

The Charted DJ Network of Resident Advisor: Detecting Collaborative Connections
& Measuring Popularity in EDM DJ Communities

1003547

Oxford Internet Institute, University of Oxford

The Charted DJ Network of Resident Advisor: Detecting Collaborative Connections & Measuring Popularity in EDM DJ Communities

With its roots in disco, beatbox, and African American culture from the mid-1980s, EDM – an umbrella term for a broad array of musical styles – emerged in the mid-1980s in Detroit, Michigan, U.S.A. and was, contemporaneously, adopted by the grungy ravers of London and Berlin then later in the discotecas of Ibiza (Rietveld: 2011; Loza: 1996). Today, EDM is enjoyed by a panoply of different people and as a genre encompasses multiple styles ranging from ambient or beatless music to 200-beats-per-minute hardcore; prime examples include house music, techno, dubstep, trance, minimal, and IDM (Intelligent Dance Music). Typified by deliberately synthetic sounds and rhythms with hints of live instrumentation or singing all mixed via analogue vinyl or digital music compiling software such as Ableton or Logic Pro, EDM recordings are produced primarily in real-time at dance clubs and parties by disc jockeys (DJs) (Montano: 2010). With the advent of Web 2.0 and the widespread commercialization of EDM culture, audiophiles and emerging DJs can now promote themselves online, grow a fan base, support or communicate with other DJs or labels, and book gigs around the world – maybe landing a prime record deal or prestigious club residence.

Founded in 2001, Resident Advisor (RA) – an online music magazine and community engagement platform – showcases the newest tracks, albums, artists, clubs, and events happening across the globe. The RA fan base is more geared towards the “underground” music scene shying away from commercial pop and electronic music that has been popularised by the likes of David Guetta, Tiësto, Avicii, DeadMau5, and Calvin Harris, in favour, of Richie Hawtin, Sven Väth, Ricardo Villalobos, Len Faki, Dillweed, Steffi, Ben Klock, and others. Since 2008, RA has polled its community in voting for the top 100 DJs per year then publishing the top tracks, mixes, albums, records, etc.; additionally, DJs and label producers can create profiles with biographical details, reviews of albums and mixes, or lists

of upcoming events and ticket purchasing information; fans can, in turn, favourite, comment, and buy tickets.

What makes the platform most interesting is how it corroborates fan development and popularity by allowing DJs to support other DJs, show fans their current tastes, and communicate musical inspiration with the creating and sharing of playlists called, “charts”, published monthly. These charts provide a treasure-trove of data not only from a fan’s point of view, but also from a social network analytical one. Because the underground music scene is debatable, shrouded in a certain connoisseurship, and not necessarily defined, it was of interest to construct a representation of this network to better unpack DJ and EDM culture by DJ charting habits. This not only elucidated, which top 1000 DJs were and are actively or passively promoting themselves, their musical genres, other DJs, and labels, but it also revealed the existence of discreet communities reflecting the assortativity of shared musical interests, geography in DJ residences, artistic collaboration, and label affiliation. By using social network analysis and graph theory, we investigate, visualize, and narrate the story of the temporal development of this online social network.

After examining actors, structures, and communities within the charted DJ network, we were able to trace the formation of mesoscopic communities and envisage overall trends in the tastes of certain DJs, labels, and their respective musical genres. In fact, the micro-activity of charting other DJs reveals a core group of tastemakers, who moderately affect macro trends that may shape or, at the very least, provide inklings concerning which DJs are collaborating or producing together and which genres of EDM are most favoured in the RA community.

Methods

Using data mining software, import.io, we scraped the entire archive of DJ chartings by the top 1000 DJs from 2007 to 2015. With the network analysis and visualization software, Gephi, the data culminated in the creation of a weighted

digraph – a network – called the Charted DJ Network (CDJNx), which totals 7,888 nodes as DJs and 54,360 edges as chartings. Each DJ in the network has 13 key attributes country of origin, number of favourites on RA, a Boolean value for whether or not the charted DJ is in the top 1000 list on RA, and 9 rankings (if applicable) of that DJ on the top 100 DJ rankings between 2007 and 2015. The dynamic and flow of the network is the following: When DJ, A, charts DJ, B, this is perceived as a directed endorsement from A to B. The number of endorsements between A to B determines the weight of each charting.

To investigate the mesoscopic community structures within the CDJNx, we use modularity – “a scaled *assortativity* measure based on whether high-strength edges are more or less likely to be adjacent to other high-strength edges” – to detect communities in an algorithm developed by Blondel et al. in 2008 (Porter et al.: 2009, p. 1089). Because modularity is fundamentally the determination of partition in a network on account of the strength of edge weight outside of random chance, it can sometimes detect finicky community clusters depending on the resolution. Nevertheless, we use modularity despite the limitations to demarcate DJ communities, which are shaped by genres, collaboration, and label affiliation.

Because of the nature of the data, i.e. annual chartings between DJs, we conducted a recursive longitudinal study tracing the generativity of the network from 2007 to 2015. Instead of comparing network activity between the years isolating the previous year from the other as if in a temporal vacuum, we chose to follow an experimental method described in recent network studies research concerning the statistical properties of community structure in large information networks. Leskovec et al. report,

A generative model, in which new edges are added via an iterative “forest fire” burning process, is able to produce graphs exhibiting a network community structure[, where] tight but almost trivial communities [are observed] at very small scales, and at larger size scales, the best possible

communities gradually “blend in” with the rest of the network [] thus becom[ing] less “community-like.” (2008, p. 695)

This method proved useful in studying the development of the CDJNx and was implemented by comparing the network structure and communities from its inception in 2007 with that of its succeeding year – cumulatively adding the edge list of each year up to 2015. For each network phase, we detected the communities created by the DJ charting and coded them according to information available from RA concerning the EDM zeitgeist of that year, then used k-core filtration to percolate the network to its critical threshold, thus, producing the core structure to identify key DJs as tastemakers (Porter et al.: 2009; Borgatti: 2005; Leskovec et al.: 2008). To aid in the process of coding the network, we visualized the Charted DJ Reciprocity Network: 2007-2015, calculated the sum of the favorites of every DJ in that network, and discussed how these mutual chartings produce a strong framework to detect and code the resultant communities. Additionally, we used eigenvector centrality to determine DJs with the most influence acting as hubs in the network, i.e. those who had the most charting activity at risk of influencing more nodes in the chain of charting DJs (Borgatti: 2005, p. 61).

From an individualistic look at influence with eigenvector centrality, we then examined a collective measure for popularity determined by actors in each DJ community. We took the sum of the favorite count of every DJ in each grouping as a rough estimation of the most favored qua popular EDM genres in the community of collaborators and label-mates. Because our favorite count data limit us to the present – not having access to the exact favorite count of DJs in the preceding years – we only conducted these inquiries on the completed network, CDJNx: 2007-2015. Finally, to determine whether or not there is a possible correlation between favorite count and degree measurements, we performed a linear regression study on the number of favorites in relation to the eigenvector centrality, in-degree, out-degree, and degree measurement

Results

Table 1. Results of Generative Analysis on CDJNx from 2007-2015									
	Cumulative Year Phases								
	2007	07-08	07-09	07-10	07-11	07-12	07-13	07-14	07-15
# of DJs	1066	2020	3032	4005	4932	5831	6630	7257	7888
# of Chartings	2932	8256	16347	25123	33798	41065	42471	50910	54360
Avg. Degree	5.5	8.2	10.8	12.5	13.7	14.1	14.1	14	13.8
Avg. w. Degree	3.3	4.8	6.4	7.3	9.9	9.8	10.5	10.2	9.9
Diameter	11	13	9	9	9	9	9	8	8
Avg. Path	4.2	3.8	3.5	3.4	3.3	3.3	3.3	3.2	3.2
Density	0.003	0.002	0.002	0.002	0.001	0.001	0.001	0.001	0.001
Modularity	0.46	0.38	0.35	0.34	0.35	0.35	0.36	0.35	0.36
# of Communities	9	9	7	7	7	6	6	6	6
Avg. Cluster Coefficient	0.052	0.056	0.075	0.092	0.11	0.12	0.12	0.13	0.13
Inter-Chartings (%)	38	53	48	48	40	51	49	48	45
Intra-Chartings (%)	62	47	52	52	60	49	51	52	55
Mutual Chartings (%)	2.1	5.1	5.8	5.8	5.9	6	5.8	5.7	5.6
Self-Loops (%)	3.4	2.3	1.7	1.4	1.2	1	0.9	0.9	0.8

Table 2. Results of K-core Degeneration Analysis on Resident Advisor DJ Charts from 2007-2015									
	2007	07-08	07-09	07-10	07-11	07-12	07-13	07-14	07-15
K till Critical Max	9	16	23	29	35	39	41	43	44
DJs Left (%)	6	5.4	5	5	4	4	3	3	3
Edges Left (%)	16	16	19	19	16.4	15	16	12	14
								822,438	# of Faves
								19	% of Total

For reference to the approach concerning this generative process and to actually see the network, please see figures 1 to 18. Please note, how overtime the structure of the community expands and fewer communities begin to form quite saliently as the modularity colors indicate. In connection with Table 1, as the number of DJs

and charts increase overtime, the diameter, average path length, and the number of communities detected with 1 resolution lessen. The calculation of the distance is interesting, but not necessarily useful for our purposes. The modularity decreasing, as the network gets larger was also observed by Leskovec et al. On account of examining the network's growth overtime via this generative process, we were able to not only find observations concerning the endogenous meanings in the network pertaining to DJ charting habits and core group identification in the creation of genre and record label oriented EDM communities but also corroborate and verify a network studies observation with empirical evidence.

