The Effect of DJs' Social Network on Music Popularity

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ABSTRACT

This research focuses on two distinctive determinants of DJ popularity in Electronic Dance Music (EDM) culture. While one's individual artistic tastes influence the construction of playlists for festivals, social relationships with other DJs also have an effect on the promotion of a DJ's works. To test this idea, an analysis of the effect of DJs' social networks and the audio features of popular songs was conducted. We collected and analyzed 713 DJs' playlist data from 2013 to 2015, consisting of audio clips of 3172 songs. The number of cases where a DJ played another DJ's song was 15759. Our results indicate that DJs tend to play songs composed by DJs within their exclusive groups. This network effect was confirmed while controlling for the audio features of the songs. This research contributes to a better understand of this interesting but unique creative culture by implementing both the social networks of the artists' communities and their artistic representations.

1. INTRODUCTION

Network science can enhance the understanding of the complex relationships of human activities. Thus, we are now able to analyze the complicated dynamics of sociological influences on creative culture. This research focuses on understanding the hidden dynamics of Electronic Dance Music (EDM) culture through both network analysis and audio analysis.

Disc Jockeys (DJs) are one of the most important elements of EDM culture. The role of DJs is to manipulate musical elements such as BPM and timbre [1] and to create unique sets of songs, also known as playlists [2]. DJs are often criticized on their ability to "combine" sets of songs, since the consistency of atmosphere or mood is influenced by the sequence of the songs [3]. Therefore, it is common for DJs to compose their playlists with songs from other DJs who share similar artistic tastes. However, there are other reasons aside from artistic tastes that contribute to a DJ's song selection. DJs sometimes strategically play songs from other DJs because they are on the same record labels; thus, playlist generation is influenced by a complex mixture of artistic and social reasons. This interesting dynamic of EDM culture has led us to ask two specific questions: What reasons are most important for DJs when selecting songs to play at a festival? How do social relationships or audio features influence the popularity of songs? By answering these two questions, we can better understand the mechanisms of how DJs gain popularity and how their artistic tastes influence the construction of playlists for festivals.

To answer the above, we conducted the following tasks: 1) DJ networks based on shared songs were collected; 2) Audio data of the songs played by the DJs were collected; 3) Network analysis was conducted on DJ networks; 4) Audio features were extracted from the collected audio data; 5) The relationships between DJ networks and audio features were identified through three longitudinal Fixed Effect Models.

2. RELATED WORKS

2.1 Social Networks of Musicians

Network analysis has been widely applied to the field of sociology and physics. Recently, researchers have started adopting network analysis to better understand the underling mechanisms of art, humanities and artists' behavior. Among the few attempts to implement network analysis in the field of music, researchers have tried to investigate how musicians are connected to other musicians in terms of artistic creativity.

The effects of collective creation and social networks on classical music has been previously studied. McAndrew et al. [4] analyzed the networks of British classical music composers and argued that it is conceptually difficult to separate music from its social contexts. This is because it is possible for creative artworks to be influenced by musicians' social interactions and collaborations, and, moreover, an artist's intimate friendships can even create his or her own styles and artistic innovations.

Gleiser and Danon [5] conducted research on racial segregation within the community of jazz musicians of the 1920's through social interaction network analysis. Park et al. [6] analyzed the properties of the networks of western classical music composers with centrality features. The results of this analysis showed small world network characteristics within the composers' networks. In addition, composers were clustered based on time, instrumental positions, and nationalities. Weren [7] researched collegiate marching bands and found that musical performance and motivation were higher when musicians were more integrated into a band's friendship and advice networks.

It is widely known that the most important elements of artistic communities are individuals' creativity and novelty. However, the literature on the social networks of musicians argues that the social relationships of artists are important elements within creative communities as well.

