Problem Chosen	2021 MCM/ICM Summary Sheet	Team Control Number
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2020

MCM&ICM Summary Sheet

Construct Artist Network

Motivated to analyze the influence of music and artist, in the report, we construct an influence network model of the complex relationship between artists to judge the similarity between songs of different time, different authors and different genres. And we use the network to analyze the revolution happened in music history, predict the changes of music genre, try to find the major trend of music in the future.

In order to analyze the influence relationship between artists, we establish the influence graph between artists, and use the Mathematical models of epidemic diseases, which enables us to quantify the influence of artists. We use the standardized cosine distance as the standard to measure the similarity between two pieces of music. One of the highlights of this is that we can respectively analyze the influence of different features of music on artists, and it is easy to see which features are "inheritable". Using the influence network and similarity modeling, we not only compare the mutual influence between the artists inside and outside the genre from the micro perspective, but also compare the influence and similarity between different genre from the macro perspective.

In addition, by adding time scale to our model, we find some characteristics that may represent the revolution of music faction. We also consider the model together with economic, political, historical and other factors. By making the model more realistic, we analyze the causes of music genre revolution, and try to predict the future development of music.

Through the model analysis, we find that the interaction between artists plays an essential role in the development of music, especially among artists from different genres. At the same time, we also find that the change of music genre is closely related to economic and other social factors.

One of the powerful things about our model is that it looks at the connections between musicians from multiple perspectives. When the problem needs to be analyzed is relatively micro, we simulate the mutual influence and similarity between any two artists; when the problem is relatively macro, we regard the genre as a whole and overall analyze the sub graph of the genre. Moreover, by adding more factors into the model, our model can fit the reality well.

Keywords: graph, influence-network, prediction model, music, artist

Handout

Dear ICM,

Through the research, we have successfully established a model that can compare and analyze the value of music.

By comparing different songs and artists, we can analyze the influence of artists within the genre and the value they bring to music progress. At the same time, we can also quantify the communication between genres and predict the future development direction of factions.

What's more interesting is that we have successfully found the influence of social and cultural factors on musicians. According to our research on economic and musical changes, when the economic begin to develop better, people will have more time to enjoy art, which will bring great changes to music. Moreover, there are some unpredictable but logical Black Swan events that will lead to changes in music. For example, the rapid popularity of PC in the 2000s brought a boom to electronic music.

But the music is always changing at a very fast rate. In order to simulate better, we may need to improve our model.

It is not difficult to find that when only the data changes, we only need to change the dataset to fit the new situation. However, we also find that as the culture becomes more and more diverse, if there are new music characteristics that we have not considered, or if there are music genres beyond the current definition, our model will no longer be applicable. After thinking about this, we come to two possible solutions:

Keep the basic network model unchanged and add more parameters for each node. This will enable our model to contain more information and better adapt to the new situation

If necessary, remodel other parts, such as the similarity system, to make it more in line with the future reality.

We believe our model is strong enough to suit majority of the common situation. Our model not only to aim to push the music forward, but also make a better combination of the music and our society.

Content

1 Introduction

1.1 Restatement of the problem

We got the data of more than 5000 artists and their 98000 songs. We need to build graph based on these data and explore various options according to the graph. Our main targets are:

1. Establish the influence network based on the influence relationship given, and defined the influence model according to the graph to obtain the influence of artists and analyze its significance.
2. Establish a music similarity model to measure the similarity between different songs, different artists and compare the similarity between different genres.
3. Analyzes the relationship between artists from same and different genre in this paper, and add time variables into the model to analyze the changes of genre as time goes by.
4. Analyze the influence degree of the influencer to the follower, and the influence ability of different characteristics of music.
5. Find out the characteristics that may indicate that great change of music will take place, and identify the artists who cause the change.
6. Analyzes the evolution of a genre's music, identifies the indicators of dynamic influencers, and explain how genres and artists change over time.
7. Looking for the influence of social factors in the model.

1.2 Expected target

By establishing the model, we hope to achieve following goals:

1. Establish a network of mutual influence among artists, and analyze the influence of each artist in the network.
2. The model can quantitatively analyze the similarity between two songs, two artists and two genres.
3. Add time variables to the model to analyze the changes of various characteristic over time and to find the characteristics that indicate the music revolution.

4. Combining the model with social and cultural factors, reveal how social and cultural factors influencing music and artists.

1.3 Basic hypothesis

Before modeling, we make the following basic hypothesis:

1. With such a large amount of data, music is the only way for artists to influence each other, ignoring the characteristics of interpersonal relationship and social influence.
2. The song data given in the title can well reflect the distribution of all songs in reality.

