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Assignment Cover Sheet

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| Candidate Number | 1085046 |
| Assignment | Data Driven Network Science: Summative Essay |
| Term | Hilary Term 2024 |
| Title/Question | A Comparison of Distance Metrics: Exploring Temporal Music Collaboration Networks |
| Word Count | 3000 |

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A Comparison of Distance Metrics: Exploring Temporal Music Collaboration Networks

1085046

1 Introduction

Network analysis entails the use of mathematical principles from graph theory to model complex relationships in a wide variety of contexts (Donnat & Holmes, 2018; Newman, 2018). In their simplest forms, mathematical graphs consist of nodes or vertices, representing entities within a system, which may be connected by a line called an edge. Details such as node attributes, edge weights and edge directions may be incorporated, depending on the nature of a given real-world network. For example, Allesina and Bodini (2005) use directed acyclic graphs to analyse the scale invariant properties of food webs. Additionally, edge weights allow for the encoding of the strength or polarity of relationships and node attributes provide information about the entities in a network at the individual level.

In recent years, there has been more scholarship regarding approaches for measuring network dynamics overtime. Donnat and Holmes (2018) investigate multiple distance formulae for operationalising dissimilarities between graphical representations of the same system across discrete states or time steps. The selection of a distance metric is largely based on the scale of the network analysis. Structural distances focus on the local structure of the graph surrounding each node, and are often used to explore instances in which small changes can lead to larger consequences for the network, such as the importance of individual weak ties in the macro-level diffusion of information through a social network (Granovetter, 1973). Conversely, spectral distances reflect global changes in the organisation of a graph, without focus on specific node identities, interactions or associations.

This paper contributes to the discussion of mesoscale graph distances, which remain

largely understudied. One structural metric and two mesoscale metrics are applied to a unique dataset of music industry collaborations on popular songs, and the practical implications of the results are compared. The main objective of this application is to address two questions: How did the number of artist collaborations on Spotify’s Weekly Top Songs Global chart change throughout the year 2017? And were there changes in the specific (types of) artists that tended to collaborate more often?

2 Literature Review

2.1 Temporal Networks

Traditional static network methods are frequently applied to aggregated representations of dynamic systems over the course of a specified time interval. This can lead to flawed inferences, given the lack of certainty as to when changes may occur. It is often assumed that interaction patterns are fixed and that rates of information diffusion remain constant, despite structural perturbations or time dependent events (Blonder, Wey, Dornhaus, James, & Sih, 2012).

Temporal network analysis permits the examination of a network’s topological evolution as well as the flow of information through the system over time. The two primary representations of temporal network data are time-ordered and time-aggregated graphs. Time-ordered graphs illustrate continuous transformations of a network within a given time frame. Each node is considered along an axis, symbolising the passage of time, and edges are drawn as demarcations of the periods in which two nodes are connected. Time-aggregated graphs may be derived from time ordered networks, as static visualisations of specific instances along the timeline. The relationship between time-ordered and time-aggregated network representations is depicted in Figure 1.

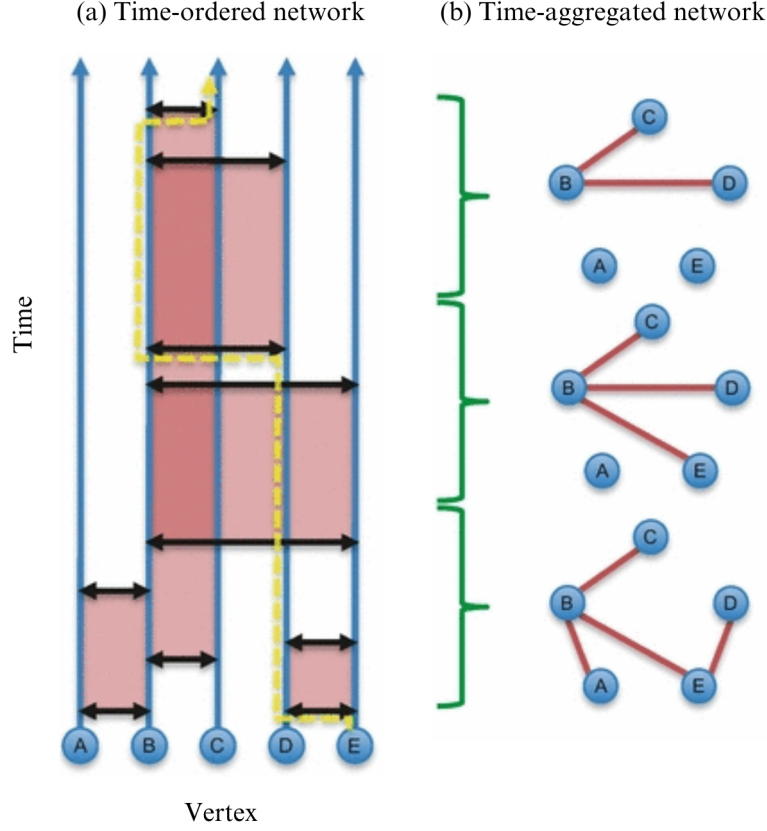


Figure 1. Examples of time-ordered and time-aggregated network models. Adapted from (Blonder, Wey, Dornhaus, James, & Sih, 2012).

