Traversing Eighteenth-Century Networks of Operatic Fame

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Abstract

This paper employs a digital project entitled "Visualizing Operatic Fame" to delve into three major issues in graph theory and network science: searching and pathfinding, influencers and hubs, and clusters and communities.

Introduction

"The public is the toughest and finest critic in the world, and yet, a clumsy folk tune is enough to amuse it for an entire year," writes J.F. Schulze with some exasperation in the *Deutsches Magazin* in 1798 [1]. The late eighteenth century witnessed a remarkable capacity for the public (rather than rulers) to act as critic and supporter of the performing arts. This new context also witnessed the rise of the classics and the much-debated musical canon, which was taking shape at the same time as Schulze's remarks. One might come away thinking that fame is fickle, subjective, and fleeting, thereby defying systematic analysis. And yet, the broader processes of collective ascriptions of value, and the emergence of the musical canon suggests that there may yet be some structure inherent these complex cultural processes. The question that lies at the heart of my current project is: how did music become famous at the time of the emergence of the classic? Did musical works acquire fame in view of criticism or performance? Are there broader patterns of attaining fame particular to specific artforms or, in the case of music, genres?

The problem of canon formation and the classic, I believe, is really a network problem: we're dealing with a dynamic network of people and things, and for the purposes of my project, people and things related to eighteenth-century opera. Librettists write operatic texts, sometimes in response to commissions or royal events; composers compose music, singers perform (and sometimes adapt arias), publishers print full operatic scores and collections of famous arias, manuscript copies of operas in full or part move via agents such as diplomats, travelers, or other composers; critics review opera performances and opera prints available to them, often via royal libraries or lending libraries. Some opera critics even comment on other critics' assessments, forming long and complex inter-related chains of aesthetic assessments leading to canon formation. In effect, all of these "actors," together contribute to processes of operatic fame. And, to be more precise, as physicist Albert-László Barabási puts it, "Networks are only the skeleton of complexity, the highways for various processes that make our world hum. To describe society we must dress the links of the social network with actual dynamical interactions between people" [2, p. 225].

My efforts to "dress the links of eighteenth-century musical networks" find their home in a large-scale team SSHRC-funded project called "Visualizing Operatic Fame". A project of this scope requires various kinds of expertise, and I gratefully acknowledge the contributions of my various team members: Austin Glatthorn (Postdoctoral Research Fellow), James Summerby-Murray (Technical Lead), Hilary McSherry (MA Candidate in Musicology); Shawn Henry (Graduate Research Assistant), Thomas Carberry (Undergraduate Research Assistant), Paul G. Doerwald (Technical Consultant).[1] *Visualizing Operatic Fame* asks the question: what factors contributed to operas being established as musical works during the latter half of the eighteenth century? Answering this question necessitates bringing together evidence from a wide range of sources (reviews, scores, performance calendars, catalogues and so forth). For computational purposes, this means a variety of data types. Each source type contains various kinds of data: for example, performance events (found primarily in

1 See the project website: http://operacanon.io This research was generously supported by an Insight Grant from the Social Sciences and Humanities Research Council of Canada.

theater calendars) includes the name of the opera, composer, date performed, names of performers (or at least the name of the troupe), and the performance space, usually, the name of the theatre.

Since my project involves a range of data, it features distributed data governed by relationships. This emphasis on relationships also determines the type of database. Most databases are relational databases, meaning that data is stored in highly structured tables; these tables can be linked using ids. By contrast, graph databases – the most famous example being facebook – emphasizes relationships between the nodes and are much easier to query. I decided to use a graph database, as the types of queries available to me in a relational database, simply didn't answer my questions. For example: early on in the project I endeavored to find out which operas were the most famous in a given timeframe. My results were typically a list of operas, which I could visualize in a bar chart. Among the limitations of relational databases is that all entries are treated equally: if one were to survey opera reviews, for example, there is no way to distinguish between an opera review that is a paragraph in length versus one that is many pages in length. Each result in a relational database is weighted the same, and relationships are difficult to foreground or query.

Visualizing Operatic Fame is a graph database powered by neo4j (the leading commercial graph database platform) and uses Cypher as query language. More recently, we have turned to using neo4j Bloom as our visualization tool, as it is now free for desktop use. The tool is designed to represent relationships not only between individuals (composers, opera singers, music publishers) but also objects related to operatic fame (scores, reviews, images of actors). The data-model has been tweaked a number of times so as to sharpen queries and visualizations.