1.4 Modeling process

We have experienced four stages in the process of modeling

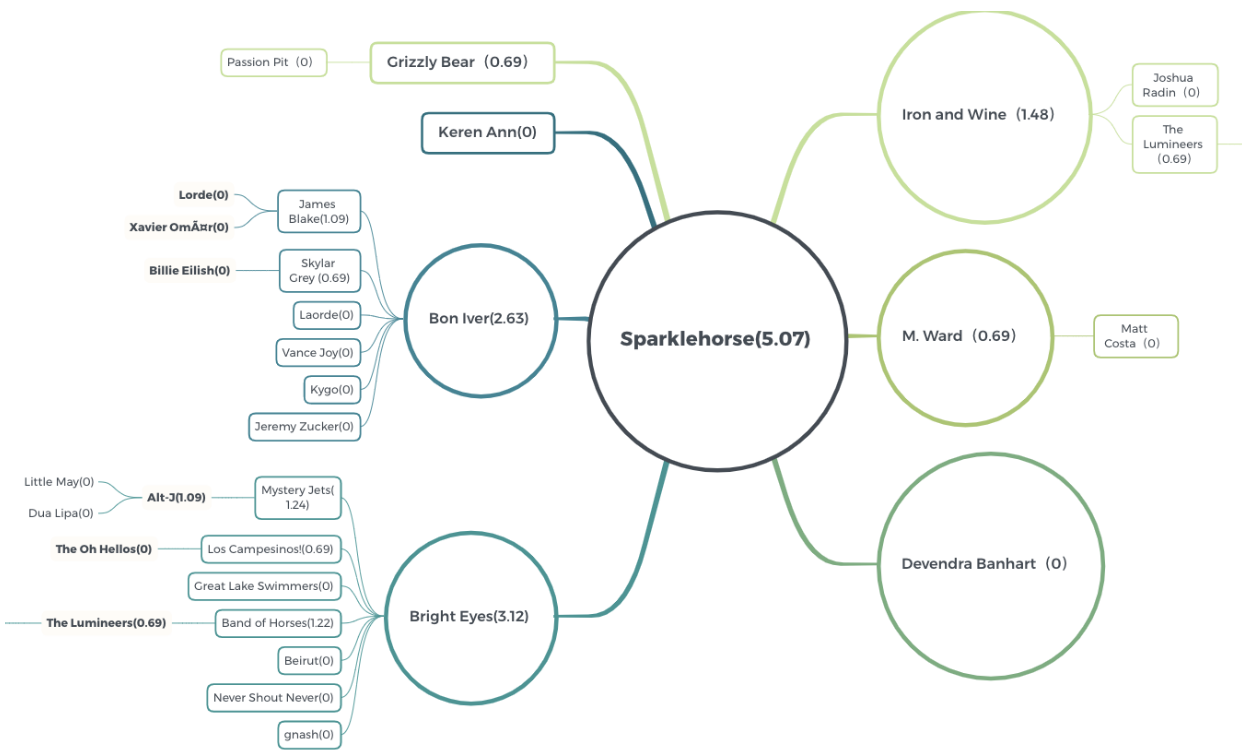
1. We regard each artist as a node, and established a link between followers and influencers according to the influence relationship between of artists in the table, and finally a complex influence relationship diagram is formed. Based on this, we define the influence of artists according to the propagation speed of songs, and then establish the influence model.
2. According to the given full_ music_ data, we calculated the D-value of characteristics between different songs, normalize the D-value, calculate the cosine distance, and take it as the similarity between these two songs. Thus, we can further calculate the similarity between artists according to this model.
3. In order to study the similarity between genres and add the influence of time variable into the model, we simplified our model to decrease the calculation amount and combined it with time variable to study the changes of genre on time scale.
4. Finally, we add the social and cultural factors into our model, combine the specific period with the music genre revolution we found, find out the characteristics that indicate the possible occurrence of music revolution, and combine the model with the reality.

2 The first part: Artist network

2.1 data processing

In the file influence_ Data records the influencers and followers of artists. An artist may have more than ten influencers or more followers. There are 42771 pieces of data that define the relationship. Faced with such a large amount of data, we choose to write Python programs to process the data.

We regard each artist as a node, link it with other nodes according to the influence relationship, and build a network containing all artists. According to the digraph, we can easily find the follower subgraph of an artist. One subgraph of our network is shown in the figure below:



2.2 Modeling

2.2.1 Assumption

We need to define a model of influence to quantify the influence of each artist in the graph.

First analyzes the model of music communication. We assume that:

1. In different times, the speed of music transmission is the same, which means the influence of artists will not be different because of different times.
2. Different musicians have the same probability of being influenced, that means, an artist's influence is only related to the number of people he affects.
3. When an artist is influenced by N artists, the influence of each artist on him is $\frac{1}{n}$ of that when he is influenced alone.
4. The spread of music is like Infectious Diseases, spreading at an exponential rate.
5. When an artist's followers influence others, they are still part of the artist's influence. But the influence will decrease.
6. Influence has nothing to do with genres. Songs have the same influence on artists of different genres.

