Research on Music Influence Based on PPMCC

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ABSTRACT

Music is an important part of human society. Artists will be affected in many ways when creating music, such as the influence between artists, politics, culture, and technology.

This article uses network science to model and analyze the influence of music, focusing on analyzing the influence between artists. There are influence and follow-up relationships between artists, and it is appropriate to describe these relationships with directed diagrams. We built a relationship model based on all existing influencers and followers data, built a relationship model subnet centered on influencers, and built a relationship model from the perspective of music genre, and conducted a multi-faceted analysis of music influence. This paper uses network science to model and analyze the influence of music, focusing on the influence between artists. This paper builds a relationship model based on all the existing influencer and follower data, build a relationship model subnet with the influencer as the center, and build a relationship model from the perspective of music genres to analyze the music influence in many aspects. This paper also develops a similarity measure MMS based on Pearson product moment correlation coefficient (PPMCC). With the passage of time, the music genre with the largest number of artists is analyzed, and it is found that some music characteristics of this school will change greatly with the passage of time. That is to say, the characteristics of the genre are not immutable, but if the change exceeds a certain limit, it will be transformed into other genres. This is the process of music development. Finally, combined with some real-world influence, our model is further extended.

Keywords: *Network Science; Music; PPMCC*

1.INTRODUCTION

Music is an art form and cultural activity. The creation, performance, meaning and even the definition of music vary according to cultural and social background. When artists create, there are many factors that affect them, and the influence of past music on existing music is an important topic for music researchers. In studying the influence of music on music, the influence of musicians, etc., network science[1][2] is one of the most common methods. This method usually makes it easy to establish relationships between artists, between music, and even music genres.

2. MUSICAL INFLUENCE NETWORK MODEL

2.1. Musical Influence Network Model

We transform the relationship between influencers and followers into directed graphs. As shown in Figure, each circle represents an artist, and the arrows point from influencers to followers. Some artists have not only pointed arrows, but also pointed arrows, which shows that he has followed this and others are followers of other artists. So far, this kind of directed graph represents our musical influence network model between influencers and followers.

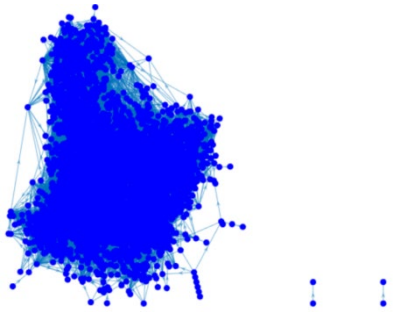

Fig.1 Musical influence network model

2.2. Music Influence Parameter

We regard the number of followers as an indicator of the influence of an artist, namely Music Influence Parameter (MIP).

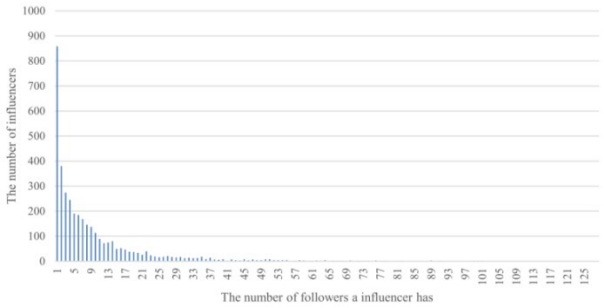

Fig.2 The number of influencers with different number of followers

According to MIP , artists are divided into three categories: among them, artists with MIP $\in$ [1,10) are called "weak influential" influencers, artists with MIP $\in$ [10,100) are called "influential" influencers, and MIP $\in$ [100 ,+∞) artists are called "most influential" influencers. According to the above division method, we constructed a music influence subnet centered on a certain influencer. As shown in Figure, MIP can still distinguish artists with different influences in the subnet.