2.2 Audio Computing

There are various feature representations in the field of Music Information Retrieval (MIR) [8]. Since the goal of the research is to find the influence of DJs' social relationships and their artistic tastes on music popularity, it is important to extract audio features that consist of rich information. Timbre is one of the most important audio features when DJs create playlists [1]. Additionally, tonal patterns are equally important in EDM songs [9]. Therefore, we extracted Mel-frequency cepstral coefficients (MFCC), Chroma, tempo and Root-Mean-Square Energy (RMSE) to cover most musical characteristics such as musical texture, pitched content and rhythmic content [10]. Beat synchronous aggregation for MFCC, Chroma and RMSE was applied to make features more distinctive [11]. The harmonic part of the spectrograms were used for Chroma, and the percussive part of the spectrograms were used for beat tracking by using harmonic percussive separation [12]. After the features were extracted, the mean and standard deviations of MFCC, Chroma and RMSE were taken to supply a single vector for each song [1]. All audio feature extraction was conducted with librosa [12].

3. HYPOTHESIS

DJs not only creatively construct their own playlists to express their unique styles, but also manipulate existing songs to their artistic tastes. This process is called remixing. DJs remix to differentiate or familiarize existing songs for strategic reasons. Therefore, the songs are the fundamental and salient elements of EDM culture. For this reasons, DJs delicately select songs when constructing playlists to ultimately satisfy universal audiences' preferences. Thus, the frequency of songs selected by DJs represents the popularity of the songs. Thus, the logical question to ask is, "What are the most important factors when DJs select songs?" Our hypotheses based on this question are as follows:

H1. Song popularity would correlate with DJs' artistic tastes, controlling for the social relationships of DJs.

H2. The social relationships of DJs would influence song popularity, controlling for DJs' artistic tastes.

4. METHODOLOGY

Songs' popularity were calculated based on DJ network, while audio features were extracted from audio clips of the songs. As a result, we collected and extracted DJ network data and audio clips. Ultimately, the dynamics of DJ networks and audio features were analyzed through the Fixed Effect Model.

4.1 Data Set

We collected 713 DJs' playlist data (from 2013 to 2015) through Tracklist.com (from a total of 9 notable festivals: Amsterdam Dance Event (Amsterdam); Electric Daisy Carnival (global); Electric Zoo (US); Mysteryland (global); Nature One (Germany); Sensation (global); TomorrowLand (Belgium); Tomorrowworld (US); Ultra Music Festival (global)); and audio clips from Soundcloud.com (within license policies)).

Three types of data were constructed based on the collected data: 1) networks of DJs playing other DJs' songs; 2) popularity of the songs by calculating the frequencies of songs played at each festival; and 3) audio features from audio clips, filtering out audio clips that were shorter than 2 minutes long. To summarize, playlist networks and audio clips of 3172 songs with 15759 edges were collected and analyzed.

4.2 DJ Network Analysis

As shown in Figure 1, DJ networks were constructed based on directed edges. When DJ_1 plays a song composed by DJ_2 and DJ_3, we consider DJ_1 as having interacted with DJ_2 and DJ_3.

The DJ networks consisted of 82 festivals that were merged down to 77 events due to simultaneous dates. Therefore, we constructed 77 time windows of DJ interaction (play) networks based on festival event occurrence. A song's popularity was calculated based on the number of songs played in each time window. We also calculated the betweenness centrality, closeness centrality, in-degree and out-degree of DJs.

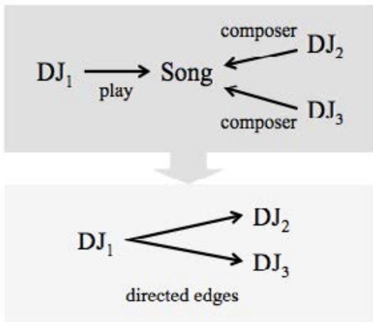

Figure 1. Construction of DJ Networks

The betweenness centrality of a node reflects the brokerage of the node interacting with other nodes in the network. For instance, a higher betweenness centrality signifies that the nodes connect different communities. A lower betweenness centrality indicates that the nodes are constrained within a community. Closeness centrality represents the total geodesic distance from a given node to all other nodes. In other words, both higher betweenness and closeness centralities indicate that the DJs tend to select songs of various DJs. Lower betweenness and closeness centralities signify that the DJs tend to select songs within the same clusters. In-degree is the number of a DJ's songs played by other DJs. Out-degree is the number of a DJ's play count of other DJs' songs.