As previously mentioned in the introduction, the distance metrics presented by Donnat and Holmes (2018) are used to measure the dissimilarity between graphs at discrete points in time. The data is appropriately partitioned into weekly intervals, because this is the frequency with which Spotify updates its global music charts. Therefore, the accuracy of the analysis is not compromised by lack of granularity, despite its focus on a finite number of static graphs.

The formal mathematical definition for a time-aggregated graph model is as follows: For the period of network evolution from time t_{min} to time t_{max} , $G_t^w(t_{min}, t_{max})$ denotes a sequence of graphs $G_{t_{min}}, G_{t_{min}+w}, \dots, G_{t_{max}}$, representing the state of the system at time steps of constant size w . Each graph in the sequence $G_t(V, E)$ is defined on a set of nodes V and a set of edges E . The graphs are aligned, meaning that the number and identities of nodes in the system remains constant for the duration of the analysis. Edges, however, may be present or absent across the various states; the set E for a given graph consists of all edges between two nodes $i, j \in V$ that were connected within the time window

corresponding to that graph (Tang, Musolesi, Mascolo, & Latora, 2009).

2.2 Distance Metrics

2.2.1 Structural Metric: The Jaccard Distance

In 1902, the Swiss ecologist and botanist, Paul Jaccard published a paper outlining the coefficient of floral community. His core argument was that the diversity of flora could be compared across two locations, using a similarity index derived from the quotient of the number of species found in both areas and the total number of species found in either area (Podani, 2021). This idea was later generalised to broader set theory applications, along with a corresponding dissimilarity index—now referred to as the Jaccard distance, defined as the difference between the union and the intersection of two sets, divided by the union of those sets.

The Jaccard distance may be applied as a measure of structural dissimilarity between mathematical graphs, by considering their edge sets. This process is streamlined by conducting operations on each graph’s respective adjacency matrix, generally an N by N symmetric matrix \mathbf{A} of the form

$$A_{ij} = \begin{cases} 1, & \text{if } v_i \text{ and } v_j \text{ share an edge} \\ 0, & \text{otherwise} \end{cases}$$

where v_i and v_j are two nodes in the set V , and 1 may be replaced with other non-zero values to indicate edge weights. The number of edges that only exist in only one of the two graphs (union minus intersection of edge sets) is equal to the sum of the magnitudes of pairwise differences in the elements of the adjacency matrices, and the union is equal to the sum of pairwise maximum elements in each adjacency matrix. As follows, the Jaccard distance between the two graphs (with edge sets and adjacency matrices E , \tilde{E} and \mathbf{A} , $\tilde{\mathbf{A}}$, respectively) is expressed as:

$$\begin{aligned}
d_{\text{Jaccard}}(G, \tilde{G}) &= \frac{|E \cup \tilde{E}| - |E \cap \tilde{E}|}{|E \cup \tilde{E}|} \\
&= \frac{\sum_{i,j} |A_{ij} - \tilde{A}_{ij}|}{\sum_{i,j} \max(A_{ij}, \tilde{A}_{ij})}.
\end{aligned}$$

For weighted, undirected graphs without self loops (such as those explored in Section 3), it does not suffice to simply consider the presence of an edge, rather the graphs should be compared in terms of their proportions of common edge weights:

$$d_{\text{Jaccard}}(G, \tilde{G}) = 1 - \frac{\sum_{i,j} \min(A_{ij}, \tilde{A}_{ij})}{\sum_{i,j} \max(A_{ij}, \tilde{A}_{ij})}.$$

Here, if an individual edge does not change in weight from one graph to the next, $\min(A_{ij}, \tilde{A}_{ij}) = \max(A_{ij}, \tilde{A}_{ij})$, which means that the edge does not contribute to the dissimilarity between the graphs. Once again, as a structural metric, the Jaccard distance is sensitive to changes on the scale of individual nodes and edges.

The results may be interpreted as the amount of edge rewiring that has occurred in a system after a period of time, with respect to the initial network structure. A distance of zero indicates that the two graphs are identical, while a distance closer to one reflects major topological changes to the network. Limitations of the Jaccard distance are that it neither accounts for how edge rewiring in relatively sparse graphs is more likely to facilitate new connections or radically disrupt paths between nodes, nor does it penalise edge removals that lead to disconnected components (Koutra, Shah, Vogelstein, Gallagher, & Faloutsos, 2016; Donnat & Holmes, 2018).

