# Analyzing Networks of Local Music Fans in Omaha, Nebraska and Austin, Texas

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## ABSTRACT
UPDATED—29 April 2017. The music scene in Omaha, Nebraska is thriving. Independent artists are everywhere, performing in venues like The Slowdown, The Waiting Room, Reverb Lounge, and more. To understand what still separates Omaha from successful national scenes, such as Los Angeles, New York, Nashville, or Austin. Because the music of Austin is the most like Omaha's in style, this city was chosen as the point of comparison with Omaha in a building a graph of the networks of fans interacting with pages within the local scenes of each community. The results indicate that Omaha's music fans have built extensive clusters of fans through the well-documented phenomena of homophily, isolating musical genres from each. This isolation was further confirmed through additional analyses, as well. The music fans in Austin have also formed similar clusters. The difference in network diameter shows that the distance between the clusters is smaller in the Austin network, but the distance between nodes within these clusters is greater. This could potentially mean that the distance between clusters needs to shrink, for Omaha to experience more growth nationally, in addition to the increased degree to which Omaha's fans engage in a friend building in a way that increases the degree to which homophily is observed. Ensuring that music fans in Omaha are more regularly exposed to greater representative samples of the entirety of Omaha's sonic output would help to ensure that. It is also quite likely that factors outside social media impact the ability for a music scene to grow, including logistics and economic development. Because of the small scope of the information studied, future studies could include more pages, people, or different cities altogether to produce more conclusive results.

## Categories and Subject Descriptors
E.1 Data; Data Structures; Graphs and Networks

## General Terms
Algorithms, Human Factors.

## Keywords
Social networks; Social network analysis; Facebook; music scenes; music fans; Omaha, Nebraska; Austin, Texas



## 1. INTRODUCTION
The music scene in Omaha, Nebraska is thriving. Independent artists are everywhere, performing in venues like The Slowdown, The Waiting Room, Reverb Lounge, and more. These venues have helped drive urban growth over the past decade [20]. Many bands have achieved commercial success and become nationally renowned [20]. Despite this, the Omaha origins of these groups are not becoming well known, and even when they are known, these origins are ignored. Additionally, profit and non-profit companies are in abundance all over the city, achieving wide success and acclaim in the region [20]. These organizations include Omaha Performing Arts, the Maha Music Festival, Saddle Creek Records, Hear Nebraska, The Slowdown, The Holland Performing Arts Center, The Orpheum Theater, and others. The question of what is creating a separation of Omaha from other more successful scenes, such as Los Angeles, New York, Nashville, or Austin (cite) was begin to develop when making these considerations. A possibility to come up was whether it was simply a product of the size of the city, much smaller than those mentioned above.

At the same time, the importance of social media continues to grow. [cite social media growth study]. The South by Southwest (SXSW) music festival makes innovative use of social media functionality to promote its yearly activities. Because of this importance, that is, the democratization of information provided by the Internet, and social media that it was decided to create a 'snapshot' of the social media connections between music fans of each city. This decision led to the formation of the research question:

*How does music spread through fans within the Omaha community and how does that compare with a successful city?*

The idea of mapping and understanding how music fans are connected to one another within a city informed the methodological design. For this reason, the social media research focused on Facebook, currently the largest social network and a hub of music sharing. The Omaha music scene is full of Facebook pages hosting Facebook Events for performances. Because the music of Austin is the most like Omaha's in style, compared to the previously mentioned cities, this city was chosen as the point of comparison. How users interact with each other on these pages and events is the point of comparison.

The research conducted in this paper will contribute to the understanding of online social networks, of which the body of knowledge is already quite large. It will more narrowly help understand social networks related to music and social networks of music fans, as well. These areas have been less tapped into in existing research, as will be demonstrated more in the related work section later in the paper.

This paper is presented in the following structure. The next section will discuss the related work, and the nature of how this new research fits into the existing body of work. The third section will present the methodology used to construct networks for interpretation. The fourth section will discuss the methods of analyzing the networks and the results of these test. The fifth section will draw conclusions from the results and present opportunities for future research.

## 2. RELATED WORK

The related work section is divided into two subsections. The first relates to principles of networks, specifically the identification of the characteristics and computations used to obtain the results of the research. The second relates to the body of work of social networks in a musical context.

### 2.1 Principles of Networks

One of the most important areas of networks is graphing. This is creating a graphical representation of a network, whether it is stored as an edge list, or a two-column list showing which nodes match with another, or an adjacency matrix. A matrix with nodes in rows and columns, having values in the spaces showing the number of occurrences of an edge between any two nodes.

