Network Analysis of the Hip Hop Community

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Abstract

In the early 2000's as hip hop was entering the popular zeitgeist there was an ongoing joke about how many artists would be featured on a single track. While collaborations were not unknown to other genres of music—occasionally 90's rockers would team up to form "supergroups" like Audioslave or the Foo Fighters—rappers took the practice to a whole new level. Eight or nine artists could be featured on a single track, a couple dozen might be credited to a single album. There were even some mercenaries with no career of their own own to speak of, but would gain fame by appearing on hundreds of others' recordings—perhaps the most notorious of these was *Lil Jon* who would show up on singles just to scream "Yeah!" a couple times.

If we view these artists and their collaborations as nodes and edges in a network we can run this graph through a gauntlet of metrics and models so that we might compare it to other commonly studied social networks and even to other genres of music. Moreover, through community detection analysis we can identify the motivations for artists collaboration, as well as which types of collaboration are most important to the overall community structure.

The Data

In November 2000 Portland based programmer Kevin Lewandowski launched a crowdsourced database called Discogs. Currently this is the largest known public database of meta-data on commercial and non-commercial audio releases, containing information on nearly 10 million releases from over 5 million artists. The data can be accessed via a XML-based RESTful API or by direct download.

For this project we downloaded the most recent database release from April 2018 and extracted the desired data with a Python based SAX parser[1] .

Because the each release[2] is stored as an XML document with an entry listing the contributing artists, it was necessary to first construct a bipartite graph from from artists to releases, then to extract our collaboration network from the projection of this graph. Additionally, it should be noted that only a subset of the database was used, namely we were only interested in releases with 'Hip Hop' as one of their genre tags, and only those that had more than one artist credited. This means that it is possible, even likely, that there are some rappers left out who released only by themselves. The decision to leave out these isolates was motivated by the fact that we are interested in the *community,* which canonically disqualifies isolates in the same sense that backyard power generators are excluded from the analysis of a power grid.

Moreover, since many of the releases we credited to groups the decision was made to break these groups down into their actual members. This was necessary to get a full picture of the network due to the sheer frequency of which artists work outside of their groups and due to the very nature of group productions. Unlike most pop or rock groups, a hip-hop group production has the same structure as one produced by multiple solo artists—each verse is given to an individual rapper, who will often write their lyrics independent of their collaborators input.

Finally, to get a genre for which we could run comparisons we went through the same process to derive a graph for 'Techno' artists. The motivation of this choice of genre is explained below.

Background

A career of a hip hop artist follows a fairly standard track. As with other genres the young rapper generally starts off locally, preforming at

1 As with the R code written for this project, the Python scripts for data wrangling can be found in the following GitHub repository: https://github.com/gonzodeveloper/netsci_hiphop

2 A release is defined as a commercially or non-commercially released album or single, not an individual track

small shows independently or along side others long before they put out their first production. However, unlike other genres where these young artists are scouted by labels then signed into single and album deals independently, budding rappers will often group up with other local MCs and DJs to increase their own notoriety before taking off on a solo career. Even in cases where local rappers are scouted by labels, they are often first debuted by recording tracks or verses on the albums of more prominent artists.

By contrast, techno artists follow a more traditional path. They start local, increase their following on the club-scene, then go on to release labeled production albums. Structurally the two genres could not be more different. While on a single track it is simple for a collection of MCs to alternate verses over a per-recorded *beat*, it is much more difficult for multiple techno DJs to contribute to same track. In fact, most collaborations for the latter that we are reviewing are over entire albums, rather then co-authorship of individual songs that we see from the former.

This domain information should help inform some of the basic metrics on the two network graphs and assist in the parameterization of our models.

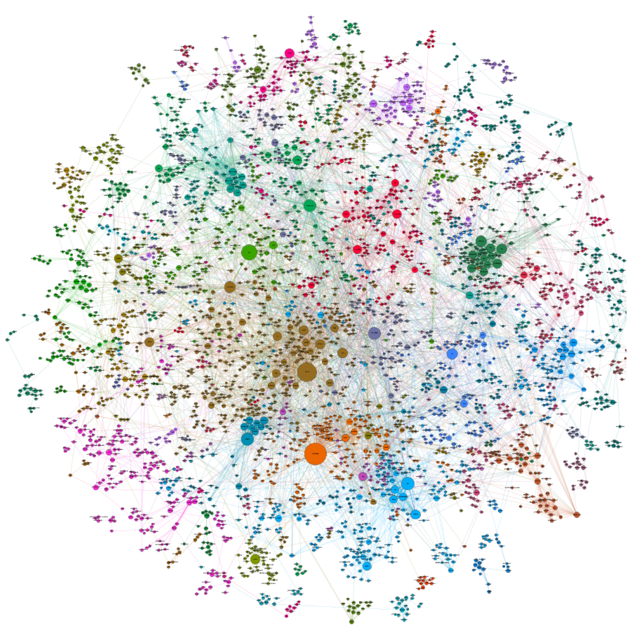


Illustration 1: Hip Hop Network- expanded with OpenOrd, colored by modularity class, sized by PageRank-- filtered for giant component

