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Research on Musical Changemakers based on Music Influence

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***Abstract*—To address the problem of how to identify musician changemakers, this paper proposes a comprehensive determination model based on musician influence and inverse influence depth. Among them, for musician influence, we introduce six sets of data describing music influence in different dimensions after establishing the influence network among musicians, using the Combination Weighting Algorithm to calculate music influence. For the inverse influence depth of musicians, we use the correlation between different musicians' works and introduce the Mutation-Depth Discriminating Algorithm to jointly score with musicians' influence. Finally, we get the musician changemakers and use them for practical testing.**

Keywords-music influence; Combination Weighting Algorithm; Mutation-Depth Discriminating Algorithm;

I. INTRODUCTION

A. Introduction

Music has always occupied a place in social change. From ancient times to now, with the evolution of society and the prosperity of culture, music has changed from the initial singleness to numerous genres and complex characteristics. Artists as creators are an important channel for the connection between music and society. Artists are affected by their predecessors to make music creation, and the music they created affects more artists. Style of an artist is affected by other artists and combined with its own characteristics. In addition to the new creation characteristics in the original creation style, the artists with similar characteristics are gathered together to obtain a common genre, which constitutes a complex relationship between artists and genres. When the music system is affected by society, science, and technology, the internal influence of the system is grown complex. There may be a complex interaction between artists of different genres and styles. If an influential artist suddenly shifts his or her creative style, it is highly likely to affect the artists who are influenced by him or her, bringing about a global change. Such an artist is considered to be a music changemaker. Exploring music changemakers along the timeline is extremely important research for understanding the evolution pattern of musical styles.

This subject has been studied by scholars for many years. For example, Bertin-Mahieus et al. [1] used 2D Fourier transform to compare the differences between songs singularly while Shalit et al. [2] applied topic-modeling tools to quantify musical influence and found that music influence is not monotonically related to musical innovation. As for the influence among artists, Brandon et al. [3] introduced two audio content-based influence identification systems, one using Constant-q transform and support vector machine algorithm while the other using deep belief network. As for the more complicated music genre classification system, Noyes et al. [4] used a probabilistic topic model to visualize music genres, interpreting audio as sample segments.

B. Our works

In order to dig into the artist-changers, we have completed the following work after drawing on previous researches.

- Using *influence_data* to build a network of artist influence relationships.
- Quantifying an artist's music influence by using the Combination Weighting Algorithm
- Utilizing Mutation-Depth Discriminating Model to unearth changemakers.

The specific processing flow is detailed in Figure 1 below.

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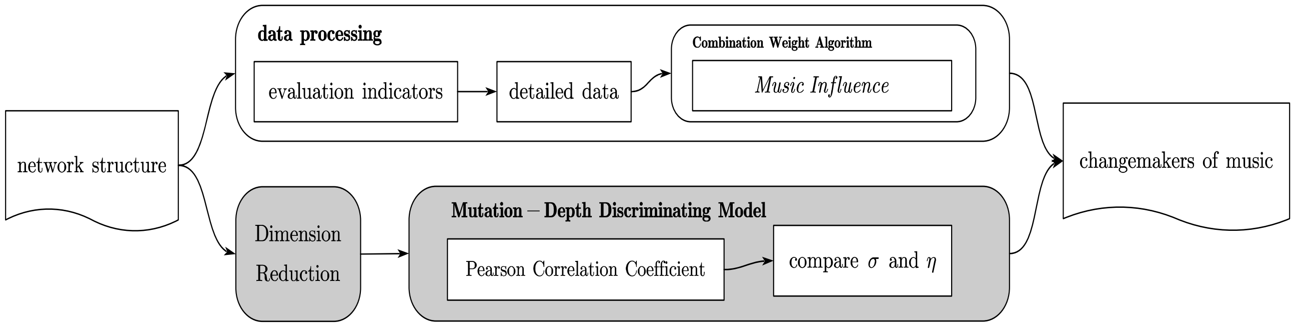

Figure 1 Processing flow

II. Data Processing

A. Data overview

To test the feasibility of our approach, we collected two sets of data from AllMusic.com and Spotify's API. Among them, *influence_data* stands for music influencers and followers, which is based on the artists' own reports and the opinions of industry experts, these data contain the influencers and followers of 5,854 artists over the past 90 years. Besides, *data_by_artist* provides 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.