An aspect of graphing that is important in any context is the layout. Many algorithms for layouts have been developed over the years. There are several algorithmic styles of how to go about laying out nodes and edges. A very prominent one is called a force-directed layout. A force-directed layout is one in which it attempts to create edges of equal length and to prevent the overlapping of edges as much as possible. One of the first of these algorithms was formulated by Eades [9]. Several others followed later, such as Kamada-Kawai and Fruchterman-Reingold [9, 13]. Other, non-force-directed layouts include graph embedder (GEM), and Large Graph Layout (LGL) [1, 8].

Another principle of networks is homophily [16]. This principle exists in some networks but not in others. It is the social tendency of people to relate to, and therefore connect with, others who are similar to them in various ways [16]. This could be political beliefs, favorite music, movies, books, location, nationality, and religion, amongst others [2]. This principle leads to the formation of clusters within networks. These clusters can be relatively isolated, or only somewhat. This variation in how hemophilic a network is called an assortativity coefficient [17]. This is a correlation coefficient of the degree between pairs of nodes [17].

A related feature of many networks is called a bridge. A bridge is a node that appear to be of relatively little importance because they are not centrally located, however they are the only nodes bridging the gaps between clusters [12]. These nodes seem unimportant initially, but without them, a message cannot travel from one group to another. They are therefore often considered some of the most important nodes in a network.

Also related to homphily is the concept of transitivity. Transitivity describes how tightly knit a cluster is [19]. This is also related to density mentioned later, but on the level of only a cluster. A tightly knit cluster is called a clique [19]. Cliques can breed extreme positivity of interaction, but when an unknown element is brought in, negativity can ensue. They can also be counterintuitive to new, innovative techniques for various tasks.

If a network is believed to be homophilic, this can be better determined through various clustering algorithms. The fastest and therefore typically the first to be used is the Fast Greedy algorithm [6]. This algorithm begins with each node in its own cluster [6]. It then adds to each by detecting which additions increase the modularity as much as possible [6]. Modularity is a means of measuring the nature of connections within the network [18]. A high modularity suggests that there is a high number of edges within clusters, but few outside them [18].

Another property of a network is a measure called coreness. Coreness measures how close a node is to the core of the network [3]. This allows for the development of how important a node is to the flow of information through a network, and when they are likely to receive that information. Nodes on the periphery of the network are less important to information flow and are likely to be the last to receive much of the information as well.

Density is another property of networks identified in the literature [12, 14]. Density is the ratio of the number of edges in the network over the total number of possible edges between all pairs of nodes [12, 14]. Like many other properties that can be computed, density is a means of measuring how connected nodes within the network are.

The final property is the diameter of the network. The diameter of the network is the shortest distance between the two nodes that are the furthest apart [7]. This is most useful for determining the ideal pathways for the travel of information as quickly as possible from one end of the network to another. There are also many other principles of networks that lie outside the scope of this research.

### 2.2 Social Media, Music, and Networks

Within social media online, people engage in networks of other friends or users. One aspect of engagement between users is called online word-of-mouth [21]. It was discovered that users who are actively involved in a subject area, such as music, were more likely to posit their own opinions, as well as to seek out those of others [21]. It also was discovered that online word-of-mouth does not contribute to involvement in music online, though [21]. Discussion of music was not determined to be a significant predictor of persuasion to purchase. This is important to consider when trying to understand how music fans distill information within a social network.

The growth of Austin’s music scene has not been without its hardships, particularly in city policy and governance. Long identified several key problems that might worsen in Austin over time, including over commercialization and a sense of detachment developing in fans [15]. This may already be evident in the amount of attention focused on SXSW from outside Austin. Has it begun to lose its self-image as it blends into the national identity? Is this something Omaha’s scene would be willing to adapt to? Or is it something to avoid? Is growth to national prominence even desirable for Omaha’s music scene in the long-term future? These are all questions that Omaha’s musicians and their fans must ask as Omaha tackles with growth, particularly in the entire metropolitan area.

It is known from Gilbert and Karahalios, that intimacy is the largest predictor of tie strength on social media [10]. Intimacy is determined through the last communication, the number of friends, and the intimacy of words used in communication. This applies to music fans on Facebook as well. Another layer can be added here as well, intimacy with page should reflect on intimacy with the user, as well.

On Last.fm, it also was discovered that friends tend to share musical interests. [4] Because we know intimacy is significantly involved online, as mentioned above, we can therefore conclude that shared musical interests, through homophily, build intimacy, between two users online [11, 17]. This could help to explain the hemophilic nature of musical interests in the networks described within this research. These fans tend to be the same age as well, further developing clusters of users by genres preferred by various age groups [4].