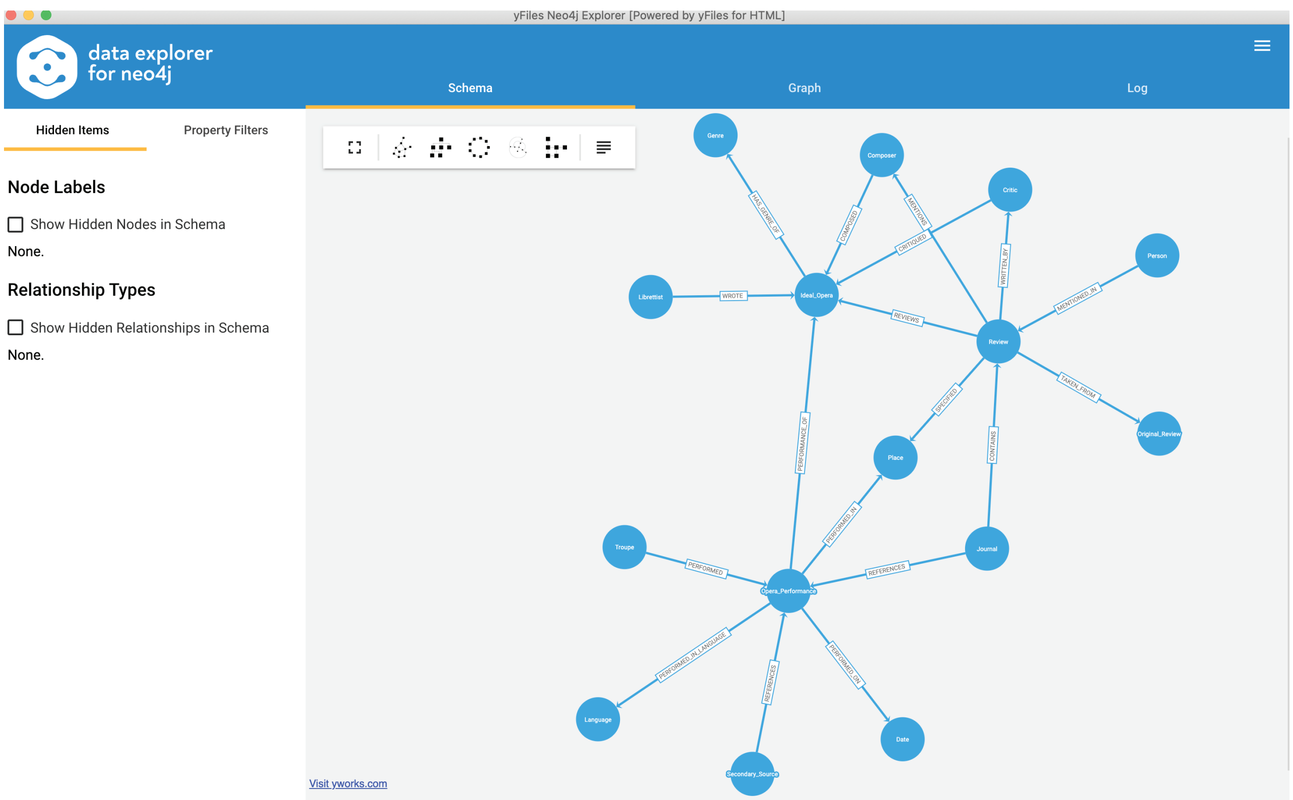

Figure 1: Current data model

Currently, we have, for instance, people such as critic and composer, and objects such as journal as nodes (incidentally, these designations are known as labels for each node). Edges (these are arrows that connect nodes) are directional in neo4j and multiple connections between two nodes are possible. One of the central questions in theories of the musical canon is whether works become famous in view of multiple performances, or whether canon is really a function of music criticism. To get to the bottom of this debate, my data model has an "ideal opera" node, which allows me to distinguish between opera performances (its own node) and opera reviews (also its own node). Put another way, I am able to distinguish between a review of a performance and the review of an operatic work, more generally. We have endeavored to be quite precise about the relationships, as it is also possible to search by relationship type. For example, in our data model a composer "composed" operas, whereas a librettist "wrote" a libretto and a critic "critiqued" an opera. This allows searches that distinguish between the librettist's and the composer's relationship to an opera, potentially routing a query through a different path in the network. Although this representation of our data model does not show them, each of the nodes also have distinct properties, which facilitate querying. For instance, my Opera Performance node has 10 properties, some of which (city, coordinates, performance date) will allow us to map the results later on.

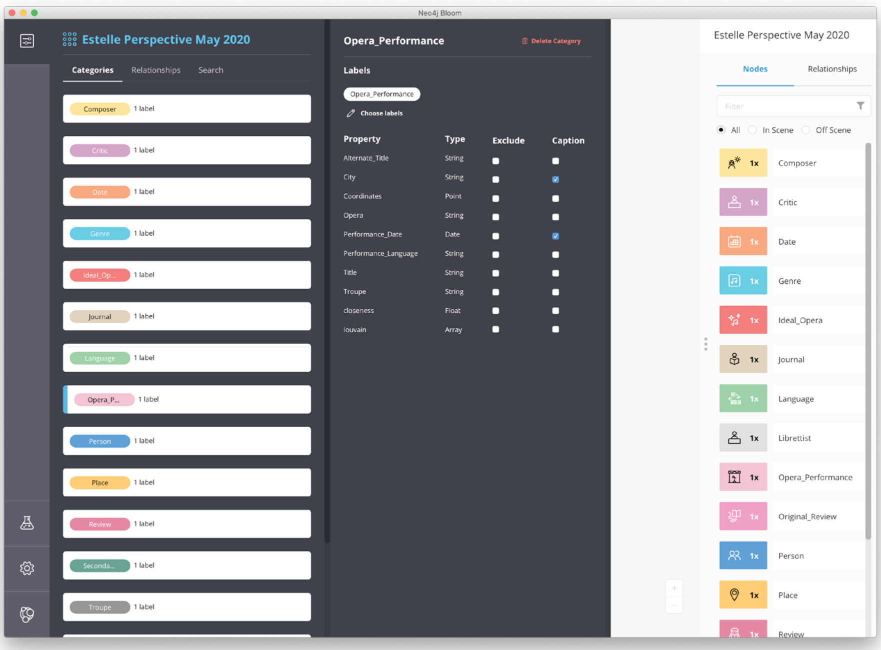

Figure 2: neo4j Bloom interface, showing node properties (left)

This also shows the datatype for each property, strings being the most common. My talk will use examples from this database, but it will focus more broadly on three common types of queries that one might encounter in graph theory: searching/pathfinding, influencers/hubs and clusters and communities.

Traversing the Network: Searching and Pathfinding

Given that my database contains over 37,000 nodes, it is obviously unworkable to call them all up at the same time. Instead, it is more productive to choose an entry-point into a graph and expand relationships as desired. I'll begin with Maria Antonia Walpurgis, Saxon Electress and composer. She is important in the history of the musical canon as her operas were the first musical works to receive reviews that included in-text music examples during the 1750s, in turn enabling detailed commentary on the score itself. Switching to neo4j Bloom, a visualization tool, the first step is to search for the composer node, Maria Antonia.

