A Comparison of Distance Metrics: Exploring Temporal Music Collaboration Networks

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 on approaches for measuring network dynamics over time. 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 organization 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 data set 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 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.

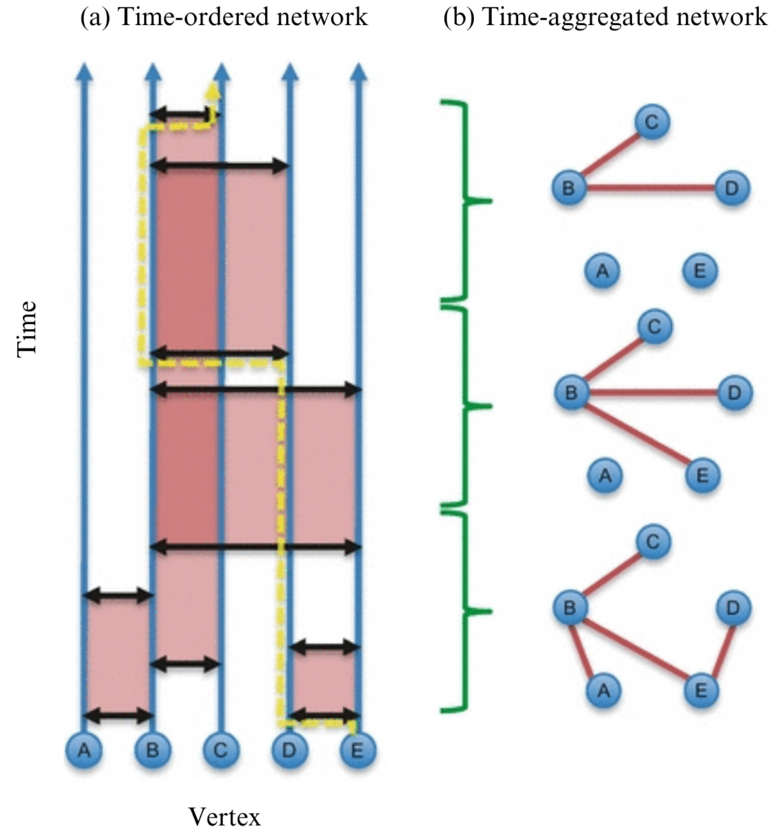


Figure 1. Examples of time-ordered and time-aggregeted network models. Adapted from (Blonder, Wey, Dornhaus, James, & Sih, 2012).

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 $G_{t_{min}}, G_{t_{min}+w}, \ldots, G_{t_{max}}$, 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 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:

$$d_{\text{Jaccard}}(G, \tilde{G}) = \frac{|E \cup \tilde{E}| - |E \cap \tilde{E}|}{|E \cup \tilde{E}|}$$

$$= \frac{\sum_{i,j} |A_{ij} - \tilde{A}_{ij}|}{\sum_{i,j} \max(A_{ij}, \tilde{A}_{ij})}.$$

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

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

This polynomial then takes an adjacency matrix as input:

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

$\mathbf{Q}$ is a matrix composed of the eigenvectors of $\mathbf{A}$, $\mathbf{W} = \Lambda_{\mathbf{A}} + \frac{1}{(N-1)^{\alpha}}\Lambda_{\mathbf{A}}^2 + \ldots + \frac{1}{(N-1)^{\alpha(k-1)}}\Lambda_{\mathbf{A}}^k$, and $\mathbf{\Lambda_A}$ is the diagonal matrix, containing the eigenvalues of 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.