2.2.2 Mesoscale Metric 1: Polynomial Dissimilarity

Donnat and Holmes (2018) introduce the polynomial approach as a spectral method for measuring the dissimilarity between two graphs, though it also reflects some mesoscale

characteristics. Generally, spectral distance metrics quantify changes in the state of an entire network system by comparing the eigenvalues of the respective graphs' adjacency (or Laplacian) matrices. These eigenvalues can provide information about global properties of a graph, such as an upper bound on the graph's diameter, or the maximum distance between any two vertices (Chung, 1995). The polynomial dissimilarity accounts for the eigenvalues of each graph's adjacency matrix while attempting to address the limitations of other metrics such as the Jaccard distance i.e. acknowledging how perturbations do not have a uniform impact on different regions of the graph.

Calculating the polynomial dissimilarity between two graphs of equal size N entails taking the eigenvalue decomposition of each adjacency matrix and constructing a polynomial of the form

$$P(x) = x + \frac{1}{(N-1)^\alpha}x^2 + \dots + \frac{1}{(N-1)^{\alpha(k-1)}}x^k.$$

This polynomial then takes an adjacency matrix as input:

$$P(\mathbf{A}) = \mathbf{Q}\mathbf{W}\mathbf{Q}^T.$$

\mathbf{Q} is a matrix composed of the eigenvectors of \mathbf{A} , $\mathbf{W} = \Lambda_{\mathbf{A}} + \frac{1}{(N-1)^\alpha}\Lambda_{\mathbf{A}}^2 + \dots + \frac{1}{(N-1)^{\alpha(k-1)}}\Lambda_{\mathbf{A}}^k$, and $\Lambda_{\mathbf{A}}$ is the diagonal matrix, containing the eigenvalues of \mathbf{A} . Each element $P(\mathbf{A})_{ij}$ of the resulting matrix corresponds to a coefficient, indicating the number of paths of length less than or equal to k that start at the node v_i and end at the node v_j ; larger values indicate more densely connected areas of the graph. α is a tuning parameter that allows for a difference in weights between higher and lower order terms. Perturbations are more impactful to a local region of the graph, if they occur closer to the centre of that region (within a smaller radius, k); therefore higher order terms should generally have smaller weights in the polynomial (Donnat & Holmes, 2018).

From here, the distance between the two graphs is achieved by taking the Frobenius norm of the difference between their polynomial matrices:

$$d_{\text{pol}}(G, \tilde{G}) = \frac{1}{N^k} \left(\sum_{i,j} \left| P(\mathbf{A})_{ij} - P(\tilde{\mathbf{A}})_{ij} \right|^k \right)^{\frac{1}{k}}.$$

2.2.3 Mesoscale Metric 2: Connectivity-based Distance

Mesoscale distances should contextualise individual node attributes and interactions as contributors to the global dynamics of a system. According to Donnat and Holmes (2018), the polynomial dissimilarity begins to bridge the gap between structural and spectral network analysis, however it still only provides neighbourhood-level insights. From here, they suggest that node interactions should be considered more broadly across graphs by assessing changes in centrality.

The centrality-based metric used in this report to calculate the distance between two graphs implemented by calculating and summing the pairwise differences between the eigenvector centralities e_{ij} for each graph, as shown in the equation:

$$d_{\text{centrality}}(G, \tilde{G}) = \left(\sum_{i=1}^n \sum_{j=1}^n (e_{ij} - \tilde{e}_{ij})^p \right)^{1/p}$$

where p is a tuning parameter that adjusts the sensitivity of the metric to changes in node interactions at different scales (e.g. larger values of p produce a distance that is more substantially shaped by more dramatic changes in the centrality of individual nodes). The eigenvector centrality of a given node assumes that its centrality or prestige in the network is proportional to the sum of the centrality of its neighbours (Bloch, Jackson, & Tebaldi, 2023). Using this specific measure of centrality is appropriate in the context of the data presented in the next section. To some extent, a musician’s future collaborations are likely shaped by the artists they have worked with in the past. Though the exact social dynamics of the global mainstream music industry are out of the scope of this report, developing a framework in which collaboration networks are compared over time in terms of changes in the prestige of individual artists (nodes) may be beneficial to future research at the intersection of social network analysis and music information retrieval.