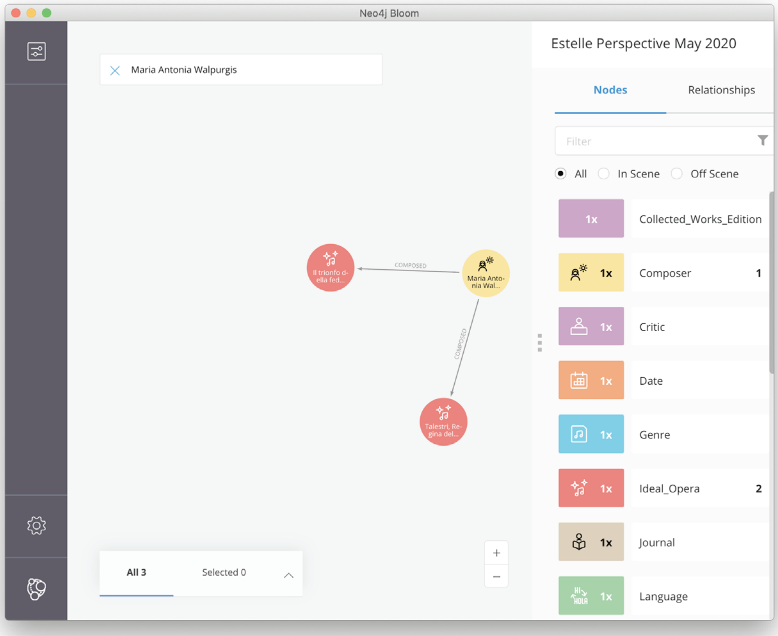

Figure 3: Searching for the composer node: Maria Antonia

Clicking on the node allows one to see the various kinds of relationships, and it is possible to reveal some or all of these (I will reveal, in this case, the nodes associated with her most famous opera, *Talestri*). We now have two Maria Antonia nodes (a second one, as librettist, appears, as she also wrote the text to her opera). The full score node, in blue, can be expanded yet again, to reveal a review of that particular score by the critic Johann Friedrich Agricola.

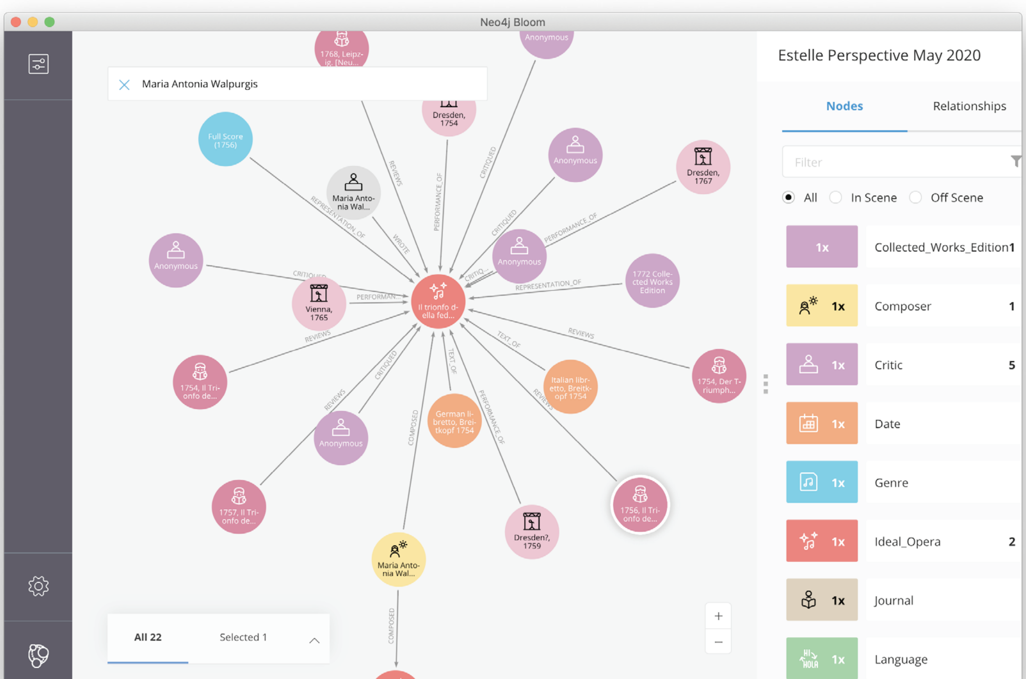

Figure 4: Expanding pathways connected to Maria Antonia's *Talestri*

A number of strengths of a graph databases come to the fore here: first, reviews are not merely ascribed to a composer, or even a work. Instead, criticism can be directly ascribed to a specific performance of a work, the printing of a libretto, or the printing of a particular score. These results seem to reinforce the material dimensions of opera criticism; unlike later Kantian ideals associated with aesthetic autonomy and canon formation, visualizing how operatic criticism was generated uncovers just how directly reviews (and consequently also aesthetic judgements) were formed in response to the material conditions of operatic performance and mobility. One curious finding is that amongst the performances and prints that received criticism, the collected works edition of 1772 received no critical attention. Visualizing these connections thus offers a much more nuanced picture of which objects related to Maria Antonia's operas actually effected fame, and which ones did not. In a sense, it prevents assumptions about what we often presume must have generated fame, and what demonstrably (or empirically) did.

