Problem Chosen	2021	Team Control Number
D	MCM/ICM Summary Sheet	2126428

Musical Contagion: Data-Mining on Musical Facts

Summary

Nowadays, music is playing an increasingly important role in human life. To better understand the role music has played in the collective human experience, we develop several useful models to quantify musical evolution, using networks to mine musical influence, and features to measure music similarity and distinguish genres.

We initially reconstructed, cleansed the given datasets and built the directed graph of musical influencers and followers, where each node represents an artist and influencers are connected to followers. Subnet extraction was performed in an attempt to reduce the calculation of the computer.

In **Task 1**, we propose a novel **Artist Influence Mining Network**, which deals with the graph structured data. This mining network utilise the graph attention machanism to mine the relationship between nodes, and learns the deep, underlying information that sealed in the graph structure. We use the summation of the attention values attached on each none as the final influence scale adopted. Finally, we come up with our exclusive influence index and use it to rank the impact of artists.

In **Task 2**, we construct an **Artists' Music Similarity Measurement Model** to quantify the similarities between artists and genres. We first use R Cluster Analysis and Principal Component Analysis(PCA) to reduce the dimensions between variables and select 8 features. Then we compare the similarity of these 8 indicators between artists of two genres using **Cosine Similarity Model** and get the similarity heat map, which help us figure out genre relevance too. Furthermore, in order to explore what features distinguish different genres, we calculate the similarity of each feature within the genre and draw another heat map. Finally, in order to explore how genres change over time, we choose R&B genre as an example and analyze its number of songs released, popularity and similarity with itself over time.

In **Task 3**, we construct a **Different-Influence Model** to concretely analyze the influence of influencers. At first, We confirm the influence of influencers on followers by comparing the changes in the similarity between artists and their followers or non-follower before and after they became active. Afterwards, to explore whether certain musical factors are more 'contagious', we analyze the similarity of each music feature between the Beatles and its follower group and get 2 corresponding graphs, which we use to get more musical features of great influence.

In **Task 4**, we use all of our models to study **musical evolution** over time. Firstly, we draw a line chart of each normalized index changing over time. We utilise the chart and find the musical revolution without difficulty. Subsequently, we identify the artists who represent the revolutionaries by a heat map of specific artists' annual output over time. Additionally, we further explore the influence processes of musical evolution that occurred over time in R&B genre. We finally add more variable effects to our network to explore our model further.

In conclusion, we successfully quantify musical influence and evolution over time through modeling and programming operations.

Keywords: Network; Musical Influence; R Cluster Analysis; PCA; Cosine Similarity

Contents

1 Introduction

1.1 Background

Music has been an attractive, inseparable part of our society ever since the origin of human civilization. With similar rhythm or structures of their songs, artists are classified into different specific genres. Many musicians have been influenced by many other artists to join the same genre, but they can also change existing genres to create new sounds.

We feel honourable being asked to develop an approach to quantify musical influence, with following tasks provided:

- Create a network connecting influencers to followers, using a subnetwork to reveal "music influence";
- Develop a measure to identify the music similarities;
- Distinguish genres with the influences and similarities;
- Differentiate whether the influencers affect music creation of followers or they just compose similar sounds;
- Identify significant revolutions;
- Analyse the influences on the musical revolution; and
- Consider other factors which can effect composition.

1.2 Our Work

Our major contributions in this work can be summarised as follows:

(i) We first cleaned and preprocessed the data provided, and constructed a directed graph consisting of 3,019 nodes and 29,775 directed edges to represent the whole artist network.

(ii) We propsed a novel attention-based graph neural network model, namely Artist Influence Mining Network, or AIMN, to learn node representations, and tried to utilise the model to mine the deep informations of the underlying directed graph.

(iii) We bring out the idea that uses the weighted summation of attention value and as the final influence scale (namely influence index) adopted by each node.

(iv) We optimised R Cluster Analysis and Principal Component Analysis (PCA) to reduce the dimensions between variables and select 8 features.

(v) We compared the similarity of these 8 indicators between artists of two genres using the Cosine Similarity Model.

(vi) We utilised all of our models alternately to study and mine the deeper knowledges of musical evolution over time.

2 Preparation of the Models

2.1 Assumptions and Notations

In this paper, our statements are provided based on the assumptions listed below:

- The genre of a song can be inferred from that of the song's producer(s).
- The musical style of a certain artist does remain stable, without large changes.
- The musical influence will come into effect immediately after an artist release new song(s).

Besides, unless the context otherwise requires, the universial notations are defined as follows.

Notation	Definitions
$\mathcal{G}$	A (directed) graph
$\mathcal{A}$	The attention matrix
v_i	A node in the graph or an artist
s_i	The influence index of node v_i
$\vec{h}_i$	The feature vector of node v_i
$\vec{h}_i^i$	The feature vector of node v_i (after transformed)

2.2 Data Preprocessing

2.2.1 Reconstruction and Cleansing of the Given Datasets

We first perform data extraction on the additional data table *data_by_artist* provided to obtain the general characteristics of each artist' s song. We add each listed artist to a collection of artists as the node set for the directed graph.

Then, we analyze the *influence_data* and *full_music_data* dataset by enumerating each follow relationship and music entry. Based on the assumption that the genre of a music is identical to that of the performer of the music, we performed a scan on both datasets as a whole, and extracted a total of 20 genres with the number of songs within that genre. The top 10 genres with the most number of artists can be found in Table 1.

Table 1: The Categories of Genres (10 Genres)

Name	Electronic	R&B	Vocal	Jazz	Pop/Rock
Songs	1439	11025	6552	8000	48725
Name	Religious	Blues	Country	Latin	New Age
Songs	745	1313	8285	5071	273

Feeling regretful to find that there is no way to uniquely identify a song or an artist's genre without being provided any sample of song information for that artist, we delete the *follow* relations that starts and/or terminates by any artist not in the aforementioned artist set, from the relation set. After the data cleansing process, each *follow* relation, denoted by a tuple in the following form, is added to the *follow* set :

$$f_{i,j} = (v_i, v_j)$$

There are 3,019 elements in the set of artists, which means there're 3,019 unique artists (after data cleansing). Meanwhile, 29,775 elements in the *follow* set, which means that there are 29,775 unique *follow* relations. We saved the two sets as separate files to disk for subsequent needs of our further processes.

2.2.2 Graph Construction

Considering the characteristics of the data, a directed graph $\mathcal{G}$ can be represented as a triple as follows:

$$\mathcal{G} = (V, A)$$

where $V \in \mathbb{R}^N$ is the node set and $V \in \mathbb{R}^{N \times N}$ is the adjacency matrix of the graph where N denotes the total number of nodes (artists). V and A can be represented as:

$$V = v_1, v_2, v_3, ..., v_N, \tag{1}$$

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1N} \\ a_{21} & a_{22} & \cdots & a_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ a_{N1} & a_{N2} & \cdots & a_{NN} \end{bmatrix} \tag{2}$$

where $a_{ij} = 1$ if the node (artist) v_i is connected to (followed by) v_j, or $a_{ij} = 0$ if otherwise.

After the aforementioned data preprocessing process, we treat the *artist* set as the node set, and use the *follow* set to construct the adjacency matrix. Then we utilised the NetworkX library and the above set and matrix to construct the whole directed graph, as shown in Figure 1[1].

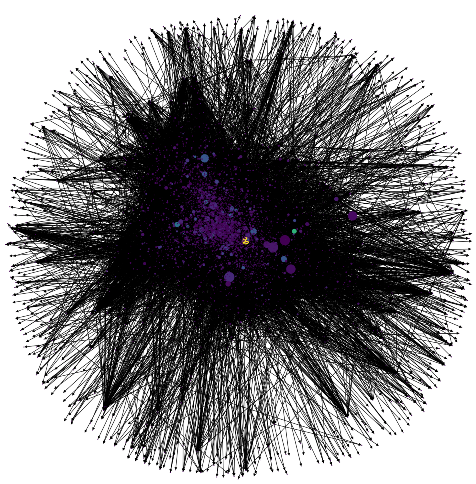

Figure 1: The Directed Graph

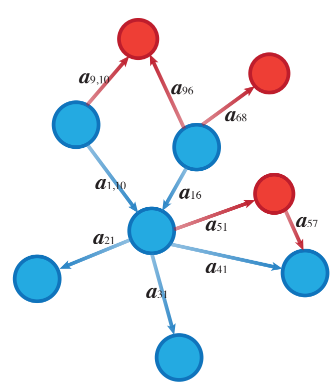

Figure 2: The AIMN Machanism

[1]The sizes and colours of nodes denotes is related to the number of the corresponding artists' followers.

3 Task 1: Mining the Influence Among Artists

3.1 Related Works

In recent years, some graph-based machine learning networks in non-Euclidean data have made the latest progress and more extensive applications. The concept of Graph Neural Networks was first proposed by Gori et al.[5] in 2005. And it was further clarified by Scarselli et al.[11]. These early studies learned the representation of target nodes in an iterative manner by circulating the neural architecture and spreading neighboring information until a stable fixed point was reached. Inspired by the great success of convolutional networks in the field of computer vision, many approaches to redefine the concept of convolution for graphs appeared recently. These methods fall under the category of Graph Convolutional Networks (GCN). Bruna et al.[6] presented the first important study on graph convolution networks by developing a variant of graph convolution based on spectral graph theory. Kipf et al.[8] applied the convolution machanism to the node classification task.

