Abstract

In this paper we employ a **Weighted Network** to analyze some of the major Musical Influences in the last century. Moreover we develop a **Generalized Musician Model** which quantifies common factors such as **popularity, energy, and danceability** of each musician's song to create a prediction we remark as the **Generalized Musician Score**. We conclude our paper with an insight on the **cultural influence** of music over time along with a note on the **external social and technological** changes affecting the music industry.

Contents

List of Figures

CHAPTER 1

Introduction

1.1 Background

The act of appropriation in music, be it conscious or unconscious, is an inevitable outcome of the practice. From folk hymns being passed down each generation, to rappers crafting remixes of their predecessors, music tends to have more similarities than not. This is additionally confirmed with musicians often sharing their most significant influences when they were formulating their style.

Not only this, but many styles are influenced entirely from previously popularized styles. A notable example of this in history is how Blues and R & B musicians were a source of inspiration for early Rock-n-Roll artists. While conscious appropriation is common in the music industry many artists also unconsciously sample popular melodies and patterns they have heard before. While entire papers can be referenced on the ethics of musical appropriation, such as "Digital Sampling v. Appropriation Art" Eckhause n.d. , we will will refrain from discussing this.

Instead the purpose of this paper is the following. First we construct a mapping of musician influences within distinct genres through the use of a **Weighted Network**. Examining critical factors such as **popularity, energy, and danceability** of each musician's song we use our **Generalized Musician Model** to quantify the overall **Generalized Musician Score.** We end with an insight on the cultural influence of music over time along with a note on the **external social and technological changes** affecting the music industry.

CHAPTER 2

Musical Influences

2.1 Our Weighted Network

In order to properly analyze the Musical Influences of different musician's we must first discuss Weighted Networks. A network is a series of points, commonly known as nodes, that are connected, traditionally with lines, to other points. Therefore weighted networks are where the connections between nodes have weights assigned to them depending on some predetermined criteria *Weighted Network* n.d. An example of a weighted network where the connections are labeled with their corresponding weights is below

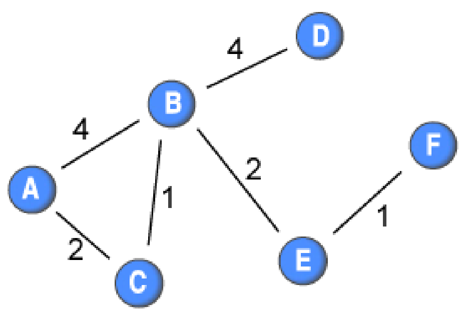


FIGURE 2.1: Example of a Weighted Network
Weighted Network n.d.

Another implementation of a weighted network is where the size of the nodes in our network are determined by the weight. In this setup a node with a larger weight than another node would be represented larger on the network. For our analysis we will be following this convention.

Now that we have a clear understanding of what a Weighted Network is, we are going to apply this to our problem statement. The first data-set $influence - data$ consists of a set of musicians and their respective influencers. Moreover the classification of a follower and an influencer are not mutually exclusive. Quite commonly one can be a follower to some and an influencer to many more. An example of this is shown below where we highlight the number of influencers and followers of the popular pop/rock band the Beatles.

Beatles	
Number of Influencers:	32
Number of Followers:	615

Therefore for any given musician we state that the status of having followers is more notable than the status having influencers. The reasoning behind this is that we believe the number of Influencers a musician has is not correlated to the outcome or image of that said musician. There are many untalented musicians which have hundreds or thousands of influencers, yet they remain unheard of. Additionally there are examples of well-known musicians who developed with only a few role models and influences. Therefore for our weighted network we will only focusing on musicians with having a substantial amount of followers.

That being said it is necessary to provide the setup for our weighted networks. In the analysis we focused on three distinct genres: **Pop/Rock, Electronic, R&B** which we respectively denote as G_1, G_2, G_3.

Additionally in each genre we restrict ourselves to only consider the top n influencers which we respectively denote as $i_1, i_2, \ldots i_n$ along with our function $f(i_j) = I_j$ where I_j is the numbers of followers given any influencer.