2.2.2 Modeling

After drawing up these assumptions, we began to build an artist's influence model:

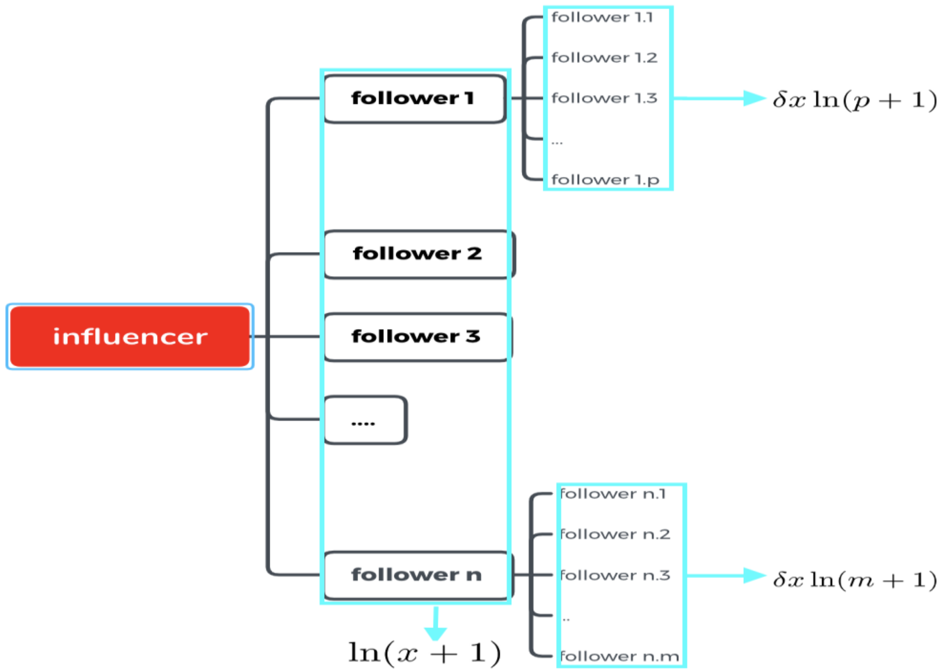
An artist's influence is related to the number of people he affects, and songs spread exponentially, similar to the infectious diseases model. But songs will not be "cured" like infectious diseases after spread, so we choose SI model of infectious diseases to describe the spread of songs. If an artist has n direct followers, his influence is $\ln(n+1)$.

At the same time, considering that artists may be influenced like teachers and students, his influence lasts from generation to generation, we try to incorporate indirect influence into our influence model:

When an artist's followers continue to influence others, they will also bring influence to the artist. However, in many rounds of influence, the influence of the initial artists will gradually decrease, otherwise it will make the influence of early artists too large, which is not conducive to comparative analysis. Therefore, we choose the exponential decay method, that is, the total influence of the affected in the n round is :

$$\delta^{n-1} \times \ln(m+1)$$

Our model of influence is shown in the figure below:



By adding indirect influence into the model, our model can better reflect the influence of artists in the network.

2.3 The significance of influence model

Using this model, we can easily get the influence subgraph of a given artist, and calculate his influence according to this subgraph. Our influence model reflects the sum of his influence on all artists affected by him in the subgraph, which is also the sum of his influence in the whole network.

2.4 Advantage and disadvantage

Advantages:

The first influence model we built considers the influence of each follower, and also includes the indirect influence between artists into the model, which can well reflect the influence of artists in the whole network, rather than just local influence.
Disadvantages:
This influence model ignores the role of genres in influence. At the same time, if indirect influence is taken into consideration, the influence of the artists who are active in the later times will be lower. Because of the time problem, they have no chance to indirectly influence the artists who are active in the later than them.

3 The second part: Similarity of songs

3.1 Assumption

In file full_ music_ Data, we can find 14 music theory characteristics of 98341 songs created by the above artists, as well as song name, release time and creator. In order to process these data effectively, we make the following assumptions:

1. The 14 data given in the file can completely describe the music theory characteristics of a song, which means the similarity between music can be obtained by comparing the fourteen characteristics.
2. The proportion of these 14 data in music is the same, there doesn't exist situation that some characteristics are more important than others.
3. Time and author will not affect the similarity between two songs, so the author and time will not be used as the comparison parameters.
4. All the 14 characteristics used for comparison are related to authors, regardless of the situation that multiple authors create different parts of a song.

3.2 Data processing

Based on the above assumptions, we hope to measure the similarity between the two songs by comparing these 13 music theory features. However, due to the different measures and ranges of these music characteristics, direct subtraction may make the proportion of characteristics different, which do not consist a good measure of music similarity. Besides, the distributions of some features are discontinuous, and another algorithm is needed to calculate the similarity of discontinuous features.

Therefore, our team first normalizes all continuous data to make all data have the same proportion in the model.

Here we adapted z-score transformation:

$$x' = \frac{x - \mu}{\sigma}$$

where μ and σ refers to mean and standard deviation of the population which x belongs to. By doing so, the transformed data of every characteristic shares a same mean 0, and a same standard deviation 1.

3.3 Modeling

Firstly, we denote the characteristic vector of a song, an artist or a genre as the value of its music characteristics. That is, a characteristic vector is

$\boldsymbol{k}$ = **[**danceability, energy, valence, tempo, loudness, mode, key, acousticness, instrumentalness, liveness, speechiness, explicit[1], duration**]**

We choose cosine distance to measure the similarity between two specific characters, regardless of if it is two songs', two artists', or two genres'. That is, if the characteristic vectors of two is characters are $\boldsymbol{k_1}$ and $\boldsymbol{k_2}$, then their cosine distance is:

$$D_{1,2} = cos < \boldsymbol{k_1}, \boldsymbol{k_2} > \ = \frac{\boldsymbol{k_1} \cdot \boldsymbol{k_2}}{|\boldsymbol{k_1}||\boldsymbol{k_2}|}$$

For discontinuous indexes (mode, key and explicit), if their values are same, we assign them both to 1; if they are not same, we arrange one to 1 and the other to -1.