4.3 Audio Analysis

We extracted audio features related to tempo, volume, key and timbre from 3172 songs. The sequential features are collapsed into mean and standard deviation values to maintain song-level value and dynamics [1]. A total of 52 dimensions are used, including tempo (1), mean of RMSE (1), mean of Chroma (12), mean of MFCC13 (13), standard deviation of Chroma (12) and standard deviation of MFCC13 (13).

5. IMPLEMENTATIONS & RESULTS

We fit a longitudinal fixed effects model:

$$Y_{k,t+1} = Y_{k,t} + \mathbf{S}_k\phi + \mathbf{W}_{ij,t}\beta + \mu_k + \tau_t + e_{k,t+1} \qquad (1)$$

, where the dependent variable, $Y_{k,t+1}$ is the frequency of a song k that was played in the event t+1. $Y_{k,t}$ is the lagged dependent variable (t). By including the lagged dependent variable, we expect to control for "mean reversion" and self-promotion effect.

μ_k is a vector of the fixed effects for every song k. By including this, the time-invariant and song-specific factors are all controlled. For example, the effects of the composer, the label, and the performing artists are all controlled for with μ_k.

τ_t is a vector of time fixed effects. Each song is assumed to be played at a particular time whose characteristics such as weather and social events would have an exogenous effect on $Y_{k,t+1}$. τ_t controls for the unobserved heterogeneity specific to the temporal points.

$\mathbf{S}_k$ is the vector of the song k's audio features which include the average and standard deviation of Chroma, MFCC, RMSE, and tempo. The value of audio features is time-invariant and, therefore, perfectly correlated with the fixed effects (μ_k). To avoid perfect collinearity with the fixed effects, we quantize the values into five levels, and make a five-point variable for each characteristic.

$\mathbf{W}_{ij,t}$ is the vector of the network covariates. Network centralities of DJ i who composed k are calculated using a network at time t. In the network matrix, the element w_{ij} is the frequency i played j's song at time t.

This research focuses on two distinctive determinants of DJ popularity in Electronic Dance Music (EDM) culture. While a DJ's individual artistic tastes influence the construction of playlists for festivals, social relationships with other DJs also have an effect on the promotion of a DJ's works. To test this idea, an analysis of the effect on song popularity by DJ social networks and song audio features was conducted. Song popularity among DJs was used as a dependent variable. We conducted three different Longitudinal Fixed Effect Models. Model 1 finds the influence

