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A study on the evolution and influence of music from the perspective of data in the last hundred years

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Abstract: *Whether in ancient or modern, as a way to cultivate sentiment, and relax the mind, music has been with mankind for a long time. With time going by, music is changing, people's creation and research on music is becoming more and more meticulous, and the major genres learn from each other. There are many factors that can influence artists when they create a new piece of music, including their innate ingenuity, current social or political events, access to new instruments or tools, or other personal experiences. Our goal is to understand and measure the influence of previously produced music on new music and musical artists. In the following report, we use four data sets collected from the ICM Association to quantitatively analyze the evolution of music over the past 90 years. By considering networks of songs and their musical characteristics, we have captured the influence that musical artists have on each other. And we also gain a better understanding of how music evolves through societies over time.*

Keywords: *Data analysis, PCA, Cluster analysis, Music influence and similarity model*

1. Introduction

1.1 Background

Nowadays, music and musical works have become a very common way of appreciating art in the world. The artists who produced those works have been playing a more and more important role in the development of culture, which also has a great impact on their artist-followers. We can not deny that music has been part of human societies and an essential component of culture. With time passing, we can find that all kinds of social or political events occurred to our life and new instruments or tools became on service, which makes the diversity of music richer. Furthermore, of course, some musical geniuses have radically changed the structure of the previous music, creating new genres, which might be more popular. They contributed to major changes in a musical genre, or create a new genre, even make music evolve.

Music is a field in which groups are very connected, and each of them has a greater influence on others than the other fields. It's not hard to see that they are more or less influenced by other musicians when marveling at their incredible creativity. There might be some similarity between the music of the influencer and the music of the affected, or at least we can say that the music within a genre has some similarity, which becomes the symbol of the genre. Obviously, we can talk a lot about the similarities and influence of music.

1.2 What the data we use contains

The Integrative Collective Music (ICM) Society provides several data sets, including “influence_data” scraped from AllMusic.com, representing musical influencers and followers, as reported by the artists themselves, as well as the opinions of industry experts, which contains influencers and followers for 5,854 artists in the last 90 years, and “full_music_data” obtained from Spotify’ s API, providing 16 variable entries, including musical features such as danceability, tempo, loudness, and key, along with artist_name and artist_id for each of 98,340 songs. And the latter data set are used to create two summary data sets, including: mean values by artist “data_by_artist”, and means across years “data_by_year”.

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1.3 Our Work

In order to understand the role music has played in the collective human experience, we want to develop a method to quantify musical evolution to understand and measure the influence of previously produced music on new music and musical artists.

To carry out this challenging project, we aim at exploring the evolution of music through the influence across musical artists over time, by doing the following goals:

1) Create a directed network of musical influence. Develop parameters that capture '*music influence'* in this network. Explore, create and describe a subnetwork of the network.

2) Develop measures of music similarity. Judge similarities of the artists between andwithin genres.

3) Compare similarities and influences between and within genres.

4) Indicate whether the 'influencers' actually affect the music created by the followers. Find 'contagious' characteristics and the role they play in a particular artist's music.

5) Identify characteristics that might signify revolutions (major leaps) in musical evolution.

6) Identify indicators that reveal the dynamic influencers and explain how the genre(s) or artist(s) changed over time

7) Express information about cultural influence of music in time or circumstances and identify social, political or technological changes within the network.

Firstly, we establish a multiple directed network model to describe the relationship of influencers and the followers. Besides, we establish a parameter to measure 'musical influence' in the network, taking advantage of the graph theory. More convincingly, we create many sub-networks in order to explain and solve the following questions. Then we develop a model of similarity to describe the resemblance of two songs. We adopt PCA, the principal component analysis based on eigenvalue decomposition covariance matrix. And we reduce each point by dimensionality to a three-dimensional point represented by characteristics of the music, types of vocals, and descriptions. At last, we use those models to solve the below questions.

2. Assumptions and Justifications

Almost every music one artist produced belongs to his main genre. Since those artists have their own major genre, we can take it for granted that they didn't concentrate too many efforts on other genres.

Those 'unknown' artists and who are not in *influence_data data set* do not play a role in our influence network model. 'Unknown' musicians make up a small percentage of the population, they might belong to any other genre, but on the whole they can be considered to have little impact on the network.

The artists who are not in *influence_data data set* are off the table in any model because they can not take part in the influence network model.

In case that two musicians collaborated on a song, we think each of them made a song of the same name. It is very useful for us to simplify the model.

3. Decide the 'music influence' in the influence relationship

Goal one suggest us use the influence_data data set or portions of it to create (multiple) directed network(s) of musical influence, where influencers are connected to followers, and determine the 'music influence' in the network. Furthermore, we are supposed to create some subnetworks to describe music influence.

We first take musicians as points, influence among musicians as directed edges, and draw a picture of network in *gephi* using all the data. We modularize the network, calculate clustering coefficient, and give different colors and different sizes to each point according to the clustering coefficient and out-degree. We use Fruchterman-Reingold algorithm to layout our network. Depending on the influence type of influencers and followers' main genre, we give each edge a different color. And we treat the processed absolute value of the active_start difference $_t$ between influencer and follower as the weight of the edge, i.e., the weight $W(x,y) = 0.02\times |\Delta_t| + 0.2$

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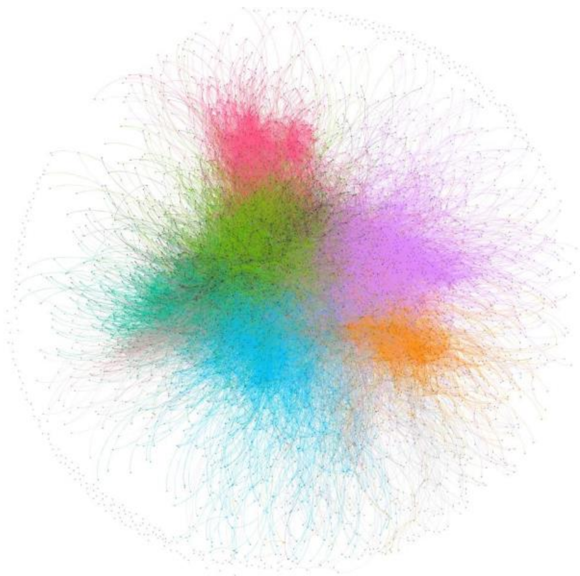

Figure 1: The whole network

3.1 The ideas of music influence network model

3.1.1 Eigenvector centrality [1]

The importance of a node depends not only on the number of its neighbor nodes (i.e., the degree of the node), but also on the importance of its neighbor node, let x_i be the value of measuring v_i importance of node, i.e.,

$$EC(i) = x_i = c\sum_{j=1}^{n} a_{ij} x_j$$

Parameter c is a proportional constant, and let $x = \left[x_1, x_2, x_3, \cdots, x_n\right]^T$ .When reaching the steady state after several iterations, it can be written in the following matrix form,

$$x = cAx$$

But we find that this parameter is undirected, which leads to a false high of importance for some people who do not affect others but are only affected by others, so this parameter can not be used as the main indicator of importance assessment. Of course, we know that PageRank is a variant of Eigenvector centrality and it is directed, which might be helpful to assess the importance [2]. But we decide to develop a unique formula to calculate the music influence, taking advantage of the Methodology of the above approaches.