The Graphs

Metrics	*Hip Hop*	*Techno*
Vertices |V|	10,117	6,078
Edges |E|	13,845	5,688
Giant Comp. |V|	3,856 (38.1%)	1,538 (25.3%)
Giant Comp. |E|	9,301 (67.2%)	2,169 (38.1%)
Avg. Degree $\langle k \rangle$	2.737	1.733
ln (|E|)	9.222	8,712
Mean Dist $\langle d \rangle$	5.623	9.323
Diameter d_{max}	26	33
Cluster Coef $_{local}$	0.6366	0.5245
Cluster Coef $_{global}$	0.2344	0.3476
Degree Assortivity	0.2150	0.3402

It is immediately obvious that the techno artists' network gives us a far more sparse graph than that of the hip hop network. This naturally leads to a lower average degree as well as a higher mean distance and diameter, which is especially notable considering the techno network's smaller overall size. In fact, when compared to other graphs we find that the latter has basic metrics similar to the mobile-phone calling network. However when we look at the hip hop network we can see that its relatively low average degree and short average path length more closely reflect that of the email network. These figures are not at all surprising. Given the differences of the two genres discussed earlier, we should have expected an overall higher level of collaboration in the hip hop network.

The difference in clustering coefficients (i.e. transitivity) in these graphs is perhaps most notable of all the basic metrics. Given the background information it is no surprise that the hip-hop artists have a higher local clustering coefficient. However, it is interesting that we find a higher—though only slightly—global clustering coefficient for the techno artists. This can perhaps be explained by their relative lack of community structure (see below), which would in turn allow them to work and collaborate across the network.

Finally, as one would expect with any real social network. Both of these graphs do fit firmly into the small world regime.

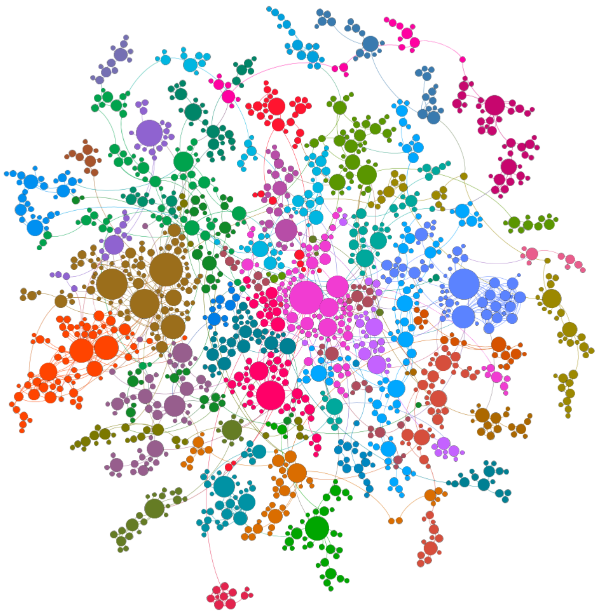


Illustration 2: Techno Network- expanded with OpenOrd, colored by modularity class, sized by PageRank-- filtered for giant component

Centrality and Artists of Interest

While the goal of this study is to examine the hip-hop collaboration network from a global scale rather than examining individual artists, we can still use established centrality metrics along with some background knowledge to identify some Artists of Interest, whose in-depth examination may further inform our understanding of the network.

Degree	Eigen-centrality	Page Rank	Between-ness	Closeness
Snoop Dogg	Ghostface Killah	Snoop Dogg	Snoop Dogg	Snoop Dogg
Lil Wayne	Raekwon	Lil Wayne	Jay-Z	Pharell Williams
Jay-Z	Method Man	Jay-Z	Nas	Busta Rhymes
Busta Rhymes	RZA	Lil' Jon	Busta Rhymes	Nas
Pharrell Williams	Inspectah Deck	50 Cent	KRS-One	T.I.

