Influence of Classical Music Composers

Hemant Heer: hheer1@binghamton.edu
Allyson Kritzer: akritze1@binghamton.edu
Nicholas Parody: nparody1@binghamton.edu
Stephanie Smith: ssmith31@binghamton.edu

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Instructor: Dr. Craig B. Laramee
TA: Arnab Roy

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1. Introduction

The aim of this project was to explore and investigate the influences of composers of classical music from the inspirational minds of Bach in the late 1600s to up and coming artists of the current 2000s. In this way, it will be clear to see how the sound and teachings of classical musical have flowed from maestro to student and later, how the talents of the past have become inspirational sources for classical musicians today. This particular topic was chosen as the subject of this network, because of our group's general music interest in music. Originally, the network was supposed to be comprised of composers of all genres of music (classical, rap, jazz, rock, etc.), however, the scale of such a network would have been far too large. As it is, we already exceeded the number of nodes required for the project using only half of a database we found.

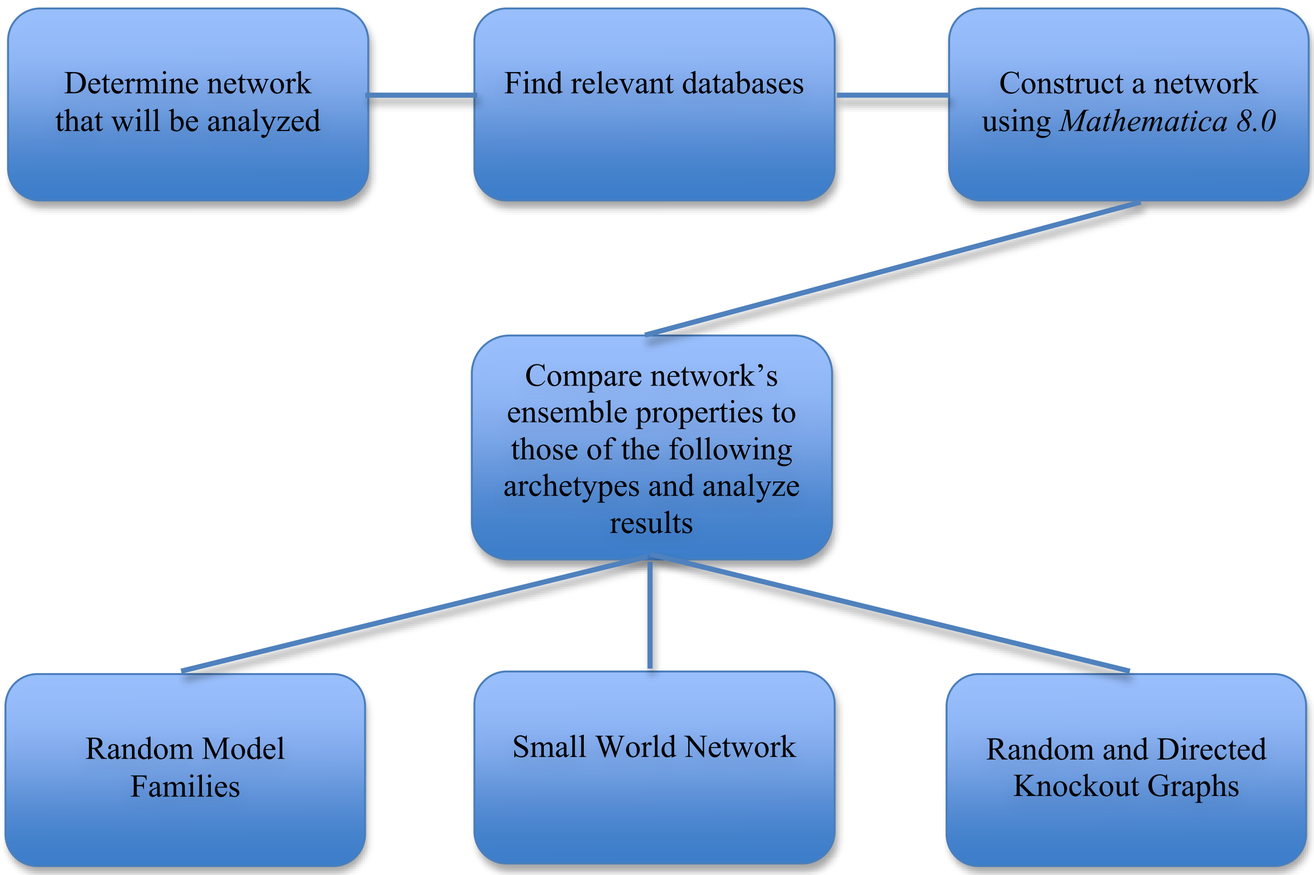
In order to properly analyze a network of this magnitude, several techniques using *Mathematica 8.0* were employed. Among these were the creation of several small world networks, random graph families, and knockout graphs (both random and directed). Each of these graphs had its own successes and failures when it came to comparing the models to the original graph. However, when these methods are used in tandem with one another, they manage to compensate for each other's shortcomings, allowing for an overall accurate interpretation of the original network and a better understanding of how classical music has passed from generation to generation of composer.