In addition to graph convolutional networks, many alternative graph neural networks have been developed in recent years. These methods include graph autoencoders[9], graph space-time networks, graph generation networks (e.g., MolGAN [4], DGMG [10], GraphRNN [14] and NetGAN [2]) and graph attention networks such as GAT proposed in [13] and GAAN proposed in [15].

We note that the Graph Attentional Networks (GAT) can be regarded as a spatial-based convolutional network. Its advantage is that it can adaptively learn the importance weight of its neighbors and obtain a better aggregation scheme when aggregating feature information, so that nodes can selectively obtain and filter the information provided by their neighbors. Therefore, we propose a novel model, namely the Artist Influence Mining Network (AIMN)[2], based on GAT as the preferred excavation scheme of influence. An introduce picture of the AIMN is on Figure 2.

3.2 The Artist Influence Mining Network (AIMN) Model

3.2.1 Network Parameters

Our AIMN model is a kind of encoder model. This mining network utilises graph attention machanism to mine the relationship between nodes and the importance degree, and updates the node representation according to the different importance degree.

At the beginning of training, our model randomly initializes some parameters, which can be divided into linear transformation matrix and attention parameters according to their types in the network.

(i) **The Linear transformation matrix**

The linear transformation matrix is utilised to transform the input dimension of each node representation vector to the output dimension. Specifically, For the input feature vector h_i of artist node v_i, we use the weight matrix $\boldsymbol{W} \in \mathbb{R}^{R \times R'}$ to carry out linear transformation into the hidden layer vector d_i, as described in (3).

$$d_i = \boldsymbol{W} h_i \tag{3}$$

In this task, the aforementioned linear transformation is implemented for each artist node in the network to reduce the dimension of the input feature vector.

[2]The source code could be found on `https://github.com/lhanlhanlhan/influence-mining`

(ii) **Attention parameters**

The so-called "attention" means that in the process of graph network aggregation, when the central node aggregates its surrounding neighbor nodes, it applies different attention weight to different neighbor nodes to aggregate more reasonable and optimized data. In particular, in our "Artist Influence Mining Network" , attention is used to discover how much influence each followed artist has on their followers when updating their features. The informal description of the attentional aggregation method is as

$$\vec{h}_i' = \vec{h}_i + \sum_{j=0}^{\mathcal{N}_i} \alpha_{ij} \vec{h}_j \tag{4}$$

where $\vec{h}_i$ refers to the eigenvector of node i, and α_{ij} refers to the attention value, or weight, of node i to node j. $\mathcal{N}_i$ refers to the neighbor node set of node i. In this task, $\mathcal{N}_i$ refers to the set of followers of Artist i's, which can be formalised as $\mathcal{N}_i = \{v_j | A_{ij} = 1\}$. We will describe our detailed approach of network aggregation in section 3.2.2.

The calculation of α_{ij} values between pairs of nodes will be discussed in the proceeding section.

3.2.2 The Propagation Model and Back Propagation Machanism

Based on the general graph attention mechanism, the attention value of our AIMN model is calculated as follows:

$$\begin{aligned}
\alpha_{ij} &= \mathrm{softmax}_j(e_{ij}) \\
&= \frac{\exp(e_{ij})}{\sum_{k \in \mathcal{N}_i} \exp(e_{ik})} \\
&= \frac{\exp(\mathrm{LeakyRELU}(\vec{a}^T \left[\boldsymbol{W}\vec{h}_i || \boldsymbol{W}\vec{h}_j\right]))}{\sum_{k \in \mathcal{N}_i} \exp(\mathrm{LeakyRELU}(\vec{a}^T \left[\boldsymbol{W}\vec{h}_i || \boldsymbol{W}\vec{h}_k\right])}
\end{aligned} \tag{5}$$

where $\cdot^T$ represents transposition of a vector, $||$ is the concatenation operation between vectors, and the value $e_{ij} = \mathrm{LeakyRELU}(\vec{a}^T \left[\boldsymbol{W}\vec{h}_i || \boldsymbol{W}\vec{h}_j\right])$ is the raw-attention value which will then be normalised through the LeakyRELU activator (equation 6) to attain an *attention value* denoted by α_{ij}.

$$\mathrm{LeakyRELU}(x) = \begin{cases} x & \text{if} x > 0, \\ 0.01x & \text{otherwise.} \end{cases} \tag{6}$$

Once obtain the attention values between the two central nodes, the propagation model of our AIMN model could be formally described as:

$$\vec{h}_i' = \mathrm{softmax}\left(\vec{h}_i + \sum_{j \in \mathcal{N}_i} \alpha_{ij} \boldsymbol{W} \vec{h}_j\right) \tag{7}$$

where the $\mathrm{softmax}$ non-linearity is acting as the final activation function of our model, mapping each dimension of the aggregated node representations to be in the range $(0, 1)$.

In this task, we trained the model on each artist node of the constructed directed graph structure. For each artist in the graph, we calculate the attention values of it to his/her followers through equation

(5), carry out the aggregation propagation among his/her adjacent artists (followers) in accordance with equation (4), and update the node representation of the artist. Finally, every artist in the graph is aggregated as the central node, and the feature vectors of all the artists can be updated within the aggregation process.

After each node gets an update, we use the following Negative Log-Likelihood (NLL) the as [13] to compare the feature vectors of each node after network transformation with the expected node output feature vectors and calculate the loss value:

$$\mathcal{L}(\mathcal{E}) = \sum_{v_i \in \mathcal{E}} \vec{y_i} \log \vec{h_i} \tag{8}$$

where $\mathcal{E}$ is the node (artist) set of the graph, and $\vec{y_i}$ is the expected node output feature (artist genre fetures) vector of the node v_i.

We utilised the backward propagation (BP) technique to update the two parameters in the model mentioned in 3.2.1 by reducing the value of the aforementioned loss function after each iteration of our model. We found that the model tends to be stable (without large scale of value fluctuation) after performing the standard training tasks like node aggregation, node representation vectors updating, loss values calculation, backward propagation and parameters updating.

3.3 Defination of the Influence Index

Based on reasonable assumptions, we design our influence scale based on the value of attention parameter when the model converges. The $N \times N$ attention values in the convergence state of our AIMN model can be denoted by an $N \times N$ matrix, namely the *attention matrix*, as follows:

$$\mathcal{A} = \begin{bmatrix} \alpha_{11} & \alpha_{12} & \cdots & \alpha_{1N} \\ \alpha_{21} & \alpha_{22} & \cdots & \alpha_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ \alpha_{N1} & \alpha_{N2} & \cdots & \alpha_{NN} \end{bmatrix} \tag{9}$$

where N is the of all artists in the network, α_{ij} has the same definition as equation 5. We notice that the value of $\alpha_{1j}, \alpha_{2j}, \cdots, \alpha_{Nj}$ of each element in each column c_j of the attention matrix represents the attention values attached on artist j when it is aggregated by artist $1, 2, \cdots, N$. In other words, the larger value of $\sum_j \alpha_{ij}$, the greater importance the adjacent artists (followers) attaches on artist i, when performing attentional aggregation by the AIMN.

Inspired by the aforementioned findings, we define the *Influence Index*

$$s_i = \sum c_i = \sum_{j=1}^{N} a_{ji} \tag{10}$$

We then try to use the value of the sum of column i of the attention matrix $\mathcal{A}$ as the influence index of artist i in the following sections. As a matter of fact, this is intuitively resonnable for the following points:

- If an artist has a higher influence, the corresponding feature of the artist will have a higher influence on the feature of its followers.
- Artists with higher influence have more control over the updating of their followers' features.
- Artists with higher influence have more weight when their followers aggregate the features of their surrounding nodes.

3.4 Training and Validating

3.4.1 Training Settings

In order to reduce the network size and computational complexity, subnet extraction is carried out in our researching process. We tried to extract a subnet from the whold graph by doing the following:

(i) Load the node set and sort them according to the followers numbers of the corresponding artists of the nodes.

(ii) Delete the artist nodes whose followers count are among the last 20% of all the artists.

(iii) Load the edge set (influence relations), and delete those who begins or terminates by the deleted artist nodes.

(iv) Form a new reduced subgraph according to the reduced node set and edge set.

Initially, we produce the adjacency matrix of the reduced directed graph, and build the AIMN model with two attentional layers. Specifically, we modified the learning rate of the optimiser to 0.005 and introduced two dropout layers before and after the attentional layer with both droupout rate set to 0.6. We trained the model 1,000 epochs on PyTorch platform and collected the last state of the attention matrix (equation 9) and the weight parameters (will be utilised in further fasks) of the last attentional layer of our AIMN model.

3.4.2 Results and Analysis

We used the collected attentional matrix to produce the influence indexes of the artists, through equation 10. The result of the artists with their influence indexes (top 8) and their followers count is as shown in Table 2. Additionally, the artists with their followers count ranking top 8 among all artists are shown in Table 3.