3.1.2 Our music influence model

By connecting each influencer to the followers in the influence_data data set with a directed edge, we can get the desired directed network. To measure the musical influence of each influencer, we need to use the number of its followers.

But for this problem, it seems not enough to consider the number of direct followers only. For example, considering the Blind Boy Fuller and The New Christy Minstrels, the number of people the former influenced is smaller than that the latter did, but the former’s followers contain Bob Dylan, The Rolling Stones who have plenty of followers.

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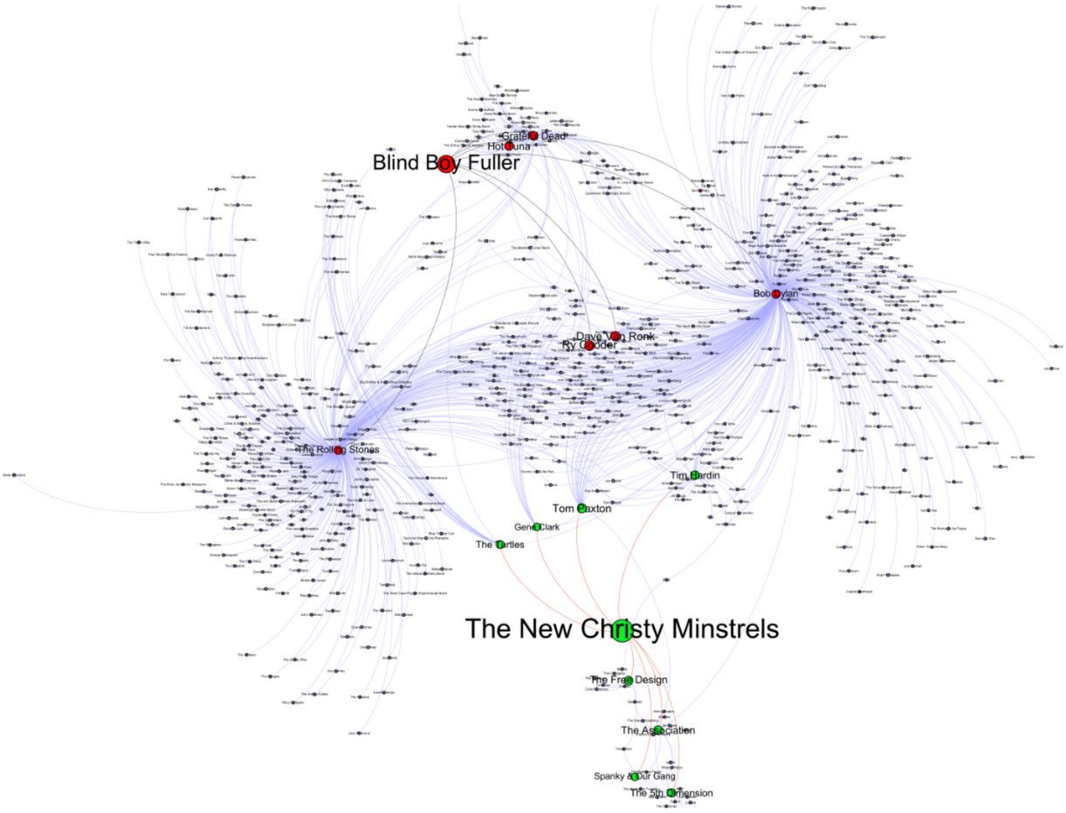

Figure 2: The contrast of their influence

Therefore, we believe that the number of indirect followers, in other words, followers' followers, should also be taken into account in evaluating the musical influence of influencers. Further, influencers might affect followers in the same genres and the different genres, which should also be given different weights.

Therefore, we use $S_1(A)$ to represent the collection of followers in the same genre and $S_2(A)$ to represent the collection of followers in different genres. We determine the following formula to calculate the musical influence of a certain influencer A:

$$\text{Influence(A)} = \sum_{i \in S_1(A)} [1 + 0.1(|S_1(i) + S_2(i)|)] + \sum_{i \in S_2(A)} 0.8[1 + 0.1(|S_1(i) + S_2(i)|)]$$

3.2 Basic assumptions

1) All influencers who influenced the certain follower are completely listed in the influence_data data set, and have the same effect on this follower. In other words, one artist is only affected by the artists in the given data

2) Indirect followers only contain followers of direct followers

3) One's genre and active_start are not decisive in his influence

3.3 Data processing

We import the influence_data data set to gephi to establish a directed network of influencers and followers. We ignore the time information of the influencers and followers, the genre information only retains whether the influencers and followers are in the same genre, and so we can get the number of the same-genre-followers and different-genre-followers of each influencer. The musical influence of each influencer can be calculated according to the above formula.

The music influence of Blind Boy Fuller and The New Christy Minstrels calculated by this model is 71.06 and 16.28. It can reflect that influence is not only related to the number of direct followers, but also "music influence" of followers to some extent, which is embodied in the number of followers' followers.

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4. Music similarity model

We know that influence might be measured by the degree of similarity between song characteristics, such as structure, rhythm, or lyrics. By considering networks of songs and their musical characteristics, we might begin to capture the influence that musical artists have on each other. So it is vital to establish a quantitative model to reflect the similarity of music. This model might help us reveal something about music influence.

4.1 The ideas of music similarity model

First of all, we see that in the full_data data set, each music is described by 15 pure numerical attributes, which are divided into three broad categories: characteristics of the music, type of vocals, and descriptions.For the purpose of accurately describing the similarity between any two pieces of music, we first consider each music as a 15-dimensional point determined by a pure numerical attribute.

