Problem Chosen	2021 MCM/ICM Summary Sheet	Team Control Number
D		**2105298**

Overall analysis on music classification, influences and prediction

Summary

As time goes by, the types of music are constantly changing. New music genres flourish, old music genres disappear or are refined into more subgenres. It is becoming increasingly urgent to quantify the evolution of musical genres and estimate music's impact on culture.

First, we build a directed network based on the contemporaneous and intertemporal influences between genres. This network is weighted by the amount of influence between genres. On the basis of this directed network, we can get two subnetworks: The first subnetwork can be obtained by screening the weight. This subnetwork eliminates small genres influences and allows us to identify the genres that had a significant impact on the genres we care about. We can also obtain the second subnetworks by selecting a few genres that interest us and see how they interact with each other.

Second, to get a more accurate measure of music similarity, we conduct Principal Component Analysis(PCA) to reduce the number of variables at the very beginning. This reduces the high degree of collinearity between musical characteristics. We retain 7 PCs to explain more than 80% of the variance. Then we can use Euclidean Distance to calculate the distance between songs, artists, and genres. Using this distance, we can perform Cluster Analysis. Combined with the analysis of the subnetwork diagram, we find that in most cases, artists from the same genre in different eras are more similar than artists from different genres in the same era. We also find that Pop/Rock developed into 4,5 and 6 sub-genres in 1960s, 1970s and 1980s respectively. This reflects the evolution and prosperity of the Pop/Rock genre. And on this basis, we analyze the reasons for the rapid rise of Pop/Rock, and the influence of Pop/Rock on social culture. In order to test the robustness of our cluster analysis model, we calculate the Euclidean Distance by directly using the original variables instead of PCA. We find that there is no substantial change in the clustering results, which indicates that our conclusion was robust.

Third, We use the distance variable to establish an index to identify the time nodes at which a genre evolves. After identifying evolution, we quantify the impact of evolution on the rate of genre innovation by establishing an Intervention Analysis Model. We find that if genres do not evolve, the speed of musical innovation will gradually slow down. That is, there is a Fishing-Out Effect (new knowledge is difficult to find) in musical innovation. However, with the continuous accumulation of innovation, the genre will evolve, and the innovation speed of the genre will increase significantly. Eventually, however, the rate of innovation will slow down until the next evolution occurs.

Finally, we further discuss the possibility of developing a APP called Music History. Our APP can provide influence graphs for specific artists and genres and give the degree of influence therein. We can also provide classification results for specific artists and genres and give similar artists and genres.

Keywords: Musical Evolution   Directed Network   Clustering Analysis   Intervention Analysis Model

Contents

1 Introduction

1.1 Background

Music plays a very important role in the culture. The creation of music has been influenced not only by previous music but also by many factors, such as the emergence of talented musicians, social changes, or technological progress. As time goes by, the types of music are constantly changing. New music genres flourish, old music genres disappear or are refined into more subgenres. With the growth of music distribution websites, like Spotify and Allmusic.com, the demand for music classification is getting more necessary. With the method to identify the similarity of songs and distinguish music genres, its much easier to study the history of music and make recommendations for users.

The mathematical models we build should finish seven tasks:

Task 1. Influence propagation network and subnetwork between artists

Task 2. Indicator of similarity between music

Task 3. How music genres change in the history

Task 4. Whether the influence between musicians exists

Task 5. How to locate a music evolution and the pioneer

Task 6. Find a dynamic indicator of musical evolution

Task 7. The influence between music and human society

1.2 Literature Review

Music is an important part of culture, and changes in the process of culture evolution(8). As music change over time, musicians can be sort into several music genres. Meanwhile each musician can influence or been influenced by other musicians, providing changes within and between genres. This leads to the similarity between different genres, which cause a problem. How to tell apart two music genres with similar features? Different approaches have been applied to category music genres. For instance, using spectrogram(5), machine learning(1), taxonomy(6), ensemble of classifiers(2), and similarity distance fusion algorithm (4). But still cant get a perfect method to category a music. Recently, more scientist from different research region came out with more solutions. Similar to natural language processing, where music evolution progress can be represented as phylogenetic trees or networks (9). Jonathan Warrell used Biology method like evolutionary genomics(10) to explain the evolution process of music.

2 Assumptions and Notations

2.1 Assumptions

- It is assumed that the musical style of the artist will be reflected in the songs he writes and that the musical characteristics of the songs will change as the artist changes.

- It is assumed that a genre is bound to develop over time: birth, development, flourish, decline/subdivision into more subgenres. During these 4 processes, there may be multiple declines and re-emergences, but eventually a decline or subdivision into more musical genres.

- It is assumed that an artist's musical style will not change dramatically within a decade. In order to be able to analyze the musical characteristics of each decade, it is assumed that an artist's musical style does not change dramatically in a short period of time.
- It is assumed that the musician himself will not remain exactly the same over time. During a musician's career, he will be influenced by social factors, other people, his own age, and his musical style will not be completely unchanged. So we need to consider that the musician himself will change over time.
- It is assumed that the musical style of the artist will be reflected in the songs he writes and that the musical characteristics of the songs will change as the artist changes.

2.2 Notations

Table 1: Notations

Variable Name	Explanation
$I(x, y)$	$I = 1$ if x influence y or 0
w	Directed network weight
X_i	Music characteristic
Z_i	PCi
$d(x, y)$	The distance between musical characteristcs
G_i	Different genres

3 Data Clean and Analyis

Although the scope of the model we have built can be interpreted beyond the present data, we have processed the data before using it since we have to use the given data. Here is an example to show part of our process. In $influence\_data$, we removed data with an impact lag of more than 20 years. For example, an artist who started his career in the 1950s believes that he was influenced by an artist who started his career in the 1970s. We consider this to be a special case and should be removed. However, we have kept other data on reverse influences, such as an artist who started his career in the 1950s may be influenced by artists from the 1960s. These removed data represent only 1.7% of the $influence\_data$.

Moreover, Elvis Presley was born in 1935, but the data shows that he released a song "Heartbreak Hotel" in 1925, which should be released under RCA Records in 1956. Therefore, the data of songs in 1925 is obviously not reasonable. Similarly, Elvis Presley passed away in 1977, and the song "heartbreak hotel" was released on the 2002 album "Elvis 30 #1 Hits". Not only that, but the song "Heartbreak Hotel" was also released on the 1968 medley single Medley, which is a 14-minute duration song. Therefore, in order to reduce the duplication of information, the data of "Heartbreak Hotel" from 1925, 1968 and 2002 were removed. Other information was treated similarly. In addition, some duplicate data that were identical were also removed to reduce the duplicate contribution of information

We can see very easily by the Figure 1 that there are clearly outlier points in duration. Our criterion for judging the outliers is the part beyond [Q25-1.5IQR,Q75+1.5IQR], i.e. the part beyond [78734.73ms, 394717.4ms]. That is, songs that exceed [1.3min, 6.6min]. Because the song that exceeds 6.6 minutes, it is likely to be a medley of several songs, such as Medley in 1968 contains eight different songs including heartbreak hotel, which causes him to be 14 minutes long. And the styles of these eight songs are different, so this data can interfere with our judgment of the category to which the song belongs, and with our quantification of the evolution of the song. So we remove it. For example, the song "Dopesmoker", released in 2003 in $full\_music\_data$, is one hour long. This affects our judgment of the characteristics of music in the Rock category, so we remove it. The same is done for other similar data.