Table 2: Artists with top 8 influence indexes

Name	The Beatles	Bob Dylan	The Rolling Stones	Hank Williams
Influence Idx.	39.91	25.56	18.00	15.43
Follower Cnt.	615	389	319	184
Name	David Bowie	Jimi Hendrix	Elvis Presley	Miles Davis
Influence Idx.	13.51	12.94	12.43	12.24
Follower Cnt.	238	201	166	160

We plot the top the identified ‘influencers’ and their followers count in stripped chart and lines in Figure 3. As the figure depicted, the macroscopic view of the shape of influence index is similar, but not completely identical, to that of followers count.

We believe that-

Table 3: Artists with top 8 follower count

Name	The Beatles	Bob Dylan	The Rolling Stones	David Bowie
Follower Cnt.	615	389	319	238
Name	Led Zeppelin	Jimi Hendrix	The Kinks	The Beach Boys
Follower Cnt.	221	201	192	186

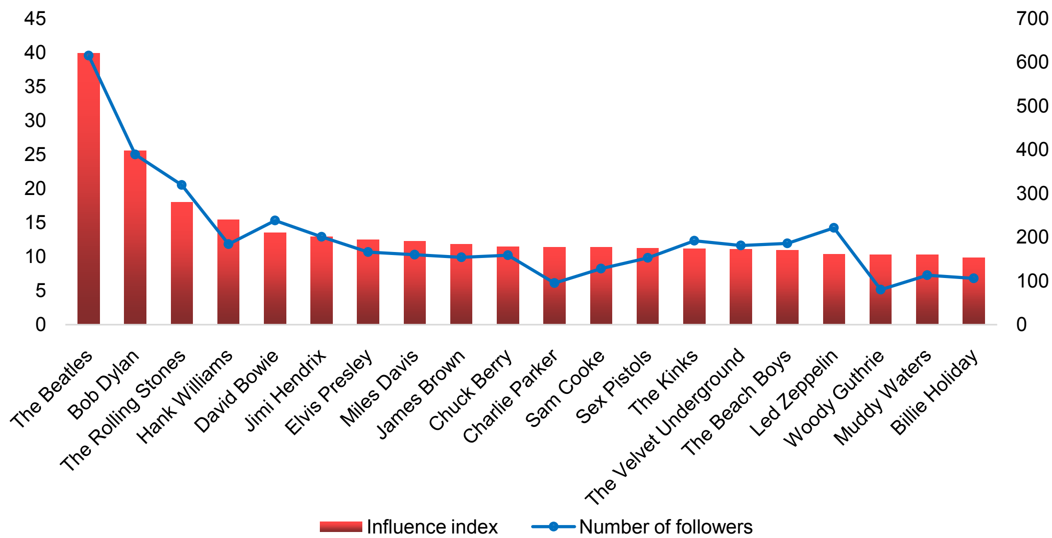

Figure 3: The Influence Index and Number of Followers in One Figure

- an artist should have adaquate followers in order to express their influences, that is, the artists with large number of followers are more likely to show higher value on his/her influence index; and
- the rankings of the artists' influence index should, but not completely, be consistent with that of their follower count.

We gladly find that our data-mining results (as shown in Table 2) and the following information in reality is almost identical, which is highly in line with our expectations. The results obviously supports with our aforementioned analysis and our model.

4 Task 2: Quantifying the Similarities

4.1 Artists' Music Similarity Measurement Model

4.1.1 R Cluster Analysis and PCA

Base on the qualitative analysis, some variables, such as energy and loudness, may have strong relevance to each other, which reduces the accuracy of models. After excluding strong relavant variables, what remains is the key factors to measure different type of genres.

Cluster analysis is a method of grouping that allows for the identification of groups containing similar objects [12].

Calculating the correlation coefficient matrix and conducting clustering analysis, we draw a cluster dendrogram as depicted in Figure 4.

As the dendrogram of clustering analysis shows, variable 2, 5 and 14 cluster together, and variable 1 and 3 have some kind of relevance, which means we can merge some variables without sacrificing too much acurracy.

To explore relevence of variables further, we can use the principal component analysis(PCA), which was presented by Hotelling [7] in 1933 rejecting variables with multiple colinearity.

Selecting five principal components with eigen value greater than 1. Accumulative contribution of these components accounted for more than 60% of variation.

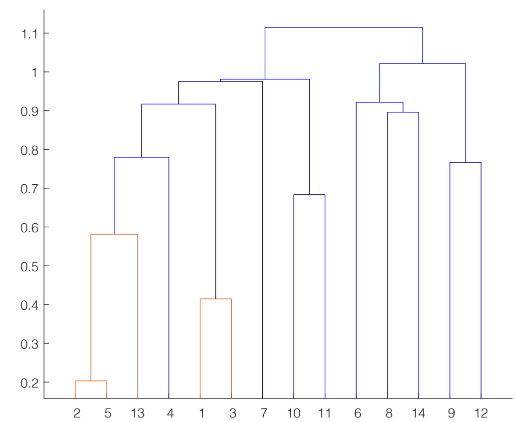

Figure 4: The Figure of Clustering Analysis

We obtain the component matrix in the PCA process, as shown in Table 4. Accordingly, the former two principal component can be listed according to Equations 11:

$$\begin{aligned} z_1 = &+ .399x_1 + .874x_2 + .478x_3 + .301x_4 \\ &+ .842x_5 - .039x_6 + .046x_7 - .810x_8 \\ &- .445x_9 + .087x_{10} + .152x_{11} + .249x_{12} \\ &- .022x_{13} + .590x_{14} \\ z_2 = &- .676x_1 + .189x_2 - .656x_3 + .139x_4 \\ &+ .098x_5 - .151x_6 + .027x_7 - .221x_8 \\ &+ .232x_9 + .334x_{10} + .123x_{11} + .249x_{12} \\ &+ .500x_{13} + .189x_{14} \end{aligned} \tag{11}$$

Note: (1) The first principle component contains energy, loudness, acousticness and popularity for major variables, besides acousticness is a negative correlation with other three factors. (2) The second principle component indicate that danceability, valence and duration are primary variables.

4.1.2 Cosine Similarity Model

Cosine similarity measure is a special type of similarity measure which is viewed as the cosine of the angle between two vectors [1][3]. When the angle close to zero, the maximum cosine value close to 1, which meanings highest similarity. Cosine can be abstracted from the dot product formula:

$$\boldsymbol{a} \cdot \boldsymbol{b} = |\boldsymbol{a}| \times |\boldsymbol{b}| \cos\theta \tag{12}$$

and the similarity is formally represented by Equation 13

$$\mathrm{sim}(\boldsymbol{a}, \boldsymbol{b}) = \cos(\theta) = \frac{\boldsymbol{a} \cdot \boldsymbol{b}}{\|\boldsymbol{a}\|\|\boldsymbol{b}\|} = \frac{\sum_{i=1}^{n} a_i b_i}{\sqrt{\sum_{i=1}^{n} a_i^2}\sqrt{\sum_{i=1}^{n} b_i^2}} \tag{13}$$

Table 4: Component Matrix

	1	2	3	4	5
Danceability	0.399	-0.676	0.056	0.332	-0.055
Energy	0.874	0.189	0.014	-0.108	0.149
Valence	0.478	-0.656	0.153	-0.033	0.281
Tempo	0.301	0.139	0.044	-0.404	0.357
Loudness	0.842	0.098	-0.067	-0.098	-0.01
Mode	-0.039	-0.151	-0.01	-0.638	-0.375
Key	0.046	0.027	0.064	0.421	0.467
Acousticness	-0.81	-0.221	0.187	0.011	-0.052
Instrumentalness	-0.445	0.232	-0.08	0.108	0.253
Liveness	0.087	0.334	0.607	-0.252	0.172
Speechiness	0.152	0.123	0.763	0.167	-0.116
Explicit	0.249	0.249	0.27	0.364	-0.524
Duration_ms	-0.022	0.5	-0.218	0.195	0.146
Popularity	0.59	0.189	-0.326	0.177	-0.291

where $\boldsymbol{a} = [a_1, a_2, \cdot, a_n]$ and $\boldsymbol{b} = [b_1, b_2, \cdot, b_n]$ are vectors of identical dimension, i.e. $\boldsymbol{a} \in \mathbb{R}^n \leftrightarrow \boldsymbol{b} \in \mathbb{R}^n$; θ is the intersection angle between $\boldsymbol{a}$ and $\boldsymbol{b}$ in the n-dimension space.

4.2 Model Application

4.2.1 Similarity Comparison Between Genres

Reviewing of principal component analysis, we find a strong positive correlation between 'danceability' and 'valence'. Besides there is also a significant positive correlation in 'energy', 'loudness' and 'popularity', while negative correlation between 'acousticness' and former three factors. the 'count' feature is a random interference factor with little influence on music style.

Therefore, we exclude 'valence', 'loudness', 'popularity', 'acousticness' and 'count' five factors after analysis, leaving eight indicators (as shown in the figure below) to measure the similarity between artists' music and genres (Figure 5). Our further comparison in the proceeding section shows that the accuracy loss is insignificant.