Table 3.		Communities within CDJNx: 2007		
Group #	% of DJs	% of charts	Genres	Top Labels & DJs
1	18	13	Berghain Techno, Deep House, Minimal	Wolf+Lamb, Ostgut Ton, Tresor, Ovum; Seth Troxler, Ben Klock, Adam Beyer, Marcel Dettmann, Marco Carola, Carl Craig
2	17	11	Techno, Technohouse, Minimal, Trance, Ambient	Minus, Cadenza, Get Physical; Richie Hawtin, Luciano, DJ Koze, Claude Von Stroke, Burial, Omar-s, M.A.N.D.Y
3	12	7	Minimal, Progressive House	Radio Slave, Dubfire, Steve Lawler, Ricardo Villalobos, Jamie Jones, Radio Slave, Dubfire, Steve Lawler
4	12	6	IDM, Electronica	Get Physical crowd, old school; Booka Shade, Sasha Digweed, Trentemoller
5	10	6	Detroit style, electronic house	Diynamics, some Innervisions, Solomun, Joris Voorn, Agoria, Deetron
6	9	9	Deep house, minimal, darker	Carl Cox, Robert Hood, Green Velvet, Yousef
7	8	3	House	Commercially successful, Justice protégé of Daft Punk; Daft Punk, Justice, Tiga, A-Trak, Kanye Wes
8	8	4	dubstep, dark	Gui Boratto, Modeselektor, Matthew Dear, Skream
9	5	3	Electro House	Innervisions; Dixon, Âme, Henrik Schwarz, Marcus Worgull

Communities within CDJNx: 2007-2015					
Table 4.					
	% of DJs	% of Charts	Genre	Top Labels	Top DJs
Community 1 – Electro House Mega- DJs	22	14	Electro House, Underground Pop, Nomadic	Kompakt, Innervisions, Warp Records, Life and Death, Dirty Bird, DFA Records, R&S Records, Ninja Tune, Dial, Rekids	Dixon, Tale of Us, Âme, Nina Kraviz, Daft Punk, Four Tet, DJ Koze, Caribou, Disclosure, Gui Boratto, Mano Let Tough, Eats Everything
Community 2 – DJ Legends	22	16	Techno, Technohouse, Minimal, Trance, Ambient	Cocoon, Minus, Drumcode, Soma, CLR, Ovum, Bedrock, Suara, Plus 8 Records, Traum Schallplatten	Richie Hawtin, Sven Väth, Adam Beyer, Marco Carola, Carl Cox, Laurent Garnier, Joris Voorn, Paul Kalkbrenner, Dubfire, Pan-Pot, Digweed, Sasha
Community 3 – Berghain Techno Giants	21	8	Berghain Techno, Pure Minimal, Dark, Industrial, & Dub	Ostgut Ton, Darkroom Dubs, Tresor, Hotflush, Hyperdub, L.I.E.S., Hessle Audio, Delsin	Ben Klock, Marcel Dettmann, Carl Craig, Jeff Mills, Recondite, Scuba, Joy Orbison, Robert Hood, Rødåd, Len Faki
Community 4 – Get Physical DJs	15	6	Electronica, IDM (Intelligent Dance Music), Minimal	Get Physical, Defected, Noir, Saved, Off, Viva, Plastic City, Katermukke	Booka Shade, Hot Since 82, Steve Lawler, Trentemoller, Groove Armada, Basement Jaxx, Frankie Knuckles, Detroit Swindle, Oliver Koletzki, And Him, M.A.N.D.Y.
Community 5 – Industry Standards	15	5	Deep House, Progressive House, Microhouse	Crosstown Rebels, Desolat, Hot Creations, Cadenza Records, Perlon, Mobelee, Wolf+Lamb, Visionquest, Diynamic, Poker Flat	Ricardo Villalobos, Maceo Plex, Seth Troxler, Jamie Jones, Nicolas Jaar, Maya Jane Coles, Solomun, Luciano, Art Department, MCDE
Community 6 – Bpitch Controllers	4	6	Electronic, IDM, Progressive House	Bpitch Control, Fabric Records, No. 19, Items & Things, Moodmusic, My Favorite Robot	Magda, Ellen Allien, Apparat, Marc Houle, Jimmy Edgar, Ivan Smagghe, Troy Pierce, Bloc Party, Visionquest, DJ Zinc

At the start of the network in 2007, the algorithm detected 9 communities. In every year following that, the number of communities slightly decreased as per the findings of Leskovec. Although this shows an arguable blending of DJs into communities without bases – bringing the modularity’s quality into question – we examined the core structures within every phase of the model (Table 2) and used the Charted Reciprocity DJ Network, which examines the mutual edges between DJs showing corroboration (see figure 19). Using this as a reference we were able to verify the key DJ collaborators in the network that would help in the process of

coding these communities.

In the next two tables, the results concerning eigenvector centrality and the relationship between the top 10 DJs are shown. As Table 6 shows the number of favorites does not necessarily determine whether or not a DJ actively uses or leverages the full potential of the charting platform. Richie Hawtin (0.08) and Dixon (0.03) for example two mega DJs, the former being a legend in the underground techno world and the latter also a longtime player in the industry but has until recently dominated the top lists as the best DJ each year since 2013.

DJ Name	Country	# of Faves	DJ Community	# Charted (in-degree)	# Chartings (out-degree)	Degree	Eigenvector Centrality	Betweenness Centrality
Richie Hawtin	CAN	22290	DJ Legends	10	15	25	0.08	1185
Ricardo Villalobos	CHL	21866	Industry Standards	64	0	64	0.6	0
Maceo Plex	USA	20301	Industry Standards	78	28	106	0.5	16255
Seth Troxler	USA	18198	Industry Standards	67	24	91	0.6	10809
Jamie Jones	GBR	17283	Industry Standards	64	8	72	0.5	1431
Ben Klock	DEU	17190	Berghain Techo Giants	86	109	195	0.8	55351
Dixon	DEU	16412	Electro House Mega-DJs	5	35	40	0.03	962
Tale of Us	ITA	16252	Electro House Mega-DJs	42	225	267	0.3	52089
Loco Dice	TUN	16244	Industry Standards	71	33	104	0.7	3780
Âme	DEU	15695	Electro House Mega-DJs	40	40	80	0.3	6999

DJ Name	Country	# of Faves	DJ Community	# Charted	# Chartings	Total Charts	Eigenvector Centrality	Betweenness Centrality
Radio Slave	GBR	6617	Electro House Mega-DJs	125	244	369	1	147507
Shed	DEU	4611	Berghain Techo Giants	115	6	121	0.99	5938
Levon Vincent	USA	6445	Berghain Techo Giants	96	67	163	0.89	69075
Mr. G	GBR	3357	Electro House Mega-DJs	100	0	100	0.88	0
Nina Kraviz	RUS	14612	Electro House Mega-DJs	82	9	91	0.83	4465
Robert Hood	USA	7758	Berghain Techo Giants	95	7	102	0.83	1726
Redshape	DEU	2900	Berghain Techo Giants	93	64	157	0.82	32622
Ben Klock	DEU	17190	Berghain Techo Giants	86	109	195	0.8	55351
Omar-s	USA	6592	Berghain Techo Giants	89	0	89	0.78	0
Mark Bloom	GBR	2848	Berghain Techo Giants	94	36	130	0.77	14985

In contrast, we have the top 10 DJs based on highest eigenvector centrality. Although these DJs have healthy numbers of favorites like Ben Klock (17,190) and Nina Kraviz (14,612)– two very important DJs, who were once romantically involved – have very high eigenvector centralities. Radio Slave tops the list, however, and is one of the most active users of RA community platform. Because many of these artists are producers by day and DJs by night, they commonly use the charting network as a means to promote fellow label mates. A good indication of this sort of behavior can be seen in the data, especially, when the number of out-degrees outnumber or are greatly larger than the number of in-degrees. This means that the DJs are consistently charted, but not hitting the radars of other DJs.