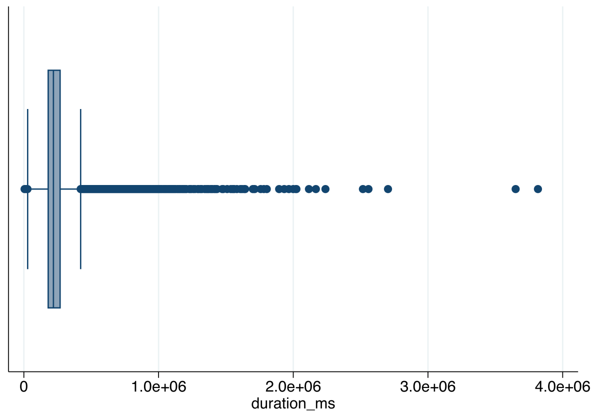

Figure 1: Box plot duration

4 Model 1: Weighted directed music network

We build a directed network based on time dimension and genre dimension. This network is weighted by the amount of influence between genres. Then we established two different subnetworks on the basis of this complete network. The first subnetwork can be obtained by screening the weight. This subnetwork eliminates small genres influences and allows us to see the development of the genre we are interested in. We can also select subnetworks by selecting a few genres that interest us and see how they interact with each other. Our analysis of our networks and subnetworks revealed several interesting findings: the genre influences occurred mainly between the major genres from the 1950s to the 1990s.The communication and integration of music culture between different genres mainly comes from the mutual influence of different genres in different eras, rather than from the mutual influence of different genres in the same era.

4.1 Establishment the influence network of different generations and genres

The music created by predecessors often has an influence on later musicians. The influence can be analyzed from two different dimensions.

- Time dimension (transtemporal influence): Generally speaking, the music of one musician has an impact on other musicians years or even decades later. Most musicians' influence is concentrated in the last decade or so, but a few great musicians have a profound impact on later generations. By comparing the number of musicians affected and the influence time. We can see the influence of different musicians quite clearly.

- Genre dimension (concurrent influence): Different musical characteristics between contemporaneous genres allow them to influence each other. This influence contributes as much to the evolution of music as the inheritance within the genre. There are two things to consider while analyzing genres in different periods. There will be mutual influence between the same genres, we call it genre inheritance; Different genres can also influence each other, for instance the blending of genres or the creation of new ones. The influence between the same genres reflects the inheritance of the genres, we can observe whether the genres are flourishing or declining; The influence of different genres reflects the innovation of music, the fusion of genres and the birth of new genres.

Based on the previous overview, we built a directed network with data from $influence\_data$. Musicians from the same genre at the same era are combined into one node. The weight w between different nodes represents the sum of the number of influences from all musicians in the "initial point" on all musicians in the "target point".

$$w = \sum_{x \in A} \sum_{y \in B} I(x, y) \tag{1}$$

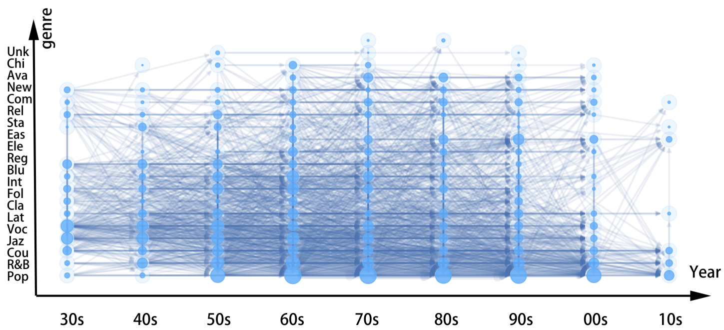

Figure 2: Music network

In Figure 2, the node size indicates the number of musicians in the genre at a given era, while the color depth of the line between two nodes represents the influence wight w.

Through the above graph we find that the musical influence is mainly concentrated in the mainstream genres in the 50s-90s, and the influence weight w is larger for genres with a larger number of musicians.

4.2 Genre inheritance analysis in subnetwork

We filter the nodes with weights w larger than 50 as Figure 4.

From the Figure 4 we can observe that the weight of influence within the Pop/Rock from the 60s-90s was significant, indicating that the Pop/Rock was flourishing during that time. Its position as a mainstream genre was becoming increasingly secure.

We present the 60s-90s Pop/Rock at a separate place for inheritance analysis.

From the Figure 5 we can see that the inheritance in Pop/Rock basically belongs to the generation-by-generation inheritance, and the influence between generations is relatively small.

But when we compare the data of Latin, we can find that the 50s-80s legacy accounts for the largest percentage of this indicates that the school may have declined between the 50s-80s,

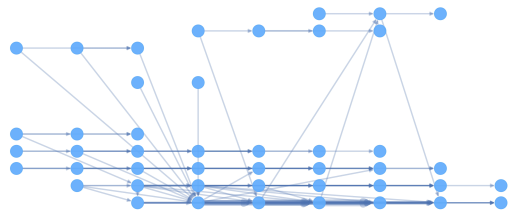

Figure 3: Weight more than 50 subnetwork

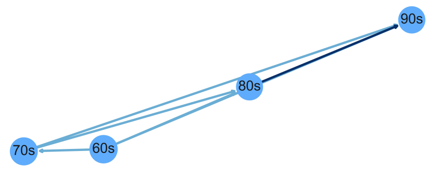

Figure 4: Nodes of 60-90s Pop network

resulting in little influence on future generations. Or the genre's style heritage deviated from its original style in the 60s and 70s and returned to its historical style in the 80s by Latin musicians.

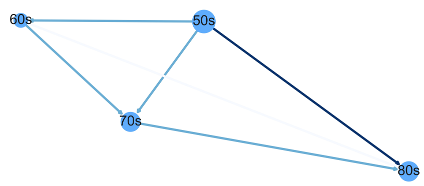

Figure 5: Nodes of 70-80s Latin network

4.3 Innovation analysis in subnetwork

We found that the number of different genres influencing each other in the same era is much smaller than the number of different genres influencing each other in different eras. Therefore, we believe that the cultural interchange between genres comes mainly from the interactions between different genres in different eras. For example, Pop/Rock in the 1960s was widely influenced by other genres, which is correlated with the flourishing of Pop/Rock genres in the following decades.

5 Model 2: Cluster Analysis Model

In this section, we will measure similarity using all seven features describing musical characteristics, four features of vocal type, and audio duration for all twelve musical characteristics in the $artist\_data$. We consider that the high correlation between some variables can create a problem of "repeated contributions" in the judgment of the degree of musical similarity. Therefore, we will first conduct principal component analysis to reduce the number of variables, so as to reduce the high degree of collinearity between variables and improve the accuracy of music similarity calculation. After the principal component analysis, we find that we would need to retain 7 PCs to explain more than 80% of the variance, which is a great improvement from 12 features. But this may doesn't help much with understanding the relationship between the features and song genres. Therefore, when we need to analyze the music features, we will use the original 12-dimensional data at the same time to avoid any possible ambiguity of information that may be caused by principal component analysis. Subsequently, we select the six music genres with the most songs, and they were also the six genres with the most musicians. Using these six genres as examples, we showed how to compare the similarities of artists. We found that, in most cases, the average differences between artists of different genres are greater than the differences between artists of the same genre. In addition, by subdividing the clustered objects into averages for each genre for each decade from 1920-2010 (clustering 60 objects at this point), we further find that in most cases the same genre from different eras are more similar to each other, but in a few cases artists from different genres in the same era may be more similar to each other, e.g. Pop/Rock in 1960s is more like R&B in 1960s rather than the Pop/Rock in 1950s. This is because genre can change dramatically over time.

