Research on Music Influence Based on Double Layer Influence Estimation Network

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Abstract: Music is a great part of human civilization whose spread and interactions between music play an important role in the development of music. In this paper, we analyze the influences and similarities within and between musical art genres through our dynamic development model of a musical double-layer influence network. It is important for analyzing the development of musical genres. In this paper, firstly, the double-layer network structure is divided into inner layer and outer layer, and point-to-point simplified form is used to study the music influence of point-to-point. Then the artists are divided into different schools, the mean and variance of different music characteristics of different schools are calculated, and the "music appeal" of different music characteristics within and between different schools is analyzed. At the same time, this paper analyzes the similarity of music data, uses ANOSIM to analyze the meaning of differences between categories, and establishes a feature similarity model. Artists and genres are regarded as vectors in multi-dimensional space respectively, and the normalized music feature index is taken as the coordinates of different dimensions. The similarity matrix of artist-artist, influencer-follower, independent artist and school-school is established. The three-dimensional similar scatter diagram is drawn and the relationship between different schools is analyzed.

1. Introduction

The music industry is an important part of the cultural industry, which creates a more colorful musical life for people. Music works as a whole present a representative and unique look and are divided into different genres based on different musical characteristics, such as R&B, disco, reggae reggae, etc [1]. Among primitive people, "the ultimate form of communication is the song or story". Musical communication began in ancient times and used music as a medium for social interaction in different arenas [2].

Throughout the history of musical culture, there have been different periods and genres that have emerged and changed from different conceptions, musical styles and technical approaches that evolved in different historical contexts [3]. Throughout the 20th century, there were many different genres of music, and they all influenced each other, intermingled and transformed each other, and blossomed.

2. The establishment of music double layer influence estimation network

2.1 MDIEN Frame

Based on the MDIEN model, the influence of influencers and their followers is quantitatively analyzed [4, 5], and the expressions of the influencing factors and the degree of influence of node-to-node unidirectional influence are given.

To study the influence of influencers on followers, we transform artists into different nodes for analysis. We construct a music influence estimation network to represent artist-to-artist and genre-to-genre relationships based on whether the nodes follow each other and the proximity of the nodes to the genre of the nodes, and this network can reflect the music influence. The process flow of estimating "musical influence" by the music influence estimation network is shown in Figure 1.

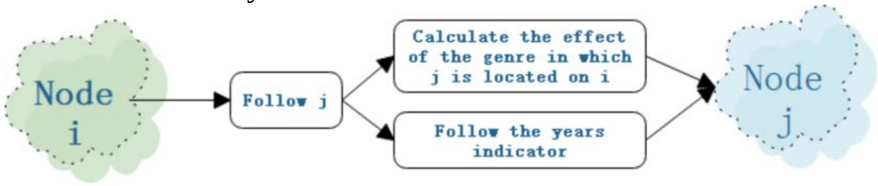

Figure 1. Node Impact Flow Chart

Create a directed graph network G=(N, Y, G, NY, NG, YY, GG, NN), where N denotes the set of |N| artist nodes to represent the input artist, Y denotes the set of |Y| creative active start nodes to represent the input active start, and G represents the genre of the artist. The edges are constructed between N and Y and N and G, NY, NG, based on the positive start and the genre of the artist, and edges YY and GG are constructed based on the positive start indicator and the genre indicator [6]. The influence relationship between the nodes is represented by the presence or absence of NN edges and the pointing of the edges. Figure 2 shows the representation of the network of musical influence relationships between nodes. Where ni and nj denote artist nodes, and years and genre denote active opening nodes and genre nodes, respectively. If i follows j, j influences i, then the edges and pointing are established as shown in the figure.