Gender and race play significant parts in the formation of friend networks and interactions online [14]. Because of understandable privacy limitations, these areas could not be examined within the context of this research. Culture also plays a prominent role within this context. These previous works informed the development of the methodology presented below.

# 3. METHODOLOGY

In this section, we will discuss the methods used to obtain information from Facebook, and how that information was used to create network graphs for both Omaha and Austin. An overview of the structure of data collection and use for each city individually is presented as follows:

1. Identify pages to capture data from for each city.
2. Divide pages into categories.
3. Obtain 50 (Austin – 25) posts from all pages.
4. Obtain 50 (Austin – 25) comments from all posts.
5. Obtain 50 (Austin – 25) comment replies from all comments.
6. Collate comments and comment replies from a post together (all possible interactions on the post).
7. Construct a network from these connections.
8. Create a graph of the network.
9. Perform analysis on the network characteristics.
10. Compare the characteristics of both city's networks.

## 3.1 Data Collection

The first set of tasks were focused on obtaining the necessary information from Facebook to be able to move to the next set of tasks and construct the networks. This set of tasks included identifying pages, categorizing them, obtaining post information, and obtaining comment and comment reply information.

### *3.1.1 Page Identification*

The first task was to identify pages to be analyzed within the two cities: Omaha, Nebraska and Austin, Texas. These cities were chosen for a variety of reasons. Omaha is a city outside the national music scene. Austin is currently a major scene for national music, focused around the South by Southwest (SXSW) annual music festival, which continually grows [5]. A comparison was chosen between these two cities to identify traits that may be lacking in Omaha's music scene, possibly preventing it from growing larger.

Next, pages were grouped into several categories: venues, jazz artists, rock, pop, and funk artists, electronic dance music (EDM) artists, hip-hop artists, and other pages. Rock, pop, and funk artists were grouped together because many of the artists' music included releases within at least two of these genres. The pages in the other category included record labels, production companies, and music festivals. The number of pages in each category is shown in Tables 1 and 2 for each page.

These pages were determined by identifying several pages within the other category. A set of artists were collected by looking through Facebook Events created by these pages for local performing acts. Several others were identified through Facebook searches. This was most notably done with EDM and Hip-Hop artists. Large venues featuring national performers were not considered. Several artists who come to the smaller venues but are not local talent were also cut. The purpose is to understand the fans within the local community, with as little outside influence as is possible.

### *3.1.2 Facebook Posts*

The R programming language was used to obtain information about posts from these pages. This language was chosen because of the flexibility and ease of use provided. This is thanks to the large amount of easy-to-install third-party commands, called packages. Two packages were primarily used in this research: RFacebook and igraph. RFacebook provides functionality for R to access the Facebook Application Programming Interface (API). The igraph package provides functionality for R to create and manipulate network graphs [7].

The most recent 50 posts were taken using RFacebook. This number of posts was chosen because data grabs are made in sets of 25 by RFacebook. This number of posts created graphs that caused the host computer to slow a significant degree, and even crash at times, and as a result, larger numbers of posts were not considered for the research. This number was cut to 25 for the Austin network because of similar reason to those above. This was mostly likely because the posts on Austin pages receive more comments on average than those in Omaha. This would make sense because the pages themselves tended to have more likes as well. The result of this information dump was a data table with the message, the post author's name and ID number, the date and time the post was created, the type of post (video, photo, link, etc.), the unique ID number of the post, the story, and the number of likes, shares, and comments.

| Category | Number of Pages |
|---|---|
| Other | 6 |
| Venues | 12 |
| Jazz | 4 |
| Rock/Pop/Funk | 15 |
| EDM | 5 |
| Hip-Hop | 5 |
| **Total** | **47** |

**Table 1. The number of Omaha pages in each category.**

| Category | Number of Pages |
|---|---|
| Other | 9 |
| Venues | 14 |
| Jazz | 5 |
| Rock/Pop/Funk | 18 |
| EDM | 7 |
| Hip-Hop | 8 |
| **Total** | **61** |

**Table 2. The number of Austin pages in each category.**

| Node | Node |
|---|---|
| A | B |
| A | C |
| A | D |
| B | C |
| B | D |
| C | D |

