# Network Analysis (Project Report)

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## Abstract

The following study uses network analysis to look at the practice of Social Media Mourning on the social media network Twitter, focusing on how users connect over a seven-day period in the wake of the announcement of the death of a musician. Three musicians who passed away between 2021 and 2022 were chosen, representing different scenes and eras of modern music (techno, modern classical, funk). Data was taken from Twitter and formatted using Python and Table 2 Net to create citation networks of users and mentions that could be analysed using Gephi to try and ascertain what properties the networks displayed as well as how users interacted.

## Context

Digital technologies have impacted many aspects of daily life since the turn of the century, including how we mourn the death of public figures. The connection between communicative technologies and death was already understood by French thinker Jacques Derrida who explained that "[...] The modern technology of images like cinematography and telecommunication enhances the power of ghosts and their ability to haunt us." (McMullen, 1983) These ghosts mentioned by Derrida have only become more tangible since and the presence of death in social media has become progressively more relevant (Öhman & Watson, 2019).

Scholars such as the Italian philosopher Davide Sisto have defined digital death studies as the research area dedicated to the evolving impact of technologies on our perception of death (Sisto, 2020). Another approach to thinking about the impact of technologies on our relationship to death has been that of Social Media Mourning (SMM), a relatively new yet growing field of study that looks at how social media platforms are used in new mourning rituals. SMM can be traced back to the mid-2000s (Tan, 2020) when empirical studies on social network-mediated death began to appear.

## Problem and Motivation

The death of a musician is not just the loss of a life, but also the loss of a component of our collective cultural heritage. According to UNESCO, cultural heritage is in its broadest sense "both a product and a process, which provides societies with a wealth of resources that are inherited from the past, created in the present and bestowed for the benefit of future generations." (UNESCO, 2014) Crucially, cultural heritage isn't just something we can touch or see — it's also something that surrounds us whether as a result of the natural world or of society. In that regard, living expressions of culture such as music are very much a part of our cultural heritage. While for many countries these living expressions are first and foremost considered to be within the realm of the market during the lifetime of the artist, and only become cultural heritage after their death and expiration of copyright, we believe it is necessary to rethink and challenge this limited and antiquated understanding of how cultural expressions such as music can constitute cultural heritage. Music is an intangible, living cultural heritage comprising not just works but also communities who actively create, consume, and share. This aspect of music feels particularly important today because artists are no longer simply representative of a specific time and place. In large part because of communication technologies and digitalisation, artists (including older ones whose career began before the dominance of digital media and communication) transcend national and geographical boundaries, in effect belonging to a global cultural sphere where cultural flows are in constant motion. It is no longer enough to wait for someone to die and for their works to be removed from the market by legal means before considering if the work is cultural heritage or not. The death of a musician today is the rupture of a flow of living cultural heritage and with it comes the very real potential for their work, and history, to be lost precisely because the current approach is one that prioritises their work's value in the market and their personal history as content to be commodified.

A study of mourning around recently deceased modern musicians could be useful to help us better understand how cultural heritage can be redefined and rethought today. The aftermath of a musician's death on social media is a real, transnational moment where the interconnected nature of music as a form of living cultural heritage on a global scale becomes visible for a brief moment.

Furthermore, the relationship between artists and their fans is an object worthy of study, especially when digitally mediated. Studies have shown that popular musicians highly influence their fans and are even idolised by them (Hoffner & Cohen, 2018; Radford & Bloch, 2012). The kind of interactions that take place on social platforms between celebrities and fans can be understood as parasocial, a term coined in 1956 by Donald Horton and Richard Wohl to describe the way mass media spectators become attached to and invested in a media character (be they real or fictional) who doesn't return the emotion. Social media networks have further enhanced this dynamic by allowing fans to more easily reach people they idolise in the hope of some sort of direct contact or peek into their 'lives.' Social media has increased people's emotional investment in parasocial relationships as well as changed the perception of intimacy between fan and artist, something clearly evidenced in the rise of so-called 'stan' culture around some of the biggest pop stars in the world such as Béyonce, Taylor Swift, or BTS (Malik & Haidar, 2020). The same parasocial bond that brings people to defend an artist they don't personally know against public attacks also feeds a sense of loss when an artist dies, pushing people to publicly celebrate their lives and work in the digital square of social media, thus contributing to a popular musician's public identity by continuing their legacy posthumously (Sanderson & Cheong, 2010).

The literature and studies around the relationship between grief, social media, and musicians are not extensive and tend to be focused on hugely popular artists such as Michael Jackson (Courbet & Fourquet-Courbet, 2014) and more recently Chester Bennington, of the band Linkin' Park (Xu, et al, 2018). Another reference study for this paper is the work of Wong & Patlamazoglou (2020) which focused on "social media users' behaviour following the death of a celebrity and observable patterns of social media activity" and used interviews to explore people's feelings towards the death of famous musicians such as David Bowie, George Michael, and Avicii.

We hope to expand the insights of these existing studies by looking at how Twitter users reacted to and interacted around the death of three different musicians who passed away in 2021 and 2022. Each of these musicians is from a different historical and social background and connected to different musical movements. They are:

- producer, DJ, and techno pioneer Kelley Hand[1] (September 15, 1964 – August 3, 2021)
- experimental musician and composer Alvin Lucier (May 14, 1931 – December 1, 2021)
- singer and songwriter Betty Davis (July 26, 1944 – February 9, 2022)

We originally collected data relating to the death of a variety of musicians between September 2021 and February 2022. The approach was to simply wait for news of a death to appear on a personal Twitter feed and to then collect data for seven days following the official date of death. When it came time to decide on which musicians to focus on for this study we decided to choose four, each with a different background and importance in a different segment of the modern music world, what most people might term as 'scenes.' This led us to choose the above mentioned musicians, with Kelli Hand — who passed in August 2021 — being added retroactively to help keep gender balance in the study as well as provide an example of a musician active within the worlds of electronic music and representative of Detroit, one of the key American cities in the history of electronic music. The fourth musician we had chosen, the late Los Angeles rapper Drakeo, was arguably the most popular in our selection however the size of the network generated from the collected data proved too large for us to handle using the tools chosen for the study and we therefore decided to remove him from the selection and focus our study on the three remaining artists.

## Datasets

The data was gathered using the Twitter API. At first, a customised Python script[2] was used to gather tweets containing an exact match for an artist's name (including potential aliases and different spellings where relevant) alongside some tweet metadata including author ID, date of tweet, language, tweet metrics (counts for retweet, quotes, likes, replies), and source. Searches were also limited to original tweets only, no retweets. These searches were conducted between September 2021 and February 2022 over seven days after the announcement of the death on Twitter. An announcement is defined as the appearance of the news of the death in our personal Twitter streams and the official date of death is then used as the beginning date of the seven day period. This timespan was a limitation of the use of a standard access token. However, considering that expressions of mourning on social media tend to be most prevalent shortly after the news of someone's death, this time limitation was not thought of as detrimental and was kept as a useful bounding parameter for our study.

In order to then build networks from this data we used Table 2 Net, an online tool developed by Mathieu Jacomy at Sciences-Po Medialab[3] that allows users to extract a network from a table and export it as a .gexf file to be used in Gephi, an open-source network analysis and visualisation software package. The Python script we'd used to query the Twitter API output .csv tables and so Table 2 Net was an ideal fit for our needs. Table 2 Net allows users to create networks based on four templates: normal, or single node type linked by shared values in columns; bipartite, or two node types linked by their common appearance in a table row;

[1] Also known as Kelli Hand, a spelling that will be used throughout this paper.
[2] The script was based on this 2021 tutorial by Andrew Edward https://towardsdatascience.com/an-extensive-guide-to-collecting-tweets-from-twitter-api-v2-for-academic-research-using-python-3-518fcb71df2a. The modified version can be found at the following link alongside a list of the artists whose data was scraped https://colab.research.google.com/drive/1SkdBXbnHEGMteUpACcVmGSZzf7J_yPKK
[3] https://medialab.github.io/table2net/

citation, where one column contains references to another column; and no link, for single nodes with no links.

Following a couple of early tests we realised that we were missing some potentially relevant and useful metadata. For example, we originally tried creating networks using both the normal and citation templates with the tweet text as nodes, as this was the one piece of data containing the name of the dead musician (our chosen musicians either did not have Twitter accounts or were not active on the platform). However, it became quickly apparent this would not work for our needs as none of the other metadata in our tables could be used to create meaningful edges to link the tweets together. Following some research, we came to the realisation that by adding mentions to our data we might be able to create a usable citation network where the mentions are edges between nodes of users.

To fix this we redid the searches using Twitter's then recently launched Tweet Downloader web interface[4], which essentially allows users to query the API directly using all available parameters but without requiring external code such as the one we'd originally written. The tool allows for searches to then be exported as .csv or .json files. The new searches were done using the same timespan (seven days from official date of death) but with additional metadata including referenced tweets, conversation id, entities, geolocation, and replies. The primary benefit of this additional metadata, in particular the entities field, was that it allowed us to create columns containing mentions of other users as well as what Twitter calls annotations, which can include the names of entities who are not Twitter users (such as public figures). These are automatically extracted from a tweet text by Twitter using a process similar to Named Entity Recognition. These new searches were made possible by the use of a token with academic access, which enables searching Twitter historically, without the seven day search limit of the standard token.