Table 8 Results of Regression Analysis			
	R	Intercept	R ²
Favourites ~ Eigenvector Centrality	7908.6	142.7	0.30***
Favourites ~ In-Degree	70.7	68.3	0.34***

The results of the regression analysis show that favorite count is significantly ($p < 2.2e^{-16}$) and positively yet moderately correlated to both eigenvector centrality and in-degree. For every 0.1 increase in eigenvector centrality, we can expect a 791 increase in the number of favorites. Additionally, every time a DJ is charted, he or she can expect the number of favorites to increase by approximately 71.

Discussion

2007 was the first year RA launched its charting system, so it is expected that the number of DJs using the platform would be significantly lower than the succeeding years. As a result the network shown in figures 1 and 2 shows a network that is still tightly structured, yet the cut between discreet partitions is not as salient. As the years progress and DJs begin to actively use the charting system, we start to see communities form. By examining the cores of the networks we can

better see how these DJ communities are formed. The communities revolve around shared EDM styles, mutual collaborators, and record label connections. The 9 communities initially detected in 2007 seem to be fragmentary measures of assortative connection, whereas by 2015 we can clearly see the development of 6 specific communities (tables 1 and 2). The 6 communities detected within the network and in context:

1. Electro House Mega-DJs: Group of DJs following electro house music appealing to wide groups of people. The DJs in this group share a nomadic DJing style, where their songs tend to guide the listener on a musical journey. In recent years, these DJs have risen to the surface of popularity. Most notably the breakthrough of Innervisions record label championed by Dixon, Âme, Henrik Schwarz, and Marcus Worgull marks a turning point for EDM of this caliber. Altogether these DJs make up 22% of the DJ community with a combined favorite count of 1,184,791 representing 27% of the total 4,390,020 favorites held by the total 7,888 DJs.
2. DJ Legends: This community of DJs represents the old guard of classic and endearing EDM. Richie Hawtin – the most favored DJ and a living legend in the industry – along with the likes of Sven Väth, a veteran of the Frankfurt school of techno, head the most prestigious record labels – Minus and Cocoon, respectively. Nevertheless, this community includes Digweed and Sasha, who were more popular before 2009, but still appear in the top 100 list annually. These DJs make up 22% of the network and are the most connected with 16% of all of the other groups. Despite these facts, they as an entire group possess 872,424 favorites roughly 20% of all the favorites.
3. The third largest group of DJs has been dubbed the Berghain Techno Giants, because most of the DJs in this group have had residencies at the Berghain – the most exclusive nightclub in the world, where only “true” ravers are allowed entrance. This Berlin institution through its label Ostgut Ton has manufactured a certain sound that is dark and eerie, yet maintains

a certain post-war German austerity. Most of the DJs in this group live in Berlin and have had residencies at the Berghain. Ben Klock and Marcel Dettmann are the two main DJs, who rose into prominence from 2008 to 2010. In figures 7, 9, and 10, the network begins to take shape with the folks at Berghain starting to form a conical flight from the 'mainstream' underground. This is a result of a cluster formation of DJs within the community that is solely connected to the Berghain Techno Giants, yet have created their own micro-community of harsher, synthetic beat lovers. Despite their starker tastes and exclusive attitude, the members in the Berghain Techno Giants tend to be the most active users of RA charting system (table 7). As a whole, the DJs in this entire community have 923,415 favorites representing 21% of the total.

4. The fourth community detected in this network is the Get Physical DJs, which is named after the record label that hosts many of these artists. Booka Shade and M.A.N.D.Y. are veterans of the Frankfurt school of techno. Many of the artists featured here are fans of Intelligent Dance Music or IDM, which has direct roots to early Detroit techno (Rietveld: 2011). The DJs in this group have the second lowest amount of favorites at 355,626 or 8%.
5. The fifth group has the same amount of people but an entirely different universe of favored talent. These Industry Standards are across the board considered some of the most important producers and visionaries in the DJ world. Right before Dixon and Âme of Innervisions in Electro House Mega-DJs took over the top of the lists, Ricardo Villalobos, Maceo Plex, Seth Troxler (of Visionquest), and Jamie Jones (of labels Crosstown Rebels, Hot Creations) were the biggest names between 2009 to 2012. These DJs are highly connected with each other and as a grand total possess 952,518 favourites, which is 22% of the total.
6. Finally, we have the BPitch Controllers, which represent a group of DJs, who tend to lean towards progressive house and IDM similar to that of the

Get Physical DJs. Nevertheless, they make up only 2% of the total favourites.

The construction of community in these networks interestingly reveals alliances between multiple different DJs across many genres. The most insular group is the Berghain Techno Giants with 17% of charting happening within the community, which may also account for their higher eigenvector values. The Electro House Mega-DJs tend to have the most inter-connections maintaining overall popularity amongst DJs. Finally, perhaps, the most intriguing factoid found within this data set that truly shows the power of collaboration, networking, and farming for favorites is the community with the highest number of favorites: the 408 DJs, who actively endorse each other in the CDJRNx (figure 19) totals to ~1.4 million favourites.

Conclusion

This project sought to examine <8,000 nodes with ~55,000 edges through a composition-decomposition, recursive longitudinal methodology and a black and white printer. Regardless, examining RA is not only fascinating from a musical and social science perspective, but it is also a commercial means by which artists can gain fans and find success. By unpacking these networks it was an interesting thought-experiment trying to localize the structural cues that would demarcate the next big trend or DJ in EDM culture. There were few instances where the core of the network did have some predictability value. Namely, the core of the CDJN_x: 2012 (figure 12). The year before Innervision dominated the charts, Âme – the DJ duo who co-founded the label with Dixon, Henrik Schwarz, and Marcus Worgull – appeared in the core group of DJs. Perhaps, a more thoughtful examination is warranted. The implicit limitation of this paper lies in the problem of quality assurance with respect to modularity and assortative scaling. Because of its random nature, it's hard to determine whether these are the verifiably true, stringent cuts and partitions of the DJ network. The objective was to visualize and

deconstruct a charted DJ network to better understand how significantly it related to popularity overtime.

References

- Bennett, Andy. (2014). Youth culture and the Internet: A Subcultural or post-subcultural phenomena? *Subcultures, Popular Music and Social Change* edited by The Subcultures Network. Cambridge, UK: Cambridge Scholars Publishing.
- Borgatti, Stephen. (2005). Centrality and network flow. *Social Networks*, 27(1): 55-71.
- Leskovec, J. et al. (2008). Statistical properties of community structure in large information networks. *WWW Consortium 2008*. ACM press: 695-705.
- Loza, S. (1996). Techno music and sonic communities: When modern markets and postmodern pleasure collide. *Journal of Popular Music Studies*, 8(1): 27-41.
- Montano, Ed. (2010). 'How do you know he's not playing Pac-Man while he's supposed to be DJing?': technology, formats and the digital future of DJ culture. *Journal of Popular Music Studies*, 29(3): 397-416.
- Nye, Sean. (2013). Minimal understandings: The Berlin decade, the minimal continuum, and debates on the legacy of German techno. *Journal of Popular Music Studies*, 25(2): 154-184.
- Osgerby, Bill. (2014). Subcultures, popular music and social change: Theories, issues, and debates. *Subcultures, Popular Music and Social Change* edited by The Subcultures Network. Cambridge, UK: Cambridge Scholars Publishing.
- Porter, M. et al. (2009). Communities in networks. *Notices of the American Mathematical Society*, 56(9): 1082-1097.
- Rietveld, H. (2011). Disco's revenge: House Music's nomadic memory. *Dancecult: Journal of Electronic Dance Music Culture*, 2(1): 4-23.
- Tjora, A. (2009). The groove in the box: a technologically mediated inspiration in electronic dance music. *Journal of Popular Music Studies*, 28(2): 161-77.