In addition to exploring the network starting with a particular node, it is also possible to search for pathways between two nodes. One of the most popular pathway searches in graph theory is the so-called "shortest path" search. This is particularly useful when trying to ascertain whether two people, or a place and person, for instance, are connected. For example, are there any direct connections between Gluck and Johann Adam Hiller? From here on forward, my queries have been done in the neo4j browser, as precise querying is easier than in neo4j Bloom.

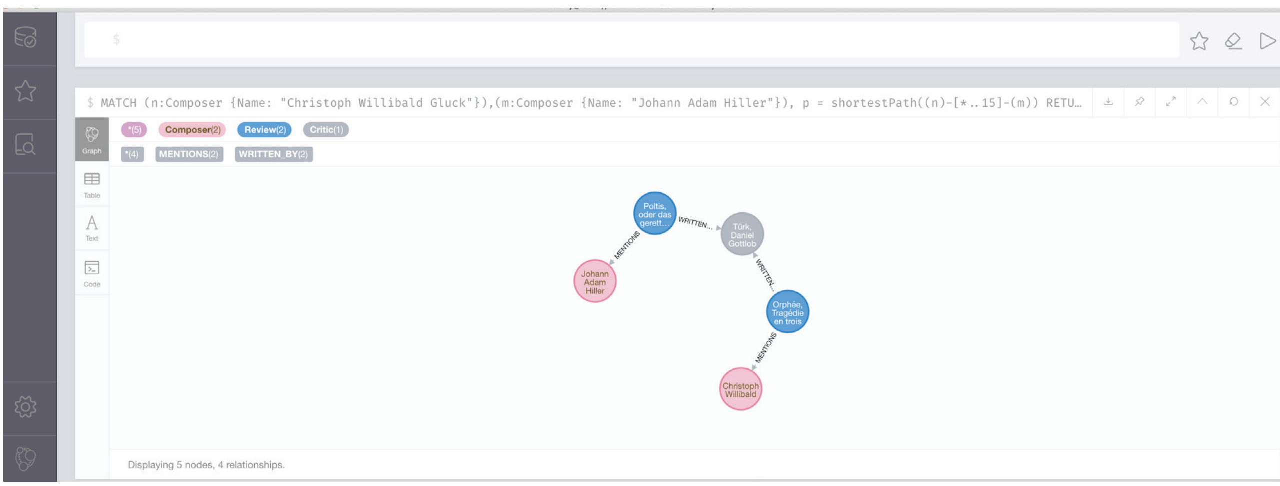

Figure 5: Shortest path search from Gluck to Hiller

Here, the result is fairly simple: there was at least one connection (this one is the shortest path; there may be other longer paths). As it turns out, Gluck and Hiller were both reviewed by Daniel Gottlob Türk. Now, for a more complex example: did Mozart have connections to Berlin? We know that he traveled there once in 1789, but we're now interested in how prominent Mozart's music was there and how Berliners came to know the composer's music.