Danceability	Energy
Tempo	Mode
Key	Instrumentalness
Liveness	Speechiness

Figure 5: Features Left After Processing

	Country
Country	0.8835
Classical	0.6408
Folk	0.8202

Figure 6: Similarity Comparison of Genre Features (Partial)

We select three genres, Country, Classical and Folk, to apply our Artists' Music Similarity Measurement Model, and calculate their similarity index with 8-feature data and full data at the same time.

By comparing the similarity of these 8-feature between artists of two genres through cosine similarity, it shows that the similarity between Country genre and itself is 0.8835, the similarity between Country genre and Classical genre is 0.6408, and the similarity between Country genre and Folk genre is 0.8202, as shown in Figure 6.

As we can see, artists within genres are more similar than artists between genres according to our Artists' Music Similarity Measurement Model. The accuracy of our model is also supported by the reality that Folk genre and Country genre share the same origin. No wonder their similarity value is pretty high.

By calculating the similarity index of different genres, we draw the similarity heatmap among the 19 known genres, as depicted in Figure 7.

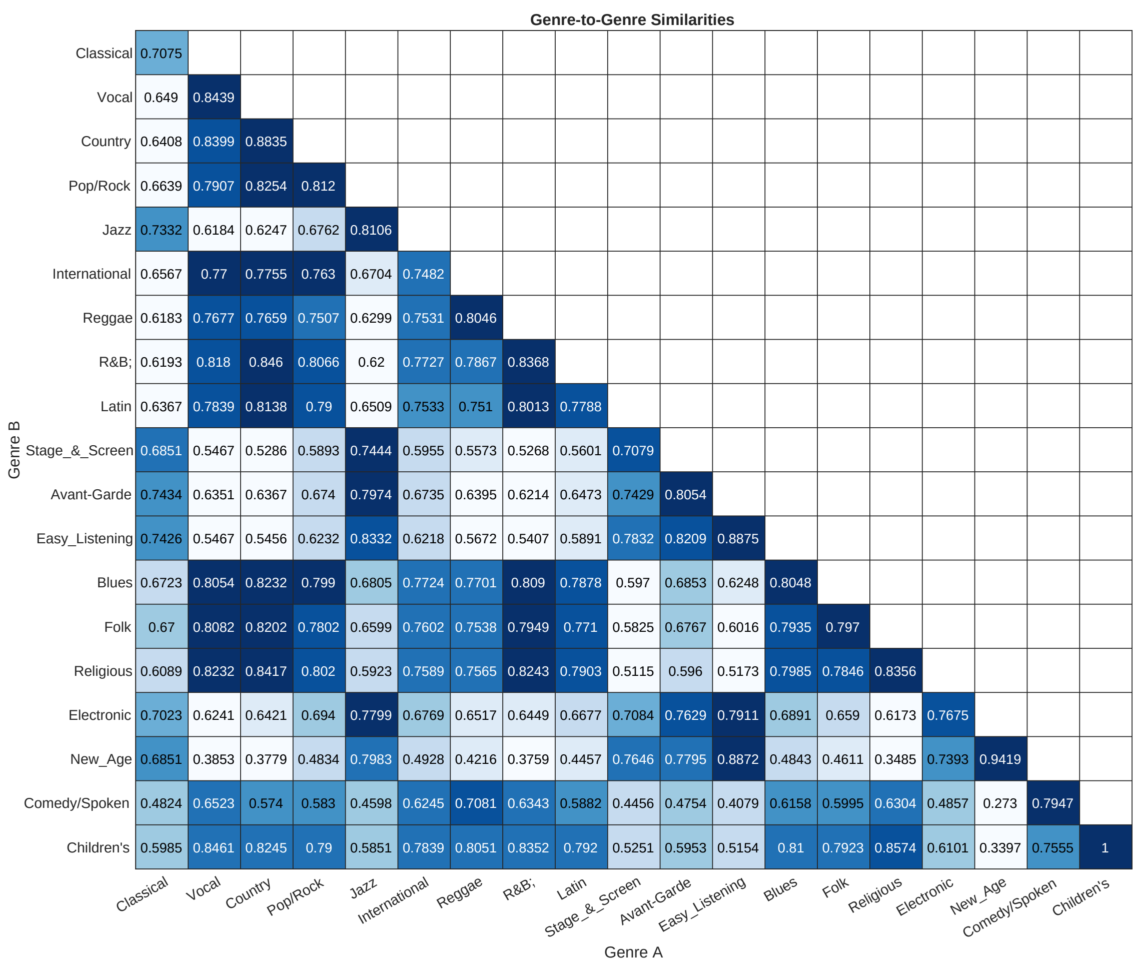

Figure 7: Genres-to-Genres Similarity Heatmap. The colour depth of the block is based on the relative size of its value in each row, and the greater the similarity, the darker the colour.

4.2.2 Distinction Among Genres

We have selected eight vital indicators to analyze the similarity through principal component analysis in 4.2.1, and drawn a mini-heatmap as shown in Figure 8.

In order to prove that the deleted features have little effect on the similarity between genres, we analyzed the similarity of country, classic and folk schools with 13 features. The results were listed as Figure 9.

Danceability	Energy
Tempo	Mode
Key	Instrumentalness
Liveness	Speechiness

Figure 8: Features Left After Processing

	Country	
	8 indicators	13 indicators
Country	0.8835	0.8850
Classical	0.6408	0.6696
Folk	0.8202	0.8353

Figure 9: Similarity Comparison of Genre Features (Total)

It can be seen that after deleting the features, the similarity comparison between genres and themselves has almost no change, while the similarity comparison with other genres has a slight decline.

Therefore, we believe that the deletion of features will not hinder the distinction between genres. What's more, the similarity between different genres decreased more after deleting the factors, which means the ability of distinguishing different genres has been strengthened due to the reduction of interference. So the eight-features model is enough to distinguish different genres.

To explore what features distinguish different genres, we calculate the similarity of each factor (feature) within the genre and draw the heatmap as Figure 10. The square in the figure is colored from large to small, from deep to light, to intuitively display the relative size of a certain index.

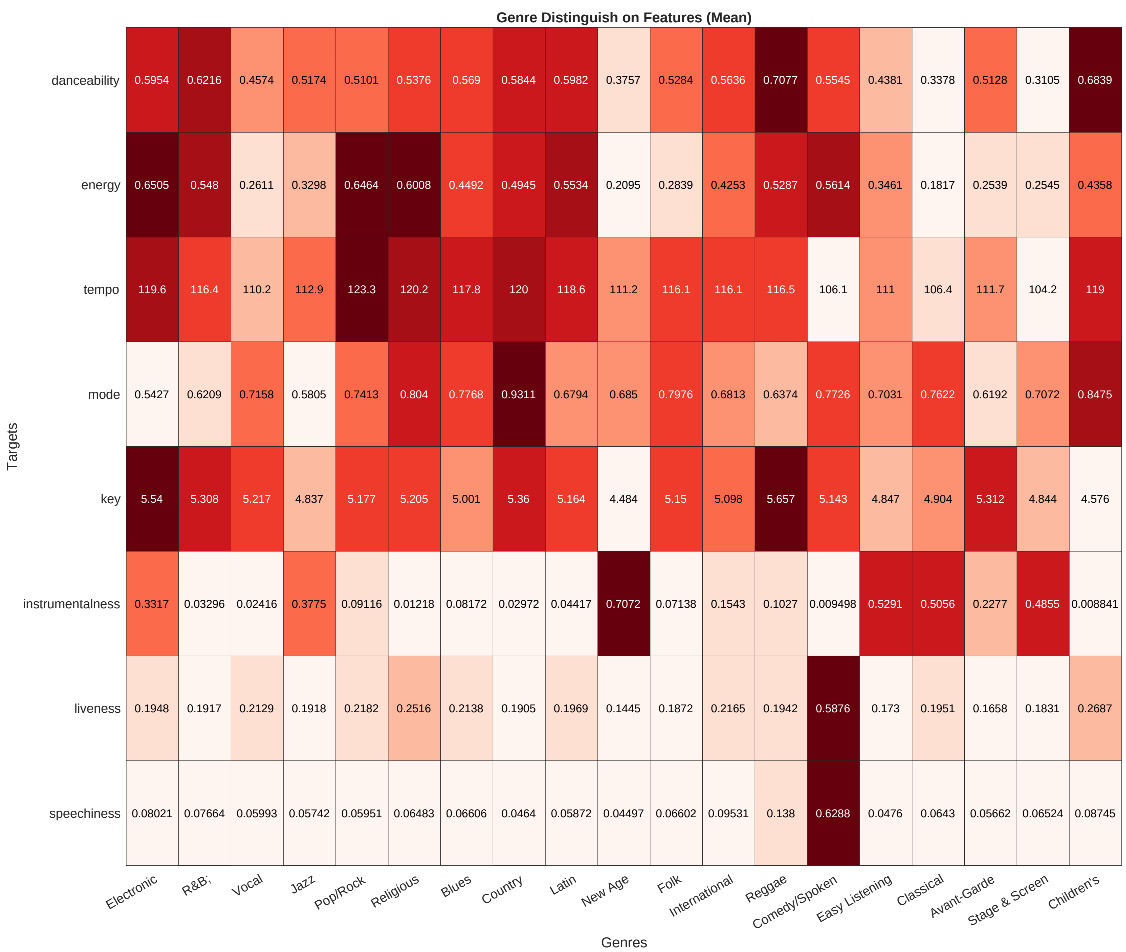

Figure 10: Genre Distinguish on Features (Mean Values)

From the diagram we can clearly see which indicators are most useful in differentiating genres. For example, from the figure, we think that Danceability, Energy, Tempo and Mode all cover dark colors, which means they have a strong ability to distinguish genres. In addition, we can also see which indicators are most useful for distinguishing a particular genre. For example, Speechiness and Liveness are good For distinguishing Comedy/Spoken, Danceability is good For distinguishing Reggae, Instrumentalness is good For distinguishing New Age, and so on.