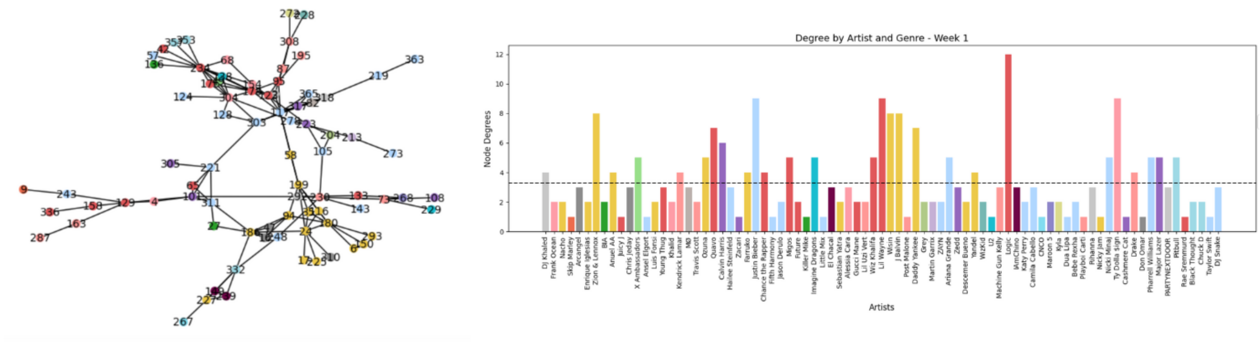
3 Application to Real-World Data

3.1 Data Source and Exploratory Analysis

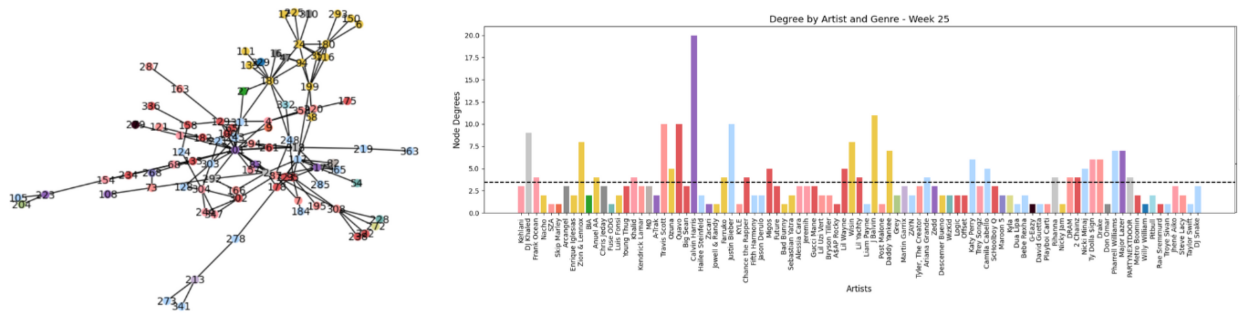
The data featured in this report was originally collected by Oliveira et al. and submitted to the 21st International Society for Music Information Retrieval Conference along with the paper "Detecting Collaboration Profiles in Success-Based Music Genre Networks." Whereas Oliveira et al. use the data to 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.