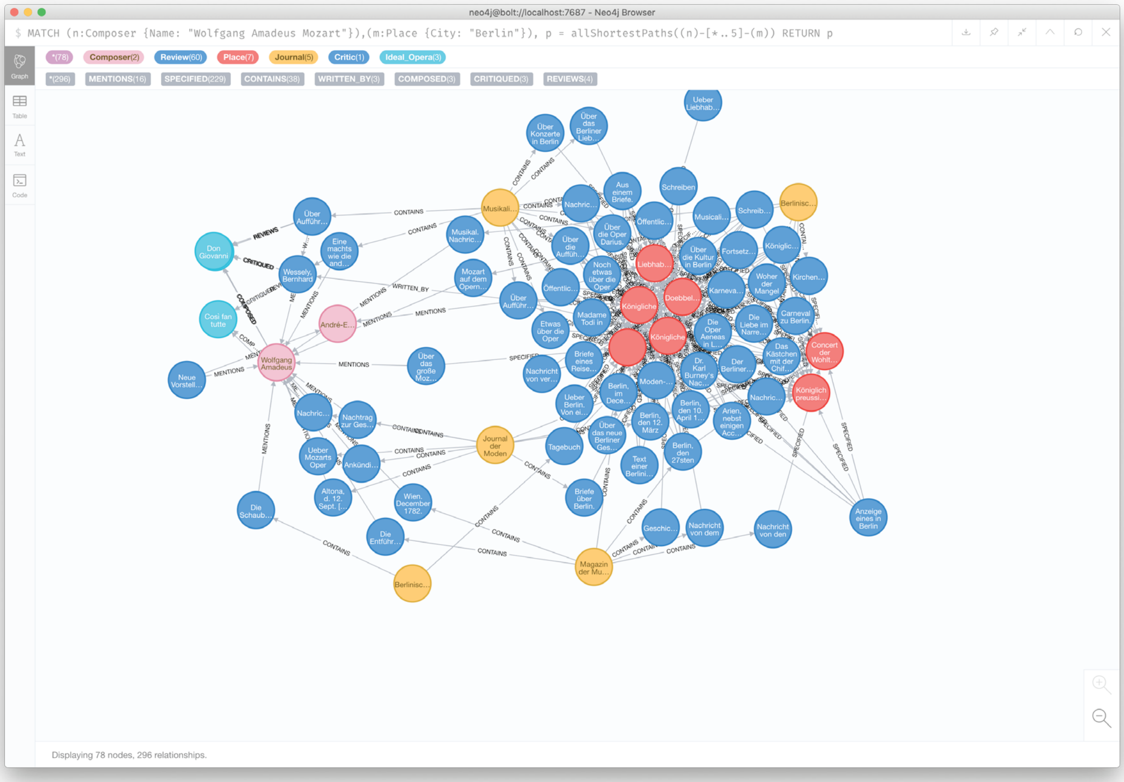

Figure 6: Paths between Mozart and Berlin

There are indeed many paths between Mozart and Berlin. The Mozart composer node is on the left-hand side; connected to it are two of his operas, *Don Giovanni* and *Così fan tutte*. Most of the connections in Berlin are reviews connected to five journals: the *Berlinisches Archiv*, *Journal der Moden*, *Magazin der Musik*, the *Musikalisches Wochenblatt* and *Berlinische Musikalische Zeitung* (these are the yellow nodes). The red node without a label is the city of Berlin, and we also have connections to some of Berlin's musical institutions, most notably the Königlich preussische Hofkapelle (the royal Prussian court chapel), the Königliche Oper (royal opera) and Döbbelin theatre troupe (these are also red nodes). Judging by the short titles of some of the reviews "Über Konzerte in Berlin" (Concerning concerts in Berlin) or "Öffentliche Musik in Berlin" (Public music in Berlin), one might surmise that some of these reviewers are describing eighteenth-century concerts, which often contained separate arias from operas, among other musical numbers.[2] While some reviews offer direct coverage of an opera performance of *Don Giovanni* and *Così fan tutte*, it seems much more likely that Berliners might have gained familiarity with Mozart's music through excerpts in public concert life and via reviews of his music (alongside publications of his scores, of course; the database does not yet list the vast quantities of sheet music circulating during this period). This search for pathways between Mozart and Berlin not only yielded a fairly complex portion of the network. It also hints at our next topic in graph theory: influencers and hubs.

Influencers and Hubs

In his ground-breaking work on network science, Albert-László Barabási examines the underlying structures of complex networks in a wide range of disciplines, including the movement of fish in oceans, the spread of disease, transportation as well as various social networks. Almost all networks, he argues, include an uneven distribution of nodes, the clustering of nodes, and ultimately the formation of hubs [4]. Music networks are no exception. For, as we are well aware, some composers received many more performances and much more critical attention than others. A search for hubs – nodes of particular importance – in the current dataset re-

2 For a discussion on programming concerts in the eighteenth and nineteenth centuries, see [3].

veals the following: the top seven influential nodes are: Johann Adam Hiller, Johann Gottlieb Naumann, Christoph Willibald Gluck, Johann Friedrich Hönicke, Antonio Bianchi, Wolfgang Amadeus Mozart, and Friedrich Ludwig Brandes (these are in orange, Figure 7). Neo4j has grouped these in clusters, surrounded by nodes representing their popular works (in pink) and reviews that generated fame in the public mind (in green).

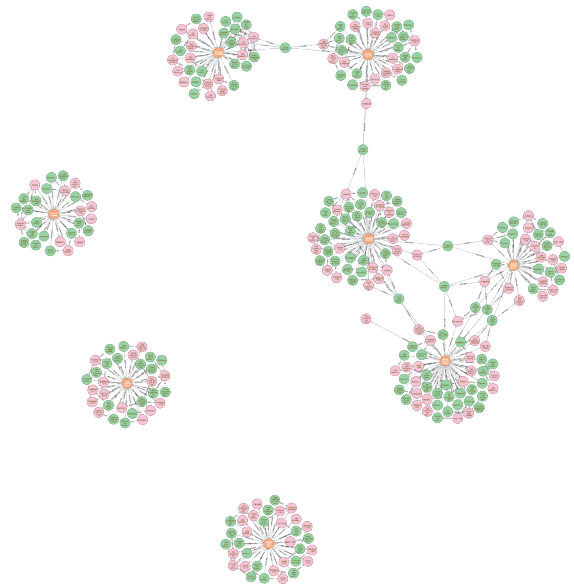

Figure 7: Composer hubs

It is also possible to get a view of these hubs in the network, and this reveals much more context surrounding these influencers. Focusing in on Gluck, for example, we notice that his composer node is close to that of his librettist, Calzabigi. The works that are most prominent (pink nodes) are *L'arbre enchanté*, *Iphigénie en Aulide*, *Alceste* and *Armide*. *Orfeo et Euridice*, a work often taught in music history surveys, seems to have far fewer connections. I would seem that *Alceste*, has many more connections to music criticism. Notably, the German version of *Alceste* (likely performed in Vienna in the early nineteenth century), did not feature prominently in criticism. What is missing here, and indeed, is a next step for this project, is the dimension of time. For fame can indeed be fleeting, and queries such as this one show only a representation of the entire period, 1750-1815. If one were to query by decade or indeed, create a dynamic time-lapse representation, one would like see that Gluck's fame was established with the discourse surrounding *Alceste*, that his fame remained relatively stable, and that toward the late eighteenth and early nineteenth century (that is, after the composer's death), his fame was sustained by performances rather than continued criticism. Performances of works such as *L'arbre enchanté*, *Iphigénie en Aulide* and *Armide* were staples in early nineteenth century Vienna, when there was a craze for French opera (often performed in German), following the arrival of Napoleon's troupes in the city in 1806. Scrolling a bit to the right, one also gets a sense of how Gluck is connected to the broader network of eighteenth-century opera: he is connected to Lully through a review entitled "Gluck und Lulli" but he is also connected to Handel and Rameau through criticism (Figure 8).