These new searches were exported as .json files and processed using another custom Python script to create dataframes with all necessary columns[5]. These data frames were then exported as .csv files. In the case of mentions and annotations, as well as hashtags and urls which are also included in tweets, these are included in the .json files as lists of dictionaries and we converted them into comma separated strings in order to make them legible by Table 2 Net.

We then ran a couple of tests using Table 2 Net once again and while we were now able to create usable citation networks by setting usernames as nodes and values from the mentions column as edges we realised that by removing retweets from our searches our resulting networks were potentially too sparse to be meaningful. Therefore we redid our searches one final time via the Tweet Downloader tool and included retweets.

The final approach to creating network files for use in Gephi, which is the software we used to compute measures on the data, was as follows:

- Query Twitter via Downloader web interface and export as .json.
- Process .json file in Python to format all metadata into its own columns and export as .csv.
- Import .csv into Table 2 Net.

[4] https://developer.twitter.com/apitools/downloader
[5] https://github.com/laurentfintoni/musicians-death/blob/main/cleaning.ipynb

- Choose citation network type with 'username' as nodes (one expression per cell) and 'clean_mentions' as edges (comma separated, as there can be more than one mention in a tweet)[6].
- Attach all other available columns in our .csv as attributes to the nodes to allow us to do additional filtering and qualitative analysis. Attach 'clean_mentions' as an attribute to edges to be able to identify them in Gephi as well as 'author_ref', 'conversation_id', and 'tweet_type'_ref as potentially useful information[7].
- Import the resulting .gexf file into Gephi and choose the option to leave out missing nodes[8].

For Kelli Hand we did searches on two alias variations: K Hand and Khand. The latter proved to be problematic as it's also a Hindi word that returned unrelated tweets. Therefore the Kelli Hand network is built using the combined results of searches for both 'Kelli Hand' and 'K Hand'. The 'K Hand' search still returned a handful of unrelated tweets in Hindi so we manually deleted the nodes and edges involved.

*Table 1. Statistics for the three selected networks*

| | Total Nodes | Total Edges | Nodes with no edges |
|---|---|---|---|
| Kelli Hand | 2,805 | 2,696 | 633 |
| Alvin Lucier | 3,248 | 3,165 | 982 |
| Betty Davis | 29,950 | 32,564 | 5,363 |

As can be seen in Table 1, in terms of overall size (total nodes and edges) the Kelli Hand network is the smallest, followed by Alvin Lucier which is around 15% larger. Betty Davis is the largest of the three networks, being around 90% larger than Alvin Lucier. Each network also has a certain number of nodes with no edges (between 17 and 30% of total nodes), meaning Twitter users who mentioned a dead musician but did not interact with other Twitter users or who mentioned users not in the dataset.

## Validity and Reliability

Due to the subject of our study we took the design approach of creating a personal network, in which we could study a specific set of egos (nodes) and their alters (ties). As the data was gathered directly from Twitter this offered us something in between primary and secondary sources for the data itself, with some data coming directly from the user (the text of the tweet) while also being limited by what the service allows us to collect (the associated metadata), which limited the potential relations we could study.

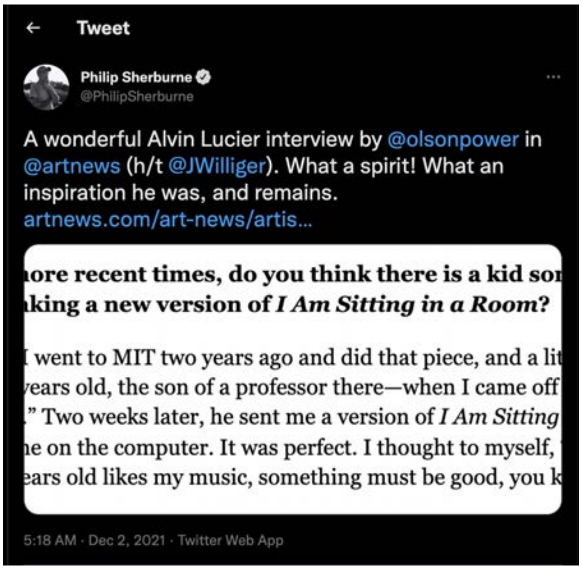
The nodes in our network are Twitter users and are only included if they tweeted about the artist we searched for. The edges are user mentions (@s) contained within a tweet. As noted

[6] A tweet with multiple mentions, or multiple mentions across multiple tweets, creates an edge to each user if they exist in the dataset. Multiple tweets by the same user create additional occurrences of the node.
[7] Multiple instances of an attribute (for example multiple tweets or mentions) are separated by a pipe in the Table 2 Net network extraction which made weighing edges a manual process we did not undertake.
[8] During our tests we discovered that if this option was checked Gephi would create nodes when a mention (edge in our network) pointed to a username that was not included in the dataset (because that user had not tweeted about the dead musician we'd searched for). We opted to remove these 'missing' nodes to make the networks more manageable, especially as Gephi did not use the mentions as labels for the created nodes.

previously, the popularity of the musician can lead to a large amount of data from the Twitter API that may require a different approach than the one we undertook in order to create a usable network file for import into a program like Gephi. We were unable to process our largest network (for Drakeo, with over 140,000 rows in a .csv file) via Table 2 Net, but there is no documentation as to the limits of the service. Manual conversion and formatting of such a large .csv file was also not practical. The Betty Davis network, which is still rather large compared to the other two, also proved more difficult for Gephi to handle. Even though we used a new Macbook Pro computer with 16GB of memory and an M1 chip, Gephi often ran out of memory when trying to compute certain measures on the network (in particular the Girvan-Newman clustering algorithm) or would be very slow in spatialising and computing. Again we're unable to say with any certainty if this is due to Gephi or the fact that as a software written in Java it may therefore perform worse on Apple computers, especially the newest models.

Beyond these issues, the biggest challenge in our design approach was figuring out how to create a network around a person that is not an active user on the social network where the data is being collected. We think that the choice we made, to create a citation network of users who tweeted about the person over a specific period of time and mentioned each other, offers a good solution. Different approaches such as looking at who follows who within a network of users who tweeted about a dead musician may also be useful.

We are dealing with nodes as co-occurrences in that users partake in the event of discussing the death of a musician, and with edges as relational events that sit somewhere between an interaction and a flow. On one hand, our edges can be considered an interaction in that someone may mention another user to let them know that the musician has died, ask a question, or to recount a story (see Figures 1 to 4). In these cases we can assume that our nodes are talking to each other, though we require more specific analysis of each interaction to better define exactly what types of interactions are taking place. These assumptions are based on a sampling of our data as well as our own experience using Twitter and being involved in communities where the death of a musician is actively discussed.



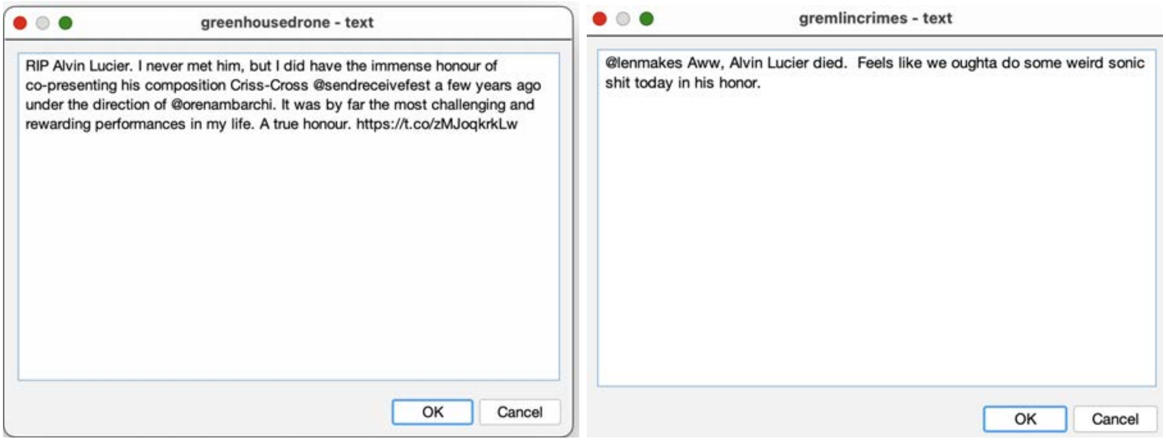




*Fig. 1-4. Examples of tweets where user mentions (edges) act as interactions.*

On the other hand, our edges can be considered flow ties in that they pass information between users. Again an example here is that of a user simply retweeting without any additional communication, a common practice on Twitter. In this case, and again based on our existing knowledge and practice of using Twitter, we can assume that the user is simply passing the information to their followers as a means of alerting them to it and showing their opinion about the matter, in a similar way to how people forward emails to each other.