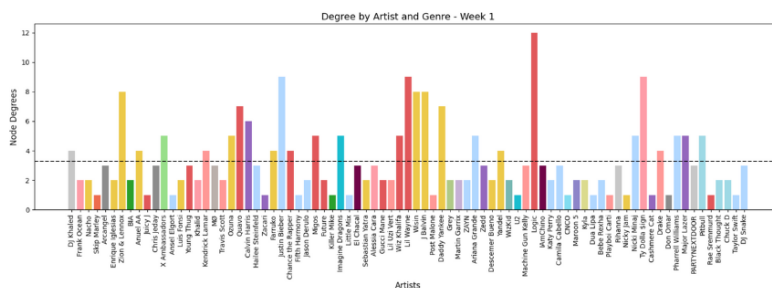
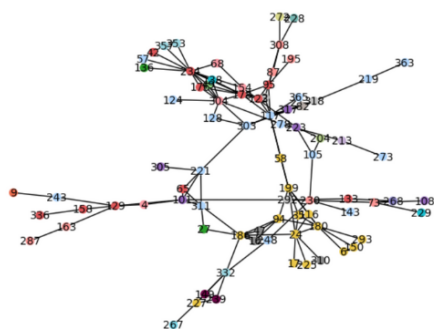
3 Application to Real-World Data

3.1 Data Source and Exploratory Analysis

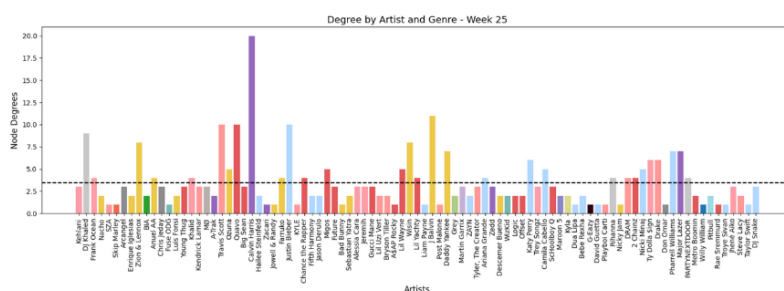
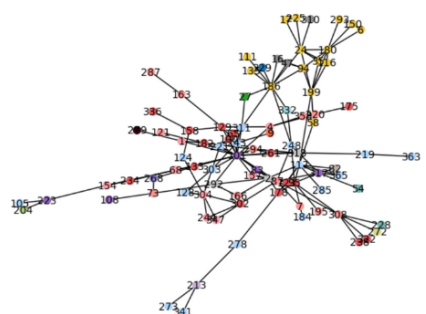
The data featured in this report was originally collected by Oliveira et al. and submitted to the 21st International Society for Music Information Retrieval Conference along with the paper “Detecting Collaboration Profiles in Success-Based Music Genre Networks.” Whereas Oliveira et al. use the data to examine the causal effects of collaboration on the number of mainstream music genres in individual countries and worldwide from 2017 to 2019, this report has a narrower focus on how the global collaboration network evolved in terms of its structure from January through December 2017 (a fifty-week period). Over the course of the year, 366 artists collaborated on tracks which appeared on the Weekly Top Songs Global chart. A time-aggregated graph was defined on a set of nodes, mapping to each of these artists. Genre was considered as a node attribute. The original dataset contained 896 genre categories and each artist was associated with a list of genres, reflecting the styles of music that appeared in their discography available on Spotify (Oliveira, Santos, Seufitelli, Lacerda, & Moro, 2020). However, for simplicity, the data used in this report only tracked the singular primary genre for each musician, and only 44 distinct genres were represented in the charting songs from 2017. The edges of each graph in the temporal network were weighted by the number of times two artists collaborated during the year.

Figure 2 showcases the largest connected components (LCCs) of the collaboration networks and the degrees of each artist node at (a) week 1, (b) week 25 and (c) week 50.

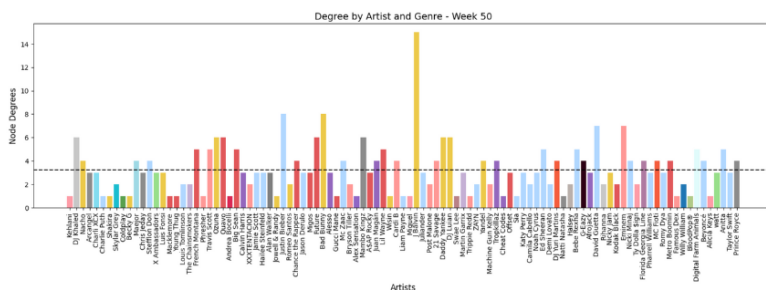
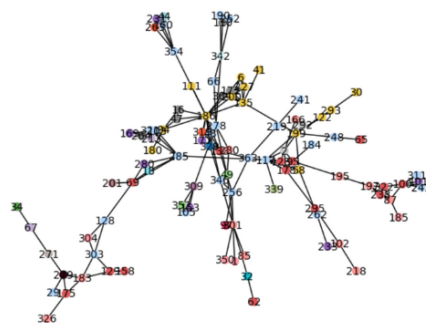
(a) Week 1



(b) Week 25



(c) Week 50



Legend

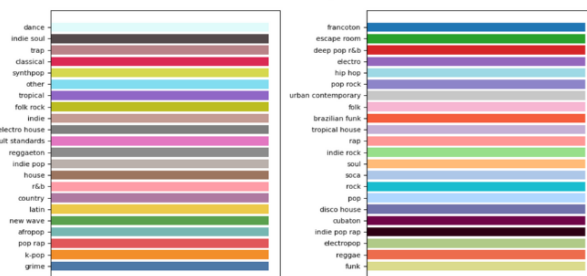


Figure 2. Largest connected component graph visualisations at three selected time steps. Plots of the degrees of the nodes in each of the three graphs. Colors correspond to the genres of the artists as seen in the legend. A mapping from artists to node indices is provided in the appendix. Unfortunately, the quality of the image is not the best; a more clear version is provided in the accompanying zip file.