And then we reduce each point by dimensionality to a three-dimensional point represented by characteristics of the music, types of vocals, and descriptions. So we use the Minkowski distance between two points to represent the similarity between them. i.e.,

$$d_q(x,y)=\left[\sum_{k=1}^{p}\left|x_k-y_k\right|^q\right]^{\frac{1}{q}},\quad q>0$$

Where $d_q(x,y)$ represents the similarity of x,y two points

4.2 Basic assumptions

To simplify our model, in addition to the above assumptions, we made the following basic assumptions.

1) In the same piece of music, the three dimensions of characteristics of the music, types of vocals, and descriptions are not related.

2) Each piece of music can be accurately described by the fifteen pure numerical attributes.

3) The similarity between each of the two songs is only related to the above three dimensions.

4.3 Data processing

To simplify our model, in addition to the above assumptions, we made the following basic assumptions. Our data processing consists of two steps, data cleaning and data standardization. Through data cleaning, we deleted some data that did not meet the set standards. For example, the loudness of a data item is 130(positive), but the loudness of the rest of the music is negative. It might affect the establishment of the model, so we delete this data. Data standardization is done through minimal method, that is to say,

$$x_{ij}^*=\frac{M_j-x_{ij}}{M_j-m_j}$$

$$M_j=\max\{x_{ij}\},\ m_j=min\{x_{ij}\},\ \text{i=0,1,2……}$$

M_j, m_j is the maximum value of their respective column. So, each column of data is in the [0,1] interval with a maximum of 1 and a minimum of 0.

4.4 Dimensionality Reduction of High Dimensional Data

In the original hypothesis, fifteen pure numeric attributes can be divided into three dimensions, Characteristics of the music (danceability, energy, valence, tempo, loudness, mode, key), Type of vocals (acousticness, instrumentalness, liveness, speechiness, explicit), and description (duration_ms, popularity, year).

If we use the fifteen attribute values to calculate Minkowski distance between two points directly, something bad could happen. For example, danceability and energy are the main difference between A

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and B corresponding values, while the main differences between A and C are danceability and instrumentalness. Now we find that A and C differ greatly in Characteristics of the music and Type of vocals, and that A and B are very different in only one dimension.

So we think, when the two songs are similar in both dimensions, in general, these two songs will be classified into the same main category. That is to say that we should weaken the influence of similarity difference on the final similarity result in a single dimension. So we're considering turning the 15 attribute values to three dimensions, Characteristics of the music, Type of vocals, Description through dimensionality reduction, in order to describe each piece of music. So the similarity difference between two music can be described more accurately.

To achieve the above purposes, we need to transform the n dimensional vector represented by the data attributes of each dimension into one-dimensional vector by a unified formula. We adopt PCA, the principal component analysis based on eigenvalue decomposition covariance matrix.

We hope to find a coordinate axis from the original space by the original n dimension vector under each dimension, which corresponds to the direction of the maximum difference in the original data. We realized the dimensionality reduction of data features by retaining the dimension features containing most of the variance and ignoring the feature dimensions containing almost 0 variance.

1) To decentralize the data, subtract the mean of the column from each data. i.e.,

$$x_{ij}^{*} = x_{ij} - \overline{x_{\iota}}$$

2) Calculate the covariance matrix P_i by n-dimension vector X_i per row

$$Xi = (x_{i1}, x_{i2}, \dots \dots, x_{in})$$

$$P_i = \frac{1}{n} X X^T$$

3) Obtain the eigenvalues of all covariance matrices, select the largest eigenvalues, and then obtain the corresponding eigenvectors.At last, we convert the original data into a linear space composed of new eigenvectors, i.e.,

$$Y = PX$$

So, we can obtain three one-dimension vectors through dimensionality reduction of each original dimension set.

On the basis of the above results, we calculate the Minkowski distance when p=2, i.e., Euclidean distance. i.e.,

$$d_2(x, y) = \left[\sum_{k=1}^{p} \left| x_k - y_k \right|^2 \right]^{\frac{1}{2}}$$

d_2 x, y is the similarity between music x and music y in this model

Based on the above model, in order to compare the similarity of musicians between and within genres, we apply the model to the data_by_artist data set, and draw a scatter plot of artist similarity between two different genres in the coordinate system of any two dimensions. It is obvious that the point density of the same genre is higher, while the points of different genres are more inclined to evacuate, so we think that the similarity of musicians within the same genre will be greater than that of musicians between different genres. This view accords with our general cognition and in turn confirms the correctness of the model.

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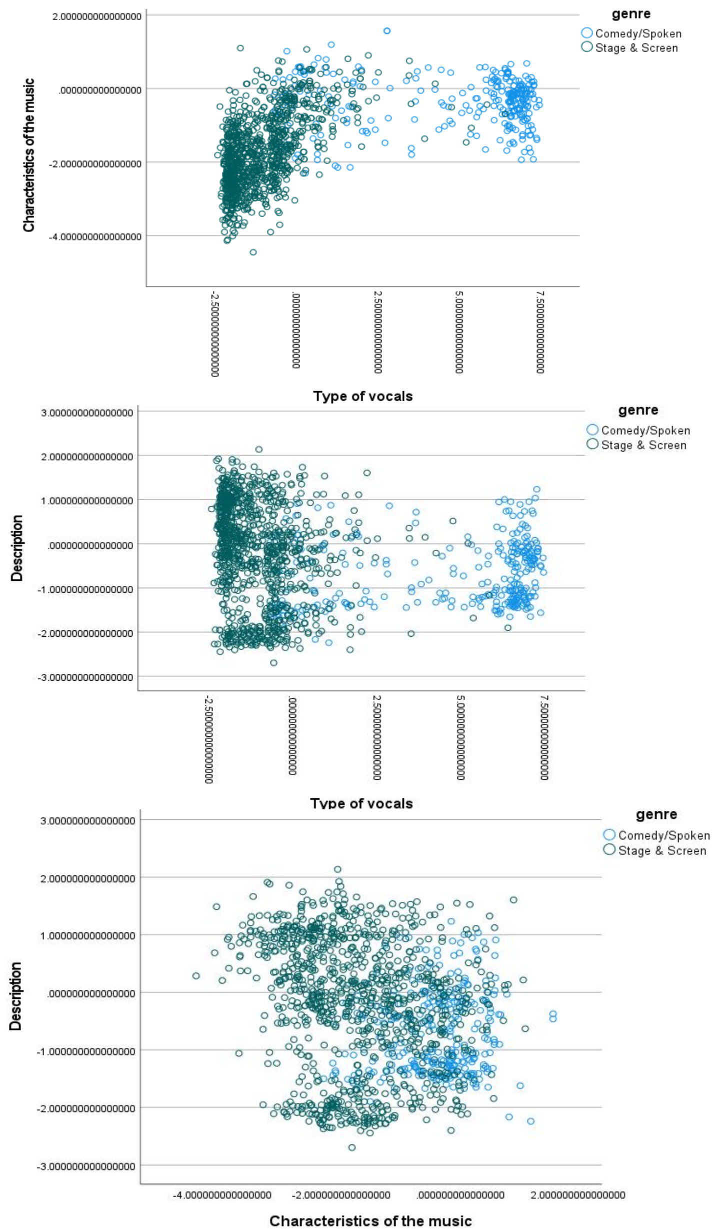