**Table 3. The edge list resulting from mathematical combination of nodes.**

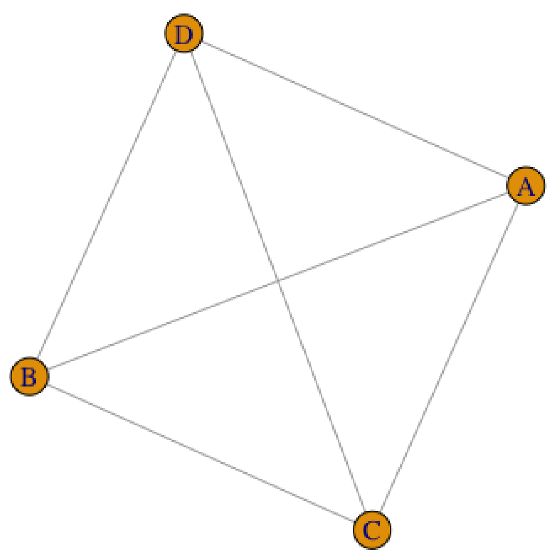


**Figure 1. A sample graph based on the edge list in Table 3.**

### *3.1.3 Facebook Comments and Comment Replies*

Once this data was taken, each post was individually used with another command to obtain comment data. This provided data tables with the name and ID number of the commenter, the message, the date and time, the number of likes, the number of comment replies, and the unique ID number. Because comment replies are not returned with standard comments in the Facebook API, the comment replies had to be compiled separately. The same data table information was returned for comment replies as with comments.

## 3.2 Network Creation

Once all the information about comments and comment replies were obtained, networks were built to understand how music fans are connected in each city, both graphically and to compute numerical characteristics describing the networks. These will be discussed in the results section.

### *3.2.1 Edge List Construction*

For each post, the users who commented or replied to a comment were linked together. That is, each commenting user serves as a node in the network, and the edges to link them were determined by the posts they shared a connection through. This was done by creating a table containing the user ID numbers for each commenter on the post. A standard mathematical probabilistic combination of all users within this table was generated to create all the possible connections between these users. This was done as a simple method of creating a link between, for example, person A on a post and persons B, C, and D, while also linking B to C and D, and C to D without having any duplicates. An example of this can be seen in Table 3 and Figure 1. This concept is applied to each post's commenters. This was repeated with each post within the set of categories defined previously. Additionally, each of the individual category edge lists were given a name column to be interpreted as an identifier for the node color. After this, the category edge lists for each city were combined to create a city edge list.

### *3.2.2 Network Graph Characteristics*

From here, network graphs were constructed between the edges. The graphs are undirected. This means a direction for information flow was not determined. In a graph this would appear as arrow points at the ends of the edges between nodes. This was done because directions would be difficult to properly account for based on the design of the research. Once built, the networks contained multiples of some edges and loops, which are edges from a node back to itself. These were removed to simplify the results obtained from the network. These characteristics likely occurred because of the same people being connected on multiple posts.

A weight for the edges based on how often two people were connected was visualized from the removal of these multiple edges. This can be seen within the graph by the color of the edge: the lighter the grey, the lower the number of connections between to commenters.

As mentioned previously, the category column in the edge lists were used to determine the color for a node. Because the colors were technically associated to an edge, if a node appeared in multiple category edge lists, the color of the node appeared transparent. This can be observed on a few nodes within the graphs.

The graph layouts were determined through the Fruchterman-Reingold algorithm [9]. This algorithm was chosen over several other force-directed algorithms as it seemed to provide the cleanest interpretable layout of nodes and edges. Other algorithms considered included the Large Graph Layout (LGL) and graph embedder (GEM) [1, 8]. The resulting graphs can be observed in Figures 2 and 3. After the initial graphs of the networks were completed, the next step was to look at various characteristics to make judgements about the graphs and other characteristics of the networks created.

# 4. RESULTS

Several analyses were conducted to determine characteristics of the resultant networks. The results are broken up by city network.

## 4.1 Omaha Network

The Omaha network had 1,223 nodes and 42,828,183 edges prior to simplification, after which 40,695 edges remained. This is an average of about 33 edges per node. Each commenter is therefore connected to approximately 33 other commenters on average. This suggests that the each of these commenters is somewhat well connected. However, there are other ways to try and understand the nature of connections in a network, of which several others were used within this research.