Also, the variables that may appear in the research are defined and explained uniformly below.

Table 1 Notions

Index	Meaning
dep	Depth of influence
lay	Artist influence level
MI	Music influence
MId	Music influence index matrix
Cor	Correlation of creation features

B. Dimensionality reduction by PCA algorithm

Considering that *data_by_artist* have higher dimensions of evaluation indicators and may cause noise. We consider dimensionality reduction of data.

We divide the indexes into music features and human voice features, which represent different evaluation dimensions. After KMO (Kaiser-Meyer-Olkin) and Bartlett test of which KMO > 0.5 and $\sigma < 0.05$, the PCA (Principal Component Analysis) algorithm is used to reduce the dimension. After dimensionally reduction, the cumulative contribution rate of the index dataset to the original data can reach 95.31% and 84.921% respectively. After dimension reduction, we reduce the seven dimensions of music features to the first principal component, which mainly represents the melody characteristics of the song. When the first principal component is large, the energy, valance, rhythm and loudness of the song are correspondingly high. The five dimensions of sound characteristics are reduced to the second and third principal components, respectively, indicating the electronic characteristics and instrumental characteristics of the song. When the second principal component is large, it means that the song is not processed by tuning equipment and closer to the original sound of the artist. When the third principal component is large, the instrumental characteristics of the song are obvious.

III. Music Influence Scoring Model based on Combination Weighting Algorithm

A. Indentification and statistics of impact factors

Considering that the measurement of a musician’s influence requires multidimensional data, referring to the relevant research, we get the evaluation index system based on “breadth, depth, speed and quantity”, which is as followed in Table 1.

Table 2 Evaluation indicators

Indicator	Meaning
Number of direct impacts	Number of musicians affected by the musicians at the next level, i.e., number of musicians directly connected
Depth of influences	Showing that the musicians influence the musicians at most (both direct and indirect)
Number of genres	In the same age, the fewer musicians of the same genre, the more fans the audience can get
Genre ranking	Ranking of musicians in the same genre in the same age (ranked by direct influence)
Number of cross-genre influences	Number of different genre musicians directly influenced by musicians
Average influence speed	The time interval between indirectly affecting the second generation and starting to be active

In response to the above table, we are able to obtain a criterion for evaluation, that is the more direct influences, the greater the depth of influence, the smaller the number of genres, the higher the genre ranking, the greater the number of cross-genre influences, the greater the musical influence of that musician.

B. Network structure determination

influence_data mainly describes the interaction between singers of different ages and genres. Through the relationship between influencer and follower, we can get a directed acyclic network from influencer to follower, and we believe that if an artist is not the follower of any other musicians, he can be regarded as a music pioneer. If the musician directly influenced by a certain musician has influence on other musicians, it is considered that other musicians are indirectly influenced by the musician. We can calculate the influence depth dep of each musicians, which is an integer-valued at [0,9]. According to our interpretation of the depth of influence, we can get the influence level of each musicians by followed formula $lay = dep + 1$. Accordingly, we can count the influence level of a total of 10 levels of influence, 557 artists pioneers who are not affected by others (but the pioneer is not necessarily in the tenth layer), and only one musicians' s influence runs through the entire network level, that is, the influence level is 10. There are 1826 musicians who have no indirectly influence on musicians. Each artist appears on the Internet only once.