[1] only available in music data from full_music_data.csv

Therefore, we can define the similarity of two pieces of music: the closer the cosine distance is to 1, the higher the similarity of two song is; the closer the cosine distance is to -1, the lower the similarity of two songs is.

Because the author's creative style is closely related to his music, after getting the similarity of music, we can easily define the similarity between authors: the author's characteristic vector is the average of all the data of his songs (which can be found in the file data_by_artist), weighed by the song's popularity. The similarity between two authors is the cosine distance of their characteristic vector.

One of the reasons why we can define author similarity in this way is that one author won't have too many songs, the author similarity and song similarity are both about the same specific issues, so we can use the same algorithm.

3.4 Similarity of artist inside and outside genre

According to our similarity model, we can compare the similarity between artists. In order to study whether the artists from the same genre are more similar than those from different genres, we seek the similarity between each two artists within the genre, and then take the average value of the whole as the similarity of artists within the genre; outside the genre, we seek the similarity of all artists from the two genres, and take the average value as the similarity of the two genres. Formula is:

$$\frac{\sum_{each\ two\ artist} S(artist1, artist2)}{n}$$

n is the number of artists compared

Processing data in this way, we get a 17 * 17 matrix, each element represents the similarity between two genre's artists:

Similai	Pop/R	Electrc	Regga	Jazz	Count	Comec	R&B;	Classic	Latin	Vocal	Folk	Easy Li	Interna	Blues	Stage	New A	Religic
Pop/R	0.048	0.032	0.032	0.03	0.049	0.025	0.05	0.04	0.054	0.036	0.031	0.051	0.046	0.026	0.036	0.036	0.044
Electrc	0.032	0.025	0.021	0.02	0.032	0.017	0.033	0.024	0.035	0.025	0.019	0.031	0.028	0.015	0.022	0.016	0.029
Regga	0.032	0.021	0.026	0.024	0.034	0.013	0.033	0.03	0.036	0.028	0.023	0.032	0.035	0.02	0.023	0.026	0.032
Jazz	0.03	0.02	0.024	0.03	0.033	0.013	0.032	0.037	0.036	0.034	0.028	0.037	0.038	0.024	0.027	0.027	0.034
Count	0.049	0.032	0.034	0.033	0.052	0.024	0.051	0.044	0.057	0.039	0.033	0.055	0.048	0.028	0.038	0.037	0.046
Comec	0.025	0.017	0.013	0.013	0.024	0.022	0.025	0.017	0.027	0.021	0.013	0.026	0.023	0.012	0.02	0.023	0.02
R&B;	0.05	0.033	0.033	0.032	0.051	0.025	0.052	0.041	0.056	0.036	0.031	0.052	0.048	0.026	0.038	0.037	0.047
Classic	0.04	0.024	0.03	0.037	0.044	0.017	0.041	0.069	0.047	0.044	0.034	0.058	0.047	0.029	0.041	0.039	0.041
Latin	0.054	0.035	0.036	0.036	0.057	0.027	0.056	0.047	0.065	0.042	0.035	0.061	0.055	0.032	0.045	0.045	0.052
Vocal	0.036	0.025	0.028	0.034	0.039	0.021	0.036	0.044	0.042	0.043	0.032	0.045	0.039	0.03	0.032	0.032	0.037
Folk	0.031	0.019	0.023	0.028	0.033	0.013	0.031	0.034	0.035	0.032	0.035	0.037	0.039	0.025	0.021	0.03	0.032
Easy Li	0.051	0.031	0.032	0.037	0.055	0.026	0.052	0.058	0.061	0.045	0.037	0.08	0.05	0.032	0.047	0.039	0.049
Interna	0.046	0.028	0.035	0.038	0.048	0.023	0.048	0.047	0.055	0.039	0.039	0.05	0.064	0.033	0.041	0.055	0.049
Blues	0.026	0.015	0.02	0.024	0.028	0.012	0.026	0.029	0.032	0.03	0.025	0.032	0.033	0.025	0.021	0.031	0.028
Stage	0.036	0.022	0.023	0.027	0.038	0.02	0.038	0.041	0.045	0.032	0.021	0.047	0.041	0.021	0.041	0.034	0.036
New A	0.036	0.016	0.026	0.027	0.037	0.023	0.037	0.039	0.045	0.032	0.03	0.039	0.055	0.031	0.034	0.064	0.038
Religic	0.044	0.029	0.032	0.034	0.046	0.02	0.047	0.041	0.052	0.037	0.032	0.049	0.049	0.028	0.036	0.038	0.047

As shown in the figure, the more green the element is, the higher the similarity between the two genre's artists is. We can see that the artists of most genres are more similar to those from the same genre. This phenomenon is particularly obvious in genre with obvious styles, for example, easy listening's intra genre similarity reaches 0.08 and classic's intra genre similarity reaches 0.069; while for some genres with less obvious styles and have branches in the genre, the similarity is generally low, for example, electronic's intra genre similarity is only 0.025. Therefore, it can be proved that the similarity of artists within the genre is higher than that of artists outside the genre.