Appendix

Figure 1. Charted DJ Network: 2007

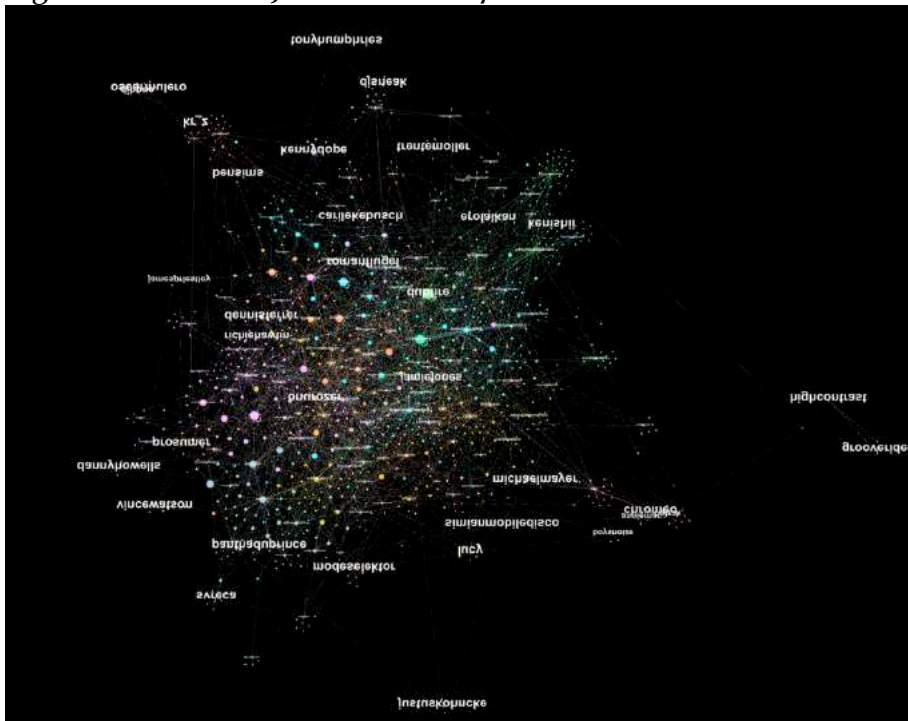


Figure 2. Charted DJ Network: 2007 (k=9)

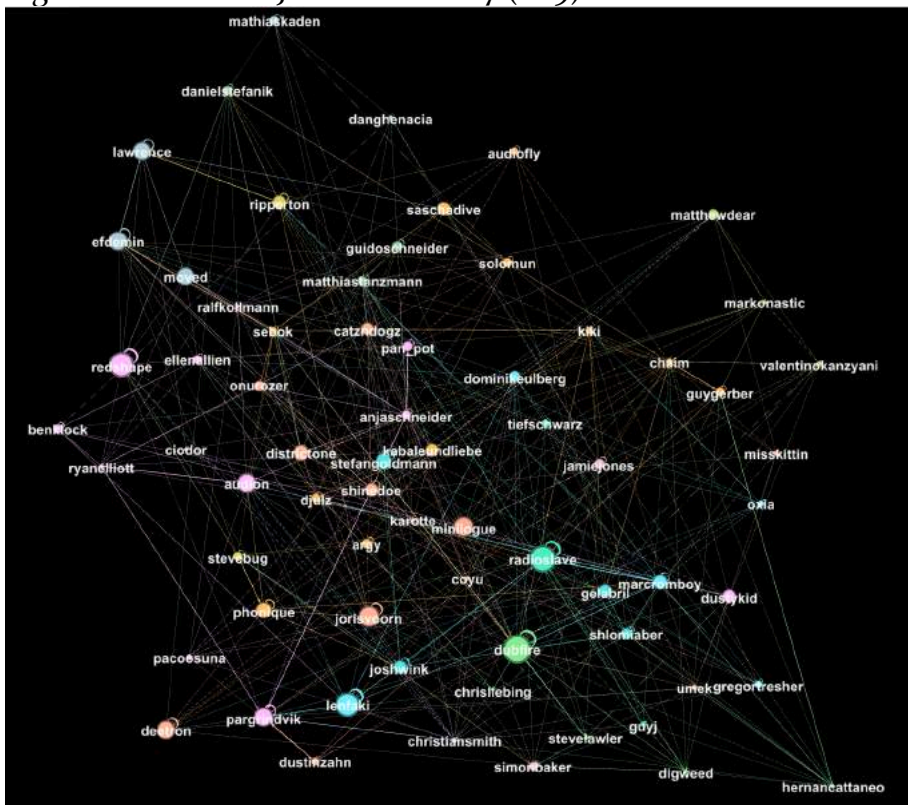


Figure 3. Charted DJ Network: 2007-2008

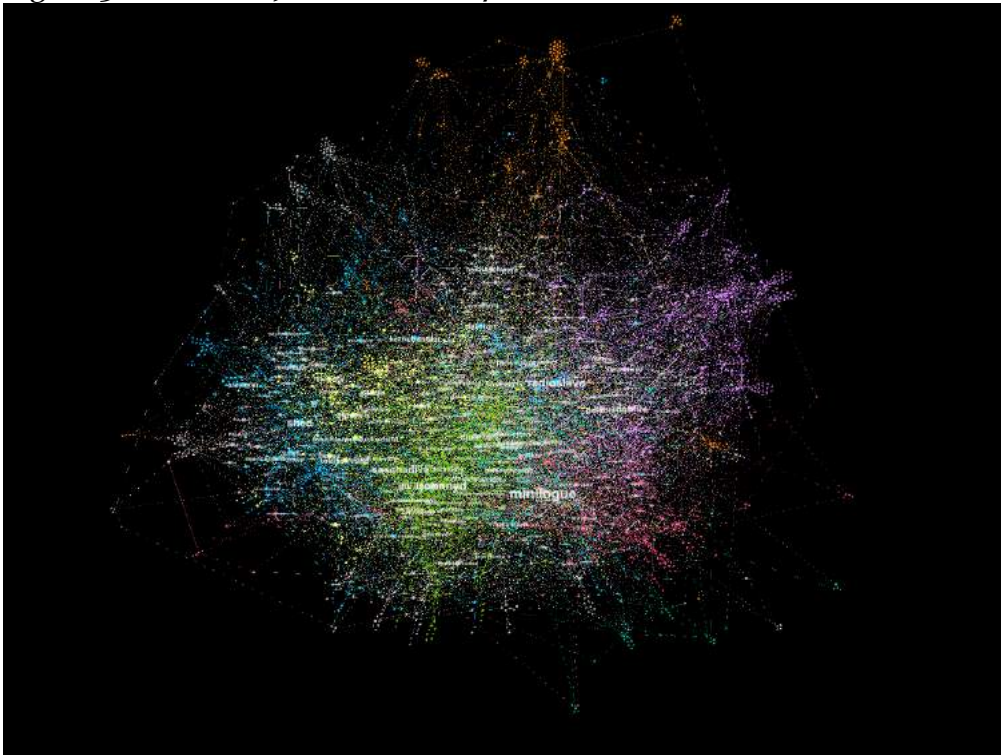


Figure 4. Charted DJ Network: 2007-2008 ($k=16$)