Figure 3: Three pieces of scatter plots of two dimensions

5. Similarities and influences between and within genres

In this goal, we'd better to compare similarities and influences between and within genres. About this task, we have different opinions. The compared thing can be 'similarities and influence' or 'between and within genres'

5.1 The main distinguishment between genres

We still use the above calculation results to compare the variance of the average value of each genre in the three dimensions, and to compare in which dimension, the difference between the genres is greater, and the results are as follows:

Table 1: The results of three dimensions

Characteristics of the music	Description	Type of vocals
0.777276833	0.729783018	1.287007254

We can see that type of vocals is significantly higher than the other two dimensions, so it can be considered as the largest gap between genres.i.e., there is a great difference in acousticness,

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instrumentalness, liveness, speechiness, and explicit between genres.

We did not choose to compare 15 attributes individually, because we thought that the main differences between the two genres could not be explained by such small features in those musical works, but we are supposed to choose the larger dimensions to explain the differences.

5.2 Cluster analysis

In order to further explain the differences and connections between genres, we first use the works in each genre to calculate the average value of each attribute, and then use K-means clustering analysis to divide the genres into three categories. The characteristics and differences of genres in this class are explained by finding the correlation between three cluster centers.

Specific steps: firstly, three points are randomly selected from the standardized data as the initial clustering center, then we calculate the distance from each sample to the cluster, and classify the sample to the class where the cluster center is closest to it. The average value of each newly formed cluster data object is calculated to obtain the new cluster center. If there is no change in the adjacent two clustering centers, the sample adjustment is over and the clustering criterion function has converged. Examine whether the classification of each sample is right in each iteration. If not, modify all samples, modify the clustering center and enter the next iteration. If all samples are correctly classified in an iterative algorithm, there will be no adjustment and there will be no change in the cluster center, which marks the convergence and results.

After cluster analysis, the results are as follows:

Table 2: The results of cluster analysis

genre	Center number	Distance to center
Children's	1	0.403369673
Comedy/Spoken	1	0.403369673
Avant-Garde	2	0.248105731
Classical	2	0.299067327
Easy Listening	2	0.16771579
Folk	2	0.357925023
International	2	0.3741693
Jazz	2	0.186971312
New Age	2	0.455260442
Stage & Screen	2	0.307358014
Vocal	2	0.370766372
Blues	3	0.324699293
Country	3	0.270027309
Electronic	3	0.457255547
Latin	3	0.165261604
Pop/Rock	3	0.18134073
R&B;	3	0.128674043
Reggae	3	0.240635261
Religious	3	0.211033746

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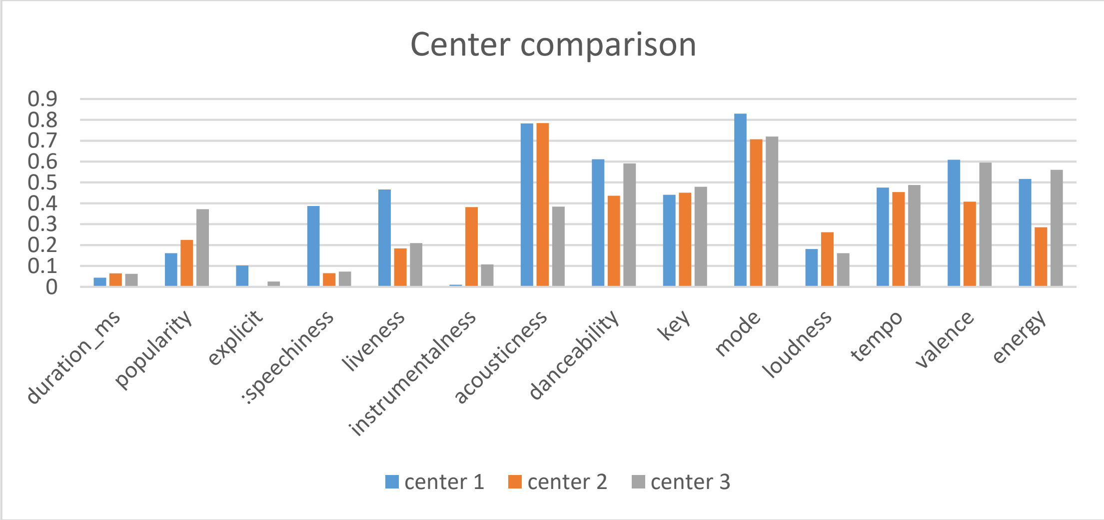

Figure 4: Center comparison

It can be seen from the table that each attribute has a small distance from the cluster center, so the clustering model is successful. By looking at the chart, we can see that, the difference between the Children's and Comedy/Spoken genres belonging to the center 1 and other genres lies mainly in the large speechiness and liveness. The difference between Avant-Garde, Classical, Easy Listening, Folk, International, Jazz, New Age, Stage &Screen, and Vocal genres belonging to center 2 and other genres lies mainly in instrumentalness and energy, the difference between the genres of center 3 and the other genres is mainly acounticness and popularity. So we know the main difference between genres.

In order to get the correlation between genres, on the one hand, we can think that there is a certain correlation between the same genres in the previous cluster analysis results. On the other hand, we hope to express the correlation between genres through the index of influence degree of genres. We define the ‘genre influence’ of genre A on genre B as the sum of the number of followers of all influencers in A to B. For example, three are two influencers A_1, A_2 in the A. Three followers of A1 belong to the B genre, and the two followers of A2 belong to the B genre. Then we can calculate that the ‘genre influence’ of the A on genre B is 5. According to the above method, we output ‘genre influence’ between any two of genres.