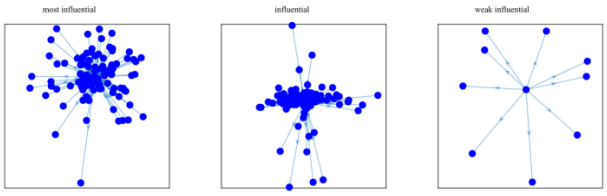

Fig.3 Music influence subnet

3. ANALYSIS OF MUSIC COMMUNICATION BASED ON PPMCC

3.1. Similarity Analysis

The data_by_artist contains author information and 14 music characteristic values, some of which have a large range, several orders of magnitude higher than other characteristic values. Therefore, it is indispensable to normalize the data. The normalization of each characteristic value uses formula

$$X_{norm} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \quad (1)$$

Where X represents a group of numbers, Xmax represents the maximum value in X, Xmin represents the minimum value in X, Xnorm represents a new group of numbers after X normalization, Xnorm $\in$ [0, 1].

3.2. Pearson Product-moment Correlation Coefficient

Pearson product-moment correlation coefficient (PPMCC)[3] is a commonly used statistical method that can be used to measure the degree of correlation between two variables X and Y (linear correlation). Its value is usually called R. R is between -1 and 1. The closer the absolute value of R is to 0, the less relevant the variables X and Y , and the closer to 1, the more relevant the two variables.

$$R(X,Y) = \frac{\operatorname{cov}(X,Y)}{\sigma X \sigma Y} \quad (2)$$

The covariance of variable XY divided by the product of their standard deviations.

3.3. Measures of Music Similarity

According to the R value obtained by PPMCC, we get Measures of music similarity (MMS). MMS is calculated as formula, that is, MMS is the absolute value of R.

$$\mathrm{MMS} = |\ R| \quad (3)$$

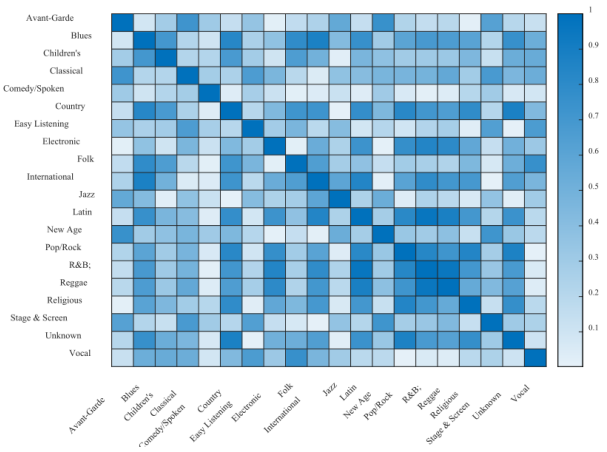

Fig.4 MMS between genres

In the same way, the similarity between music belonging to the same genre can be calculated, and 20 graphs similar to Figure can be obtained. By averaging the MMS in these figures. It can be seen that only three of the average MMS values of each genre of music are lower than the average MMS value between genres and genres. They are “Avant-Garde”, “Children's” and “Unknown”. This shows that 85% of artists within genre more similar than artists between genres.

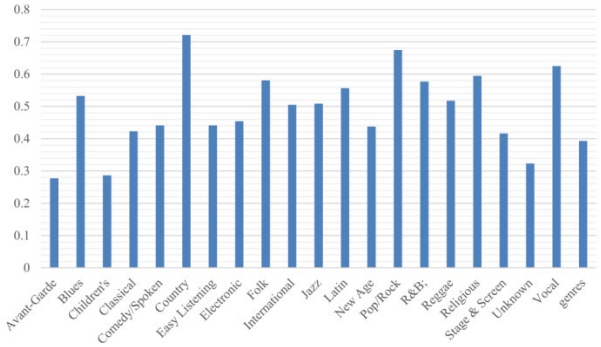

Fig.5 The Mean(MMS) between and within genres

4. GENRES ANALYSIS

The influence network between genres is obtained from influence_data, and the result is shown in Figure 6. The influence between genres is still a more complicated topology.