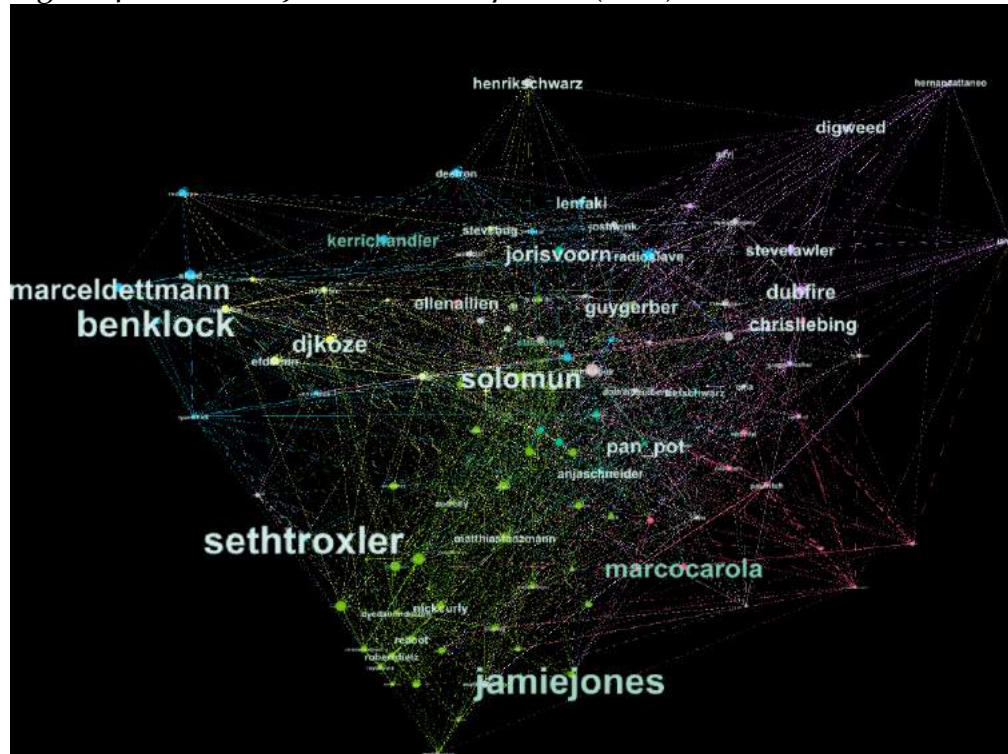


Figure 5. Charted DJ Network: 2007-2009

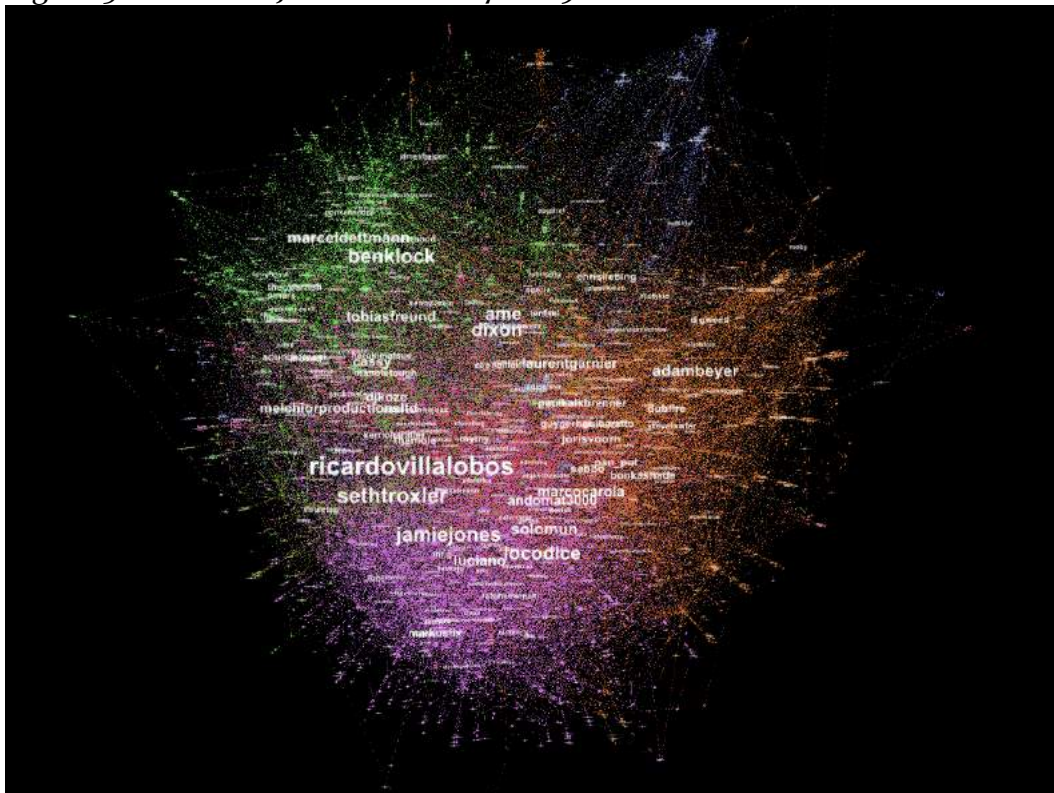


Figure 6. Charted DJ Network: 2007-2009 (k=23)

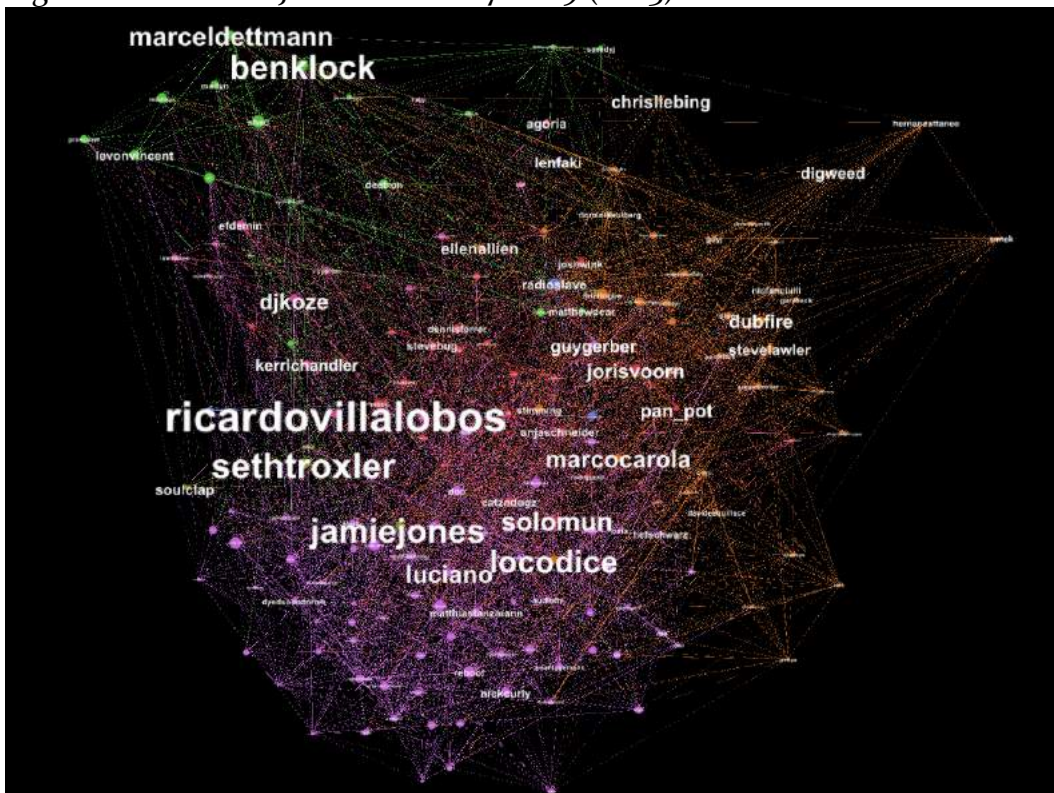


Figure 9. Charted DJ Network: 2007-2011

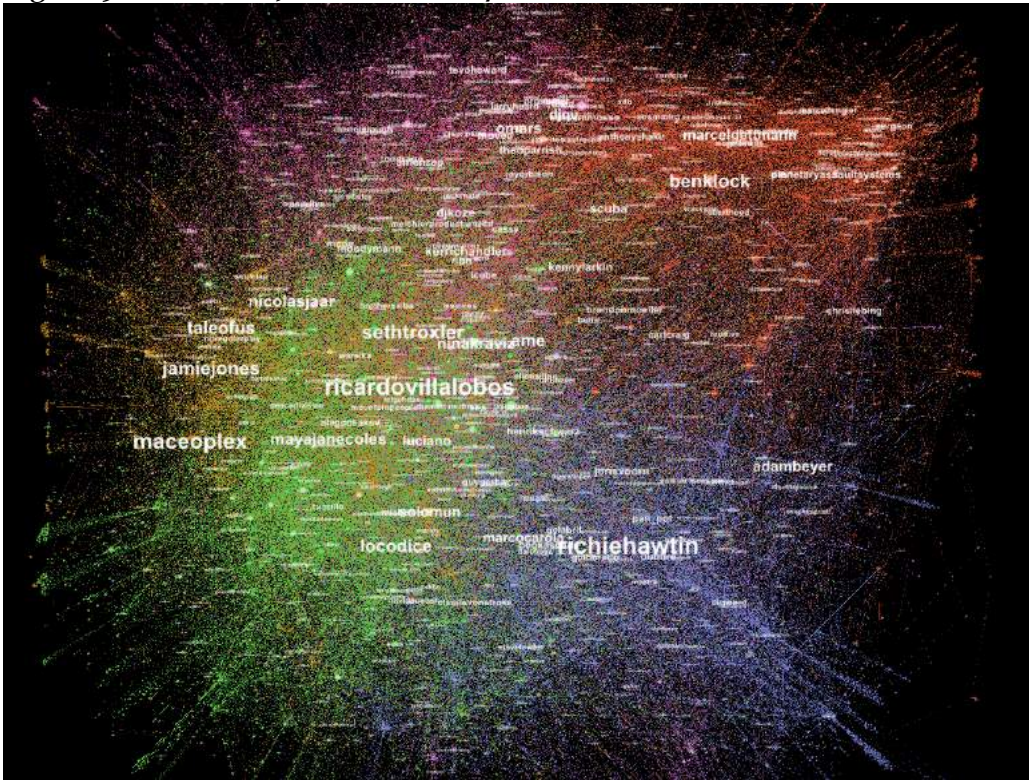
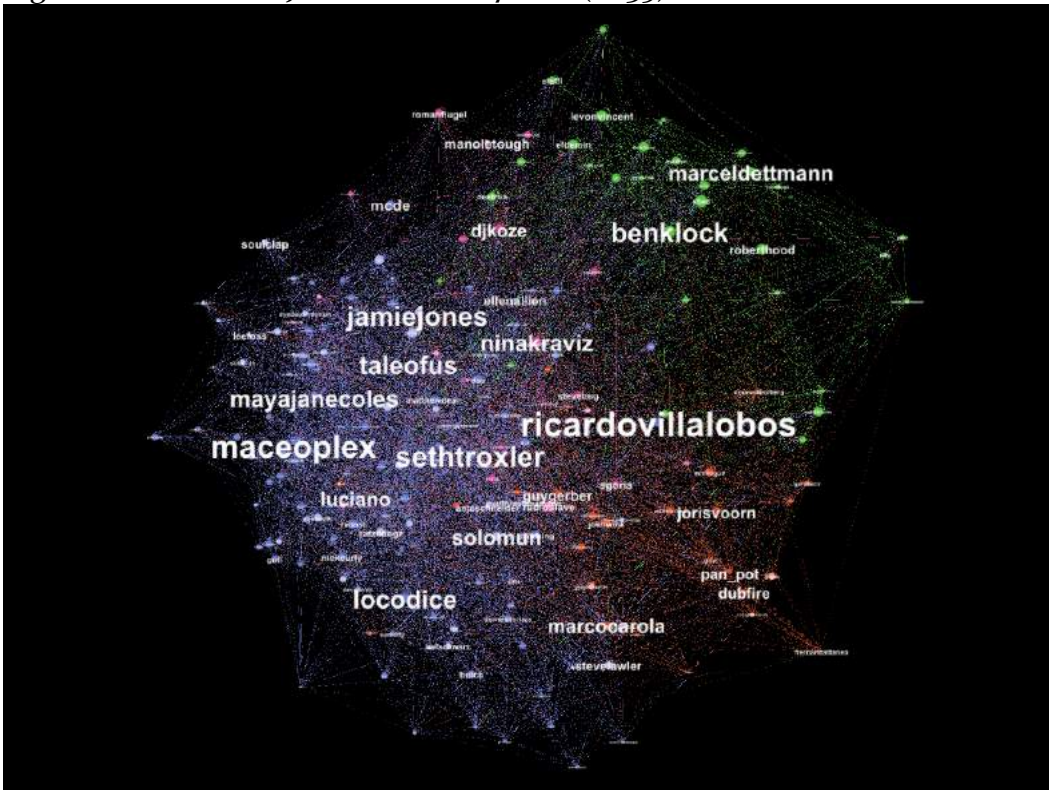
Figure 10. Charted DJ Network: 2007-2011 ($k=35$)