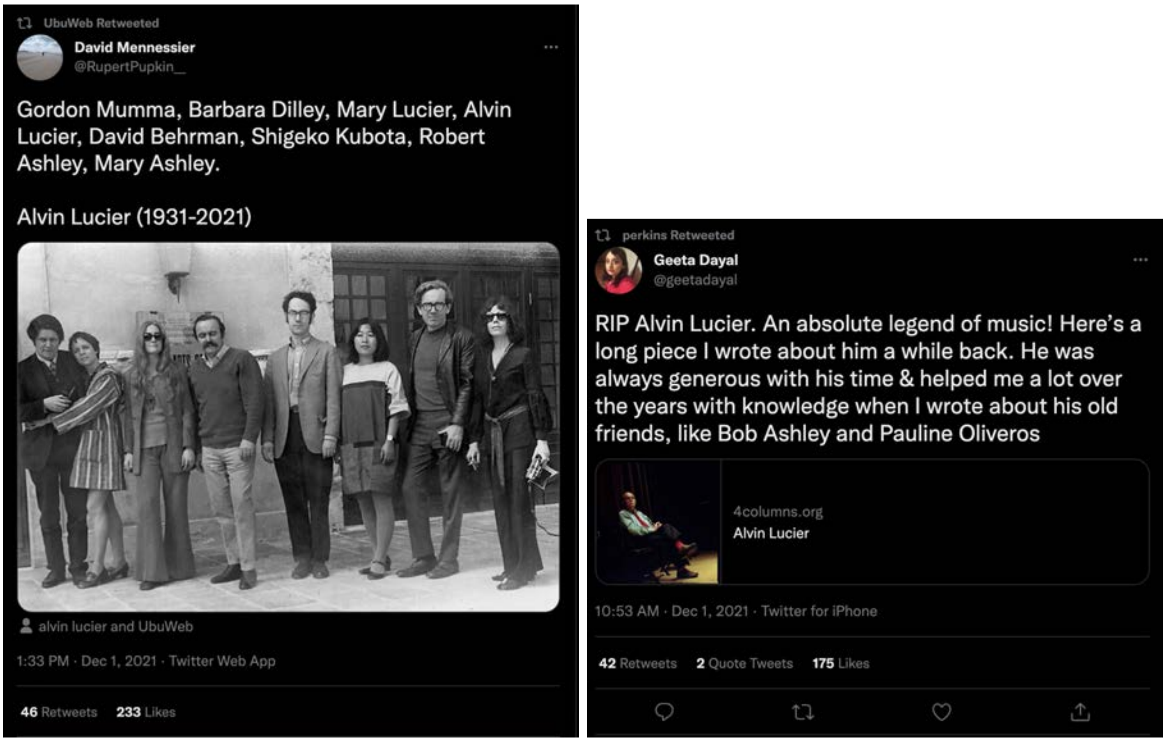



*Fig. 5-8. Examples of tweets where user mentions (edges) act as flow ties via retweets.*

Considering that the aim of our study is to investigate how users on Twitter interact around the death of a musician in the week following their death, we feel this approach allows us to draw out a useful network from the available tweets by focusing on the mentions as links between users while also allowing us to investigate which tweets proved popular in this period via their user, as actions such as retweets and quote tweets, the two most popular ways of simply resharing information on Twitter, would show up as a mention. Therefore users who received a lot of mentions in the period would have higher degree counts, indicating their potential importance as spreaders of information. The edges between our nodes are purely functional, in that they require a mention to exist, however they do have a potential affective dimension which could only really be ascertained by qualitative studies of the tweet text itself.

With regards to sampling, we chose a nominalist strategy where an objective criteria — whether or not a user mentioned a musician within a set period of time — was used to classify Twitter users as part of the network we wanted to study. As such any tweets about the musicians that didn't include a full name or were misspelt would be left out. This is somewhat mitigated by Twitter's use of semantic reasoning in its API where it will try to infer the full or correct name of an entity and include it as a potential match which will in turn trigger a potential positive result in the search.

This approach also helped to set the boundaries of our network, as the mentions of the musician's name and the seven day time period limit the potential nodes for inclusion. Equally edges are limited by whether or not a user chose to mention another user in their tweet. Thus we were able to create a boundary around what is in effect a hard to define group of people united by an external factor and limited by the use of a specific social network.

The choices we have made in data selection and formatting undoubtedly have an impact on the validity of our model, how closely it represents reality and allows us to measure what we intend to. For example, as detailed in the Datasets section, we opted to leave out missing nodes when importing the network into Gephi, a choice that certainly has an impact on centrality measures as well as on the number of nodes with no edges. However, considering that these missing nodes represent users that are mentioned in our dataset but did not tweet about the musician used as the sampling criteria, we believe this omission is acceptable. Our data collection process was iterative and we certainly did make some errors early on, however we do think that the final approach we settled on, which took in the lessons from these errors, is appropriate. As for edge/node attribution, again we did struggle with this at first but believe that the choice to have the edges as mentions and nodes as users is a suitable approach to what we intend to study. One last note can be made of the fact that due to this approach, occurrences of nodes are related to how many times a user tweeted about a dead musician in a seven day period of time (and therefore multiple tweets are included in the attributes of one node) and edges are not weighted (for example by using multiple mentions of the same user across tweets) due to how Table 2 Net formats citation networks.

As for our model's reliability, whether or not someone else could perform this study and achieve the same results, there are some potential issues. The first one is that Twitter users delete their tweets and therefore the networks may not be identical if the same searches were performed in the future. This is something that we noticed during various tests as we tried to access certain tweets to check their content or metadata and were confronted with dead pages and a notice from Twitter that the tweet had been deleted. As far as we can tell Twitter appears to hold a copy of the deleted tweets and these can be accessed via the API when using an academic token however we're not sure how long these copies are held for (and their availability goes against what Twitter claims in its Premium API FAQs, leading us to think that their availability is the result of using an academic token). In terms of objectivity, the data holds as it is, in essence, a public record, and we are not applying any subjectivity to our approach other than in the choice of which musician to focus on. We believe that we were able to account for most of the formatting errors that may have occurred in the process of going from Twitter API to Gephi via Python and Table 2 Net. As mentioned, we picked up issues around one of the aliases of Kelli Hand (Khand) also being a Hindi word which originally threw off the shape of the network. Twitter metadata is also subject to issues, such as for example identifying the common expression ‘RIP’, or ‘Rest In Peace’, as being Estonian language.

## Measures

We decided to use a short set of four questions we felt were relevant within the context of our study in order to decide which measures to apply.

The first question we asked was: which are the key nodes in each network in terms of importance and influence? Measuring nodes in this way would allow us to understand which Twitter users are central to the spread of news about a musician’s death on the social network. The terms themselves should also be defined. The “importance” of nodes within a network can be assessed in a variety of ways, related to centrality measures, and we choose to define it using the most common one: a node’s importance is related to how many connections (inbound or outbound edges) it has to other nodes, including nodes that are themselves important. “Influence” for its part is traditionally more dependent on what type of network one is analysing (social network, transportation, etc…) and generally refers to a node’s ability to have more access to things that might matter within the network or a greater capability to attract other nodes to it. In our case, we define a node’s influence as its capability to attract others to it as well as its control over the flow of information. For example, a user receiving a high number of retweets for their tweet about a dead musician might denote a level of attraction, while a user that acts as a bridge for the information contained in a popular tweet might denote a level of control over the flow of information in the network. In this sense importance and influence are fairly similar in the context of our study.

In order to answer this first question, we decided to rely on a variety of centrality measures. We looked first at degree centrality, and in particular at in-degree centrality - the count of inbound edges to a node - as this would likely provide a more robust measure within directed networks such ours where edges equate mentions. In addition to in-degree centrality we also used Eigenvector centrality and PageRank as they offer different approaches to measuring node importance and influence than simple degree centrality. Eigenvector centrality is a measure of the influence of a node in a network. Relative scores are assigned to all nodes in the network based on the concept that connections to high-scoring nodes contribute more to the score of the node in question than equal connections to low-scoring nodes. A high eigenvector score means that a node is connected to many nodes who themselves have high scores. PageRank is a variation of Katz centrality, whereby each node is given a small amount of centrality regardless of position in the network or neighbour centrality. PageRank attempted to fix the potential issues Katz centrality created, of a node with high centrality giving its neighbours high centrality, by deriving the centrality of neighbours as proportional to their own centrality divided by their out-degree. Thus high scoring nodes would only pass a small amount of centrality to neighbours, even if they have a lot of them.

By assessing all three different types of degree centrality for nodes in our networks we would be likely to find the more important and influential nodes as those that score highly across all three measures.

Lastly we also chose to apply betweenness centrality, as a way to assess a node’s influence on the flow of information. Betweenness centrality is based on shortest paths (the smallest amount of edges needed to be traversed to get from one node to another) and assesses the extent to which a node lies on paths between other nodes. Therefore a node with high betweenness centrality is assumed to lie on a path that is trafficked to get to other nodes and may therefore play a role in the network as a gateway. In the case of our networks we would expect to see nodes with high betweenness centrality scores being connected to the most important/influential nodes, most likely via a retweet or mention, and in turn spreading this information (the tweet) to others while not necessarily having high scores on degree centrality measures.

The second question we asked was: does our network exhibit a small-world effect? The small-world effect typically indicates shorter distances between nodes than might be expected, as exemplified in the famous six degrees of separation idea. The small-world effect would indicate that Twitter users expressing grief about a certain musician might be closely connected. Watts & Strogatz (1998) gave the following technical definition of a small-world network: "A small-world network is a type of mathematical graph in which most nodes are not neighbours of one another, but most nodes can be reached from every other by a small number of hops or steps." One common approach to try and assess the small-world-ness of a network is to look for spatial structure reflected by a high clustering coefficient (the degree to which nodes cluster together) and efficiency in communication reflected by a low shortest path length (indicating the number of edges between two nodes). Thus we measured both average clustering coefficient and path length for each network.