By glancing at Figure 2, it is noticeable that the nodes tend to congregate together within the pre-defined categories. This illustrates the concept of homophily. In case of the networks in this study, the similar traits would be similar musical interests. This causes the development of clusters, within the network. In the Omaha network, the assortativity coefficient was computed to be 0.8548527. This suggests that the network is more assortative than

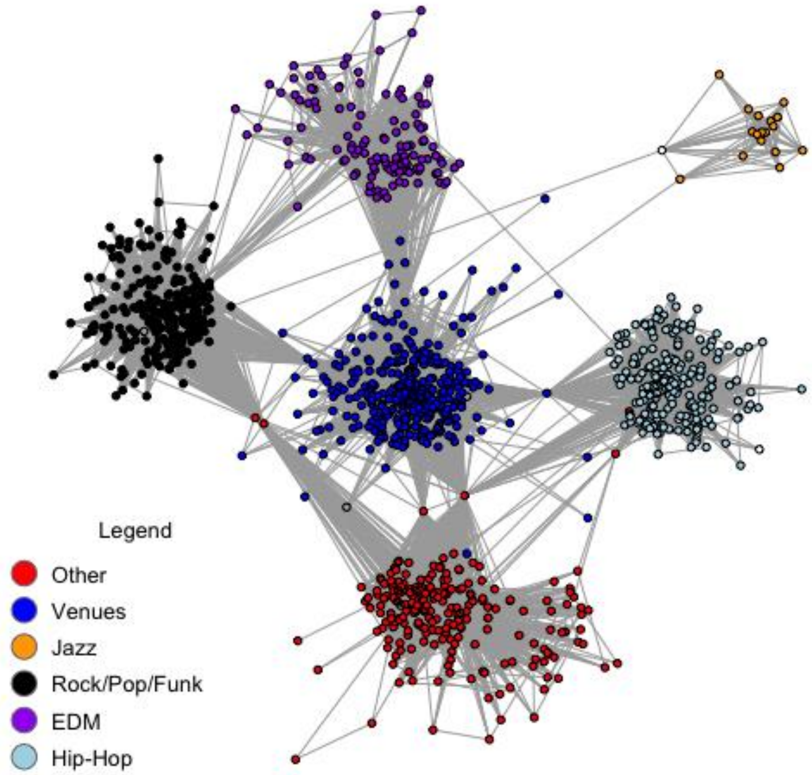


**Figure 2. A network of music fans in Omaha, Nebraska.**

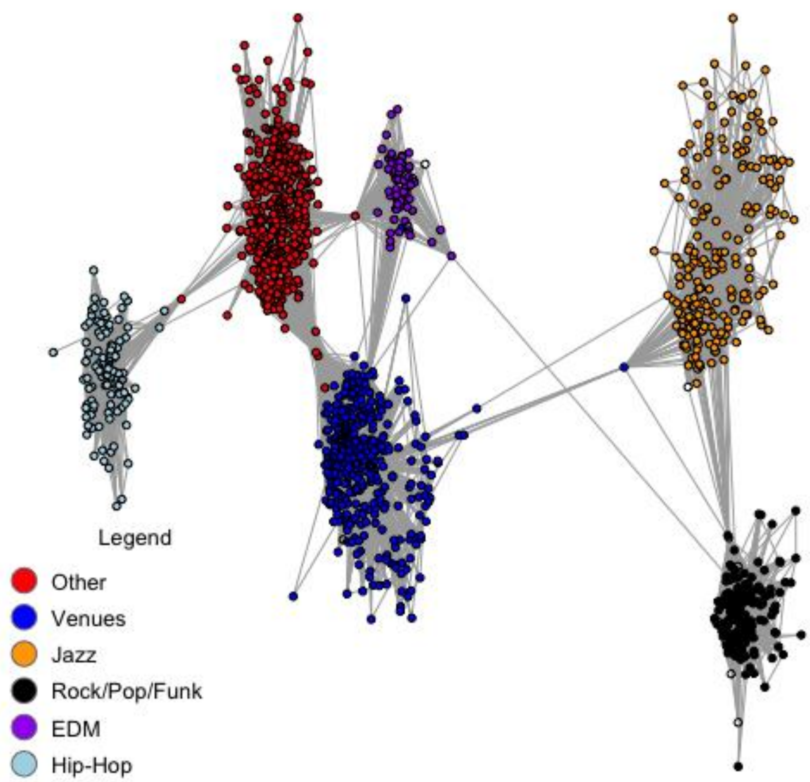


**Figure 3. A network of music fans in Austin, Texas.**

dissortative. The network is very homophilic.

These groups are not completely homogenous, which is illustrated simply from reading the coefficient; it is not equal to one. A coefficient of one would make the clusters completely homogenous. This idea can be observed as well, at least when the category is being considered. This can also be observed in the graph. Several nodes from one category are between clusters or in a different one altogether. There are a few notable bridges between the clusters. There are several bridges present within the graph as well. These bridges also highlight an interesting trait in the network; in many cases a single tie exists between two nodes that are much more connected to different clusters.