Figure 11. Charted DJ Network: 2007-2012

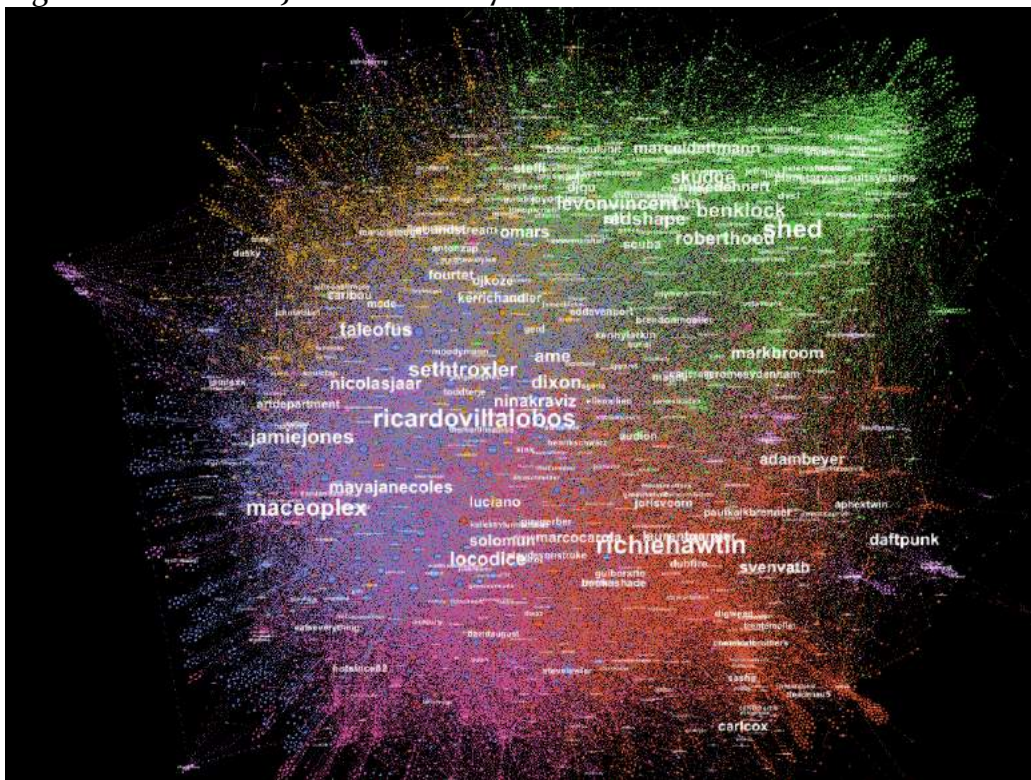
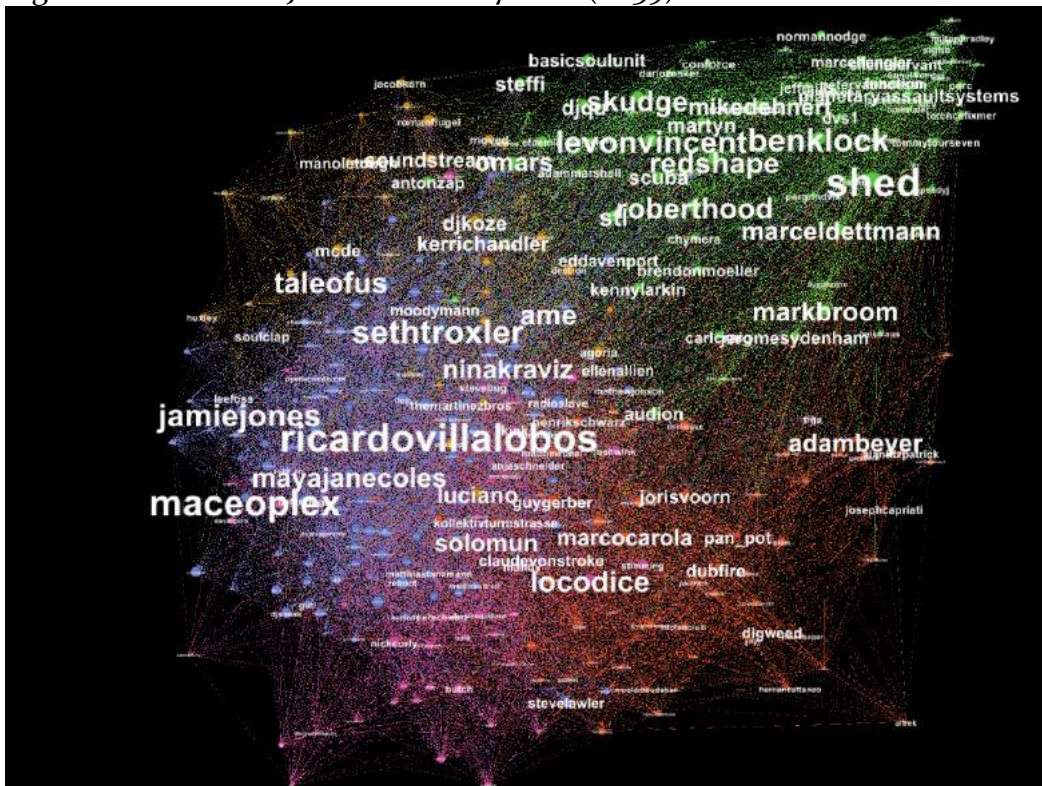
Figure 12. Charted DJ Network: 2007-2012 ($k=39$)