5.1 Measuring Music Similarity by Distance

5.1.1 Using principal component analysis to reduce the repeated contribution of information

In this section, we will use 12 variables from $data\_by\_artist$ to consider similarity. Figure 6 shows that danceability and valence have a correlation coefficient of 0.585, while energy and loudness have a correlation coefficient of 0.797, so there exists a high degree of covariance. If these indicators are used directly to calculate similarity, it will lead to overlapping information, for example, energy and loudness, if they exist at the same time, may lead to singers who are originally very similar to be more similar and singers who are originally less similar to be more different. principal component analysis can transform multiple indicators into a few unrelated composite indicators, which can reduce duplicate contributions and make the calculation of similarity more accurate.

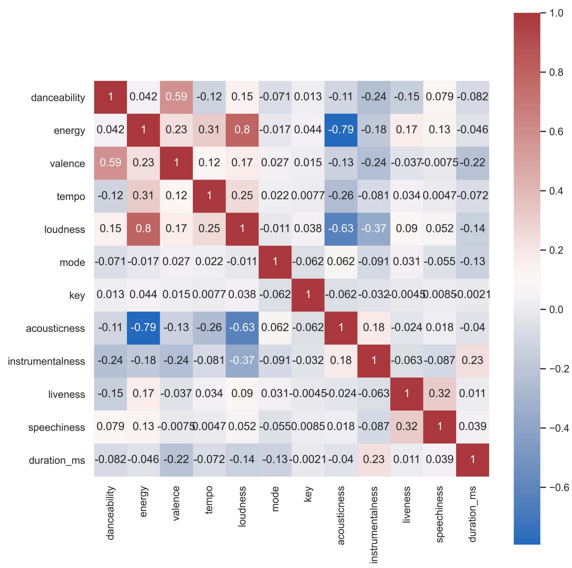

Figure 6: Correlation coefficient matrix of the 12 variables

However, we also consider that the meanings of the newly generated music features after the principal component analysis (PC1, PC2, PC3...) were ambiguous and not as clear and precise as the meanings of the original variables. Therefore, we will further compare the results of both to determine the validity of the method of principal component analysis. We conduct principal component analysis, and select seven principal components. Compared with the original 12 features, this is a huge improvement. Considering its cumulative contribution from Figure 7, it reaches over 80. We show two main principal components in Figure 8.

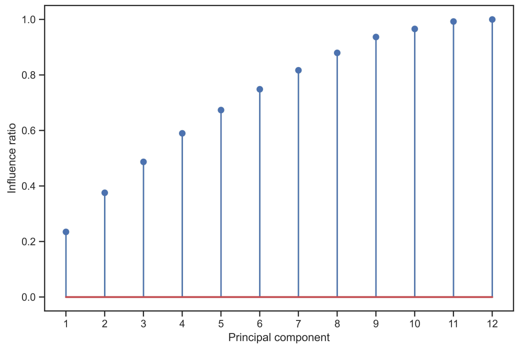

Figure 7: Accumulating contribution rate

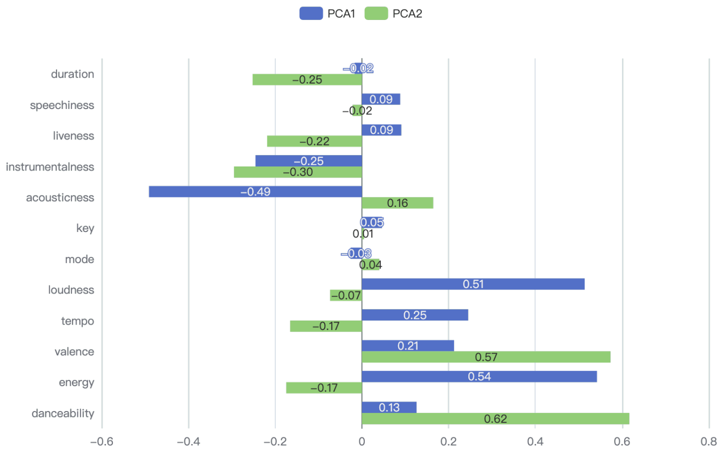

Figure 8: Principal Component Loadings

Further considering the contribution of the principal components to the original variables in Table 2, we can see that the seven principal components represent 99% of the information of key characteristic and 97.9% of the information of mode characteristic.

$$\rho_i = \sum_{j=1}^{7} r^2(z_j, x_i) \tag{2}$$

5.1.2 Measuring Music Similarity

First, we convert the 12-dimensional data into the 7-dimensional data according to the different weights of the seven principal components.

Table 2: Contribution to the original variable

Classes	Danceability	Energy	Valence	Tempo	Loudness	Mode
Influence	0.8459	0.8952	0.8195	0.8838	0.8246	0.9791
	Key	Acousticness	Instrumentalness	Liveness	Speechiness	Duration
	0.9991	0.8207	0.6152	0.6718	0.7092	0.7878

Then, we calculate the Euclidean distance between the indicators using formula3 to obtain our similarity index "the distance between musical characteristics " d.

$$d(x,y) = [\sum_{k=1}^{p} |x_k - y_k|^2]^{\frac{1}{2}} \tag{3}$$

Through "the distance between musical characteristics "d we can analyze the similarities between musicians of different genres. First, we ignore the change of genre over time for now. At this point we first classify the artists in $artist\_data$ by genre. We can calculate the distance between any two artists in $artist\_data$ by formula3. We consider that there are 20 genres in the given data, but as we can see in Figure 9, the six genres with the highest number of songs contain 87.44% of the songs. These six genres are also the six genres with the highest number of artists, containing 83.87% of the artists. Therefore, we will use these six genres as examples for our analysis. The analysis between the other genres is exactly the same.

$$D(G_1, G_2) = \frac{1}{n_1 n_2} \sum_{x \in G_1} \sum_{y \in G_2} d(\vec{x}, \vec{y}) \tag{4}$$

Then we can calculate the average distance between any two musicians between two genres based on the different genre to which the artist belongs according to formula 4. Likewise, we can calculate the average distance between any two artists belonging to the same genre according to formula 4. The results of the calculation of the average similarity d between genres are shown in Table 3. As we can see from Table, in the vast majority of cases, the distance between artists from two different genre will be larger, i.e., the diagonal element is the smallest in each row. This means that artists within genre are more similar than artists between genres. e.g. the average distance between two artists belonging to Pop/Rock is 3.68, while the average distance between an artist belonging to Pop/Rock and an artist belonging to R&B is 3.87. However, there is one case where artists within genre are less similar than artists between genres. i.e., the element on the diagonal at this point is not the smallest in the row he is in. Specifically, the average distance between two Latin artists is 3.58, but the distance between a Latin artist and a Country artist is only 3.48. This indicates that Latin and Country music styles have a high degree of similarity, ignoring changes in genre style over time.

In addition, we consider that the style of genre changes over the years. To analyze this situation, we divide Pop/Rock into a total of ten categories such as 20's rock, 30's rock, etc. as we did in task1, and do the same thing for the other five genres. Finally we cluster these sixty categories, and the results are shown in Figure 9. The results are shown in figure(x). Number 0

Table 3: Average distance between/within genres

	Pop/Rock	R&B	Country	Jazz	Vocal	Latin
Pop/Rock	3.68	3.87	3.68	4.86	4.61	3.89
R&B	3.87	3.6	3.60	4.64	4.44	3.63
Country	3.68	3.60	3.05	4.49	3.88	3.48
Jazz	4.86	4.64	4.49	4.13	4.45	4.56
Vocal	4.61	4.44	3.88	4.45	3.49	4.31
Latin	3.89	3.63	3.48	4.56	4.31	3.58

to 9 on the abscissa represent Pop/Rock from 1920 to 2010.