The following report will explain our interpretation of this classical music composer network. In Section-2, we will elaborate on the process by which the network was established and developed using *Mathematica 8.0*. Following this, Section 3 will show the results of each test and provide a detailed explanation on what can be taken away from each test in terms of the original network's traits such as: degree distribution, connectivity, robustness, etc. In Section 4,we will explain noteworthy features uncovered from running the various codes and cover the shortcomings of our network. Finally, Section 5 will contain all of the sources of data and references we used to construct this network.

2. Method

The entirety of the data used in the creation of our network was collected from a single database that specialized in classical music composers. However, due to limitations in the size of the network we could use, we only used half of the database, displaying composers with last names running from A-K. This database also had an interactive network of composers that allowed users to click on a node and see all of the direct connections associated with that particular node. In this way, it was possible for us to see the degree of influence that renowned musicians, such as Bach and Beethoven, had on those who would come to follow in their footsteps, whether it be a few years to a century or two later.

Figure 1. Flowchart detailing process of network creation and analysis

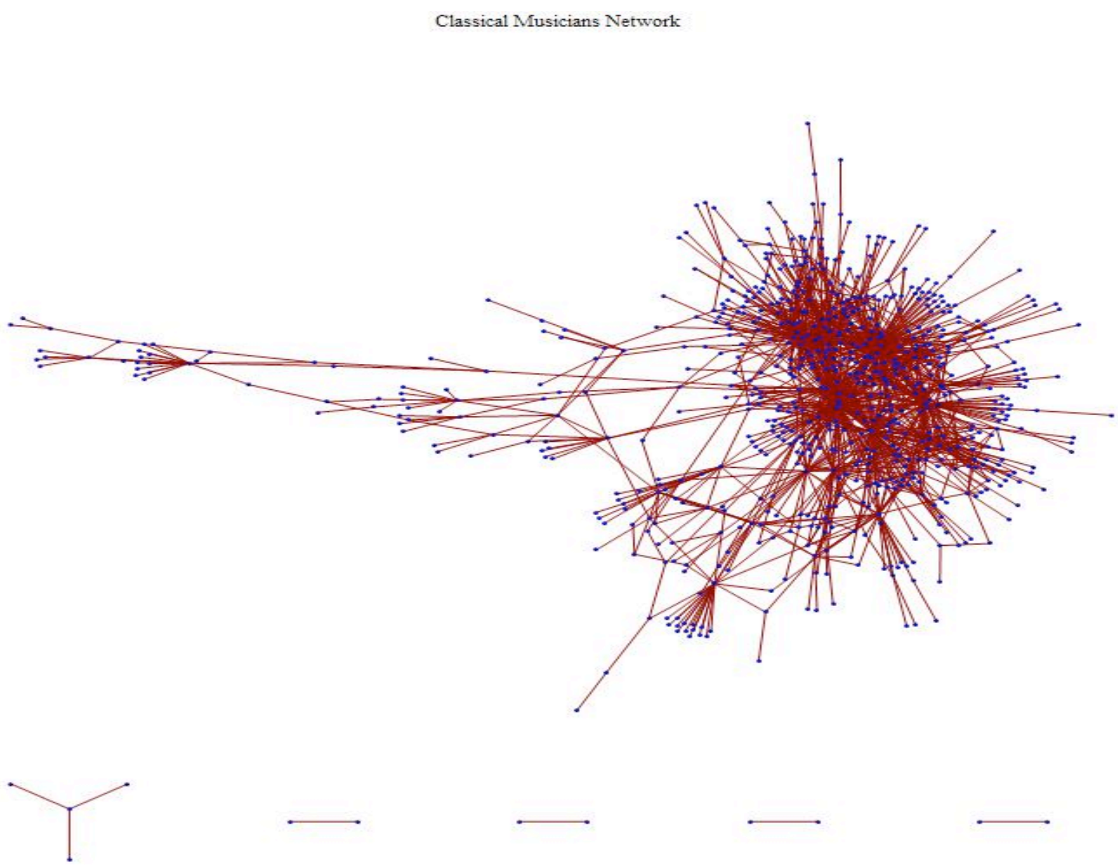


After picking a topic that interested all of the members of the group – in this instance, classical music – each member was to find a database that could be used as a viable source for studying the influential roles of notable composers. Although we were given a list of potential data sources in class, we were able to find one ourselves that had everything required to construct a complete network. After pulling the necessary data from the database, a network was constructed using *Mathematica 8.0*, giving us an original model that would then be analyzed by comparing its ensemble properties to those of: a family of random models, a series of small world networks, and knockout graphs (both random and directed). These three tests were the means by which the nature of our original network was determined, however, other tests can be implemented to find out more about this network if possible.

In the network displayed in *Figure 2*:

- Nodes represent composers from the genre of classical music. This encompasses both teachers and those who learned from them or drew inspiration from their works.
- Edges represent the influence of musicians from one composer to the next; there were 1,532 edges in our network.
- The number of nodes simply denotes how many composers were used to assemble the network. In this case, 716 composers can be seen, although this exceeds the 500 node limit that was recommended for the proje

Figure 2: Original Composer Network



3. Results

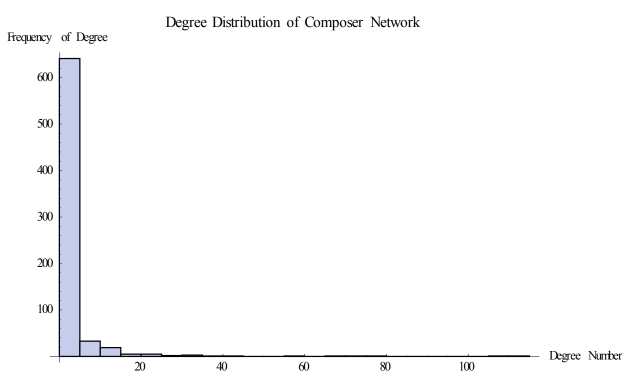
Your network Vs. Random network

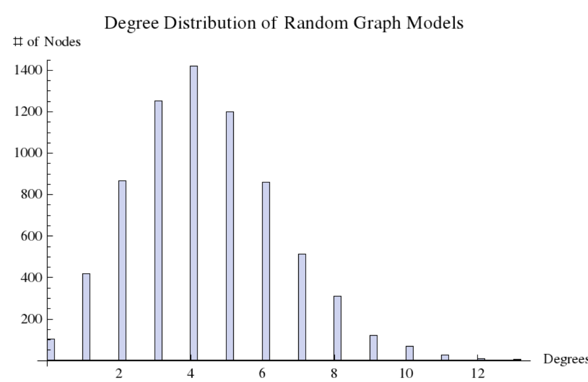
Ensemble properties

	Your network	**Random model Avg. over at least 10 trials***
Avg. Degree	2.15223	4.17235
Avg. Path Length	∞	∞
Global Clustering coefficient	0.0525135	0.00587395
Avg. Local Clustering Coefficient	0.140926	0.0000263286
Number of connected components	6	12.7
Size of the largest component	704	703.9
Entropy	3.721	3.35762

Degree distribution:

Figure 3. Degree Distribution comparison of Original Network (left) and Random Models (right)





Explain the above results:

As can be seen in the data table, our original network is not very similar to a random model. The only qualities that the two networks have in common are their average path lengths being infinity (a result of the isolated networks), the size of the largest component, and their entropy value (a measure of resilience/uncertainty). While the random graph has about twice the amount of connected components as our original networks, the two networks have largest connected components that are roughly the same size. The fact that the random graph has almost twice the average degree distribution value of the original network is unsurprising, given that how random models are known for their unrealistic degrees distributions. They are also terrible at determining clustering coefficients, which can be clearly seen in the difference between the local clustering coefficients. Based on the relatively high values of the clustering coefficients of our original network, we can say that it has high transitivity.

What most clearly shows that our network is not like a random model, is that the histogram of the original network in *Figure 3* does not follow the Poisson degree distribution that is characteristic of random graphs. Instead, our network seems to have a descending exponential distribution that is more affiliated with a real world's scale-free distribution.