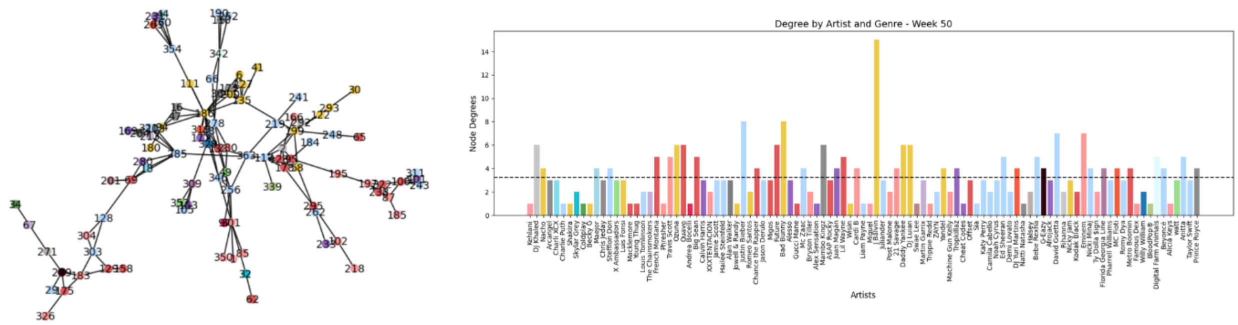
(a) Week 1



(b) Week 25



(c) Week 50



Legend

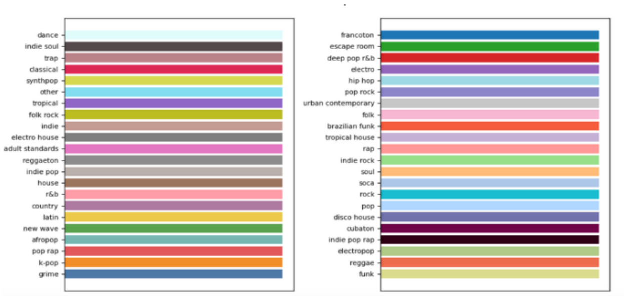


Figure 2. Largest connected component graph visualisations at three selected time steps. Plots of the degrees of the nodes in each of the three graphs. Colors correspond to the genres of the artists as seen in the legend. A mapping from artists to node indices is provided in the appendix. Unfortunately, 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.

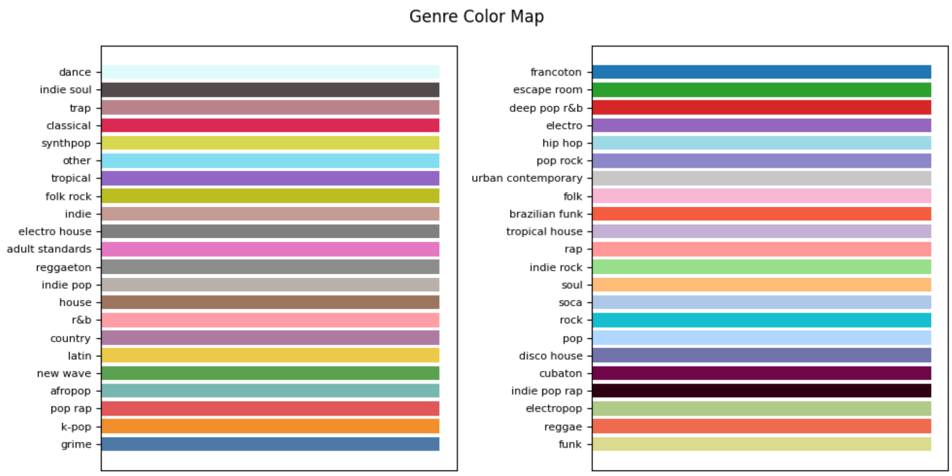


Figure 1: Enter Caption

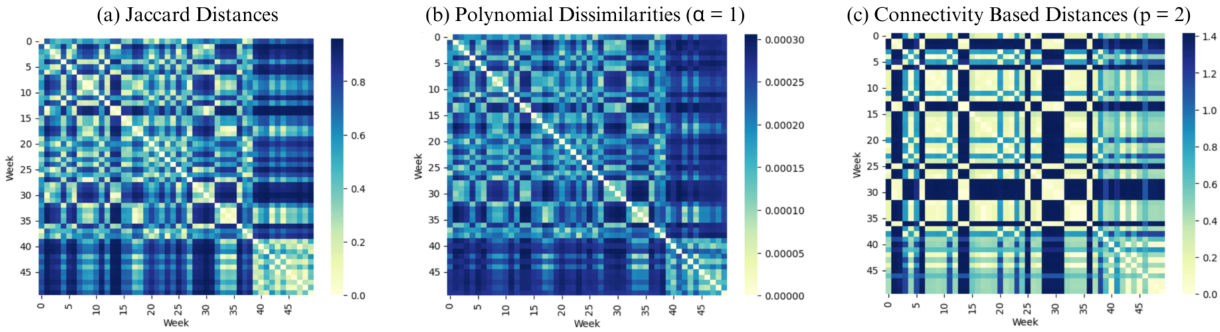


Figure 3. Heatmap visualisations depicting the (a) Jaccard distance, (b) polynomial dissimilarity, and (c) connectivity-based distances between graphs at each time step in the temporal network. A more clear version of the image is provided in the accompanying zip file.

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
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

	name
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