A Study of Music Data Influence Under Machine Learning and Directed Network

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Abstract. As we all know, the twentieth century has undergone earth-shaking changes, whether it is historical background, philosophical and aesthetic thoughts, political situation, military atmosphere, science and technology, etc. This situation also provides a good development environment for music. Based on this background, we study the relevant music data since the 20th century; build relevant models to understand and measure the influence, evolution and development of music. In order to build a bridge between music data, the musicians are classified as followers and influencers and the relationship between them is explored, and then the data is established by directed network link. Considering the irreversibility and difference of the influence between followers and influencers, this paper, on the basis of the traditional directed network link, fully considers the structural characteristics of the directed network, establishes a linear programming model, constructs a similar matrix by solving the optimal solution of the contribution matrix, and constructs a directed network linear programming index; Finally, the influence between follower and influence is reflected by the size of contribution value.

Keywords: Linear programming, Directed network, Machine learning, Time series.

1. Overview

Before and after the 20th century, the historical background, philosophy and aesthetic trend of thought, the musician's own aesthetic view and the progress of science and technology all had a great influence on the form, content and style of music, which led to the gradual disintegration of the traditional romantic music form and the germination of the new modern music structure. In a short period of 50 years, two world wars have been experienced, which has caused social unrest, sharp deterioration of contradictions, and social psychological changes, resulting in more tension, uneasiness and other emotions. At the same time, with the rapid development of society, the psychological requirements of musician innovation are intensified. This makes the 20th century western music appeared the phenomenon of various genres and styles.
2. Model Establishment and Solution

2.1. The Establishment of Music Influence Network

In order to study the influence of music, we must first bind the relationship between influencers and followers. We build the directed network based on the existing data, but the traditional directed network link method does not fully take into account the characteristics of the directed network structure, and does not distinguish the contribution difference between the directed neighbors to the edge formation. The final result is limited.

2.1.1. Model preparation. Given a directed network $D(V, E)$: $V$ is the Point set, is the Edge set $E$. Let the network adjacency matrix be:

$$A = [a_{i,j}]_{N \times N}$$

$N$ is the number of nodes and $a_{i,j}$ is the element of adjacency matrix as an adjacency matrix element.

Let $U$ be the set of all possible connected edges in the network, then $U - E$ be the set of nonexistent edges, and each nonexistent edge $e(v_1, v_2) \in U - E$ is given a similarity index $s_{v_1v_2}$ to represent the possibility of the existence of the edge.

2.1.2. Directed network infrastructure. A given directed network starts from any node and can generally form three types of connected edges: connected edge, connected out edge and reciprocal edge.

Then all neighbors $\Gamma(v)$ of any node $v \in V$ and $v$ in the directed network can be expressed as:

$$\Gamma(v) = \Gamma_{in}(v) \cup \Gamma_{out}(v) \cup \Gamma_r(v)$$

Where $\Gamma_{in}(v)$ is the set of connected neighbors; $\Gamma_{out}(v)$ is the set of connected neighbors; $\Gamma_r(v)$ is the set of reciprocal connected neighbors.

In the directed network, because of the different direction of information transmission, the three neighbor nodes have different contributions to the formation of the connected edges, and in order to distinguish the contribution degree of the neighbor nodes to the connected edges, the weighted adjacency matrix $R$ of the directed network is introduced.

For a directed network $D(V, E)$, let the weighted adjacency matrix $R = [r_{v_1v_2}]_{N \times N}$, $\alpha \in R$ be adjustable and the elements satisfy:

$$r_{v_1v_2} = \begin{cases} 
1, & e(v_1, v_2) \in E, e(v_1, v_2) \notin E \\
\alpha, & e(v_1, v_2) \notin E, e(v_1, v_2) \in E \\
1+\alpha, & e(v_1, v_2) \in E, e(v_1, v_2) \in E 
\end{cases}$$

Compared with the adjacency matrix $A$, the weighted adjacency matrix $R$ adjusts the information contribution value of each type of contiguous edge by parameter $\alpha$.