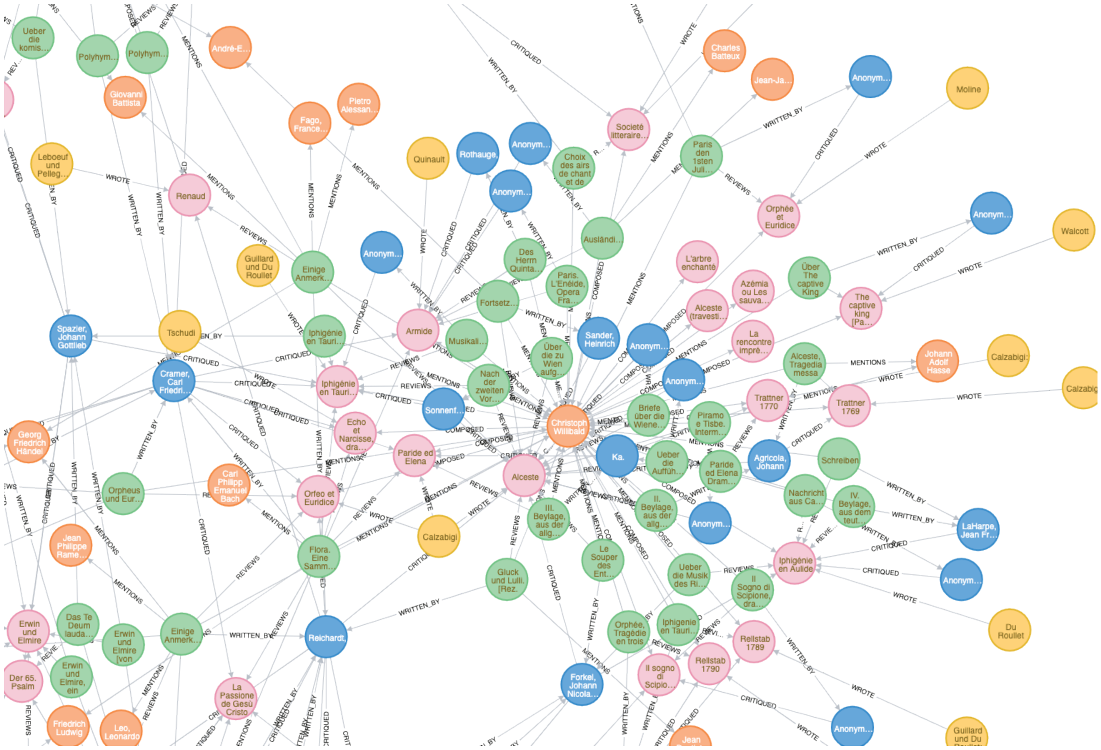

Figure 8: Close-up of composer hubs

Moving to the lower left-hand corner, we also see the prominent hub of a lesser-known composer and musician: Antonio Bianchi.

Figure 9: Structures of composer hubs

And here, the obvious question is: do the hubs of canonic composers look different in structure compared to those who are lesser known. And, for scholars interested in machine learning and AI, the obvious next step is: can one predict fame, especially for musicians today? Neo4j does offer some predictive algorithms in their graph data science playground, though they are relatively new and still experimental. At first glance, Bianchi seems to have composed a similar number of operas, compared to Gluck and most of his operas are connected to a review, an ideal opera and a librettis.

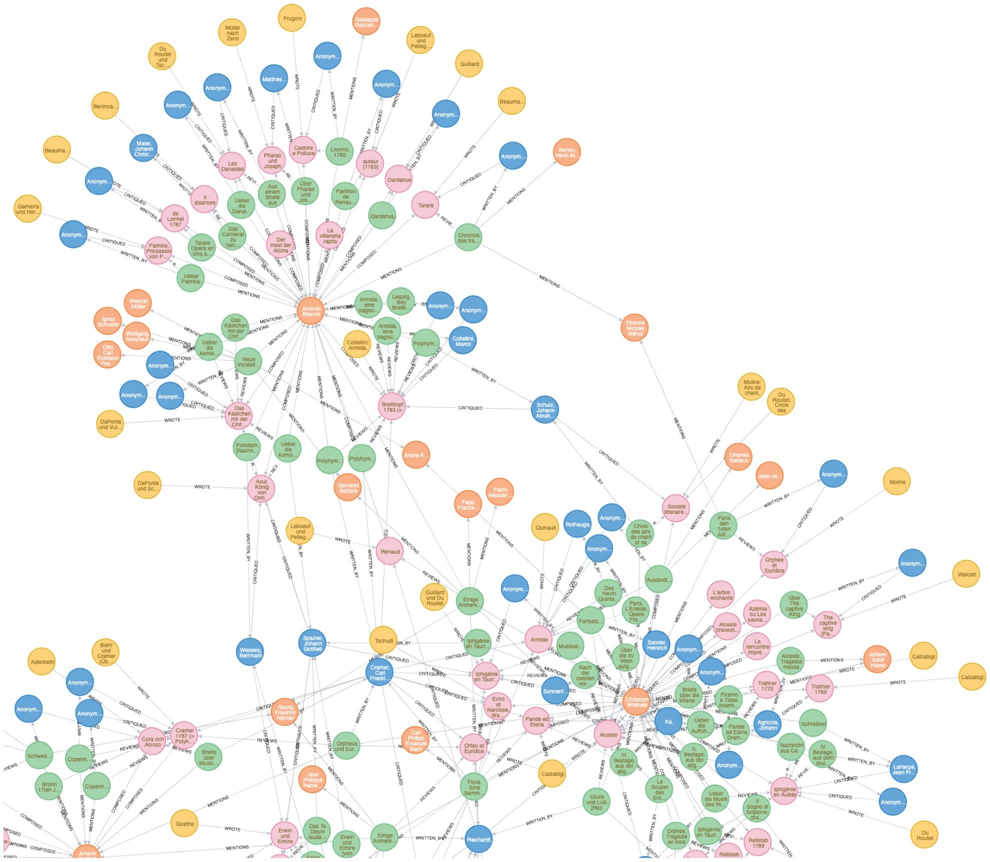

Figure 10:

Yet somehow the Bianchi hub simply looks much cleaner than the Gluck hub; fewer pathways traverse through the node, and the context seems "less messy" if you will. While it is far too soon to connect messy networks structures to lasting fame – clearly much more work remains to be done on this – this idea of patterns of fame surrounding hubs holds much promise.