Since the number of people in each genre is different, we divide the "genre influence" of A to B by the number of genre B as the correlation coefficient of A to B, and we consider the coefficient that is less than 0.1 as 0, which means they have nothing to do with each other. The remaining results are as follows:

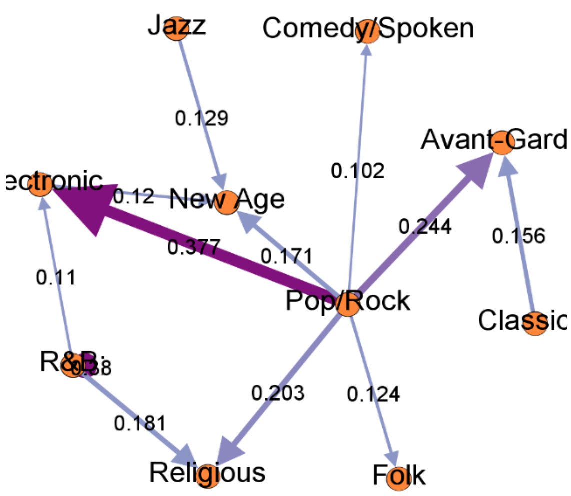

Figure 5: A network of correlation

We can clearly see that both Pop/Rock and Jazz are related to New Age. As to the former, the degree of correlation is greater. So we can say that we establish the correlation degree model between genres.

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6. Application of similarities and the influence network model

6.1 The main distinguishment between genres

In order to explore whether the influencer really affects the followers' music creation, we use the similarity model in the second question to represent each work with a three-dimensional vector. We use the center of gravity of the three-dimensional vector of all his works, that is, the average value, to express the coordinates of each person. Then the center of gravity of all the people in each genre is calculated, which is the coordinates of the genres. The distance between two points is expressed by the Euler distance between two coordinates.

For a single influencer, we set up a scoring model. If the distance between one of his followers and the influencer is smaller than the distance between his followers' genre and the influencer, then we can think that the influencer has an impact on his followers' music creation. If the final score is greater than 90% of the followers of the influencer, we can assume that the influencer influences the followers' music creation.

We take the Beatles, the most influential one in the influence model, as an example. After the calculation of the above model, the final score is 490. The total number of followers of the Beatles is 511, and the score is more than 90%. Therefore, the hypothesis is true, and the conclusion is that the influencers affect the music creation of the followers, making the characteristics of their works closer to the direction of the influencers.

In order to explain whether some musical features are more "infectious" than others, or whether they all play similar roles in influencing the music of a particular artist, we use correlation coefficient to build a model. We still take the Beatles as an example and use the data processed above. We calculate the correlation coefficient of influencer and follower under each attribute, namely

$$X = (X_1, X_2, \dots\dots, X_n)$$

$$Y = (Y_1, Y_2, \dots\dots, Y_n)$$

Where n is the number of followers,

$$\mathrm{r} = \frac{\sum(X-\bar{X})(Y-\bar{Y})}{\sqrt{\sum(X-\bar{X})^2}\sum(Y-\bar{Y})^2}$$

R is the correlation coefficient.

According to the output results of the model and the analysis of a series of correlation coefficients, it is found that the correlation coefficients are close to 1, so we can assume that these attributes are not different between influencers and followers, and together constitute the influence of influencers on inheritors, so as to draw a conclusion: these musical features play a similar role in influencing artists.

6.2 Revolutions in musical evolution

In order to find out the characteristics that might be revolutionary (major leap) in the evolution of music, we believe that such data should require one of the following characteristics:

1) Since the year represented by a certain point, the development trend of a certain characteristic of musical works has changed greatly, and the change lasts not less than 10 years

2) Before and after the year represented by a certain point, the overall average value of a particular feature of musical works has changed significantly, and the duration of the change is not less than 10 years

In order to illustrate the above features better, we will use images to explain. First, after we have completed the data cleaning and data standardization, we calculate the average value of all works in each year on all pure numerical attributes except the year. i.e., we can know approximately the ever-changing characteristics of the history of music development by year.

We want to find revolutionary feature changes, which should either change the original feature trend and last for a period of time, or greatly increase or decrease the order of magnitude of the original feature and keep this trend for a period of time.

Other changes of features, we think, are short-lived and can not be called revolutionary. Of course, in

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the image description, we have deleted the year in which the number of works is less than 20, which is used to avoid the influence of contingency errors. We take ‘energy’ for example to illustrate the above models:

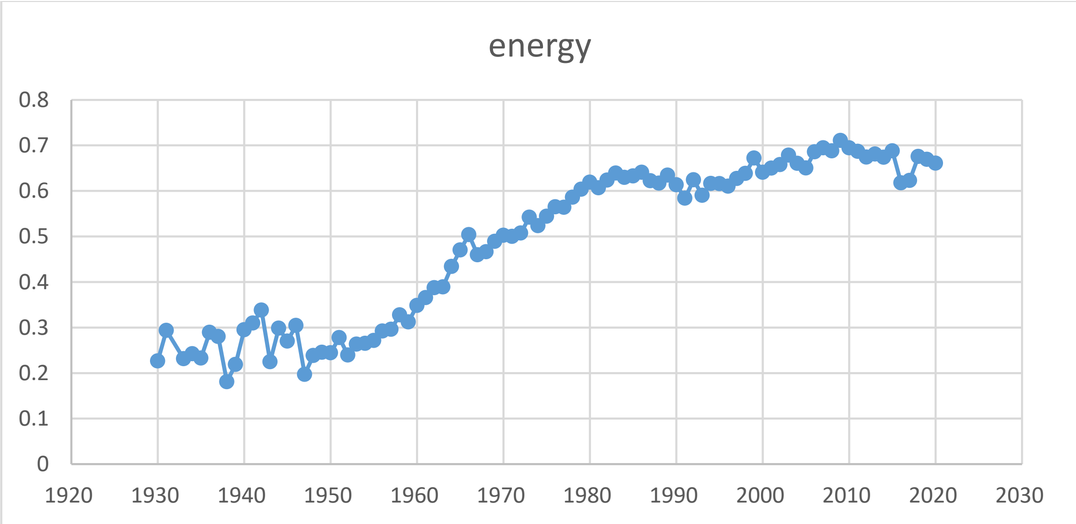

Figure 6: The change of ‘energy’ feature by time

We can see that the value of the energy has been fluctuating greatly before 1947, but the fluctuation has been jumping and has not brought about a continuous change, so we do not think it can be called "revolutionary" change. From around 1947, the value of energy has changed from fluctuating up and down to rising for about 30 years, so we can guess that some changes have taken place in that era, which has led to the gradual acceptance of more dynamic music. Composers are also willing to try more ‘energy’ works.