Before we define our connections C_i we must define another property, the number of shared followers between influencers $S_{i,j}$ where j,k represent two distinct nodes.

$S_{j,k} = f(i_j) \cap f(i_k) = I_j \cap I_k$

Along with the following function

$$g(G_i) = \frac{\sum_{k=1}^{n} \sum_{j=1}^{n} S_{j,k}}{n^2}$$

where $g(G_i)$ represents the average amount of shared followers in a particular G_i

Lastly we decided to define our connections, $C_{j,k}$ as such

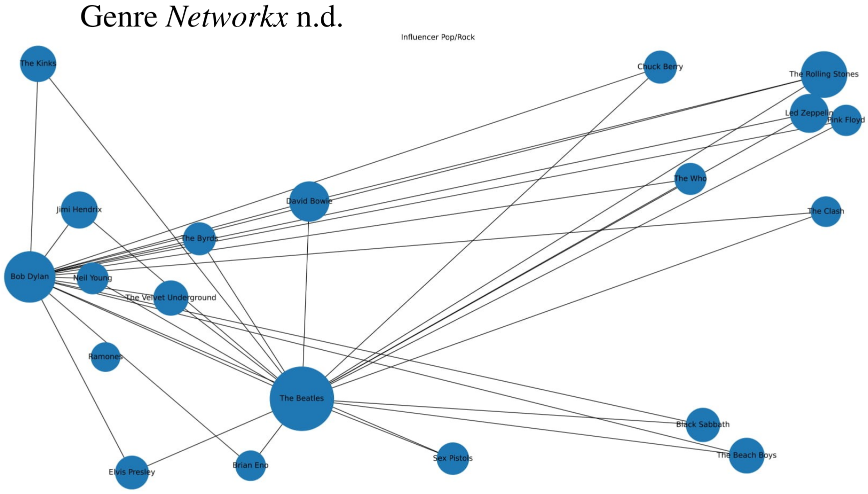
$$\text{If} S_{j,k} > g(G_i) \text{ Then } C_{j,k} = 1$$

$$\text{Otherwise } C_{j,k} = 0$$

where 1 represents an existence of a connection and 0 represents the non-existence of one.

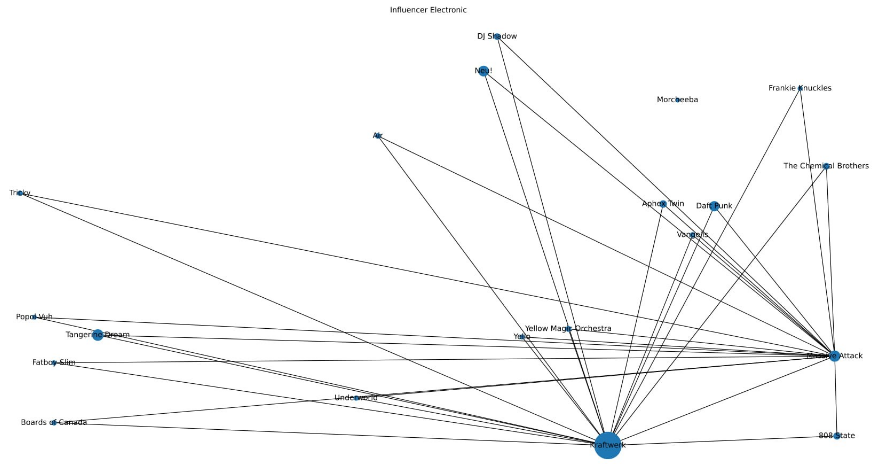
One last point to note is the size of each node is determined by the number of followers, larger nodes have a larger amount of followers. Moving forward, we can examine which influencers have the largest direct effect on other musicians. Just as important however, by analyzing the connections we can infer the overall structure between influencers and followers within the genre as well. We will apply this to our data in the next three examples.

FIGURE 2.2: Weighted Network for the Rock/Pop Genre *Networkx* n.d.