To understand other interpretations of clusters that do not consider the predefined categories, the Fast Greedy algorithm mentioned earlier, was used [6]. This algorithm detected 28 clusters within the Omaha network. A graph of the network was created showing the detected clusters as shapes around the nodes, and can be observed below in Figure 4.

Additionally, the coreness of nodes within the network was measured. A third graph to understand where these nodes are within the network was constructed. You can see in Figure 4 that the jazz group is very much in the periphery of the network. The core of the network is 121 nodes. Within the other cluster these core nodes tend to form a core within the node itself.

The density of the network was also calculated. This is another way of measuring how connected a network is. The density of the Omaha network is 0.05445947. This suggests the number of edges within the network is very far from the maximum possible. This makes sense because there are relatively fewer edges between clusters compared to within these clusters. It also echoes the statement made earlier related to the assortativity coefficient not being equal to one. If every node was connected to every other node, that is, the density was one, the assortativity would also be one. There is a distinct relationship between these two.

Similarly, transitivity of the network describes the nature of edge connections, but with the clusters of the network. In this network, the transitivity was 0.4459396. This somewhat low value reflects the nature of the cliquishness of the clusters. The nodes within the clusters are well connected to each other, but not anywhere near enough to define them as cliques.

The final measure observed was the diameter of the network. Again, this gives a rough indication of the size of the network. This distance was computed to be 8147, compared to the average distance between nodes, 2.932125. Most nodes are very close to their neighbors, but because of the isolation of the clusters, information must travel a great distance to reach the other end of the network.

## 4.2 Austin Network

The Austin network had 1,441 nodes and 38,667,023 edges prior to simplification, after which 36,603 edges remained. This is an average of about 25 edges per node, and each commenter is connected to approximately 25 other commenters on average. This is a little less than in the Omaha network. This suggests that commenters are less well connected, which could be expected from having more nodes than the other network. I used the same other methods as illustrated previously with the Omaha network.

By glancing at Figure 5, it is noticeable that the nodes tend to congregate together even more through homophily than in the Omaha network. However, that is not the case. In the Austin

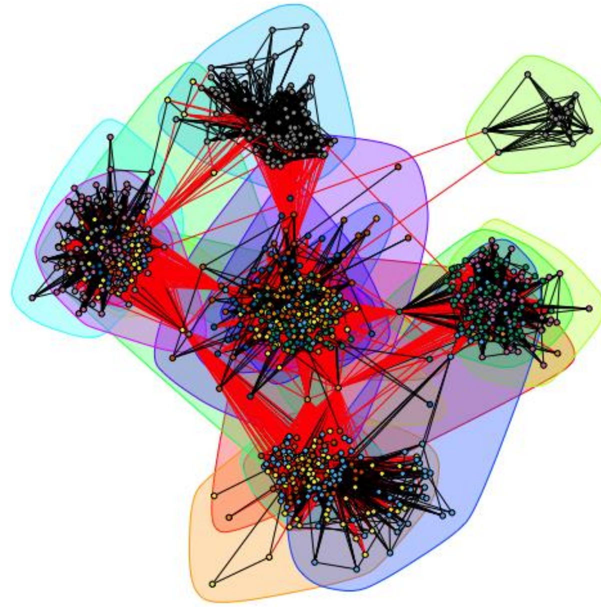

**Figure 4. Fast Greedy Clusters in the Omaha Network**

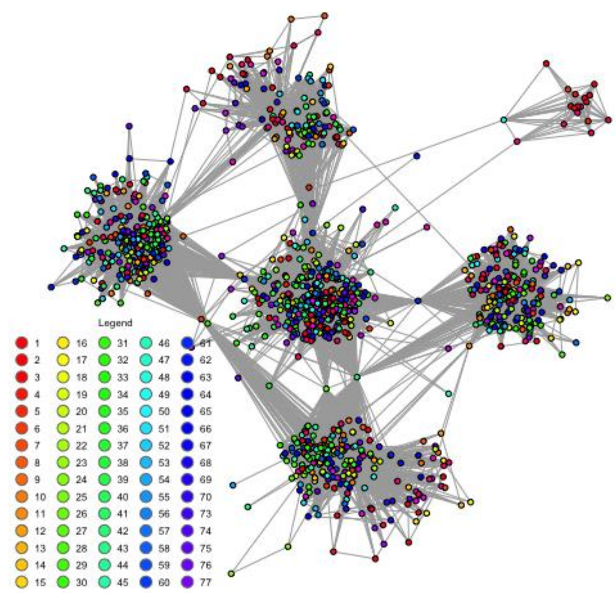


**Figure 5. The coreness of the Omaha network.**

network, the assortativity was computed to be 0.8267087. This network is very hemophilic, but not quite as much as the Omaha network. The values differ by only about 0.03. Overall, the degree to which the networks demonstrate homophily is about the same.