The previous table shows the top five artists ranked by commonly cited graph centrality metrics. As one would expect, each metric gives us a distinct artist ranking, yet there is enough overlap to reasonably conclude that an artist with a high ranking in one category will also rank fairly high in another. From here we can pick our Artists of Interest, with the objective of finding MCs who share high metrics and overall notoriety, yet who differ in individual style.

Snoop Dogg: an extremely popular West Coast rapper, whose lengthy career, cross-genre prominence and film career make him one of the few actual household names from this network. He tops nearly all of the centrality measures.
Ghostface Killah: New York "gangster rapper". Prominent member of the popular Wu Tang Clan. He has perhaps the most notable solo career of the Clan members, and while his group-mates have all worked on outside collaborations, Ghostface is notable for later signing with industry powerhouse Def Jam records which resulted in a far broader range of collaborations.
Lil' Jon: Atlanta-based rapper and hype man. The large body of his work has been based on collaborations with other artists. As a hype man he can be found on hundreds of tracks screaming quick interjections between verses recorded by other rappers.
Nas: New York based MC notable for his highly successful solo career—having released 8 consecutive multi-platnum albums. Though he has collaborated with artists across the spectrum, the work is often one sided, others are featured on *his* tracks, not the other way around.
Pharrell Williams: less a rapper than a singer and producer, Williams has spent his career working across genres. As one half of the production-duo The Neptunes, Williams has recorded tracks with everyone from Nas and Jay-Z to Daft Punk, Britney Spears and Dave Matthews. He is not usually associated with any geographic style.

As suggested by the background information each of the AoI's have unique centrality rankings. With their broad portfolios, it is no surprise to see the most commercially successful of the group (i.e. Snoop, Nas and

Pharell) have the highest path based centralities, while the node based metrics give us different results.

Out of the centrality rankings, perhaps the most interesting is the eigen-centrality. The top ten artists as scored by this metric were exactly the ten members of the hip hop group *Wu Tang Clan*. Because we can simplify our understanding of eigen-centrality to mean that *nodes will gain higher rank when connected to other nodes with high rank*, it is safe to conclude that in such a large graph, populated with many other such group ensembles, Wu Tang is particularly notable for its' members work with a spectacularly broad range of other artists.

Aside from the variations near the top of the rankings, and the interesting allocation of eigen-centrality, the other centralities produced fairly similar results[3].

Finally we generated ego networks for each of the top artists and ran some metrics to compare each to the entire graph.

Network	***Degree Assortivity***	***Cluster Coef.*** $_{local}$
Hip Hop - Full	0.2149805	0.6365912
Snoop - Ego	-0.2429614	0.7571265
Nas - Ego	-0.2994587	0.8160505
Lil' Jon - Ego	-0.3484328	0.7595058
Ghostface - Ego	-0.2488484	0.8791565
Pharrell - Ego	-0.2524449	0.7987071

The negative degree assortitvity of the AoI's as compared to the full graph gives a good indication that artists have unique collaborative preferences when they are in the orbit of high degree nodes. Whereas the rest of the graph connections have a tendency—albeit slight—to form between nodes of similar degree, the opposite is true of the ego networks of our AoIs. This phenomenon would lend itself to the narrative that upcoming MCs will work together until one gets discovered, at which point they will start collaborating with more established artists.

Furthermore, we can see that the artists in the ego networks of the AoI's have a significantly higher local clustering coefficient than the overall graph. This suggests that either the high degree nodes (i.e. our AoI's) are benefiting from their comparatively close-knit ego networks, or vice versa.

Community Structure

To examine the community structure of the hip hop collaboration network we used both the Louvain and Infomap clustering algorithms. For comparison we also ran these algorithms on the techno network. The following table shows modularity figures for each of the results.

Network	***Louvain***	***Infomap***
Hip Hop	0.8496378	0.785544
Techno	0.9697976	0.9312459

While it is clear that the Louvain clustering method resulted in higher modularity for each network, the overall higher modularity of the techno network suggests a more insular community structure. This conforms to the narrative of a much more collaborative and open hip hop network. Moreover, with such a more open community structure, we can predict that ideas may spread more quickly through the network for the hip-hop collaborators. This will be discussed in more detail in the next section.

Aside from this simple metric on the overall clustering results. We were able to dive in and explore the individual communities, and by examining the commonalities between intra-community artists, we were able to draw up some conclusions on what factors motivate collaboration.

Since both the Louvain and Infomap methods produced over 2,000 clusters, we simplified the task by restricting our analysis to the largest 20 clusters (via Louvain) present in the giant component. From here we found a set of rather unique themes that tied these communities together.