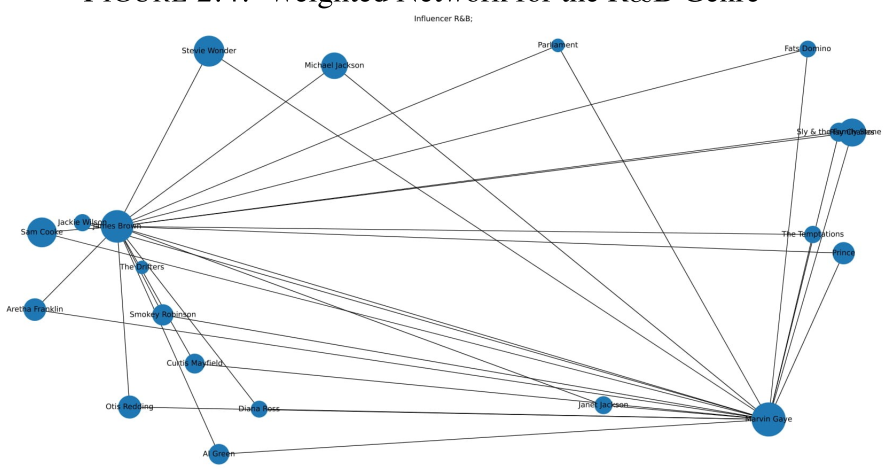
In the above Weighted Network we examine the top fifteen influencers of the Rock Genre. After reviewing the network we conclude there are multiple sources of influence, notably, The Beatles, Bob Dylan, and the Rolling Stones. Additionally, due to the frequency of connections between nodes we conclude that the influencers share followers quite often. We believe this is due to rock/pop bands commonly having mixed styles that lead to the classification of rock/pop sub-genres to be ill-defined.

FIGURE 2.3: Weighted Network for the Electronic Genre



In our next example we examine the top fifteen influencers of the Electronic Genre. Unlike our Rock/Pop network we note there is only one major source of influence in terms of the number of followers, Kraftwerk. However if we examine the number of shared influencers we see that Massive Attack shares a similar number of followers with other members of the top fifteen influencers just as frequently as Kraftwerk. Interestingly enough, while Kraftwerk had a larger raw follower base, it seems both groups had a similar influential effect on the Electronic Genre

FIGURE 2.4: Weighted Network for the R&B Genre



Our last genre to review exhibits interesting results. We remark how five musicians had a similar amount of followers; Sam Cooke, James Brown, Stevie Wonder, Marvin Gaye, and Michael Jackson. Despite the similar amount of followers the musicians have a varying level of connections. While musicians such as Marvin Gaye and James Brown shared a large amount of followers with other members of the top fifteen influencers, other musicians such as Stevie Wonder and Michael Jackson did not. This leads up to infer there are distinct sub-genres in R&B with separate follower bases outside of the rest of the community.

CHAPTER 3

Similarities in Music

Many people might argue music can be subjective however certain qualities of a song can be measured to judge the outcome of the track. In the following chapter we will define which qualities we chose to study in our Generalized Musician Model along with our Generalized Musician Score. As our goal is to find similarities between musicians we compute the differences between scores with the objective to find minimums which we note represent similar musicians.

3.1 The Generalized Musician Model

Given a musician x_i we denote their n_i songs as the set $x_i = y_1, y_2, \ldots, y_n$. Reviewing the $full - music - data$ we chose to analyze the popularity, energy and danceability of each song, which we will refer to respectively as $p_{x_i,y_j}, e_{x_i,y_j}, d_{x_i,y_j}$. Enforcing we want a single **Generalized Musician Score** for each musician we calculate an average of each factor from their set of songs, as shown as below

$$p_{x_i} = \sum_{j=1}^{n_i} \frac{p_{x_i,y_j}}{n_i}$$

$$e_{x_i} = \sum_{j=1}^{n_i} \frac{e_{x_i,y_j}}{n_i}$$

$$d_{x_i} = \sum_{j=1}^{n_i} \frac{d_{x_i,y_j}}{n_i}$$

Before we can analyze these factors in our model however we must standardize our data to a similar scale. While the energy and danceability of each song are measured on a scale of $[0, 1]$, popularity is measured between $[0, 100]$. Therefore adjusting for popularity we remark our **Generalized Musician Model** is

$$GM(x_i) = \frac{p_{x_i}}{100} + e_{x_i} + d_{x_i}$$

where x_i represents our musician.