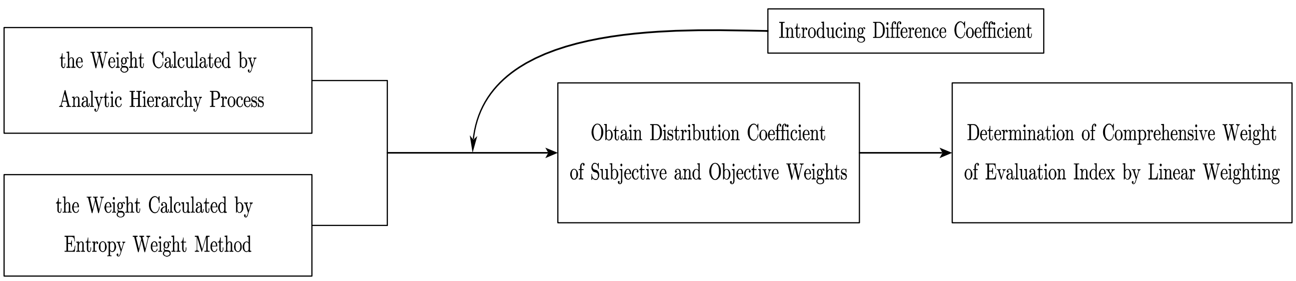

Figure 2 Combination weighting algorithm flow

C. Evaluation of music influence

After the standardization and normalization of the evaluation system index given above, we can get a 5603×5 index matrix MId. In order to ensure the objectivity of the information carried by the index itself, and considering the different emphasis on different indicators under the influence of human factors, we adopt the combination weighting method based on entropy weight method and assisted by analytic hierarchy process to synthesize the influence of objective and subjective music influence score. The algorithm flow is shown in Figure 3.

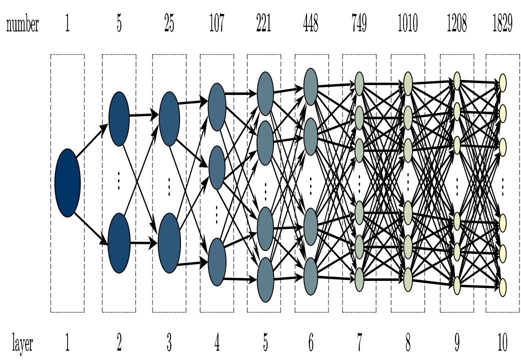

Figure 3 Network level topology

We first use the Analytic Hierarchy Process (AHP) [5] and the Entropy Weight Method to calculate the weight vectors W_1 and W_2 of each index in turn. In order to score, the AHP people mainly refer to the relevant research and the survey results of similar problems on the network. Using the linear weighting method to determine the combination weight vector W. α and β represent the weight ratio of AHP and entropy weight method respectively.

$$W = \alpha W_1 + \beta W_2 \tag{1}$$

The coefficient α and β are solved by Difference Coefficient Method, in which $P = (i = 1,2, \dots, n)$ is the vector of subjective weight sorted in ascending order. n is the number of evaluation indexes.

$$\alpha = \frac{n}{n-1}\left[\frac{2}{n}(P_1 + 2P_2 + \dots + nP_n) - \frac{n+1}{n}\right] \tag{2}$$

$$\beta = (1 - \alpha) \tag{3}$$

Accordingly, we can calculate the music influence of each musicians .

$$MI_i = \sum_{j=1}^{6} W_{ij} \times MID_{ij} \tag{4}$$

Taking into account the depth and breadth of the entire network are too large, we select the initial part of the network subnetwork analysis. Using the depth of influence and followers of each musicians, we can also uniquely determine a subnetwork level. Finding Black Flag, an artist whose influence runs through the network, as the starting point for the subnetwork, and map the subnet as shown in Figure 4.

Among them, each circle marks each different artist, circle radius size should be the value of the musicians' s music influence MI. Through the analysis of the network, it can be found that MI decreases with the deepening of the influence level. When the musicians directly affect more musicians, the MI value of the musicians will be slightly larger. When an artist is affected by multiple musicians, the MI value of the musicians is relatively small. In the meantime, there is a relationship between cross-level influence in the network, that is, how many levels have one of the directly affected musicians crossed with the musicians.

Figure 4 Subnet structure

In this subnetwork, the MI index mainly reveals the closeness of the relationship between musicians and the affected people and its influence on the subnet where the affected people are the starting position of the network.

IV. Mutation-Depth Discriminating Model

A. Pearson correlation coefficient calculation

In order to judge whether the "influential people" in the network really affect the followers, as long as we judge whether there is a correlation between the creation characteristics of the followers and the influencer, the Pearson correlation coefficient [6] is used to judge the characteristics of the two in the dataset *data_by_artist*. For artists X and Y , the correlation $Cor(X,Y)$ is as follows:

$$Cor(X,Y) = \frac{E(XY) - E(X)E(Y)}{\sqrt{E(X^2) - \left(E(X)\right)^2}\sqrt{E(Y^2) - \left(E(Y)\right)^2}} \tag{5}$$

The correlation coefficient graph is drawn as Figure 5. It is found that most of the influencers and the followers have at least a weak correlation, so the influence can be judged.