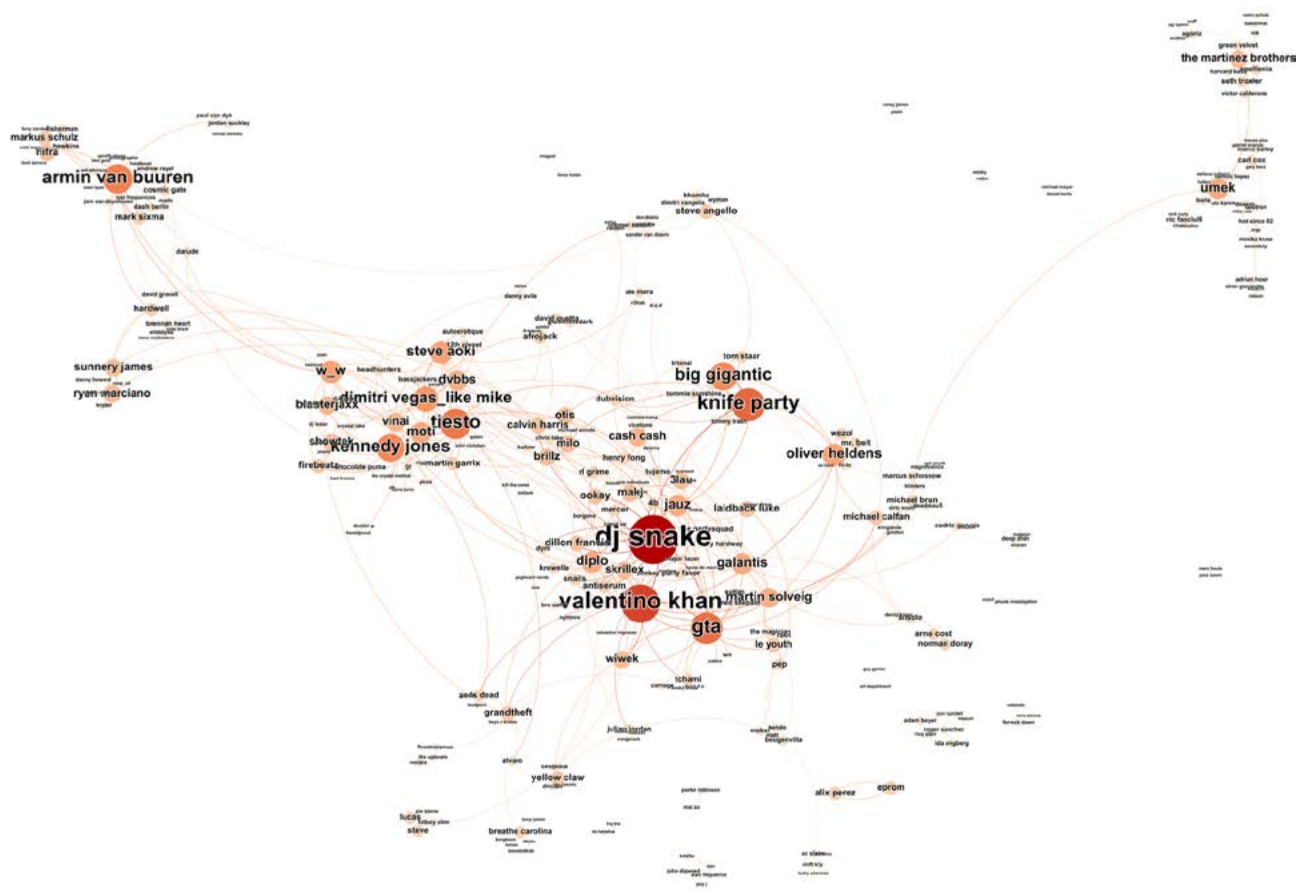

Figure 2. Backbone Network Graph of Ultra Music Festival 2015 Miami.

of audio features on song popularity, and Model 2 determines the effect of social relationships on song popularity. In this case, social relationship information such as betweenness, closeness, in-degree and out-degree were used as independent variables when audio features such as RMSE, tempo, Chroma and MFCC were used as control variables. This analysis was based on 77 different time windows. For Model 3, we combine Model 1 and Model 2, controlling the audio features and social relationships on song popularity.

Model 1 shows stable results indicating the presence of shared audio features within DJ networks (Appendix 1). In particular, the mean of Chroma 10 negatively correlated with song popularity ($p < 0.001$). Chroma 10 represents "A" pitch, which can be expressed as "A" key. Considering that song popularity is calculated based on DJs playing other DJs' songs, this result suggests that DJs tend to avoid using "A" key when composing songs. Therefore, we can argue that commonly shared artistic tastes exist. However, artistic tastes will continue to change depending on trends. Further study is needed to better interpret the relationships between audio features and song popularity (Table 1).

Popular songs	Popularity	Chroma10
W&W – The Code	92	0.3003
Hardwell - Jumper	104	0.3012
Blasterjaxx – Rocket	84	0.2890
Martin Garrix – Turn Up The Speaker	88	0.2349
Markus Schulz	52	0.2201

Table 1. Example of songs' popularity and Chroma 10, (mean of entire song's Chroma 10 = 0.3770; mean of entire songs' popularity = 7.4943)

On the other hand, social networks of DJs are expected to be more consistent than artistic tastes. Based on Model 2, the effect of DJ social relationships on song popularity showed firm stability (Appendix 1). Based on Model 3, audio features and DJ social networks independently influence song popularity. Despite socially biased networks of DJs, DJs appeared to have shared preferences on audio features within their clusters. Table 2 shows negative correlations of song popularity on both betweenness ($p < 0.05$) and closeness ($p < 0.001$) of DJ networks. In other words, the more popular a song is, the more often the song is played within the cluster (Figure 4).