3.5 Advantage and disadvantage

Advantage:

The advantages of this modeling method are obvious. It can clearly measure the similarity between two songs and two artists. The values are normalized so it's easy to be further processed and used in other models. The application of cosine distance model also makes the similarity very convincing. At the same time, using the same model to measure the similarity between artists and music reflects the close relationship between artists and music, so that we can use the same standard to analyze artists and music, which is more convenient.

Disadvantages:

The biggest drawback of this modeling is mentioned later, that is, it cannot directly measure the similarity of the internal elements of a set. We can only compare the differences between different artists, but not the overall differences of the music created by an artist himself. In order to solve this problem, we give a simple and effective solution to this question in the third part.

4 The third part: Similarity in and between genres

In the second part, we use the similarity model to measure the similarity between artists of different factions. But when we need to measure the similarity between the two genres, this model is no longer suitable for use. Because it cannot well reflect the similarity of genres as a whole, it can only reflect the similarity between different artists.

Moreover, the above algorithm needs to deal with the data of each artist, which will make the complexity of the program difficult to accept after adding the time variable. In order to complete the calculation with a more concise algorithm on the macro scale, we need to simplify our algorithm, so that our model can be better combined with time to solve the macro problems.

4.1 Modeling

First, instead of analyzing each artist individually, we regard the genre as a whole. Traverse our artist graph and the file full_music_data, we divided the songs by genre, and then calculated the average characteristics of the whole genres.

At the same time, we consider the influence of different songs' popularity. The proportion of songs with high popularity should be high. We normalize all the popularity, and then take it as the weight of the song to calculate the weighted average of all the genre's song characteristics.

The data obtained are as follows:

	danceal	energy	valence	tempo	loudnes	mode	key	acousti	instrum	liveness	speechi	explicit	duratio
Pop/Ro	-0.053	0.462	-0.029	0.141	0.391	1.000	9.000	-0.510	-0.155	0.019	-0.053	-1.000	0.028
Electror	0.473	0.507	-0.358	0.029	0.415	1.000	1.000	-0.630	0.634	-0.067	0.216	-1.000	0.316
Reggae	1.365	0.125	0.832	-0.049	0.293	1.000	7.000	-0.653	-0.268	-0.143	1.120	-1.000	0.082
Jazz	-0.054	-0.741	-0.222	-0.225	-0.805	1.000	5.000	0.791	0.888	-0.160	-0.129	-1.000	0.768
Country	0.348	-0.001	0.205	0.072	0.160	1.000	7.000	-0.020	-0.384	-0.099	-0.245	-1.000	-0.325
Comedy	0.238	0.287	-0.219	-0.374	-0.400	1.000	9.000	0.726	-0.423	1.864	6.869	-1.000	-0.185
R&B;	0.669	0.103	0.239	-0.098	0.307	1.000	0.000	-0.289	-0.354	-0.115	0.232	-1.000	0.115
Classica	-1.239	-1.336	-0.745	-0.416	-1.996	1.000	7.000	1.459	1.736	-0.230	-0.099	-1.000	0.532
Latin	0.666	0.308	0.543	0.053	0.511	1.000	0.000	-0.071	-0.367	-0.074	0.005	-1.000	-0.029
Vocal	-0.432	-0.973	-0.415	-0.279	-0.530	1.000	0.000	1.018	-0.404	-0.030	-0.104	-1.000	-0.370
Folk	-0.003	-0.853	-0.091	-0.079	-0.716	1.000	2.000	0.825	-0.191	-0.083	-0.069	-1.000	-0.260
Easy Lis	-0.305	-0.647	-0.290	-0.211	-0.628	1.000	5.000	0.784	1.465	-0.200	-0.249	-1.000	-0.534
Internat	0.454	0.010	0.328	-0.081	-0.078	1.000	2.000	0.159	-0.144	-0.004	0.148	-1.000	0.464
Avant-(	-0.274	-1.152	-0.551	-0.375	-1.437	1.000	7.000	0.973	0.787	-0.307	-0.113	-1.000	-0.036
Blues	0.247	-0.191	0.467	0.036	-0.128	1.000	2.000	0.251	-0.197	0.104	-0.011	-1.000	0.010
Stage &	-1.456	-1.129	-1.343	-0.502	-1.467	1.000	2.000	0.945	1.674	-0.251	-0.084	-1.000	-0.044
New Ag	-0.966	-1.165	-1.228	-0.238	-1.437	1.000	0.000	1.179	1.984	-0.314	-0.278	-1.000	0.513
Religiou	0.115	0.293	-0.312	0.061	0.591	1.000	0.000	-0.311	-0.422	0.250	0.011	-1.000	0.251
Unknov	0.504	0.576	0.819	0.109	0.450	1.000	7.000	-0.744	-0.442	-0.273	-0.408	-1.000	-0.295
Childrer	1.123	-0.467	0.588	-0.106	-0.056	1.000	0.000	0.533	-0.444	0.133	0.292	-1.000	-1.029

We believe these data can reflect the characteristics of a whole genre. So, we can use these data to analyze how genres change as time goes by.