In order to determine similarities now we state how given any two Generalized Musician Scores, the absolute difference between them represents the (dis)similarity between the artists. Given any two pairs of artists, we conclude the pair with the smaller difference in Generalized Musician Scores are more similar than the other pair. We formulate our next steps below.

We note all the musicians in a Genre can be represented as $x_1, x_2, \ldots x_{ni} \in G_i$. Therefore lets define our similarity function as the following.

$$SI(G_i) = \min \sum_{k=1}^{n_i} \sum_{j=1}^{n_i} GM(x_j) - GM(x_k)$$
$$\forall j \neq k$$

Where $SI(G_i)$ returns the two most similar musicians in any given genre. Further studies can examine similarities between genres along with analyzing the smallest $p\%$ of minimums (which is associated with the top $p\%$ of similarities).

CHAPTER 4

Conclusion

We end our paper with a note on the cultural impact of musical influences and similarities. After examining the top influencers across different genres, we could not conclude whether there is an equilibrium structure between top influencers and their respective follower bases. While the Pop/Rock network displayed multiple sources of influences and connections, the Electronic Network showed two distinct hubs of influence. Moreover, as we discussed in the R&B section, the property of having a large follower base does not imply a large amount of shared followers with other influencers. Some instances of this were with Michael Jackson and Stevie Wonder having the former but not the latter. All in all, these findings highlight the fact that we cannot conclude whether a universal structure between influencer and followers exist, as the distribution of influencers within each genre are not uniform.

Another point worth mentioning is the degree to which technological forces such as the internet, affected musical influences. Again referencing our networks, the top influencers in Pop/Rock had larger raw follower bases and shared followers than their electronic genre counterparts. One possible factor to consider is the effect of the internet. While the Pop/Rock genre was at its height in the latter half of the 20-th century, the electronic genre did not reach peak popularity until decades later. Due to the availability of the internet, we infer that followers within the electronic genre had a much more diverse set of influencers. This is supported by the existence of only two hubs of influence in the electronic network compared to multiple in both the Pop/Rock and R&B genres.

1 Document for ICM Society

Music plays a substantial role in our society as it reflects our culture and social interactions. Different genres of music can be used to express emotions or to be accompanied by an event. As it is important to understand how music plays a role in our culture, we decided to analyze musical influence using a weighted network.

Our approach of using a weighted network to identify influences between artists in the same genre provides valuable insight into cultural driving forces in our society. As the node size of a particular artist grows, their total influence also grows. Nodes are connected based on if a threshold of the number of followers is satisfied. Thus, artists which are connected share many of the same followers. With this, we can identify how diverse or one-sided a genre may be. This is important because having a popular artist does imply that the underlying genre is also popular. For a genre to be popular, there must be several artists with a large influence that share many of the same followers. This insight is valuable as it can help researchers identify cultural shifts.

If we were to expand our data set to include geographical locations of followers, a whole new set of possibilities would emerge. Not only would we be able to better analyze cultural differences between regions, but we can analyze the mental impact of a catastrophic event. For example, if a hurricane occurs in Florida, do people listen to sad music to cope with the additional stress? If so, we can generate insight into the mental well-being of those affected. To continue research, we recommend further study on the distribution of followers along with cross-genre examinations.

Bibliography

Eckhause, Melissa (n.d.). 'Digital Sampling v. Appropriation Art: Why Is One Stealing and the Other Fair Use? A Proposal for a Code of Best Practices in Fair Use for Digital Music Sampling'. In: (). DOI: http://dx.doi.org/10.2139/ssrn.3224724.

Networkx (n.d.). URL: https://networkx.org/. (accessed: 02.07.2020).

Weighted Network (n.d.). URL: https://en.wikipedia.org/wiki/Weighted_network. (accessed: 02.07.2020).

Weighted Network (n.d.). URL: https://toreopsahl.com/tnet/weighted-networks/shortest-paths/. (accessed: 02.07.2020).