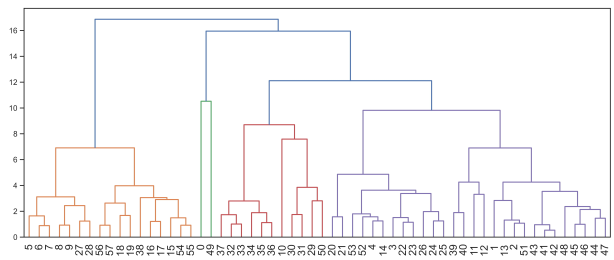

Figure 9: Cluster analysis of 60 genres

Number 10 to 19 are R&B from 10 decades, 20-29 are Country, 30-39 are Jazz, 40-49 are Vocal, 50-59 are Latin.

We find that for the most of the cases, the same genre from different eras are more similar to each other (i.e. first to be clustered together), such as Pop/Rock from 1980s,1990s (No.6 and No.7); Pop/Rock from 2000s,2010s (No.8 and No.9), Country from 1980s, 1990s (No.16 and No.17), Latin from 1980s, 1990s (No.56 and No.57), R&B from 2000s, 2010s (No.18 and No.19), R&B from 1970s, 1980s (No.15 and No.16), Jazz from 1940s to 1990s (No.32 to No.37).

However, in some cases, different genres from the same era are clustered together first, such as Pop/Rock in 1960s and R&B in 1960s (No.4 and No.14). In general, for the most part, the same genre from different eras are more similar to each other. (compared to two genres belonging to different genres of the same era)

5.1.3 Test of model 2

The degree of similarity is the most important index for conducting cluster analysis. Considering the information ambiguity that may come from the dimensionality reduction of principal component analysis, we need to further test its accuracy to confirm that our approach is reasonable and thus increase our confidence in the results of cluster analysis. We used 7-dimensional data to calculate the distances and clustering, and compared the results with the results of using 12-dimensional data. The results are shown in Figure 10, Figure 11. We found that the two results are very similar. They both first put Jazz, Vocal in one category while Country and Latin in one category, and then added R&B to the Country-Latin category. At this point, the Jazz, Vocal, Country, Latin and R&B were divided into one category before they were finally divided into one category with Pop/Rock. This further strengthens our confidence in the results of the principal component analysis.

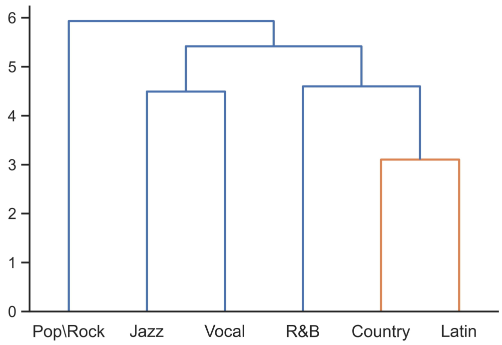

Figure 10: Clustering results of original data

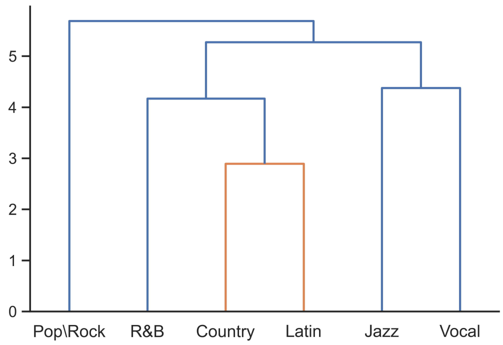

Figure 11: Clustering results after PCA

5.2 The evolution of genres

5.2.1 Distingishing genres

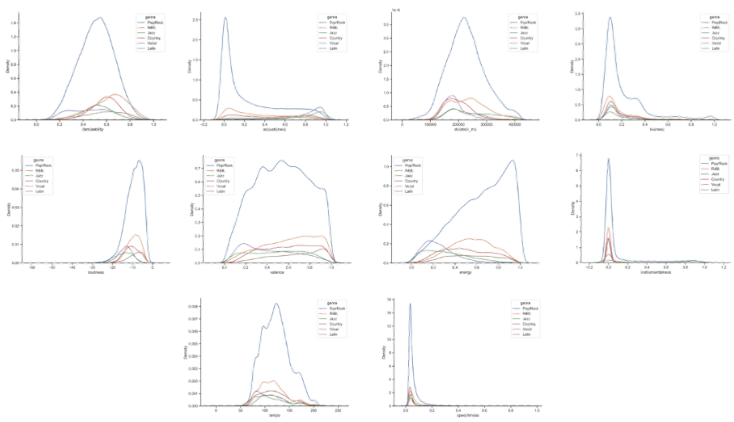

Figure 12: Density by Genre

Breaking things out by genre, from Figure 12 we find that Vocal tracks are likely to be acoustic with low valence (sad or depressed); Latin tracks have high valence (are positive or cheerful) and danceability; Pop/Rock songs are most likely to have high energy and low acousticness; Country tracks tend to have high duration and acousticness; Country tracks tend to have high duration and acousticness;

Based on the density plot, it looks like energy, valence, danceability, duration and acousticness may provide the most separation between genres during classification, while speechiness and liveness may not help much.

5.2.2 The evolution of genres over time

We use $influence\_data$ to filter Pop/Rock for influential artists from the 1960s, 1970s, and 1980then we conduct cluster analysis.

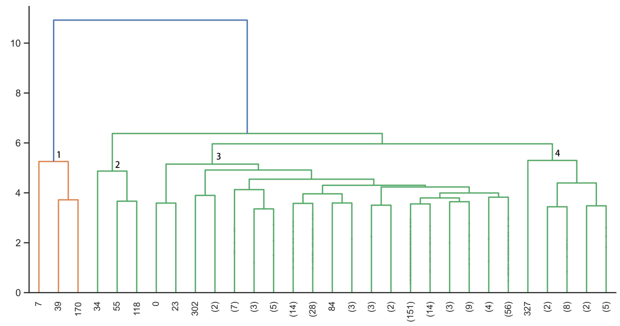

Figure 13: Cluster analysis of 1960s

According to Figure 13, we can see that Pop/Rock of the 60s can be divided into 4 subgenres.

Based on the original data, we have a surprising finding: Bob Dylan and The Band, two Folk Rock musicians, are in cluster 2; The beatles, Jimi Hendrix, and The Beach Boys, Psychedelic Rock musicians, are in cluster 3; Led Zeppelin, Black Sabbath, and Deep Purple are in cluster 4. Also, since the clustering algorithm always produce outgroups, which is a collection of data that is far from the normal data. We use the outgroup as a reference indicator for the distance within the cluster. Due to the presence of outgroup, we identified cluster 1 as the music genre inherited from the 1950s music genre.

This result illustrates that our cluster analysis is correct and consistent with the historical situation. Not only that, this result also illustrates how Pop/Rock evolved in the 1960s: it further subdivides into the subgenres of Folk Rock, Psychedelic Rock and Hard Rock.