According to the model, we start from three dimensions to find the characteristics of transformative change:

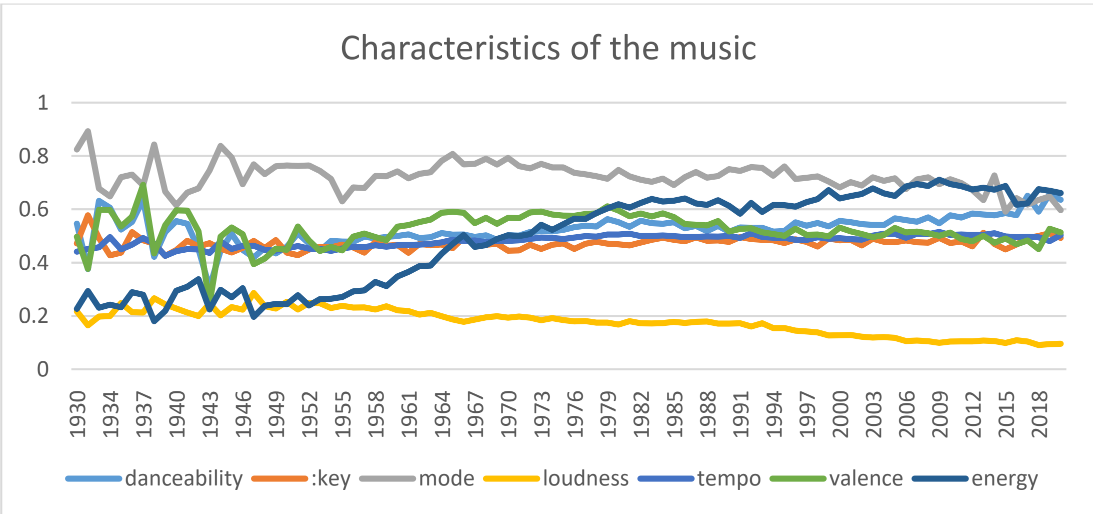

Figure 7: The change of ‘Characteristics of the music’ by time

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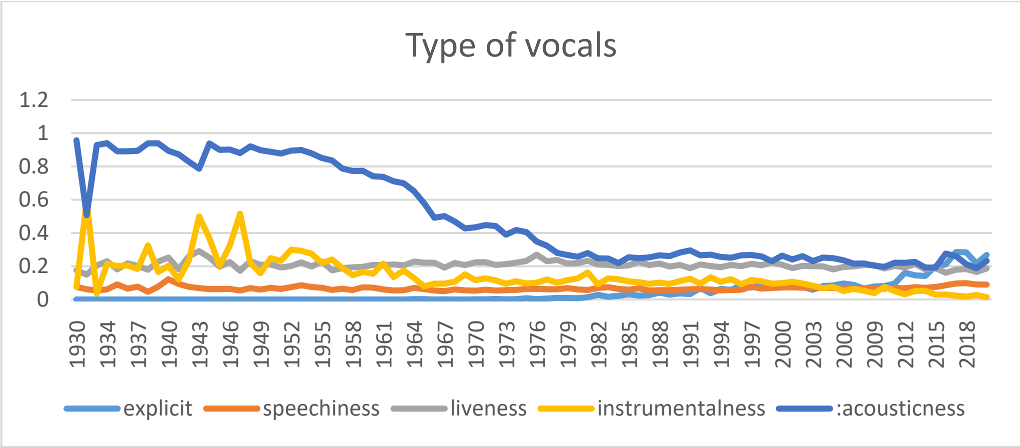

Figure 8: The change of 'Type of vocals' by time

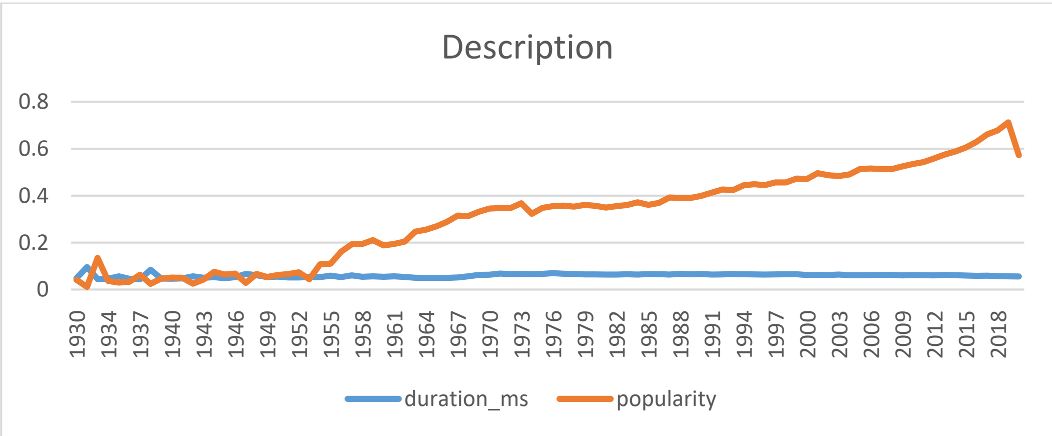

Figure 9: The change of 'Description' by time

We can see from the analysis of the above three dimensions that the acousticness in 1951, energy in 1947 and the popularity in 1953 have revolutionized the original trend of its feature, so we have come to the conclusion that the history of music in the vicinity of 1947-1953 has taken a major turn in energy, acousticness and popularity, which is the revolutionary change we have found.

Through the above analysis, we find that the history of music has changed greatly in 1947-1953. In order to find the artists who bring about the change, we hope to find the artists who meet at least one of the following conditions during this period:

1) Have a lot of publications

2) Average popularity of works

3) Have published a work and great influence (According to Goal one)

We believe that artists who meet one of the above requirements, in the 1947-1953 period, have a greater influence on the music industry and are more likely to be the influencers of major changes. We have selected artists who meet the above requirements:

Table 3: The most likely influencers of major changes judged by song amount

id	song amount
26350	351
132940	340

Table 4: The most likely influencers of major changes judged by influency

id	influency
46861	332.62
423829	319.24

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Table 5: The most likely influencers of major changes judged by popularity

id	popularity
79016	0.25125
345734	0.220476

7. Time analysis and cultural analysis

In these two questions, we will analyze the influence process of time, identify the dynamic influencers, and explain the change by time. And we also are supposed to express information about cultural influence of music in our network and identify the effects caused by social, political or technological changes.