These clusters are not completely homogenous, just as in the Omaha network. This is again demonstrated by the coefficient not being equal to one. A coefficient of one would make the clusters completely homogenous. This is again true when looking at the category. Interestingly, it can still also be observed in the graph. Though it occurs to less of a degree than in the Omaha network, several nodes from one category are between clusters or in a different one altogether. There are also a few notable bridges between hip-hop and other categories, just like in the other network. These bridges show the same intriguing trait as well; in many cases a single tie exists between two nodes that are much more connected to different clusters.

The Fast Greedy algorithm was again used to understand other interpretations of clusters that do not consider the predefined categories. The algorithm detected 35 clusters within the Austin network, a few more than in the Omaha one. Another graph of the network was created showing the detected clusters in Figure 6.

The coreness was measured here as well. The nature of the core of the network is the same as the Omaha graph, but since the jazz community is much more established, at least on Facebook in Austin, that this entire category is not in the periphery of the network. Each cluster has its own developed core, just like in the Omaha network. The core of the network is 102 nodes, slightly smaller than in the Omaha network.

The density was considered again, too. In this network the density is 0.03527932, slightly less than in the Omaha network. Suggesting that the number of edges within the network is even further from the maximum possible than in the Omaha network. This makes sense because the simplified network has more nodes, but less edges than the Omaha one. This again makes sense because there are again relatively fewer edges between clusters compared to within them.

Transitivity of the network was again used to describe the clusters of the network. In this network, the transitivity was 0.2942997. This somewhat low value also reflects on the nature of the cliquishness of the clusters. The nodes within the clusters are well connected to each other, but not anywhere near enough to define them as cliques. Compared to the Omaha network, the clusters here are less cliquish.

The final measure observed was, as before, the diameter. The rough size of the network by diameter is 301. This is much smaller than in the Omaha network by a significant amount. This suggest that the distance along edges between nodes is much smaller, leading to the conclusion that the nodes are, in general, closer together in the Austin network, even between clusters. This is still larger than the average distance between nodes, 3.607706. Compared to the Omaha network, this distance is a little larger. These diameter metrics lead to the conclusion that the distance between clusters is smaller in the Austin network, but the distance between nodes within these clusters is greater. These results have informed the conclusions presented next.