Community 1: Mainstream artists, all popular within the last 5 years. No particular geographical or stylistic ties unless you count "commercial/mainstream hip hop" as a sub-genre.

3 See Appendix for top 50 artists for each metric.

Community 2: These artists fit into the "party-rap" sub-genre. Largely from the "Dirty South"

Community 3: More lyrically oriented MCs, focused more on creative wordplay and rhyme then mainstream artists, yet not political. Could be considered "stoner rap".

Community 4: Socially and politically charged acts. Similar in content more than style. No geographic ties.

Community 5: Artists whose styles are more of a blend of R&B than pure "rap". Most of these artists peaked in the late 90's and early 2000's.

Community 6: Many artists who have come to the hip hop community from other genres (i.e., reggae, R&B, pop).

Community 7: Arena rap/rock. Hip hop artists who work outside the genre, often collaborators with pop/rock starts.

Community 8: European acts, mostly German or Dutch.

Community 9: West Coast based or affiliated artists. Mostly prominent in the early 90's. At the time most of these acts were classified as "gangster rap".

Community 13: Combination of the Miami Bass sub genre—most notably the 2 Live Crew and associated acts—and Los Angeles gangster rappers similar to Community 9.

Community 15: Almost exclusively "old school" New York rappers, prominent in the mid to late 80's.

Community 16: Combination of electronically styled "party rap" and artists from the second wave of gangster rap that came up in the early 2000's. No geographic ties.

Community 19: Wu-Tang Clan and affiliates. Almost entirely based in New York.

Communities 10, 11, 12, 14, 17, 18: Groups of artists too diverse to make any general statements about.

With this list we can see several factors that drive collaboration, namely temporal ties, similar styles, geography, and affiliation.

Temporal ties refer to collaborations between artists who achieved popularity in the same generation. While even some of the oldest artists in the network are still active today, temporal ties refer to the collaborations they engaged in at the peak of their careers.

Stylistic ties refer to collaborations between artists with similar lyrical content and musicality. For example, stylistic preference may motivate a joint release between two geographically separated artists or discourage collaboration between incomparable sub-genres—such as political rap and party rap.

Geographic ties can bring artists together from the same city, state, region or country. These often overlap with stylistic ties as certain sub-genres' popularity are concentrated in a particular area (e.g. Miami Bass).

Affiliate ties refer to the preference of artists to repeat their work within certain established groups or labels. Naturally this overlaps with stylistic ties and occasionally geographic ties, such as the nearly West Coast exclusive Death Row Records.

Whereas these previous node-based clusters were able to give us an idea of what brings artists together, an examination of the link-based overlapping clusters can reveal what sort of collaborations are most important to the overall community structure.

First, using the clustering method implemented by the `LINKCOMM` package in R, we were able to identify 1,301 communities. From here we calculate the modularity for each of these and take the inverse, which gives us a metric called *community connectedness.* This tells us which of the clusters are least insular and therefore more effective at bridging diverse collections of artists. Below are members the top five connected communities.

Node-Comm 1: All members of the Wu Tang Clan, Nas and J-Love.

It's no surprise so see The Clan here. Although its members are tied by style and geography, as they developed Wu Tang began to branch out and collaborate across and outside the genre. The same could be said for Nas, whose inclusion in the cluster certainly increases its connectedness.

Node-Comm 2: Mary J. Blige, Snoop Dogg, Bobby Brown, Charlie Wilson, Kardinal Offishall, Damian Marley, Colby O'Donis, DJ Vadim, The Electric, Yarah Bravo, Shaggy, Sway, Maxi Priest, Two Fingers.

Unlike the previous cluster, this node community is an extremely diverse group of artists—West Coast, East Coast, Canadian, British, Swedish, Canadian, Brazilian and Jamaican. Moreover their styles are equally diverse, from mainstream rap to electronic and reggae.

Node-Comm 3: Usher, Lil Wayne, Rick Ross, Chris Brown, DJ Khaled and Young Jeezy.

This group consists entirely of popular artists from the American South—though not Atlanta or Miami, surprisingly. Each has a wildly successful solo career and a broad portfolio of cross-genre collaborations.

Node-Comm 4: Q-Tip, A Tribe Called Quest, Fugees, Busta Rhymes, John Forte, Lauryn Hill, Wyclef Jean, Pras Michel, Phife Dawg, Ali Shaheed Muhammad, Jarobi White and Kelis.