In this paper $\alpha = 1$, in the weighted adjacency matrix $R$, all the unidirectional edge weights are 1, and the reciprocal edge weights are 2. The connected and connected nodes of any node have the same contribution value;
2.1.3. Directed Network Linear Programming Indicators. Let two nodes $v_1, v_2 \in V$, $v_1$ neighbor $z \in \Gamma(v)$ of node $a$ has some information contribution to the formation of connected edge $e(v_1, v_2)$, which is represented by $c_{zv_2}$, a neighbor node of the node has a certain information contribution to the formation of the connecting edge.

For connected edge $e(v_1, v_2)$, the similarity index is the linear sum of the contributions of all neighbors of node $x$ to connected edge $e(x, y)$ information.

$$s_{v_1v_2} = \sum_{z \in \Gamma(v_1)} r_{v_1z} c_{zv_2}$$

$$= \sum_{z \in \Gamma(v_1)} c_{zv_2} + \alpha \cdot \sum_{z \in \Gamma(v_1)} c_{zv_2} + (1 + \alpha) \cdot \sum_{z \in \Gamma(v_1)} c_{zv_2}$$

In the form of a matrix:

$$S = AC + \alpha A^T C = RC$$

Among them,

$$R = A + \alpha A^T C$$ is the Contribution matrix

In order to solve the contribution matrix $C$, the linear programming method is introduced. It can be seen from the above that the similarity index $s_{v_1v_2}$ is related to the adjacency matrix element $a_{v_1v_2}$, and the difference between the adjacency matrix $A$ and the element corresponding to the similarity matrix $S$ should be as small as possible. If the norm of a specific matrix is used to measure the distance between matrices, $\|S - A\| \rightarrow 0$ should be satisfied. Based on this, a linear programming model of variable $C$ is constructed. By optimizing the objective, the minimum matrix norm of $S$ and $A$ is obtained as:

$$\text{arg min}_C \|S - A\|$$

In order to reduce the number of effective features and prevent parameter overfitting, the parameter norm penalty term $\lambda \|C\|$ is added to the objective function;

The optimal objective function is:

$$\text{arg min}_C \|S - A\| + \lambda \|C\|$$

2.1.4. Model Solution. In this paper, the norm of matrix is represented by 2-norm:

$$\|A\| = (\|A\|_2)^2 = (\sqrt{tr(A^T A)})^2 = tr(A^T A)$$

Order:
\[
E = \text{tr}\left((S - A)^T (S - A)\right) + \lambda \cdot \text{tr}(C^T C)
\]
\[
= \text{tr}(S^T S - A^T S - S^T A + A^T A) + \lambda \cdot \text{tr}(C^T C)
\]
\[
= \text{tr}(C^T R^T RC - A^T RC - C^T R^T A + A^T A) + \lambda \cdot \text{tr}(C^T C)
\]

Derivation of \(E\) with respect to matrix \(C\), the derivation formula of matrix trace is used
\[
\text{dtr}(XA) = A^T \text{d}X
\]
Available:
\[
\frac{dE}{dC} = \frac{\text{dtr}(C^T R^T RC)}{dC} - \frac{\text{dtr}(A^T RC)}{dC} - \frac{\text{dtr}(C^T R^T A)}{dC} + \frac{\text{dtr}(A^T A)}{dC} + \frac{\text{dtr}(\lambda C^T C)}{dC}
\]
\[
= 2R^T RC - R^T A - R^T A + 2\lambda C
\]

According to the structure of directed network:
\[
\left|R^T R + \lambda \cdot M\right| \neq 0
\]
Let the derivative \(\frac{dE}{dC} = 0\) of the above formula be the optimal solution \(C^*\):
\[
C^* = (R^T R + \lambda \cdot M)^{-1} R^T A
\]

The similarity matrix \(S\) is calculated with the optimal solution \(C^*\) and the linear programming index of directed network is constructed as follows:
\[
S^\perp = RC^* = R(R^T R + \lambda \cdot M)^{-1} R^T A
\]
Among them,
\[
R = A + \alpha A^T
\]

2.2. Model introduction and analysis
The existing data influence_data are brought into the above model and processed through MATLAB. Figure 1 When the result is near 1, it shows that there is a connection between the two nodes, and the possible influence value for prediction is small. Through the construction of direct relationship bridge between "influencer" and "follower" and the prediction of indirect relationship bridge, the directional network system between them is described more completely, and the directed network link prediction under linear programming is described. On the basis of the contribution calculation of the original edge, the potential edge mining and calculation are carried out to perfect the whole directed network system.
3. Feature vector extraction of genre based on machine learning

3.1. Model Establishment
The genre of all artists in data_by_artist dataset is first obtained according to the influence_data dataset.