4.2 The affect of influence relations

We have been able to measure the similarity between the two artists. The question we want to analyze at this time is: how much effect does the influencer have on the followers? Are there more similarities between influencers and followers? If so, will some indicators be more similar than others?

We use each pair of influencers and followers in the file influence_data, the similarity of each characteristic is calculated, and the data is normalized and shown below:

danceabili	energy	valence	tempo	loudness	acousticne	instrumen	liveness	speechine	duration_r
-0.05812	-0.28091	0.134355	-0.09076	-0.32196	0.335905	0.046858	0.09423	-0.00144	-0.10624

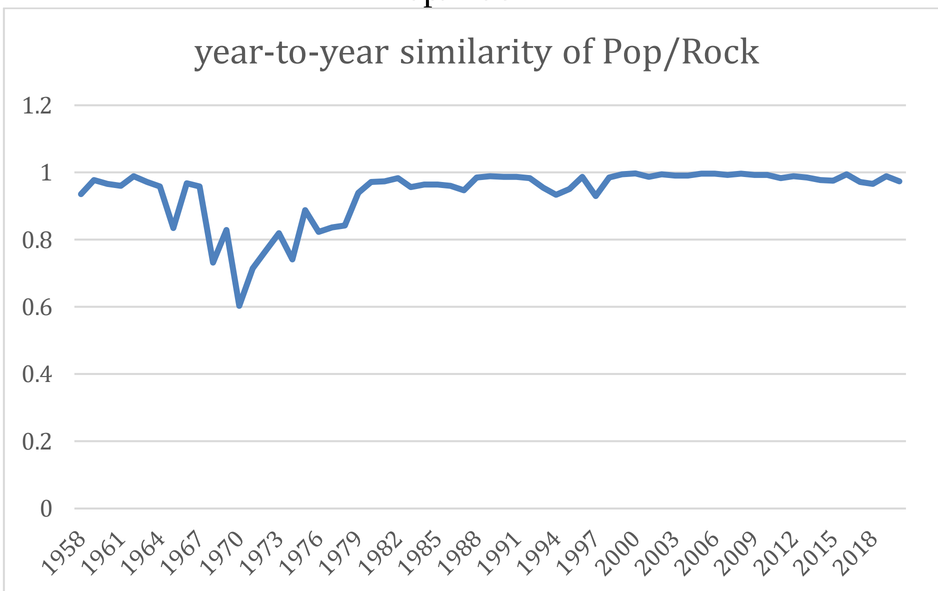
We can find that acousticness and instrumentalness have a very strong influence on the follower. But for the loudness and valence, the influence is much lower. We think this is because acousticness and instrumentalness have strong personal characteristics, so they have strong influence on the follower; but loudness and valence are very common characteristics, so they don't have a strong influence.

4.3 Characteristics and leaders of Music Revolution

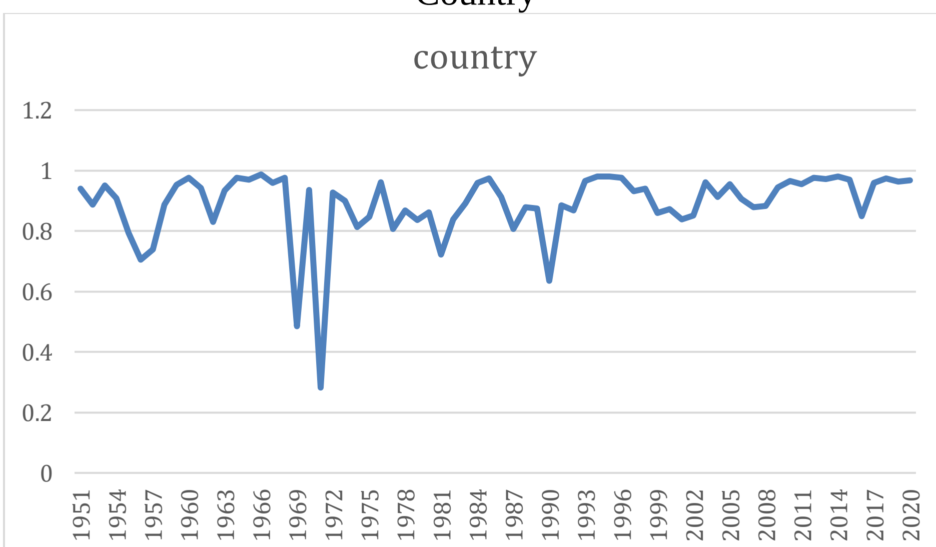
We add time variable to classify songs by year and analyze the indicators of different factions in different years. In order to clearly reflect the changes of genres over time, we calculated the similarity between each genre and itself one year ago. The lower the similarity is, the greater the genre changed in that year.