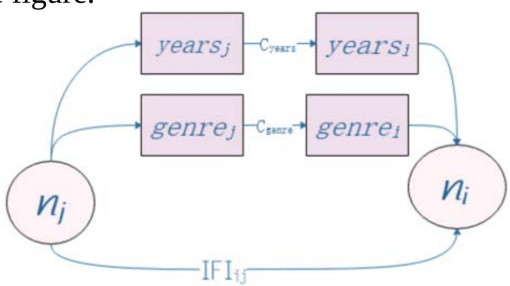

Figure 2. Inter-node music influence network

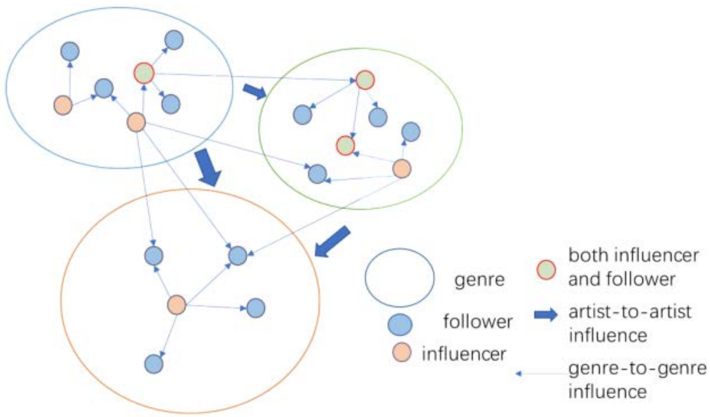

Figure 3. Music Double Layer Impact Estimation Network (MDIEN)

2.2 Peer-to-peer influence

Nodes and nodes are taken as the object of study to investigate the degree of influence of nodes on nodes from the perspective of influencing factors.

1) Music Genre Index C_{genre}

$$C_{genre} = \begin{cases} 1, Node\ i\ and\ Node\ j\ belong\ to\ the\ same\ genre \\ 0, Node\ i\ Node\ j\ are\ not\ in\ the\ same\ genre \end{cases} \tag{1}$$

Used to describe whether the node *i* s of the same genre as the node *j*.

2) Following index C_i:

$$C_{ij} = \begin{cases} 1, i \ is \ following \ j \\ 0, i \ is \ not \ following \ j \end{cases} \tag{2}$$

Used to describe whether a node *i* follows a node *j*.

3) Positive start indicator $C_{years} = \ln\left(\frac{\text{Year of active creation by Node}i - 1925}{\text{Year of active creation by Node}j - 1925} + 1\right)$

When the year difference between node i and node j is small, we consider that node i is more influenced by node j. When the year difference between node i and node j is large, we consider that node i is less influenced by node j.

4) Impact weights W_{ij}

$$w_{ij} = \frac{\sum_{k=m}^{h} k}{\sum_{k=1}^{h} k} = \frac{2h - m + 1}{h^2 + h} \tag{3}$$

Node The total number of influencers followed by n; the number of influencers of the same genre as itself followed by node i m; we consider the weight of the genre index to be related to n and m. For example, let's say a follower follows five different influencers A1, A2, B, C, and D, and four different genres ABCD, but finally chooses genre A. Then we define the genre index weights according to the following rules, ranking A1, A2, B, C, D's and forwarding, then the five influencers of A1, A2, B, C, D are ranked as 4.5, 4.5, 3, 2, 1. The genre index weight of A1 influencer for this follower is $\frac{1 \times 4.5}{1+2+3+4+5}$, and so on.

5) Impact Factor Index:

$$IFI_{ij} = \frac{C_{years} + \alpha w_{ij} \cdot C_{genre}}{1 + \alpha} \cdot C_{ij} \tag{4}$$

2.3 Infectiousness of musical identity in the region

Based on the established MDIEN model, artists (nodes) are classified according to the genre to which they belong, and the mean and variance of each genre (region) are calculated and analyzed.

The mean value of indicators *k* in genre *p* is calculated as

$$\mu_{kp} = \frac{1}{n} \sum_{j=1}^{n} y_{kj} \quad k = 1, 2, \cdots, 14 \tag{5}$$

n is the number of artists in the genre .