One other characteristic of our graph that we were able to test using the random model was whether or not our network could be considered either ordered or chaotic. This was determined by finding the critical point, which denotes the beginning of the transition phase characteristic of random graphs. Our network's edge probability was found to be 0.005985, while the critical point was found to be 0.001397. This means that our original network falls into the transition phase, leading away from chaos and towards order.

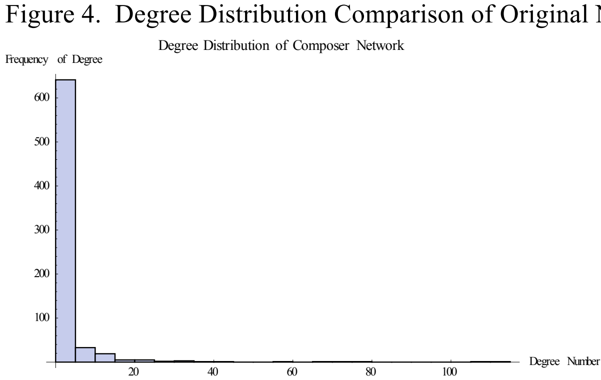
Your network Vs. Small world network

Ensemble properties

	Your network	**Small world model Avg. over at least 10 trials***
Avg. Degree	2.15223	8
Avg. Path Length	∞	5.9
Global Clustering coefficient	0.0525135	0.32
Avg. Local Clustering Coefficient	0.140926	0.5
Number of connected components	6	1
Size of the largest component	704	716
Entropy	3.721	1.4

Degree distribution:

Figure 4. Degree Distribution Comparison of Original Network (left) and Small World Network (right)



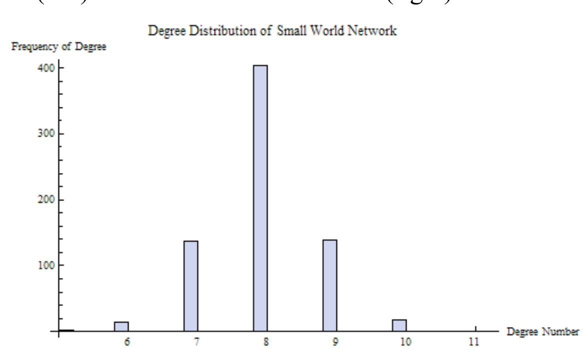
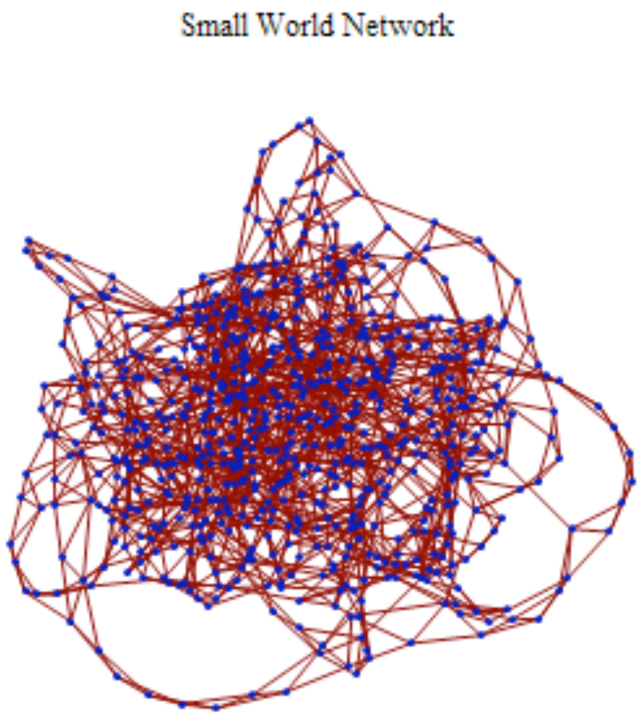


Figure 5. Generated Small World Network



Explain the above results:

There are several interesting features that needed to be pointed out regarding our small world network sample. Firstly, as can be seen in *Figure 4*, the histogram of the small world network (seen on the left) looks very similar to the Poisson distribution typically seen in random models (see *Figure 3*). This is because we used an edge probability around 1 when constructing the small world network, meaning that the edges of our network have been reconfigured so much, that our small world network has practically become a random graph. Altering the value of the edge probability did alter the overall structure of the small world network. As stated earlier, and seen in *Figure 4*, our network's degree distribution does not correlate with that of our generated small world network.