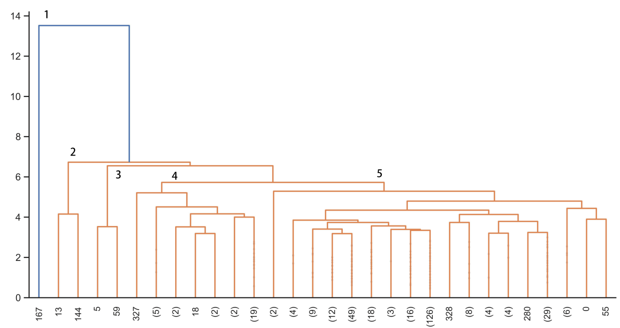

Figure 14: Cluster analysis of 1970s

Similarly, we conduct cluster analysis of Pop/Rock in the 1970s. The results show that Pop/Rock from the 1970s should be divided into 5 clusters, 1 of which is Outgroup. This time, we found that when we looked at the original data again, we found that: AC/DC and Thin Lizzy, Metal musicians, are in cluster 2; Brian Eno and Roxy Music, Art Rock musicians, are in cluster 3; David Bowie and KISS, Glam rock musicians, are in cluster4; The Sex Pistols, The Clash and Joy Division, Punk Rock musicians, are in cluster 5. The result is shown in Figure 14.

This result shows that in the 1970s Pop/Rock was further subdivided into the subgenres Metal, Art Rock, Glam Rock and Punk Rock.

Similarly, we conducted a cluster analysis of Pop/Rock of the 1980s. The results show that 1980s Pop/Rock can be supposed to be divided into 6 subgenres, Metal, Grunge, Post-punk, New wave, Alternative rock, and Outgroup.

In addition, by analyzing the clustering results in combination with network, we can determine whether two genres are related or not. We believe that if two genres are related, they should satisfy two conditions. First, they should influence each other, i.e., the weight of their linkage in network is not 0. Second, the similarity between them should be relatively high. Therefore, we can use the number of influences between them and the clustering results to determine whether these two genres are related or not.

In other words, using the subnetworks in 4.2 or 4.3, we can determine whether there is a mutual influence between genres and genres. Then, we combine the results of the clustering analysis to make the judgment. If there is an influence between two genres and the distance between them is relatively close at the time of cluster analysis, we can assume that they are highly correlated; if one condition does not hold, we are skeptical about the correlation between these two genres; if both conditions do not hold, we can assume that there is no association or a small association between these two genres.

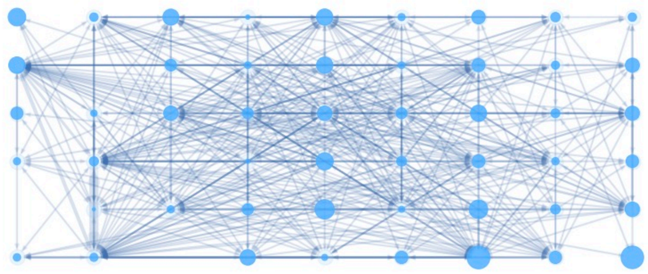

Figure 15: The filtered subnetwork

5.3 Do the influencers actually affect the music created by the followers

Many artists have stated that they were influenced by previous artists (whether they were within a genre or not). To find out if this influence really exists or is just an "illusion" on their part, we further analyzed Figure 2 of 4.2.2 by zooming in on it, and the result is shown in Figure 16. When an artist indicates that he is influenced by another artist, we look at the genres they are in. If the influencer and the influenced are in very close clusters to each other, we have a higher degree of confidence that the artist is indeed influenced. Conversely, if the influencer and the influencer are far apart, we can assume that the "influence" is an illusion.

After comparison, we find that some of the so-called "influences" were just the illusion of the musicians. These musicians were not as influenced by their predecessors as they thought they were. We filtered out the Latin genres from the 1950s-1980s to obtain a subnetwork graph, which is shown in Figure 5. From Figure 5, it is clear that many artists from the 1970s claim to be influenced by artists from the 1950s and 1960s. For example, Gilberto Santa Rosa, a Latin music singer in the 70s, stated that he was influenced by Cheo Feliciano (a Latin singer in the 50s) and Ismael Miranda (a Latin singer in the 60s). However, the results of the cluster analysis graphs show that their musical styles are quite different, as shown in the Figure 16, where the

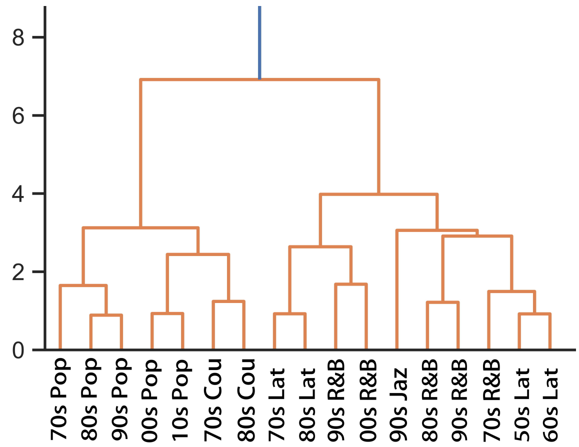

Figure 16: Part of the clustering results

distance between Latin from the 70's and the 50's and 60's is relatively large. Therefore, we can assume that there is no great influence between them. That is, these so-called "influences" are just the illusion of the musicians.

However, we find that overall influencers did have an impact on the music of later artists. We filtered out the Pop/Rock genre from the 1960s-1990s to obtain a subnetwork graph, the results of which are shown in Figure 4. From Figure 4, we can see that many artists from the 90s claim that they were influenced by artists from the 80s. For example, 90s Pop/Rock singer Radiohead stated that they were influenced by 80s Nirvana, R.E.M., The Smiths, etc. In fact, their music is indeed similar, which is reflected in Figure 16 80s Pop/Rock is less distant from 90s Pop/Rock . The same goes for Weezer in the 90s, whose songs are very similar to those of the 80s "influencers" like Sonic Youth and the Pixies. There are many more examples like this. Of all the $influence\_data$, the influences that actually happened account for the majority.

Among these real effects, we wanted to know whether there are some music characteristics that will be more 'contagious' than others. To make sure that the impact of our analysis is real and not an illusion, we chose to analyze the annual average musical characteristics of Pop/Rock from 1970s-2010s. This effect is real because the distance between Pop/Rock from 1970s-2010s is relatively small as seen in the cluster Figure 16, and from the network Figure 15 we can see that the impact between them is very large.

We perform Entropy Weight Method (EWM) analysis on this data. According to the explanation of the basic principle of information theory, information is a measure of the degree of system order, and entropy is a measure of the degree of system disorder. If the information entropy of the characteristic is larger, the information provided by the characteristic is larger, The results of EWM are shown in Figure 17. The dispersion degree of acousticness is very large, indicating that the index fluctuated relatively large in the evolutionary process, that is to say, it is likely that the acousticness is significantly different from that of the last 10 years. This indicates that "contagion" in acousticness is smaller compared with other characteristics.