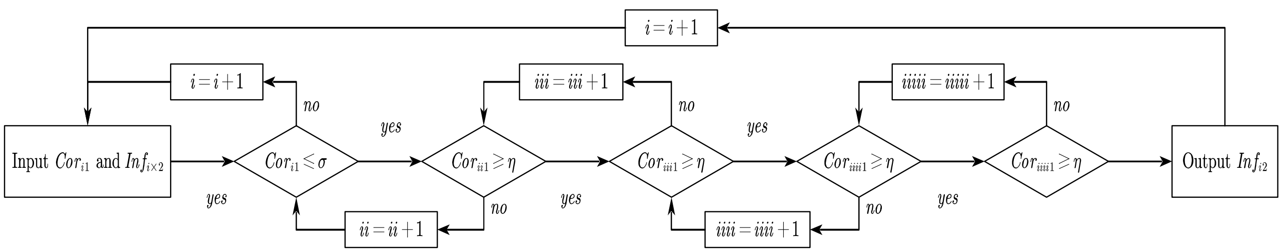

Figure 5 Process of Mutation-Depth Discriminating Model

For the correlation coefficient between the influencer and the influenced, we can also assume that the greater the influence of an artist. He greater the correlation of the musicians influenced by him, which may be positive but may also be negative.

B. Mutation-Depth discriminant

If we want to excavate musicians who bring great changes, we first need to define major changes. We believe that in the network we created, if an artist is very different from his own influencer's creation characteristics and his followers in the following layers maintain similar creation characteristics with themselves, we consider that the musicians has brought great changes. We use the correlation coefficient Cor between artists' creation characteristics to represent the similarity, and construct the catastrophe-depth search model. We define very dissimilarities as $Cor < \sigma$, and very dissimilarities as $Cor > \eta$, which are searched in the network according to the following algorithm steps in Figure 6.

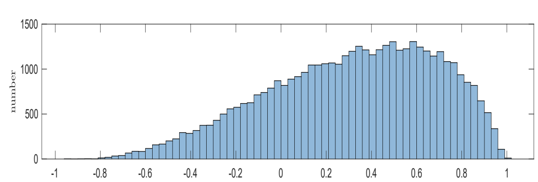

Figure 6 Distribution statistics of correlation coefficients between influencers and followers

For a more integrated consideration of the role of musical influence in the decision-making of musical changemakers, we introduce MI to represent the new correlation coefficient based on the previous use of Pearson's coefficient to represent music influence. The new correlation coefficient Cor_{new} is defined as follows.

$$Cor_{new} = \omega Cor + (1-\omega)\frac{MI}{\tau} \tag{6}$$

In the above Eq.5, ω is the relationship coefficient and τ is the scaling factor which ensures that MI and Cor are comparable. For the convenience of the experiment, here ω is taken as 0.5.

If an artist has multiple influence paths in the network to meet our requirements, it can be considered that the artist brings greater change. In order to facilitate the display, we set $\sigma = -0.3$, $\eta = 0.75$ and set the influence level index to four levels, so as to obtain Figure 7 below where the abscissa represents the ID number of musicians representing the changer.

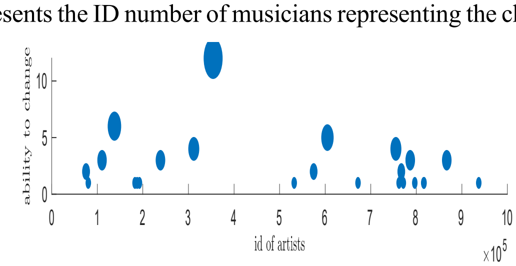

Figure 7 Major changemakers

V. Conclusion

To explore music changemakers in the direction of musical influence, we first create an influence network using the specified dataset and create parameters to describe the artist's influence. We then determine the influencer's music influence from another perspective by calculating the correlation coefficient between the influencer and the influenced. Finally, we found the revolutionary changes in the evolution of artists by searching deeper into the layers.

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