The third question we asked was: how do nodes in our network group together and what patterns of interaction do they exhibit (none, 1-to-1, 1-to-many)? In terms of grouping we decided to look at k-core values within the networks, that is groups of nodes where each node is connected to at least k other. Furthermore the k-core approach would also allow us to assess the core-periphery structure of our networks, based on the assumption that high scoring k-core nodes reflect the core of our network with the others being peripheral. As for interaction we decided to use in- and out-degree measures to detect what types of interaction our networks might exhibit: no interaction would be indicated by nodes with zero degree, meaning Twitter users who tweeted about a dead musician but did not engage in any wider conversation (except nodes that mentioned a user not included in the network), as well as nodes with self-loops, indicating users who referenced themselves; nodes with in- and out-degree of at least one would indicate potential one to one conversations as long as those edges are reciprocated; nodes with higher in- and out-degree values would potentially indicate a one to many conversation as long as the outbound edges are contained within one tweet, indicating for example one user talking to or calling out to various others as part of their tweet.

The last question we asked was: do nodes in our network exhibit assortative mixing properties? Assortative mixing, also known as homophily, is the tendency of nodes in a network to connect with nodes that are similar to them. This is normally assessed based on the characteristics of nodes, be they ordered or unordered. In our case, we attached some attributes to our nodes which could be used for assessing assortative mixing however our use of Gephi made this difficult, if not impossible, as the program would only allow us to filter node attributes using the Equal filter rather than the Range filter and the most interesting attributes we had, such as follower counts, could not be meaningfully filtered this way. As such we decided to try and assess assortative mixing by looking at the modularity of our networks which measures the strength of division of a network into communities (or clusters). High modularity scores reflect dense connections within communities but sparser connections between nodes across communities. Gephi uses the Louvain method for calculating modularity and we also installed plugins to use the Girvan-Newman algorithm and Leiden algorithm as alternative ways to assess community structures in our networks. Girvan-Newman detects community structure within a network by iteratively eliminating edges that have the highest number of shortest paths between nodes passing through them, while Leiden aimed to improve the Louvain algorithm with a three-step approach that moves nodes locally, refines the partition, and then aggregates the network based on the refined partition (Traag, Waltman, & van Eck, 2019). The idea being that using community detection we could assess clusters of nodes and more easily see if they had similar features, such as for example follower and following counts or language.

Lastly, we also relied on visual assessment of the networks' spatialisation to assess potential assortative mixing by degree. Assortative networks would show clumps of high-degree nodes sticking together with lesser degree nodes in the periphery while disassortative networks would show high-degree nodes connected to low-degree nodes in easily visible star-like features.

## Results

In Table 2 we summarise the various measures that interest us based on the questions asked as a way to get overall insights into the networks. All of these measures were conducted using Gephi. In the case of the Betty Davis network, the Girvan-Newman algorithm could not be run due to a lack of memory on our machine.

*Table 2. Summary of measures for the three selected networks*

| | Kelli Hand | Alvin Lucier | Betty Davis |
|---|---|---|---|
| Avg. Degree | 0.961 | 0.9 | 1.087 |
| Avg. Path Length | 1.69 | 1.78 | 2.327 |
| Avg. Clustering Coefficient | 0.021 | 0.019 | 0.017 |
| Modularity | 0.779 | 0.754 | 0.74 |
| Number of Communities (Modularity) | 633 | 945 | 5569 |
| Max Modularity (Girvan-Newman) | 0.155 | 0.138 | N.A |
| Number of Communities (Girvan-Newman) | 637 | 949 | N.A |
| Number of Clusters (Leiden) | 1,179 | 1,147 | 17,655 |
| Number of k2 Paths | 209,105 | 112,568 | 26,810,011 |
| Number of Triangles | 133 | 193 | 1,867 |
| Density | 0 | 0 | 0 |
| Diameter | 11 | 14 | 17 |
| Radius | 6 | 7 | 9 |

The first thing we want to note is that according to Gephi's density measure, all our networks have a density of zero. Density in a directed network is represented by the fraction of actual edges against all possible edges. In the case of our networks these results appear at the fourth decimal after zero (0.0003 for each network) but Gephi's measure limit is three decimals, hence the zero result. This very low density is likely a result of how we built our networks, which as previously mentioned limits the potential for edges. Based on this measure we can assume that one aspect of the Social Media Mourning rituals we've observed is that Twitter users commemorate dead musicians without directly mentioning or communicating with other users who are also commemorating the same dead musician.

The measures summary in Table 2 also allow us to answer our second question, whether or not our networks exhibit a small-world phenomenon. Based on the technical definition we outlined in the Measures section, we can see that our networks only have one of the properties of a small-world network, that of a short average path length, with the lowest at 1.69 and highest at 2.327, while the spatial structure of the network as denoted by the average clustering coefficient is very low, ranging from 0.017 to 0.021. Furthermore, the triangle count in each network is low compared to its overall size and each network's diameter, representing the longest shortest path in the network, ranges from 11 to 17, while the radius, representing the minimum eccentricity (or maximum distance of one node to all others), ranges from 6 to 9. As such we do not believe that we can confidently say our networks exhibit small-world properties, which we think is not surprising considering that while closely connected users would be likely to commemorate the same dead musician, the wider fan group of a musician is likely to represent diverse communities that are not themselves connected.

With regards to our first question, asserting the key nodes in terms of importance and influence, Tables 3, 4, and 5 summarise the results for the top 5 highest scoring nodes in each network for the centrality measures we applied: in- and out-degree, betweenness, Eigenvector, and PageRank.

*Table 3. Summary of centrality measures for the top 5 scoring nodes in the Kelli Hand network*

| | In/Out Degree | PageRank | Eigenvector Cent. | Betweenness Cent. |
|---|---|---|---|---|
| @mikeservito | 418/1 | 0.09 | 1 | 1,031 |
| @ghostly | 295/2 | 0.11 | 0.75 | 1,102 |
| @blackartistdata | 291/0 | 0.03 | 0.55 | 0 |
| @mixmag | 164/1 | 0.06 | 0.33 | 237 |
| @musthaverecords | 90/0 | 0.008 | 0.17 | 0 |
| @funster_ | 3/1 | 0.05 | 0.07 | 0 |
| @truants | 16/0 | 0.05 | 0.16 | 0 |
| @alan_oldham | 84/1 | 0.008 | 0.16 | 225 |
| @diethrough | 27/6 | 0.002 | 0.05 | 187 |

*Table 4. Summary of centrality measures for the top 5 scoring nodes in the Alvin Lucier network*

| | In/Out Degree | PageRank | Eigenvector Cent. | Betweenness Cent. |
|---|---|---|---|---|
| @normalcomposers | 298/0 | 0.03 | 1 | 0 |

| | | | | |
|---|---|---|---|---|
| @ubuweb | 174/1 | 0.01 | 0.65 | 225 |
| @cafeoto | 132/0 | 0.01 | 0.48 | 0 |
| @robinrimbaud | 131/0 | 0.01 | 0.44 | 0 |
| @dddrewdaniel | 94/0 | 0.008 | 0.36 | 0 |
| @goodwillsmith | 14/9 | 0.002 | 0.07 | 685 |
| @zzzzaaaacccchhh | 22/3 | 0.003 | 0.08 | 534 |
| @jwilliger | 50/1 | 0.004 | 0.25 | 421 |
| @olsonpower | 15/5 | 0.005 | 0.18 | 402 |
| @rupertpupkin__ | 67/0 | 0.02 | 0.42 | 0 |

*Table 5. Summary of centrality measures for the top 5 scoring nodes in the Betty Davis network*

| | In/Out Degree | PageRank | Eigenvector Cent. | Betweenness Cent. |
|---|---|---|---|---|
| @rollingstone | 5,268/0 | 0.07 | 1 | 0 |
| @sunmoon24_lee | 3,843/0 | 0.04 | 0.72 | 0 |
| @mjfinesselover | 2,322/0 | 0.02 | 0.44 | 9539 |
| @dusttoodigital | 1,249/0 | 0.01 | 0.24 | 0 |
| @mayascade | 1,074/0 | 0.01 | 0.20 | 0 |
| @polishedsolid | 32/27 | 0.0005 | 0.006 | 13,308 |
| @sopesoetan | 303/7 | 0.002 | 0.05 | 11,376 |
| @so14below | 22/8 | 0.0005 | 0.005 | 9,280 |
| @lightintheattic | 43/23 | 0.0007 | 0.008 | 6,541 |

As these results show some of the top scoring nodes in each network score highest across the three degree centrality measures we applied: three for the Kelli Hand network (@mikeservito, @ghostly, @mixmag); four the Alvin Lucier network (@normalcomposers, @cafeoto, @robinrimbaud, @ubuweb); and all five for the Betty Davis network (@rollingstone, @sunmoon24_lee, @mjfinesselover, @dusttoodigital, @mayascade). Of these some are also among the highest scoring for betweenness centrality: @mikeservito, @ghostly, and @mixmag for Kelli Hand; @ubuweb for Alvin Lucier; and @mjfinesselover for Betty Davis. The remaining top scoring nodes are either highest scoring for betweenness centrality, PageRank (@funster__, @truants for the Kelli Hand network), or Eigenvector centrality (@rupertpupkin_ for the Alvin Lucier network).

For the Kelli Hand and Alvin Lucier networks, 1.5% and 1.9% of nodes, respectively, have an in-degree higher than 10, while for the Betty Davis network 0.12% of nodes have an in-degree higher than 100. For Eigenvector centrality, nodes with scores of 0.1 or higher are found within the top 10 for Kelli Hand and Betty Davis and the top 25 for Alvin Lucier, while nodes with PageRank scores of 0.01 or higher are found within the top 10 for all three networks. Taken together, these results show how importance and influence within our networks appear to be concentrated among a small number of nodes, relative to the entire size of the network.