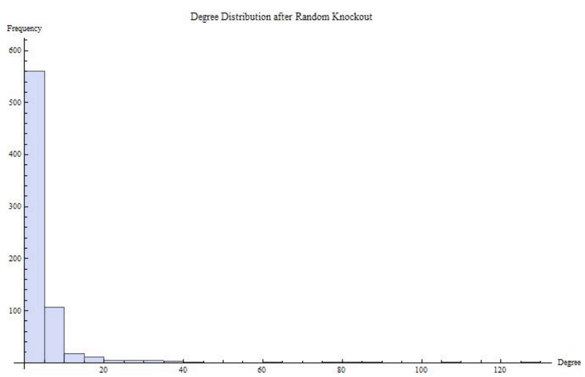
Also, further evidence that shows how our network does not match a small world network is that the results of the small world network do not match up well with the original data. For instance, although small world is also known for calculating unrealistic degree distributions, the average degree distribution of our small world networks is four times that of the original network's value. This is an even greater discrepancy in values than we saw with the random graphs. Also, the entropic value of the small world network is considerably lower than the entropic value of our original network, meaning that our small world network is much more ordered than the original, and as a result, more robust in nature.

Random Vs. Directed Knockout results:

	Your network (Random knockout) Avg. over at least 10 trials*	Your network (Directed knockout) Avg. over at least 10 trials*
Avg. Degree	3.898802	2.464589
Avg. Path Length	4.09	5.62
Global Clustering coefficient	0.04989144	0.0373802
Avg. Local Clustering Coefficient	0.2347466	0.09925996
Number of connected components	34.34	134
Size of the largest component	631.86	558

Degree distribution:

Figure 6. Degree Distribution Comparison of Random Knockout (left) and Directed Knockout (right)



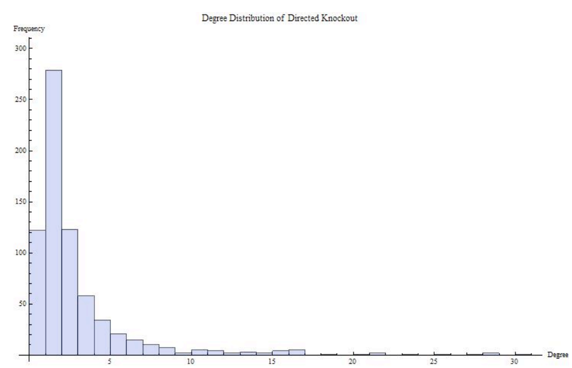
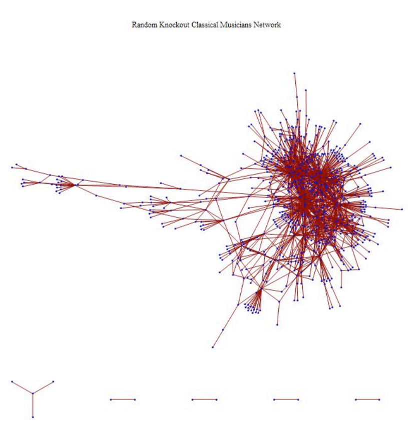
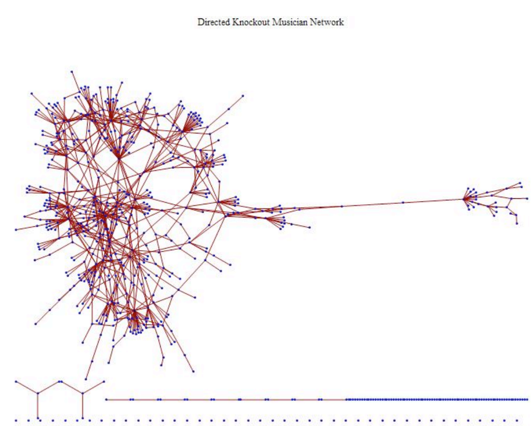


Figure 7. Comparison of Random Knockout Network (left) and Directed Knockout Network (right)





Explain the above results:

By analyzing the results from our knockout tests, it was possible to examine the robustness of our network. The purpose of the random knockout was to remove a random node, and see how this affected the network as a whole and to what extent. We also performed a directed knockout, removing some of the most connected nodes (in this case the nodes representing the composer Johannes Sebastian Bach and Ludwig Van Beethoven) and seeing how their removal altered the network (see *Figure 7*).