Figure 13. Charted DJ Network: 2007-2013

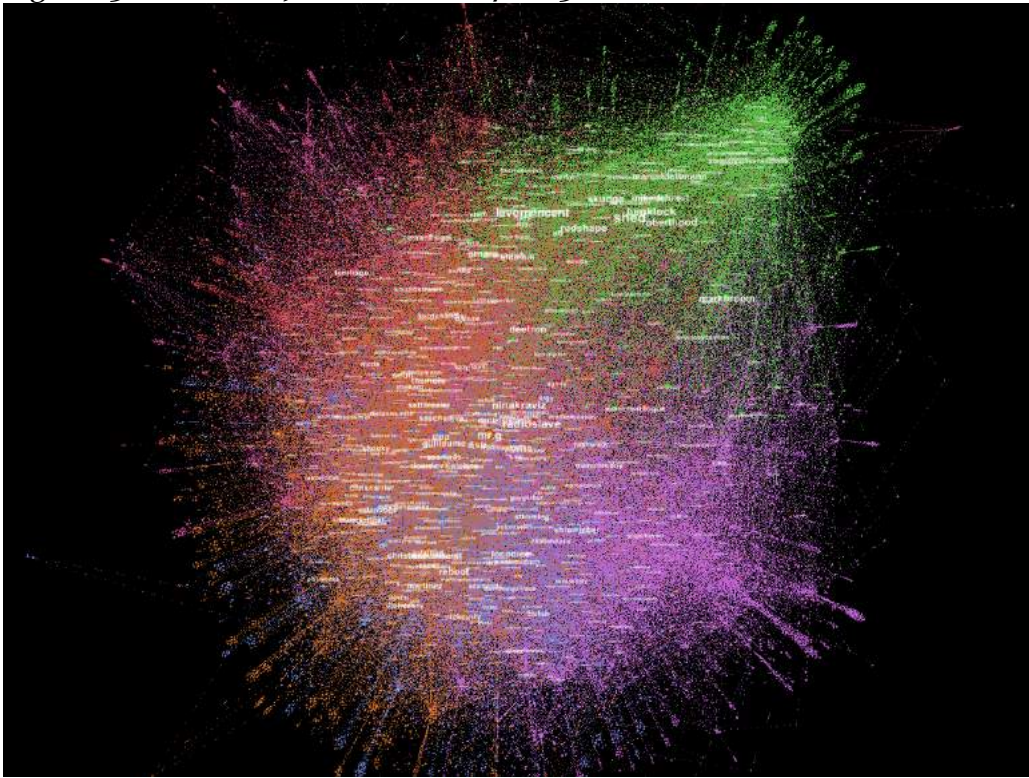
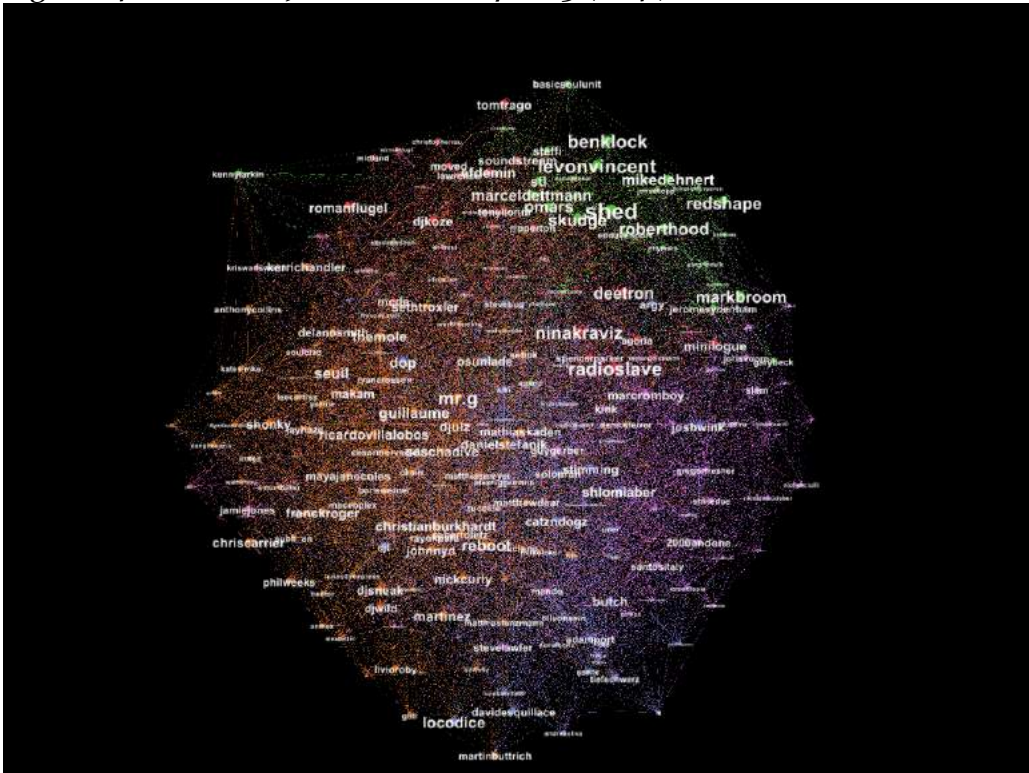
Figure 14. Charted DJ Network: 2007-2013 ($k=41$)

Figure 15. Charted DJ Network: 2007-2014

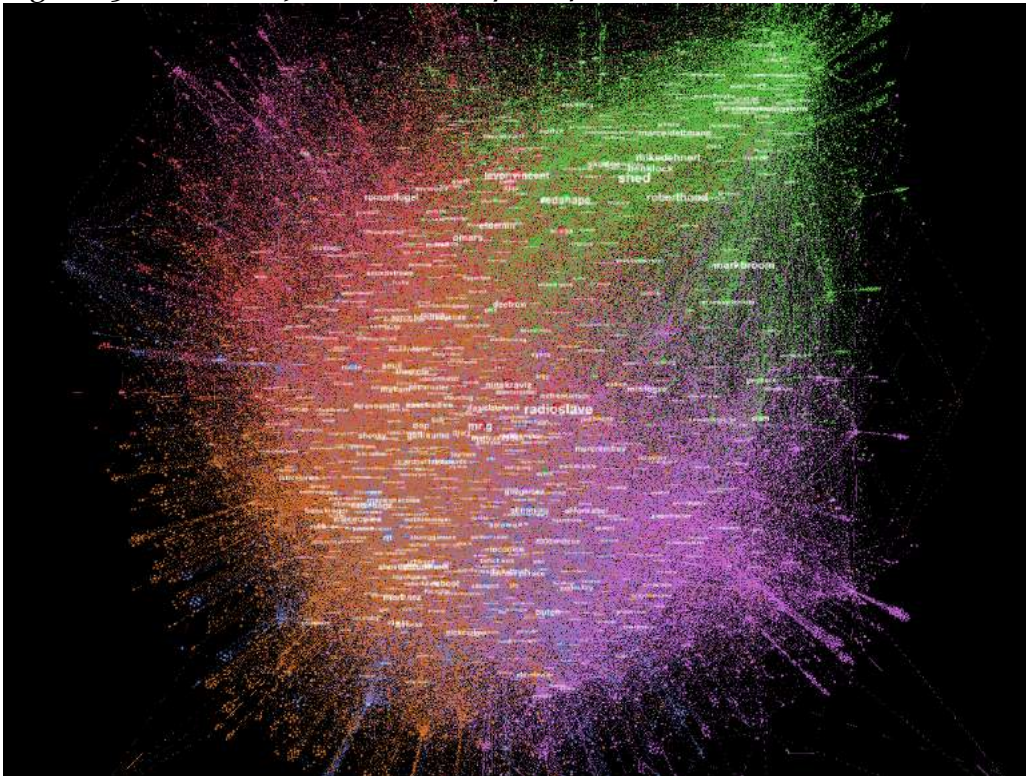
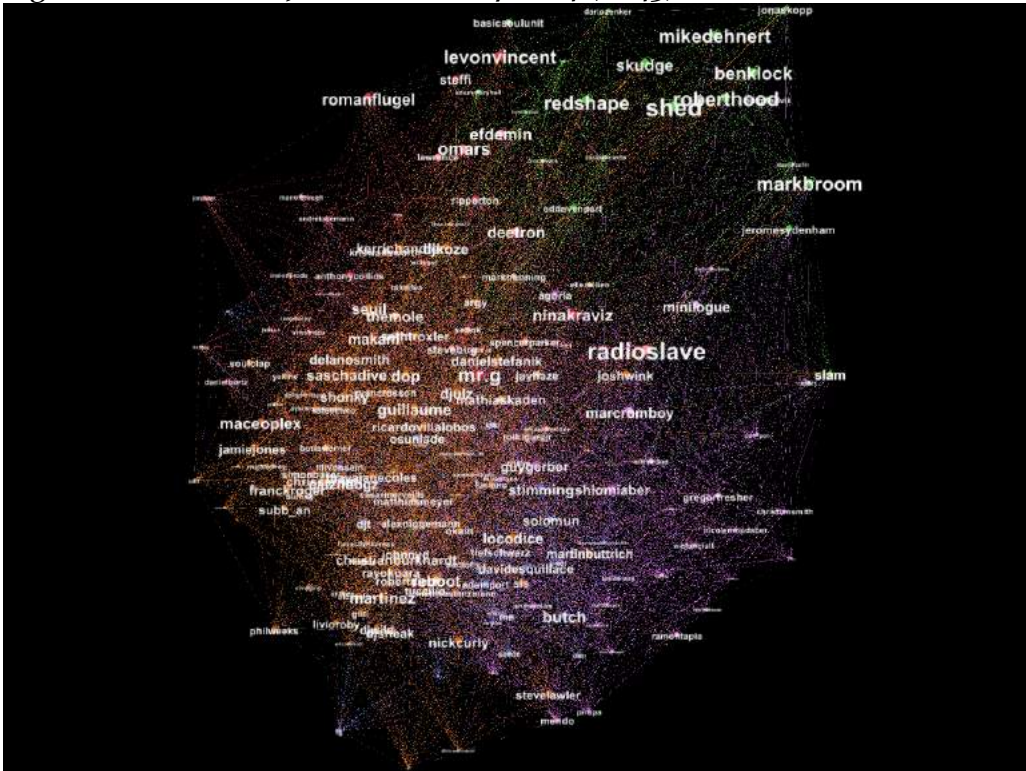
Figure 16. Charted DJ Network: 2007-2014 ($k=43$)