A closer look at the top scoring nodes across degree centrality measures highlighted in Tables 3, 4, and 5 also reveals some interesting qualitative insights. For the Kelli Hand network these nodes are a fellow DJ and artist from Detroit (@mikeservito), a Michigan-based electronic music label associated with Detroit (@ghostly), and a British electronic music magazine (@mixmag). Two of the three most important sources in the network are from the same city and music scene as Kelli Hand while the third was an international publication that ran an obituary, focused on Hand's importance to Detroit techno. For the Alvin Lucier network these nodes include a meme account (@normalcomposers), a pirate online library (@ubuweb), a venue in London (@cafeoto), and a musician associated with the experimental electronic scene Lucier had inspired (@robinrimbaud). Here importance appears slightly more spread out, reflecting the wider impact of Lucier's avant-garde practices. On the other hand, the top scoring node (@normalcomposers) reflects the importance of meme accounts on Twitter as information/idea spreaders, which has been highlighted by previous research (Veerasamy & Labuschagne, 2014). Lastly, for the Betty Davis network these nodes include a national music publication (@rollingstone), a pop culture commentator (@mjfinesselover), a music blog (@dusttoodigital), a scholar (@mayascade), and an average user (@sunmoon24_lee). This last one is interesting because it is the second highest scoring node for all three measures but has the lowest number of followers among all the other top scoring nodes in all networks, with only 286 followers. They tweeted four times during the seven day period with their third tweet, a photo of Davis performing in 1973, receiving a high number of retweets and quotes (see Fig. 9). Comparatively the other top scoring nodes reflect Davis' cultural importance, with national news coverage and remembrances from members of the Black cultural sphere. The presence of @sunmoon24_lee among the most influential nodes remind us of the power of virality and the capacity of a relatively random tweet to become popular regardless of the user's standing.


*Fig. 9. The most popular tweet about Betty Davis from @sunmoon24_lee.*

Figures 10, 11, and 12 show a spatialisation of each network with nodes sized by degree and Eigenvector centrality and colored based on modularity. For the layout we used the Fruchterman-Reingold algorithm as this provided us with what we felt was the clearest visualisation of potential communities across all three networks. Due to its size, attempts at spatializing the entire Betty Davis network kept running into memory issues and so we filtered it to remove all nodes with degree less than two, shrinking the network down to 19.33% of its total nodes and 41.73% of its total edges. We felt this was acceptable as nodes with zero or one degree reflected no or minimal interactions.

While the algorithm we chose was useful for clearly visualising peripheral zero degree nodes (in the Kelli Hand and Alvin Lucier networks) as well as potential communities (as discussed later), it did leave us with some ‘spaghetti’ like concentration of edges in the centre of the spatialisation which we felt was an acceptable drawback for the clarity it provided us elsewhere, such as highlighting the concentration of importance and influence in each network on a small set of nodes.

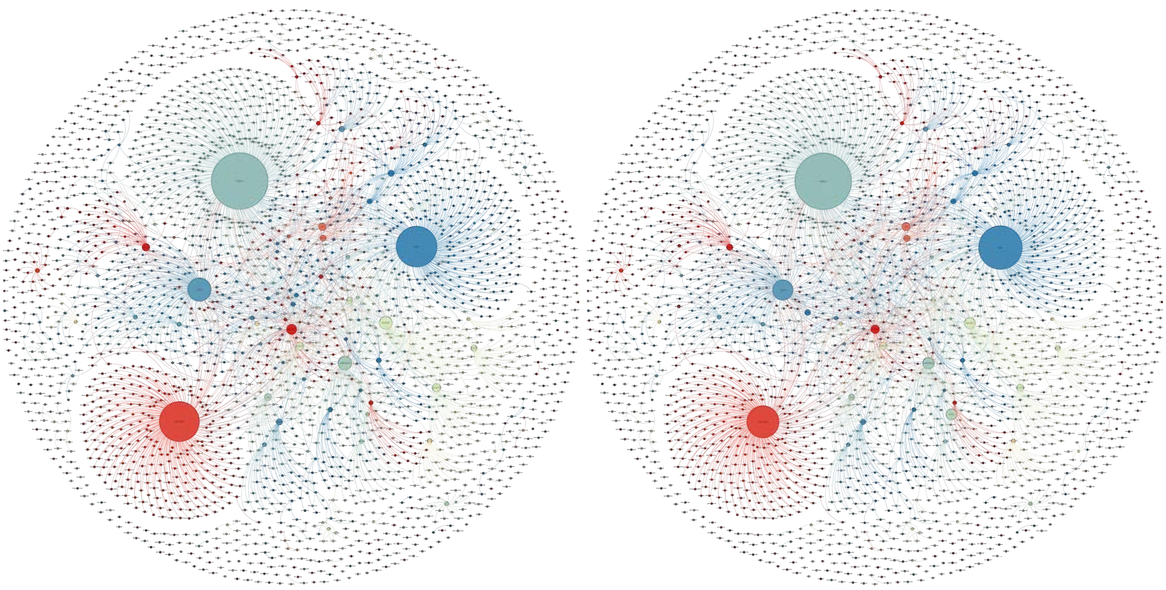


*Fig. 10. Kelli Hand network, nodes sized by degree (left) and Eigenvector (right) centrality, colored by modularity.*

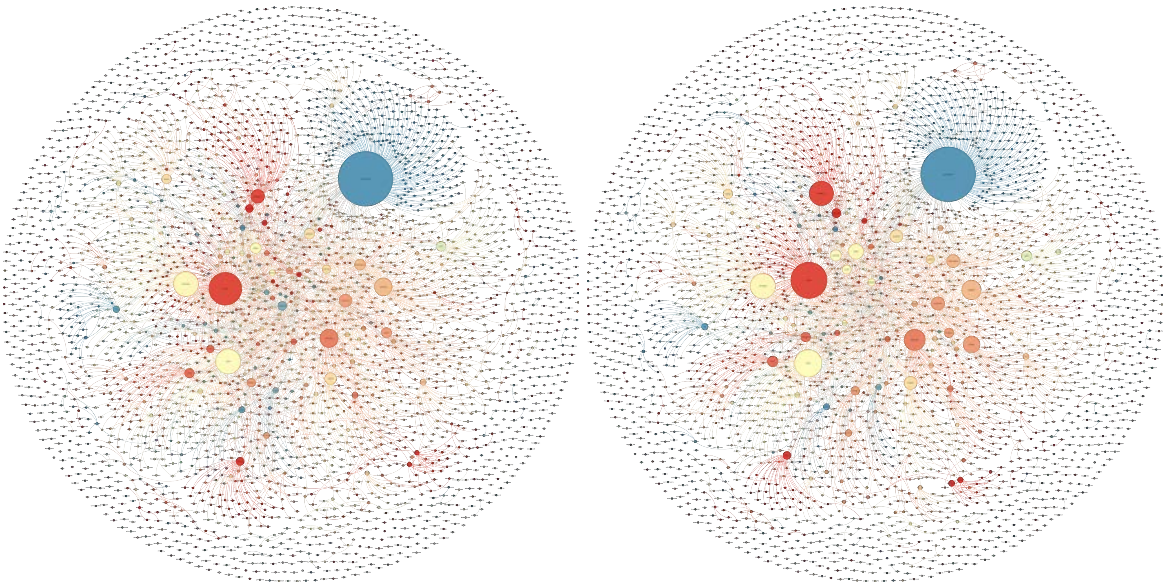


*Fig. 11. Alvin Lucier network, nodes sized by degree (left) and Eigenvector (right) centrality, colored by modularity.*

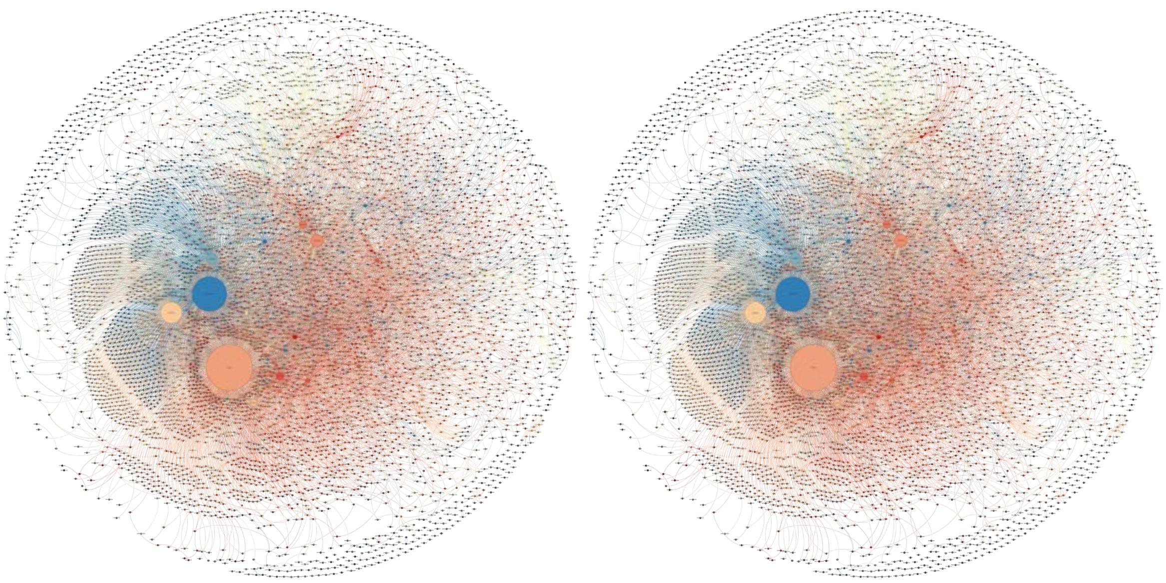


*Fig. 12. Betty Davis network, nodes sized by degree (left) and Eigenvector (right) centrality, colored by modularity.*

As for information flow, which we assessed using betweenness centrality, we can see from Tables 3, 4, and 5 that some of the nodes with high scoring betweenness centrality are different than those which scored highly on degree centrality measures: four different nodes for Alvin Lucier and Betty Davis, but only two for Kelli Hand (and in fact one of those is the sixth highest scoring node by degree centrality, so we can say that it's only one different node for this particular network). We assume that the smaller size of the Kelli Hand network might be the reason why in this case information flow is also concentrated among nodes that scored highly in degree centrality.