The largest connected component for week 1 (the first week of January) consists of 81 nodes, with an average degree of 3.28. As shown in the bar chart, musicians in the pop-rap genre such as Logic, Quavo and Lil Wayne, and Latin music artists such as J Balvin, Wisin and Daddy Yankee tend to participate in more collaborations than average. By week 25 (around late June to early July), the LCC has increased to comprise 91 nodes with an average degree of 3.45. Latin, rap and pop artists continue to collaborate more frequently than average, however the Scottish DJ and music producer, Calvin Harris, (electro genre) may be observed to contribute greatly to the increased average degree. This week coincided with the release of Harris’s fifth studio album, “Funk Wav Bounces Vol. 1,” with guest features from twenty different artists including Frank Ocean, Snoop Dogg and Ariana Grande. Lastly, the LCC for week 50 (mid to late December) has 101 nodes, with an average degree of 3.23. The fact that the largest connected component seems to grow over the year suggests that more niche artists (found in smaller connected components or individual nodes surrounding the LCC) are working with prominent or interconnected musicians in the industry at an increasing rate. This observation corroborates findings from Oliveira et al. (2020), which show that emerging artists in region-specific genres such as reggaeton, K-pop and Brazilian funk are beginning to achieve more mainstream, global success.

3.2 Results Comparison

Figure 3 displays heatmap visualisations of the (a) Jaccard, (b) polynomial and (c) eigenvector centrality-based distance metrics for the graphs at each of the fifty week-long steps in the time aggregated network. Although the plots use the same colour coding, it is important to note the differences in scales (seen to the right of each heatmap). As a normalised measure, the values of the Jaccard distance, for example, range from zero to one. The white squares along the diagonal of each heatmap indicate that the distance between each graph and itself is zero.

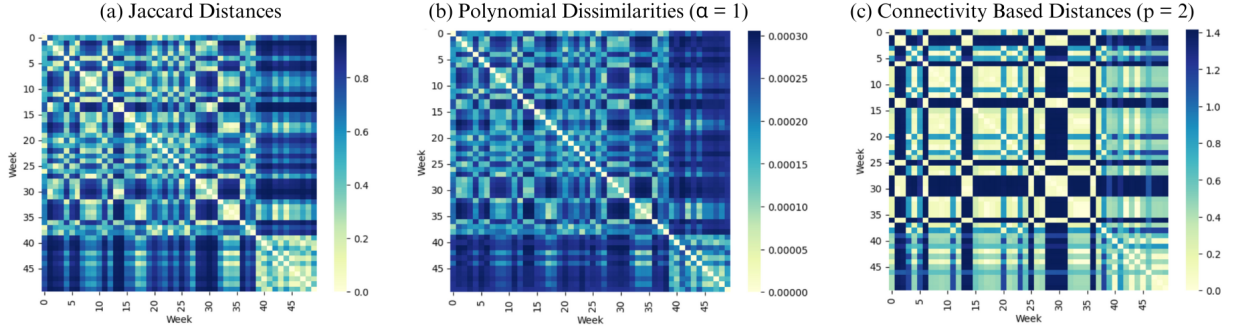


Figure 3. Heatmap visualisations depicting the (a) Jaccard distance, (b) polynomial dissimilarity, and (c) connectivity-based distances between graphs at each time step in the temporal network. A more clear version of the image is provided in the accompanying zip file.

Figure 3 shows that the graphs at time steps zero to about 38 vary inconsistently in terms of their Jaccard distances from one another. However, graph states after week 38 (late September to early October), are clearly less similar to previous states; these graphs are also more similar to each other, as shown by the small block of light-coloured squares in the bottom right corner of the visualisation. More specifically, the states of the temporal network from weeks 38 to 50 have a maximum graph-wise Jaccard distance of about 0.6, and most of these graphs are much more similar, with what seems to be an average distance between 0.1 and 0.3.