This group consists of the members from the groups A Tribe Called Quest and The Fugees, as well as Busta Rhymes and Kelis. The collaboration of these groups brings together the worlds of R&B-Reggae via the Fugees and the lyrical beat makers of the early 90's via Tribe.

Node-Comm 5: Identical to Node-Comm 2, substituting Snoop Dogg for Pharell Williams.

That a one-off substitution gives us a different yet equally influential community is a testament to the unique and important roles played by our AoI's.

With these node communities we can see that there are three distinct sorts of collaborations that are important to the connectedness of our graph.

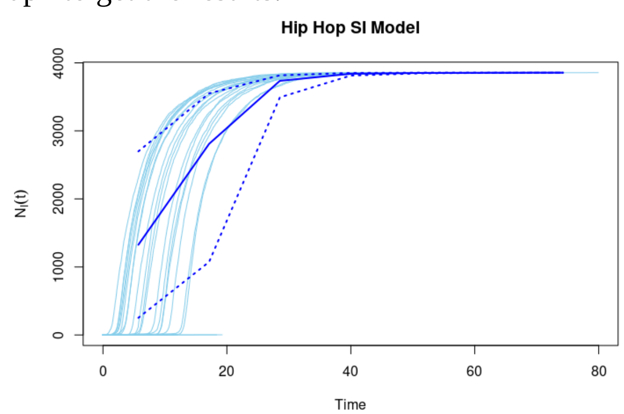
The first type is the established group of artists whose members independently collaborate across the community. This was the case with Wu Tang in Node-Comm 1, and The Roots whose community connectedness had them ranked just outside the top 5.

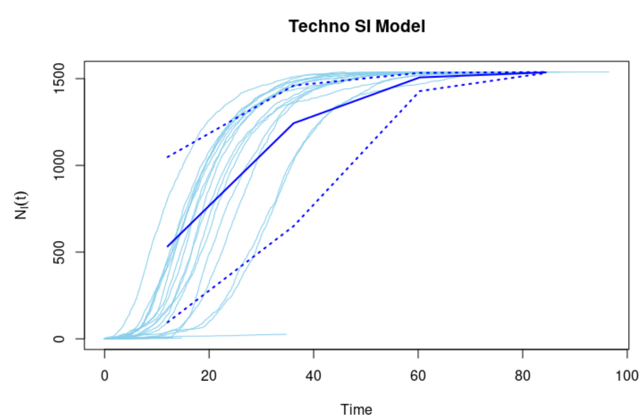
Secondly, we have collections of influential solo artists from different sub-genres and geographies. Node-Comms 2 and 5 were illustrative of this.

Finally, when two distinguished groups from unique sub-genres come together, as was the case with Node-Comm 4.

Cascading Ideas

We can use the existing Susceptible-Infected (SI) model to explore how fast ideas might spread in both of these networks. Whereas this model is regularly used for predicting the spread of disease in a network, we can just as well use it for the spread of ideas. For the model we chose the somewhat arbitrary *beta*—infection rate—to be 0.25, then ran 50 simulations on each graph to get the results.





As predicted earlier, it is clear that ideas (or infections) spread much faster through the hip hop network. This is largely to to the high number of prominent artists with links spreading across the graph, which results in a relatively open community structure. Moreover, we can see the reflection of this in reality with the speed and pervasiveness of trends in rap music—DJ-808 drum machines, Auto-Tune, Mumble Rap, etc.

Modeling

The degree distributions for both of these networks does do not quite lend themselves to Barabasi's preferential attachment model. After many nights of fiddling with the various parameters the we found it impossible to properly fit the models' geodesic distances, gamma values, and transitivity figures to the original degree distribution. This motivated the a somewhat more simplistic approach.