In the Kelli Hand network, @diethrough, the fifth highest scoring node by betweenness centrality, tweeted 16 times during the seven day period, retweeting the three most popular nodes (@ghostly, @mikeservito, @mixmag). This is a Japanese user and their other tweets were all in Japanese, so one assumption could be that their access to users in a different language might be a reason for their higher connectivity within the network, allowing the information from the important nodes to flow to users that would not have necessarily been exposed to it.

For the Alvin Lucier network, the two highest scoring nodes by betweenness centrality (@goodwillsmith, @zzzzaaaacccchhh) tweeted eight and five times respectively and both have high follower counts (over 7,000 and 11,000 respectively). Across all their eight tweets @goodwillsmith only retweeted users that are in the top 20 of highest scoring nodes by degree centrality while @zzzzaaaacccchhh shared personal remembrances of being a student of Lucier. The other two highest scoring nodes by betweenness centrality (@jwilliger, @olsonpower) followed a similar pattern but tweeted less (once and three times respectively) and tweeted at each other, @jwilliger mentioned an interview @olsonpower had conducted with Lucier and @olsonpower retweeted this.

Lastly, for the Betty Davis network we also have a pattern where four of the highest scoring nodes for betweenness centrality have a high amount of tweets within the seven day period (ranging from nine to 40) which were primarily retweets of the top 20 highest scoring degree centrality nodes.

Based on these results, information flow within our networks appears to be linked to both a higher rate of tweeting within the seven day period as well as to the sharing of tweets from nodes that score highly in degree centrality measures. By retweeting popular tweets users are passing information to their network, thus enabling the information to flow further, and by tweeting multiple times they increase their potential to do this by keeping the news about a dead musician visible. Thus these two behavioural patterns appear to be the ones that define information flow as a form of influence within our networks.

Figures 13, 14, and 15 show spatialisation for each network using the same layout algorithm as Figures 10, 11, and 12 but with the nodes sized by betweenness centrality and colored by modularity. The changes in which nodes are more important is readily visible.

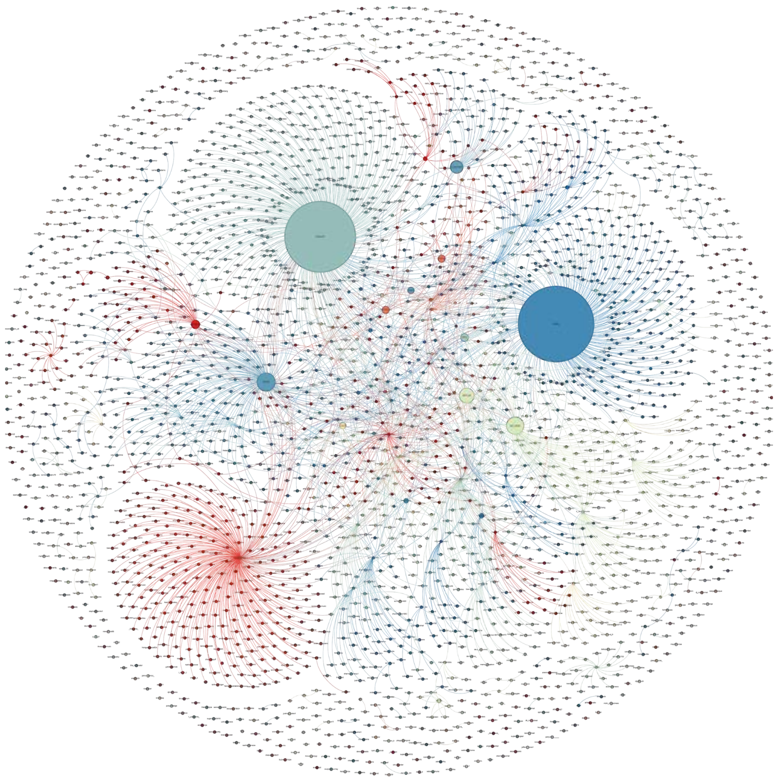


Fig. 13. Kelli Hand network, nodes sized by betweenness centrality, colored by modularity

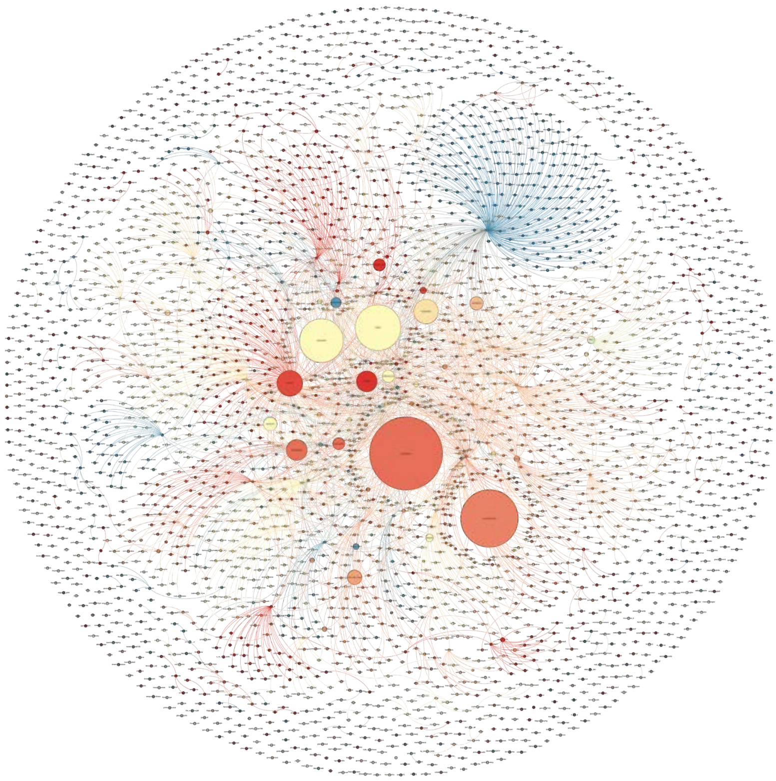


Fig. 14. Alvin Lucier network, nodes sized by betweenness centrality, colored by modularity

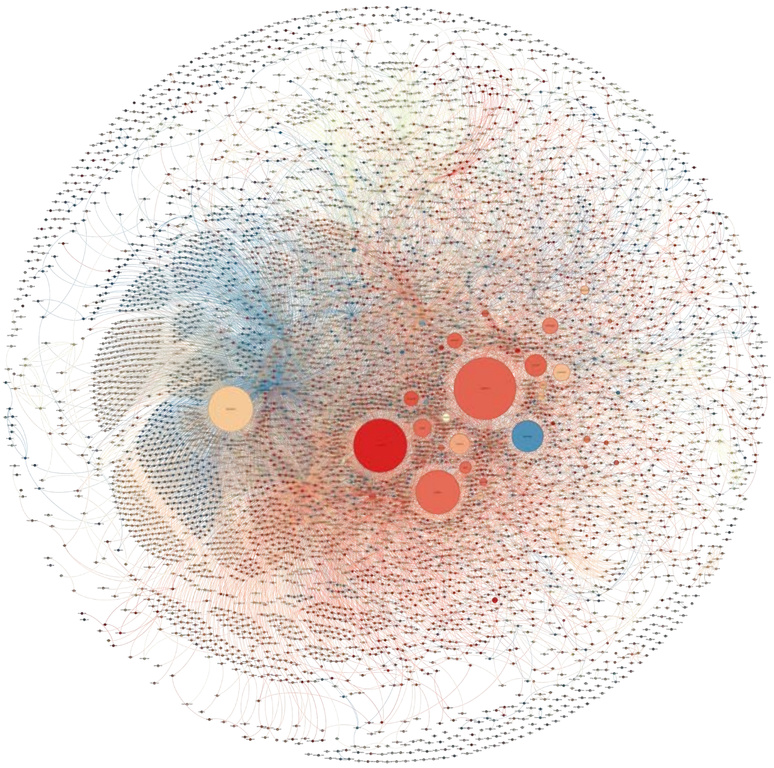


Fig. 15. Betty Davis network, nodes sized by betweenness centrality, colored by modularity

Moving on to our third question, how do nodes in our network group together and interact, we applied k-core filters via Gephi. Beginning with 1-core we continued to increase the value of the filter until we were left with the highest possible value for k, thus revealing the central core of the network. Looking at the nodes that make up each central core within our networks we also began to see some patterns: cores tend to be made up of nodes that score highly on degree centrality measures as well as nodes that tweeted multiple times over the seven day period and have high out-degree scores.