4.2.3 Change of Genres

In order to explore how the genre changes over time, we choose the R&B genre as an example. We use the data from 1921 to 2019 to calculate the similarity value (brown dots), the average popularity (blue line) and the average number of songs (green column) of the artists of this genre in different years, and the results are shown in Figure 11.

As can be seen from the chart, the similarity between the R&B genre and itself has generally declined from 1921 to 2019, indicating that the music within the genre has become increasingly diverse and rich. However, 'popularity' rises from 1955 to 1973, then declined slowly until 1989, when 'popularity' began to rise tortuously. The trend of released count also coincided with that of popularity. This is in line with the history of the R&B genre. R&B was born in the mid 40, originally is only the black music, R&B music in the 50s began to attract more and more white, with the emergence of more influential R&B singer, R&B also entered into a high-speed development period. Famous Motown company was founded in 1959, and it began to decline in 1971, with popularity of R&B music declines.

In the late 1980s and early 1990s, hip-hop started to capture the imagination of America's youth. R&B started to become homogenized, with a group of high-profile producers responsible for most R&B hits. It was hard for R&B artists of the era to sell their music or even have their music heard because of the rise of hip-hop, but some adopted a "hip-hop" image, were marketed as such, and often featured rappers on their songs.

This attempt was very successful and promoted the second wave of R&B fever. Since 1989, the popularity of R&B has been on the rise. In recent years, R&B combines elements of pop, soul, funk, hip hop and electronic music. Contemporary R&B vocalists are popularized by vocalists such as Michael Jackson, Stevie Wonder, Whitney Houston, Mariah Careyand Beyoncé [3].

5 Task 3: Exploring Musical Influence & Countagions

5.1 Identifying Influence on Different Groups

5.1.1 The Different-Influence Model

In general, an artist is said to have a specific influence on followers if influencers affect followers far beyond that of non-fans.

Our Different-Influence Model was designed accordingly to the above theory. The model is aiming at confirming the impact between artist and both their followers and non-followers. To do so, the model compares the changes in the similarity between artists and their followers and non-followers, before and after they became active, assuming that there are no major changes in musician style. Our methods are as follows:

[3] https://en.wikipedia.org/wiki/Contemporary_R%26B

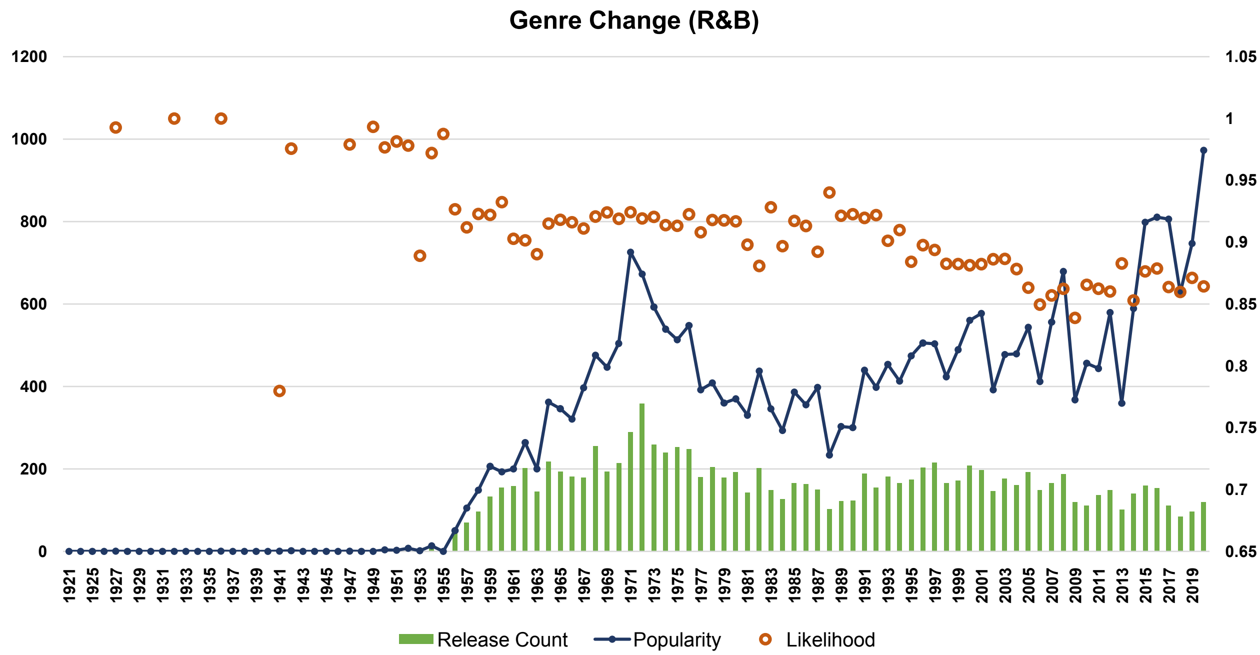

Figure 11: Similarity of Genre Over Time (R&B)

- Select an artist i as influencer in our model. i is considered a representative of i genre.
- Identify followers of artist i. Merge and average data in a moving time window sized two years, from 1920 to 2020. Calculate similarities with the selected artist.
- Repeat the above process on non-followers of artist i.

We note that for any artist in the POP/ROCK genre, most of his/her non-followers are of the POP/ROCK genre, too. As a result, averaging the random sampling is likely to make the non-follower samples more similar to the POP/ROCK genre, resulting in insignificant differences between follower and non-follower groups. To solve this issue, when sampling an artist, we select non-followers from the genres other than that artist's genre to solve the problem arised.

5.1.2 The Model Results

We selected the artist James Brown[4] (ranked 10 in influencial index) to perform the method described above and make further analysis. We plot some of the influencial facts about James in Figure 12.

It is clear to see that before James issued the first album in 1959, the value of both followers and non-followers are relatively discrete. Even in the late 1950s, similarity degree between followers and James is very low. When James became active, similarity of followers converges and start consistently higher than that of non-follower group. This reveals that the artist's influence its specific followers more than non-followers.

On the aforementioned phenomenon, we can conclude that James influences his followers. When James became active, he converged his followers from different type of music to one genre, which is more similar with himself.

[4]1933.5.3-2006.12.25.

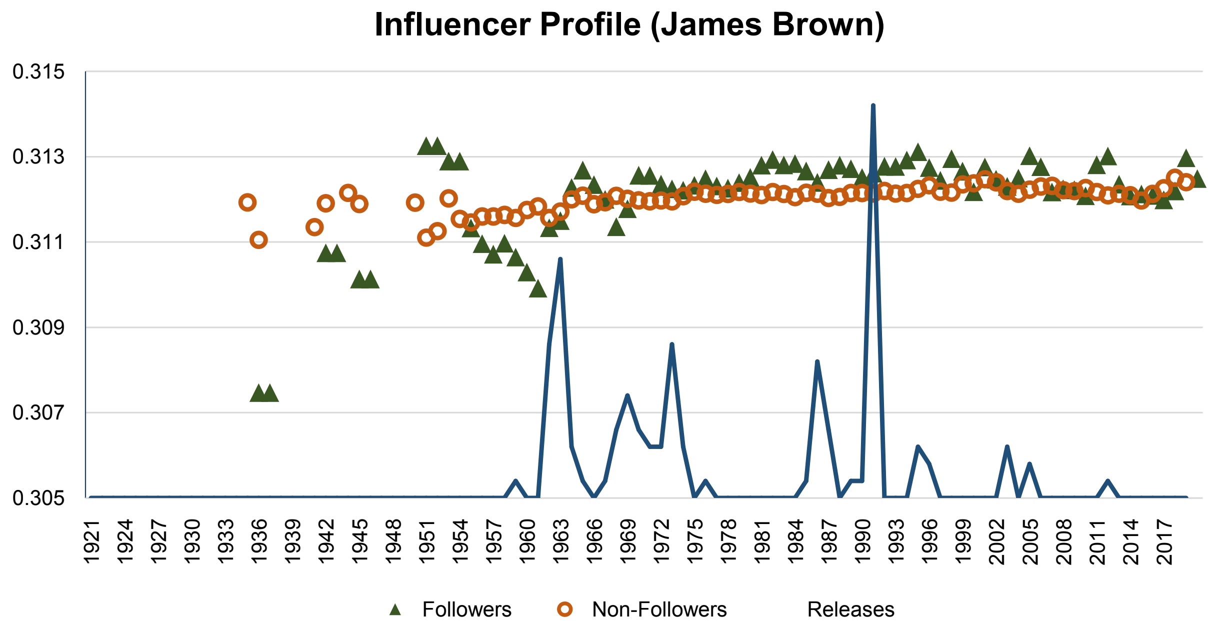

Figure 12: Influencial Facts about James Brown from 1921 to 2020

5.2 Measuring the Contagious Characteristics

To explore whether certain musical factors are more "contagious", we analyze the similarity of each music feature between The Beatles and its follower group, and plot several factors as Figure 13.