Clusters and Communities

Hubs bring to prominent nodes (individuals or works) to foreground, while community detection in graph theory is concerned with similar things naturally grouping together. In a social network, some nodes naturally have more connections than others, and musical communities form around performance events, genres, debates in music criticism, societies in particular cities and star singers, to name only a few. It is fair to assume that communities play a substantial role in generating musical fame and by extension, canon formation. Much more challenging, however, is to uncover these communities in a given network and analyze patterns within those communities. Let's begin with a relatively simple example: a search for troupes connected to performances of Mozart's *Die Zauberflöte* (Figure 11).

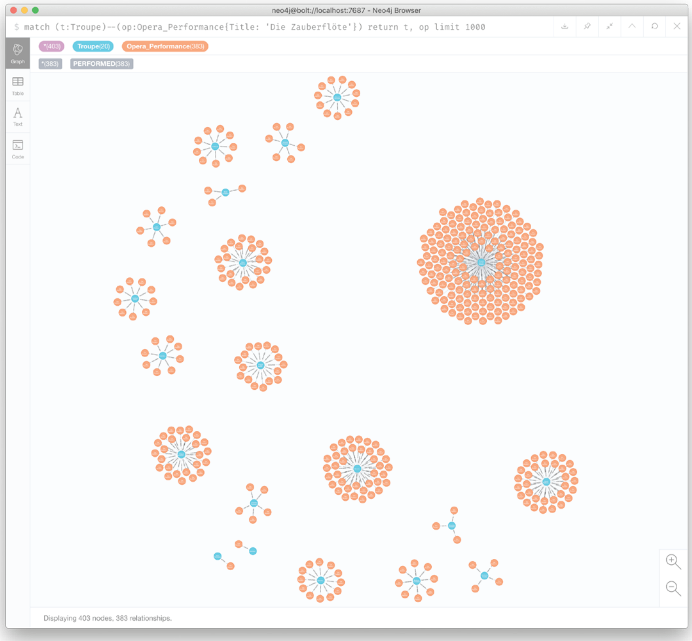

Figure 11: Performances of Mozart's *Die Zauberflöte*

The query returns a range of clusters of performances, each stemming from a theatre troupe or resident theatre company. The largest cluster, of course, is the Theater auf der Wieden in Vienna, where the Mozart's famous opera was premiered. But, as is evident, the opera was also performed at the Kärntnertortheater in Vienna, the National Theatre in Berlin and the Prague National Theater (these are three second largest communities). Subsequently, we have even smaller centers such as Mannheim and Innsbruck as well as traveling troupes such as the Schuch and Vollotini companies. Queries such as this one tell us about the relative size of performance clusters for a famed opera, which is a useful for a broader bird's eye-view perspective, perhaps prior to zeroing in on a particular group.

Yet along with communities comes the challenge that social networks do not only have bi-directional edges, but in some cases, especially in global music mobility, there are asymmetrical power-relationships at play. Here, I turn to an example from the work of one of my students, Sr. Ilaria Culshaw, and her paper for my research seminar on operatic mobilities [Figure 12].

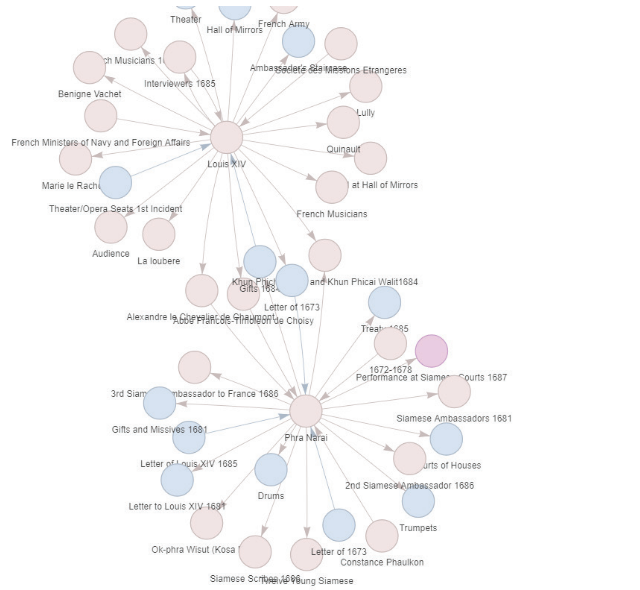

Figure 2 The main hubs which form around the two monarchs.

	Louis XIV	Phra Narai
Total Number of Connections	22	22
Number of Connections representing the monarch's own agency	18	15
Number of connections representing the monarch being acted upon	4	7

Figure 12: Sr. Ilaria Culshaw's visualization of French-Siamese relations using graph9

Culshaw graphed (using our custom graph visualization software called graph9) French-Siamese musical encounters between Louis XIV and the Phra Narai in the late seventeenth century [5]. Her work was based on primary source documents analyzed in a study by my colleague David R. M. Irving in his article, *Lully in Siam* (present-day Thailand).[3] One of the figures in her essay represents the two communities, each with their respective monarch in the centre. That all the arrows point back to each of the monarchs arguably illustrates an important point about these societies: power is concentrated at the centre and in a single person in monarchical societies. In this particular diplomatic visit, cultural exchange could only be facilitated by people and things represented here by a few common nodes: some ambassadors from both parties and a letter of 1673. With so few commonalities, it is perhaps unsurprising that this cross-cultural encounter went awry, like so many others in the early modern period. This example illustrates two notable features of graph theory: that two communities can exist entirely on their own, at great geographic distance, and that it only takes a few (sometimes even one) connecting node to suddenly collapse the distance between two far-away communities. Of course, important nodes that connect two otherwise separate communities appear, disappear, and reappear over time. Second, at least on French soil there was an asymmetrical power-relationship at play. More sophisticated graphing tools and algorithms able to cope with weighted nodes would bring these asymmetrical relationships into relief.