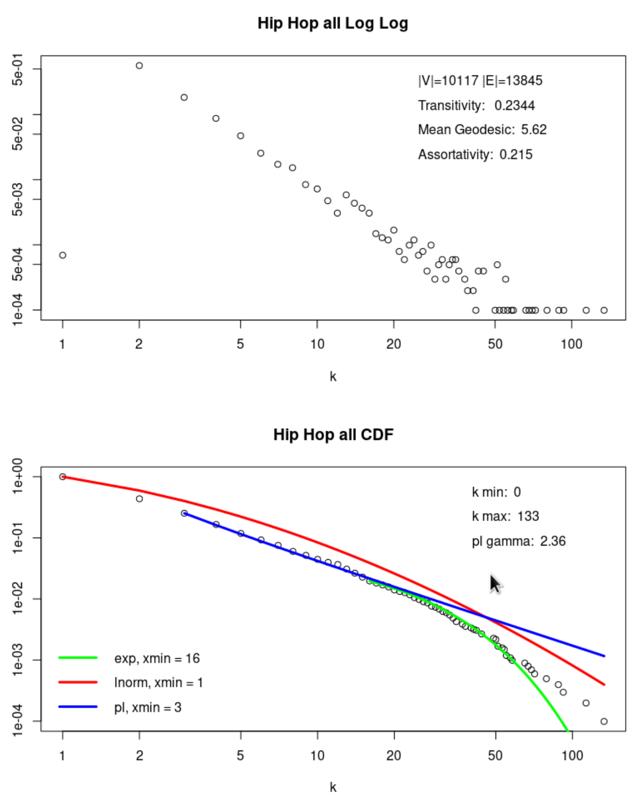


Illustration 3: Hip Hop Degree Distribution

With both of these networks we see the existence of hubs along side a relatively low degree cutoff. This suggested the possibility of a stretched exponential or log -normal degree distribution.

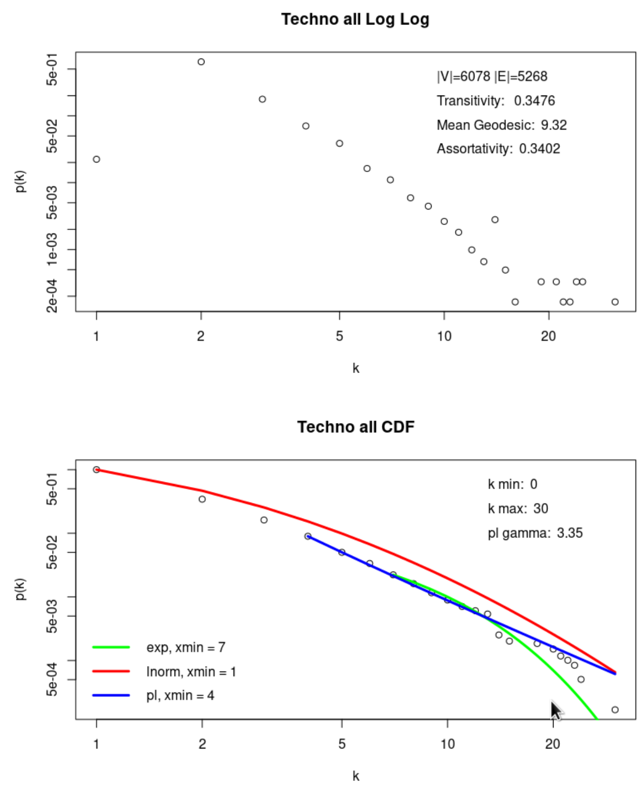


Illustration 4: Techno Degree Distribution

Informed by these plots we ran distribution comparison metrics on each, measuring fit of the log normal vs. the power law distribution. For both, though especially for the hip hop network, the test statistics strongly suggested that a log normal was a better fit.

Log Normal vs. Power Law	Hip Hop	Techno
Two-sided p-value	0.000498521	0.278343
One-sided p-value	0.0002492605	0.1391715
Test Statistic	3.48155	1.084049

Considering the fact there is indeed an upper limit of how many artists can collaborate on a single release, and the reality that no artist, electronic or rapper can reasonably work with thousands of others over their career---as a fat tailed distribution might suggest—the stretched exponential does seem a sensible fit.

Unfortunately this leaves us without a model to explain other more pertinent graph metrics such as transitivity, distance, and assortitvity, so we will leave further discussion to the following sections.

Discussion

The metrics gathered on these graphs, particularly those relating to the hip hop network, do lead us to several conclusions, some more obvious than others.

In contrasting the two genres we did learn that each possesses a unique network structure. The differences in these structures can in turn be explained by the differences in the domains from which the emerged. Additionally, by exploring the background of each of the genres we were able to accurately predict certain graph metrics such as transitivity and average path length.

Using centrality metrics to identify several unique Artists of Interest was useful for revealing certain characteristics about their immediate networks—namely higher transitivity and lower degree assortitvity—that further distinguished them from the rest of the graph.

On the other hand, community detection proved an effective tool for exploring motivations behind collaborative ties formed between artists as well as identifying the types of collaborations most important to the overall network structure.

The use of the SI model to show the potential spread of ideas within these genres did give us a for more novel insight. The model showed the high susceptibility of the hip hop network to new ideas, thereby confirming a somewhat long-shot assumption given earlier in the paper.