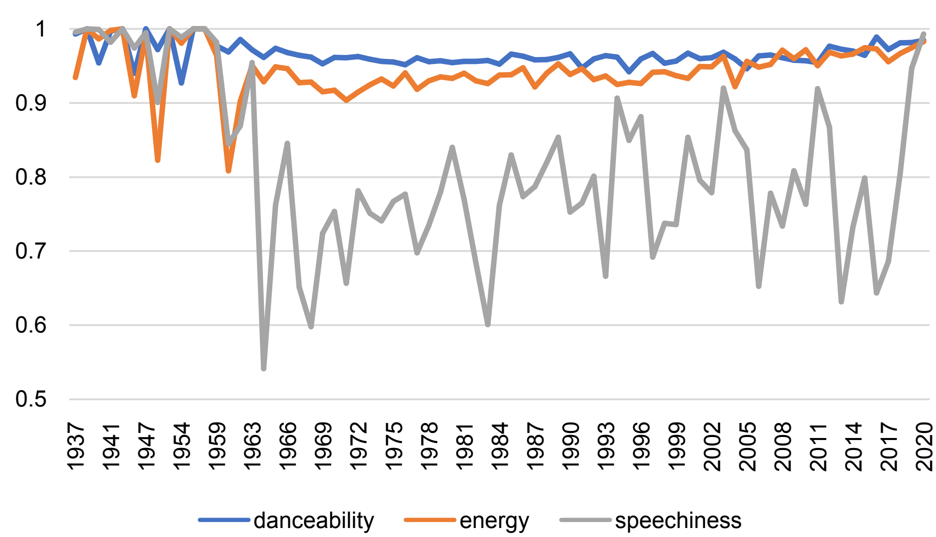

Figure 13: Similarity Between The Beatles and its Follower Group (Normalised)

Before The Beatles began to be active in 1962, data were relatively scattered. In 1962, both 'energy' and 'danceability' values increased significantly, indicating that the similarity between The Beatles and followers is increasing. Subsequently, the indicators of energy and danceability remained at a high level, while 'speechiness' decreased. It shows that on the 'speechiness' feature, The Beatles has far less influence on followers compared to other factors.

Meanwhile, to validate our methods and see the contagious among the features more distinct, we drew a heatmap to indicate the similarity (calculated using the Artists' Music Similarity Measurement Model in section 4.1) of The Beatles and its followers on every musical features over years, as shown on Figure 14. Specifically, we narrowed down the year interval by delaying the starting year to 1960, where The Beatles became active[5]. We utilise the figure drawn in Task 4 (Figure 17) to get some facts about The Beatles. We could find out that the similarity value of energy, tempo, mode and instrumentalness vary

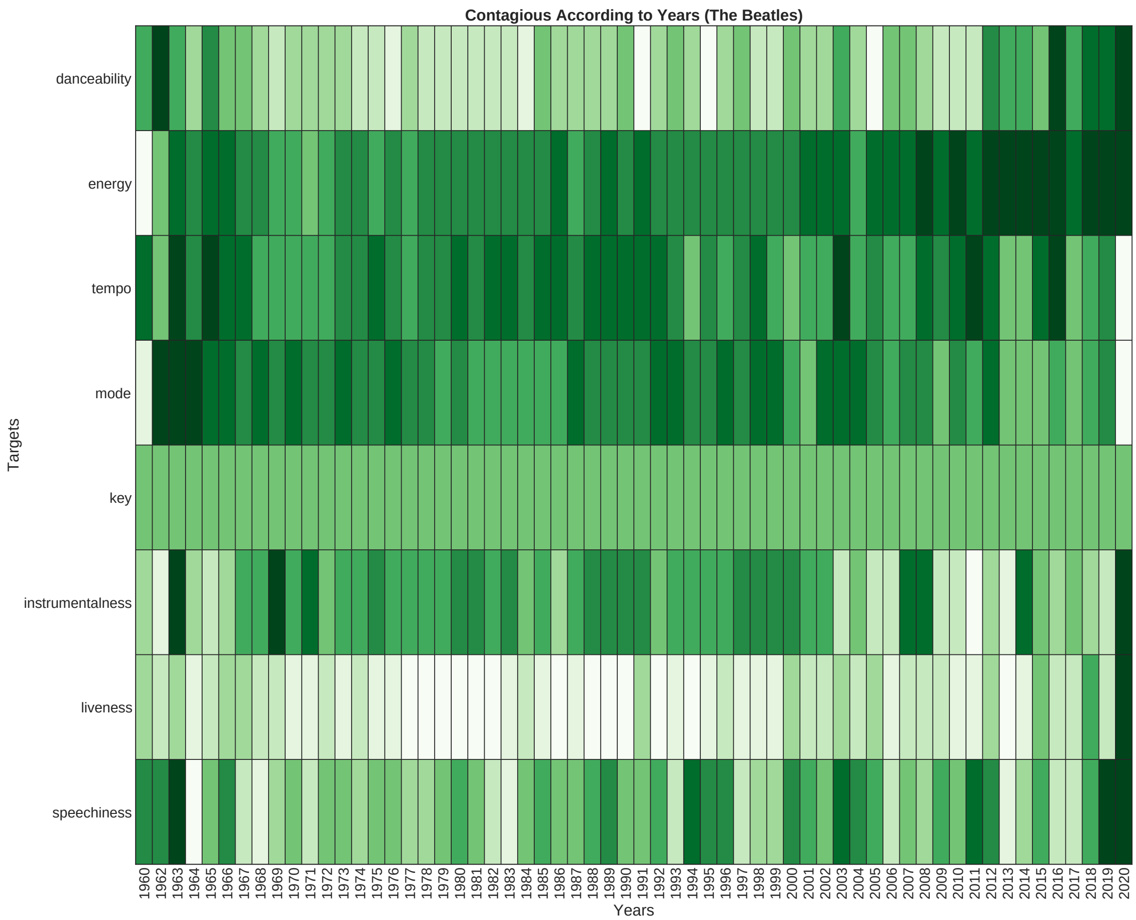

Figure 14: Similarity of Every Musical Features Among The Beatles and Its Followers Over Years

over time, while the others like key and liveness remain unchanged for a long period, despite the fact that The Beatles was releasing piles of songs in certain years.

With Figure 14 and 17, we can draw out the some results:

- There are often leaps in the similarity among The Beatles and its followers on tempo as time went by, and the leaps are in general accordingly to the release peaks of The Beatles, according to the both Figures as a whole;
- Similarities of danceability does not change so often according to Figure 14. However, this feature does have a leap in recent years (after 2014), which accords to a small release peak on 2013 of The Beatles. We searched on the Internet and learning some facts about The Beatles-

[5] https://en.wikipedia.org/wiki/The_Beatles

(1) The team was breaked up in the year of 1970[6]; and

(2) An album named *The Beatles: Stereo Box*, was released on 9 September 2009[7]. The album is a set of remastered recordings by The Beatles, which gained its popularity from The Beatles' old fans [8] and many songs of The Beatles' were then be applied to dance songs [9].

From the two facts drawn above, we could conclude that the fans', or followers', overall danceability factor is absolutely affected by The Beatles, even though the band remained break-up for so many years. The reproduce of the band's songs is still attracting the followers.

Therefore, we believe that some indicators are more influential and different indicators do not have similar roles in influencing a particular artist's music. And through data analysing and information searching, we proved our assumptions.

6 Task 4: Studying Musical Evolution Over Time

6.1 Musical Revolution

6.1.1 Process of Musical Change

In order to explore the process of musical evolution and music revolution, we utilised the *data_by_year* data set. We normalised the annual data of each index by dividing it by the average value of the data of this index in the whole time, and then drew the line chart of musical evolution over time with year as the horizontal axis (Figure 15).

By observing the general trend of the line chart, we can find that before 1960, the indicators were relatively scattered and fluctuated greatly, but after 1960, they tended to be stable and close. "Speechiness" and "Instrumentalness" are particularly impressive, both of which have fluctuated significantly from 1920 to 1950. "Instrumentalness" begin to decline after 1945, since then it has been a downward trend, and in recent years it has reached new lows.

We know that instrumentality is the proportion of voices on a track, and the lower the voice, the higher the index. The decrease in the value of this index indicates that over time, the proportion of human voices in music is increasing. This may have something to do with the impact of more new music and the decline of neoclassical music. "Speechiness" means the presence of spoken words in a track. In the 1920s to 1940s was the most unstable time in American history. Under the influence of economic panic and World War II, the audience entered the theater not only for entertainment, but also for comfort and introspection. So Musical Comedy came into being.The popularity of Comedy/Spoken genre led to the popularity of "Speechiness" . However, in the 1960s, it entered the dark period of Comedy, and "Speechiness" began to decline continuously. After 1990, the popularity of rap made it rise again.In addition to these two features, the index with the biggest change was "Energy" , which showed an upward trend after 1960.According to the analysis in Task 2, "Energy" and "Popularity" are found to be positively correlated, which is consistent with the fact that more popular music has been produced since 1960.