The variance value of indicators *k* in genre *p* is calculated as

$$\sigma_{kp} = \frac{1}{n} \sum_{j=1}^{n} |y_{kj} - \mu_{kp}| \tag{6}$$

	danceability	energy	valence	tempo	loudness	mode	key	acousticness	instrumentalnes	liveness	speechiness	duration_ms
Avant-Gard	0.177334722	0.165341373	0.205431487	0.06260147	0.140720837	0	0.291051102	0.241444133	0.311147204	0.028550275	0.039757457	0.050682595
Blues	0.100402517	0.166053597	0.140431024	0.116347469	0.096861196	0.35154	0.309237768	0.269315139	0.17281561	0.10736229	0.058303033	0.048560844
Children's	0.125930994	0.061602616	0.12954979	0.051668006	0.06177367	0	0.38769823	0.156151075	0.005798143	0.158970841	0.038003396	0.039775304
Classical	0.092149028	0.120408075	0.133818307	0.085614456	0.190836863	0.319486	0.318412273	0.109512082	0.374668907	0.062068013	0.021462411	0.080772928
Comedy/Sp	0.112495294	0.224085336	0.211429159	0.113303686	0.112685866	0.362433	0.31372378	0.296469258	0.118798597	0.299819896	0.384086086	0.121167707
Country	0.091585746	0.171212492	0.166671515	0.101939966	0.093237921	0.110693	0.293167489	0.243296691	0.145136013	0.089156286	0.039886936	0.028694967
Easy Listen	0.153409953	0.117190246	0.18102625	0.065025034	0.085622789	0.281771	0.257797215	0.214316279	0.249538064	0.068525843	0.038913054	0.045336378
Electronic	0.152986775	0.187804197	0.215495279	0.102563986	0.113247748	0.481538	0.32981199	0.243823968	0.339455175	0.123918375	0.066264675	0.066309475
Folk	0.096408213	0.15671871	0.179324349	0.10772417	0.087147436	0.244449	0.311442026	0.191017889	0.168858188	0.14327117	0.075696443	0.045610441
Internationa	0.144360282	0.215858135	0.223081342	0.126436452	0.119168809	0.398136	0.308141621	0.287017239	0.247308737	0.110052021	0.055912858	0.093551071
Jazz	0.131666157	0.18590015	0.196688564	0.100826165	0.115013356	0.466208	0.301982881	0.260528287	0.285333935	0.107123365	0.06020456	0.08346001
Latin	0.12917935	0.178149426	0.189843944	0.081177708	0.089729697	0.425789	0.304914876	0.239685379	0.188362593	0.089641469	0.039953514	0.04809642
New Age	0.167744748	0.16322311	0.200000884	0.142529354	0.135662407	0.46483	0.282458797	0.277668573	0.282962032	0.160978602	0.009984051	0.144090784
Pop/Rock	0.143808707	0.187859951	0.197561982	0.105882909	0.093520423	0.345447	0.322307494	0.223844922	0.198474798	0.115383912	0.044838208	0.048041978
R&B;	0.121087182	0.135545143	0.186608103	0.099740666	0.074783475	0.452658	0.330434447	0.218318722	0.110560425	0.0954174	0.067130131	0.048018
Reggae	0.098227335	0.148638674	0.143289733	0.122326481	0.083011742	0.455073	0.331375031	0.21079638	0.175680178	0.07508957	0.099314389	0.037073114
Religious	0.128530022	0.179997612	0.188579441	0.113597072	0.089212666	0.250741	0.33734165	0.246230821	0.090275406	0.174541154	0.050437551	0.064937395
Stage & Sc	0.143673632	0.124332829	0.178832263	0.108168438	0.109895022	0.427083	0.28064271	0.205089301	0.35592405	0.071035675	0.045701757	0.042322198
Unknown	0.155415395	0.180675528	0.101722675	0.07558995	0.065717972	0	0.214274782	0.285538492	0.038785147	0.051055197	0.003975049	0.026463174
Vocal	0.12722207	0.119956894	0.180108482	0.101215604	0.082938514	0.323494	0.324896678	0.143227091	0.099909781	0.129748557	0.066482184	0.034770896

Figure 4. Variance color scale charts for different genres

The smaller the variance of a musical characteristic indicator, the higher the degree of similarity of this musical characteristic in this genre. Through cluster analysis, a threshold value of 0.11 is set, and when the variance is less than 0.11, the music indicator is considered to be "infectious" in this genre, and it is considered to be a similar characteristic in the genre.