Variables	Coefficients
Song Popularity	0.112*** (0.011)
In-Degree	-0.001 (0.001)
Out-Degree	-0.000 (0.001)
Closeness	-0.382*** (0.079)
Betweenness	-0.000* (0.000)
Constant	-3.274 (2.296)

Table 2. The Result of the Fixed Effect Model (Standard Errors in Parentheses; *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$)

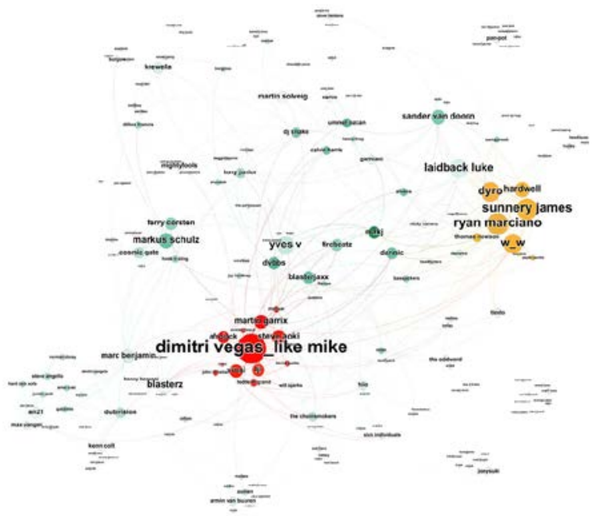

Figure 4. Composers of popular songs colored within the DJs clusters. (Tomorrowland 2014, Belgium)

Based on this result we can conclude that DJs tend to play songs composed by DJs from their exclusive groups independently from audio features. To conclude, H1 is supported by Models 1 and 3. H2 is supported by Models 2 and 3.

6. CONCLUSION

This research focuses on understanding the mechanism of artistic preferences among DJs. The artistic preferences of universal audiences are not considered in this research. Thus, the network cluster effect shown in this research needs to be considered as a social bias effect among DJs' artistic collaboration networks rather than the popularity of universal audiences. However, the result of the research shows that DJs tend to prefer DJs who are centered within their clusters. Therefore, the social networks of DJs influence on their song selection process.

The contributions of this research are as follows. Firstly, creative culture consists of complex dynamics of artistic and sociological elements. Therefore, it is important to consider both the social networks of artist communities and their artistic representations to analyze creative culture. Secondly, the proposed research methodology can help to unveil hidden insights on DJs' creative culture. For instance, DJs have unique nature of composing new songs by manipulating and remixing existing songs created by themselves or other DJs. Burnard [14] stated that the artistic creativity is often nurtured by artists who build on each other's ideas by manipulating the existing artworks. The understanding of this interesting collaborative culture can unveil novel insights on creative collaboration.

For future works, we will research the mechanism of artistic preferences of universal audiences along with DJs' collaboration networks. In addition, more detailed research on the effects of audio features on each cluster can provide deeper insights on understanding EDM culture. By analyzing the networks of DJs' remixing behavior and state of the art audio analysis, we can further investigate the clusters of DJs' artistic tastes and their collaboration patterns.