[6] https://en.wikipedia.org/wiki/The_Beatles
[7] https://en.wikipedia.org/wiki/The_Beatles_(The_Original_Studio_Recordings))
[8] https://today.yougov.com/topics/entertainment/explore/music_artist/The_Beatles
[9] https://www.reddit.com/r/beatles/comments/8pomaj/best_beatles_songs_to_dance_to/

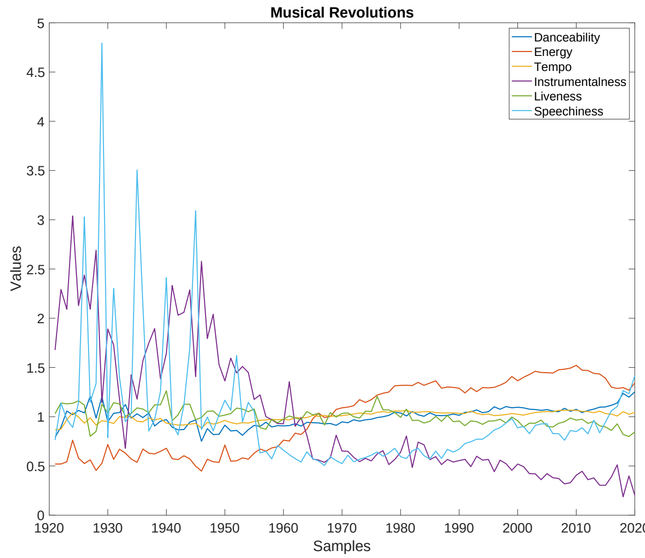

Figure 15: Features Evolution Over Years

Therefore, we believe that these three features are the characteristics that mark the revolution in the evolution of music, and the musical revolution occurred in 1960s. When we look at the history of Western music in the 20th century, we find that this is indeed the case, and there have been a lot of changes in Western music during this period. The introduction of multitrack recording in 1955 and the use of mixing had a major influence on pop and rock music. The development of sound recording and audio engineering technologies gave rise to new subgenres of classical music.1960s saw dramatic innovations in musical forms and styles. For example, composers and songwriters explored new forms and sounds that challenged the previously accepted rules of music of earlier periods. The development of powerful, loud guitar amplifiers and sound reinforcement systems in the 1960s and 1970s permitted bands to hold large concerts. At the same time, composers and songwriters experimented with new musical styles, such as genre fusions. As well, composers and musicians used new electric, electronic, and digital instruments and musical devices[10].

6.1.2 Musical Revolutionaries

In order to identify the artists who represent the revolutionaries, we selected the top 20 artists in our Influence Index from the AIMN constructed in Section 3.1 and created a heat map of their annual output over time, as shown in Figure 16.

We defined Musical Revolutionaries as those who were in the top 20 most influential and most active in the 1960s. So from the heat map we can conclude that the Musical Revolutionaries in our network are The Beatles, Bob Dylan, The Rolling Stones, Elvis Presley, Miles Davis, Sam Cooke, The Kinks, The Beach Boys, and Led Zeppelin.

Finally, we choose The Beatles, which ranks first in influence, to test. We utilised the Figure 17 (the similarity of The Beatles), and find his followers and non-followers with the change of years and the number of songs released by The Beatles each year.

It can be seen that before The Beatles began to post songs in 1961, whether the artist was the follower of The Beatles or not, the similarities between the artists and The Beatles later were scattered. However, in 1960s, when The Beatles were active, the similarities between artists and The Beatles began to become consistent and stable, which also shows that The Beatles were really a revolutionary of music (An influencer of major changes).

[10]https://en.wikipedia.org/wiki/20th_century_music

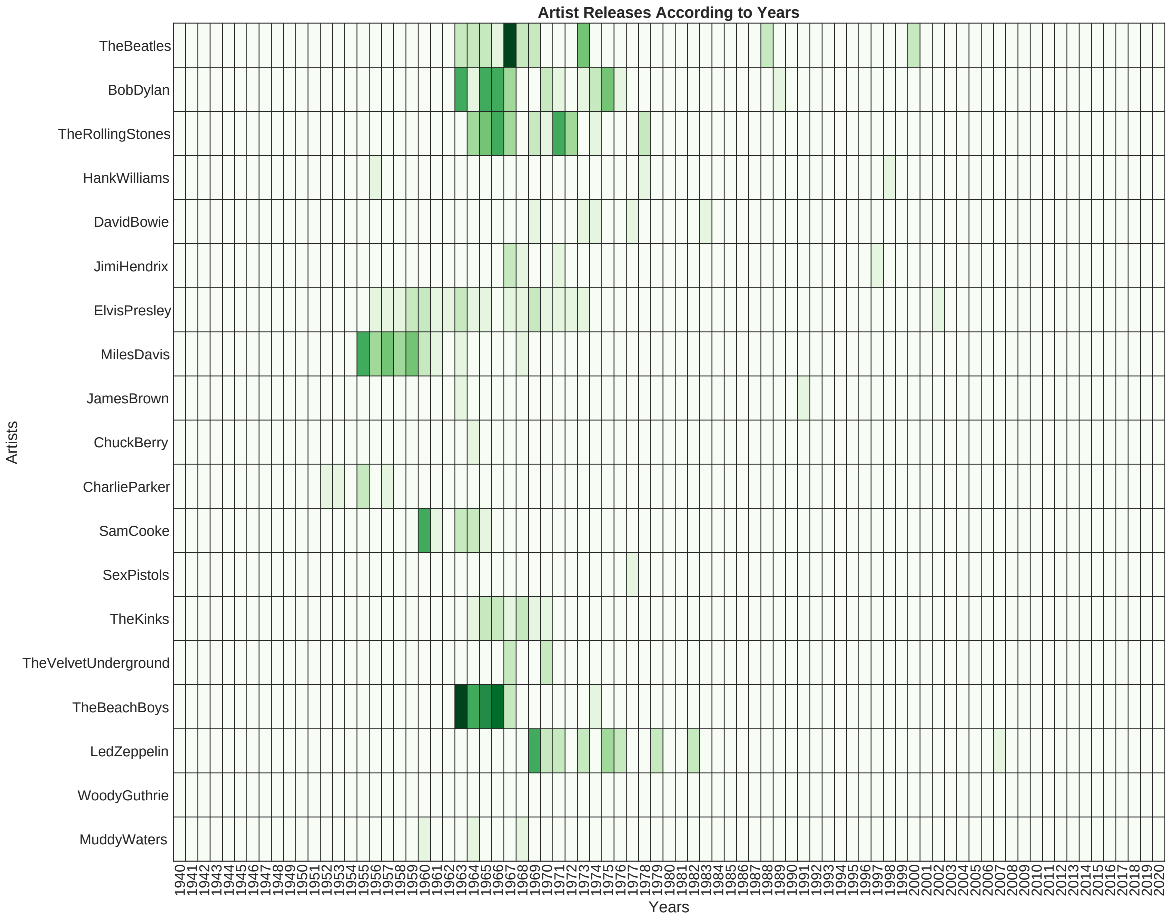

Figure 16: Artist Releases Over Years

6.2 Analysis of a Genre Over Time

In the preceding Section 4.2.3, we explored the R&B genre's own similarity, popularity, and the number of songs released over time. Here we will further explore the influence processes of musical evolution that occurred over time in R&B genre. We used 8 dynamic influence indexes in Section 4.2.1, *influence_data* and *full_music_data* to draw the heat map of 8 influence indexes and similarity of R&B genre in each year, as shown in Figure 18.

The change in color of the heat map from dark to light indicates the change in value of the index from large to small. Therefore, we can intuitively see the dynamic change and influence of each indicator. For example, over time, "Danceability" and "Energy" of R&B genre have generally increased and remained at a relatively high level, indicating that the music of this genre has become more intense and active and closer to heavy metal. "Tempo" and "Mode" show a downward trend. The decline in "Tempo" indicates that the rhythm of the music of this genre is gradually slowing down from a more intense style to adding more soft and lyrical elements. The decline in "Mode" index indicates that the music of this genre is changing from more major to minor, giving people a feeling from bright to melancholy. What's more, "Key" of the genre is generally stable and maintains at a low level, indicating that the music of this genre is in a low tone. "Instrumentalness", "Liveness", and "Speechiness" were all very low, and only high in