The polynomial dissimilarities depicted in Figure 3b follow a comparable pattern to the Jaccard distances: inconsistent variation in distances between graphs before week 38, increased dissimilarity between graphs from before and after week 38, and slightly more agreement among the later graph states. Given the heatmap’s darker hue, the graphs may be interpreted as being more different to each other overall in terms of polynomial dissimilarity. However, this is not the case, since the upper bound on polynomial dissimilarity is 0.0003 (as shown by the scale). At a higher level, there actually seems to be very little evolution of the network with respect to this metric. This observation suggests that most of the change in the networks over the fifty weeks occurs at the periphery (Donnat & Holmes, 2018), further supporting the previous statement that niche (more peripheral) musicians were starting to connect with more central artists (in the LCC) as time passed.

Figure 3c depicts a wide variation in the eigenvector centrality distance throughout the time period. According to Donnat and Holmes (2018), this could mean that some artists

are moving towards the centre of the network and gaining prominence, while others are receding into the periphery. Songs can remain on the Spotify charts for different amounts of time, so if a dominating track suddenly falls out of the top rankings, this may cause dramatic changes in the level of influence of each node (such a shock may be exacerbated by the fact that this analysis does not account for each song’s exact place on the chart).

4 Conclusion and Implications

To summarise, this report examined three of the distance measures for time-aggregated network models discussed by Donnat and Holmes (2018): the Jaccard distance, polynomial dissimilarity, and (eigenvector) centrality-based distance. Each metric was implemented and applied to temporal network data on collaborations in popular music. In doing this, observations may be made regarding broad changes in the network structure as well as individuals who influenced collaboration patterns and the mainstream adoption of more diverse music genres. Future research in this area might more explicitly consider changes in the diffusion of information (or creative inspiration, in this case) that may result from cross genre collaboration.

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A Appendix

This is a list of artists, indexed by their node in the set of graphs. Not all artists are shown in the LCC visuslisations in Figure 2.

| | name |
|----|-------------------|
| 0 | Stefflon Don |
| 1 | Kendrick Lamar |
| 2 | Skip Marley |
| 3 | French Montana |
| 4 | FRENSHIP |
| 5 | Maty Noyes |
| 6 | Mc Zaac |
| 7 | Calvin Harris |
| 8 | Fuse ODG |
| 9 | CMC\$ |
| 10 | Ed Sheeran |
| 11 | Usher |
| 12 | Starley |
| 13 | OneRepublic |
| 14 | Gavin James |
| 15 | Arcangel |
| 16 | 21 Savage |
| 17 | Future |
| 18 | Axwell / Ingrosso |
| 19 | Farruko |
| 20 | Dante Klein |
| 21 | Kid Ink |
| 22 | Danelle Sandoval |
| 23 | Bryant Myers |
| 24 | Famous Dex |
| 25 | Quintino |

| | name |
|----|----------------------|
| 26 | Big Sean |
| 27 | Camila Cabello |
| 28 | Ansel Elgort |
| 29 | Kali Uchis |
| 30 | Kirsty MacColl |
| 31 | Vince Staples |
| 32 | Takeoff |
| 33 | Vice |
| 34 | Sandro Cavazza |
| 35 | Pretty Sister |
| 36 | Rudimental |
| 37 | Little Mix |
| 38 | Coldplay |
| 39 | Charlie Puth |
| 40 | Justin Jesso |
| 41 | Digital Farm Animals |
| 42 | Shakira |
| 43 | Shaggy |
| 44 | G-Eazy |
| 45 | Bahari |
| 46 | DJ Snake |
| 47 | Labrinth |
| 48 | Kyla |
| 49 | JP Cooper |
| 50 | Daddy Yankee |

| | name |
|----|------------------------|
| | <hr/> |
| 51 | Romeo Santos |
| 52 | DJ Yuri Martins |
| 53 | JAY-Z |
| 54 | The Chainsmokers |
| 55 | NAV |
| 56 | Marshmello |
| 57 | Giggs |
| 58 | Willy William |
| 59 | Descemer Bueno |
| 60 | Steve Aoki |
| 61 | Mike Posner |
| 62 | A Boogie Wit da Hoodie |
| 63 | David Guetta |
| 64 | BloodPop® |
| 65 | Perry Como |
| 66 | Mura Masa |
| 67 | Nicki Minaj |
| 68 | X Ambassadors |
| 69 | Huncho Jack |
| 70 | Kane Brown |
| 71 | Chris Jeday |
| 72 | Ariana Grande |
| 73 | Rita Ora |
| 74 | Cash Cash |
| 75 | Natti Natasha |

| | name |
|-----|-------------------|
| 76 | Bryson Tiller |
| 77 | Eminem |
| 78 | Skizzy Mars |
| 79 | Nacho |
| 80 | Yandel |
| 81 | Galantis |
| 82 | Kungs |
| 83 | Ozuna |
| 84 | Jesse & Joy |
| 85 | Pharrell Williams |
| 86 | Lauren Jauregui |
| 87 | Maren Morris |
| 88 | Carlos Vives |
| 89 | Shania Twain |
| 90 | Machine Gun Kelly |
| 91 | Alan Walker |
| 92 | Shawn Hook |
| 93 | Metro Boomin |
| 94 | Prince Royce |
| 95 | IAmChino |
| 96 | Matoma |
| 97 | Stevie Nicks |
| 98 | Fetty Wap |
| 99 | The Pogues |
| 100 | J Balvin |