Further Study

The real success of this project is actually the construction of these networks so that they can be loaded and analyzed more in the future. There are many questions that still remain of which the author lacked the time and initiative to follow up on.

First and foremost, in the original proposal of this paper, we asked whether or not hip hop artists were more likely to collaborate based on certain attributes. While we were able to utilize community detection to loosely classify certain collaborative motivations, the addition of node attributes to our graph such as *region*, *age*, and *success*[4] would give us a more definitive answer through assortitvity analysis. However, because of the Discogs dataset did not include any of this information for their releases, such attributes would either have to be added manually or parsed from another database.

As mentioned in the last section, we also need to find a better model that could cover all of the various metrics of our networks in question. Perhaps the preferential attachment model could serve this purpose if more time was given to finding the correct parameterization, yet it seems more likely that the answer lies in the employment of exponential random graph models (ERGMs).

Finally, additional curation of the graphs themselves may be necessary. While the author did take the time to remove duplicates, merge aliases, and split up groups, because much of this was accomplished by hand, there likely still exist some minor inconsistencies in the data.

References

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4 As the definition of success remains subjective, candidates for its definition as an artists node attribute are perhaps limited to album sales and online streaming figures.

Appendix

Snoop Dogg	133
Lil Wayne	113
Jay-Z	92
Busta Rhymes	88
Pharrell Williams	79
Kanye West	71
Nas	69
50 Cent	67
Akon	65
Lil' Jon	58
Method Man	57
Ludacris	55
Eminem	54
T.I.	54
Drake	54
LL Cool J	53
Mos Def	51
KRS-One	50
RZA	50
Notorious B.I.G.	50
Fat Joe	50
Rick Ross	50
Wyclef Jean	49
Missy Elliott	44
Mase	44
Ghostface Killah	44
Pitbull	44
Q-Tip	42
Lil' Kim	42
R. Kelly	42
P. Diddy	42
Mary J. Blige	41
Various	40
T-Pain	40
Masta Ace	38
Redman	38
Nate Dogg	37
Dr. Dre	37
Master P	37
2Pac	35
Daz Dillinger	35
DJ Khaled	35
2 Chainz	35
Raekwon	34
Ol' Dirty Bastard	34
Fabolous	34
Trick Daddy	34
Chris Brown (4)	34
Future (4)	34
Common	33
Biz Markie	33
Inspectah Deck	33

Table 1: Top artists by Degree

Ghostface Killah	1
Raekwon	0.989206
Method Man	0.970057
RZA	0.956132
Inspectah Deck	0.952635
GZA	0.929675
Ol' Dirty Bastard	0.884657
Wu-Tang Clan	0.882876
U-God	0.882876
Masta Killa	0.882876
Tom Caruana	0.215021
Cappadonna	0.166217
The Genius	0.162067
J-Love	0.143528
Nas	0.123868
Bobby Digital	0.108867
Jimi Hendrix	0.108706
The Beatles	0.108692
Vingthor The Hurler	0.106582
Onyx	0.106342
Texas	0.106265
Allah Mathematics	0.106244
Killa Sin	0.083474
DJ Muggs	0.075804
Myalansky	0.051688
Joe Mafia	0.051688
Redman	0.050563
Timbo King	0.049915
Sunz Of Man	0.049902
Wu-Tang Killa Bees	0.04989
Black Knights of the North Star	0.04989
Tony Starks	0.045299
The Soul Assassins	0.038623
Funkmaster Flex	0.036747
The Harlem Hoodz	0.034524
B-Real	0.032296
LL Cool J	0.025619
MF Doom	0.025201
Method Man & Redman	0.025141
Busta Rhymes	0.023662
D'Angelo	0.023549
Rollie Fingers	0.023546
American Cream Team	0.023207
B-Twizzy	0.023207
Chip Banky B	0.023207
Polite	0.023207
Nino	0.023207
Mary J. Blige	0.0232
BadBadNotGood	0.022861
Adrian Younge	0.0228
DJ Thoro	0.022649
Xavier Naidoo	0.021934
Prodigal Sunn	0.021681