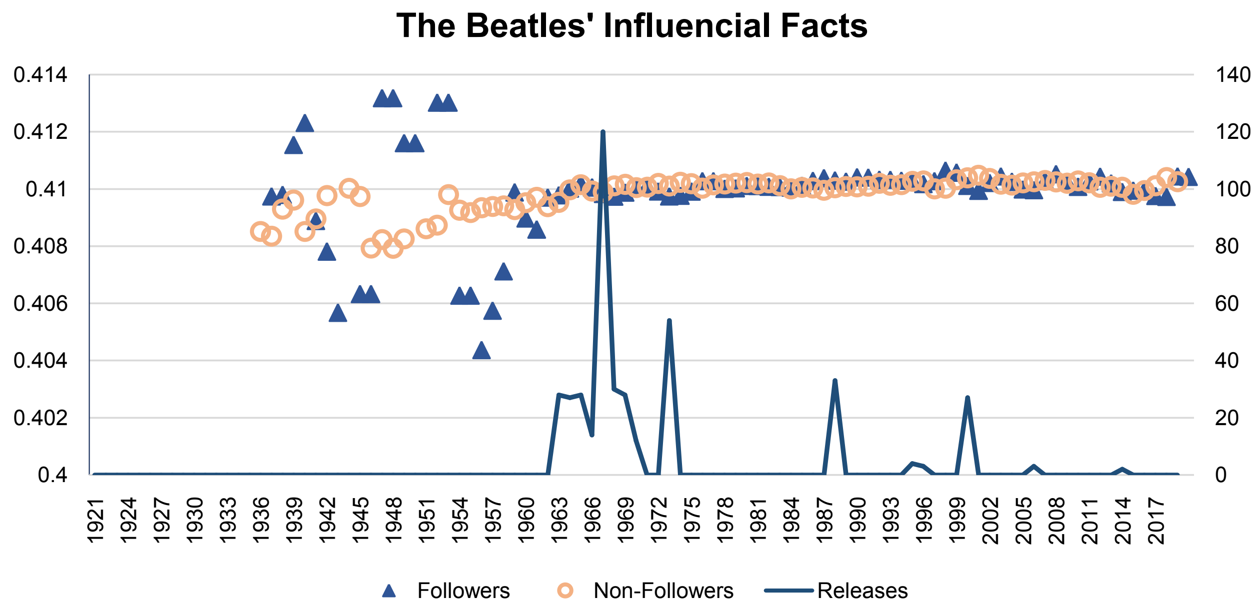

Figure 17: Influencial Facts about The Beatles from 1921 to 2020

some years, which may be related to the small sample size in those years.

In addition, with the passage of time, the similarity of R&B genre with itself has decreased significantly and then increased slightly, indicating that it has experienced a process from a single style to a hundred flowers blossomed style because of the artists' continuous attempts in many directions, and finally it became gradually mature and stable. This evolution process is also influenced by the changes of the above eight indicators, and gradually formed the R&B that we love today.

6.3 Effects of More Variables

Based on the aforementioned analysis, it could be pointed out that the influences among artists and/or their songs will subsequently be detected through similarity analysis, which is proposed in Section 4.1. We believe that cultural influences will effect the creation of new musics, bring slim changes to their feature values as a whole, and gradually affect among and within genres.

In order to identify the effects of social, political or technological changes, we further explore the results of Task 4. In Figure 15, we can see that between 1939 and 1949, during World War II, the value of "Speechiness" and "Instrumentalness" are pretty high and scattered. After the war, they both began to decline and tended to be stable. This shows the influence of war and social environment on music. And we consider that war and society affect music by affecting people. For example, under the influence of economic panic and World War II in 1940s, the audience entered the theater mainly for comfort and introspection. So Musical Comedy became popular. The popularity of Comedy/Spoken genre led to the popularity of "Speechiness" .

Therefore, we believe that in order to identify the influence of exogenous variables, such as society, in our constructed network, we need to observe the curve of changes of various characteristics of music over time.When we observe abnormal factors that cannot be explained by the internal variables of the model, it represents the interference of exogenous variables.Finally, we combine the major events of the year to analyze what exogenous variables affect music and how exogenous variables affect music.

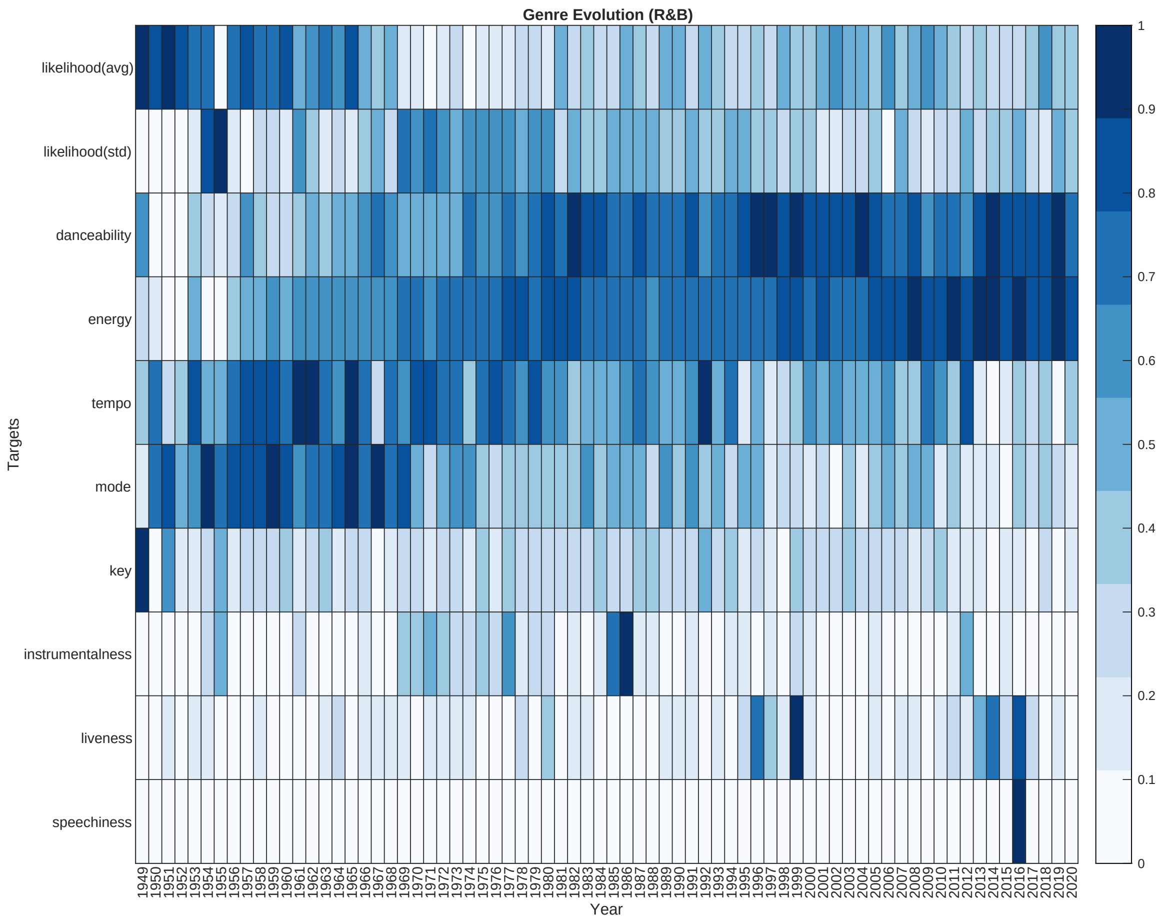

Figure 18: Genre Evolution of R&B

7 Strengths and Weakness

We analysed and validated our models based on our practicing, and put forward the strengths and weakness as follows.

- In the application of the similarity model, the data of breakpoints are cleverly selected, and a series of problems are dealt with by means of variable control and so on.
- The similarity model uses PCA and other methods to optimize the variable selection and enhance the recognition degree of the model.
- The model visualization is successful, intuitive and easy to analyze.
- The application of similarity model lack of statistical test, which reduces the persuasiveness.

8 Document

TO: ICM
FROM: Team # 2126428, ICM 2021
DATE: 08 Feb 2020
SUBJECT: The value of using our approach to understand the influence of music through networks

To whom it may concerned,

Its our honour to cooperate with your society on researches on the topic of musics. In our recent practice, we proposed several novel models to mine the underlying information within a giant musical data. Here are some brief description of their values:

- Our Artist Influence Mining Network model can be utilised to determine the influence ranking of artists in given data set. In our tests, the model successfully confirmed the key position of some outstanding artists such as The Beatles in musical revolutions.
- Our optimised similarity model through PCA and other methods are able to obtain several key factors that affect classifying music genre.

By applying the models, we compared the relationship between different genres by measuring their similarity, and introduce time changes to witness the development of different genres. We've seen the rise of pop music in 1960s, and the low tide of classical music. By doing a large amount of work on model visualization, we are capable to visually understand the data and interpret what it means.

Due to the limitations of the data set, we have not been able to do in-depth and detailed research on the impact of social factors on music. In the process of adding data to the improved model, we think we should pay attention to the influence of information media. From the early records and tapes to radio, TV and mobile Internet, media not only make the society turn upside down, but also inevitably lead to the change and development of music characteristics. We can analyze feelings of music from data set. Combine the popularity of different emotional music, we can outline the basic social environment prosperity or depression.

We are working hard to optimise our models, targeting the future datasets of larger sizes. For example, we will apply the MapReduce technique to do data preprocessing, or apply graph neural networks with gates and/or other noval machanisms. All of our attemps are aiming at the needs of the current big-data era.

In the near future, our direction of research is focused on mine the effect of culture on musics. For the next step, we plan to import **outside knowledge** of different cultural topics into our artist influence mining network, to better understand how cultural affects.

The detailed description of our approach is in the main text of this paper. We hope our models will fulfill their values to your society and look forward to a long-term association with you.

Yours sincerely,
Team # 2126428

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