The music similarity characteristics in genres are: speechiness, duration_ms.

In different genres, we use the mean value of the musical characteristics to compare, when the difference between the mean values of the selected musical characteristics is small, the musical characteristics [7] are similar between genres. The difference threshold is determined as 0.25, and when the maximum value of music difference between categories is less than 0.25, it is called category music similar characteristic; otherwise, it is called category music distinguishing characteristic. Therefore, the category music similarity characteristics are: duration_ms, tempo, key; music characteristic difference characteristics are the remaining characteristic indicators [8].

3. The establishment of feature similarity model

The paper need to analyze each artist in different genres by considering the artist as a community and the indicators as species that constitute this community. Following the above rules, the indicators of the musical characteristics of the artists composing music [9] are used as multidimensional coordinates to assess the degree of similarity / difference within and between genres by comparing the average distance between artists within each genre and between genres.

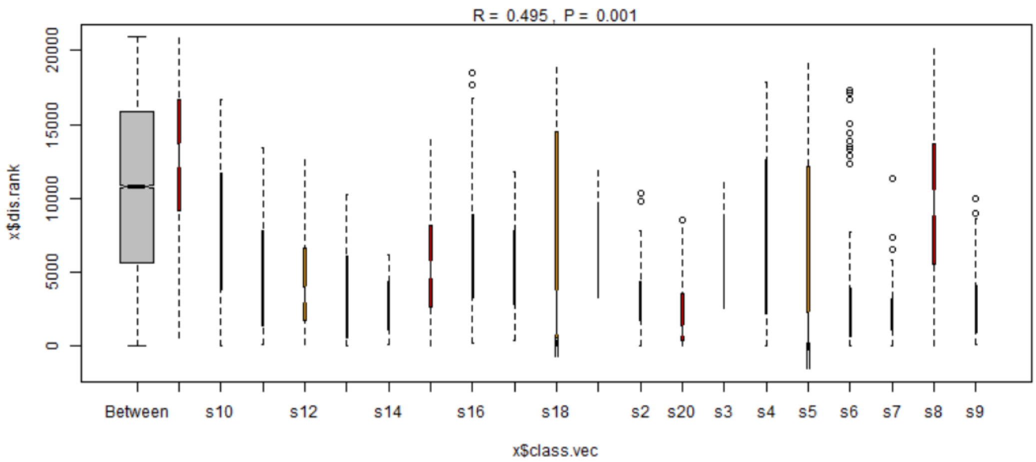

Figure 5. Rank between communities

The Between group has a higher rank relative to the other groups, a higher R-value (0.495), and a significant p-value (0.001) obtained from the Bartlett's spherical test, learning that the genres are inconsistent at the overall level. Differences between groups are more pronounced than differences within groups, so artists of the same genre are more similar than artists of different genres. Therefore, the following model begins to model feature similarity.

Different indicators are used as coordinates in the multidimensional space, and vectors in the multidimensional space are constructed to calculate the similarity matrix. The musical characteristics (danceability, energy, valence, tempo, loudness, mode, key, acousticness, instrumentalness, liveness, speechiness, duration_ms) indicators of different artists are K for different metrics.

$$\overline{y_{kj}} = \frac{x_{kj} - \min(x_k)}{\max(x_k) - \min(x_k)} \quad k = 1, 2, \cdots, 14 \tag{7}$$

The vectors of the different artists

$$\phi_j = \begin{bmatrix} y_{1j} \\ y_{2j} \\ \vdots \\ y_{14j} \end{bmatrix} \quad j = 1, 2 \cdots, n \tag{8}$$

j indicates different artists and x_{kj} is a different metric for the same artist. n is the number of artists.