Symbolic definitions of 20 genres are given as follows:

| Table. 1 indicator symbol definition |
|--------------------------------------|
| danceability | energy | valence | tempo | loudness | mode | key |
| $x_1$          | $x_2$  | $x_3$   | $x_4$ | $x_5$    | $x_6$ | $x_7$ |

Extract the music vector of each artist: $X_i = x_j (j = 1, 2, 3...7)$.

The following vector dimensionality processing, the standard music vector, as follows:

$\begin{align*}
  x_j &= \frac{x_{ij} - \min x_{ij}}{\max x_{ij} - \min x_{ij}} \\
  j &= \sum_{j=1}^{n} \frac{x_{ij}}{x_j}
\end{align*}$

Considering that we need to compare the artist similarity between the artist and the artist in the genre, we extract the feature vector $X^*$ of the genre from each genre. And ensure that the distribution of the feature vector and the music vector distribution of musicians in the genre is basically consistent.

In order to ensure the consistent distribution of feature vectors between genres, we take the average value of cross entropy of all artists between feature vectors and genres as a loss function. Notes:

$\begin{align*}
  P(x_{ij}) &= \frac{x_{ij}}{\sum_{j=1}^{n} x_{ij}} \\
  \text{loss} &= \frac{\sum_{j=1}^{n} \sum_{j=1}^{n} p(x_{ij}) \ln \frac{1}{p(x_{ij})}}{n}
\end{align*}$

Based on this, the problem can be transformed into a nonlinear optimization problem, that is:

$\begin{align*}
  \min \frac{\sum_{j=1}^{n} \sum_{j=1}^{n} p(x_{ij}) \ln \frac{p(x_{ij})}{p(x_j)}}{n}
\end{align*}$

3.2. Model Solution
We take the given data set as the training set and the feature vector $X^*$ as the training parameters. The final results are obtained by gradient descent training. The steps are as follows:

In order to ensure the convergence of the model, we define the loss function by taking the average value of each index of the genre as the starting point:
Considering that there are many objective functions, we introduce a RMSprop method to dynamically adjust the learning rate, to ensure that the direction of fast convergence speed uses a larger step size, and the direction of slow convergence speed uses a smaller step size.

The iterative rules are:

\[
g^{(t)} = \rho g^{(t-1)} + (1 - \rho)\left(\frac{\partial f}{\partial x_{(t)}}\right)
\]

\[
x_{(t+1)}^* = x_{(t)}^* - \frac{\eta}{\sqrt{g^{(t)} + \epsilon}} \frac{\partial f}{\partial x_{(t)}}
\]

Among them, \(\rho, \epsilon, \eta\) are hyperparameters, need to be constantly adjusted in training.

In order to prevent some parameters from moving back and forth because the learning rate is too large to converge, we introduce Momentum indicators so that the gradient can be offset before and after to prevent divergence.

**Table. 2** The input parameters are shown in the table below:

|   |   |
|---|---|
| \(\eta\) | 0.0001 |
| \(\rho\) | 0.9  |
| \(\epsilon\) | \(10^{-8}\) |
| Momentum | 0.9  |
| TRANIN_STE PS | 500  |

Iterate many times until the function converges to get the result.

3.3. Selection of similarity index

We use Euclidean distance to describe the similarity between music vectors, that is, notation

\[
sim(x_m, x_n) = \sqrt{\sum_{j=1}^{n} (x_{mj} - x_{nj})^2}
\]

The smaller \(\sim(x_m, x_n)\) is the more similar \(x_m, x_n\) are.

For the similarity analysis of artists of two different genres \(P, Q\), they are described by the similarity of feature vectors \(p^*, q^*\) of two genres:

\[
sim(P, Q) = \sqrt{\sum_{j=1}^{n} (p^*_j - q^*_j)^2}
\]
For the similarity analysis within the genre, the similarity between the music vector and the feature vector of all artists is averaged:

\[
\text{sim}(P, Q) = E\left(\sum_{j=1}^{7} (p_j - \bar{p})^2\right)
\]

### 3.4. Results analysis

For the correlation analysis between genres, the Euclidean distance between feature vectors is used; for the correlation analysis within the genre, the average distance between the musician and the feature vector is obtained.