The trend of genre change over time is given in the next page:

Pop/Rock

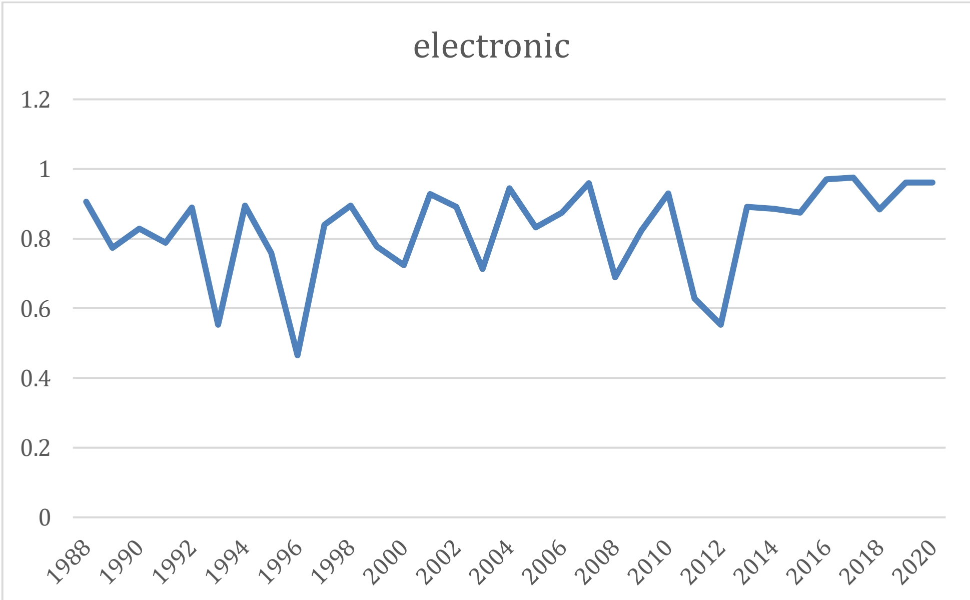


Country



We can see that under normal circumstances, the similarity between genre and itself one year ago is very high. When there is a big revolution in genres, the similarity of different time will drop significantly every year, which means that the genres are changing greatly every year during this period.

We can also find that the Pop/Rock and the Country music both show a significant decline in the similarity in 1970s, which is accurate the time these two genres experienced revolution. After the revolution, they showed stability for a long time.



As for the electronic music which developed rapidly in the 2000s, it shows low similarity almost every two years. This shows that this genre is very dynamic and is in constant development. At the same time, the popularity of computers after the 2000s also brought convenience to the production of electronic music, making it develop rapidly

The music revolution was started by a small number of people who led the change of music genres. This means that their musical style has led to a change in the genres. So we choose the artist who created the most popular songs at the revolution period as the leader.

For example, in the 1970s, the Pop/Rock music experienced a revolution. Some popular artists and songs at that time is:

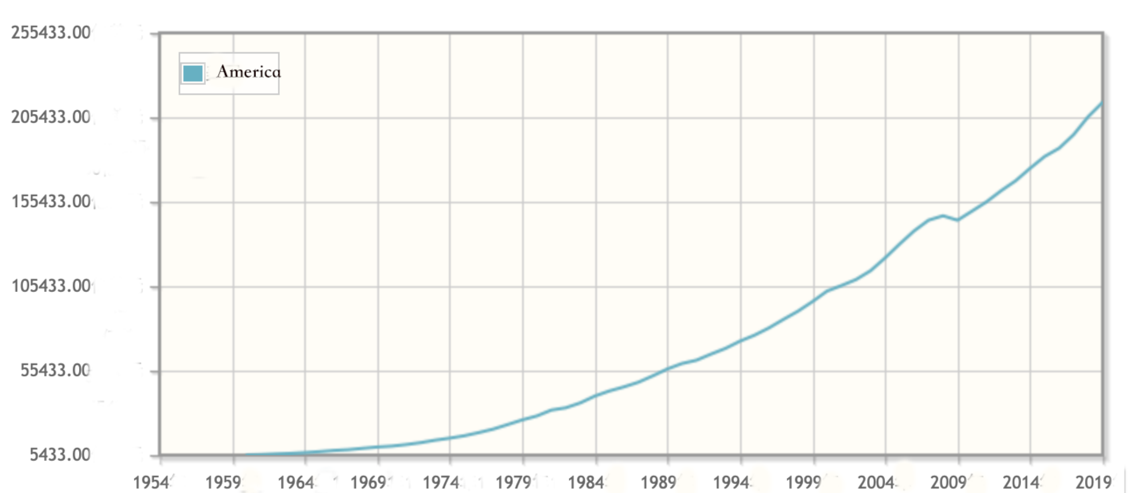
Genre	Artisit	Popularity	Release time	Song name
['Pop/Rock']	['The Beatles']	83	9/26/1969	Here Comes The Sun - Remastered ****
['Pop/Rock']	['Elton John']	81	5/19/1972	Rocket Man (I Think It's Going To Be A Long, Long Time)
['Pop/Rock']	['Creedence Clear	80	11/2/1969	Fortunate Son
['Pop/Rock']	['Elton John']	80	11/5/1971	Tiny Dancer
['Pop/Rock']	['Creedence Clear	78	8/3/1969	Bad Moon Rising
['Pop/Rock']	['Led Zeppelin']	78	11/8/1971	Stairway to Heaven - **** Remaster
['Pop/Rock']	['Neil Diamond']	78	6/6/1969	Sweet Caroline
['Pop/Rock']	['The Beatles']	78	9/26/1969	Come Together - Remastered ****
['Pop/Rock']	['The Beatles']	78	5/8/1970	Let It Be - Remastered ****