7.1 Influence processes of musical evolution

1) Change by time

In order to calculate the variation of each genre over time, we can approximately use the variation of the average value of the genre's work in each numerical attribute to express those changes. Firstly, we take advantage of the results of data cleaning and standardization carried out before to calculate the average value of each numerical attribute of all works of each genre every year. Using the broken line diagram, we can easily see the change of each genre over time.

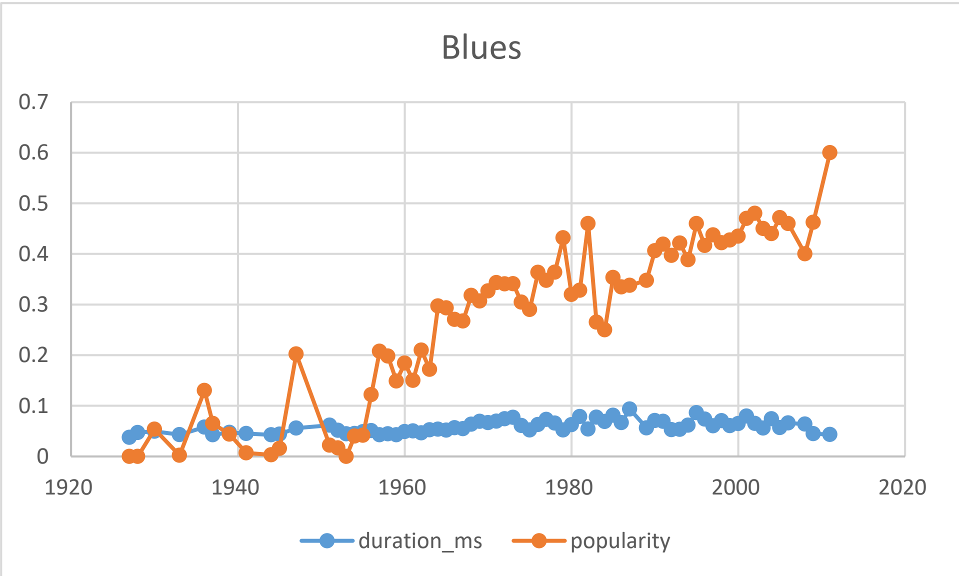

Figure 10: The change of Blues over time

Such as Blues, through the broken line diagram, we can see that the duration_ms of the genre remains basically the same, and the popularity has gradually increased since 1955. Through this method, it is easy to see the change of each genre over time, and to see the invariance and change of each genre in each musical feature. Because of the large number of features, we only describe the change of popularity. Here we pick up a few large-amount-of-data, and representative genres.

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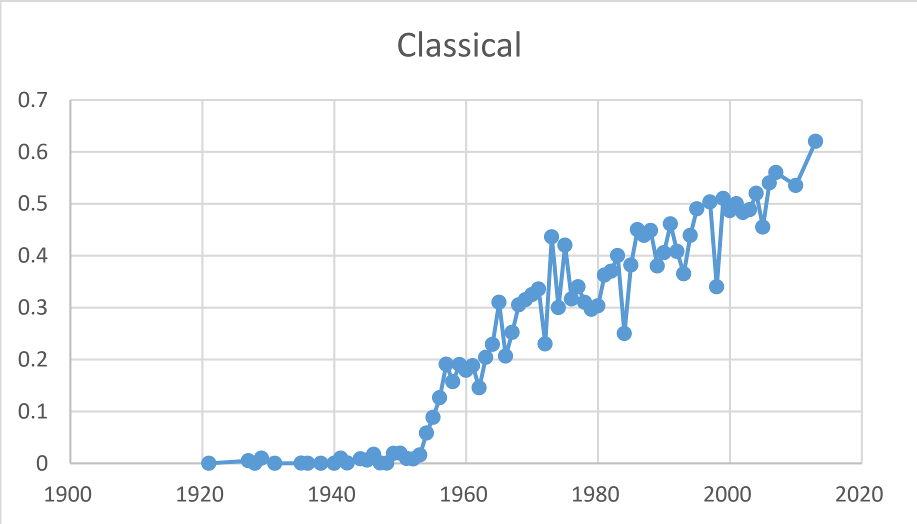

Figure 11: The change of 'Classical' in popularity

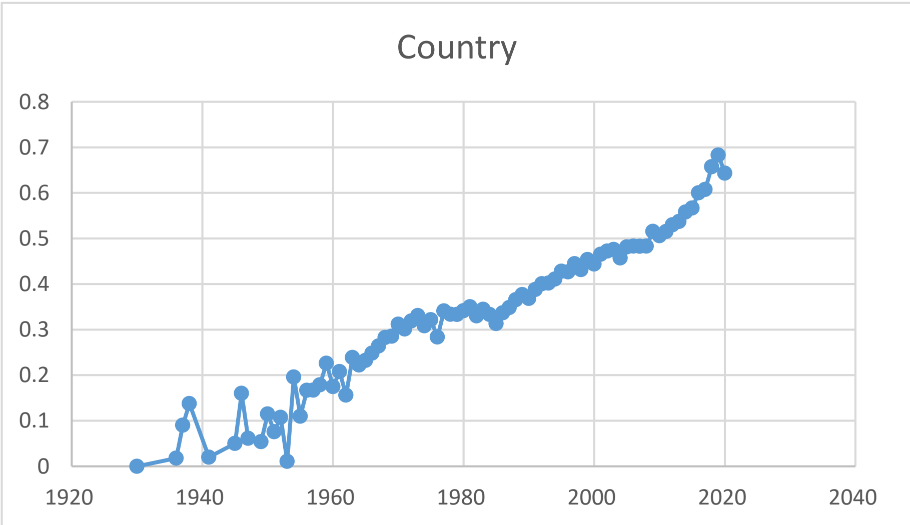

Figure 12: The change of 'Country' in popularity

As we can see, the average popularity of musical works of each genre is increasing year by year. According to the history of music development, it can be considered that with the barriers to enjoying and creating music fall and the emergence of DVD and other means of communication methods, the range and speed of music communication increase and accelerate by time. This can be a change over time for all genres.

2) Describe the changes of genres over time

In order to describe the changes of genres over time, we choose Classical genre with long duration and large number of works to analyze and reduce contingency errors.