| | name |
|-----|---------------|
| 101 | El Chacal |
| 102 | U2 |
| 103 | Mike Perry |
| 104 | Katy Perry |
| 105 | BTS |
| 106 | Thomas Gold |
| 107 | Macklemore |
| 108 | Liam Payne |
| 109 | Max B |
| 110 | Conor Maynard |
| 111 | Cheat Codes |
| 112 | Jason Derulo |
| 113 | Anuel AA |
| 114 | ROZES |
| 115 | Bebe Rexha |
| 116 | Cashmere Cat |
| 117 | Lil Wayne |
| 118 | Felix Jaehn |
| 119 | Lana Del Rey |
| 120 | Juicy J |
| 121 | Gucci Mane |
| 122 | Trap Capos |
| 123 | Nate Dogg |
| 124 | R3HAB |
| 125 | Zedd |

| | name |
|-----|-------------------|
| 126 | James Blunt |
| 127 | Sampha |
| 128 | De La Ghetto |
| 129 | Post Malone |
| 130 | Anna of the North |
| 131 | Rihanna |
| 132 | Sia |
| 133 | Ky-Mani Marley |
| 134 | Juhn |
| 135 | Billy Raffoul |
| 136 | Ty Dolla \$ign |
| 137 | Travis Scott |
| 138 | John Legend |
| 139 | Iggy Azalea |
| 140 | Zion & Lennox |
| 141 | Nause |
| 142 | CVBZ |
| 143 | Cali Y El Dandee |
| 144 | Swae Lee |
| 145 | William Singe |
| 146 | SZA |
| 147 | Fifth Harmony |
| 148 | Ellie Goulding |
| 149 | Young Thug |
| 150 | Maggie Lindemann |

| | name |
|-----|-------------------|
| 151 | Jhené Aiko |
| 152 | Imagine Dragons |
| 153 | Chuck D |
| 154 | Bad Bunny |
| 155 | Daya |
| 156 | Stormzy |
| 157 | Cedric Gervais |
| 158 | Lauv |
| 159 | John Lennon |
| 160 | Tory Lanez |
| 161 | Ryan Riback |
| 162 | Afrojack |
| 163 | Avicii |
| 164 | PnB Rock |
| 165 | Zara Larsson |
| 166 | Joey Montana |
| 167 | Emma Stone |
| 168 | Kash Doll |
| 169 | Jax Jones |
| 170 | Jamie Scott |
| 171 | 2 Chainz |
| 172 | Chance the Rapper |
| 173 | DJ Luian |
| 174 | Thomas Rhett |
| 175 | Seeb |

| | name |
|-----|----------------------|
| 176 | Miguel |
| 177 | Juliander |
| 178 | RAYE |
| 179 | Nick Jonas |
| 180 | Alok |
| 181 | Black Coffee |
| 182 | Kris Kross Amsterdam |
| 183 | CNCO |
| 184 | Ella Eyre |
| 185 | Arrhult |
| 186 | Gente De Zona |
| 187 | Christian Daniel |
| 188 | Lil Yachty |
| 189 | Charli XCX |
| 190 | Maite Perroni |
| 191 | Tyler, The Creator |
| 192 | gnash |
| 193 | Kanye West |
| 194 | Alessia Cara |
| 195 | Lil Uzi Vert |
| 196 | Charly Black |
| 197 | Jowell & Randy |
| 198 | Becky G |
| 199 | Alex Aiono |
| 200 | Joakim Lundell |

| | name |
|-----|---------------------------|
| 201 | Chino & Nacho |
| 202 | ScHoolboy Q |
| 203 | Tropkillaz |
| 204 | Stargate |
| 205 | Logic |
| 206 | Killer Mike |
| 207 | Sean Paul |
| 208 | Phoebe Ryan |
| 209 | Kehlani |
| 210 | Quavo |
| 211 | Rex Orange County |
| 212 | Enrique Iglesias |
| 213 | Maluma |
| 214 | Gzuz |
| 215 | Pabllo Vittar |
| 216 | Lauren Alaina |
| 217 | Louane |
| 218 | Frank Ocean |
| 219 | Gorillaz |
| 220 | Dimitri Vegas & Like Mike |
| 221 | A-Trak |
| 222 | Romy Dya |
| 223 | Mark Ronson |
| 224 | Black Thought |
| 225 | Jennifer Lopez |