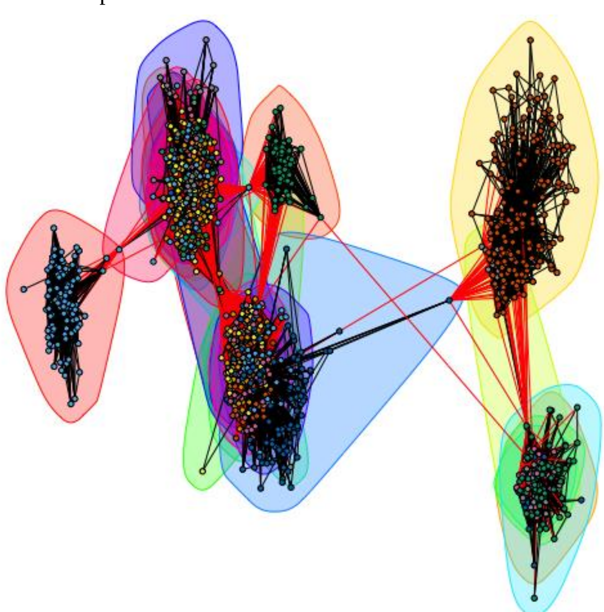

**Figure 6. Fast Greedy Clusters in the Austin Network.**

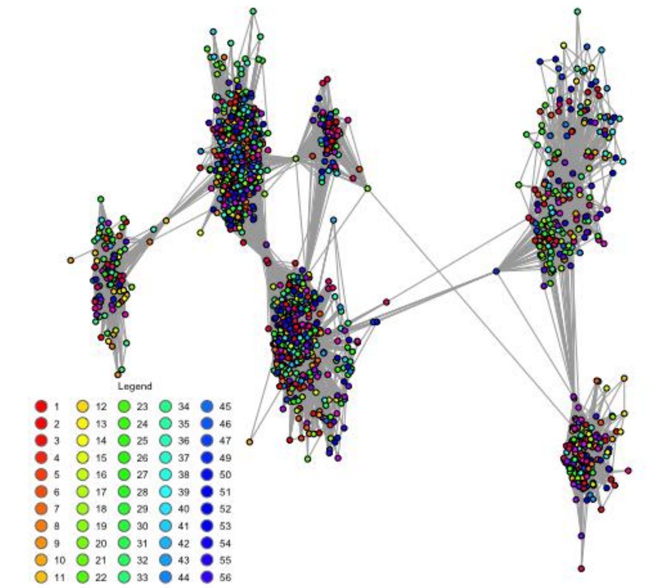


**Figure 7. The coreness of the Austin network.**

# 5. Conclusions

While the results may be impacted by the sample size, we can conclude from these results that there are a relatively few individuals who are highly connected and influential in both networks. In fact, the networks are more similar than they are different. They both feature very homogenous, although not completely, clusters, generally centered on the category of the page from which the post they are commenting on is from. The Fast Greedy algorithm also detected very similar cluster patterns between the networks. This could potentially be reflective of Facebook or the methods used to obtain and parse the data. There are several bridge nodes, as well between the clusters of both networks. There are more of these similarities than were expected going into the research. This impacts the applicability of results, because although some similarities were expected the general focus was to be on the key differences, of which there were still several.

The average node in the Austin network is less connected to other nodes than in the Omaha network. Additionally, the assortativity coefficient is slightly smaller. The Fast Greedy algorithm detected more clusters in the Austin network, this may be due in part to the fact that it has more nodes than the Omaha network.

The jazz community is much more established amongst fans in Austin than in Omaha, pushing it out of the periphery and having a core of its own within the Austin network. This could mean that there is a larger audience for jazz music in Austin than in Omaha. This could also be the result of a larger population in Austin, which potentially increases both the number of jazz artists and the number of jazz fans. There is too much uncertainty to say for, but it's possible that growth in jazz music in Omaha would fuel national growth. This would make little sense of course, because of the relative unpopularity of jazz music, at least compared to other genres in modern times.

It was concluded that the difference in diameter show that the distance between clusters is smaller in the Austin network, but the distance between nodes within these clusters is greater. This could potentially mean that the distance between clusters needs to shrink, for Omaha to experience more growth nationally, in addition to the increased degree to which Omaha's fans engage in a friend building in a way that increases the degree to which homophily is observed. Ensuring that music fans in Omaha are more regularly exposed to greater representative samples of the entirety of Omaha's sonic output would help to ensure that.

Additionally, the Omaha network is much more cliquish than the Austin network. The development of cliques can eventually lead to hostilities with those outside the clique. This more standoffish nature toward those in the outgroup could be hurting the ability for growth in the size of the overall network. Lowering the cliquishness of the Omaha network might improve the ability for growth to occur.

It is quite likely that factors outside of social media, or at least Facebook, have a significant influence on the growth of a music scene, even in the modern age of social media. These could include logistics and economic development. The ethical need to ensure privacy of users and other privacy considerations of Facebook have understandably, hurt the ability to gauge the characteristics of individuals in the network as people, and not just network actors. Demographics, such as gender and racial designations might have provided some interesting results to present within this work. Because of the shortcomings of this research, there are several applications for future research on this topic.

### 5.1 Future work

The hardware limitations in this research prevented the ability to perform statistical test between the network characteristics to identify whether differences were significant, which hurts the usefulness of the study. Any future work should emphasize this aspect of comparison. These hardware limitations can be easily overcome with sufficient workstation-class machines or other high-powered computers.

In the future, developing networks of many cities, particularly the centers of music in the United States, New York, Los Angeles, and Nashville could provide more points for comparisons. Cities outside the United States could provide points for cultural comparisons within networks of music fans as well. These comparisons could provide more examples of changes that could improve the Omaha community, as well as further general knowledge about the spread of music through social media.

Comparisons with larger sample sizes of posts, comments, and comment replies, could improve the representative nature of the network graphs. There is always room for improvement in this area, since social networks are never complete; they are always a subset of something greater. Enhanced computer power would be necessary to take this step. Improvements in this area would increase the accuracy of results and conclusions. It is possible that the conclusions reach here could range anywhere from completely invalidated to substantially improved upon through this.

Additionally, mapping the pages representing the network better, whether through additional pages or better identifying categories, could also improve the network graphs. In the same vein as mentioned above, this would be another way to improve the representative nature of the network graphs. There is always room to improve in this area as well.

Finally, future studies could attempt to understand how music fans communicate through the language they use and other social media platforms, such as Twitter.

## 6. References


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