For the Kelli Hand network, the maximum k-core value was 4 revealing a central core of 40 nodes, or 1.43% of the total network. Within this 15 nodes had an in-degree of 10 or higher, and 22 nodes had a higher out-degree than in-degree with the out-degree appearing to correlate to the amount of times they tweeted. In the Alvin Lucier network, the max k-core value was 5 revealing a central core of 50 nodes, or 1.54% of the total network. Within this 22 nodes had an in-degree of 10 or higher, and 27 nodes had a higher out-degree than in-degree and some apparent correlation between out-degree value and number of tweets. As for the Betty Davis network, the max k-core value was 9 revealing a central core of 40 nodes or 0.13% of the total network. Within this 17 nodes had an in-degree of 100 or higher, and 19 nodes had an in-degree of 0 but an out-degree of 10 or higher which also appeared to correlate with a higher number of tweets. The Davis network is the only one where one of the top five high scoring nodes by degree centrality (@dusttoodigital) does not appear in the central core.

Figures 16, 17, and 18 show these cores with nodes sized by degree and colored by modularity, taken from the application of the K-core filter in Gephi to our existing spatialisations. These clearly show the mix of important and influential nodes with nodes that engaged in multiple tweets and outbound mentions. The small size of each core compared to the total network size also underlines how critically important these cores are in the spreading of information about a dead musician. In terms of core-periphery structure, the k-core breakdown of each network shows that the periphery constitutes a vast majority of each network with 1-core nodes making up between 75 and 83% of the network for each of our networks.

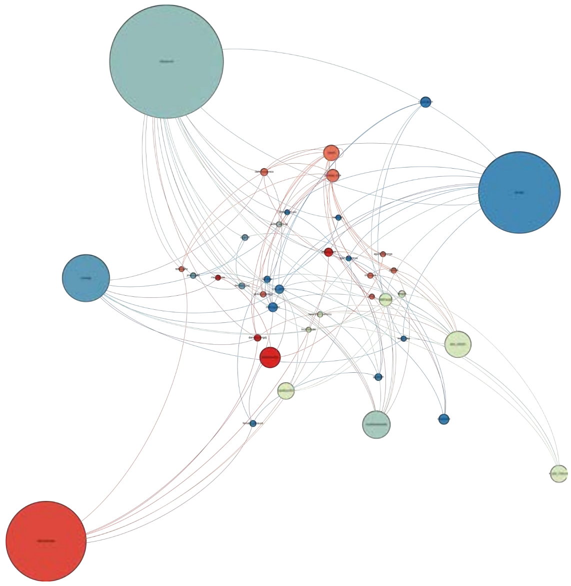


*Fig. 16. Central core for Kelli Hand network, with k = 4, nodes sized by degree and colored by modularity*

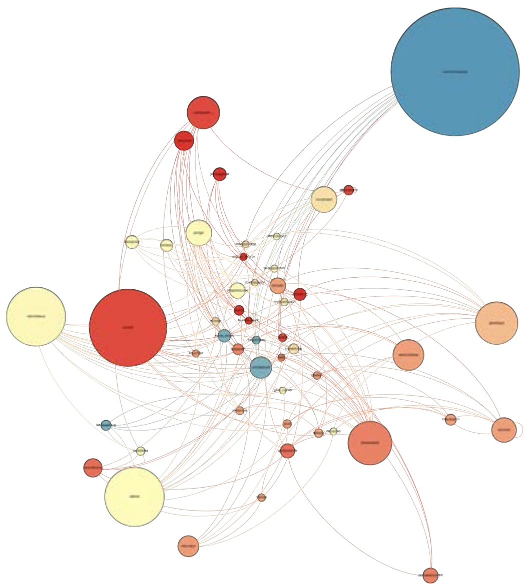


*Fig. 17. Central core for Alvin Lucier network, with k = 5, nodes sized by degree and colored by modularity*

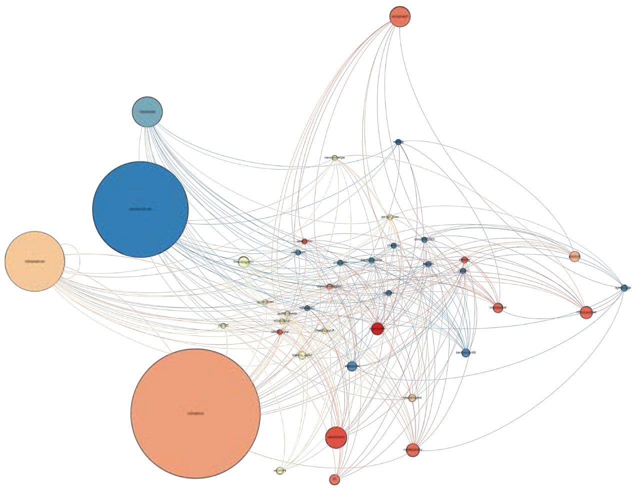


*Fig. 18. Central core for Betty Davis network, with k = 9, nodes sized by degree and colored by modularity*

To analyse patterns of interaction between the nodes in our networks we also used Gephi filters to focus on the patterns that interested us.

Firstly we did a degree filter to find all nodes with zero degree values and then analysed the results to further remove nodes that did mention users not in our dataset (and would thus still show up as having zero degree in our networks). The results were 466 nodes, or 16.6% of total nodes, for Kelli Hand, 739 nodes, or 22.7% of total nodes, for Alvin Lucier, and 4,189 nodes, or 13.9% of total nodes, for Betty Davis. In addition we also applied a topology filter to find nodes with self-loops, indicating users who engaged with themselves, most likely via retweets of their own tweets (some users with self-loops did also mention other users across different tweets so they are not necessarily only engaging with themselves). For the Kelli Hand network 13 nodes, or 0.46%, had a self-loop including one of the top scoring nodes by degree centrality (@mixmag), while the Alvin Lucier network had 24 nodes, or 0.74%, including one of the top scoring nodes by betweenness centrality (@olsonpower), and the Betty Davis network had 205 nodes, or 0.68%, with a self-loop which also included one of the top scoring nodes by degree centrality (@mjfinesselover).

Next we looked at whether or not nodes engaged in 1-to-1 conversations, which was achieved by applying multiple filters starting with range filters for in/out degree of at least 1 and then a mutual edge filter to show reciprocal mentions. We then manually assessed the results of these filters using both visualisation and the table view in Gephi. What this revealed was that in the Kelli Hand network there were only two 1-to-1 conversations, in the Alvin Lucier network there were none, and in the Betty Davis network there were more than 10. These conversations generally revolved around users commiserating or simply sharing information with each other about the dead musician (see Fig. 19).


*Fig. 19. Example of a 1-to-1 conversation within a 1-to-many conversation in the Betty Davis network.*

Lastly we also looked for potential 1-to-many conversations, however Gephi does not make this very easy. We applied a range filter for out-degree with values of 2 or more but the resulting data in each network was quite sizable and required extensive time to go through to manually assess each tweet. We made some preliminary passes on these results looking for specific patterns either visually or via use of the @ sign at the start of the text (which tends to denote a conversation) and could only find a handful of instances where users engaged in reciprocal 1-to-many conversations, including one in the Kelli Hand network between Dutch users and one in the Betty Davis network (see Fig. 20). Again the subject matter appeared to focus on sharing the news and discussing its implications or the musician themselves.