Considering the large amount of data of 20 genres and the fact that many cold-door music genres are not representative, we select 8 of them to enumerate and explain the data.

By Python training the existing data, the feature vectors of the 8 categories are obtained as follows:

**Table. 3** The extraction of eigenvectors

| Country | Electronic | Jazz | Latin | Pop/Rock | R&B | Reggae | Vocal |
|---------|------------|------|-------|----------|-----|--------|-------|
|         | 0.1059     | 0.1176 | 0.0940 | 0.1147   | 0.1016 | 0.1194 | 0.1667 | 0.0845  |
|         | 0.0986     | 0.1301 | 0.0671 | 0.1091   | 0.1407 | 0.1077 | 0.1050 | 0.0603  |
|         | 0.1166     | 0.0881 | 0.0942 | 0.1316   | 0.1087 | 0.1161 | 0.1662 | 0.0793  |
|         | 0.0968     | 0.0966 | 0.0859 | 0.0920   | 0.1101 | 0.0910 | 0.0901 | 0.0852  |
|         | 0.1452     | 0.1595 | 0.1095 | 0.1596   | 0.1541 | 0.1607 | 0.1582 | 0.1195  |
|         | 0.2159     | 0.1302 | 0.1331 | 0.1675   | 0.1815 | 0.1578 | 0.1629 | 0.1856  |
|         | 0.1048     | 0.1073 | 0.0936 | 0.0971   | 0.1107 | 0.1018 | 0.1081 | 0.0926  |

Based on the above data, the similarity between the eight genres is as follows:

**Table. 4** The similarity between genres

| Country | Electronic | Jazz | Latin | Pop/Rock | R&B | Reggae | Vocal |
|---------|------------|------|-------|----------|-----|--------|-------|
|         | 0.0004     | 0.0047 | 0.0050 | 0.0015   | 0.0017 | 0.0020 | 0.0046 | 0.0026  |
|         | 0.0047     | 0.0004 | 0.0037 | 0.0019   | 0.0018 | 0.0011 | 0.0051 | 0.0055  |
|         | 0.0050     | 0.0036 | 0.0004 | 0.0037   | 0.0055 | 0.0031 | 0.0077 | 0.0016  |
|         | 0.0015     | 0.0019 | 0.0037 | 0.0004   | 0.0012 | 0.0002 | 0.0020 | 0.0040  |
|         | 0.0017     | 0.0018 | 0.0055 | 0.0012   | 0.0000 | 0.0013 | 0.0048 | 0.0049  |
|         | 0.0020     | 0.0011 | 0.0031 | 0.0002   | 0.0013 | 0.0004 | 0.0024 | 0.0037  |
|         | 0.0046     | 0.0051 | 0.0077 | 0.0020   | 0.0048 | 0.0024 | 0.0004 | 0.0093  |
|         | 0.0026     | 0.0055 | 0.0016 | 0.0040   | 0.0049 | 0.0037 | 0.0093 | 0.0004  |

It can be seen from the above table that for the same genre, the distance between them is smaller than that between him and other genres, which shows that the similarity within the same genre is higher than that of different genres.

Besides, for the mainstream genres of modern music, like Pop/Rock. Electronic. R&B, their similarity is very high and their distance is relatively small. It is not difficult to analyze the trained data from this objective fact. The results of the training are still very practical. The results are better.
3.5. Distinction and connection between genres

Number 20 genres 1~20, as follows: Avant-Garde. Blues. Children's. Classical. Comedy/Spoken. Country. Easy Listening. Electronic. Folk. International. Jazz. Latin. New Age. Pop/Rock. R&B. Reggae. Religious. Stage & Screen. Unknown. Vocal; remember the collection of all genres: \( Q = \{ q_1, q_2, \ldots, q_{20} \} \)

Following is a secondary standardization of the restored data with the data_by_year, as shown in the table below:

Table. 5 The secondary standardization 3

| genres          | danceability | energy | valence | tempo | loudness | mode     | key  |
|----------------|--------------|--------|---------|-------|----------|----------|------|
| Avant-Garde     | 0.2282       | 0.1637 | 0.3747  | 0.5374| 0.0000   | 1        | 0.4333|
| Blues           | 0.5585       | 0.5584 | 0.7921  | 0.7772| 0.6375   | 1        | 0.5435|
| Children's      | 0.7932       | 0.5917 | 0.9577  | 1.0000| 0.9198   | 1        | 0.0000|
| Classical       | 0.0235       | 0.0000 | 0.1001  | 0.5815| 0.0112   | 1        | 0.5556|
| Comedy/Spoken   | 0.4687       | 0.7404 | 0.5409  | 0.6442| 0.4601   | 1        | 0.5188|
| Country         | 0.3466       | 0.5272 | 0.5804  | 0.5019| 0.7562   | 1        | 0.5348|
| Easy Listening  | 0.2503       | 0.4009 | 0.4037  | 0.6632| 0.4752   | 1        | 0.4118|
| Electronic      | 0.4943       | 0.8289 | 0.4023  | 0.5424| 0.7815   | 1        | 0.5538|
| Folk            | 0.4158       | 0.2372 | 0.5949  | 0.8477| 0.4354   | 1        | 0.5370|
| International   | 0.4727       | 0.4636 | 0.6775  | 0.7408| 0.5328   | 1        | 0.5236|
| Jazz            | 0.1350       | 0.1859 | 0.3449  | 0.1075| 0.7363   | 1        | 0.4289|
| Latin           | 0.4066       | 0.6021 | 0.6690  | 0.3656| 0.8063   | 1        | 0.4779|
| New Age         | 0.0093       | 0.0579 | 0.0000  | 0.6195| 0.1187   | 1        | 0.3333|
| Pop/Rock        | 0.3296       | 0.8912 | 0.5303  | 0.7429| 0.8576   | 1        | 0.5655|
| R&B;            | 0.4335       | 0.5690 | 0.5500  | 0.3333| 0.8078   | 1        | 0.5061|
| Reggae          | 1.0000       | 0.6238 | 1.0000  | 0.5100| 0.7279   | 1        | 0.5850|
| Religious       | 0.3810       | 0.7015 | 0.4948  | 0.8060| 0.7725   | 1        | 0.4604|
| Stage & Screen  | 0.0000       | 0.1532 | 0.1480  | 0.5964| 0.2663   | 1        | 0.4379|
| Unknown         | 0.2581       | 0.5445 | 0.4681  | 0.3364| 1.0000   | 1        | 0.4238|
| Vocal           | 0.0096       | 0.0895 | 0.2081  | 0.0000| 0.8158   | 1        | 0.3908|

Before we have extracted the eigenvalues of each genre, so we only need to calculate the distance between the music vector of each year and the eigenvector of the corresponding genre; take the small result as the popular genre of this year. The evolutionary relationship between genres is obtained. The specific results are attached.

Suppose that the music vector of year \( i \) is \( \mathbf{y}_i \). The similarity between the vector and each feature vector is calculated below, and the most similar feature vector is found.

Take the 1921 data as an example, as follows:

Table. 6 Standard Music Vector 1921

| year | danceability | energy | valence | tempo | loudness | mode | key |
|------|--------------|--------|---------|-------|----------|------|-----|
| 1921 | 0.21400      | 0.11172| 0.41348 | 0.45947| 0.23166  | 1    | 0.7 |

Calculate the distance of each genre feature vector for the year, as shown below.
Table. 7 Eigenvector distance between genres, 1921

| Jazz      | Latin     | New Age    | Pop/Rock   | R&B;       |
|-----------|-----------|------------|------------|------------|
| 0.68444   | 0.85507   | 0.62335    | 1.06055    | 0.81340    |
| Avant-Garde | Blues    | Children's | Classical  | Comedy/Spoken |
| 0.36779   | 0.86699   | 1.45525    | 0.48095    | 0.77168    |
| Reggae    | Religious | Stage & Screen | Unknown | Vocal |
| 1.2191    | 0.9204    | 0.4546     | 0.9349     | 0.8558     |
| Country   | Easy Listening | Electronic | Folk | International |
| 0.72270   | 0.51861   | 0.96108    | 0.54199    | 0.67925    |

Predict the most popular genres of each age

According to the KNN algorithm, the data of each year are classified and estimated, and every 10 years as a cycle, the music pop genres in 10 years are counted, and the evolutionary relationship between the following genres is made:

**Figure. 1** the evolutionary relationship between genres

Four examples are selected to construct the annual variation line diagram:

**Figure. 2** Four examples are selected to construct the annual variation line diagram
From the above figure, for Pop/Rock, the distance between feature vectors has become smaller and smaller, so its popularity is also increasing; the other three music genres have gradually lost their popularity.

