an impact on music, thus indicating that social, political or technological changes had a huge impact on music, the formula for network connectivity is as follows.

$$\text{Network connectivity} = \frac{\text{Sum of the nodes' connecting edges}}{\text{Number of nodes}}$$

9.2 Solution of NCEM

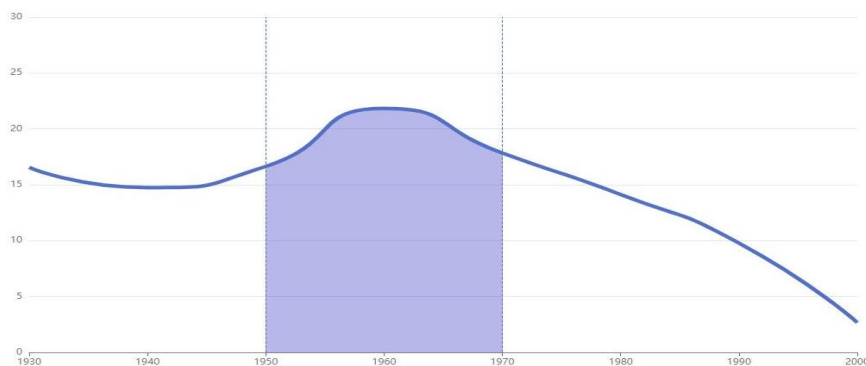


Figure 25. The Trend of Network Connectivity

The graph above shows the time series of network connectivity over time in the network created in this paper. It can be seen that in the middle and first pages of the 20th century, the network connectivity was large and the artists' compositions were widely influenced and affected many people. The 20th century was marked by two world wars, economic crises, fascist dictatorships, etc., which led to social unrest and intensified conflicts, causing psychological changes in society and generating more tension and

anxiety; The rapid development of science and technology, which influenced all aspects of life, made composers more eager to innovate and many genres emerged during this period; The tendency of composing without regard to public reaction and social effects became common. In the second half of the 20th century, society gradually became more peaceful and stable. Although the development of music was still diversified and no one style took center stage, the new music trend had passed and was no longer focused on creation as it had been in the 1950s and 1960s.

The emergence of each genre in the 20th century is more or less inseparable from these general circumstances. But in reality, each genre has its own external causes, which need to be analyzed in detail. Electronic music, for example, was mainly due to the development of technology, which showed the prospect of using new means to create music instead of ordinary instruments and vocals, and attracted composers to experiment in this area. Another example is that, as far as the musical representative John Cage is concerned, his influence was mainly in the 1960s, which I am afraid is related to the unstable social and political life of the West in that decade, with various trends of thought, and young people were prone to adopt a more indifferent and skeptical attitude towards tradition. Based on the social situation at that time, the society gave them a different way of music creation and creative thinking, which made their works closely match with the situation shown by the society at that time.

10. Strengths and Weaknesses

Strengths:

Modeling the intricate relationships of musicians over a 90-year period as a complex network is very innovative and intuitive.

Music impact is measured from multiple indicators, and its weight is obtained by the entropy method, which is reasonable and reliable.

Instead of simply using the cosine distance, the similarity measure is weighted and optimized for each feature, making the similarity measure more reasonable.

Scalable, the model can also be used to analyze the impact of paintings, articles, etc.

Weaknesses:

Unable to explain some special cases.

11. Conclusion

According to the above-mentioned studies, the 20th century saw a radical change in the type of music, with timbre and acoustics becoming the main means of musical expression, a variety of languages and styles, and the formation of different genres, and it was during this century that the modernization of music took place. Composers concentrated on creating and discovering new techniques and patterns in the 50s and 60s; after the 70s, the development of music gradually moved towards stability. The development of music happens to be closely related to the development of society, politics, science and technology.

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