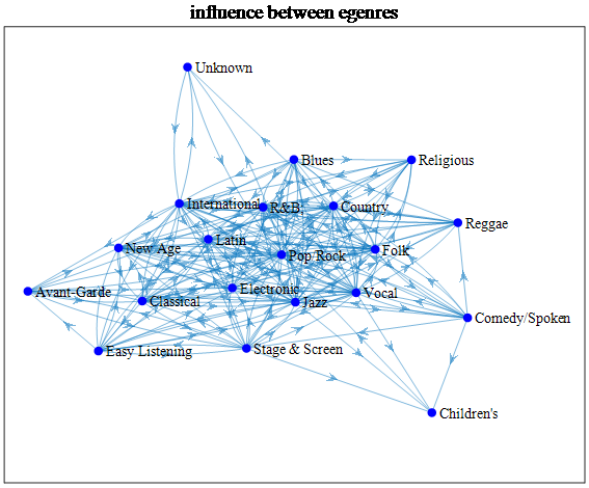

Fig.6 Influence network between genres

Combining data_by_year, analyze the various music characteristics of each year, and infer the most popular music types each year. Combining Figure 6, we can see that the most popular music genres changes each year: Electronic was more popular from 1921 to 1963, Children's was more popular from 1963 to 1973, New Age was more popular from 1973 to 1986, and New Age was more popular from 1986 to 2004. Country, Jazz is more popular in 1996-2020.

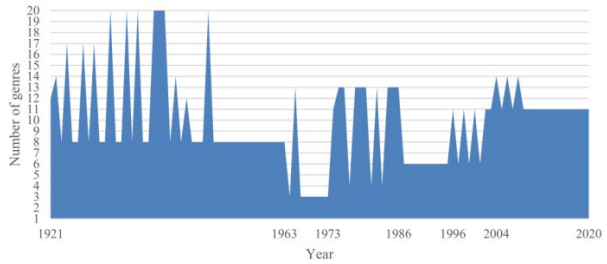

Fig.7 Genres changes with year

5. CONTAGIOUS ANALYSIS

With each influencer as the center, construct the influence subnet in Figure , find each music feature of all artists in the subnet one by one, normalize it, and then calculate the standard deviation (STD). The obtained variance is plotted in Figure .

The boxplot[4] in Figure 8 records the information of 3774 influencers. The horizontal axis represents 14 music characteristics, and the vertical axis is the variance of the music characteristic values of the influencers and their followers. The red line of the boxplot represents the median of the data. It can be seen that, except for the mode characteristic, the boxplots of the other 13 characteristics are relatively similar. The overall STD value of Mode is much lower than the STD of other characteristics, indicating that the data of mode in each influencer subnet is very concentrated. This seems to indicate the mode characteristic is more 'contagious' than others. But, considering that the values of the mode characteristics are only 0 and 1, we can only consider those characteristics all have similar roles in influencing a particular artist's music.

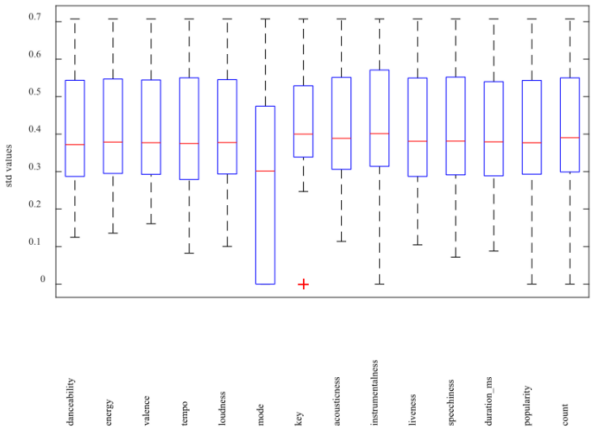

Fig.8 Boxplot of STD

It is not difficult to find that every time there will be a music genre that appears the most frequently, which we call "the current mainstream genre". When the "current mainstream" has changed for a period of time, which is different from all the "current mainstream" in the past, we think that a revolution has taken place. As shown in figure 6.4, around 1963, 1973, 1986 and 2004, our model believes that a revolution has taken place in the development of music genres.