The results are shown in the "distance.xls" and "genres change over time.xlsx" in annex 3.

3.6. Build genres Network
The following construction genre network, and then explain the relationship between genres.

Based on the first question of the network $D$, we build a network $D'$ between genres, the establishment process is as follows:

traversing each edge of the network $D$, if the similarity $s_{ij}$ of the two artists $v_1, v_2$ is higher than the given threshold $c$, the corresponding genre $q_j, q_i$ has a directed edge $v'_{ij}$ from $q_j$ to $q_i$. namely:

$$
\begin{cases}
    v_{ij} = v_{ij} + 1, s_{ij} \geq c \\
    v_{ij} = v_{ij}, s_{ij} < c
\end{cases}
$$

Based on the evolutionary relationship between the pushed genres, we think that the following two situations are the successful influence of the influencers on the followers:

The same genre of followers as influencers;

The genre of followers is transformed by influencers.

In the above table, horizontally, the genre affects other genres; vertically, the other genres influence the genre. From the above table, it is not difficult to find that each genre has a high degree of association with itself; for the genre numbered 14, it has the highest degree of association with itself, that is, Pop/Rock not only has a high degree of association with itself, but also sees its shadow from the evolution of other music genres. Draw the above data into a network, as shown below:

![Network Diagram](image)

**Figure. 3** Draw the above data into a network

3.7. Practical Impact Analysis of Music
Through the analysis of the proportion of influence times and successful influence times of 20 genres, the following table data are obtained:
Not difficult to see from the above table, Blues the early emergence of modern music genres, his influence on the emergence and development of other genres is not to be underestimated; in the early stage of many music, Unknown and other genres have not been too obvious wiring, has not yet formed their own characteristics, so often classified into unknown genres, at this time it is based on the influence or influence of other genres; Pop/Rock as the most popular form of music at present, it great help to the emergence of other new music genres or the development of the original music genres; Finally, we calculated that the total proportion of successful influence was 22.6. It can be seen that this proportion is still relatively small. It is not difficult to analyze that in the course of music development in the last century, it was influenced by various social factors. To some extent, the artists' pursuit of innovation.

3.8. Major changes in the evolution of music
In the description of the related musical characteristics, the change of musical characteristics often brings about the change of musical style or genre, and promotes the emergence of new genre. We have heard a lot of literature search and collation found that the change of music is not only the change of music characteristics, but also the thrust of the external environment. For the 20th century musicians, they face tension and unease from the world war; in such an environment, there will be a strong gap in their hearts, and unexpected changes in their attitudes towards music. Many of them even deny the original music genres and innovate according to the breeding environment, which provides an internal and external environment for the music changes of the 20th century.

4. Effects of the Internet on Music
The development of network technology and the continuous popularization of network in the public have a great influence on music from the external environment. When romantic and classicist music appeared, music was regarded by most people as a luxury in the upper class, but the emergence of the Internet dispelled people's thoughts. In addition, music no longer needs to be produced to please others, it has become more the carrier of people's emotions, which also provides the possibility for the pluralistic development of music.

References
[1] Yang Yanhua, Yao Ligang. Solving flexible job shop scheduling problem based on time recursive modeling and cross entropy algorithm [J / OL]. Computer integrated manufacturing system: 1-17 [2021-01-06 10:06]
[2] Zhao Xuelei, Ji Xinsheng, Liu Shuxin, Zhao Yu. Directed network link prediction method based on generalized common neighbor [J]. Journal of network and information security, 2020,6 (05): 89-100
[3] Gao Xiang, Chen Li. Grouping random gradient descent method: balance between lag and delay [J / OL]. Journal of University of science and technology of China: 1-10 [2021-01-26 14:12]
[4] Jia Mingzhu. Research and application of time series analysis method based on machine learning [D]. Xi'an University of science and technology, 2020