Acknowledgments

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APPENDIX

VARIABLES	Model (1)	(2)	(3)
Chroma_mean1_quint	0.279 (0.208)		0.277 (0.208)
Chroma_mean2_quint	0.081 (0.077)		0.081 (0.077)
Chroma_mean3_quint	-0.003 (0.016)		-0.004 (0.016)
Chroma_mean4_quint	-0.306* (0.125)		-0.305* (0.124)
Chroma_mean5_quint	-0.043*** (0.012)		-0.044*** (0.013)
Chroma_mean6_quint	0.525* (0.242)		0.528* (0.242)
Chroma_mean7_quint	0.008 (0.009)		0.007 (0.009)
Chroma_mean8_quint	-0.008 (0.019)		-0.009 (0.019)
Chroma_mean9_quint	-0.105 (0.063)		-0.106 (0.063)
Chroma_mean10_quint	-0.089*** (0.011)		-0.090*** (0.011)
Chroma_mean11_quint	-0.052* (0.021)		-0.053* (0.021)
Chroma_mean12_quint	0.096 (0.111)		0.097 (0.112)
Chroma_std1_quint	-0.019 (0.033)		-0.019 (0.032)
Chroma_std2_quint	-0.252 (0.177)		-0.253 (0.177)
Chroma_std3_quint	-0.016 (0.140)		-0.015 (0.139)
Chroma_std5_quint	-0.042*** (0.009)		-0.042*** (0.008)
Chroma_std6_quint	0.729* (0.330)		0.725* (0.328)
Chroma_std7_quint	-0.004 (0.030)		-0.003 (0.030)
Chroma_std8_quint	0.653* (0.306)		0.650* (0.306)
Chroma_std9_quint	-0.043* (0.022)		-0.044* (0.023)
Chroma_std10_quint	-0.185*** (0.035)		-0.185*** (0.034)
Chroma_std11_quint	-0.036 (0.075)		-0.035 (0.075)
Chroma_std12_quint	0.340 (0.205)		0.338 (0.204)
MFCC_mean1_quint	-0.059*** (0.016)		-0.058*** (0.015)
MFCC_mean2_quint	0.078 (0.194)		0.079 (0.193)
MFCC_mean3_quint	-0.169*** (0.048)		-0.167*** (0.047)
MFCC_mean4_quint	-0.032 (0.020)		-0.032 (0.021)
MFCC_mean5_quint	0.108 (0.055)		0.108 (0.056)
MFCC_mean6_quint	0.020 (0.044)		0.019 (0.042)
MFCC_mean7_quint	0.046 (0.116)		0.046 (0.115)
Continued (…)	Continued (…)	Continued (…)	Continued (…)

Continued (…)	Continued (…)	Continued (…)	Continued (…)
MFCC_mean8_quint	0.050 (0.049)		0.051 (0.048)
MFCC_mean9_quint	0.148* (0.076)		0.147* (0.075)
MFCC_mean10_quint	-0.097 (0.069)		-0.097 (0.069)
MFCC_mean11_quint	0.016 (0.014)		0.015 (0.015)
MFCC_mean12_quint	-0.087* (0.036)		-0.089* (0.035)
MFCC_mean13_quint	0.005 (0.011)		0.005 (0.011)
MFCC_std1_quint	-0.042 (0.035)		-0.043 (0.034)
MFCC_std2_quint	0.034 (0.086)		0.035 (0.086)
MFCC_std3_quint	-0.053 (0.047)		-0.052 (0.046)
MFCC_std4_quint	0.038 (0.037)		0.038 (0.037)
MFCC_std5_quint	-0.100** (0.031)		-0.100** (0.032)
MFCC_std6_quint	-0.318** (0.097)		-0.318** (0.096)
MFCC_std7_quint	-0.103 (0.071)		-0.104 (0.070)
MFCC_std8_quint	0.141** (0.053)		0.142** (0.054)
MFCC_std9_quint	-0.053* (0.022)		-0.052* (0.024)
MFCC_std10_quint	0.175 (0.106)		0.177 (0.107)
MFCC_std11_quint	-0.017 (0.014)		-0.018 (0.014)
MFCC_std12_quint	0.017 (0.011)		0.019 (0.012)
MFCC_std13_quint	0.020 (0.025)		0.020 (0.025)
RMSE_mean_quint	0.005 (0.019)		0.005 (0.019)
Tempo_quint	0.010 (0.006)		0.010 (0.006)
Song popularity	0.109*** (0.011)	0.114*** (0.011)	0.112*** (0.011)
In_degree		-0.001 (0.001)	-0.001 (0.001)
Out_degree		-0.000 (0.001)	-0.000 (0.001)
Closeness Centrality		-0.383*** (0.079)	-0.382*** (0.079)
Betweenness Centrality		-0.000* (0.000)	-0.000* (0.000)
Constant	-3.853 (2.298)	0.567*** (0.115)	-3.274 (2.296)
Song fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Observations	241,072	241,072	241,072
R-squared	0.1335	0.1323	0.1338
Adjusted R-squared	0.1214	0.1205	0.1218
Number of id	3,172	3,172	3,172

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Appendix 1. Fixed Effect Model for Model (1), (2) and (3).