We analyze each attribute of this genre year by year, and get the image to see which attributes change most with time. After analysis, we find that the most fluctuating index is 'instrumentalness', the following is the image:

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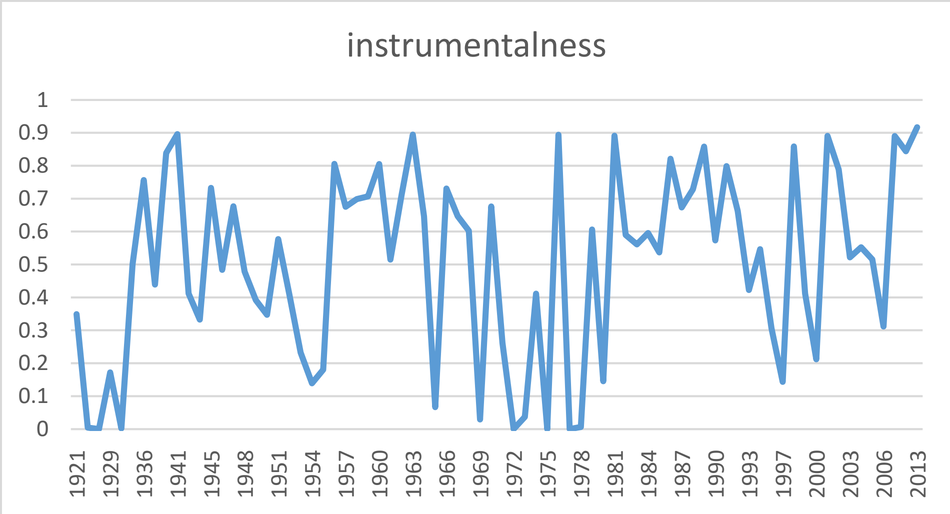

Figure 13: The change of 'instrumentalness' of classical

As we can see, instrumentalness vary greatly over year.So we can think of it as the most significant indicator of this genre. Then we look at the popularity of the genre:

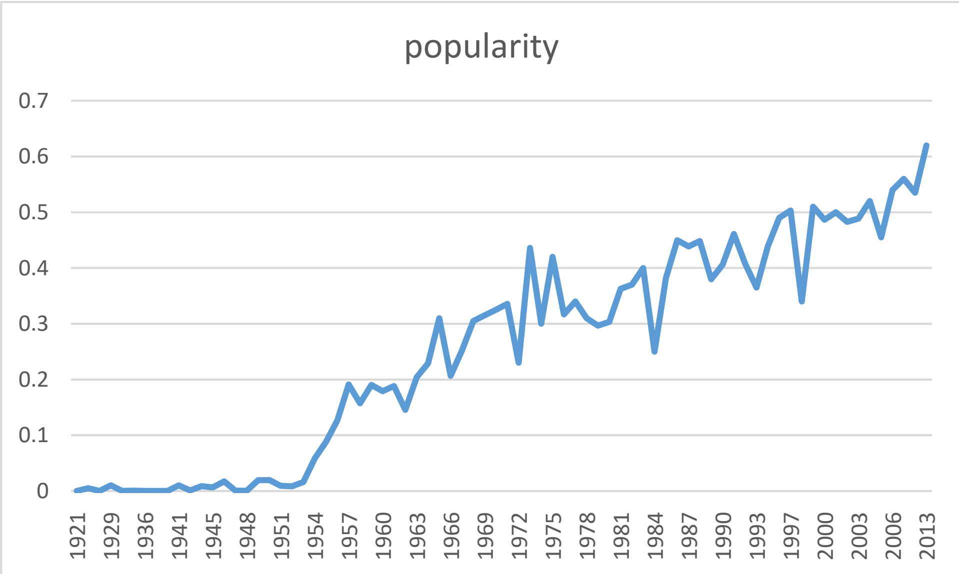

Figure 14: The change of 'popularity' of classical

It can be seen that although the overall trend in popularity is increasing, the volatility is equally large. Considering that in the previous history of music development, we concluded that the development of the whole music with time, the popularity of the premise is a steady increase, we can think that this school in the continuous change of the instrumentalness, of the work also led to its development is not stable, but the overall is still more popular with the audience.

7.2 Culture influence and identification of changes within the network

To some extent, a trend of music has revealed the reasons for the prosperity of music. In this period, the new music genres continue to produce, to learn and blend, finally forming an intricate situation like the network model. [3]

On the other hand, the music of the 19th century looked colorful, but no music was separated from the system of big tone and minor tone, and still persisted in the way and road of music development before. Until the 20th century, music produced great changes, both in creative ideas and in the form of music.

Composers tried various possible ways to create music in a wider field. For example, sequential music can be regarded as the continuation and development of 12-tone music. It arranges twelve scales in a fixed order to form melody and harmony, but its sequence content is more extensive than that of 12-tone music before World War II. In addition to using the pitch sequence of 12-tone music, Sequence music also enhances rhythm, intensity, timbre and other skills. [4]

Reflected in our model, we can partly explain the revolutionary changes found near 1947-1953.At the same time, the vigorous development of computer and Internet technology has also promoted the innovation of music form and the spread of music to the public, such as the emergence of accidental music and electronic music. This can also explain the gradual increase in music popularity from the middle of the 20 th century.

We can see that one influence's followers are almost the same genre with the influencer, which means the music produced by the influencer changed creation concept of other musicians. This change is obvious a cultural influence. If we construct our directed network for the influence of the people who sing at each time period, when we find that the musical characteristics between the influencer and followers change obviously, we will say that social, political or technological changes might happen at this time.

8. Conclusion

Our network is valuable for studying and understanding the influence of music. Our network can clearly and comprehensively show the relationship between influence and followers, their genre relationship, and the time span information of this influence. And it has some flexibility to generate subnets to explain various problems in more detail.

FR algorithm can make the overall layout uniform and round, which will be very convenient to see the evolution and inheritance between genres. In the calculation of music influence, we consider not only the influence of the influencer is not only related to the number of his followers, but also has something to do with the influence of the followers. We reduce the number of computational iterations because the influence of followers' followers has little effect on the influence of the influence.

We do not use eigenvector centrality and degree centrality of modern graph theory. Because they do not consider the directionality of the network, many existing algorithms, including pagerank, are added to our model as a correction.

Adding more data has little effect on our network model, but the conclusion of analysis may change. It is possible to change the average characteristics of a genre and their evolution. Similarly, our similarity algorithm and data are separated, and the increase of data will only affect the conclusion.

The rapid development of music promotes the development of multiple musical aesthetics and influences the creation concept of musicians, thus having a direct and indirect impact on social culture. It is not difficult to know that music causes complex cultural characteristics and shows complex and diverse attributes of cultural functions, even with internal contradictions and conflicts. These cultural functions have the function of being positive and promoting social development

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