Figure 17. Charted DJ Network: 2007-2015

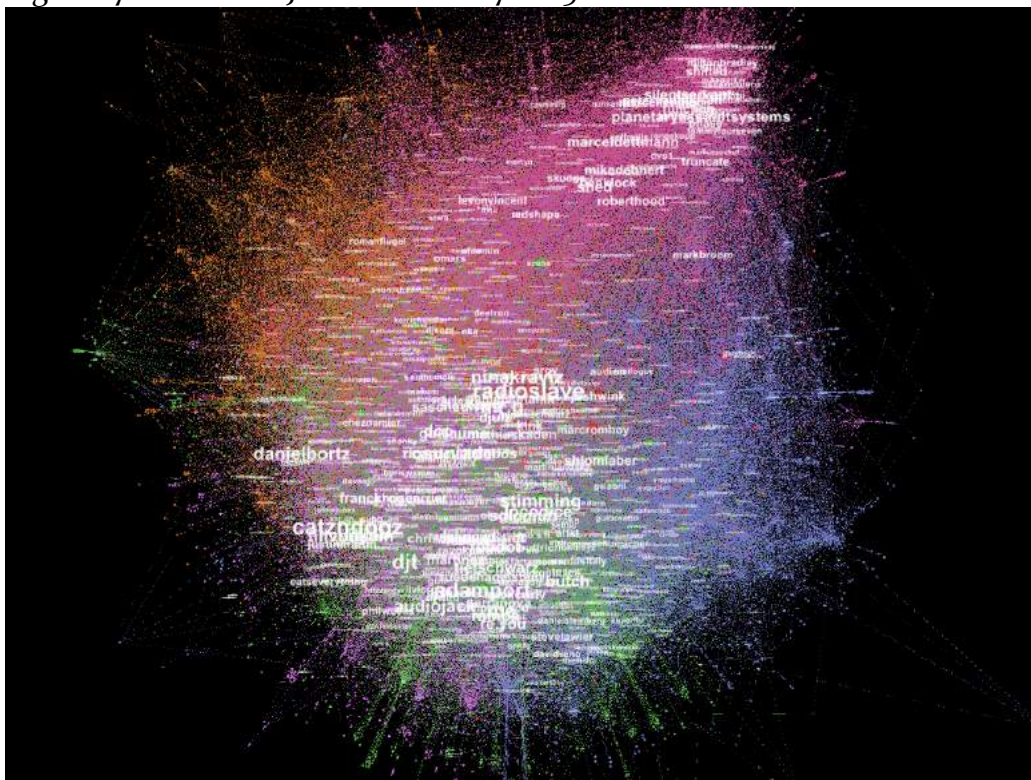
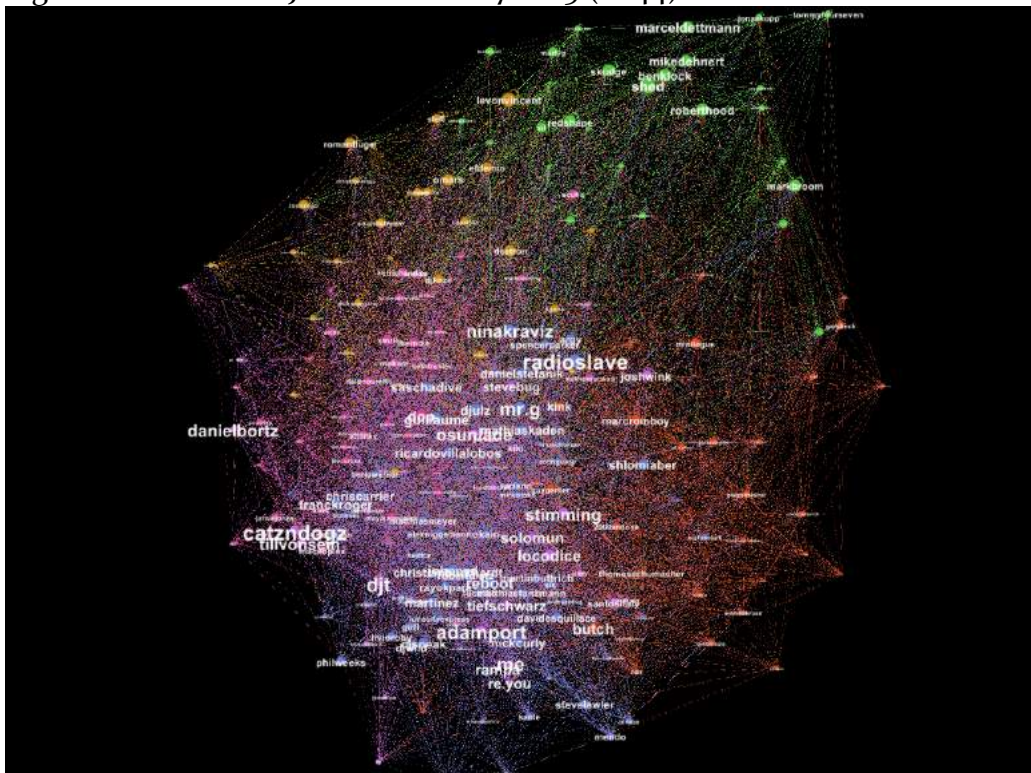
Figure 18. Charted DJ Network: 2007-2015 ($k=44$)

Figure 19. Charted DJ Reciprocity Network: 2007-2015

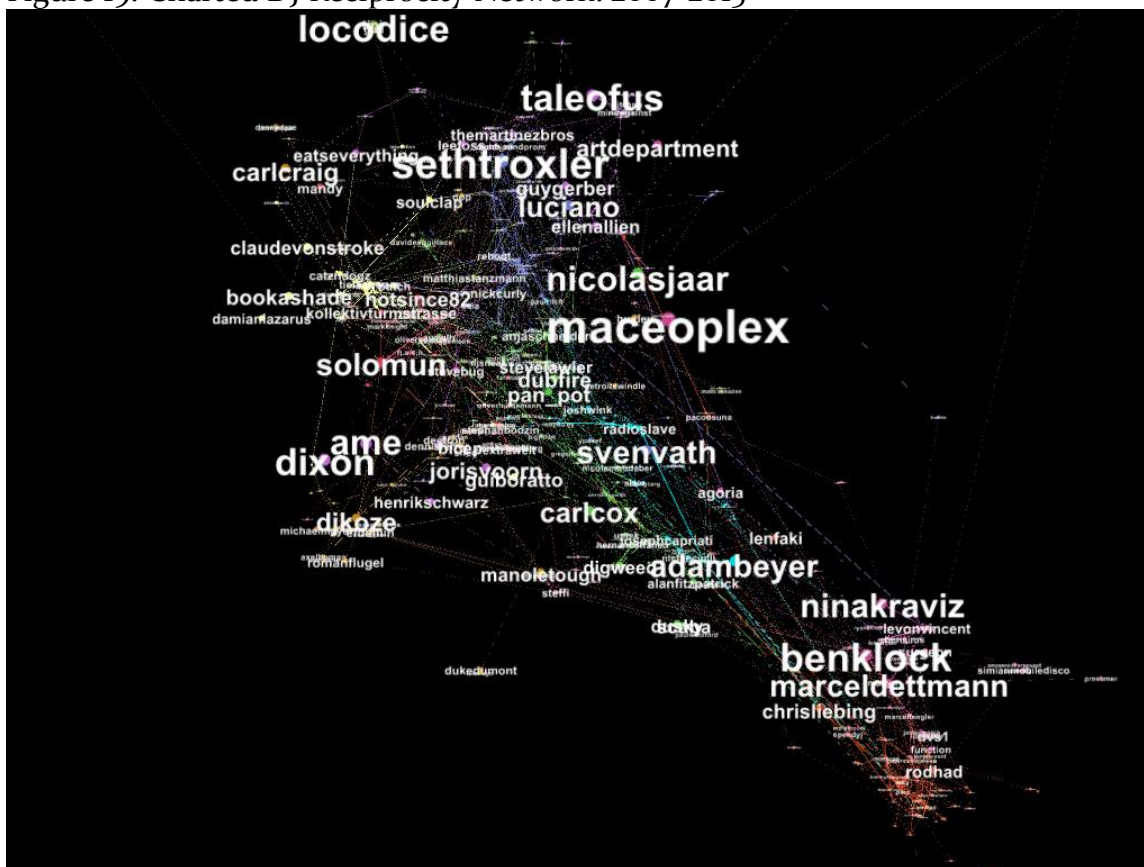


Figure 20. Plots showing Regression Analysis