Table 2: Top artists by eigen-centrality

Snoop Dogg	0.00242
Lil Wayne	0.002022
Jay-Z	0.001607
Lil' Jon	0.001289
50 Cent	0.001269
Pharrell Williams	0.001207
Busta Rhymes	0.001201
Kanye West	0.001094
Method Man	0.001045
Nas	0.001003
RZA	0.000973
Akon	0.000947
Various	0.000935
Ludacris	0.000893
Ghostface Killah	0.000893
KRS-One	0.000878
Eminem	0.000877
Drake	0.000861
Rick Ross	0.00085
Wyclef Jean	0.000824
T.I.	0.000816
Notorious B.I.G.	0.000802
GZA	0.000778
Missy Elliott	0.000777
Master P	0.000756
Mos Def	0.000753
Pitbull	0.000747
Raekwon	0.000745
R. Kelly	0.000724
Ol' Dirty Bastard	0.000721
T-Pain	0.000707
Inspectah Deck	0.000696
Lil' Jon & The East Side Boyz	0.000685
Big Sam	0.000685
Lil' Bo	0.000685
Fat Joe	0.000672
Redman	0.000667
DJ Whoo Kid	0.000658
Dr. Dre	0.000635
Black Thought	0.000634
2Pac	0.000626
Lil' Kim	0.00062
Lloyd Banks	0.000618
DJ Khaled	0.000616
LL Cool J	0.000615
P. Diddy	0.000613
Q-Tip	0.000601
Nate Dogg	0.000597
Awol One	0.000593
James Poyser	0.000583
Young Buck	0.000582
Jermaine Dupri	0.000581

Table 3: Top artists by PageRank

Snoop Dogg	0.015524
Jay-Z	0.010661
Nas	0.010499
Busta Rhymes	0.010308
KRS-One	0.007759
Lil Wayne	0.007179
Pharrell Williams	0.007034
Kanye West	0.00617
Eminem	0.006078
Mos Def	0.006047
Various	0.005824
Masta Ace	0.005247
Akon	0.005123
Q-Tip	0.004894
LL Cool J	0.004858
Method Man	0.004444
The Game (2)	0.004309
Xzibit	0.004209
Mary J. Blige	0.00408
T.I.	0.003701
Ludacris	0.003698
50 Cent	0.003636
Apollo Brown	0.003602
Lil' Kim	0.003533
RZA	0.003518
Jermaine Dupri	0.003215
Drake	0.003165
DJ Tomekk	0.003148
Lil' Jon	0.003141
Fat Joe	0.003127
R. Kelly	0.002967
Juvenile (2)	0.002905
J-Love	0.002861
MF Doom	0.002833
Ice-T	0.002808
Gentleman	0.00273
Notorious B.I.G.	0.002716
Wyclef Jean	0.002696
Pitbull	0.002687
Cut Killer	0.00262
Daz Dillinger	0.002611
Rick Ross	0.002508
Missy Elliott	0.002497
Kurupt	0.002435
DJ Magic Mike	0.002432
Kelly Rowland	0.002425
Common	0.00239
2Pac	0.002389
Mr. Lif	0.002378
Nate Dogg	0.002375
T-Pain	0.002355
Tinie Tempah	0.002351

Table 4: Top artists by Betweenness

Snoop Dogg	0.0001596661
Pharrell Williams	0.0001596653
Busta Rhymes	0.0001596651
Nas	0.000159665
Lil Wayne	0.0001596647
T.I.	0.0001596646
Ludacris	0.0001596645
Akon	0.0001596644
50 Cent	0.0001596644
Kanye West	0.0001596644
Rick Ross	0.0001596642
Mary J. Blige	0.000159664
Jay-Z	0.000159664
Eminem	0.0001596638
Mos Def	0.0001596638
The Game (2)	0.0001596637
Fat Joe	0.0001596636
Q-Tip	0.0001596635
Jermaine Dupri	0.0001596634
Future (4)	0.0001596631
Method Man	0.0001596631
P. Diddy	0.0001596629
Lil' Kim	0.0001596628
Kelly Rowland	0.0001596628
LL Cool J	0.0001596627
KRS-One	0.0001596627
B-Real	0.0001596627
DJ Khaled	0.0001596625
R. Kelly	0.0001596625
Wyclef Jean	0.0001596623
Missy Elliott	0.0001596622
Nate Dogg	0.0001596622
Fabolous	0.0001596622
T-Pain	0.0001596621
Eve (2)	0.000159662
DMX	0.000159662
Too Short	0.0001596619
Notorious B.I.G.	0.0001596619
Mase	0.0001596619
Drake	0.0001596619
2Pac	0.0001596619
Funkmaster Flex	0.0001596618
Juvenile (2)	0.0001596618
Coolio	0.0001596617
Sizzla	0.0001596617
Common	0.0001596616
Wiz Khalifa	0.0001596616
Mick Boogie	0.0001596615
Keri Hilson	0.0001596615
Memphis Bleek	0.0001596614

Table 5: Top artists by closeness