6 Model 3: Intervention Analysis Model

Past music, social change, and technological change all have an impact on the evolutionary process of musical genres. Evolution is essentially a qualitative change caused by a quantitative change. To better understand the evolutionary process of music genres, we constructed a

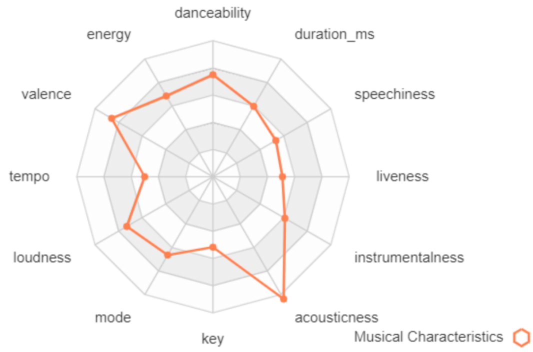

Figure 17: Radar map of musical features

comprehensive indicator to identify the time points in history when the evolution of music genres occurred. After identifying the time at which evolution occurred, we quantified the effect of dramatic change on genre evolution by building an intervention analysis model. First, we estimated that if genre evolution did not occur, the rate of musical innovation would gradually slow down, i.e., there is a Fishing-out effect (new knowledge is difficult to find) on musical innovation. However, as innovation accumulates, the genre will evolve, and the rate of innovation in the genre will have a significant increase. However, the rate of innovation will gradually decline until the next evolution occurs eventually. This suggests that, to some extent, the time interval between genres evolving will gradually become longer as musical innovation becomes progressively more difficult. However, when we consider the gradual acceleration of technological development, i.e., the "standing on the shoulder of giants" effect, (existing knowledge helps discovering new ideas), innovation in music may not necessarily become more difficult. Finally, we analyze the interaction between music and other cultural developments in society.Past music, social change, and technological change all have an impact on the evolution of musical genres. Evolution is essentially a qualitative change caused by quantitative change.

6.1 Identify major leaps and influencers

When a major leap occur, there will be a sudden change in the distance of musical characteristics in two years. In addition, there should also be a change in the rate of change of the number of newly released songs. Therefore, we propose an indicator (distance, speed) to determine the time of genre development and change. This is a binary indicator, and when any one of the variables exceeds a set threshold, we can conclude that a revolution in the genre has occurred. By analysis the of all music genres. We can determine the threshold. For the rate of change of the number of new releases in the year (speed) we set the threshold to 4. For the distance of musical characteristics, we set the threshold to 20.

By using Figure 18 we find that exceeds the threshold in 1956, 1969, and 1977, which means Pop/Rock changed in these three periods.

Analyzing the for 1956, the speed is far above the threshold, indicating that the change came from the "popularity" of the Pop/Rock genre. Using data from $full_music$, we note that Pop/Rock released only 111 songs in total before 1950. In the 1950s, Pop/Rock released 428 songs. The result is shown in Figure 19.

Among them, the number of songs released each year from 1950 to 1955 was no more than 5, while the number of rock songs released in 1956 was 35, in 1957 was 85, in 1958 was 143 and in 1959 was 154. Thus we can determine that Pop/Rock started in the mid 1950s.

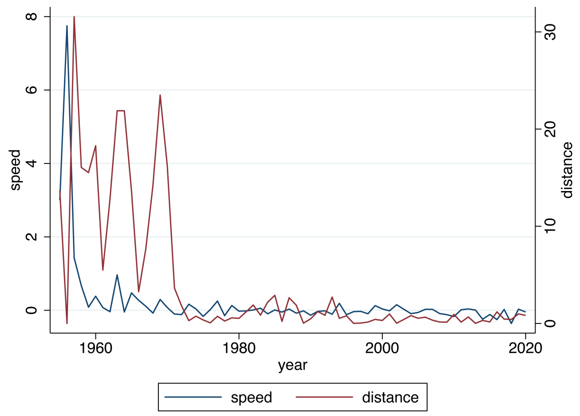

Figure 18: Indicator variation figure

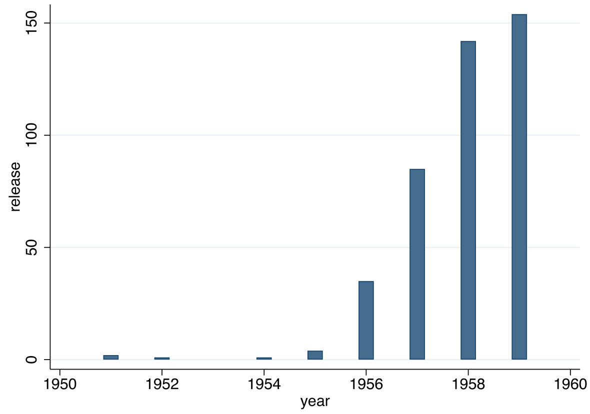

Figure 19: Number of songs released speed variation in 1950s

In order to find specific influences, we used the data in $influence\_data$ to look at the musicians who had the most influence on later generations in the 1950s. Chuck Berry, Elvis Presley, Buddy Holly and Little Richard were the most influential. This indicates that they both had the most influence and had the greatest impact on change.

Combined with the approach in 5.2, we distinguish genres. We find a rapid decrease in acousticness in the 1969 period, which implies a substantial increase in Pop/Rock's dependence on electrical amplification, when Pop/Rock used more electronic sound effects. this suggests that our composite metrics are accurate.

Using the same methodology, we find that the change was represented by The Beatles, Bob Dylan, and The Rolling Stones. The Beatles influenced a total of 595 musicians, well ahead of everyone else. Bob Dylan and The Rolling Stones both influenced over 300 musicians. It is also worth noting that the Pop/Rock musicians of the period have been very influential throughout history. The result are shown in Figure 20.

Even the "third tier" of David Bowie, Led Zeppelin, Jimi Hendrix, The Kinks, The Velvet Underground, The Beach Boys, Black Sabbath's influence is also very strong. This meant that the change had a very big impact on Pop/Rock.

Therefore, we identified the indicator that can reflect whether the musical change happened,

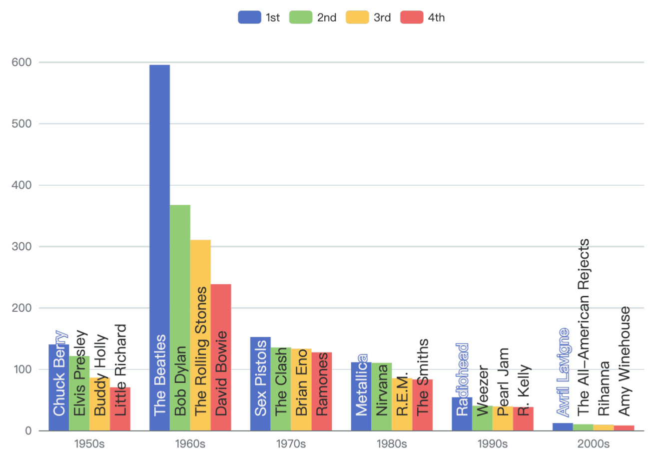

Figure 20: The most influential singer from 50s to 00s

i.e. . After finding the time when the change happened, using $influence\_data$, we can find the musicians who led the change.

6.2 Identify major leaps and influencers

In 6.1, we found when the evolution occurred through . In this task, we will quantify the evolutionary process of genres using the change of Pop/Rock genre as an example. By building an intervention analysis model, we create a dynamic indicator to quantify the effect of influencers that cause genre revolutions.

6.2.1 Intervention analysis modeling

During the development of a musical genre, a few famous artists often play the role of promoting a great change in the genres, which is reflected in a sudden change in the musical similarity d of that genre. After the change has occurred, the magnitude of the change in musical characteristics becomes progressively smaller, which can lead to a progressively smaller distance d between the musical characteristics of the genre in two years. This trend will continue until the time when the next genre change occurs. From 6.1, we determine when this mutation occurs, so here we will quantify the effect of the change occurring in terms of the musical similarity d between the two years, using the Pop/Rock genre as an example, when the time of the change is known.