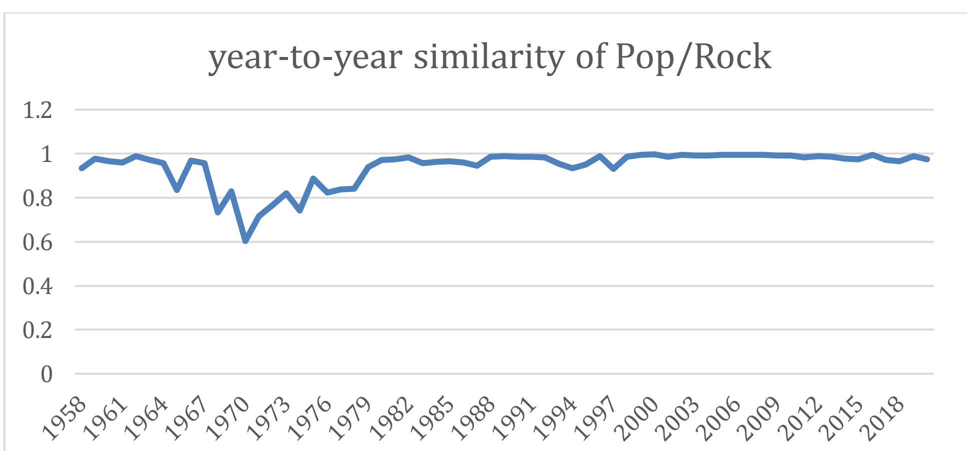
The Beatles won three of them, which is in line with the fact that the Beatles led the Pop/Rock Revolution. Our model accurately identifies the characteristics and leaders of music revolution.

5. Social and cultural influence to the model

Music is inseparable from our society. We have analyzed the characteristics and initiators of music revolution, but we have not studied the causes of music change. Therefore, we will combine the model of the previous part with the factors in the real world, and analyze the influence of social factors on music by comparing the changes of music and society.

We choose the economic as the research factor. First, we will look at the 1970s, which saw a lot of changes. We search the GDP of America from 1920s to 2000s, the data is given below:





We found that the U.S. economy began to rise rapidly in the 1970s, and the growth rate gradually increased. This is in line with the time point of music reform, which explains the indispensable role of economy in the development of music.

This means our model can not only find the characteristics of music revolution, but also reveal the social factors' influence on artists and genres.

6. Model evaluation

Advantage:

1. Our model only uses the data given in the question, and the data format is unified. This means that our model has high applicability and can be used to analyze any artist network.
2. Modeling on different scales can reduce the amount of calculation in a large range and keep the information complete in a small range.
3. The model uses high-level abstraction for artists, so that people who are not proficient in music theory can use also use this model to analyze artists and their songs.
4. The model makes full use of the data given in the title, and all the data in the four tables are used, which means that our model contains all the information given in the title, and the final result is related to all aspects of music.

Disadvantage:

1. In the comparison of genres' similarity, we intend to use clustering algorithm. The similarity calculated by this algorithm can better reflect the degree of gathering of genres, but the amount of calculation is too large after adding the time variable. Because of the time problem, we choose the current model to reduce the amount of calculation while losing part of the accuracy.
2. Our model does not consider the effect of time variables when analyzing influence and popularity parameters. In theory, the earlier the music, the greater the influence.
3. Because of the different models, the local similarity and global similarity can not be well unified, and the comparison is not intuitive enough.

7. Sensitivity analysis

For our network model, to measure its sensitivity, we chose to change the three most influential people in each genre. Three of their characteristics were randomly changed, and the final impact on the whole faction was observed. We calculated the difference of genres before and after the data was changed, and it's shown below:

Pop/Rock	Electronic	Reggae	Jazz	Country	Comedy/S	R&B;	Classical	Latin
-0.00018	-0.00047	-1.3E-10	-0.00039	1.81E-10	2.92E-10	0.000145	1.51E-10	1.11E-10
Vocal	Folk	Easy Lister	Internatio	Blues	Stage & S	New Age	Religious	
-0.00175	-4.5E-10	-4.5E-10	-0.00305	4.48E-10	0.000225	3.18E-10	-0.00223	

It's obvious that genres that have many artists almost didn't change, but tiny genres like International was influenced on a high level.

That's because our model is built on a macro level, taking into account the influence of every artist. Even if a few artists make great changes, they can't have a great influence on the whole big genre. But little genres only have a few members, each one of them changes will make the genre change, too.

8. Conclusion

We have established a network of artists to digitize the influence relationship between artists in the past 100 years. Based on this network, we analyze the style of artists' music works from the micro perspective, and get the similarities and differences of each influencer and follower, find that the relationship between artists has a significant impact on their works.We also studied the similarities and differences between the artists within the genres and found that they are more similar than the artists from different genres.

Then we expand the scale of the problem, explore the similarities and differences within and between each music genres, observe the development of a music genres and the interaction and penetration between different genres, and find that the communication between musicians is an indispensable part of the music revolution.

Finally, by combining with the real world, we find that the fundamental reason for music reform is still social factors. So we make a prediction for the future: with the continuous growth of American economy, music will continue to develop at a very fast speed, and more new music genres will appear.

9. Reference

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