When compared to the original network, the average degree for both knockouts was higher. This was to be expected, because removing a node broke up some connections, leading to fewer nodes with relative higher degrees. The average path length was found to be infinity for both knockouts, because the graph is not completely connected. The global clustering coefficient is lower for both knockouts than the original network, again due to the connections that were broken when nodes were taken out of the network. Comparing local clustering coefficients, the random knockout has a higher value than the original. This is most likely because the most connected nodes were not knocked out. The directed knockout value for local clustering coefficient was lower than the original's value since we took out the most connected nodes. Lastly, the number of connected components for each knockout was higher than the original, but the size of the largest connected component was lower. This makes sense, since a greater number of connected components will lead to a decrease in the size of connected components, because we are splitting them up.

The random knockout showed us that our graph was somewhat robust to knockouts – our values did not vary too much from the original network analysis. This can be seen clearly by the almost identical resemblance between the networks in *Figure 2* and *Figure 7 left*, as well as their average degree distribution histograms (*Figure 4 left* and *Figure 6 left*). Meanwhile, the directed knockout reflected how influential one or two nodes could be on the entire network as a whole. By simply removing Bach or Beethoven, the entire evolution of music could have occurred much differently and affected present musical technique and influences. By comparing the original network in *Figure 2* with the much more dissociated network seen in *Figure 7 right*, the significance of these historical composers became quite evident. There wasn't much of a difference in regards to the shape of the degree distribution between the original network and the directed knockout, but there are some variations in the quantity of nodes recorded and the number of out degrees.

[*] It is important to note that the average path lengths for the knockout networks aren't infinity, because R only looks at the network with the highest number of nodes. It does not take into consideration all of the smaller isolated networks.

4. Conclusion

From the data that can be seen in Section 3, we can classify our original network as a real world network. The ensemble properties of our original network did not display the Poisson distribution evident in random models nor did the other ensemble properties from random model and small world networks match up nicely with those of the original network. The average degree distribution histogram was what led us to this conclusion, as it contains the descending exponential trend that is associated with scale-free real world networks.

While our network has provided insight into the structure of organized cultural musicians, there are certain aspects of the network that we are not able to include. In addition, certain parameters that need much more depth, such as the parameter of "Has Influenced," will pose a problem due to the nature of quantifying it. The fundamental network we created is based on composers influencing other classical musicians, but how do we determine the degree of influence? Also, what exactly constitutes an influence? To solve this problem, we could add certain restrictions and create a standard for determining if a connection exists between certain composers. Additional data would need to be gathered that quantifies this standard, and allows subsequent standardization of all the nodes in the network with respect to this reference. Using this, we could add edge weights that correspond to the degree of influence between a composer and a succeeding classical musician.

When developing this network model, there were multiple shortcomings. For starters, there was the sheer size of the network itself; the network we created using the database we found was composed of 716 nodes. While, the number of nodes we used exceeded the recommended limit for this project, this wasn't even the entire database. The database was split into two pages alphabetically, going A-K and then L-Z. The network seen in this project was made using only the data from the A-K page, eliminating a large portion of available data. It is most likely because of this that there are those five isolated networks below the main one seen in *Figure 2*. Also, even though we only used half of the data, we were still limited in the number of tests we could run. Both the random model and small world network comparisons had to be run the minimum of 10 iterations, otherwise the code would have continued running for at least a day. The size of the network also prevented us from running degree and closeness centrality tests. Fortunately, the database provided us with a list of influences for each respective classical composer.

Based on the results from this project, we would be curious to see the size and connectivity of the entire database we found, however, we don't know how feasible it would be to effectively analyze such a voluminous network. We hypothesized that the network would actually assume the same ensemble properties of a small world network given the increased degree of transitivity and connectivity, but again this is only an educated guess. In terms of a real world application for this project, music industries and aspiring classical musicians would do well to look into which composers are seen as the most successful based on the number of degrees extending from each node. Agents working for the music industry could also use background searches to see who potential talents have learned from, possibly aiding in the selection process of a new aspiring artist. As can be seen from the original network, those nodes that contain the most out degrees can be regarded as the most successful and influential composers, and people from all over history have turned to these maestros for guidance and direction in their own musical profession. Another possibility for future research would be to revisit our original idea and explore the connectivity of the various genres of music across time and the globe.

5. References

- www.isophonics.net/cmu
- http://people.wku.edu/charles.smith/music/index2.htm