First we persistently intervene with the variable S, and the lag operator B. Where T is the point in time when the change accumulates to a certain level and then mutates, and B represents the lag period, e.g.

$$BY_t = Y_{t-1} \tag{5}$$

$$S_t^T = \begin{cases} 0, & t < T \\ 1, & t \geq T \end{cases} \tag{6}$$

Second, the impact of any event can be divided into two categories: temporary impact or permanent impact. Here, considering that the impact of an artist who triggers a genre change is long-lasting (e.g., the Beatles' impact was so profound that their songs are still missed to this day), we define the dynamic impact factor g as shown in equation

$$g_t = \frac{\omega B^b}{1 - \omega_1 B - \cdots - \omega_r B^r} S_t^T \quad (0 < \omega_i < 1) \tag{7}$$

The meaning is that when t<T, the dynamic impact factor is gt=0*w/(1-0*detaB)=0. And when t>=T, the dynamic impact factor gt is actually an autoregressive function.

$$g_t(1 - \omega_1 B * 1) = w * 1 \tag{8}$$

$$g_t - \omega_1 g_{t-1} = w \tag{9}$$

In a more general form, where the Bb of the numerator represents the fact that this impact does not occur at t<T+b, reflecting the property of the lag of the impact. The denominator represents the different autoregressive functions, reflecting the fact that the impact will change gradually with time, and finally the impact will stabilize at w/1-deta1-deta2.... We assume that the impact of change is of the formular(x).

6.2.2 Quantifying genre development using intervention analysis models (Pop/rock as an example)

As we know from before, the first evolution after the birth of the pop/rock genre occurred around 1964. In 1964, The Beatles had a huge and lasting impact on the change of musical style in the pop/rock genre. Therefore, we define S=1 IF t>=1964

We then follow Figure 21 for estimation

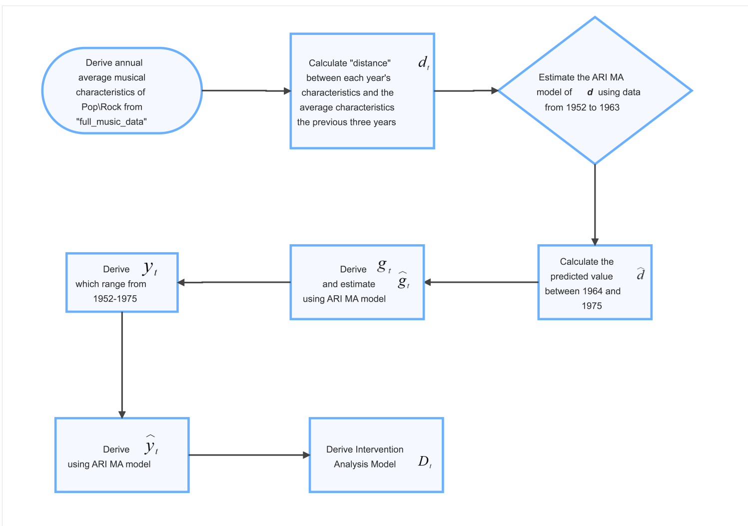

Figure 21: Flow chart of the intervention analysis model

1. Derive distance dt between two years musical characteristics.
2. Estimate the ARIMA model of dt using data from 1952 to 1963.

   First, we need to do Dickey-Fuller test for unit root on dt to test whether its a stationary series. The p-value of this test is 0.0148, which support that dt is a stationary series.

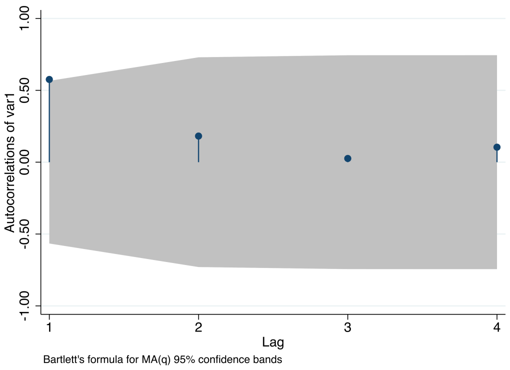

Figure 22: AC

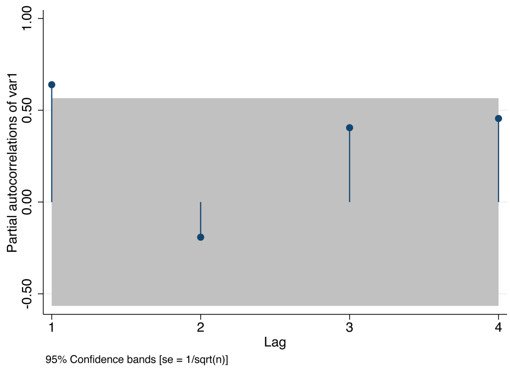

Figure 23: PAC

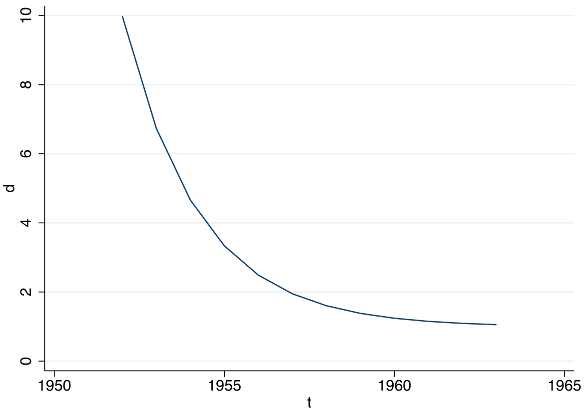

Figure 24: The speed of genre innovation without revolution

Then, we need to decide order of autoregression AR(p). From Figure 22, 23, we decide to use AR(1)

Finally, we need to make sure that there is no sequence correlation of residuals in this regression. Or we will need to decide the order of moving average regression MA(q). From Figure 25 correlogram of the residual, the Q-statistic are all insignificant. This result support that there is no sequential correlation of residuals.

LAG	AC	PAC	Q	Prob>Q	-1 0 1 [Autocorrelation]	-1 0 1 [Partial Autocor]
1	0.1182	0.1211	.19996	0.6548		
2	-0.4640	-0.5031	3.6214	0.1635		
3	-0.2680	-0.2116	4.9049	0.1789		

Figure 25: Test of residual sequence correlation

This result is reasonable because it means that without dramatic genre change, the rate of innovation within the same genre will decrease. Eventually, the rate of innovation (the difference from the previous year) tends to zero.

3. Estimate g_t

In this section, first we need to derive the predicted value of d_t in 1964-1969. This is the pace of innovation without dramatic genre change. Then we derive the innovation effect brought by revolutionaries gt use x. These influencers increase the rate of innorvation so that the distance between two years will increase compared with before.

$$g_t = d_t - d_{that} \tag{10}$$

Then we use g_t from 1964-1969 to estimate

$$g_t = \frac{\omega}{1-\delta B} S_t^T \quad (0 < \delta < 1) \tag{11}$$

We're actually estimating a first order autoregressive model

$$g_t = \delta g_{t-1} + \omega \tag{12}$$

By using OLS, we derive that

$$g_t = \frac{0.675}{1 - 0.246BS_t} \tag{13}$$

4. Estimate 2 again to get a more accurate estimates

$$y_t = \begin{cases} d - g_{that}, & t \geq 1963 \\ x_t, & t < 1963 \end{cases} \tag{14}$$

We derive the distance in 1964-1975 if there is no revolutions using x. So that we can use more data to estimate ARIMA in (b). Then by repeat what we did in (b), we find that:

$$y_t = 0.687y_{t-1} + 0.07 \tag{15}$$

5. Derive Intervention Estimation Model Dt

$$D_t = y_t + \frac{0.675}{1 - 0.246B} S_t^T \tag{16}$$

In this way, we establish a dynamic indicator $gt = \frac{0.675}{1-0.246B}$ St to estimate the influence processes of musical evolution that occurred over time in one genre. From Figure 26, we find that without evolution, the distance to the previous year tends to be zero.(Shown as y). When the evolution happen, the distance to the previous year will suddenly increase, and finally it will begin to decline until the next evolution occurs. (Shown as real distance) Our Intervention Analysis Model described such a trend greatly.(Because D is close to real distance)

To sum up, we take Pop/Rock as an example, and quantified the first major evolution of Pop/Rock genre. From before we knew that the second major evolution of Pop/Rock genre took place around 1977. We can repeat the above process to quantify the second evolution. In addition, we can quantify evolutionary processes in exactly the same way for other genres.