While monarchical societies have a particular structure, so do democratic societies, and my database reflects society at a time in which liberal-democratic ideals were just beginning to take hold. Public perceptions of fame reigned supreme by the eighteenth-century, as Schulze, the critic commenting on the year-long pop-

3 https://github.com/ejoubert/graph9

ularity of a clumsy folk-tune suggests. Yet even within the public sphere, musical communities might differ in their structure, make-up and impact on generating musical renown. One of the advantages of graph theory is that it has the potential to both detect community formation and, with appropriate algorithms, detect patterns distinct to individual communities. The neo4j graph data science playground is a relatively new plug-in intended to facilitate the exploration of datasets with complex algorithms. The idea behind the playground is that one does not need to deal with the code directly but can still benefit from the power of often-called algorithms through an easier-to-use interface. However, the tool is still experimental. I was able to get some preliminary results for the community-detection (Figure 13).

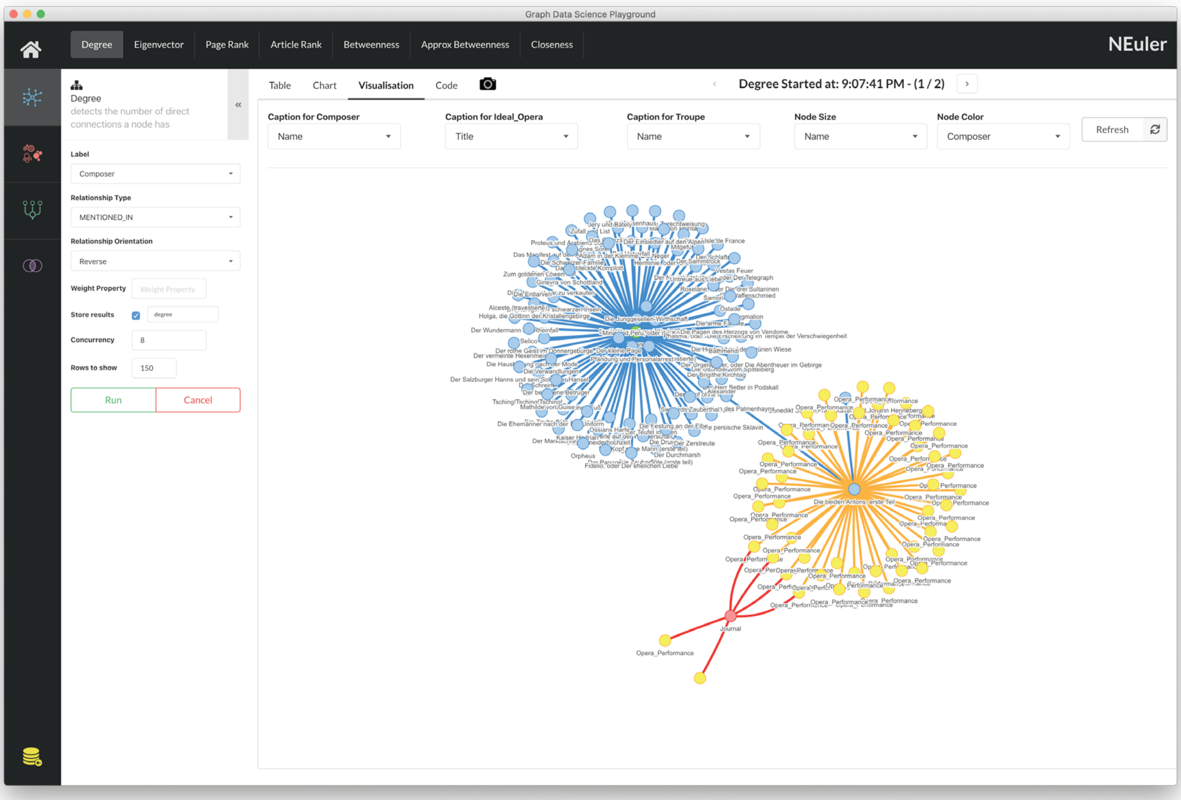

Figure 13: Emerging communities using neo4j Graph Data Science Playground

The largest community seems to be centered, unsurprisingly, around genre: the German opera node. A subset of that community is centered on an opera that opened the Theater auf der Wieden just two years before Mozart's *Die Zauberflöte* was premiered there: Benedict Schack's *Die beiden Antons*. In fact, this suggests that the community for *Die beiden Antons* is likely stronger (or perhaps larger) compared to that of Mozart's opera. Future research for this project will be focused on pattern detection to see how various communities (once identified) are structured, and how that structure has an impact on canon formation. Some interesting questions might include: did communities for symphonic music look different than communities concerned with opera? Do the subcommunities have similar structural patterns or do some of them differ (and why?). Does the behaviour of musical communities change over the course of time? While graph theory has already provided valuable insights into how operatic fame is generated in my dataset, many more insights remain to be discovered traversing these networks of operatic fame.

Works Cited

[1] Schulze, J.F., "Publikum" *Deutsches Magazin* 15 (1798), 332-6.

[2] Barabási, Albert-László, *Linked: The New Science of Networks.* Cambridge, MA: Perseus Publishing, 2002.

[3] Weber, William, *The Great Transformation of Musical Taste*. Cambridge: Cambridge University Press, 2008.

[4] Barabási, Albert-László, *Network Science.* Cambridge: Cambridge University Press, 2016.

[5] Irving, David R. M., "Lully in Siam: Music and Diplomacy in French-Siamese Cultural Exchanges, 1680-1690" *Early Music* 40 n. 3 (2012), 393-420.