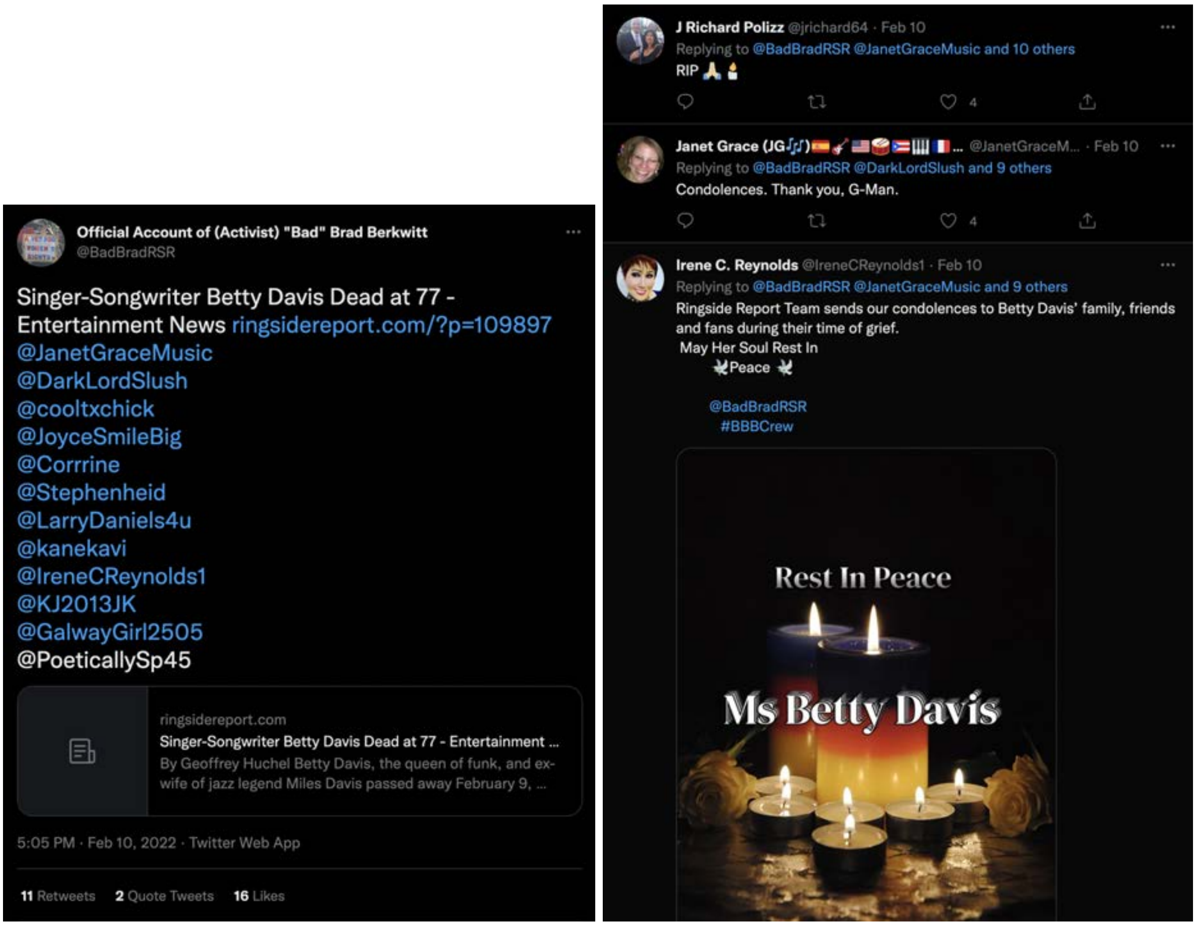



*Fig. 20. Example of a 1-to-many conversation in the Betty Davis network.*

The last question we asked regarded potential assortative mixing properties for the nodes in our networks, and therefore whether or not they had a tendency to draw ties with other similar nodes.

One approach involved looking at the spatialisation of our networks to discern potential telling patterns that would indicate assortative mixing by degree. As mentioned above, we chose the Fruchterman-Reingold algorithm because we felt it produced layouts for our networks that made it easiest to see potential communities as well as assortative mixing. One aspect that was immediately apparent (see Figs. 10, 11, and 12) was that each network featured star-like elements representing low-degree nodes connected to each of the top 5 highest scoring nodes by degree or Eigenvector centrality. Such patterns are normally representative of disassortative networks, which is not expected within social networks (as people tend to connect with those similar to them) however considering that we built our networks based on who mentioned who with regards to a dead musician within a specific period of time it is perhaps to be expected that the networks would not exhibit expected assortative mixing properties by degree. Furthermore, within each network's top five scoring nodes by degree and Eigenvector centrality we found that in the Kelli Hand and Betty Davis networks only two of the five nodes mentioned each other, while none did in the Alvin Lucier network. This pattern changes somewhat as you go down the highest scoring nodes, with more occurrences of mentions of other high scoring nodes, however, taken together with the previous mention that Eigenvector values of 0.1 or more are concentrated in the top 10 nodes of each network, we feel confident that our networks do not exhibit assortative mixing properties.

We also looked at community formation within our networks using Gephi's inbuilt Louvain method for measuring modularity as well as two plug-ins that assessed modularity using the Girvan-Newman and Leiden methods. As noted in the results in Table 2, we can see that the Louvain and Girvan-Newman methods found approximately the same amount of communities within each network while the Leiden method found more, which is to be expected as it was developed as an answer to perceived problems with the Louvain method and "uncovers better partitions" (Traag, Waltman, & van Eck, 2019). In our assessment of Louvain vs Leiden communities/clusters for key nodes we found similar communities but smaller sizes for Leiden.

The communities detected by each algorithm show the same patterns as were revealed by our visual assessment of the networks, namely that high degree nodes tend to be connected to low degree nodes. Filtering each network by detected community (only possible for the Louvain and Leiden methods) allowed us to do some more granular reading of community formation. One pattern we did notice was that higher degree nodes (10 or above for Kelli Hand and Alvin Lucier, 100 or above for Betty Davis) tend to not mention other users (and thus have no outbound edges) but find themselves connected to other parts of the networks via retweets or mentions. Fig. 21 gives an example of this in the Alvin Lucier network with a cluster centred on @nprmusic, a trusted source of news in the United States, and their connection to another news source, @stereogum, focused on music, via low-degree nodes that simply retweeted tweets about Alvin Lucier from different sources and thus ended up acting as bridges within the community.

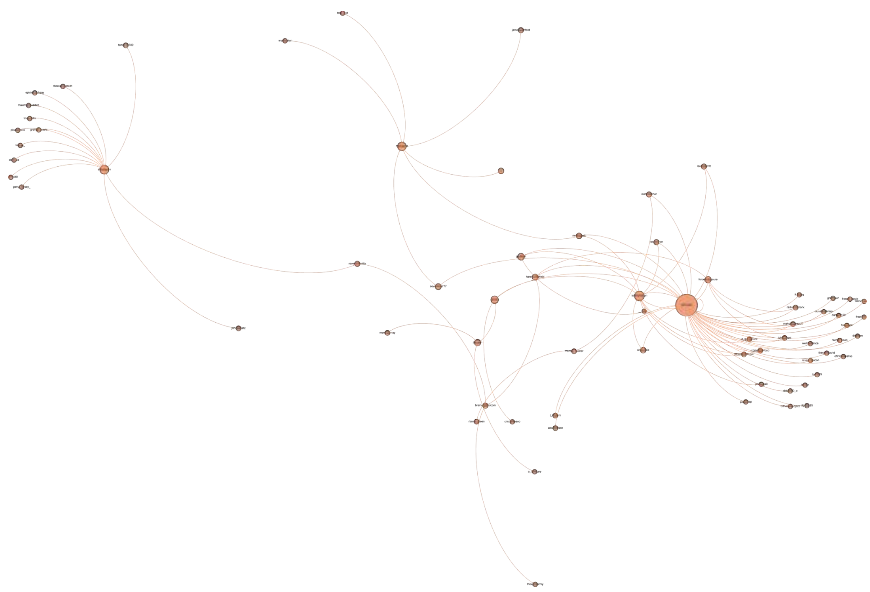


Fig. 21. Cluster within the Alvin Lucier network centred on @nprmusic.

Lastly, we took a look at some metrics and attributes that may indicate similarity between nodes within a community or cluster. One metric we looked at was follower counts, based on the assumption that nodes with high follower counts may engage with each other, and we also looked at language as an attribute, based on the assumption that nodes that speak the same language would be bound together in clusters. With regards to followers we did not find any meaningful pattern that might indicate attraction between nodes of similar status based on follower counts, instead within communities we found a wide mix of follower counts. However language, as expected, proved somewhat more likely as a shared feature of nodes within a community. We ignored English as this is the primary language of all networks (between 76 and 87% of total nodes in each network) and instead looked at some of the other prominent languages such as Japanese and Spanish. In the Kelli Hand network, where 7.45% of nodes used Japanese in their tweet, we could see four clusters of at least 10 nodes or more that belonged to the same communities and used the language while in the Alvin Lucier network, where Japanese accounted for 5.11% of nodes, we could see three such clusters. In the Betty Davis network we looked at Spanish, which accounts for 3.39% of nodes, and found seven clusters that shared the language.

## Critique

While we believe that we have achieved our stated scope of analysing Social Media Mourning through the lens of network analysis, issues remain with our approach which could be improved for future research.

The first, fundamental issue regards the way we built the networks. Our networks are citation networks with users as nodes and mentions as edges. We adopted this approach due to the particular nature of our study and the available data. We were interested in a particular moment on social media in which many different users are talking about the same topic. Yet, this is not easily translatable into a network structure due to the fact that the musicians themselves were not active users of the network and the tweets users shared did not necessarily include an easily quantifiable Twitter metric, such as a mention or a hashtag (particularly when talking about less known musicians). We ultimately relied on mentions as the one available metric with which to create our citation network and believe it was a good choice but are aware it was from perfect. The presence of a sizable, sparse peripheral area in all our networks of nodes that did not engage with the dead musician is evidence that this approach doesn't fully catch the interconnectedness of Twitter. Perhaps another way to do this could be to use metrics such as followers / following to look at who follows who and has also tweeted about a dead musician. Equally further subdivision of the networks using time or language might prove interesting. We did evaluate the partition of the network under these two metrics and noticed that in terms of time there is a clear drop off in activity within the seven day period, with over 80% of tweets happening within the first two days.

Another issue with our approach was the lack of weights on edges. Due to our use of Table 2 Net to build the Gephi files we were not able to meaningfully weight the edges, whether by using mentions or retweets as a metric. This is undoubtedly a flaw of our approach and could have provided a better insight into how important retweets are within our networks.

Finally, a more general criticism regards the nature of our research. The characteristics of Social Media Mourning are more qualitative than quantitative: they encompass ideas related to subjects like philosophy, media studies, and sociology of technology and therefore a network analysis can only reveal so much. This is reflected in the kind of answers we found to the questions (for example the disassortative nature of the networks). While network analysis clearly is able to offer some insights into the overall activity of SMM, qualitative analysis is required to really get to the how and why users mourn musicians on Twitter the way they do.

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