If we want to quantify the evolution of a particular artist's style, we just need to calculate the distance between two years for the artist in the first step using $full\_music\_data$. And then the process is exactly the same.

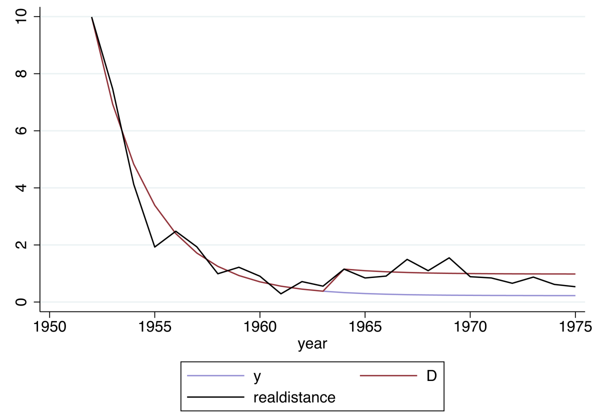

Figure 26: Prediction of the intervention analysis model

7 Analysis of the Advantages and Disadvantages of the Model

7.1 Model Advantages

1. When capturing musical influence, we innovatively propose to establish directed network from two perspectives of time and genre. This approach greatly improves the visibility of the network. At the same time, we can better observe the inheritance and integration of genres.

2. Before clustering, we use PCA to alleviate the problem of high collinearity. This improves the accuracy of our clustering.

3. Our dynamic indicator can produce time-different effects by increasing the order of autoregressions. In addition, We can control the delay of the effect by changing the order of B(Lag factor) in the dynamic indicator.

7.2 Model Disadvantages

- Due to the limited data available, we can only analyze some of the artists.

  In addition, due to the lack of sub-genre data, we can not accurately describe the process of genre evolution.

- The level of technology has a huge impact on the evolution of genres. And different levels of technology in different countries can lead to different rates of genre evolution. Because data is not available, we ignore this potential discrepancy.

8 Infulence between music and social

To explore the influence of society on music requires us to combine additional historical information. We use the number of songs released in each eras to calculate the share of Pop/Rock in all genres.

We can note from Figure 27 the rapid increase in the share of Pop/Rock in the 60s/70s and the simultaneous increase in the number of songs released. This is closely related to the young people who were born in The post-World War II baby boom. Through historical information, we learn that these young people, unlike their parents, were not troubled by material life. They wanted to prove to the world that they still had first-class creativity, imagination and plenty of drive. So, they put a lot of effort into the creation of their culture. At the same time, the rise of the civil rights movement and the counterculture movement during the 1950s made such cultural themes as equality, civil rights, freedom and anti-war emerge. We know from Figure2 that Pop/Rock was mainly influenced by Blues, Country and R&B. This makes Pop/Rock a common music for both blacks and whites, loved by people of all colors. Moreover, Pop/Rock's style made it a very good representation of the main theme of the counterculture movement and the baby boomers' love of democracy and desire for freedom. In addition, along with the popularity of television technology in the 1950s, it made it easier for people to access musicians and their songs. Artists within the Pop/Rock genre continued to innovate, and the British Invasion, represented by The Beatles in the mid-to-late 1960s, attracted more musicians to create Pop/Rock. The Beatles influenced a lot of musicians.

As a result, we can see an explosion in the number of releases of songs that emerged in the 1950s, as well as the popularity of Pop/Rock in the 60s and 70s.

Relatively speaking, the rise of Pop/Rock has also had a great impact on society. First, the prevalence of music has attracted more young people to join the music business. As we can see from Figure27, there are more and more people becoming musicians. Music has also had a huge impact on other cultures. For example, many musicians have entered the film industry and made many movies, such as "A Hard Day's Night" by The Beatles; "Evita" by Madonna; "Renegade" by Bob Dylan; "Freejack" by Mick Jagger (member of The Rolling Stones). In addition to movies where the musicians acted or directed, the musicians' own influence has also led them to appear in movies many times. For example, the appearance of Elvis Presley and John Lennon in Forrest Gump. At the same time, we have reason to believe that the popularity of Pop/Rock, in turn, contributed to the development of Anti-war protests and Civil Rights Movement. At the same time, music was also pushing technology forward due to the need for higher fidelity and the need for convenient music recording technology.

This means that music, in turn, contributed to the development of society, and the two were mutually influential and developed together.

9 Document: Analysis Network For Music Evolution

Analysis Network For Music (ANFME) is a music relationship analysis package for relating, analyzing, evaluating, and predicting the relationships of musical genres or musicians and analyzing their impact on culture and history by creating networks of influence.

ANFME provides:

- Create influence graphs for specific artists and genres and give the degree of influence therein;
- Provide classification results for specific artists and genres and give similar artists and genres;
- Evaluate the impact of specific artists and genres on historical development;
- Predict the cultural and historical impact of specific artists and genres and the development of genres;

How it works:

- Create Weighted directed music network to analyze the influence between artists and genres by using the influence data provided by ICM Association;
- Clustering of artists and genres with music data from the ICM Society to classify artists and genres;
- ARIMA and intervention analysis models were used to assess the cultural and historical impact of musicians and genres and to predict future trends;

Support in future:

- We are trying to obtain and analyze historical data from music-related industries such as film, television, and games to analyze the impact of music development on other related industries;
- The high level of music development as a part of culture has always been considered as one of the indicators of high development. We are trying to correlate the level of music development in different regions and countries and the impact of its development;

APP based on ANFM: Music History

We have developed an app based on ANFM to provide a music relationship analysis service for non-specialists. It has all the features of ANFM, plus the ability to visualize influence relationship maps and evaluate or predict quantitative data and provide online playback capabilities.

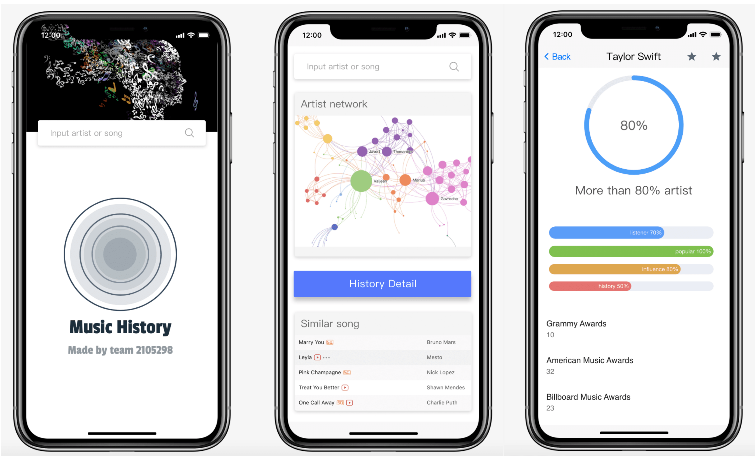

Figure 27: "Music history" APP

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