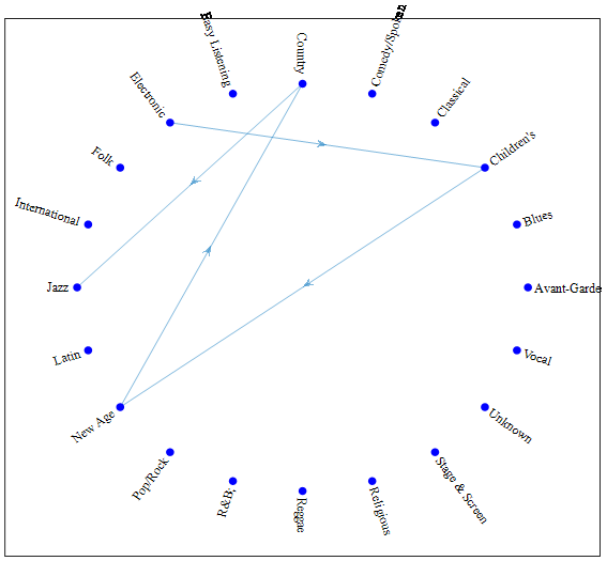

Fig.9 The evolution of genres

6. CHANGES WITHIN THE MUSIC GENRE OVER TIME

Combine all the data to find the Pop/Rock music genre with the most artists. All artists of the genre are divided into years, and all the musical characteristics of the artists are averaged and normalized in each year. The final data is shown in Figure 9. It can be observed from the figure that some features have similar changing trends, such as the values of 'danceability', 'energy', 'tempo', 'loudness' and 'duration_ms' in 1930-1940, but in 1940. After rising rapidly. From the rise of these characteristics, I seem to see that the enthusiasm revealed by Pop/Rock music is gradually rising. This means that this music genre is moving in an established direction.

However, based on the above research, we know that the combination of various music characteristics can represent a certain music genre. If some of the music characteristics change too much, then this music genre may derive new music genres.

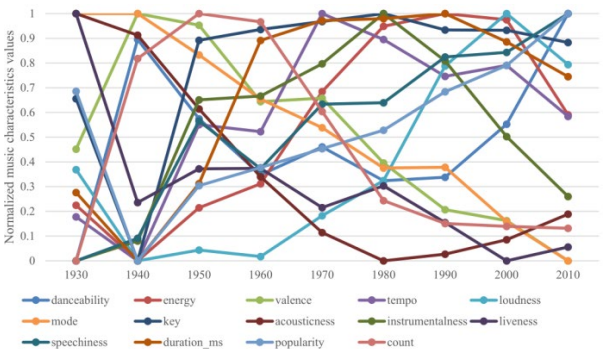

Fig.10 Changes in music characteristics over time

Social, political and technological changes usually affect the creation of music indirectly. For example, by influencing the artist's life to influence the artist's creative style, technological changes may change the way of dissemination of music, making it easier for various music genres to merge or influence each other. In our work, changes in the music influence network model can express cultural changes in the environment. For example, the network between the previous genres was disconnected, and they were connected again after a while, which may represent a "Renaissance" of varying degrees. As time changes, mainstream genres are constantly changing, and the characteristics of music within each genre are also changing.

7. CONCLUSION

This paper focuses on the influence of music. firstly, it uses network science to model and analyze the influence of music, focusing on the influence between artists. It is not difficult to find that there are influence and follow-up relationships between artists, so digraphs are used to describe these relationships. Then construct the relationship model subnet with the influencer as the center, and construct the relationship model from the perspective of music schools, and analyze the music influence in many aspects. The similarity of Pearson product moment correlation coefficient (PPMCC) is used to measure MMS. From this, we can analyze the similarity between the two kinds of music, as well as the similarity between different artists and different music genres. It can be found that the similarity within the artist genre is higher than that between the entertainer genres. You can compare music with a school, get the school that is closest to a particular music, and infer which school the music belongs to. MMS compares all music data with genre data each year to infer the trend of music popularity and the changing process of genres each year. From this process, we can find the changing points of music and the revolutionaries who lead these changes. With the passage of time, the music genre with the largest number of artists is analyzed, and it is found that some music characteristics of this school will change greatly with the passage of time. That is to say, the characteristics of the genre are not immutable, but if the change exceeds a certain limit, it will be transformed into other genres. This is the process of music development. Finally, combined with some real-world influence, our model is further extended.

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