| | name |
|-----|----------------------|
| 226 | Demi Lovato |
| 227 | Ricky Martin |
| 228 | Florida Georgia Line |
| 229 | Trippie Redd |
| 230 | Cardi B |
| 231 | Kranium |
| 232 | KYLE |
| 233 | Troye Sivan |
| 234 | ZAYN |
| 235 | Juan Magán |
| 236 | CADE |
| 237 | KREAM |
| 238 | Pusha T |
| 239 | Offset |
| 240 | Kiiara |
| 241 | Noriel |
| 242 | Rvssian |
| 243 | A\$AP Rocky |
| 244 | Hearts & Colors |
| 245 | Grey |
| 246 | Michael Bublé |
| 247 | Anne-Marie |
| 248 | Jorja Smith |
| 249 | Rae Sremmurd |
| 250 | Luis Fonsi |

| | name |
|-----|------------------------------|
| 251 | watt |
| 252 | Dalmata |
| 253 | BIA |
| 254 | Noah Cyrus |
| 255 | Jon Bellion |
| 256 | Poo Bear |
| 257 | Yo Gotti |
| 258 | Julia Michaels |
| 259 | KAROL G |
| 260 | Anitta |
| 261 | Clean Bandit |
| 262 | Lorde |
| 263 | Bipolar Sunshine |
| 264 | MØ |
| 265 | Olivia O'Brien |
| 266 | Vargas & Lagola |
| 267 | The Night Game |
| 268 | Mark Morrison |
| 269 | Maejor |
| 270 | Mykola Dmytrovych Leontovych |
| 271 | Bonez MC |
| 272 | The Fontane Sisters |
| 273 | Taylor Swift |
| 274 | Wiz Khalifa |
| 275 | Halsey |

| | name |
|-----|------------------|
| 276 | Flume |
| 277 | Yoko Ono |
| 278 | Manuel Turizo |
| 279 | Skylar Grey |
| 280 | Khalid |
| 281 | Desiigner |
| 282 | Zacari |
| 283 | Robin Schulz |
| 284 | Hook N Sling |
| 285 | Francesco Yates |
| 286 | DRAM |
| 287 | Sebastian Yatra |
| 288 | Jeremih |
| 289 | Drake |
| 290 | The Weeknd |
| 291 | XXXTENTACION |
| 292 | Louis Tomlinson |
| 293 | Bruno Mars |
| 294 | DJ Khaled |
| 295 | Skrillex |
| 296 | Hailee Steinfeld |
| 297 | Diplo |
| 298 | Phresher |
| 299 | Chris Brown |

| | name |
|-----|----------------------|
| 300 | 187 Strassenbande |
| 301 | Sigala |
| 302 | Linkin Park |
| 303 | The Puppini Sisters |
| 304 | DVBBS |
| 305 | Nego do Borel |
| 306 | SHY Martin |
| 307 | Maroon 5 |
| 308 | Don Omar |
| 309 | Jonas Blue |
| 310 | Wisin |
| 311 | Emily Warren |
| 312 | Trey Songz |
| 313 | Clara Mae |
| 314 | Oh Wonder |
| 315 | Justin Bieber |
| 316 | Burak Yeter |
| 317 | N.E.R.D |
| 318 | Rich The Kid |
| 319 | Andrelli |
| 320 | Alesso |
| 321 | Kygo |
| 322 | Kesha |
| 323 | Cookin' On 3 Burners |
| 324 | John Williams |
| 325 | Pitbull |

| | name |
|-----|------------------|
| 326 | James Arthur |
| 327 | Dimitri Vegas |
| 328 | PARTYNEXTDOOR |
| 329 | Snakehips |
| 330 | Migos |
| 331 | Jillian Edwards |
| 332 | Ryan Gosling |
| 333 | Vanessa Hudgens |
| 334 | Andrea Bocelli |
| 335 | Kodak Black |
| 336 | Jasmine Thompson |
| 337 | Major Lazer |
| 338 | Piso 21 |
| 339 | MC Fioti |
| 340 | Nicky Jam |
| 341 | Bruno Martini |
| 342 | blackbear |
| 343 | AlunaGeorge |
| 344 | WizKid |
| 345 | Abraham Mateo |
| 346 | Dua Lipa |
| 347 | Alicia Keys |
| 348 | Beyoncé |
| 349 | Zeeba |
| 350 | Knox Fortune |

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|-----|----------------------|
| | <hr/> |
| 351 | Martin Garrix |
| 352 | Playboi Carti |
| 353 | Marc E. Bassy |
| 354 | Steve Lacy |
| 355 | Popcaan |
| 356 | The Vamps |
| 357 | Daft Punk |
| 358 | The Plastic Ono Band |
| 359 | Selena Gomez |
| 360 | XYLØ |
| 361 | Mambo Kingz |
| 362 | Alex Sensation |
| 363 | Hight |
| 364 | P!nk |
| 365 | Tove Lo |