Analyze the similarity of different indicators for music composed by different artists.

$$SI_{ij} = \frac{{\phi_i}^T \cdot \phi_j}{|\phi_i|\,|\phi_j|} \tag{9}$$

SI_{ij} represents the degree of similarity between artist i and artist j.

Then the obtained artist-artist similarity matrix is:

$$D = \begin{bmatrix} SI_{11} & SI_{12} & \cdots & SI_{1h} \\ SI_{21} & SI_{22} & \cdots & SI_{2h} \\ \vdots & \vdots & \ddots & \vdots \\ SI_{h1} & SI_{h2} & \cdots & SI_{hh} \end{bmatrix} \tag{10}$$

The vector of genres is $\delta_p = (\mu_{1p}, \mu_{2p}, \cdots, \mu_{14p})^T$, and the similarity is $GSI_{ij} = \frac{{\delta_i}^T \cdot \delta_J}{|\delta_i|\,|\delta_J|}$, and the similarity matrix is the number of genres.

$$GD = \begin{bmatrix} GSI_{11} & GSI_{12} & \cdots & GSI_{1p} \\ GSI_{21} & GSI_{22} & \cdots & GSI_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ GSI_{p1} & GSI_{p2} & \cdots & GSI_{pp} \end{bmatrix} \tag{11}$$

p is the number of genres.

4. Model solving

4.1 Characteristic similarity

The paper randomly select 200 artists for similarity analysis, the degree of artist-to-artist similarity is as shown.

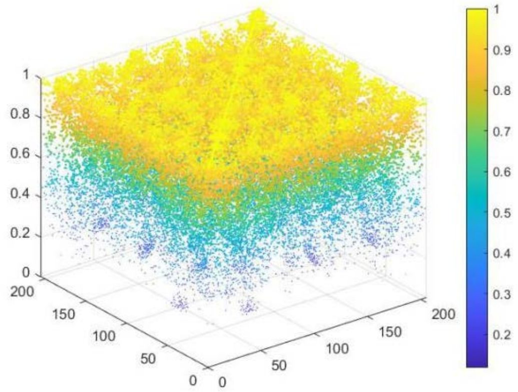

Figure 6. Artist-artist similarity 3D scatter plot

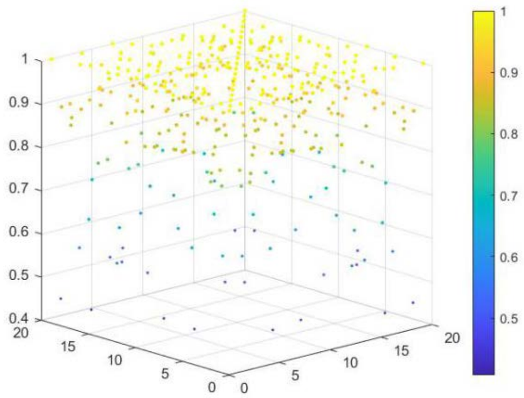

Figure 7. Three-dimensional diagram of genre-genre similarity

The threshold is 99.95%, and genres greater than 99.95% are associated. The associated genres are shown in Appendix 1, and include Blues and Folk, International and Folk, and so on. It is also possible to see in general which genres are merged or evolved from other genres, but without going into details.

4.2 Classification discussion and processing

Find the similarity relationship between followers and influencers and the similarity relationship of unrelated nodes.

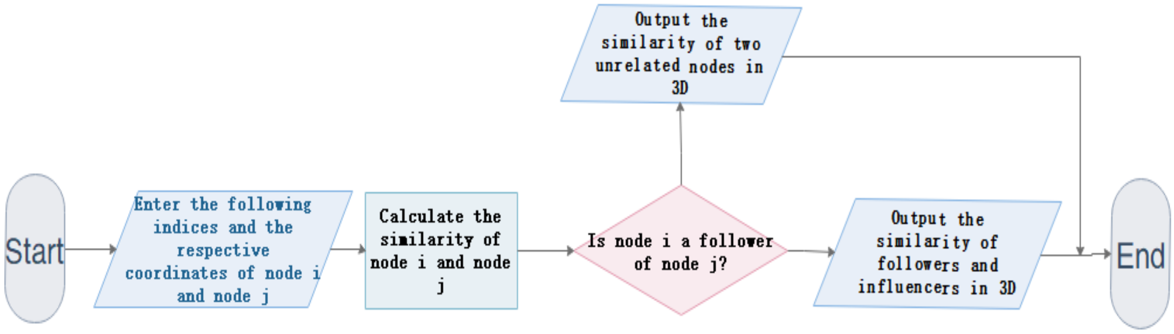

Figure 8. Flow chart of classification discussion

Therefore, the similarity three-dimensional diagrams of followers and influencers and the similarity three-dimensional diagrams of disjoint nodes are as Figure 9 and Figure 10.

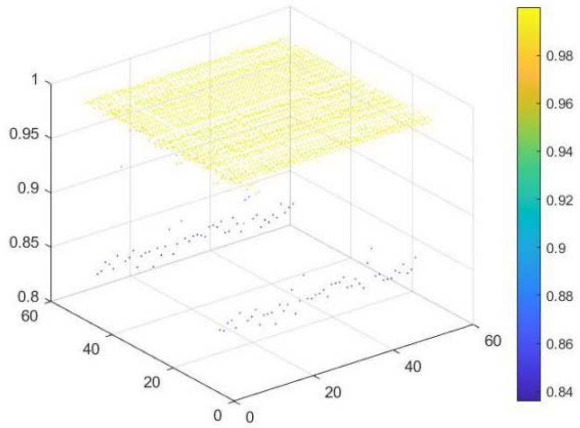

Figure 9. Influence-following similarity three-dimensional diagram

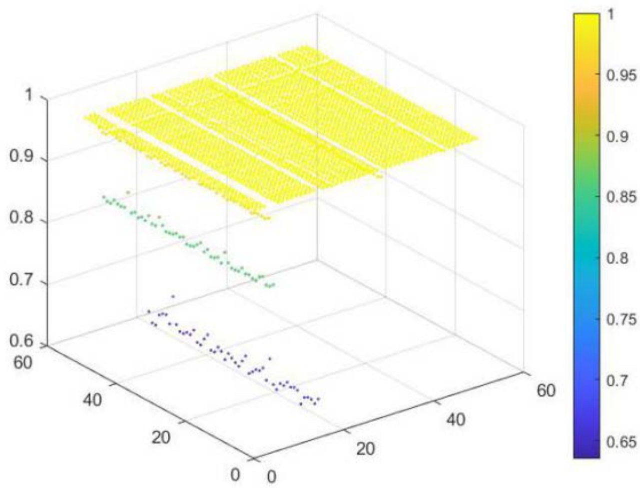

Figure 10. Disjoint node similarity three-dimensional diagram

It can be seen that the similarity values of the follower-influence 3-D plot are mainly distributed in the (0.84, 1.00) interval, while the similarity values of the irrelevant 3-D plot are mainly distributed in the (0.65, 1.00) interval.

Therefore, influencers do influence the musical characteristics of their followers' com-positions.

5. Conclusion

In this paper, a network model is developed to analyze the development of music. firstly, a double-layer music influence estimation network is constructed to obtain the "music influence" between artists and genres. The variance and average of genres are calculated to analyze the "music influence" of different music characteristic indicators within and between genres. The variance and mean of genres are calculated to analyze the "music influence" of different music characteristics within and between genres. Then a music influence network estimation network is established to obtain the "music influence" between artists and genres, and to calculate the "music influence" of different music characteristic indicators within and between genres. Finally, a similarity model is constructed to analyze the similarity between artists and artists, schools and schools, influencers and followers, and unrelated artists. It shows the influence of influencers on the music creation of fans.

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